DISSERTATION

# THREE ESSAYS ON PANDEMIC-DRIVEN SHIFTS IN FOOD PURCHASING AND POLICY: INSIGHTS FOR STRENGTHENING FOOD SYSTEM RESILIENCE

Submitted by

Mackenzie Gill

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

Summer 2025

Doctoral Committee:

Advisor: Dawn Thilmany
Co-Advisor: Becca B.R. Jablonski

Alessandro Bonanno
Lauren Chenarides
Megan Mueller

ABSTRACT

THREE ESSAYS ON PANDEMIC-DRIVEN SHIFTS IN FOOD PURCHASING AND POLICY: INSIGHTS FOR STRENGTHENING FOOD SYSTEM RESILIENCE


These three essays explore how pandemic-era shifts in (1) consumers' purchasing behaviors and (2) federal food policy may inform strategies to improve current and future food system outcomes. The COVID-19 pandemic caused significant shifts in food consumption patterns, some of which have persisted into the current food environment. Given the supply chain disruptions that occurred during this time, the pandemic also provides a case study for examining the tradeoffs of policy that supports flexible supply chains. Through three essays, this work examines purchasing behaviors and policy responses to uncover insights that can bolster the resilience of food markets in the face of future disruptions.

The first essay explores the relationship between consumers' selection of multiple food market types and their usage of online FAH shopping options. National consumer survey data and latent class regression is used to capture various food shopping behaviors in the post-pandemic food environment. Two classes of online shoppers are discussed: values-driven consumers who use online options to find niche products, and frugal consumers who rarely use online options, but sometimes do so to save time and find bargains. The second essay uses Circana Retail Scanner Data to analyze consumers' stockpiling behaviors in response to pandemic-induced fears changes in pandemic-related public policies. The stockpiling of specific food categories is explored, with delineations made between perishable and non-perishable food. The third essay uses recent Difference-in-Difference techniques to evaluate the Farmers to Families Food Box (FFFB) program's impact on contracted businesses' employed labor, survival, and market opportunities. This analysis informs ongoing federal and state-level efforts to enhance food assistance programs and ensure food system resilience in times of crisis.

# ACKNOWLEDGEMENTS

I would like to extend a heartfelt thanks to my incredible advisor, Dawn Thilmany. This dissertation would not exist without her wise input, compassionate understanding, and unwavering encouragement throughout my entire doctoral program. I would also like to thank my other committee members: Becca Jablonski, Alessandro Bonanno, Lauren Chenarides, and Megan Mueller. Each of you have gifted me your invaluable time, and your support and instruction have shaped me into the researcher that I am today.

I also want to thank my wonderful family. My grandparents - David, Doris, Lenore, and Lester - whose financial support and inspiring resilience made it possible for to pursue this degree. I felt your love in many of the hardest moments. My mom, Karen, for all of the trips to the South Knoxville Library that led to my love of knowledge. My dad, John, for the “walking around the world" that instilled deep curiosity in me. My step-parents, Dale and Deborah, for always being a source of brevity and a shelter in the storm. My sister and best friend, India, for never failing to pull me back from the brink of self doubt - or to make me laugh hysterically. My soul-dog, Scout, for being an infinite well of comfort and for literally being by my side as a I typed every word of this dissertation. And to my husband, Ethan - you support me in a thousand ways. The endless dinners, chores, laughs, hugs, cups of water all got me to the finish line. But more importantly, I never would have pursued this dream if it weren’t for the journey we’ve taken together. I love you all endlessly.

## DISCLAIMERS

The findings and conclusions in this dissertation are those of the author and should not be construed to represent any official USDA or U.S. Government determination or policy. The analysis, findings, and conclusions expressed in Chapter 3 of this dissertation should also not be attributed to Circana (formerly IRI). Additionally, the analysis, findings, and conclusions expressed in Chapter 4 of this dissertation should not be attributed to Walls & Associates or Dun & Bradstreet (D&B).

# DEDICATION

*This dissertation is dedicated to the women who came before me; to those who broke glass ceilings and paved the way, and to anyone who has ever struggled to believe that they are capable of achieving their wildest dreams.*

*May this work stand as a testament that we all deserve a seat at the table.*

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

# Chapter 1

# Introduction and Literature Review

In 2020 and 2021, the COVID-19 pandemic shock dramatically affected food systems in ways that shifted consumer purchasing behaviors, supply chain resilience strategies, and the food policy landscape. Soon after the onset of the pandemic, lockdown measures were enacted in the United States (US), which included stay-at-home orders, closures of schools, restaurants, and other congregation places, and social distancing restrictions (Centers for Disease Control and Prevention (CDC), 2022). One major implication of the pandemic on food systems was that the food-away-from-home (FAFH) channels shut down, and food-at-home (FAH) channels suddenly needed to adjust to meet the shifting demand and purchasing patterns of consumers and institutional buyers (Hobbs, 2020). This supply chain challenge was exacerbated by temporary labor shortages from illness and subsequent bottle-necking of supply chains, substantial increases in household need for food assistance due to income losses and school closures, and significant changes in consumers' food shopping patterns (Chenarides et al., 2021a; Finck and Tillmann, 2022; Hobbs, 2021; Thilmany et al., 2021b).

The U.S. federal and state governments quickly responded to provide much needed support to food system participants. "Urgent and compelling" food policies that were implemented included Pandemic-EBT dollars that supplemented school meal program participants' income, bolstering of food pantries and food businesses via food box programs, and historically high benefit allocations to Supplemental Nutrition Assistance Program (SNAP) and Women Infants and Children (WIC) program participants (Jones, 2022; USDA Agricultural Marketing Service, 2023).

The dynamic nature of these shocks, and the relatively quick policy response, are an interesting empirical context to explore consumers' shifting shopping behaviors, food business adaptation strategies, and policy roll-outs all morphed in response to the changing COVID-19 environment. The pandemic-induced changes were non-uniform over time, as viral waves and associated mitigation policies fluctuated across time and spatial regions. Bonanno et al. (2025) investigate this dynamic, measuring shifts in consumer expenditures at various retail channels across lockdown, winter wave, summer wave, vaccination, and new normal periods of the pandemic (Bonanno et al., 2025). Furthermore, consumer heterogeneity added a layer of complexity to the pandemic effects, as household experiences varied tremendously throughout the pandemic, depending on essential worker status, perceived health vulnerability, presence of children, and access to food markets (Chenarides et al., 2021a; Ellison et al., 2021; Finkelstein et al., 2024; Jensen et al., 2021). Among food markets,, local and regional markets' flexibility made them well-suited to adapt to these heterogeneous responses to pandemic-era shifts.

In the wake of the pandemic, there has been much discussion about food system resiliency. To better prepare for future disruptions, it is important to understand what factors allowed the US food system to adapt to uncertainty and which aspects diminished markets' ability to respond so that we can understand the tradeoffs of prioritizing these factors, even in the absence of disruption. This dissertation includes three papers which each investigate a particular way in which US food markets exhibited resilience in response to the historic COVID-19 pandemic, and together convey how diverse markets and consumer heterogeneity contribute to the ability of the food system to withstand substantial uncertainty. Before beginning this exploration, a scan of the literature provides important context and background from the market and consumer fields aligned with each of these studies.

## 1.1 Heterogeneous Impacts of COVID-19 Pandemic on Households

Shifts in consumers' food shopping habits and panic buying behaviors during the COVID-19 pandemic not only affected food supply and prices. The resulting shifts in demand also rippled across the food supply chain, requiring food retailers, distributors, manufacturers, and producers to quickly adapt (Hobbs, 2020). Given that future events will inevitably continue to affect food systems and how heterogeneous behavior affected supply chain dynamics, it is important to better understand how food markets responded to high levels of uncertainty and supply chain disruptions, including the factors driving consumers' shopping responses.

Consumer characteristics like demographics, location, and shopping preferences are a known source of heterogeneity that affects purchase decisions. However, the COVID-19 pandemic presented new ways in which household characteristics became relevant to food shopping behaviors. The first consumer characteristic that affected the magnitude of their food shopping shifts was how vulnerable their household was to the COVID-19 virus (and influenced their perceived access to markets). Especially before the availability of COVID-19 vaccinations and implementation of mass mandates (see figure 3.2 for these timelines), households that included elderly, children, and the immunocompromised were more likely to engage in illness-avoidant behaviors (Dickins and Schalz, 2020). In addition to populations that were vulnerable to COVID severity, consumers who were most worried about contracting COVID-19 or perceived it to be dangerous were also likely to engage in illness-avoidant shopping behaviors (McFadden et al., 2020; Omar et al., 2021; Sim et al., 2020). Illness-avoidant behaviors that related to food shopping included streamlining shopping trips, stockpiling food, shopping for food online and even selecting retailers that were less likely to be crowded (El Baba and Fakih, 2023; Harris-Lagoudakis, 2022; Jensen et al., 2021; Sadus et al., 2023; Seo, 2024). Shamim et al. reported that many respondents aimed to shop quickly and efficiently, minimizing their time spent in stores to reduce exposure risk (Shamim et al., 2021). This behavior aligns with findings from other studies that noted that a significant percentage of consumers increased their online shopping to avoid germs and the risk of COVID-19 infection (Chenarides et al., 2021a; Jensen et al., 2021; Lo et al., 2021). The urgency to complete shopping tasks efficiently was also a common theme, as consumers sought to limit their interactions with others (Lo et al., 2021). Regarding reports of stockpiling and other panic buying behaviors, Alaimo et al. observed that consumers engaged in hoarding food items to ensure they had sufficient supplies while minimizing the need for frequent shopping trips (Alaimo et al., 2020). Several studies found that perceived risks associated with shopping led consumers to adopt online grocery shopping as a safer alternative (Chenarides et al., 2021a; Gao et al., 2020; Jensen et al., 2021). Motivated by this literature, the first and second chapters of this dissertation investigate online shopping and stockpiling behaviors as two of the key consumer responses to COVID-19: one focused on market choice and the other on product choices and volumes.

Consumers' valuation of food attributes, commonly referred to as “food values", were also a source of consumer heterogeneity affecting food purchasing behavior(Lusk and Briggeman, 2009). A study by Ellison et al. (2021) found that food values were largely stable over the pandemic, but evidence of a lower priority for nutrition and price (Ellison et al., 2021). On the other hand, Ogundijo et al. reported that consumers shifted their purchasing patterns towards healthier food options, driven by a belief that their food choices could significantly impact their health and well-being during the pandemic (Ogundijo et al., 2021). Another study which found evidence of shifts in food values suggested that consumers with a strong sense of environmental responsibility were more likely to purchase local food products during the pandemic (Bimbo et al., 2021). This trend reflects a growing awareness of the impact of food choices on local economies and the environment, as consumers sought to support local farmers and businesses in the face of economic uncertainty. Similarly, Edmondson (2021) reported that some consumers prioritized purchasing from local sources, driven by their personal priority to support the local economy (Edmondson et al., 2021).

Another food value that some consumers were found to reevaluate was their food safety perceptions. Liboredo et al. found that consumers became more concerned about the safety of food, including the origin of ingredients and hygiene practices during food preparation and delivery (Liboredo et al., 2022). This heightened awareness of food safety influenced purchasing decisions, with consumers increasingly favoring brands and retailers that prioritize safety measures. Similarly, Wang et al. reported that consumers now have heightened expectations for hygiene practices in grocery stores, resulting in reduced frequency of store visits and longer shopping durations (Wang et al., 2020). This heightened awareness of food safety issues is likely reflected in shifts in consumers' retail selection decisions, and in particular, their choice to utilize online shopping options. We explore this dynamic in the first essay of this dissertation.

During the COVID-19 pandemic, the conceptualization of household type was somewhat different compared to pre-pandemic approaches. Traditionally, household type was treated as a relatively static characteristic defined by demographic composition, income level, or labor force status. However, the pandemic introduced new dimensions of vulnerability and adaptability that necessitated a more nuanced understanding. Household structure became increasingly fluid, with trends such as multigenerational living, adult children returning home, and informal cohabitation arrangements emerging in response to economic and caregiving pressures (He and Jia, 2024). Moreover, the presence of dependents and high-risk individuals within a household gained importance as determinants of exposure risk, labor supply decisions, and access to public assistance (He and Jia, 2024). School and childcare closures amplified heterogeneity of experiences across household types, with single-parent households and those without remote work flexibility being particularly challenged (Hertz et al., 2021; Naito et al., 2022). These shifts facilitated a broader move toward modeling household type (and other heterogeneous household experiences) not only as a socioeconomic descriptor but as an indicator of resilience, constraint, and policy relevance in times of crisis. For example, households with school-aged children became responsible for providing their education, as well as preparing all meals, when schools were closed. This shift within the household presented a challenge for both essential workers who were required to continue commuting to work and non-essential workers who may have been home, but were forced to either hire help or take time away from their work day for childcare. For both these groups, the convenience of online food shopping options may have been appealing (Jensen et al., 2021), and for those with more time available for shopping, the availability of online food shopping options may have made it easier to skip the one-stop shopping experience and diversify their retailer selections (Houghtaling et al., 2023). This concept is explored in depth in the first essay of this dissertation.

## 1.2 Time Allocations and Shopping Decisions

One outcome of the COVID-19 pandemic was that, for many individuals, there were substantial shifts in the amount of time spent at home. In addition to the heightened levels of unemployment that occurred during the COVID-19 lockdown period (US Bureau of Labor Statistics (US BLS), 2020), many non-essential workers worked from home during the pandemic. On the other hand, essential and frontline health workers were in high demand and may have experienced decreased time available for home responsibilities as their work hours increased. A National Bureau of Economic Research working paper surveyed with 25,001 consumers about their job status at the onset of the pandemic: 37.1% reported continuing to commute to work, 35.2% reported switching to a work from home environment, 15.0% reported continuing a work from home environment, and 10.1% reported being recently furloughed or laid off (Brynjolfsson et al., 2020). This implies that around 65% of the labor force was spending more time at home at the onset of the pandemic in April and May. Changes in the restrictiveness of consumers' time available for shopping and meal preparation likely contributed to changes in consumers food shopping habits. In the first essay of this dissertation, we explore how differences in time allocations across subsets of the population contributed to disparities in consumers' market selection decisions (including in-person vs. online), with further implications for disparities in food assistance participation, food security, and the nutritional quality of diets.

While the share of those working from home may have decreased in later phases of the pandemic, such as after vaccine roll-outs, working from home was a persistent experience throughout the pandemic. Moreover, consumers who were most vulnerable and/or concerned about mitigating virus exposure stayed at home when possible (Seo, 2024). A US Household Pulse survey conducted in August 2020 found that 46.8% of respondents reported exclusively engaging in protective, or illness-avoidant, behaviors, with 48.8% reporting that they changed their behavior because they were "concerned about going to public or crowded places" (US Bureau of Labor Statistics (US BLS), 2020). For households with children at home, spending more time at home did not necessarily mean that a household had more time available for preparing food. Yet, for other household types, it did mean that time budgets were made less restrictive (Restrepo and Zeballos, 2020).

Previous research has shown that the time-inclusive cost of preparing food at home (FAH) varies across subsets of the US population, and, there are tradeoffs between preparing healthier

FAH meals and time. For example, work by Davis and You (2010) found that the cost of time in at-home food preparation is typically 26% higher for food stamp participants compared to the general population. This implies the existence of an incentive for food insecure individuals to purchase pre-prepared food and/or food away from home (FAFH), yet, increased FAFH purchases have been found to result in reduced diet quality (USDA Economic Research Service, 2010a). Not to mention, there were times during the pandemic when FAFH retailers were closed (Centers for Disease Control and Prevention (CDC), 2022). Prior research also indicates that there is a relationship between those who work from home and the amount of time spent preparing food at home. Research on pre-pandemic data has shown that individuals working from home spend 25 more minutes preparing food at home on average (Restrepo and Zeballos, 2020). When considering these correlations in the context of the pandemic-era labor force dynamics, it is plausible that the food security disparity may have been amplified during the pandemic as essential workers spent more time away from home and nonessential workers experienced more time available for home responsibilities.

Time allocation is also relevant when considering households' participation in food assistance programs. The time intensiveness of procuring food via public food assistance programs varies depending on the program. For example, SNAP is accepted by more food retailers compared to WIC, and benefits are distributed electronically (USDA Food and Nutrition Service, 2024). Additionally, just before the pandemic, efforts were made to support online utilization of SNAP. During the pandemic, participants were able to apply for benefits online and make online food purchases with their benefits at many major grocery retailers' websites (USDA Food and Nutrition Service, 2023). A recent study which leverages the staggered implementation of the SNAP Online Purchasing Program across states found that the SNAP OPP was associated with higher frequency and expenditures at online grocery outlets, which increased the healthfulness of FAH purchases by participating households (Kuan et al., 2025). This finding exemplifies how low-income households may particularly benefit from time-saving aspects of food assistance programs. However, WIC still requires in-person appointments to register, and in most states, benefits are physically distributed rather than via an electronic card. The federal response to school meal program access loss was to implement Pandemic-EBT dollars, which was similar to SNAP in terms of time-intensiveness in that emergency federal funds were distributed to school meal program participants.

In summary, the heterogeneity of time budgets during the COVID-19 pandemic reflected a complex interplay of factors including employment status, health concerns, and access to resources. Essential workers found their time at home significantly reduced, thereby impacting their ability to engage in home food preparation. Meanwhile, nonessential workers often experienced an increase in home-bound time, potentially enhancing their capacity for such meal preparation activities. Differences in the restrictiveness of consumers' time budgets contributed to disparities in consumers' market selection decisions (including in-person vs. online), as well as disparities in food security and the nutritional quality of diets between different segments of the population. The pandemic also accelerated the adaptation of food assistance programs to the digital age, improving access for some but still leaving gaps due to the variability in program requirements and technological integration. These shifts in time allocation and resource access underscore the importance of accounting for consumer heterogeneity in our analysis of food purchasing behaviors, including market selection and stockpiling behaviors, during the pandemic.

## 1.3 Heterogeneous Responses to Supply Chain Vulnerabilities

Consumers' diverse characteristics also led them to respond to food supply uncertainty and supply chain disruptions in differing ways, in terms of where they chose to shop and how much they chose to buy. One way that some consumers responded was a new interest in purchasing from local, niche and independent food retailers. A subset of consumers expressed interest in local food systems, as they perceived them as safer and more reliable alternatives to disrupted global supply chains (Thilmany et al., 2021b). Thilmany et al. (2021b) conveyed evidence of this trend by highlighting a surge in community-supported agriculture (CSA) memberships and increased patronage of local farmers' markets as consumers sought fresher and perceived safer food sources.

As mentioned previously, other studies posited that this shift also reflected a broader desire to support local economies during a time of economic uncertainty (Bimbo et al., 2021).

Consumers also responded to supply chain disruptions during the pandemic by using online options at higher rates (Chenarides et al., 2021a; Harris-Lagoudakis, 2022; Jensen et al., 2021). While the usage of online tools for food shopping was rising prior to the pandemic, the interplay of a higher number of food business offering new or enhanced online shopping options and consumers newly interested in avoiding time spent in public accelerated adoption of online shopping during the pandemic (Jensen et al., 2021; Verdon, 2020). Perhaps more than any other food purchasing habit shift, online food shopping has persisted beyond the pandemic and even continued to rise (USDA Economic Research Service, 2023). With the persistence of this behavior in mind, it is important to understand the factors driving various consumer subsets to use online purchasing tools for food shopping. This literature is described in more detail in the next chapter of this dissertation.

Previous studies highlight the panic-buying behaviors that some consumers exhibited when food supply shortages were perceived or even expected (Finck and Tillmann, 2022; Omar et al., 2021; Schumacher and Micheli, 2024). While previous literature on stockpiling focuses on non-perishable good purchasing, we find preliminary evidence that consumers also stockpiled perishable food, as discussed in the third chapter of this dissertation (Erdem et al., 2003; Wang et al., 2014). This is aligned with other literature that found evidence of increased food waste from over-purchasing of perishable food (Cosgrove et al., 2021; Li et al., 2024). The impulse towards stockpiling highlights how such behavior likely exacerbated ongoing supply chain vulnerabilities during COVID, a time of unprecedented uncertainty and dynamic policy changes.

### 1.3.1 Resilience of Local and Regional Markets

While the specifics of the food system resilience definition remains in flux, generally, food system resiliency refers to the capacity of a food system to withstand and recover from disruptions while maintaining essential functions such as food production, distribution, access, and affordability (Hadachek et al., 2024a; Rude, 2021; Tendall et al., 2015). According to this literature, we understand resilient food systems to be those that are able to adapt to both sudden shocks—such as natural disasters, pandemics, or supply chain failures—and long-term stresses including climate change, market volatility, and systemic inequities. Beyond simply returning to a pre-crisis state, resilient systems can also transform in response to changing conditions, fostering sustainability, equity, and improved food security over time (Béné, 2020; Meuwissen et al., 2019).

**Local and Regional Markets' Contributions to Resilience**

Local and regional food markets are well suited to promote food system resiliency due to their decentralized and diversified and responsive supply chains. These regionalized supply chains may play a role in reducing dependence on large-scale, centralized distribution systems that are more vulnerable to disruption (Thilmany et al., 2021b). Being composed of a larger number of small- and mid-sized farms, many of which produce specialized crops and/or food that is sold to value-added supply chains, local and regional markets encourage diversified agricultural production, which enhances ecological resilience and reduces the risks associated with monoculture and long-distance food transport (Meuwissen et al., 2019). Furthermore, shorter supply chains within local and regional food systems often enable quicker adaptation during crises by maintaining local access to food when national or global systems falter (Béné, 2020; Hobbs, 2021; Meuwissen et al., 2019; Thilmany et al., 2021b).

In addition to the benefits stemming from the structure of local and regional food systems, these markets contribute to resilience by promoting more diversified regional economies. Local and regional markets tend to recirculate financial resources within communities, strengthening local economies and supporting vulnerable populations (Jablonski et al., 2021; Watson et al., 2007). They also foster closer social networks among producers, and between producers and consumers, enhancing economic opportunity for stakeholders, and increasing trust and transparency between the sellers and buyers (Rocker et al., 2022; Thilmany et al., 2021a). Moreover, local and regional markets often serve as testing grounds for innovative, community-led governance and policy approaches that can inform broader systemic change (Béné, 2020).

Together, these features suggest local and regional food markets can be key contributors to a resilient and adaptive food system. The COVID-19 pandemic tested food systems' resilience and provided an opportunity to understand how markets respond to simultaneous stressors, including shifting of consumers' shopping behaviors, wholesale distribution and supply chain disruptions, and increased food insecurity (because of these disruptions and broader economic volatility). Further research is needed to understand the full impact of these shifts and to guide policy and business strategies that foster more resilient supply chains and respond in a more informed way to consumers' behavior patterns. The goal of the following three essays is to contribute to the growing literature on food supply chain resilience during and since the COVID-19 pandemic.

## 1.4 Dissertation Structure and Contributions

This dissertation follows a three-essay format. The first of the tree essays (Ch. 2) investigates consumers' usage of the nascent growth in online food shopping options, specifically exploring consumers' propensity to select several types of market channels for food-at-home shopping in the post-pandemic food environment (October 2023). The post-estimation analysis provides details about where each class of consumers are shopping in-person and online, as well as how they have reported changing their food shopping behaviors in other ways since the COVID-19 pandemic. Findings shed light on one example in which the food system was resilient to consumers' behavioral shifts; we provide insights into the ways in which increased incidence of online food shopping options may have catalyzed and accelerated consumers' exploration of food market types. We also contribute to an understanding of challenges and opportunities emerging in this new era of online shopping behavior, including curbside pick-up and delivery options, for a variety of market channel types in the current food environment.

As another approach to explore consumers' responses to pandemic-related fears and emerging policy initiatives, the second essay (Ch. 3) investigates consumers' decision to stockpile both non-perishable and perishable food-at-home in response to various COVID 19-era shocks. The investigation of these shocks is intended to disentangle whether fear of COVID mortality, social distancing policies, or uncertainties related to supply chain failures / food shortages impacted produce stockpiling decisions. We use Circana Scanner Data in this analysis, combined with policy data from the Center for Disease Control and Prevention (CDC) and Google Trend search results. Findings from this investigation highlight how consumers shift their food shopping patterns in response to market uncertainties regarding food supply, food prices, and federal policies affecting market access.

Lastly, the third essay (Ch. 4) provides an ex-post analysis of the effectiveness of the Farmers to Families Food Box (FFFB) program by examining its impacts on contracted vendors' performance during and after the pandemic. One of the first policies that the government deployed to defend food system resiliency was to create the FFFB program. The FFFB Program was established as a way to replace the sales and market channels that vulnerable food businesses lost as FAFH outlets were forced to close, and also served as a policy lever to quickly provide food assistance in hard-to-reach areas (USDA Agricultural Marketing Service, 2023). Using data from the USDA National Establishment Time Series (NETS) database as well as USDA AMS Commodity Procurement data, we explore a specific, policy-driven case of how smaller food businesses' market response contributed to food system resilience. These findings thoughtfully consider factors that improve the efficacy of government procurement programs, both during stable periods and as a response to market disruptions. Specifically, our results find little evidence that this program affected employment levels, which highlights the importance of fully understanding the opportunity costs of implementing a program that aims to provide temporary relief to participants.

# Chapter 2

# Exploring the Relationship Between Growth in Online Shopping and Multichannel Food Consumers

## 2.1 Abstract

Moving beyond the COVID-19 pandemic, it is important to assess which responses to supply chain disruptions may persist, and also, which of these responses have the potential to increase market access for local and regional farms and food producers. During the pandemic, many food retailers began offering online food shopping options for the first time, either directly or through the use of e-commerce platforms (CSA Innovation Network, 2020; Thilmany et al., 2021b; Verdon, 2020). Many consumers began using these online food shopping options, driven by pandemic era shocks including shortages at major food retailers from supply chain disruptions, fear of viral contagion and food availability, and heterogeneous shifts in the amount of time that consumers had available for food shopping (Chenarides et al., 2021a; Harris-Lagoudakis, 2022; Jensen et al., 2021). Yet, the usage of online food shopping options has persisted beyond the pandemic. For example, 2022 inflation-adjusted data from the Food Expenditure Series shows that real mail order and home delivery food expenditures are 26% higher than they were in 2019, and even 5% higher than they were in 2021, during the pandemic (Conlin et al., 2024; USDA Economic Research Service, 2023).

This paper investigates how the recent increased incidence of online food shopping options, and consumers' usage of these options, may relate to consumers' propensity to select a diverse set of market channels for food-at-home shopping in the post-pandemic food environment. In the US, national market concentration increased substantially between 1990 and 2019 (458 percent). In comparison, average county-level market concentration has remained relatively constant over the past 30 years, and trends in localized markets are likely more relevant for consumers, food-retail

competitors, and policymakers such as those seeking better market access for local producers and food companies (Zeballos, 2023). This shift to shopping at more diverse channels could be viewed as a potential opportunity to capture local food dollars at more seasonal and limited selection stores owned and operated locally (farmers markets, butchers, independent grocers).

We use consumer survey data from a nationally representative sample, collected in January 2024. We account for consumers' heterogeneity of preferences using latent classes defined by consumers' food values. Using latent class regression, we find a positive relationship between consumers' spending more of their budget on online food-at-home (FAH) compared to their 2019 spending and selection of a diverse set of FAH market channels. For this consumer segment, online options seem to be freeing up time and budget for shopping at niche, local, and independent food retailers. The post-estimation provides details about where each class of consumers are shopping in-person and online, as well as how they have reported changing their food shopping behaviors in other ways since the COVID-19 pandemic. Findings shed light on the mechanism that drives associations between increased online food shopping and consumers' selection of varied food market types in the post-pandemic food environment.

## 2.2 Introduction

The COVID-19 pandemic was a disruption that led consumers to shift their food shopping behaviors in many ways, including the portfolio of food-at-home (FAH) market channels where consumers choose to shop.[1] COVID-era events that affected market channel selections included: shortages at major food retailers from supply chain disruptions (Hobbs, 2020), increases in the number of smaller businesses offering delivery and curbside-pickup options (Thilmany et al., 2021b; Verdon, 2020), and heterogeneous shifts in the amount of time that consumers had available for food shopping. In response to these events, consumers exhibited fear of both viral contagion and food availability (Finck and Tillmann, 2022; Omar et al., 2021).

[1]Throughout this manuscript, we use the term "market channel" to describe the type of food retailer. These retailer types are delineated by the breadth of products offered and the selling environment. Figure **??** details the market channels, or retailer types, investigated in this study.

In turn, one way that consumers shifted their behavior was to try new market channels whose supply chains differed from major retailers; a consumer survey conducted in the fall of 2020 found that 35% of respondents reported trying at least one new food marketing channel since the pandemic began (Edmondson et al., 2021). A second way that consumers shifted their behaviors was to stockpile certain foods in attempt to counter uncertainty about the food supply, as investigated by the second paper of this dissertation. A third behavioral response to pandemic-era fears was that many more consumers chose to use online food purchasing options for FAH shopping, and this has persisted beyond the pandemic (Chang and Meyerhoefer, 2021; Chenarides et al., 2021a; Conlin et al., 2024; Etumnu and Widmar, 2020; Jensen et al., 2021; USDA Economic Research Service, 2023). Thus, events that occurred during the pandemic highlighted the need to explore consumers' market selection tradeoff matrix in the context of recently exacerbated growth in online shopping for FAH and exploration of non-traditional market channels.

In order to better understand the factors driving consumers' decisions of where they shop, how many markets to visit, and how online options affect those decisions, it is important to consider the attributes of markets (and how they may have changed in the mind of consumers during the COVID era). Attributes of online FAH shopping markets make them distinct from in-person shopping; online options primarily offer increased convenience and ease of product searching for selective consumers, yet online-only retailers are limited by the perishability of products that can be offered. Despite huge shifts toward online FAH shopping, it is still unclear how the usage of online FAH shopping options relates to the factors underlying consumers' market channel selection decisions. This paper investigates how recent increases in spending on online FAH options relates to consumers' propensity to select multiple types of market channels for FAH shopping in the post-pandemic food environment (October 2023). Our conceptual framework allows for various types of online shopping behavior to be captured; in addition, we account for a heterogeneous set of factors that may influence why and how consumers incorporate online food shopping into their food market selections. We posit that some choose to do so for added convenience and saving shopping time, while others do so as a method to lessen search costs of online browsing. In both cases, the minimized “time spent per market" may be a means for consumers to lower the aggregate transaction costs of obtaining their preferred assortment of goods by accessing multiple types of food markets.

The contributions of this research to the current literature are threefold. First, to our knowledge, no previous research has used clustering techniques to investigate the heterogeneity of online shopping behaviors in the post-pandemic food environment. Much of the previous literature classifies the decision to shop online without considering variance of shopping patterns, despite evidence that a diverse set of consumers shop online for a variety of reasons, and such heterogeneity may represent a market opportunity for food markets seeking to align with consumer values. Using latent class regression in our approach accounts for otherwise unexplained heterogeneity of shopping behavior. Secondly, we identify how a variety of consumer characteristics are associated with the likelihood of shopping at more than three types of market channels, conditional on belonging to a class of purchasing behavior, including: time spent shopping for FAH, FAH budgets, proximity to grocery stores, essential worker status during the pandemic, food assistance participation, and demographics. While previous literature has used consumer demographics and preferences to understand market selection decisions, our data is uniquely rich, and we have not found previous research that simultaneously incorporates these factors despite evidence and theory that they are relevant to the shopping decision. Lastly, to our knowledge, no other research has accounted for the variety or assortment of a retailer's product offerings for such a detailed set of potential retailers in the investigation of the consumer's decision to select a set of market channels. We categorize many different food retailer types by the breadth (or niche) aspect of their product offerings, which allows us to understand the relationship between using online food shopping options and the tendency to be a multichannel food shopper[2].

Participation in online food shopping is one of the few pandemic-era shifts in consumer behavior that seems to be strongly persisting. Yet, from previous literature, we know that there are differences in how and why consumers choose to shop online for FAH Chenarides et al. (2021a);

[2]Multichannel consumers are those who shop at several of these market types, either in-person or online.

Jensen et al. (2021); Omar et al. (2021). Understanding these nuances is important and timely as food retailers, both large and small, seek to both understand the implications of increased usage in online shopping for FAH, and to recognize opportunities for capturing market shares in the current food environment.

## 2.3 Background and Motivating Literature

Soon after the onset of the pandemic, US consumers experienced household mobility restrictions, stay-at-home orders, and the closure of schools and other congregation places, leading consumers to shift their food expenditures away from food-away-from-home (FAFH) outlets and towards FAH outlets (Bonanno et al., 2025; Marchesi and McLaughlin, 2024). These shifts in demand challenged food markets and, combined with illness across the food sector workforce, led to the aforementioned supply chain disruptions (Ellison et al., 2021; Hobbs, 2020). The subsequent response among some consumers was to engage in new shopping behaviors, including: trying new market channels (Edmondson et al., 2021; Schmidt et al., 2020), stockpiling goods (Omar et al., 2021), and using online food shopping at unprecedented rates (Chenarides et al., 2021a; Jensen et al., 2021; USDA Economic Research Service, 2023). The pandemic-induced changes were not uniform throughout phases of the pandemic or across different regions. While the initial “lockdown" phase of the pandemic was characterized by a spike in FAH demand and changes in consumer purchase behavior that challenged all types of food retail outlets, the later phases of the pandemic saw a return to normalcy in some consumer food shopping behaviors, while others, such as online shopping, persisted (Bonanno et al., 2025; Chang and Meyerhoefer, 2021).

The consideration of consumers' shifts in online spending since the pandemic began provides an interesting lens through which to consider evolving food market choices. Not only does it seem that consumers formed new online shopping habits during this time, but more deeply, the pandemic may have exacerbated the underlying forces driving such habit changes. These factors include the perceived tradeoff matrix and consumer heterogeneity with respect to time use (convenience valuation) and the selection of markets that are more closely aligned with food values and product assortments. For example, consumers' time budgets were affected by the pandemic in different ways. During the early phases of the pandemic, both heightened levels of unemployment (Brynjolfsson et al., 2020) and non-essential workers' transitions to work-from-home environments led to more discretionary time available when their home environment fostered productivity (or possibly less time if childcare duties added demand to their time budgets). Simultaneously, essential workers were in high demand and may have experienced decreased time available for food shopping as their work hours increased[3]. There was also substantial variance in the fear of contracting COVID-19, and subsequent intensity of behavioral changes. Findings from the August 2020 U.S. Household Pulse Survey revealed that around half (47%) of respondents engaged in illness-avoidant behaviors (U.S. Census Bureau, 2020). These examples highlight the need to account for differences in the ways in which increased online food shopping may interact with market channel choices.

The persistence of increased online FAH shopping behavior is evident in consumer expenditure data. After adjusting for inflation (base 1988), data from the USDA Food Expenditure Series shows that real consumers' expenditures from using mail order and home delivery options to purchase food at home (FAH) in the US increased by 21% in 2020, then increased by another 5% in 2021. Even in 2022, when many food purchasing behaviors had normalized, real mail order and home delivery FAH purchases were 26% higher than they were in 2019 (USDA Economic Research Service, 2023). Before the COVID-19 pandemic, the online food retail environment was dominated by retailers who offered broad selections and were able to invest in the infrastructure needed for online retailing, even when it was not being heavily utilized by consumers (e.g. Walmart and Amazon) (Etumnu and Widmar, 2020). However, during the pandemic, many food retailers began offering online food shopping options, either directly or via an e-commerce platform like Instacart, for the first time (Thilmany et al., 2021b; Verdon, 2020). In particular, small and independent food businesses that had not previously used online retailing entered the e-commerce space as part of

[3] A survey by Brynjolfsson et al. (2020) conducted soon after the onset of the pandemic found that 37.1% reported continuing to commute to work, 35.2% reported switching to a work-from-home environment, 15.0% reported continuing a work from home environment, and 10.1% reported being recently furloughed or laid off (Brynjolfsson et al., 2020).

their strategy to adapt to pandemic-era vulnerabilities. By offering online ordering or contracting with an e-commerce platform, they sought to reach consumers who were staying home to avoid virus exposure (CSA Innovation Network, 2020; Thilmany et al., 2021b; Verdon, 2020). But more importantly, online shopping through any market channel may have changed the tradeoff matrix for consumers who could use the time saved shopping online to visit new markets that allow them to optimize their choice of food products.

While consumer expenditure data of direct-to-consumer (DTC) sales does not reflect large increases in market shares or even sales from pandemic-era shifts (Bonanno et al., 2025; U.S. Department of Agriculture National Agricultural Statistics Service (USDA NASS) Census of Agriculture, 2020; **?**)[4], survey data and community-of-practice-coordinators from this project and other projects reflected that pandemic conditions, including new e-commerce platforms, consumers' exploration of market channels, and shifts towards FAH, led to both increased sales and new customers (Thilmany et al., 2021b; USDA Agricultural Marketing Service, Colorado State University, University of Kentucky, and others, 2023). For example, Thilmany et al. (2021b) describe results from interviews of 10 e-commerce platforms that serviced LRFS during the pandemic, finding that online orders and expenditures of local food sales increased by 189% and 71% in April and May of 2020, respectively. Our own project experiences are aligned with these findings; both consumer survey data from 2020 to 2023 and discussions with coordinating partners suggest that local food sellers experienced increases in economic opportunity during this time. This suggests that the existing expenditure data on direct-to-consumer sales may not be accurately capturing the experiences of local and regional food businesses. Previous studies have pointed to this issue, highlighting the growth in intermediated local food sales that have made up an increasingly large portion of farm-gate sales in recent years (Low, S.A. et al., 2015; O'Hara and Low, 2020; Richards et al., 2017; Thilmany et al., 2021b; **?**). While the 2020 Local Food Marketing Practices

[4] U.S. Department of Agriculture National Agricultural Statistics Service (USDA NASS) Census of Agriculture (2020) shows a 3% increase in direct-to-consumer (DTC) sales from 2015 to 2020, and Bonanno et al. (2025) found that DTC sales from 2020 to 2021, based on Food Expenditure Series data, were actually lower than they would have been if the pandemic never occurred.

Survey provided a baseline metric of intermediated local foods sales in the US., a second survey that would indicate change over time has not yet been published (U.S. Department of Agriculture National Agricultural Statistics Service (USDA NASS) Census of Agriculture, 2020). Indeed, one contribution of our larger project has been to call for and exemplify an analysis of local food systems that incorporates both quantitative and qualitative measures of local food system health. As one facet of that wider project, this investigation provides novel insights for consumers' decision to select local and regional channels in the post-pandemic food environment.

Indeed, despite the exploration of market channels that occurred during the pandemic and the persistent increase in online shopping behavior, nuances regarding how the increased availability and utilization of online shopping offerings has impacted the set of food market channels selected by consumers has not yet been studied. Given previous literature that highlights the need to account for differences in consumers when analyzing their behavioral responses, we expect that the nature of this relationship will vary across consumers (Chang and Meyerhoefer, 2021; Kilders et al., 2024). It is conceivable that some consumers view online FAH shopping options as a substitute for non-perishable purchases at large food retailers, which then allows them to allocate their freed shopping time towards more niche food retailers with narrower product offerings. Or, other consumers may view online food shopping as a convenient time-saving tool that is complementary to their pre-pandemic market channel selection habits. As such, we hope to broadly yield an understanding of the heterogeneous market selection decisions that consumers are making given increased familiarity and usage of online shopping options. And, we also hope to yield tangible insights related to marketing strategy for small and independent food businesses during a time of uncertainty and vulnerability.

Previous literature has characterized the market channel selection decision as being a factor of store attributes, for which influence is modulated by access to store, and buyer attributes (Arnold et al., 1983; Cadwallader, 1981; Goldman and Hino, 2005; Lusk and Briggeman, 2009; Palardy et al., 2023; Smith, 2004; Ver Ploeg and Wilde, 2018; Volpe et al., 2018). Examples of store attributes include: product offerings, location, prices offered, loyalty programs, shopping experiences, etc. On the other hand, buyer attributes include demographics, food preferences, access to transportation, food shopping budget, and more. Figure 2.1 illustrates our theoretical model of the consumer selection decision-making that incorporates these factors. The market selection decision investigated in this study is perplexing because the experience of shopping for food online has distinct attributes that separate it from the in-person shopping experience; it likely requires a lower time burden than shopping in-person, it can lower search costs for highly selective consumers, and the valuation of distance-to-store changes within the consumers' channel selection decision. Yet, shopping online (for FAH in particular) is often limited by perceived perishability and availability constraints. The following section delves into the literature on online shopping, and frames our contributions within this literature.

### 2.3.1 Previous Literature on Consumers' Online Shopping Behaviors

Prior to the pandemic, the consumer demographic that was most often associated with a higher likelihood of shopping online was age. Many studies found that younger consumers had a higher propensity to use online food shopping options, which is unsurprising, as younger consumers are generally more familiar with online shopping platforms Etumnu et al. (2019); Farag et al. (2007); Van Droogenbroeck and Van Hove (2017). In a survey carried out in the early phases of the pandemic (June 2020), Jensen et al. (2021) found that age continued to be negatively associated with the propensity to shop online, but, older shoppers who did shop online were more likely to report an intent to continue utilizing online shopping options. Thus, if older shoppers adapted and shifted towards online purchasing options later in the pandemic, this consumer segment could represent an important expansion opportunity for food retailers. Other consumer characteristics that the literature suggests are positively associated with a higher likelihood of shopping online are income and education (Etumnu et al., 2019; Hansen, 2007; Jaller and Pahwa, 2020; Van Droogenbroeck and Van Hove, 2017). If we assume that most goods available from online food retailers and shopping options are normal, it makes intuitive sense that those with higher incomes would spend more on online grocery purchases. However, as mentioned previously, Jensen et al. (2021) did not find income to be a significant factor in estimating the likelihood of shopping for food online. With the move towards online availability of SNAP-EBT, one plausible explanation for this could be that more low-income consumers are shopping online, and the supplementary SNAP "income" used for grocery purchases is not reflected in their reported household income. On the other hand, low-income shoppers in the Jensen et al. (2021) survey were more likely to report their intent to discontinue online shopping beyond the pandemic, so further investigation of these patterns in the "New Normal" period is needed.

Results from the literature regarding associations between gender and online shopping are less clear. In a study using structural equation modeling of the American Time Use Data to evaluate both in person and online shopping behaviors, Jaller and Pahwa (2020) found that female grocery shoppers were more likely to use online shopping options. On the other hand, Etumnu et al. (2019) and Farag et al. (2007) found negative associations between being female and propensity to shop online in their respective consumer survey analyses.

Several studies have previously found evidence of convenience as a draw of online shopping to consumers. Distance to the grocery store has been found to be positively associated with a higher propensity for the consumer to spend more of their FAH budget at online food retailers Melis et al. (2016). In their 2016 study, authors hypothesized that this was likely due to transportation costs. However, consumers in urban areas, where distance to store is lower on average, also have been found to be more likely to use online shopping options Etumnu and Widmar (2020). This points to another dimension of convenience that draws consumers to online shopping options: time. This dimension is less studied as it relates to online shopping, but previous literature does indirectly describe consumer characteristics that are associated with more constrained time budgets, such as fully employed consumers and parents. Consumers who work full time were found to be more likely to use online shopping options Jensen et al. (2021); Van Droogenbroeck and Van Hove (2017). Another study's findings captured the changing tradeoffs between convenience, product assortment, and market choice when online food shopping options are available; Farag et al. (2006)

found that online food shoppers in the Netherlands make more quick in-person trips to the grocery store, while consumers who don't shop online make fewer and longer trips to the store.

In a post-pandemic survey, being an essential worker (who often worked longer hours than non-essential workers during the pandemic) was positively associated with a propensity to shop online as well Jensen et al. (2021). And, in a May 2020 survey, Chenarides et al. (2021a) found that lack of childcare and challenges associated with in-person shopping with children were reported motivations for using online food shopping options. This is consistent with prior literature, in which the presence of children in the household was found to be consistently associated with higher likelihoods of shopping for food online Etumnu et al. (2019); Hansen (2007); Jaller and Pahwa (2020); Melis et al. (2016). All of these factors are indirectly related to the opportunity costs of consumers' time and travel expenses. This motivates the direct investigation of time spent shopping on FAH options and proximity to store as they relate to classes of online food shopping behavior, as is done in this paper.

Regarding the value set driving often unobserved heterogeneity of consumers' shopping patterns, one study does consider both consumers' behavior and value set as they relate to the decision to shop online at several channels. In their 2020 paper, Brand et al. (2020) draw from the Theory of Planned Behavior and the Technology Acceptance Models in the psychology literature to conceptualize the consumer's shopping decision. Using a survey of  2000 UK consumers that was carried out in 2017, authors used a two-stage cluster analysis in which consumers were first segmented using hierarchical clustering based on their beliefs and attitudes, then were again clustered using K-means clustering based on their demographic and grocery shopping behaviors. Authors found existing heterogeneity of consumers' preferences; some consumers are attracted or resistant to online grocery shopping depending on convenience valuation, positive/negative experiences in past, enjoyment of new technologies, time pressures, and social/environmental values Brand et al. (2020). While these findings do reiterate this paper's motivation for considering heterogeneity of the online grocery shopper and provide a starting point for factors to consider, this paper does not follow the latent class analysis literature's accepted procedure for achieving unbiased and correctly specified clustering results. Furthermore, they fail to justify their use of attitudinal variables as primary indicators of grocery shopping behavior segmentation.

The application of clustering analysis to investigate consumers' decision to shop for groceries online has been done for quite some time. The first study to use this technique used exploratory factor analysis and clustering to find four types of online grocery shoppers, which were influenced by convenience, orientation of the store, usage of information, and product variety valuation (Rohm and Swaminathan, 2004). Other subsequent studies used factor and cluster analysis to define types of online grocery shoppers based on information searching, consumer characteristics, shopping preferences, purchase planning, strength of product preference, and valuation of effort, money, and time (Atkins et al., 2016; Hansen, 2008; Harris et al., 2017). Many more studies have used clustering, including latent class analysis, to understand consumers' heterogeneity of online shopping preferences for non-food goods. Common factors found to be impactful in defining types of online shoppers in these studies included: shopping enjoyment, loyalty, personal values, previous experiences with online, price and time consciousness, impulsiveness, environmental concern, convenience valuation, channel attributes, channel preferences, innovativeness, and socio-demographics (Ganesh et al., 2010; Konuş et al., 2008; Mokhtarian et al., 2009; Wang et al., 2014). However, none of these studies have used clustering techniques to account for these factors since the expansion of online offerings and usage of those offerings that occurred during the pandemic.

Many COVID-19 era studies on the shift toward online shopping for food found that the top reasons for utilizing online options were pandemic-specific (e.g. "Scared of COVID-19", "Feeling Unsafe") Chenarides et al. (2021a); Ellison et al. (2021); Melo (2020). However, in a 2020 survey by Chenarides et al. (2021a) in which respondents were asked about their reasons for using grocery pick-up and delivery services, much of the sample cited time constraints(27%), issues with access (22%), and lack of childcare (22%) (Chenarides et al., 2021a). The varied findings of these studies reiterate the need to account for consumers' heterogeneity in our analysis. To that end, in addition to the rich respondent data that we collected, we also utilized USDA Economic Research Service's data products to observe the average proximity to grocery stores in respondents' zip codes. As such, one secondary research question of this investigation is to understand how distance-to-store may be associated with a higher likelihood of shopping at more food market channels. Table 2.2 conveys the directional expectations of all covariates included in our analysis, based on this literature.

For the first step of our analysis, following previous literature (Alemu and Olsen, 2019; O'Neill et al., 2014; Palma et al., 2017), we account for consumers' heterogeneity of preferences using latent classes defined by consumers' food values. Food values have been found to be stable over time, and previous research has found that this was generally true through the pandemic (Ellison et al., 2021; Lusk and Briggeman, 2009). By segmenting consumers by their food values, we can then use subsequent regressions to understand how consumers' attributes, including increases in online FAH spending since the pandemic began, related to their propensity to select several types of food market channels for various stable classes of consumers.

As a second step of our analysis, we investigate associations of consumers' characteristics, online food spending patterns, and the food access environment where the consumer resides as they relate to the decision to shop at several market channel types. To investigate the question of how online purchasing relates to the multichannel food shopping, we include whether consumers are spending more of their budget on online food-at-home spending as a covariate for their propensity to shop at four or more types of market channels[5]. The median number of market channel types selected by the survey sample was three, so delineation of four or greater market channel types was chosen to represent shoppers who select a relatively high number of food market channel types.

While these findings allow us to see the general dynamics of the relationship between online food shopping and multichannel food market selections, further investigation is needed to understand the implications for specific food markets. Accordingly, a post-estimation discussion

[5]The categories of retail types included in this research were: full-selection stores (supermarkets, supercenters, and wholesalers), limited-selection grocers (small-format grocers, health stores, and niche-selection retailers), discount and convenience stores, local and regional stores (direct-to-consumer, independent, and artisan sellers), and seller-based limited selection (food boxes and meal kits).

investigates where each class of consumers is shopping in-person and online, as well as how they have reported changing their food shopping behaviors in other ways since the COVID-19 pandemic began. Little is currently known about the way that various consumer segments use online food shopping options and how this may affect the multichannel selection of markets and dollars spent at those markets, particularly in the post-pandemic food environment. Findings may highlight how the increased usage of online food shopping options may yield opportunities for local and independent food retailers and those who participate in their supply chains, even if they do not directly invest in online food shopping infrastructure. We conclude with a discussion of whether it is an opportunity to expand local markets, a tool for resiliency, and/or a hindrance to smaller food businesses' ability to compete.

## 2.4 Conceptual Framework

### 2.4.1 Cognitive Gravity Model of Consumer Decision Making

We use a gravity model to cognitively illustrate how the increased availability of online purchasing options disrupts the consumers' food retailer selection decision. Gravity models have been used in the regional development and international trade literature to illustrate how a decision might be impacted, generally by a spatial factor that acts as a gravitational centroid, modulating other variables in the model (Anderson, 2011,1; Ghosh, 2011). The analogy stems from Newton's Law of Gravitation in that a "mass" of independent factors together draw toward a "mass" outcome decision, but the gravitational force is modulated by the distance between these forces (Anderson, 2011). In 1981, Cadwallader was the first to use a cognitive gravity model to understand relationships between various retail factors and the distance to a given store (Cadwallader, 1981). More recent regional development literature has highlighted the importance of including other factors, such as consumer attributes, as interacting with the pull of the centroid in the conceptualization of a retail gravity model (Palardy et al., 2023; Verhetsel et al., 2022) use a cognitive gravity model to illustrate how the introduction of beer into grocery stores and convenience stores in Colorado may impact consumers' shopping behavior. In this study, authors propose that the policy change impacts both the range and selection of beverage offerings for a given retailer and the distance to store (Palardy et al., 2023). Interestingly, our gravity model frames a similar dynamic, but related to a market disruption rather than a policy disruption.

In this case, the outcome “mass" is the consumers’ decision to shop at a given retailer, the "mass" of independent factors includes variables related to store and buyer attributes, and the consumer’s access, as represented by proximity to a store and ability to travel to the store, affect the magnitude (gravitational force) of the independent factors. In the post-pandemic food environment, we have seen the availability of new online purchasing options and consumers’ growing familiarity with these options, and we presume that this dynamic has affected the gravitational pull of those markets toward consumers. In particular, convenience is impacted - with delivery of FAH goods, distance to store becomes zero and thus proximity to store likely becomes less important. Even with curbside pickup options, the search time required to shop for food is lessened. We also presume that the importance of a store’s variety of product offerings may also be impacted, as online food shopping options supply goods that may not be offered by a limited-selection retailer. For example, a consumer may now be able to “re-balance their market portfolio" by purchasing nonperishable dry goods from an online retailer (saving the time to procure those goods) and then reallocating that time to shop at a farmers market for more perishable foods. This is further supported by findings in the next chapter of this dissertation, which highlight consumers’ stockpiling of non-perishable goods that occurred during the pandemic, when new online shopping habits were being formed. The overarching takeaway from these relationships is that increased incidence of online shopping tools may lead to decreased appeal of the convenient one-stop-shop supermarket, at least for some subset of consumers. Figure 2.1 conveys the cognitive gravity model that represents these dynamics.

By considering the factors in our gravity model that influence the consumers’ decision to shop at a given retailer type (in-person or online), it becomes clear that any approach to understanding consumers’ decision to use online options at a given retailer type will need to account for differences in consumers’ preferences and demographics. In other words, these factors may impact the decision to select a retailer in different ways, and the utility obtained by choosing a set of market channels and whether to shop online or in-person will be heterogeneous across consumers. Some consumers may spend more of their FAH budget on online food shopping options because of the added convenience, while others who have strong opinions about food values or other food preferences may appreciate the relatively low search costs (to find their preferred product and brand attributes) associated with online shopping. Thus, we expect to see multiple different types of online shopping behavior, and we start with two potential scenarios which can be defined by the amount of time they spend shopping for FAH: one group that continues to prefer a one-stop-shop experience but appreciates the time-saving potential of shopping online, and one that uses online shopping to lower their search costs and allow them to acquire food that is aligned with their values and preferences. We hypothesize that the latter group, with strong food preferences (such as valuing local and/or organically sourced food) and less constrained time budgets, are likely to shop from more types of food markets. In order to observe this heterogeneity, we use clustering techniques that allow the data to first be segmented by relatively stable food value preferences (Ellison et al., 2021; Lusk and Briggeman, 2009). Due to dimensionality limitations of latent class analysis, we were not able to include all eleven of Lusk and Briggeman's food values (Lusk and Briggeman, 2009). Some of Lusk and Briggeman's food values such as taste and origin are product-centered rather than market channel-specific, which helped to narrow our choice. As such, four food values that capture diverse dimensions of consumers' market channel selection decisions were chosen: affordability, which captures general price valuations; locally grown, which captures both local economic support and environmental concerns related to food miles; organically grown, which captures food safety valuations; and traditional/cultural preferences, which captures additional consumer heterogeneity and adds a society-centered element (Bougherara et al., 2009; Lusk and Briggeman, 2009). We then subsequently estimate the propensity to be a multichannel shopper from a variety of consumer characteristics, including an increased share of FAH budget spent on online shopping options since the pandemic began.

## 2.5 Empirical Methods

### 2.5.1 Latent Class Analysis and Regression

Clustering analysis can be a useful econometric approach when one is interested in understanding otherwise unobserved heterogeneity across multivariate data. Traditional clustering uses a chosen distance measure to cluster the data by finding similarities between observations. Latent Class Analysis, while resulting in similar outcomes, is fundamentally different; it is a Finite Mixture Model, which allows clusters to be derived using a probabilistic model. As such, it has been used in academic fields such as sociology, political science, and criminology when unobserved heterogeneity limits the variables that can be included in traditional regression models (Vermunt, 2002). By making an assumption about the distribution of the data, it is possible to obtain estimates for class probabilities and/or conditional probabilities, which is not true for other types of clustering analysis. Due to the statistical nature of this analysis, it is also possible to use model selection criteria and assess goodness of fit (Vermunt and Magidson, 2002). Within classes, errors are assumed to be independent and identically distributed. When deciding how many classes to include in the analysis, the Bayesian Information Criterion (BIC) is commonly used to compare models, where the model with the smaller BIC is preferred. The BIC indicates which model has the highest likelihood of explaining the data and penalizes for the number of variables included in the model (Nylund et al., 2007). The Bootstrap Likelihood Ratio Test is also commonly used to determine the optimal number of classes, although it was not used in this analysis (Tekle et al., 2016). Lastly, notable benefits of using latent class analysis are: allowing covariates to predict observations' class membership, allowing within-cluster regression models such as latent class regression, and modeling changes over time given the latent structure of the data (Hagenaars, 2002).

In this study observing consumers' retailer choices, the one-period nature of certain variables such as household income, food assistance participation, and reported experiences from the COVID pandemic contributed to the issue of unobserved heterogeneity. Other unobserved heterogeneity impacting the consumer's choice to shop online likely includes shopping preferences, such as retailer loyalty, that are not accounted for in our data. Additionally, the notion that groups of respondents may be experiencing similar shocks related to income loss, food security, and time spent at home implied that a latent structure may be present in the data. These factors motivated the selection of the latent class analysis method. As all variables chosen to convey online shopping behaviors were indicators, 0-1 variables, the logistic distribution was chosen as a density to estimate the probabilistic outcomes. The resulting mixed latent class model is represented by equation 1, and the application of the logistic distribution is represented by equation 2.2.

The literature suggests that to avoid misspecification of behaviors, the step of sorting the data into classes based on the indicator variables should be taken first, before any covariate regression is included (Vermunt, 2010). Then, after the appropriate number of classes is selected via comparison of BIC values, the covariates are regressed on the indicator variables, conditional on class. Equation 2.1 shows the mixed logit model used to sort survey respondents into classes of behavior. It fits a logit model for each class, with no covariates, as such:

$$L = f(y; \theta_1) * P(C1) + f(y; \theta_2) * P(C2) \tag{2.1}$$

Where

$$f(y; \theta_k) = \prod_{i=1}^{6} p_{jk}^{y_j} * (1 - p_{jk})^{1-y_j} \tag{2.2}$$

and $p_{jk} = \frac{exp(cons_j k)}{(1+exp(cons_j k))}$,

$j$ = indicator variable, $k$= class number, $y_j$ is the affirmative binary value for the $jth$ indicator variable

Applying this to the research question, let there be $J$ different food values for which a consumer may view as important to their purchasing decision, where $j = (1, 2, ..., 4)$ such that:

- $j = 1$ represents valuing affordability
- $j = 2$ represents valuing locally grown food
- $j = 3$ represents valuing organically grown food
- $j = 4$ represents valuing that traditional/cultural preferences are met

In order to observe how consumers' online shopping behaviors vary across retail types, we grouped FAH retail outlets with a particular focus on aligning them by the variety and nature of their product offerings. Supermarkets, supercenters, and wholesalers were labeled as "full selection", small-format grocers and health stores were labeled as "limited selection", discount and convenience/corner stores were labeled as "discount and convenience", direct markets, farmers markets, and gourmet/artisan sellers were labeled as "local and independent", and food boxes and meal kits were labeled as "seller-based limited selection". The sample sizes and market channel usage percentages of the whole sample (N= 4562) are shown in Table 2.9. These categories were used to define the outcome variable, which is being a multichannel shopper. The binary multichannel shopper variable was defined as 1 if the respondent selected more than three[6] types of retail channels in October 2023.

To estimate the mixed latent class analysis, the Expectation-Maximization (EM) algorithm is used in STATA. The EM algorithm iteratively estimates the mixing proportions and the response patterns for each latent class while maximizing the log-likelihood function.

In the second step of the latent class analysis, we compare the BICs of several different latent class models and choose the latent class model with the lowest BIC, which was the latent class model with three classes. Table 2.4 shows the goodness of fit tests used to choose the latent class model with two classes. This table also includes entropy values, likelihood ratio tests, and average latent class posterior probabilities that further validate the choice of the two-class latent class model.

In the third step of the latent class analysis, we include covariates that estimate the probability that an individual will shop online at more than three types of FAH market channels, within a given class. Equation 2.3 expresses this model:

$$P(Y_i = 1|\mathbf{X}_i) = \sum_{k=1}^{2} \pi_k \cdot P(Y_i = 1|\mathbf{X}_i, C = k), \tag{2.3}$$

[6]This "more than three" threshold was determined by observing the distribution of market channel selection; three was the median number of channel types selected.

Where $P(Y_i = 1|\mathbf{X}_i)$ is the probability of individual $i$ selecting more than three market channel types, conditional on a vector of covariates $\mathbf{X_i}$, $\pi_k$ is the mixing probability for latent class k, and $P(Y_i = 1|\mathbf{X}_i, C = k)$ the probability of individual $i$, belonging to a given class $C$ equal to $k$.

To convey the mixed logit nature, the probability $P(Y_i = 1|\mathbf{X}_i, C = k)$ uses the logistic density function, such that:

$$P(Y_i = 1|\mathbf{X}_i, C_i = k) = \int \frac{e^{\mathbf{X}_i}}{1 + e^{\mathbf{X}_i \beta_k}} f(\beta_k|\theta_k) d\beta_k, \tag{2.4}$$

where $\beta_k$ is a vector of parameters specific to latent class $k$, $\theta_k$ is a vector of parameters governing the distribution of $\beta_k$, $f(\beta_k|\theta_k)$ is the density function for $\beta_k$ expressed in equation 2.3.

### 2.5.2 Vector of Covariates

We define the vector of covariates $X_{ij}$ so that we can estimate their impacts on the probability of an individual shopping online at a given retailer when they belong to a certain class $k$. This is expressed in equation 2.4. We include the following consumer characteristics and convenience indicators in vector $X_{ij}$:

- Age Category
- Female = 1, 0 otherwise
- Household size
- Education
- Rural = 1, 0 otherwise
- Income Category in 2023
- Weekly FAH Budget in Oct. 2023 (logged dollar amount)
- Higher Online FAH Budget Share since Pandemic = 1 if delivery, 2 if curbside pick-up, 3 if both, and 0 otherwise
- Low Access Zipcode
- Time Spent Shopping for FAH per week in October 2023 (logged minutes)

- Essential Worker = 1, 0 otherwise
- High risk for COVID severity = 1, 0 otherwise
- SNAP user in Oct. 2023 = 1, 0 otherwise

Summary statistics and more detailed descriptions in these variables are included in Table 2.3.

### 2.5.3 Data Sources

Data for this market channel investigation comes from a US consumer survey of 5000 households that was distributed via Qualtrics in the winter of 2023. This consumer survey was part of a larger project, funded by the US Department of Agriculture Agricultural Marketing Service (USDA AMS), that sought to facilitate the resiliency of local and regional food systems[7]. We used quotas to ensure that the sample was representative of US households in regards to race and ethnicity, income, gender, and age. We screened for the respondents to be the primary grocery shoppers in their household and at least 18 years old. The survey asked respondents to report food shopping habits for two time periods- October 2023, and a year prior, October 2022. We asked respondents to use bank statements and receipts to help recall their shopping behaviors, when possible. However, only responses related to specific market selections and FAH expenditures for the year 2023 were used in this analysis. To discern shifts in online FAH shopping over time, we directly asked respondents whether they felt that they are now spending a higher share of their budget on online food shopping (including separate questions for delivery and curbside pick-up) since the pandemic began.

Sections of the survey included:

- Categorical food expenditures
- Selection of food market channels
- Participation in online purchasing options at the market channels, including curbside pick-up and delivery options

[7]This larger project was a collaboration of USDA AMS, Colorado State University, the University of Kentucky, Penn State, and around 30 community of practice organizations. Please see https://lfscovid.localfoodeconomics.com for more information.

- Weekly expenditures at a variety of market channels
- Food acquisition methods, including food assistance and home production
- Food security questionnaire
- Time spent shopping for FAH, FAFH, and preparing meals
- Food values via a 5-point Likert scale
- Perceived consumer effectiveness via a 5-point Likert scale
- Reported food shopping behavior changes since the pandemic began
- Demographics

We utilized two other sources of data in this study, both being data products by the USDA Economic Research Service. First, the 2020 Food Environment Atlas data provided the percent of households in a respondent's zip code that had low proximity to a grocery store. Low proximity was classified as being more than one mile away from a grocery store in urban areas and more than ten miles away in non-urban areas (USDA ERS, 2020). This variable was used to give some indication of how far the respondent may have needed to travel to shop at a mainline grocery store to align with the spatial aspect outlined in the gravity model of consumers' market selection choice (Figure 2.1. Since shopping online eliminates travel costs, it was important to be include this information in our model. We matched our respondents' zip codes to Federal Information Processing Standards (FIPS) codes, which allowed us to utilize this data. Second, we classified our respondents as residing in rural or non-rural areas using the 2010 Rural Urban Commuting Area (RUCA) codes. This data assigns a given FIPS code a value from one to ten based on where the primary commuting flow is directed (USDA Economic Research Service, 2010b). The literature classifies a FIPS code as rural if the commuting flow is within an urban center of 10,000-49,000 or smaller (RUCA code of 4-10) (Long et al., 2021).

Table 2.3 provides means, standard errors, and descriptions for all variables that are included in this study. We used the U.S. census categories for the Age, Income, and Education (U.S. Census Bureau, 2020). The categories for age are as follows: 18-24, 25-35, 35-44, 45-54, 55-64, 65 and older. In our sample, the median age fell into the 35-44 category. When considering that we require respondents to be 18 or older, our age distribution is representative of the U.S. population U.S. Census Bureau (2020). In our sample, the median household income fell into the $50,000 to $59,000 category[8]. Income was representative of the U.S. population, and this was expected given the quotas sent to the surveying partner. Our sample seems to also be very close to the U.S. population's educational distribution[9], but we did not include this demographic as a quota, so this sample does seem skewed towards more graduate or professional degrees compared to the general population U.S. Census Bureau (2020). Our sample is also slightly more concentrated in non-rural areas compared to the general population, as 13% of our sample is classified as rural compared to the 18% in the U.S. However, it should be noted that this could be, in part, a result of the way that the rural variable was coded. We managed duplicate classifications of a given FIPS code by choosing the first entry, which was always the lowest (corresponding to most populated) RUCA code. In other words, our sample may be less concentrated in non-rural areas than our "rural" variable indicates.

[8]The categories for annual household income in 2023 are as follows: Less than 10,000, 10,000 - 19,999, 20,000 - 29,999, 30,000 - 39,999, 49,999 - 49,999, 50,000 - 59,999, 60,000 - 69,999, 70,000 - 79,999, 80,000 - 89,999, 90,999 - 99,999, 100,000 - 149,999, and 150,000 or more.

[9]The categories for the highest level of education obtained are as follows: Less than 9th grade, Some high school, High school graduate or equivalent, Trade/technical/vocational training, Some college, Associate degree, Bachelor's degree, and Graduate or professional degree.

## 2.6 Results

After the first stage of the latent class analysis, two classes of consumers, segmented by differences in food values, emerged. As previously described, the food values used to segment consumers were valuation of local, organic, availability of culturally representative products, and affordability. With a BIC value of 5425.148, the two-class model had a lower BIC than the no-latent class model, indicating that it better describes the data (Vermunt and Magidson, 2002). The latent class models with more than two classes did not converge. We believe that the non-convergence of the three-class model is due to consumers exhibiting binary importance valuations for the food values that distinguished the classes. In other words, consumers either exhibited strong valuation, or not strong valuation, of the availability of local, organic, and culturally representative products. Expectedly, affordability was widely valued. The LR Test of the “full" 2 class model compared to the “restricted" no-latent class model indicates that we reject the null hypothesis that the restricted best fits the data. This, combined with the lower BIC and rejection of LR null for the two class vs. no latent class model shown in table 2.4 implies that consumers' food values are well represented by two classes of consumers. To further confirm that the two-class model is justified, we calculated entropy values and average latent class posterior probabilities. These are reported in table 2.4. Entropy is a model performance statistic that conveys how well the model defines classes. Entropy values close to 1 are preferred, with the accepted threshold above 0.8 (Wang et al., 2017; Weller et al., 2020). The entropy value for the two-class model is 0.884, and is thus acceptable. The average latent class posterior probability describes the average probability that a respondent was correctly segmented into a given class. Similarly, higher average latent class posterior probabilities are preferred, with an overall accepted threshold above 0.8 (Weden and Zabin, 2005; Weller et al., 2020). With the two-class model having the lower BIC, acceptable entropy, and acceptable overall average latent class posterior probabilities, we proceed with the two-class model.

The two classes of behavior reflect one group of consumers (class one) who place relatively high importance on their food being locally grown and organically grown, as well as that their cultural preferences are met by the available products, while the other group (class two) either slightly disagreed with the importance of those values or remained neutral. Both classes of consumers reportedly valued affordability. Accordingly, 38% of the sample was sorted into class one, labeled the Values-Driven Multichannel Class, and 62% was sorted into class two, Frugal Consumers. While this segmentation of consumers' market selection decision is unique, this finding is aligned with previous literature that used latent class analysis to segment consumers by their food-related lifestyle preferences and found that "passionately involved" and "nutrition focused" consumers made up 41% of their sample (akin to our values-driven consumers), and "moderately involved", "convenience-oriented", and "uninvolved" consumers made up the remaining 59% of the sample (Chen and House, 2022). Table 2.3 shows the differences in means for food values, as well as all other variables included in the subsequent latent class regression analysis. From table 2.3, it is also evident that the Values-Driven Multichannel class, the group with relatively strong food values, is comprised of more shoppers visiting at least four market channel types, which we term "broad shoppers", on average compared to Frugal Consumers; 80% of the former were broad, multichannel shoppers compared to just 5.1% of the latter: this finding motivated the name of the class. The final takeaway from the comparison of means from table 2.3 is that, on average, the Values-Driven Multichannel class (who expressed a higher emphasis on food values) was younger, had children under 18 more often, had larger household sizes, had higher income and spent more on FAH shopping, spent more time shopping for food, and spent more of their budget on online food shopping.

Going beyond means comparisons, table 2.5 shows the results of the latent class regression that estimated the likelihood of being a multichannel shopper, conditional on a respondent's class membership. As expected, the Values-Driven Multichannel class was found to be more likely to be a multichannel shopper than the Frugal Consumers. The next observation which is perhaps most important to our hypothesis is that among those with strong food preferences, the largest marginal effect when estimating the propensity to be a multichannel shopper was reporting a higher share of a FAH budget spent on online food shopping. This implies that for a segment of consumers, we find confirmatory evidence for our hypothesis that there is a positive association between allocating a higher share of a FAH budget towards online shopping and selecting a larger variety of food market channels. Still, results for the Frugal Consumers show that the majority of consumers have returned to (or remained true to) the pattern of limiting FAH shopping to three or fewer market channels.

The latent class regression also sheds light on the consumer segment that is more likely to be a multichannel shopper, and perhaps also spend more of their FAH budget on online shopping in the case of the Values-Driven Multichannel consumers. We find that across both classes, multichannel shoppers were more likely to be younger and spend more on FAH shopping. Among those with strong food preferences (the Values-Driven class), multichannel shoppers were also more likely to be male, have children, be in an area with fewer food access issues, spend more time shopping for FAH, and reported being an essential worker during the pandemic. After the marginal effect of spending a higher share of one's budget on online shopping, the second largest marginal effect observed for the Values-Driven Multichannel Class was spending more time shopping for FAH, followed by being an essential worker during the pandemic. For those with less strong food value preferences (the Frugal Consumers), the largest observed marginal effect associated with the likelihood of being a multichannel shopper was spending more on FAH shopping.

While these findings help to identify a target market segment for those who shop at more market channels and perhaps spend more on online shopping, we are still left wondering whether multichannel shoppers do indeed shop at more niche markets that have relatively limited product assortments, whether multichannel shoppers' market selection decisions were truly altered by the pandemic, and where exactly these classes of consumers are shopping both in-person and online.

Our post-estimation analysis addressed these questions. Table 6a and 6b report the share of each class that shopped in-person and online at various market channel types. For the Values-Driven Multichannel Class, it is evident that online food shopping is being used to complement in-person shopping. These consumers are continuing to shop in-person at several market channels, most prominently at full selection, limited selection, and discount and convenience stores. Notably, half of these consumers are shopping in-person at local and regional stores. For online shopping, the highest usage rates were for delivery from discount and convenience stores and for meal kits and food boxes, as well as for both curbside pick-up and delivery from full selection retailers like supermarkets. Despite asking respondents to report their Amazon purchase behavior for online-only markets, we suspect that the delivery from discount and convenience stores may be capturing Amazon purchases.

The shopping behavior of the Frugal Consumers, who had less strong food value preferences, represents a more streamlined food shopping approach. Almost all of these consumers shop in-person at full selection stores, and the majority (57%) also shopped in-person at discount and convenience stores. These consumers shopped online at much lower rates compared to the Values-Driven Multichannel consumers; the highest percent of online shopping was evident for curbside pick-up at full selection stores at 14%, followed by 11% at delivery for discount stores. These consumers seem to be using online very sparingly, and when doing so, likely as a time-saving and bargain-finding tool rather than as a search tool.

Lastly, table 6c shows the share of respondents that reported various shifts in food purchasing behavior since the pandemic began. The first notable result from this analysis are that more consumers in the Values-Driven Multichannel Class reported spending a higher share of their budget on food-away-from-home (FAFH) since the pandemic began, compared to the Frugal Consumers, even while more respondents from the Frugal Consumers class reported increased spending on food overall since the pandemic began. This implies that the Values-Driven Multichannel Class may be extending their propensity to shop and spend more across a variety of market channel types to food away from home (FAFH) markets. Another notable observation from this analysis is that more respondents from the Values-Driven Multichannel class reported considering their food values when making decisions about brand and market channel selections more since the pandemic began compared to the Frugal Consumers.

## 2.7 Discussion

Food market behaviors shifted during the pandemic (2020-2022), and our findings illustrate the heterogeneity of those shifts among consumers, thereby highlighting the need to account for differences in preferences as market dynamics continue to unfold. While the majority of consumers still signal a strong preference for affordability, fo a sizable group of consumers, local food, organic food, and cultural preferences are also important drivers for their decisions[10]. Beyond understanding values that drive food purchases, this work explores the alignment of retail channel selection factors with recently increased online spending for FAH; we consider which of these have contributed to the trend among values-based consumers to shop from an increasing variety of food market channel types. Overall, it seems that post-COVID dynamics signal a need for market and policy supporters to facilitate technical assistance with regards to food businesses entering the online food retail space, and ensure that stakeholders adapt marketing strategies that account for varied consumer purchasing patterns. These findings also highlight the need for policymakers to assure that there are a variety of food access points for consumers, including diverse in-person market channels and online options (which themselves have interesting policy implications given the current emphasis on broadband access across the rural-urban continuum of US communities). In short, shopping online is likely positively associated with being a multichannel food market shopper, and spending time shopping for FAH may now be redistributed across various types of food markets.

Since we posited that COVID food supply chain disruptions may have permanently shifted food shopping behavior, perhaps shifting the "weight" of some factors drawing shoppers to particular channels, it is important to understand potential market implications of these dynamics. For Values-Driven Multichannel consumers, their complementary relationship between shopping for FAH online and shopping for FAH in-person may signal the use of online options as a means to secure commonly purchased, "standardized pantry" items with little search costs. Particularly since the negative correlation with the low food proxy implies these consumers are in close proximity

[10]This delineation of consumers is aligned with previous literature that has found correlation between positive valuation of organic, local, and other expressions of product preferences (Aslihan-Nasir and Karakaya, 2014; Chryssohoidis and Krystallis, 2005; Thompson, 1998). In their identification of organic consumer segments using clustering techniques, Aslihan-Nasir and Karakaya (2014) similarly found that consumers can be segmented into those who view it favorably, neutrally, and unfavorably.

to stores[11], they are well positioned to seek out local, independent and specialty markets for those items not easily found or shipped from online sources.

In contrast, Frugal Consumers streamlined using online options and shopped at fewer market channel types compared to the Values-Driven Multichannel consumers (5% compared to 80%). However, it is still conceivable that when these consumers use online food shopping tools, they do so for a different reason. For instance, since this group has the highest rate of curbside pick-up at full-selection stores (14%)[12], online may also save the time that they would normally spend shopping in the store. Additionally, these results reinforce the need for efforts to expand online food shopping options for food assistance programs, such as the SNAP Online Purchasing Program.

Overall, these findings imply that continued increased spending through online FAH shopping options may bode well for the market shares of food markets targeting consumers who seek out particular food values (organic, local, minority-owned), including independent retailers, artisan sellers, and direct-to-consumer markets. Even if such markets do not offer online shopping options, those options among full selection players "opens up" shopping time that can be spent seeking out food items in niches where specialty markets might compete well (freshness, local sourcing). Since it is primarily the Values-Driven Multichannel shoppers who spend more on online FAH shopping, and they also seek out unique offerings from smaller food retail markets, such markets would be wise to invest in or elevate their online purchasing options. Policymakers at the state, federal and local levels have been supporting local and regional food markets for over two decades through market development programs, and perhaps now some of the technical assistance and grants can go to supporting producers who want to adopt or refine their online presence.

One key limitation of this research is that we assumed reliable food purchasing recall across fairly significant periods of time: a weakness we feel was somewhat mitigated because we asked

[11]Lacking data on proximity to store, we used a proxy from the Food Environment Atlas. This variable reported the percent of households in the respondent's zipcode that were at low access Low access was defined by the USDA as 33% of the population being greater than one mile away from a grocery store for urban consumers and more than ten miles away from a grocery store for non-urban consumers (USDA ERS, 2020).

[12]Additionally, online market channels utilized by over 25% of the sample included curbside pick-up at full selection stores, delivery at discount stores, and delivery at seller-limited stores.

at the market channel level (where credit card and bank statements often give summaries) rather than at the more delineated food product level. Also, we did not directly ask consumers to report their food access environments, including proximity to grocery stores and access to transportation. While we are grateful for the availability of the Food Environment Atlas, there is a certain level of uncertainty about the respondent's true level of access that remains. Additionally, we asked respondents to classify Amazon as an online-only retailer, but it is possible that some reported their Amazon usage as "discount" store usage or some other designation. This may have led to an over-reporting of shopping online at discount stores and an under-reporting of shopping online at online-only stores.

Our findings emphasize the importance of understanding how the dynamics of food shopping have changed in the past several years, and one of the most notable dynamics is consumers' online shopping behaviors. Particularly for those food entrepreneurs seeking access to marketing models that complement large national supply chains, it is important to understand that they are leveraging the heterogeneity of consumers' food values, and track where and how they are seeking out their preferred food offerings. These insights can also guide more specialty and locally-focused food retailers, through which those food entrepreneurs may find their best marketing options, as they adapt their strategies to meet the diverse drivers of market choices and values underlying food purchases among customers in the post-pandemic food environment.

## 2.8 Conclusion

This study explored the relationship between consumers' selection of a market channel set and their online shopping behavior for food-at-home (FAH) during the "New Normal" food environment era that has succeeded the COVID-19 pandemic. The research used latent class analysis to identify distinct classes of consumers based on their food value preferences, allowing us to account for the heterogeneity of consumers when estimating their behavior. Online shopping behavior was studied for a relatively broad variety of food retailers compared to prior studies of online food shopping. In total, we surveyed consumers about their online FAH shopping behavior at twelve different types of food retailers, then aggregated these according to the variety of products offered by the retailer. The first identified class represented shoppers who had relatively strong food value preferences, and the second class represented consumers who felt neutral or disagreed with the importance of the food values surveyed. When estimating the likelihood of shopping at a diverse set of FAH market channels, spending a higher share of one's budget on online FAH shopping was the largest marginal effect for consumers with strong food value preferences.

This provides evidence of a positive association between shopping at a variety of market channels and spending a higher budget share on online food shopping for consumers who have strong food value preferences. However, these consumers are continuing to shop both in-person and online at a variety of market channel types. So, they seem to be using online FAH shopping options to more easily find certain products and assure product availability. These shoppers spend more time shopping for FAH and may be re-allocating time saved from finding products online towards shopping in-person at food retailers with relatively limited selections who do not offer online shopping options. 50% of these consumers shopped in-person at local and independent markets. On the other hand, consumers with less-strong food preferences exhibit more streamlined FAH shopping habits. They use online shopping options sparingly, and when doing so, as a time-saving and bargain-finding tool.

This research sheds light on the evolving landscape of online FAH shopping behavior as consumers' familiarity with and usage of online platforms continues to increase. Our findings emphasize the importance of understanding variance in consumers' online shopping behaviors across different types of food retailers and the heterogeneity of consumers' characteristics and food values that may drive with these behaviors. These insights can guide food retailers in adapting their strategies to meet the diverse values of their customers in the post-pandemic food environment.

## 2.9 Tables

**Table 2.1:** Expectations of Covariate Impacts on the Propensity to Shop for Food Online from Pre-pandemic Literature

| | Impact | Citations |
|---|---|---|
| Age Category | - | (Etumnu et al., 2019; Farag et al., 2007; Jensen et al., 2021; Van Droogenbroeck and Van Hove, 2017) |
| Female = 1 | Mixed | (Etumnu et al., 2019; Farag et al., 2007; Jaller and Pahwa, 2020) |
| Children under 18 / Household size | + | (Etumnu et al., 2019; Hansen, 2007; Jaller and Pahwa, 2020; Jensen et al., 2021; Melis et al., 2016) |
| Education Category | + | (Etumnu et al., 2019; Hansen, 2007; Jaller and Pahwa, 2020; Van Droogenbroeck and Van Hove, 2017) |
| Income | + | (Etumnu et al., 2019; Hansen, 2007; Jaller and Pahwa, 2020; Van Droogenbroeck and Van Hove, 2017) |
| Grocery Budget | N/A | |
| Rural | - | (Etumnu and Widmar, 2020) |
| Distance to Store | + | (Melis et al., 2016) |
| In-Person Shopping Frequency | Mixed | Farag et al. (2006); Melis et al. (2016) |
| Full time employment | + | (Jensen et al., 2021; Van Droogenbroeck and Van Hove, 2017) |
| Essential Worker = 1 | + | (Jensen et al., 2021) |
| Concern about COVID illness | + | (Chenarides et al., 2021a; Jensen et al., 2021) |
| SNAP | N/A | |
| Value Affordability | N/A | |
| Value Locally Grown | N/A | |
| Value Organically Grown | N/A | |

**Table 2.2:** Expectations of covariate impacts on the propensity to shop for food online from previous literature

| | Impact | Citations |
|---|---|---|
| Age Category | - | (Etumnu et al., 2019; Farag et al., 2007; Jensen et al., 2021; Van Droogenbroeck and Van Hove, 2017) |
| Female = 1 | Mixed | (Etumnu et al., 2019; Farag et al., 2007; Jaller and Pahwa, 2020) |
| Children under 18 / Household size | + | (Etumnu et al., 2019; Hansen, 2007; Jaller and Pahwa, 2020; Jensen et al., 2021; Melis et al., 2016) |
| Education Category | + | (Etumnu et al., 2019; Hansen, 2007; Jaller and Pahwa, 2020; Van Droogenbroeck and Van Hove, 2017) |
| Income | + | (Etumnu et al., 2019; Hansen, 2007; Jaller and Pahwa, 2020; Van Droogenbroeck and Van Hove, 2017) |
| Grocery Budget | N/A | |
| Rural | - | (Etumnu and Widmar, 2020) |
| Distance to Store | + | (Melis et al., 2016) |
| In-Person Shopping Frequency | Mixed | Farag et al. (2006); Melis et al. (2016) |
| Full time employment | + | (Jensen et al., 2021; Van Droogenbroeck and Van Hove, 2017) |
| Essential Worker = 1 | + | (Jensen et al., 2021) |
| Concern about COVID illness | + | (Chenarides et al., 2021a; Jensen et al., 2021) |
| SNAP | N/A | |
| Value Affordability | N/A | |
| Value Locally Grown | N/A | |
| Value Organically Grown | N/A | |

+ indicates positive association, - indications negative association, Mixed indicates both + and - are found in the literature, and N/A indicates that the literature has not been established.

**Table 2.3:** Means and standard errors of variables, conditional on class

| | **Values-Driven Multichannel Class** | | **Frugal Consumers** | | | |
|---|---|---|---|---|---|---|
| | Mean | Std. Err. | Mean | Std. Err. | T-test | Description |
| **Food Values** | | | | | | |
| Affordability | 6.110 | 0.026 | 5.954 | 0.023 | *** | 1…7 Likert scale with 1=Strongly Disagree, 7= Strongly Agree |
| Locally Grown | 5.197 | 0.034 | 3.818 | 0.030 | *** | 1…7 Likert scale with 1=Strongly Disagree, 7= Strongly Agree |
| Organically Grown | 5.020 | 0.039 | 3.237 | 0.032 | *** | 1…7 Likert scale with 1=Strongly Disagree, 7= Strongly Agree |
| Cultural Preferences | 5.036 | 0.038 | 3.580 | 0.031 | *** | 1…7 Likert scale with 1=Strongly Disagree, 7= Strongly Agree |
| **Dependent Var.** | | | | | | |
| Multichannel Shopper | 0.800 | 0.009 | 0.051 | 0.004 | *** | 1 if shopped at more than 3 types of market channels |
| $X_i$ | | | | | | |
| Age | 3.559 | 0.034 | 4.135 | 0.028 | *** | Age categories from U.S. Census. 3= 35-44, 4=45-54 |
| Female | 0.500 | 0.012 | 0.518 | 0.009 | | 1 if Respondent is Female, 0 otherwise |
| Children | 0.856 | 0.026 | 0.485 | 0.018 | *** | 1 if Children under 18 in household |
| Household Size | 2.943 | 0.034 | 2.502 | 0.026 | *** | Number of people in household |
| Education | 5.918 | 0.043 | 5.556 | 0.033 | *** | 5=some college or 6=associates degree |
| Rural | 0.133 | 0.008 | 0.385 | 0.002 | *** | From RUCA codes. 1 if micropolitan high commuting area or more dense |
| Income in 2023 | 8.076 | 0.085 | 7.011 | 0.067 | *** | Income categories from U.S. Census. 7= $60-70K, 8=$70-80K |
| ln(weekly expenditures on FAH Shopping) | 7.864 | 0.021 | 7.491 | 0.014 | *** | $216.86 for Values-Driven Class, $149.28 for Frugal Consumers |
| Higher Online Budget Share | 0.493 | 0.021 | 0.296 | 0.013 | *** | 1 if spending more share of budget on online FAH |
| Low Access | 20.227 | 0.283 | 21.719 | 0.076 | *** | 1 if 33% of pop. in zip. is >1 mi. from grocer in urban, >10 mi. in rural |
| SNAP user in October 2023 | 0.267 | 0.011 | 0.219 | 0.008 | *** | 1 if used SNAP in October 2023 |
| ln(minutes spent FAH shopping per week) | 4.381 | 0.015 | 4.187 | 0.012 | *** | 80 mins. for Values-Driven Class, 66 mins. for Frugal Consumers |
| Essential Worker | 0.403 | 0.012 | 0.290 | 0.009 | *** | 1 if essential worker |
| High Risk of Severe COVID | 0.283 | 0.011 | 0.280 | 0.008 | | 1 if at high risk to COVID |

T-test of statistical differences in means across classes. *indicates statistical significance at the $\alpha$=0.1 level, ** at the $\alpha$=0.05 level, and *** at the $\alpha$=0.01 level.

**Table 2.4:** Justification of 2 latent class model, where consumers are segmented by their food values

| **Comparing Bayesian Information Criterions (BIC)** | |
|---|---|
| Number of Classes | BIC |
| No latent classes | 5837.006 |
| 2 | 5425.148 |
| 3 | No convergence |
| **LR Test of "full" 2 class vs. "restricted" no latent class model** | |
| Lr chisq(6) = 462.41 | P >chisq = 0.000 |
| **2 Class Model Goodness of Fit Evaluation** | |
| **Entropy Value** | ent = 0.884 |
| **Average Latent Class Posterior Probabilities** | |
| Values-Driven Multichannel Class | 0.780 |
| | (0.004) |
| Frugal Consumers | 0.908 |
| | (0.002) |
| Overall Average | 0.858 |
| | (0.003) |

The food values used to segment consumers were valuation of local, organic, availability of culturally representative products, and affordability. Lower BICs indicate better fit (Vermunt and Magidson, 2002). Entropy values close to 1 are preferred, with the accepted threshold above 0.8 (Weller et al., 2020). Higher average latent class posterior probabilities are preferred, with overall accepted threshold above 0.8. Standard errors are reported in parentheses.

**Table 2.5:** Estimated coefficients and marginal effects of covariates, and average likelihood of dependent variable conditional on classes

| | **Values-Driven Multichannel Class** | | **Frugal Consumers** | |
|---|---|---|---|---|
| | Coefficient | Marg. Effect | Coefficient | Marg. Effect |
| **Food Values** | | | | |
| Affordability | 0.0109 | ***-0.0172 | base | |
| Locally Grown | ***0.1687 | 0.0088 | | |
| Organically Grown | ***0.2052 | ***0.0483 | | |
| Cultural Preferences | ***0.1821 | ***0.0365 | | |
| _cons | ***-2.5420 | | | |
| **Dependent Variable** | | | | |
| Multichannel Shopper Likelihood | 0.5496 | | 0.1587 | |
| Standard Error | (0.0502) | | (0.0254) | |
| $X_i$ | | | | |
| Age | ***-0.3801 | ***-0.0648 | **-0.2987 | **-0.0269 |
| Female | **-0.4079 | **-0.0696 | -0.4343 | -0.0392 |
| Children | *0.3721 | **0.0635 | 0.2409 | 0.0217 |
| Household Size | 0.0568 | 0.0097 | **-0.3640 | **-0.0328 |
| Education | 0.0005 | 0.0001 | 0.0091 | 0.0008 |
| Income in 2023 | 0.0457 | 0.0078 | 0.1061 | *0.0096 |
| ln(weekly expenditures on FAH Shopping) | ***0.4359 | ***0.0743 | **2.0343 | ***0.1834 |
| Rural | -0.2927 | -0.0499 | -0.1329 | -0.0120 |
| % of pop. At low access | *-0.01510 | *-0.0026 | 0.0128 | 0.0012 |
| ln(minutes spent FAH shopping per week) | ***0.5841 | ***0.0996 | -0.3452 | -0.0311 |
| Essential Worker | **0.4752 | **0.0810 | 0.1969 | 0.0178 |
| High Risk of Severe COVID | 0.3408 | 0.0581 | 0.2408 | 0.0217 |
| SNAP user in October 2023 | 0.1358 | 0.0232 | 0.8870 | *0.0800 |
| Higher Online Budget Share | ***0.6441 | ***0.1098 | 0.1486 | 0.0134 |
| _cons | ***-4.6695 | | ***-15.9276 | |
| Likelihood Ratio Test of Full vs. Restricted model: | LR chisq(28) = 964.88*** | | | |

*indicates statistical significance at the $\alpha$=0.1 level, ** at the $\alpha$=0.05 level, and *** at the $\alpha$=0.01 level. Standard errors are reported in parentheses beneath the estimated coefficients. The coefficient and marginal effect estimates for food values refer to findings from the Latent Class logit used to initially segment consumers. Class one, used as the base outcome, was labeled frugal consumers as their food value ratings were close to zero, suggesting price and value most influenced their choices.

### 2.9.1 Post-Estimation Tables

**Table 2.6:** Percent of values-driven multichannel class shopping in-person and online at various FAH market channel types, share of N=1773

| | | Online Shopping | | |
|---|---|---|---|---|
| | **In Person Shopping** | **Curbside Pick-up** | **Delivery** | **Both** |
| Full Selection | 98.2% | 25.6% | 20.5% | 7.9% |
| Limited Selection | 84.7% | 17.5% | 20.3% | 7.0% |
| Discount and Convenience | 84.4% | 17.9% | 33.8% | 5.9% |
| Local and Independent | 50.0% | 17.6% | 10.7% | 8.1% |
| Seller-Limited | 34.4% | 18.4% | 27.7% | 1.3% |
| Online-Only | n/a | n/a | 18.0% | n/a |

**Table 2.7:** Percent of frugal consumers shopping in-person and online at various FAH market channel types, share of N=2789

| | | Online Shopping | | |
|---|---|---|---|---|
| | **In Person Shopping** | **Curbside Pick-up** | **Delivery** | **Both** |
| Full Selection | 96.8% | 13.6% | 10.0% | 3.0% |
| Limited Selection | 40.3% | 5.4% | 5.5% | 1.0% |
| Discount and Convenience | 57.4% | 5.4% | 11.2% | 1.0% |
| Local and Independent | 9.8% | 7.3% | 3.3% | 0.0% |
| Seller-Limited | 3.4% | 5.3% | 10.5% | 0.0% |
| Online-Only | n/a | n/a | 7.5% | n/a |

**Table 2.8:** Percents of values-driven multichannel consumers and frugal consumers that shifted various food shopping behaviors since the pandemic began, shares of N= 1773 and N=2789, respectively

| | **Values-Driven Multichannel Class** | **Frugal Consumers** |
|---|---|---|
| Higher Food Budget Share | 61.1% | 68.3% |
| Higher FAFH Budget Share | 22.6% | 16.9% |
| Increased attention on values when selecting markets | 29.7% | 18.3% |
| Increased attention on values when selecting brands | 21.8% | 11.4% |
| Started an online food shopping subscription service | 4.5% | 3.8% |

## 2.10 Figures

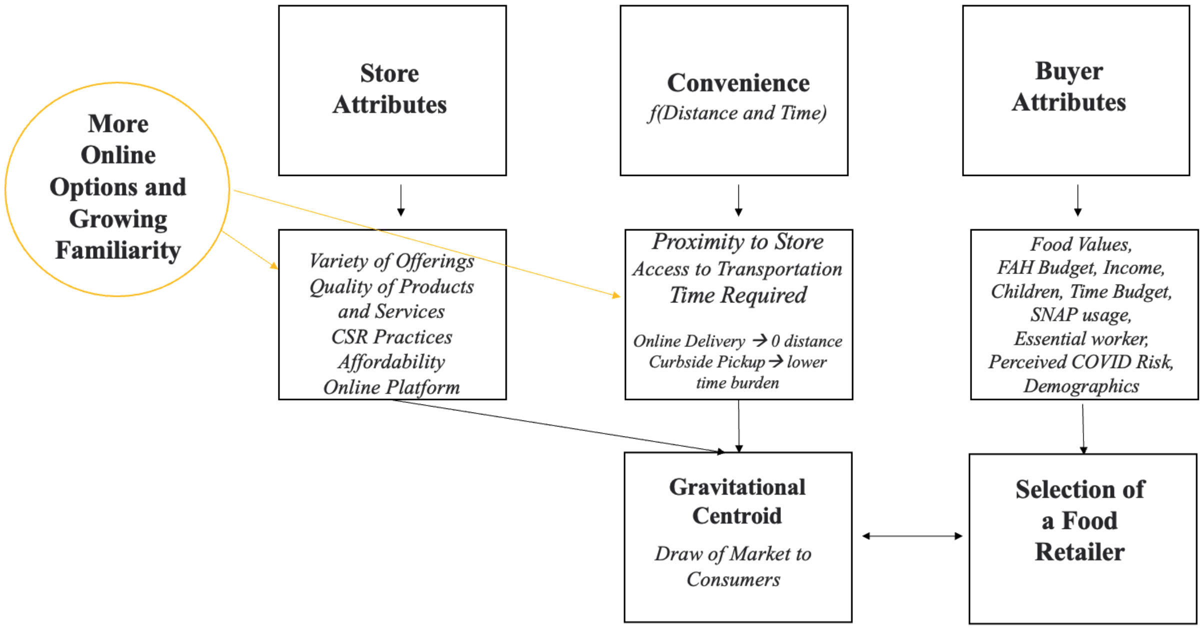



**Figure 2.1:** Gravity model of consumers' market selection decisions

Illustrates how the increased availability of online purchasing options and consumers' growing familiarity with online platforms in the post-pandemic food environment interacts with consumers' food retailer selection.

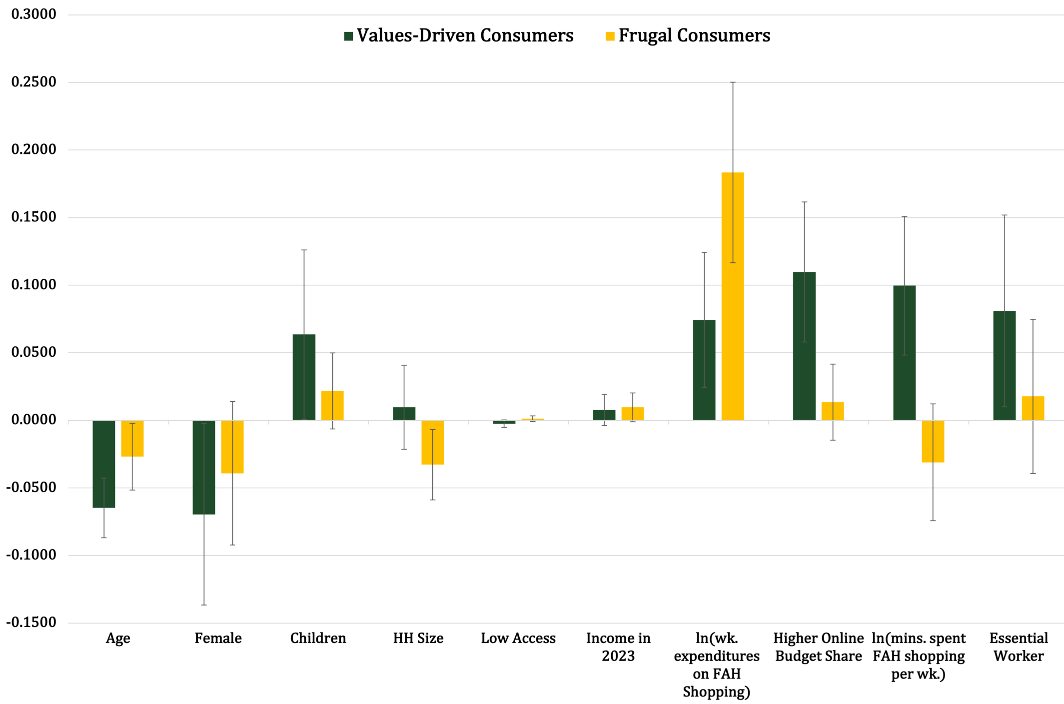



**Figure 2.2:** Marginal effects of selected covariates across classes of respondents


**Figure 2.3:** Aggregations of food markets into types

Respondents were asked about their selection of a variety of food markets in October 2023. To address our research question based on selection of market types, we aggregated these markets into types based on the variety of product offerings and convenience attributes (namely, distance-to-consumers).

## 2.11 Appendix

**Table 2.9:** Online food shopping utilization across market channel types, % of total shoppers in channel

| | **Full Sel.** | **Limited Sel.** | **Disc. & Conv.** | **Local** | **Seller-based Lim. Sel.** |
|---|---|---|---|---|---|
| N in 2022 (out of 4562) | 83% | 51% | 58% | 25% | 15% |
| N in 2023 (out of 4562) | 97% | 57% | 66% | 25% | 15% |
| Used in both years*** | 22% | 11% | 18% | 11% | 27% |
| Used in 2022 only* | 13% | 19% | 20% | 24% | 31% |
| Used in 2023 only** | 5% | 13% | 12% | 25% | 37% |
| No online in either year** | 52% | 52% | 48% | 46% | 26% |

*base N using channel in 2022, **base N using channel in 2023, ***base N using channel in 2022 and 2023

# Chapter 3

# Changes in Food Stockpiling Behavior During the COVID-19 Pandemic

## 3.1 Introduction

While consumers may stockpile in response to promotions or sales (Griffith et al., 2009), stockpiling behavior that disrupts supply chains and leads to shortages occurs during heightened uncertainty and is a form of panic buying (Prentice et al., 2022; Wahdat and Lusk, 2024). This study is concerned with the latter - stockpiling as the purchasing of larger than usual amounts of products for future consumption, in response to supply shortages during a time of crisis (Baker et al., 2020; Beatty et al., 2019; Prentice et al., 2022; Tsao et al., 2019). Throughout the COVID-19 pandemic, many consumers engaged in panic buying of food-at-home grocery items in reaction to fear of viral exposure, expected shortages and other supply chain disruptions, and/or uncertain future food prices (Baker et al., 2020; Biondi et al., 2021; Keane and Neal, 2021; Noda and Teramoto, 2024; Omar et al., 2021). Fluctuating COVID-19 severity was associated with risks of exposure, which translated to shifts in consumers' demand for food while also leading to periodic labor shortages and subsequent downstream supply chain challenges (Bonanno et al., 2025; Chenarides et al., 2021a; Hobbs, 2020; Thilmany et al., 2021b). In the Spring of 2021, the distribution of vaccines ushered in a new stage of the pandemic during which risk of exposure was lowered and price levels steadily increased (Adjemian et al., 2024; Bonanno et al., 2025).

Previous literature modeling consumers' decisions to stockpile food focuses on non-perishable, or shelf-stable foods, as these are most easily stored (Erdem et al., 2003; Wang et al., 2014). This is particularly true of the industrial organization and marketing literature, which largely focuses on studying stockpiling in response to temporary efforts to promote sales via price reductions (Blattberg et al., 1981; Ching and Osborne, 2020; Currim and Schneider, 1991; Hendel and Nevo, 2006b; Mela et al., 1998; Neslin et al., 1985; Osborne, 2018; Salop and Stiglitz, 1982). Yet, seeking to understand how firms strategically anticipate stockpiling is not useful in the case of "panic" stockpiling, as firms have no control over the uncertainty to which consumers are reacting in these cases. While there have been studies of consumers' food purchasing and stockpiling behaviors during the pandemic, they focus on either storable goods or aggregated expenditures (Baker et al., 2020; Dunn et al., 2021; Noda and Teramoto, 2024; Omar et al., 2021; Wahdat and Lusk, 2024); little is known about how consumers shifted the composition of their food shopping baskets by engaging in panic buying behavior in response to shocks that varied in type and intensity.

This paper measures consumers' stockpiling of both non-perishable and perishable food in response to COVID-19 related shocks, including pandemic-related fears and policy interventions. We characterize the nature of these panic buying behaviors across monthly purchases of food categories including perishable fruits and vegetables, non-perishable fruits and vegetables, perishable other food-at-home (FAH), and non-perishable other FAH. We use a dynamic model of consumers' decision making, closely following Hendel and Nevo (2006a)'s household maximization model that allows for inventory storage. Similar to Hendel and Nevo, our consumer maximizes the expected value of future utility flows while facing shocks and uncertain prices. In each period, the consumer chooses how much of a given category of food to purchase, choosing among different options that include perishable and non-perishable fruit and vegetable vs. all other food categories. Following Hendel and Nevo (2013), consumption in each time period is held constant. Any purchased food that is not consumed is stored at a cost and can be consumed in a future period if it is non-perishable. These type of dynamic models allow the observation of heterogeneous price sensitivity across consumers, as well as relatively accurate substitution patterns across perishable and non-perishable products (Hendel and Nevo, 2013; Wang et al., 2016). Unlike Hendel and Nevo (2006a), our shocks are observed rather than stochastic. We model shocks as proxies related to fears about food shortages, COVID-19 mortality, and food prices (captured by Google searches), as well as intensity of COVID-19 policies in a given month including lockdown measures, mask mandates, and emergency allocation of school meal program benefits (using policy data from the Centers for Disease Control (CDC)). Information on household food-at-home purchases come from Circana household and trip scanner data accessed via a Third-Party-Access-Agreement (TPAA) with the U.S. Department of Agriculture (USDA) Economic Research Service.

Consumers' responses to policy shocks and food scarcity are driven by psychological factors such as anxiety and uncertainty, which may lead to behaviors such as stockpiling and brand switching for those households seeking to better control current and future food access (El Baba and Fakih, 2023; Omar et al., 2021; Parker and Lehmann, 2011; Sim et al., 2020). Research shows that fear of future shortages triggers stockpiling, further exacerbating product availability issues, as was evident during the early stages of the COVID-19 pandemic (Biondi et al., 2021; El Baba and Fakih, 2023; Hobbs, 2020; Keane and Neal, 2021; Omar et al., 2021). Various models capture consumers' stockpiling behavior, highlighting the role of dynamic decision-making and the negative societal welfare impacts of such behaviors (Cosgrove et al., 2021; Crawford, 2018; Erdem et al., 2003; Hendel and Nevo, 2006a; Noda and Teramoto, 2024; Schmidt et al., 2023; Wahdat and Lusk, 2024; Wang et al., 2014). By comparing stockpiling of perishable and non-perishable food categories, we will contribute to an understanding of whether stockpiling behaviors exacerbated negative societal welfare impacts such as food waste and food sufficiency (Ellison and Kalaitzandonakes, 2020; Klumpp, 2021; Noda and Teramoto, 2024; Roe et al., 2021).

Figure 3.1 below uses data from the USDA Food Expenditure Series (USDA FES) to illustrate consumers' aggregate FAH and FAFH expenditures from Jan. 2019 to Dec. 2021. The pandemic-era shocks are shown by the sharp decreases in FAFH expenditures and increases in FAH expenditures that begin in March 2020 (USDA Economic Research Service, 2023). Many recent studies have sought to understand the nature of consumers' epxnediture shifts during the pandemic, including how much increases in FAH stem from decreases in FAFH, what portion of expenditures can be attributed to behavior changes compared to food price level changes, and which industries were most impacted by these shifts ((Andersen et al., 2022; Bachas et al., 2020; Balagtas et al., 2023; Bina et al., 2023; Biondi et al., 2021; Bonanno et al., 2025; Chronopoulos et al., 2020; Zeballos and Dong, 2022). For example, one study found evidence of a 12% increase of FAH expenditures and a 21 percent decrease in FAFH expenditures in the first 8 months of 2020 from U.S. Census Retail Sales data (Zeballos and Dong, 2022). Other authors found that shifts during this time period stemmed mostly from changes in shopping habits (Bonanno et al., 2025). In an analysis that compares observed expenditures with estimated food expenditures for a counterfactual scenario in which the pandemic never occurred, Bonanno et al. (2025) found that much of the greater-than-expected consumer expenditures after mass COVID-19 vaccinations can be attributed to rising food price levels. Another study which is aligned with these inferences used Google search data to find that consumers' panic and related responsiveness was highest during the lockdown phase of the pandemic (Keane and Neal, 2021).

Several studies analyzed expenditure shifts during the lockdown phase, when pandemic mitigation policies were first enacted (March-May 2020). During months when the most intense lockdown policies were in place, which often correlated to school and restaurant closures, changes in food purchasing habits were largest (Bonanno et al., 2025). Figure 3.2 illustrates the average number of days that these policies were implemented from 2020 to 2021 across all U.S. states. It is evident that these policies were most heavily implemented in the mid- to late-2020s, while mask mandates persisted through 2021 in some areas. These initial "lockdown" months of the pandemic were characterized by unprecedented increases in food-at-home (FAH) demand and changes in consumer purchase behavior that challenged all types of food retail outlets, with food retailers recording shortages of key food categories, including non-perishable food items (Hobbs, 2020). The many empty supermarkets shelves reported in the early phases of the pandemic led some consumers to feel uncertain about their future food supply, which then catalyzed panic buying behaviors and subsequent worsening of supply chain disruptions (El Baba and Fakih, 2023; Schmidt et al., 2023). Figure 3.3 illustrates how fears about food shortages, COVID-19 severity, and food prices fluctuated throughout the pandemic. This heterogeneity over the course of the pandemic, and the aforementioned previous findings which emphasize its importance, motivate our investigation of how expenditures of various food categories may have responded to a variety of different policy shifts and types of uncertainty that occurred throughout the pandemic, with a focus on unique dynamics related to different phases.

This research makes four major contributions to the literature. First, we contribute to the literature on consumers' dynamic decision-making under uncertainty. Specifically, we provide a fuller understanding of how consumers may stockpile across both perishable and non-perishable food when responding to fear related to food shortages, food prices, and/or public health emergencies, and the resulting policies. Second, we analyze shifts in behavior across food categories, which may help food system operators to face future disruptions. Third, in the comparison of policy interventions' impact on stockpiling, we allow policymakers to better understand how interventions such as urgent school meal program increases affected stockpiling, and we consider whether there may be implications for participating households' nutrition and food security levels. Finally, we contribute to the literature studying consumers' food shopping decisions during the pandemic. Understanding consumers' responses to the investigated uncertainty will yield important insights regarding which behaviors may be expected to reemerge, how policy might address challenges given consumers' stockpiling responses, and how food system institutions and policies can be better positioned to face future shocks.

## 3.2 Previous Literature

### 3.2.1 Panic-Induced Stockpiling Behavior

Consumers' responses to supply chain shocks and food scarcity are driven by psychological responses such as anxiety, uncertainty, and frustration. Research demonstrates that consumers exposed to these types of shocks exhibit heightened perceptions of risk and vulnerability. When the shocks are substantial, these psychological responses lead to defensive behaviors such as panic buying or brand switching to regain a sense of control over their consumption patterns in the face of uncertainty (Omar et al., 2021; Parker and Lehmann, 2011; Sim et al., 2020). Previous literature suggests that demand for panic-bought products is at its peak before a supply shock takes place, implying that these behaviors are driven by fears of future shortages (O'Connell et al., 2021; Schmidt et al., 2023). Using a probit model to analyze survey data, El Baba and Fakih (2023) found this to be true in the case of the COVID-19 pandemic; psychological disorders associated with increased anxiety levels were found to be positively associated with likelihood of stockpiling during the COVID-19 pandemic (El Baba and Fakih, 2023).

One type of panic buying that is often seen in response to supply chain shocks is stockpiling behavior, in which consumers buy large quantities of food that they believe will be less available for some significant amount of time[13]. In turn, this type of panic buying furthers product scarcity, compounding the original shock(Noda and Teramoto, 2024). This pattern was observed during the COVID-19 pandemic (Biondi et al., 2021; Hobbs, 2020; Keane and Neal, 2021; Klumpp, 2021; Omar et al., 2021). For instance, Keane and Neal (2021) created a panic index from Google search trends and policy announcements, and found that both domestic and global virus intensity drove consumer panic, as well as governments' policy announcements, though the panic induced by policy changes was found to be more temporary (lasting only 7-10 days) Keane and Neal (2021).

Other recent studies, as well as some that are still emerging, have considered stockpiling of storable goods during the COVID-19 pandemic. As one example, in their paper investigating Italian households' food purchasing behavior during the COVID-19 pandemic, Biondi et al. use fixed effect panel regression with scanner data to find differences in the magnitude of purchase behaviors across consumer segments. To measure stockpiling behavior, Biondi et al. observed changes in storable (non-perishable) food purchases. Authors found a modest increase (2.5%) in storable food purchases during the lockdown phase, which was smaller than was observed in other countries like the US and the UK (Biondi et al., 2021). A working paper by Klumpp (2021) investigates the stockpiling of toilet paper, finding evidence that welfare losses are greatest in the phase following a supply shock when households replenish their inventories.

In addition to the aforementioned psychological dimensions, others have considered implications for food waste from increased expenditures, or over-purchasing of food (Babbitt et al., 2021;

[13]As explained in the Introduction section, traditional or commonplace stockpiling also occurs in response to temporary price reductions (Griffith et al., 2009; Wahdat and Lusk, 2024). However, this paper seeks to understand panic-induced stockpiling.

Cosgrove et al., 2021; Ellison and Kalaitzandonakes, 2020; Roe et al., 2021). One study found evidence of increased food waste, as households accumulated more food than they could consume, leading to spoilage (Babbitt et al., 2021; Cosgrove et al., 2021). This phenomenon seemed to have been exacerbated by the initial panic buying, which prioritized quantity over quality, resulting in a surplus of perishable items that were ultimately wasted ((Fabusoro et al., 2023). Another study investigated the relationship between perceived pandemic risk, household food stocks, and food waste from online survey data, finding evidence of heterogeneity across food categories; frozen food was found to be stocked more than fresh fruits and vegetables, yet unsurprisingly, fresh fruits and vegetable purchases generated the most waste (Li et al., 2024). On the other hand, another study found that some consumers adopted better food management strategies, such as pre-shopping planning and creative cooking methods, to reduce waste and make better use of their stockpiled goods (Berjan et al., 2022; Murphy et al., 2020).

Studies in the observational learning field of psychology were also interested in stockpiling behavior in the context of pandemic-era fears. Observational learning, where individuals mimic the behaviors of others, was found to be a significant factor influencing stockpiling decisions. This social learning mechanism was particularly evident in the context of panic buying, where consumers felt compelled to stockpile after witnessing others do the same (Roos, 2024; Smith and Thomas, 2021). Additionally, demographic factors such as socioeconomic status and personality traits influenced stockpiling behavior, with individuals from lower socioeconomic backgrounds and those exhibiting higher anxiety levels being more likely to engage in stockpiling (Sadus et al., 2023; Wang and Gao, 2021).

Previous literature has used economic models to measure stockpiling behavior differently; Hendel and Nevo (2006a) consider the dynamic purchasing and consumption decisions made by consumers in the face of uncertain future shocks and random future prices. Hendel and Nevo (2006a) build on the earlier Erdem et al. model that demonstrated consumers' dynamic decision to purchase branded and storable goods while facing uncertain prices (Erdem et al., 2003). In the Hendel and Nevo (2006a) model, stockpiling behavior is prompted by a stochastic shock to future utility flows. Consumers maximize the expected value of their utility flows by balancing inventory storage costs with potential savings in the future, taking into account tastes and brand preferences. Hendel and Nevo (2006a) find that failing to account for dynamic decision-making in the measurement of stockpiling behavior may lead to substantial overestimation of own-price elasticities and substitution effects by 30% and 200%, respectively, as well as the underestimation of cross-price elasticities.

A recent dynamic model of stockpiling behavior was used by Schmidt et al. (2023) to demonstrate how panic buying behavior can cascade across periods, leading to intensification of the consumer response as was experienced during the recent pandemic. Similar to Hendel and Nevo (2006a), the consumer maximizes expected future utility flows subject to inventory storage costs. However, Schmidt et al. (2023)'s model is different in that the expected shock to utility is a negative supply shock, consumers and goods are homogeneous, and consumption is held constant to one unit per period. Using the observation that stockpiling behaviors do not solve supply shortages, but rather pass the burden of non-consumption to a different consumer, Schmidt et al. illustrate the negative welfare to society that is generated by panic buying and suggest policy to limit such behavior (Schmidt et al., 2023). A more recent paper by Noda and Teramoto (2024) provide a "consumer-search theoretic equilibrium model", which incorporates inventory storage decisions and finds that panic buying leads to overpurchasing of storable goods and welfare loss. Authors make several policy suggestions for mitigation of panic buying behaviors, including purchase quotas and reductions in sales taxes (Noda and Teramoto, 2024). On the other hand, another recent study which modeled shopping and inventory decisions used a lab experiment to quantify stockpiling, and found that purchase quotas may lead to stockpiling during trips when such quotas were not in place (Wahdat and Lusk, 2024).

It is understood in the literature that product categories most affected by stockpiling behavior are storable goods, including staple food-at-home items (Cavallo et al., 2014; O'Connell et al., 2021; Schmidt et al., 2023). Most of the economic literature modeling stockpiling behaviors empirically focuses on storable goods (Erdem et al., 2003; Hendel and Nevo, 2006a; Klumpp, 2021;

Noda and Teramoto, 2024; Schmidt et al., 2023). This makes intuitive sense, as storable goods are shelf-stable, and can generally be stockpiled for more time. However, many households may also find ways to store perishable food over time, such as via freezing or canning. Yet, previous research modeling stockpiling behavior has not examined how a uncertainty affecting perishable food (or the entire shopping basket) may impact the consumer's dynamic consumption and purchasing decisions of both perishable and storable food. By investigating this question and its extensions, this paper builds on the literature focused on dynamic consumer decision making in the face of uncertain future supply and prices. This research remains relevant today as uncertainty surrounding food markets, including the possibility of price fluctuations and supply disruptions from tariff negotiations, remains at the forefront of consumers' minds.

### 3.2.2 Fruit and Vegetable Purchase Habits and Food Assistance Programs

While previous literature on stockpiling sheds light on our understanding of perishable and non-perishable food purchasing, it is also critical to understand the impact of demographic factors on the purchasing behaviors of fruits and vegetables by U.S. households. This knowledge is critical to both the success of food industries and the efficacy of nutrition assistance and food security programs like the Supplemental Nutrition Assistance Program (SNAP) and the Women, Infants, and Children (WIC) program. The following literature synthesis summarizes findings from various economic and marketing journals and studies to develop our expectations of how household characteristics relate to propensity to purchase fruit and vegetables compared to other food categories.

Socioeconomic status (SES) is a primary determinant of food purchasing behavior, particularly for fruits and vegetables. Households participating in SNAP often face economic constraints that limit their ability to purchase fresh produce. Research indicates that SNAP participants tend to buy fewer fruits and vegetables compared to higher-income households, primarily due to budget limitations and the higher cost of fresh produce (Hernández-Vasquéz et al., 2022; Miller et al., 2016). Additionally, studies have shown that the benefits provided by SNAP are often insufficient to cover the costs of a healthy diet, leading to lower consumption of fruits and vegetables among low-income families (Hernández-Vasquéz et al., 2022; Miller et al., 2016). For instance, a study found that households receiving both SNAP and WIC benefits had poorer dietary quality compared to those receiving only WIC, highlighting the challenges faced by families relying on these assistance programs (Acciai et al., 2021).

Education level also plays a significant role in fruit and vegetable purchasing behaviors. Higher educational attainment is associated with greater awareness of the health benefits of consuming fruits and vegetables, which we may expect to lead to increased purchases (Taylor et al., 2012; Xaba and Dlamini, 2020). However, among low-income households, educational disparities can exacerbate the challenges of accessing and consuming healthy foods. For example, WIC participants with higher education levels reported more favorable experiences with food retail environments, which facilitated better access to fruits and vegetables (Martinez et al., 2022). This suggests that educational interventions could enhance the effectiveness of food assistance programs in promoting healthier eating habits.

Household composition further influences purchasing behaviors, particularly in relation to food assistance programs. Families with children, especially those enrolled in WIC, are found to be more likely to prioritize fruits and vegetables to support their children's health (Alakaam and Lemacks, 2015). However, logistical barriers such as transportation and access to stores that sell fresh produce can hinder these families' abilities to purchase fresh fruits and vegetables (Haynes-Maslow et al., 2020; McElrone et al., 2021). Research indicates that WIC participants often face challenges in utilizing their benefits effectively, which can lead to lower consumption of fruits and vegetables despite the program's intent to promote healthy eating (Martinez et al., 2022; Melnick et al., 2022). Moreover, the COVID-19 pandemic has significantly impacted food purchasing behaviors, particularly among low-income households. As discussed in the first chapter of this dissertation, the pandemic prompted a shift towards online grocery shopping, which presented both opportunities and challenges for SNAP and WIC participants. While online shopping can enhance access to fresh produce, barriers such as delivery fees and restrictions on using benefits for online purchases have limited its effectiveness for many low-income families (Brandt et al., 2019). Studies have shown that during the pandemic, households utilizing SNAP benefits reported changes in their food purchasing patterns, often opting for lower-priced foods with longer shelf lives, which can negatively affect fresh fruit and vegetable consumption, but perhaps, increase stockpiling of non-perishable fruits and vegetables (Ellison et al., 2021; Trude et al., 2025).

In conclusion, demographic factors such as socioeconomic status, education level, and household composition significantly influence the purchasing behaviors of U.S. households for fruits and vegetables, particularly in the context of food assistance programs like SNAP and WIC. Accounting for these household characteristics when comparing purchases of fruits and vegetables to other food purchases will allow us to understand how various populations might respond differently to uncertainty.

## 3.3 Methods

### 3.3.1 Theoretical Model

To model the consumer's decision about which food-at-home goods to stockpile in the face of uncertain food supply and price volatility, we follow Hendel and Nevo's model of inventory behavior, substituting perishability and private-label classifications for brand types and including a food category dimension (Hendel and Nevo, 2006a). The per-period (monthly) utility of household $h$ is defined such that:

$$u(c_{kht}, v_{ht}; \theta_{kh}) + \alpha_h m_{ht}$$

where $c_{kht}$ is the consumption of a $k$ category of good by household $h$ in period $t$, $v_{ht}$ is a vector of shocks to the household's utility that changes its marginal utility of consumption, $\theta_{hk}$ is a vector of household and food category-specific taste parameters, $m_{ht}$ is the consumption of the outside good, and $\alpha_{mt}$ is the marginal utility of consuming the outside good.

Different from Hendel and Nevo's model, $v_{ht}$ is observed and represents fears about food shortage events experienced during the pandemic. We will use monthly values, granular by state, of Google Trend Searches for "food shortage", "covid mortality", and "food prices" to quantify these fears and impose them econometrically. We hypothesize that $v_{ht}$ is subtractive in consumption, such that $u(c_{ht}, v_{ht}; \theta_h) + \alpha_h m_{ht} = u(c_{ht} - v_{ht}; \theta_h) + \alpha_h m_{ht}$. In other words, we expect high levels of $v_{ht}$ to be associated with higher perceived need, higher demand, and lower demand elasticity.

Let there be $K$ different categories of food-at-home goods, where:

- $k = 1$ represents fruits and vegetables
- $k = 2$ represents other food purchases

Then, let there be $J$ different classifications of a given good, where:

- $j = 1$ represents perishable (refrigerated food and fresh fruits and vegetables)
- $j = 2$ represents non-perishable; shelf-stable and frozen items

With $x_{jkht}$ representing the purchase quantity, the decision to purchase type $j$ and quantity $x$ of category $k$ is represented by $d_{hjkxt}$, where $x = 0$ represents no purchase. We assume that $\sum_{j,k} d_{hjkxt} > 0$ for all $t$. In other words, the household purchased at least one of the $j$ and $k$ combinations in a given month.

The consumer's choice is represented with the following Bellman equation:

$$V(s_1) = max_{c_{hjk}(s_t), d_{hjkx}(s_t)} \sum_{t=1}^{\infty} \delta^{t-1} E[u(c_{hjkt}, v_{ht}; \theta_{hjk})$$

$$-C_{hjk}(i_{hjk,t+1}; \theta_{hjk}+$$

$$\sum_{J,K} d_{hjkxt}(\alpha_{hjk} p_{jkxt} + \gamma_{hjkx} + \epsilon_{hjkxt})|s_1]$$

s.t.

$$0 \leq i_{hjkt}$$

$$0 \leq c_{hjkt}$$

$$0 \leq x_{hjkt}$$

$$\sum_{J,K} d_{hjkxt} > 0$$

$$i_{hjk,t+1} = i_{hjkt} + x_{hjkt} - c_{hjkt}$$

where $s_t$ represents the state at time t (comprised of inventory, current prices, utility shocks $v_t$, and stochastic error), $\delta$ represents the discount factor, $C_h(i_{hjk,t+1}; \theta_{kh})$ represents the cost of storing inventory $i$, $\gamma$ represents the taste for type $j$ of category $k$ that depends on quantity and varies between households, and $\epsilon_{hjkxt}$ is a random error term.

Additionally, the inventory storage cost function follows Erdem et al. (2003), such that: $C_h(i_{hjk,t+1}) = (hc + \delta_j) \cdot i_{hjkt} + sc$ ,where $hc$ is the per unit holding cost, $\delta_j$ is the degradation level, dependent on a good's perishability classification, and $sc$ is the fixed storage cost. Note: in the following econometric estimation, as consumption $C_h$ is unobservable, we instead estimate expenditures ($Y_{hjkt}$ of each food category and dynamically quantify stockpiling amounts.

### 3.3.2 Data

For this study, we combine data from several sources. First, we use scanner data from the Circana OmniMarket Core Outlets database[14], as well as trip data from the Circana Consumer Network panel, accessed via a Third-Party-Access-Agreement with the USDA Economic Research Service. Within the consumer network panel, we use the static household panel. This is a national consumer panel dataset with approximately 60,000 households participating in a static panel, from which we use monthly expenditure data from 2017 to 2021. Table 3.1 describes the variables obtained from the Circana static panel (as well as variables obtained from the datasets described below). As described in the table, we aggregated households' monthly purchases into four categories: perishable fruits and vegetables, non-perishable fruits and vegetables, perishable "other" food purchases, and non-perishable "other" food purchases [15]. Perishable food included fresh fruits and vegetables and refrigerated food, while non-perishable food included frozen and shelf-stable purchases. These delineations were chosen in order to facilitate analysis of stockpiling behaviors across these food categories in response to (in-part) fears about food supply uncertainty. This is discussed further in the following section.

Second, we obtained data from the Center for Disease Control (CDC) about federal and state policies related to COVID-19 mitigation that may have affected consumers' purchasing and stockpiling decisions. These data describe the number of days in a given month that lockdown measures, extended benefits programs[16], and mask mandates were in place. To obtain this information, the CDC collected data on distance learning and supplemental feeding programs from a stratified sample of 600 school districts (Centers for Disease Control and Prevention (CDC), 2022). We converted these data to represent the percent of a month that the policy was in place, in order to compare coefficient estimates to the final dataset used - our third and final data source was from Google Trends. We obtained indices of monthly searches of "food supply", "food prices",

[14]Circana was previously known as IRI, and this database was previously termed as InfoScan data.

[15]Fluid milk was included in this analysis, but other beverages were excluded.

[16]Extended benefit programs represent whether funding was allocated to supplement school meal programs in a given state.

and “COVID mortality", granular by state. These search terms were selected after comparison to several other search terms, including: “food supply", “supply chain", “COVID deaths", and “COVID virus". The selected search terms were chosen because they made up a higher proportion of searches compared to all other Google searches given the time frame (2019 to 2021) and geographical granularity (state), and thus exhibited more variety that could be leveraged in the stockpiling estimation.

The Google Trend Index creates its 0 to 100 index based on the proportion of searches for a specific term relative to the total searches on Google over a given time period and location (Google, 2024; Schmidt et al., 2020). Thus, these Google Trend searches are inherently normalized by population. Google Trends Indices have been used in previous literature to study impacts of disease outbreaks (Arora et al., 2019; Carneiro and Mylonakis, 2009; Ginsberg et al., 2009; Mavragani et al., 2018; Nuti et al., 2014), as well as more recently, to track consumers' food sourcing during the COVID-19 pandemic (Schmidt et al., 2020). Several studies have used Google Trends data to understand households' fears related to health, crime, stock market performance, and even COVID mortality (Awijen et al., 2022; Correia and Mammola, 2024; Rathke et al., 2023; Subramaniam and Chakraborty, 2021; Timoneda and Vallejo Vera, 2021). Most closely related to this study, Keane and Neal (2021) created a “panic index" from Google search terms and government policy announcements to understand consumers' panic related to the dynamic COVID-19 pandemic across the globe (Keane and Neal, 2021). The selected Google Trend search terms, “food supply", “food prices", and “COVID mortality", may reflect households' fears, but may also be associated with reduced fear when a given search resulted in better-than-expected news. For example, if a household searched “COVID mortality" and found that mortality was greatly reduced, they may be inclined to engage in less-restricted public exposure behavior. To avoid relying on the assumption that increases in the number of searches are correlated with increased fears related to the search term, we name the Google trend variables “search" variables, and will interpret them in the context of a specific pandemic phase of interest.

Together, the CDC and Google Trend data sources will be used to understand how stockpiling behaviors responded to policy changes and virus dynamics that occurred across various phases of the pandemic. Table 3.1 describes the variables obtained from these data, and table **??** describes the means of these variables conditional on pandemic phase. We follow the pandemic phases specified by Bonanno et al. (2025) in their investigation of pandemic impacts on food expenditures at various market channels. These five phases were based on viral waves and policy events, such as the vaccine roll-out in Spring of 2021:

- Lockdown: March 2020 to May 2020
- Summer: June 2020 to September 2020
- Winter: October 2020 to February 2021
- Vaccine: March 2021 to July 2021
- New Normal: August 2021 to December 2021

### 3.3.3 Econometric Estimation

Our empirical approach of stockpiling estimation is comprised of several steps:

1. A 2-step estimation procedures is used to estimate (1) the purchase decision and (2) monthly expenditure amounts.
2. From these parameter estimates, we predict monthly expenditures from 2017 to 2021.
3. We quantify monthly stockpiling amounts from the difference in observed and predicted expenditures (with more complexity explained below).
4. Finally, we regress monthly stockpiling amounts for each food category on the policy and fear variables from the CDC and Google Trends data.

**2-Step Estimation Procedure**

When considering how to obtain predicted monthly expenditure values for a given food category and perishability level $jk$, we must take into account that expenditure values are censored;

they are non-negative and sometimes observed as zero when corner solutions in the consumers' utility framework occur (households that decided not to purchase category *jk* in a given month). Furthermore, as there are multiple (four) food category and perishability level combinations, censoring may occur in multiple equations for a given month. In order to deal with the issue of bias stemming from households that decided to make a monthly purchase of a certain *jk* food category and type vs. those that did not, we follow Shonkwiler and Yen's selection correction method for systems of equations that have limited dependent variables (Shonkwiler and Yen, 1999).

In this paper, we consider the following system of equations estimating monthly expenditures of four food category/perishability levels. For brevity, the $t$ index has been excluded from the equations in this section.

Let:

- $h$: households
- $jk = 1, 2, 3, 4$: index for food category/perishability level
- $y_{hjk}$: observed monthly expenditure on food category $jk$ for household $h$
- $y^*_{hjk}$: latent (desired) expenditure
- $\mathbf{x}_{hjk}$: vector of explanatory variables
- $\boldsymbol{\beta}_{jk}$: parameter vector for category $jk$
- $\epsilon_{hjk}$: error term
- $d_{hjk}$: indicator variable: $d_{hjk} = 1$ if $y_{hjk} > 0$, and $0$ otherwise

**Latent Demand System (Unobservable)**

$$y^*_{hjk} = \mathbf{x}'_{hjk}\boldsymbol{\beta}_{jk} + \epsilon_{hjk}, \quad jk = 1, 2, 3, 4$$

Observed expenditures:

$$y_{hjk} = \begin{cases} y^*_{hjk}, & \text{if } y^*_{hjk} > 0 \\ 0, & \text{if } y^*_{hjk} \leq 0 \end{cases}$$

Then, following Shonkwiler and Yen (1999), we obtain IMRs from selection equations, which are then used to correct for selection bias in the estimation of monthly expenditures.

**Step 1a: Probit Selection Equations**

Probit model estimates the probability of a household's positive monthly expenditure of a given food category and perishability level:

$$\Pr(d_{hjk} = 1 \mid \mathbf{z}_{hjk}) = \Phi(\mathbf{z}'_{hjk}\boldsymbol{\gamma}_{jk})$$

where:

- $\Phi$ is the standard normal cumulative distribution function (CDF)
- $\mathbf{z}_{hjk}$ are a vector of explanatory variables, including one, two, three, and four month lagged expenditures, as well as the household characteristics shown in table 3.1.

Then, we compute the inverse Mills ratio (IMR):

$$\lambda_{hjk} = \frac{\phi(\mathbf{z}'_{hjk}\boldsymbol{\gamma}_{jk})}{\Phi(\mathbf{z}'_{hjk}\boldsymbol{\gamma}_{jk})}$$

where $\phi$ is the standard normal probability density function (PDF), calculated only for observations where $y_{hjk} > 0$.

**Step 1b: Outcome Equations (Conditional on Positive Expenditures)**

The modeled observed system includes the IMR, such that:

$$y_{hjk} = \mathbf{x}'_{hjk}\boldsymbol{\beta}_{jk} + \rho_{jk}\lambda_{hjk} + u_{hjk}, \quad \text{for } y_{hjk} > 0$$

- $\mathbf{x}_{hjk}$: is a vector of explanatory variables, including the household characteristics in table 3.1, monthly seasonal effects, and a one-month lag of expenditures.
- $\rho_{jk}$ captures selection bias
- $u_{hjk}$ is an error term with cross-equation correlation

**Step 2: Prediction of Monthly Expenditures Using Two-Step Estimates**

Using the parameters estimated from the two-step censored system, we then predict monthly expenditures for each household and food category/perishability level.

**Latent Expenditure Prediction from Step 1a**

Let:

- $\hat{\boldsymbol{\beta}}_{jk}$: estimated coefficients for explanatory variables
- $\hat{\rho}_{jk}$: estimated coefficient on the inverse Mills ratio
- $\lambda_{hjk}$: inverse Mills ratio computed from the probit model

The predicted latent (unobserved) expenditure for household $h$ and food category $jk$ is:

$$\hat{y}^*_{hjk} = \mathbf{x}'_{hjk}\hat{\boldsymbol{\beta}}_{jk} + \hat{\rho}_{jk}\lambda_{hjk}$$

**Predicted Actual (Observed) Expenditure from Step 1b**

Because the observed expenditure is censored at zero, we compute the expected actual expenditure conditional on selection (i.e., for all households, not just those with positive expenditures). This is given by:

$$\hat{y}_{hjk} = \Phi(\mathbf{z}'_{hjk}\hat{\boldsymbol{\gamma}}_{jk}) \cdot \hat{y}^*_{hjk}$$

- $\hat{\boldsymbol{\gamma}}_{jk}$: estimated coefficients from the first-step probit model
- $\Phi(\mathbf{z}'_{hjk}\hat{\boldsymbol{\gamma}}_{jk})$: estimated probability that $y_{hjk} > 0$

**Final Expenditure Prediction**

For each household $h$ and food category $jk$, the predicted monthly expenditure is:

$$\hat{y}_{hjk} = \Phi(\mathbf{z}'_{hjk}\hat{\boldsymbol{\gamma}}_{jk}) \cdot \left(\mathbf{x}'_{hjk}\hat{\boldsymbol{\beta}}_{jk} + \hat{\rho}_{jk}\lambda_{hjk}\right)$$

This prediction accounts for both the likelihood of a positive expenditure and the expected value of expenditure, conditional on that likelihood.

**Step 3: Stockpiling Quantification**

Next, we quantify the gap between expected and observed purchases, $\hat{Y}_{hjkt} - Y_{hjkt}$. This is a measurement of total over-purchasing in a given month. Then, we use this gap and the lag of the gap (over-purchasing in the previous month), to identify the stockpiling amount. By including the lag of purchasing the previous month, we incorporate the dynamic nature of the stockpiling decision; put more simply, this provides some measure of inventory from one period to the next.

In the following equation that quantitatively defines stockpiling, the terms in the first bracket represent the over-purchasing of a given food category compared to the previous month, using expected monthly purchases. The following terms in equation 3.1 capture the difference in the gap between observed and predicted expenditures compared to the previous month. Together, these terms capture the dynamic stockpiling decision. To see the steps taken to arrive at this equation, see section 3.10.1 in the Appendix.

$$Stockpiling_{hjkt} = [\hat{Y}_{hjkt} - \hat{Y}_{hjk(t-1)}] + ([\hat{Y}_{hjkt} - Y_{hjkt}] - [\hat{Y}_{hjk(t-1)} - Y_{hjk(t-1)}]) \tag{3.1}$$

**Step 4: Stockpiling Regression**

To empirically estimate stockpiling behavior of various food categories during the pandemic, we first limit our data to post-pandemic years (2020 and 2021), and secondly, we specify the phases of the pandemic for which we want to estimate separate coefficients in order to understand how fears and policy shifts impacted stockpiling heterogeneously throughout the pandemic. Although previously described in the Data section, as a reminder, the investigated pandemic phases were defined from viral waves and policy events, as such:

- Lockdown: March 2020 to May 2020
- Summer: June 2020 to September 2020

- Winter: October 2020 to February 2021
- Vaccine: March 2021 to July 2021
- New Normal: August 2021 to December 2021

(Bonanno et al., 2025).

Finally, using a pooled OLS estimator[17], we regress households' monthly stockpiling amounts on factors that drove stockpiling behaviors, including the shocks regarding fears about food shortages and shifts in COVID-era policies.

We ran separate regressions for each $jk$ food category, and interact the policy variables and fear proxies with the aforementioned pandemic phases in order to have separate coefficient estimates per pandemic phase:

$$Stockpiling_{hjkt} = \alpha + \sum_{m=1}^{6} \sum_{p=1}^{5} \beta_{mp}(Shock_{st}^{m} * Phase_{t}^{p}) + \tag{3.2}$$

$$t_m + state_h + metro_h + e_{hjkt}$$

where:

- Shock$_{st}^{(m)}$ is the $m$-th state and time-varying shock variable (including the three Google Trend and three CDC policy variables),
- Phase$_{t}^{(p)}$ is an indicator for pandemic phase $p$,
- $\beta_{mp}$ is the effect of shock $m$ during phase $p$,
- $t_m$, $state_h$, and $metro_h$ are dummies for each month, state where the household resides, and metro status where the household resides.

[17] Pooled OLS treats all observations as independent, which is useful in this instance when we are estimating average effects across all households and pre-defined time periods. We assume that unobserved individual-specific effects are not correlated with explanatory variables. Note, many individual-specific effects were used to estimate the monthly estimated stockpiling value.

- $e_{hjkt}$ is the error term.

Since we have national effects that impact everyone at a similar time, as well as effects that vary across time but within states, robust standard errors were obtained by clustering errors on state and month-year.

## 3.4 Results

### 3.4.1 Two-Stage Selection Correction to Predict Monthly Expenditures

In order to predict monthly expenditures for the four $jk$ food categories: *perishable fruit and vegetables*, *non-perishable fruit and vegetables*, *perishable other*, and *non-perishable other*, a two stage model was used to address bias stemming from the censored nature of the expenditure data. In the first stage, the decision to purchase (or not) is estimated with a probit model, and the second stage estimates monthly expenditures with a linear regression that includes the inverse mills ratio (IMR), derived from the first stage's coefficient estimates. Tables 3.2 and 3.3 convey the coefficient estimates and standard errors of the first and second stage models, respectively. Importantly, it is in these first two stages- the estimation of the purchase and expenditure decisions- that demographics are included in the analysis. Then, from the predicted expenditures in these stages, stockpiling was quantified. Finally, the stockpiling regression in the fourth stage measures the impact of Google search results related to pandemic events and COVID-19 mitigation policies on pandemic-era stockpiling behaviors. Table 3.4 describes the coefficient estimates from the stockpiling regression, and table **??** conveys the average impact on stockpiling amounts across the defined pandemic phases. The primary contribution of this paper is to analyze consumers' stockpiling behaviors in response to dynamic COVID-19 fears and policy shifts. Accordingly, this will be the primary focus of the Discussion section (3.5), with implications of the demographic results (as they relate to estimated expenditures) integrated into the subsequent results reporting.

**Decision to Purchase a $jk$ Food Category**

In the estimation of the purchase decisions, households with an older head of household, larger households, households without children, White and non-Hispanic households, and those with higher pre-pandemic income were more likely to purchase all $JK$ food categories. Non-metro status of residency location and gender of the household head showed mixed results regarding likelihood of purchase across the food categories. Households in non-metro areas (county population less than 49,999[18]) were more likely to purchase *non-perishable fruit and vegetables* and all *other* food, but less likely to purchase *perishable fruit and vegetables*. This is likely a reflection of food environments associated with non-metro areas; particularly the lack of outlets selling fresh fruits and vegetables in counties where the population is less than 49,999 (USDA ERS, 2020). For gender, households with a female head of household were associated with an increased likelihood of purchasing *fruit and vegetables* (both perishable and non perishable) but decreased likelihood of purchasing *perishable other* food. Employment status of a female parent was only statistically significant for one food category - households in which a female parent worked were less likely to purchase non-perishable fruit and vegetables.

On average (from 2017 to 2022), participation in SNAP and WIC food assistance programs was associated with a decreased likelihood of purchasing perishable fruit and vegetables, *perishable other* food, and *non-perishable other* food; estimates for non-perishable fruit and vegetables were not statistically significant. While we control for pre-pandemic income in this estimation[19], this negative association may, in part, be reflecting that households participating in food assistance lost income during the pandemic, and were therefore less likely to purchase food overall.

In general, expenditures in the preceding four months were positively associated with likelihood of purchasing in the current month. This association was strongest for the most recent months, and decreased as time from the current month increased. The positive relationship of the

[18]Following USDA Economic Research Service definition of non-metro (USDA, Economic Research Service, 2025).

[19]Inclusion of household income during the pandemic (2021) was excluded due to multicollinearity with pre-pandemic household income.

lagged expenditures is likely indicative of the habitual nature of the decision to purchase a given food category in each month.

**Estimated Expenditures of a $jk$ Food Category**

After analyzing the decision to purchase in the first stage, the second stage estimated monthly expenditures of *positive purchases*. So, table 3.3 illustrates the average (from 2017 to 2021) estimated impact of seasonality, demographics, and lagged expenditures on positive monthly expenditure amounts in dollars. As a reminder, the Inverse Mills Ratio (IMR) connects the stage one coefficient estimates to the estimation of positive expenditures, and therefore controls for selection bias that stems from estimating only positive purchases.

The first group of covariates are the month dummy variables, which capture seasonality of positive expenditure purchases. Generally, the month-to-month trend, meaning whether the dummy variable in the next month increases or decreases compared to the January base, is similar over the $JK$ food categories. Two exceptions, in which a food category's trend differs from the others, are observable for the *perishable fruit and vegetable* category- the large positive increase in expenditure impact that occurs from February to March, as well as the decrease in expenditure impact that occurs from July to August. This likely reflects the availability of fresh fruit and vegetables that increases during the summer. It is important to note that compared to the base month, January, almost all of the coefficients on the monthly variables are negative. Generally, U.S. households are understood to spend more during the winter holiday months, but less in January (Wilson Sinclair and Eliana Zeballos, 2025). So, this may indicate that there is a lag in the reporting of expenditures that occur late in the month for this dataset. Or, as this estimation included data from the COVID-19 pandemic, another potential explanation may be that there were changes in seasonality trends during the pandemic. For example, if a virus wave was very severe in January 2021, leading to panic buying and/or fewer FAFH expenditures, other months may have had comparatively lower expenditures. Further examination of monthly expenditure data, including the reporting dates, is needed to understand the unusual seasonality trends.

The second group of covariates to consider are the household panel's demographics. In some cases, the estimated associations between demographics and higher expenditure amounts differed from the patterns found in the stage one decision to purchase. In fact, age of the household head, gender of the household head, female employment, race, Hispanic ethnicity, metro status, presence of children, and food assistance participation all exhibited different patterns from the first stage. Households with younger heads of the household were found to be less likely to purchase food, but spent more on all $JK$ food categories when they did make a purchase. Households with female heads of household spent more on *perishable fruit and vegetables*, *perishable other* food, and *non-perishable other* food, but less on *non-perishable fruits and vegetables* when they did make a purchase. Yet, households in which a female parent was working spent less on all food categories compared to households that did not have an employed female parent.

When estimating expenditures, racial ethnicity of household heads exhibited more heterogeneity than in the purchase decision estimation. Household heads that identified as Black and Asian spent more on *non-perishable fruit and vegetables* compared to White household heads, but less on the *other* food categories. Household heads that identified as another racial ethnicity spent more on all *fruit and vegetables* compared to White household heads, but less on *other* food. Hispanic household heads spent substantially less on *other* food compared to non-Hispanic household heads, but estimates for *fruit and vegetable* expenditures were not statistically significant.

Households in non-metro counties (population less than 49,999) still spent less on *perishable fruit and vegetables* compared to households in metropolitan counties, which is aligned with the first stage findings. Yet, they were also found to spend less on *non-perishable fruit and vegetables* as well as more on other food when they did make a purchase. This may reflect the tendency for non-metro households to make larger purchases and fewer trips to the store, since travel time to the store is often longer in rural areas.

Households with children spent less on *non-perishable* food, but more on *perishable other* food. Much of this is likely attributable to higher purchases of dairy products among households with children. There was no statistically significant difference found for *perishable fruit and vegetables*.

Findings for households participating in food assistance programs were quite different from the first stage results. Households participating in SNAP and WIC who did purchase a $jk$ food category were found to spend more on all categories compared to non-participating households. (Note, we have controlled for income in this estimation.) This is aligned with expectations, given that these programs allocate benefits that must be spent at food retailers. There is also much literature which has also found that food assistance participation leads to increased food expenditures (Beatty and Tuttle, 2015; Fox et al., 2004).

The nuances of the expenditure estimates for food assistance participation across the food categories investigated provide more novel considerations. While it is difficult to directly compare coefficient estimates for fruit and vegetables to the other categories since the other categories are much more aggregated, we can compare these coefficient estimates to those for income to understand how the effect of participating in SNAP and/or WIC are different from the effect of increased income. For instance, we estimate that increasing a household's income would increase expenditures of *perishable other* food (e.g. meat and poultry) most, followed closely by *non-perishable other* food and perishable fruit and vegetables. We find that increasing income would not substantially increase estimated expenditures on *non-perishable fruit and vegetables*. Instead, participating in SNAP and WIC is estimated to most strongly increase expenditures of *non-perishable other* food (e.g. bread and cereals, canned other food, frozen other food, etc.), followed by *perishable other* food, then *non-perishable fruit and vegetables* and *perishable fruit and vegetables*. This pattern difference is likely a reflection of both the product selection that is eligible for SNAP and WIC benefits and the heterogeneity of spending habits across U.S. households' income levels - for example, the relatively high prices of meat and poultry may imply that increases in income for lower-income households may lead to proportionally higher expenditures on *non-perishable other* food. However, investigation of more disaggregated food categories is needed to confirm these implications.

Lastly, the one month lag of monthly dollars spent on each category is positive for *perishable fruit and vegetables*, but negative for all other categories. This suggests that *perishable fruit and vegetables* are not stored from month to month, but rather, increased expenditures in the previous month indicate a shopping habit of spending more on fresh fruit and vegetables. For the other categories, spending more in the previous month led to lower expenditures in the current month, suggesting that these foods may be stored. This is unsurprising for the non-perishable categories, but is notable for the *perishable other* category, as previous literature on stockpiling does not often take perishable food into consideration. Yet, households are commonly known to sometimes stock up on relatively expensive meat and poultry when it is on sale and freeze it for later consumption. This should be kept in mind as we consider the investigation of stockpiling behaviors in the subsequent sections.

### 3.4.2 Impacts of COVID-era Fear Dynamics and Virus Mitigation Policies on Food Stockpiling

After the coefficient estimates were used to predict expenditures for each month, stockpiling quantities were calculated from the difference between observed and predicted expenditure purchases given inventory from the previous month. This calculation is described in section 3.3.3 and is detailed in the Appendix. Finally, stockpiling quantities are regressed on Google Trend search variables capturing consumers' fear dynamics and the CDC mitigation policy variables. Table 3.4 includes the coefficient estimates and standard errors from this second-stage regression, and tables 3.5,**??**, 3.7, and 3.8 convey the average impact of each variable on monthly stockpiling levels across phases of the pandemic for each food category. The coefficient estimates in the stockpiling regression reflect the comparison to the “base" pre-pandemic months (January 2019 to February 2020).

For brevity and ease of interpretation, this section will focus on the average impact of each variable on monthly stockpiling results reported in tables 3.5,**??**, 3.7, and 3.8. As hypothesized, we do find evidence that stockpiling behaviors were impacted by the fear dynamics (indicated by

Google search variables) and policy changes that fluctuated through each phase of the pandemic. Stockpiling of *other* food appears to have been impacted by the investigated covariates more often than *fruit and vegetables*. However, when comparing magnitudes across categories, it is important to remember that the *other* food category is much more aggregated than *fruit and vegetables*, and therefore makes up a larger portion of the household budget.

In the lockdown phase of the pandemic, which encompassed March to May 2020, searches related to “Food Prices" led to the largest increases in average monthly stockpiling amounts. The average index value of the “Food Prices" Google search index during the lockdown phase was around 12, which is estimated to yield a $7.22 increase in monthly stockpiling of *perishable other* food and a $10.51 increase in monthly stockpiling of non-perishable other food. Similarly, the average index value of the “COVID Mortality" Google search index during the lockdown phase was around 13, which is estimated to yield a slight ($0.23) increase in monthly stockpiling of *non-perishable fruit and vegetables*, a $4.43 increase in monthly stockpiling of *perishable other* food and a $8.06 increase in monthly stockpiling of *non-perishable other* food.

Regarding policy impacts during the lockdown phase, we generally observe somewhat smaller impacts on monthly stockpiling compared to the Google search variables. Notably, we find a negative relationship between lockdown measures and stockpiling tendencies during this time. The average percent of the month in which lockdown measures were in place during this phase was around 46%, which is estimated to yield a decrease in stockpiling of -$3.49 for *perishable other* food and -$7.02 for *non-perishable other* food. Contrastingly, the extension of benefits programs (e.g. emergency allocations for school meal programs) and mask mandates were associated with increased stockpiling of *other* food during the lockdown phase. This discrepancy is analyzed in the following Discussion section.

For the summer and winter waves, which lasted from June to September 2020 and October 2020 to February 2021 respectively, higher “Food Prices" searches were associated with lower stockpiling of *perishable other* and *non-perishable other* food. This negative association was also observable for “COVID Mortality" searches in the summer wave (for *perishable fruit and* *vegetables*), and “Food Supply" in the winter wave (for *other* food categories). “Food Supply" searches were not found to impact stockpiling in the summer wave, while “COVID mortality" searches were not found to impact stockpiling in the winter wave. The extended benefits policy was positively associated with stockpiling in the summer and winter waves. In fact, it was the only variable to have a consistent directional impact on stockpiling from lockdown through the winter phase, and the only variable to positively impact stockpiling behaviors during the summer wave. Lockdown measures were not found to significantly impact stockpiling during the summer and winter waves, while mask mandates were not found to be significant in the summer but negatively impacted stockpiling behaviors in the winter wave. Clearly, these results imply that the impact of a fear or policy was heterogeneous throughout the investigated pandemic phases, and must be considered within the context of that phase.

A final takeaway to note before considering these findings in more depth is that we found no evidence that the search or policy variables impacted stockpiling behaviors during the Vaccine or New Normal periods. This may imply that after the roll-out of vaccines that occurred in the Spring of 2021, consumers no longer engaged in stockpiling behaviors and largely returned to pre-pandemic food-at-home shopping behaviors. This finding is aligned with recent literature that arrived at a similar conclusion (Bonanno et al., 2025; Marchesi and McLaughlin, 2024; Zeballos and Dong, 2022). Given this, the following Discussion section will analyze the dynamics of factors driving stockpiling behavior that occurred during the Lockdown, Summer, and Winter waves.

## 3.5 Discussion

The main contributions of this investigation are findings related to stockpiling behaviors of various food categories in response to fluctuating fears and policies during the COVID-19 pandemic. From previous (both pre-pandemic and post-pandemic) stockpiling literature, it is understood that non-perishable goods are subject to stockpiling behaviors[20], while perishable food is not studied

[20]As a reminder, stockpiling is calculated from both over-purchasing of food from the previous month and over-purchasing compared to predicted expenditures. Equation 3.1 describes this calculation.

in the stockpiling literature due to its inherently less-storable nature (Cavallo et al., 2014; Erdem et al., 2003; Klumpp, 2021; Li et al., 2024; Noda and Teramoto, 2024; O'Connell et al., 2021; Schmidt et al., 2023). Yet, this literature neglects to account for the ability of consumers to find ways to store perishable food, such as freezing, canning and dehydrating. The first takeaway from this paper's findings is that we do find evidence that consumers stockpile perishable food, and in particular- perishable "other" food. The degree to which food was stockpiled fluctuated throughout the lockdown, summer, and winter waves of the pandemic; we do not find evidence that stockpiling occurred after the roll-out of vaccinations in the Spring of 2021. This finding, in itself, signals that consumers' stockpiling behaviors respond to policy and (and associated fear) dynamics. Indeed, consumers' stockpiling responded to various policies in different ways, and heterogeneously across phases of the pandemic. This general finding is aligned with a related recent study that classified consumers' panic with Google trend searches and counts of policy announcements (Keane and Neal, 2021).

One aspect that the Keane and Neal (2021) study considered was the possibility that a policy reduced consumers' expected future severity of the pandemic, which then lowered their panic. Similarly, we acknowledge that higher intensity levels of the COVID-19 mitigation policies analyzed, as well as the Google search terms, "food supply", "food prices", and "COVID mortality", may reflect households' fears, but may also be associated with reduced fear, depending on if the disturbance resulted in better-than-expected news. Keane and Neal (2021) found that consumer panic was most responsive to restrictions in the Lockdown phase, and then was less responsive when consumers had more information about the pandemic in later phases. Our paper's findings are aligned with this pattern; the average impacts on stockpiling were highest in the Lockdown phase- and consumers' stockpiling behaviors even responded in opposite directions in later phases. We discuss the possible implications of our findings in the following chronological analysis.

In the Lockdown phase, the results describe evidence that households stockpiled both *perishable and non-perishable other* food in response to high searches for food prices and COVID mortality. In areas that searched for information about COVID mortality the most, households were found to stockpile non-perishable fruit and vegetables. Given the context of this phase in which uncertainty about the COVID-19 pandemic was very high, as well as findings from previous literature that suggest consumer panic was high during this time(Keane and Neal, 2021), these findings suggest that high search levels in this phase do correspond to high fear levels. Thus, fears about food prices and COVID mortality were found to increase stockpiling behaviors, while there was no evidence of an association between food supply fears and stockpiling.

The lack of evidence regarding food shortage fears is curious, as its average Google index for the Lockdown phase was higher than in other phases of the pandemic. Searches for “food supply" were not associated with stockpiling behaviors during the Summer phase either, and were actually found to lower stockpiling of *other* food during the Winter phase. This may be an example that searches for “food supply" represented information-seeking behavior that served to reduce uncertainty. If the available information reassured consumers that shortages were temporary or being addressed, they may have felt reassured and thus less likely to engage in stockpiling behaviors. Following this same line of thought, there may have been a correlation between consumers who searched for “food supply" and a likelihood of seeking alternative retail outlets, such as direct-to-consumer outlets or artisan grocers, that may not have been reported in the grocery trip data. Previous research did indeed find that some consumers tried new market channels during the Lockdown and Summer wave phases of the pandemic (Edmondson et al., 2021). However, confirmation of this is needed by future research in order to definitively say that fears about food shortages were allayed by information-seeking, which led to less stockpiling.

Returning to the analysis of stockpiling in the Lockdown phase, higher intensity of lockdown measures (meaning that measures were in place for a larger portion of the month) were found to decrease stockpiling of *perishable and non-perishable other* food. There was much variation of lockdown measures across states during this time, and this variation did not always correspond to viral intensity. For example, some public officials had doubts about the efficacy of shelter-in-place orders, and opted to forgo such interventions (Jacobsen and Jacobsen, 2020). So, consumers' decreased stockpiling response to lockdown measures may be similar to the “food supply" search response, in that consumers felt reassured when they saw the government taking action to mitigate the spread of the virus. The intensity of lockdown measures was not statistically significant after the Lockdown phase[21]. On the other hand, the extension of school meal program benefits and the implementation of mask mandates were associated with higher stockpiling of *other* food (both perishable and non-perishable for school meal program benefits, and only non-perishable food for mask mandates). School meal program benefit extensions occurred when families could no longer access school meal programs due to school closures. It is unsurprising that these are associated with higher stockpiling levels, as this program functioned as an electronic benefit card (akin to an EBT card) and thus likely allowed families to purchase more food than they would have been able to otherwise afford.

One may expect mask mandates to exhibit the same stockpiling effect as lockdown measures during the Lockdown phase. However, mask mandates become widely adopted in later phases of the pandemic; the average value in the Lockdown phase was 9.4% of the month, compared to 52.6% in the Summer wave and 71.6% in the Winter wave. It is therefore likely that locations that implemented mask mandates during the Lockdown phase were in highly urban areas that were hardest hit by the virus, and therefore where consumers' panic was likely to be highest.

Moving onto the Summer wave phase, we observe that the effects of "food price" and "COVID mortality" searches change; the former is found to decrease stockpiling of *perishable and non-perishable other* food, while the latter is found to decrease stockpiling of *perishable fruit and vegetables*. This may imply that during the Summer wave, Google searches led to information that was reassuring for consumers, which then drove a decrease in stockpiling compared to the Lockdown phase. Indeed, the average estimated effects on stockpiling are all lower in magnitude compared to the Lockdown phase. One notable dynamic during the Summer wave is that the extension of school meal program benefits occurred at high rates; the average value of this variable was 93.7% throughout the Summer wave. This was done in an effort to mitigate children's food

[21] The last lockdown measures in the U.S. took place during the winter wave of 2020-2021 (Centers for Disease Control and Prevention (CDC), 2022).

insecurity during a volatile time (Severn et al., 2023). The extension of these benefits was found to increase stockpiling of *perishable fruit and vegetables* during this Summer wave phase, a continuation of the positive effect seen for *other* food during the Lockdown phase. Since this was a transfer of monetary benefits, it is likely true that the stockpiling that we observe from this policy is better described as “over-purchasing", rather than stockpiling in response to panic.

The positive relationship between the extension of school meal program benefits and “stockpiling" (or over-purchasing) continued during the Winter phase with respect to both *perishable and non-perishable other* food. The average impact of this factor on stockpiling was larger than it had been in the Summer or Lockdown phases, which could be a result of the “rolling over" of benefits that were not used in previous months. This was the last phase when the average value of the extension of these benefits exceeded 50% of the month- benefits began to taper off as vaccines became available and students returned to normal school attendance patterns. If families knew that this was the case, they may have been inclined to use up their rolled-over benefits before the program ended. Importantly, the extension of school meal program benefits was the only examined factor that increased “stockpiling" during either the Winter phase or the Summer phase. During the Winter phase, we observe a continuation of the negative effect that information-seeking seems to have had on stockpiling, with respect to searches for “food supply" (as previously discussed) and “food prices". For “food prices" searches, another potential explanation for the negative effect on stockpiling is that there was a positive correlation between searches for food prices and concern about affordability. It follows logically that concern about affordability would have led to a lower likelihood of stockpiling food, especially if such searches indicated hope that the trend would reverse and future prices would decrease. While the mask mandate variable was not significant during the Summer wave, it lowered average stockpiling levels in the Winter wave. This implies that similar to lockdown measures in the Lockdown phase, mask mandates reassured consumers that policies were mitigating their risk of COVID exposure, which lowered their panic and subsequent stockpiling levels.

As mentioned previously, we did not observe effects of fear dynamics and/or policy shifts on stockpiling after the Winter phase, when the availability of vaccines largely led to a return to normalcy. The vaccine roll-out phase was also associated with a rise in food price inflation, which may have also served to stop consumers' stockpiling behaviors as shopping baskets became more expensive (Bonanno et al., 2025; Conlin et al., 2024; Zeballos and Dong, 2022). However, it is equally important to emphasize that after the Lockdown phase, the only factor found to increase stockpiling was the extension of school meal program benefits. And, this was likely better described as substantial over-purchasing compared to predicted amounts and the previous month, rather than stockpiling as a panic response. So, one major takeaway of our results is that panic-induced stockpiling truly only occurred during the Lockdown phase of the pandemic, when uncertainty was highest. The finding that stockpiling, and thus consumer panic, was highest during the Lockdown phase is aligned with previous literature (Keane and Neal, 2021). In subsequent phases, virus mitigation policies and information-seeking seemed to reassure consumers, lowering panic and any associated stockpiling behaviors. Even in the Lockdown phase, policies like shelter-in-place and stay-at-home orders that were perceived by some to be quite restrictive lowered stockpiling levels, implying that these policies may have lowered consumer panic, possibly because consumers related government action to increased safety. Another important takeaway is that there is evidence that the extension of school meal program benefits substantially increased eligible families' food purchases throughout the disruption of schooling that occurred during the earlier phases of the pandemic. One area of potential future research may be to limit the scope of this investigation to households who received these benefits in order to better discern the impacts of the program. Lastly, our findings imply that future research on stockpiling ought to also consider perishable food categories, as households likely find ways to store perishable food (e.g. freezing meat and poultry, blanching vegetables, canning) during times of very high uncertainty.

## 3.6 Limitations

When carrying out this estimation, we were limited by a number of factors. Our initial research question included more detailed food categories than fruit and vegetables versus other. However, the simultaneous consideration of perishability level led to many “zero purchase" observations and therefore necessitated further aggregation. There is room for future research to consider other food categories beyond fruit and vegetable stockpiling with the valuable perishability dimension. A second limitation is that we did not account for the distribution of stimulus checks that occurred at various points during the first three phases of the pandemic. Since households did not receive checks at a single uniform time- rather, many stimulus checks were delayed- we did not feel able to reliably predict the impact of stimulus check data on stockpiling levels. However, if the data becomes available, investigating this policy would be a valuable extension of this research. Lastly, it should be noted that much of the discussion around the fear dynamics and policy variables are interpreted in the context of events that occurred in each phase of the pandemic, and given previous findings in the literature. Many of the implications related to consumers' fears are inferences, and are and not directly knowable from the Google search variable results. Further research is needed to confirm these inferences; in particular, investigations that combine survey data on consumers' fears with expenditure data may either validate these findings or yield new understandings.

## 3.7 Conclusion

This study investigates the stockpiling behaviors that emerged during the COVID-19 pandemic, using Circana Scanner data to understand households' dynamic stockpiling of perishable and non-perishable fruit and vegetables vs. all other food. We combine CDC data and Google Trend search data to understand how stockpiling decisions responded to shifts in COVID-19 mitigation policies and with respect to fluctuating fears related to the COVID-19 pandemic shock. A 2-step Selection model is used to predict expenditures for each food category, from which stockpiling is calculated. We then regress stockpiling on various factors that indicate consumers' fears, as well as specific virus mitigation policies.

Overall, our findings suggest that panic-driven stockpiling was largely confined to the Lockdown phase, when uncertainty was highest, consistent with prior research (Keane and Neal, 2021). In later phases, mitigation policies and access to information appeared to reduce panic and related behaviors. Notably, restrictive policies like stay-at-home orders even reduced stockpiling during the Lockdown phase, potentially signaling reassurance through government action. We found no evidence that fear dynamics or policy shifts influenced stockpiling behavior after the Winter phase, when vaccine availability marked a return to normalcy. Rising food price inflation during the vaccine roll-out may have further discouraged stockpiling by increasing the cost of shopping baskets (Bonanno et al., 2025; Conlin et al., 2024; Zeballos and Dong, 2022). We do find evidence that consumers stockpile perishable food during times of high uncertainty, perhaps through alternative storage methods. Future investigations on consumers' grocery stockpiling should consider perishable foods in addition to the storable foods, which are traditionally studied.

Findings from this paper also illustrate the protective, social safety net role of food assistance programs such as school meal program benefits during the pandemic. The increased allocations to these programs enabled vulnerable households to maintain food security when disruptions were most acute. This aspect of our findings provides empirical support for the value of such programs in mitigating food insecurity during future economic shocks. At the same time, our findings show that such programs may exacerbate shifts in demand for food. This information will be useful as policymakers consider how to simultaneously maintain food sufficiency and food system resiliency in the face of future uncertainty.

In conclusion, by leveraging dynamic variation of factors that contribute to consumer panic in combination with consumer expenditure data, this research has shed light on the determinants of stockpiling behavior during a time of unprecedented uncertainty. The implications of these findings extend beyond the immediate context of the pandemic, offering lessons on consumer behavior and policy effectiveness that are relevant for managing future crises. Moving forward, this groundwork will facilitate more targeted and effective interventions to support food security and food system stability during times of uncertainty.

## 3.8 Tables

**Table 3.1:** Descriptions, Means, and Standard Deviations of Variables

| **Demographic Variables** | **Description** | **Mean** | **St. Dev.** |
|---|---|---|---|
| Age | Age of household head in 2020, and median if two heads present | 56.061 | 13.414 |
| Female | 1 if female household head, 0 otherwise | 0.797 | 0.402 |
| Race = White | 1 if household head is White, 0 otherwise | 0.769 | |
| Race = Black | 1 if household head is Black, 0 otherwise | 0.117 | |
| Race = Asian | 1 if household head is Asian, 0 otherwise | 0.045 | |
| Race = Other | 1 if household head is other race, 0 otherwise | 0.070 | |
| Hispanic | 1 if Hispanic, 0 if non-Hispanic | 0.100 | 0.311 |
| Female Employment | 1 if a female head is employed, 0 otherwise | 2.430 | 0.869 |
| Children | 1 if there are children in the household, 0 otherwise | 0.200 | 0.400 |
| HH Size | Number of people in HH | 2.388 | 1.290 |
| State | US State | . | . |
| Non-Metro | 1 if county population is less than 49,999, 0 otherwise* | 0.300 | 0.400 |
| HH Income 2019 | HH income in 2019 | 8.796 | 2.975 |
| HH Income 2021 | HH income in 2021 | 8.818 | 3.008 |
| SNAP_y | 1 if SNAP panelist in June of year y, 0 otherwise | 0.050 | 0.219 |
| WIC_y | 1 if WIC panelist in June of year y, 0 otherwise | 0.015 | 0.074 |
| **Shopping variables** | | | |
| Purchase Date | Month and year of shopping trip, by HH | . | . |
| Food Category | Purchases divided by fruit and vegetables vs. other | . | . |
| Perishability Level | Purchases divided by perishable vs. non-perishable (shelf-stable or frozen) | . | . |
| Dollars Paid | Monthly expenditure for the categorized purchase, by HH | . | . |
| | Fruit and Vegetable, Perishable ($FV_P$) | \$10.04 | \$16.03 |
| | Fruit and Vegetable, Non-Perishable ($FV_{NP}$) | \$1.86 | \$5.96 |
| | Other Food, Perishable ($O_P$) | \$13.94 | \$30.46 |
| | Other Food, Non-Perishable ($O_{NP}$) | \$20.91 | \$48.53 |
| **Google Trend Variables** | *By state and month, means for post-pandemic period* | | |
| Food Supply | Index of google searches for "food supply" | 20.971 | 11.540 |
| Food Prices | Index of google searches for "food prices" | 12.053 | 8.443 |
| COVID Mortality | Index of google searches for "COVID mortality" | 9.431 | 13.501 |
| **CDC Policy Variables** | *By state and month, means for post-pandemic period* | | |
| Lockdown Measures | Number of days in a month with lockdown in place | 2.428 | 7.626 |
| Extended Benefit Programs | Number of days in a month with sustained school meal program benefits | 11.660 | 14.391 |
| Mask Mandate | Number of days in a month with public mask mandate in place | 12.565 | 14.622 |

*Source: (USDA, Economic Research Service, 2025).

**Table 3.2:** Coefficient Estimates and Standard Errors of the Probit Selection Equation Estimating Likelihood of Purchasing Food Category $jk$ in a given month from 2017 to 2021

| Term | Perish. F&V | Non-perish. F&V | Perish. Other | Non-perish. Other |
|---|---|---|---|---|
| (Intercept) | -1.667*** | -1.750*** | -1.815*** | -1.674*** |
| | (0.014) | (0.016) | (0.018) | (0.017) |
| Age | 0.005*** | 0.002*** | 0.002*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| HH Size | 0.018*** | 0.016*** | 0.008*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Female | 0.016** | 0.014*** | -0.006+ | 0.000 |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Race = Black | -0.060*** | -0.012*** | -0.037*** | -0.012*** |
| | (0.003) | (0.003) | (0.004) | (0.004) |
| Race = Asian | -0.019*** | -0.044*** | -0.015* | -0.009 |
| | (0.005) | (0.005) | (0.006) | (0.006) |
| Race = Other | -0.035*** | -0.019*** | -0.023*** | -0.012* |
| | (0.004) | (0.005) | (0.006) | (0.005) |
| Hispanic | -0.047*** | -0.021*** | -0.024*** | -0.016 |
| | (0.004) | (0.004) | (0.005) | (0.004) |
| Fem. Emp. | -0.001 | -0.004+ | -0.001 | -0.001 |
| | (0.0012) | (0.002) | (0.003) | (0.003) |
| Children | -0.005 | -0.006+ | -0.006 | -0.005 |
| | (0.003) | (0.004) | (0.004) | (0.004) |
| HH Income 2019 | 0.016*** | 0.003*** | 0.003*** | 0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| SNAP_y | -0.060*** | -0.008 | -0.010 | -0.011+ |
| | (0.005) | (0.005) | (0.006) | (0.006) |
| WIC_y | -0.052*** | -0.023 | -0.034+ | -0.029+ |
| | (0.013) | (0.015) | (0.017) | (0.016) |
| Non-Metro | -0.006* | 0.003*** | 0.003* | 0.002* |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| State dummies | X | X | X | X |
| 1M Lag of $ Spent | 0.875*** | 1.056*** | 1.799*** | 1.475*** |
| | (0.002) | (0.003) | (0.004) | (0.003) |
| 2M Lag of $ Spent | 0.655*** | 0.760*** | 0.883*** | 0.868*** |
| | (0.002) | (0.003) | (0.004) | (0.003) |
| 3M Lag of $ Spent | 0.539*** | 0.565*** | 0.482*** | 0.553*** |
| | (0.002) | (0.003) | (0.005) | (0.004) |
| 4M Lag of $ Spent | 0.514*** | 0.505*** | 0.418*** | 0.483*** |
| | (0.002) | (0.003) | (0.005) | (0.004) |
| N | 2679772 | 2679776 | 2679767 | 2679769 |

+denotes statistical significance at $\alpha = 0.1$, * at $\alpha = 0.05$, ** at $\alpha = 0.001$, and *** at $\alpha = 0.0001$. For brevity, estimates of state dummies were excluded, but are available upon request. 1M, 2M, 3M, and 4M denote a one month, two month, three month, and four month lag of dollars spent, respectively.

**Table 3.3:** Coefficient Estimates and Standard Errors of the Outcome Equation Estimating Monthly Expenditures of Food Category $jk$ in a given month from 2017 to 2021

| Term | Perish. F&V | Non-per. F&V | Perish. Other | Non-per. Other |
|---|---|---|---|---|
| (Intercept) | 12.100*** | 10.854*** | 53.179*** | 82.991*** |
| | (0.168) | (0.150) | (0.512) | (0.769) |
| Feb. | -1.334*** | -0.205*** | -2.651*** | -0.786** |
| | (0.058) | (0.053) | (0.165) | (0.261) |
| Mar. | 0.582*** | -0.114* | -4.551*** | -4.091*** |
| | (0.057) | (0.051) | (0.162) | (0.255) |
| Apr. | -0.175** | -1.261*** | -9.254*** | -13.261*** |
| | (0.058) | (0.052) | (0.163) | (0.257) |
| June | -1.121*** | -2.277*** | -13.324*** | -18.893*** |
| | (0.054) | (0.054) | (0.164) | (0.255) |
| July | -1.373*** | -2.092*** | -12.267*** | -18.145*** |
| | (0.054) | (0.054) | (0.164) | (0.255) |
| Aug. | -1.852*** | -1.828*** | -11.843*** | -18.005*** |
| | (0.054) | (0.054) | (0.164) | (0.255) |
| Sep. | -2.539*** | -1.759*** | -12.842*** | -19.694*** |
| | (0.054) | (0.054) | (0.164) | (0.255) |
| Oct. | -2.099*** | -1.005*** | -9.642*** | -14.851*** |
| | (0.054) | (0.052) | (0.163) | (0.254) |
| Nov. | -2.204*** | -1.061*** | -9.654*** | -16.839*** |
| | (0.054) | (0.051) | (0.163) | (0.252) |
| Dec. | -3.142*** | -2.389*** | -15.395*** | -22.378*** |
| | (0.054) | (0.052) | (0.162) | (0.251) |
| Non-Metro | -1.135*** | -0.091** | 0.798*** | 0.631*** |
| | (0.032) | (0.030) | (0.092) | (0.145) |
| State dummies | X | X | X | X |
| Age | -0.033*** | -0.015*** | -0.106*** | -0.085*** |
| | (0.001) | (0.001) | (0.004) | (0.006) |
| HH Size | 1.169*** | 0.727*** | 6.866*** | 8.665*** |
| | (0.015) | (0.014) | (0.042) | (0.066) |
| Female | 0.199*** | -0.229*** | 0.765*** | 1.172*** |
| | (0.033) | (0.032) | (0.097) | (0.152) |
| Race = Black | -1.534*** | 0.326*** | -7.839*** | -3.825*** |
| | (0.044) | (0.041) | (0.126) | (0.195) |
| Race = Asian | -1.032*** | 0.402*** | -7.425*** | -7.286*** |
| | (0.067) | (0.068) | (0.193) | (0.298) |
| Race = Other | 0.755*** | 0.860*** | -1.409*** | -0.580*** |
| | (0.062) | (0.058) | (0.174) | (0.270) |
| Hispanic | 0.007 | 0.073 | -2.000*** | -4.227*** |
| | (0.052) | (0.049) | (0.148) | (0.229) |
| Female Emp. | -0.332*** | -0.421*** | -1.661*** | -3.353*** |
| | (0.029) | (0.028) | (0.085) | (0.133) |
| Children | 0.064 | -0.231*** | 2.271*** | -1.820*** |
| | (0.048) | (0.044) | (0.136) | (0.213) |
| HH Income 2019 | 0.575*** | 0.079*** | 0.653*** | 0.579*** |
| | (0.005) | (0.005) | (0.014) | (0.022) |
| SNAP_y | 0.245** | 0.470*** | 5.950*** | 11.682*** |
| | (0.071) | (0.062) | (0.188) | (0.296) |
| WIC_y | 1.009*** | 0.954*** | 3.405*** | 12.515*** |
| | (0.216) | (0.176) | (0.554) | (0.864) |
| 1M Lag of $ Spent | 1.965*** | -0.312*** | -13.994*** | -19.280*** |
| | (0.055) | (0.043) | (0.269) | (0.357) |
| IMR | -9.128*** | -3.712*** | -26.798*** | -49.305*** |
| | (0.057) | (0.034) | (0.167) | (0.232) |
| N | 1744505 | 650988 | 1011626 | 1082164 |
| R2 | 0.084 | 0.056 | 0.119 | 0.130 |
| R2 Adj. | 0.084 | 0.056 | 0.119 | 0.130 |

+denotes statistical significance at $\alpha = 0.1$, * at $\alpha = 0.05$, ** at $\alpha = 0.001$, and *** at $\alpha = 0.0001$. For brevity, estimates of state dummies were excluded, but are available upon request. IMR is the Inverse Mills Ratio.

**Table 3.4:** Coefficient Estimates from Pooled OLS Regression Estimating Stockpiling ($ per month) during the COVID-19 Pandemic

| Term | Perish. F&V | Std. Err. | Non-per. F&V | Std. Err. | Perish. Other | Std. Err. | Non-per. Other | Std. Err. |
|---|---|---|---|---|---|---|---|---|
| (Intercept) | 1.396* | (0.679) | 0.973* | (0.393) | 5.763* | (2.505) | 6.254+ | (3.791) |
| Feb. | -1.840** | (0.714) | -0.097 | (0.518) | 6.556 | (6.716) | 14.454 | (10.227) |
| Mar. | 0.778 | (0.643) | -0.601 | (0.406) | -6.427+ | (3.365) | -8.319 | (5.947) |
| Apr. | -1.430* | (0.631) | -1.399** | (0.476) | -7.647* | (3.638) | -10.008+ | (5.995) |
| June | -1.908** | (0.653) | -2.219** | -0.758 | -15.040* | (6.091) | -19.861* | (8.968) |
| July | -1.264* | (0.639) | -0.810* | (0.406) | -4.416 | (3.375) | -4.566 | (5.532) |
| Aug. | -1.893** | (0.663) | -0.808* | (0.394) | -3.891 | (2.722) | -3.391 | (4.400) |
| Sep. | -1.825** | (0.661) | -0.822* | (0.387) | -4.277 | (2.614) | -3.738 | (4.311) |
| Oct. | -1.084 | (0.668) | -0.549 | (0.396) | -1.532 | (3.111) | 0.883 | (5.728) |
| Nov. | -1.165+ | (0.668) | -0.685+ | (0.374) | -2.602 | (2.712) | -1.854 | (4.747) |
| Dec. | -1.919** | (0.651) | -1.686*** | (0.497) | -6.450** | (2.489) | -4.290 | (4.508) |
| State dummies | X | X | X | X | X | X | X | X |
| Non-Metro | -0.000 | (0.041) | 0.004 | (0.015) | 0.028 | (0.085) | -0.002 | (0.162) |
| "Food Supply" × LD phase | 0.005 | (0.017) | 0.007 | (0.012) | 0.042 | (0.106) | 0.236 | (0.194) |
| "Food Supply" × Sum. phase | -0.004 | (0.007) | -0.003 | (0.008) | -0.081 | (0.068) | -0.112 | (0.093) |
| "Food Supply"× Wint. phase | -0.015 | (0.018) | -0.001 | (0.008) | -0.212** | (0.077) | -0.373+ | (0.214) |
| "Food Supply" × Vacc. phase | -0.007 | (0.008) | -0.013 | (0.010) | -0.076 | (0.078) | -0.138 | (0.145) |
| "Food Supply"× NN phase | -0.006 | (0.018) | 0.002 | (0.005) | -0.069 | (0.057) | -0.094 | (0.097) |
| "Food Prices" × LD phase | -0.038 | (0.055) | 0.033 | (0.026) | 0.600* | (0.291) | 0.873* | (0.442) |
| "Food Prices" × Sum phase | -0.007 | (0.025) | -0.004 | (0.004) | -0.069+ | (0.040) | -0.109+ | -0.058 |
| "Food Prices" × Wint phase | 0.011 | (0.014) | 0.002 | (0.010) | -0.213 | (0.157) | -0.348+ | (0.202) |
| "Food Prices" × Vacc. phase | -0.019 | (0.020) | -0.011 | (0.031) | -0.066 | (0.233) | -0.003 | (0.359) |
| "Food Prices" × NN phase | 0.004 | (0.021) | -0.005 | (0.008) | -0.067 | (0.058) | -0.123 | (0.096) |
| "COVID Mortality" × LD phase | -0.024 | (0.015) | 0.018* | (0.008) | 0.343*** | (0.085) | 0.624** | (0.224) |
| "COVID Mortality" × Sum. phase | -0.014+ | (0.008) | -0.003 | (0.006) | 0.033 | (0.049) | 0.086 | (0.077) |
| "COVID Mortality" × Wint. phase | -0.003 | (0.021) | -0.002 | (0.021) | 0.163 | (0.154) | 0.257 | (0.228) |
| "COVID Mortality" × Vacc. phase | 0.002 | (0.024) | 0.024 | (0.048) | 0.122 | (0.352) | 0.063 | (0.461) |
| "COVID Mortality" × NN phase | 0.010 | (0.022) | -0.011 | (0.009) | 0.046 | (0.097) | 0.060 | (0.169) |
| % month in Lockdown × LD phase | -0.007 | (0.005) | -0.003 | (0.003) | -0.075** | (0.027) | -0.151** | (0.052) |
| % month in Lockdown × Sum. phase | 0.001 | (0.002) | -0.000 | (0.002) | -0.008 | (0.014) | -0.014 | (0.020) |
| % month in Lockdown × Wint. phase | -0.000 | (0.004) | 0.000 | (0.003) | 0.003 | (0.013) | 0.003 | (0.022) |
| % month Ext. Ben. avail. × LD phase | -0.003 | (0.006) | 0.003 | (0.004) | 0.085* | (0.042) | 0.129+ | (0.069) |
| % month Ext. Ben. avail. × Sum. phase | 0.006* | (0.003) | -0.002 | (0.004) | -0.007 | (0.026) | -0.017 | (0.039) |
| % month Ext. Ben. avail. × Wint. phase | 0.002 | (0.002) | 0.003 | (0.002) | 0.040+ | (0.023) | 0.067+ | (0.038) |
| % month Ext. Ben. avail. × Vacc. phase | -0.000 | (0.002) | -0.001 | (0.001) | 0.002 | (0.006) | 0.004 | (0.013) |
| % month Ext. Ben. avail. × NN phase | -0.000 | (0.003) | 0.002 | (0.002) | 0.002 | (0.011) | 0.002 | (0.015) |
| % month in mask mandate × LD phase | -0.004 | (0.004) | 0.001 | (0.004) | 0.026 | (0.017) | 0.057* | (0.025) |
| % month in mask mandate × Sum. phase | -0.001 | (0.001) | 0.002 | (0.003) | 0.017 | (0.022) | 0.021 | (0.030) |
| % month in mask mandate × Wint. phase | -0.001 | (0.005) | -0.000 | (0.002) | -0.041* | (0.016) | -0.073* | (0.035) |
| % month in mask mandate × Vacc. phase | -0.003 | (0.003) | 0.002 | (0.002) | 0.016 | (0.016) | 0.016 | (0.028) |
| % month in mask mandate × NN phase | -0.000 | (0.002) | 0.001 | (0.001) | -0.002 | (0.005) | -0.006 | (0.011) |
| N | 1742555 | | 1742552 | | 1742537 | | 1742551 | |
| R2 | 0.003 | | 0.010 | | 0.042 | | 0.042 | |
| R2 Adj. | 0.003 | | 0.010 | | 0.042 | | 0.041 | |

+denotes statistical significance at $\alpha = 0.1$, * at $\alpha = 0.05$, ** at $\alpha = 0.001$, and *** at $\alpha = 0.0001$. For brevity, estimates of state dummies were excluded, but are available upon request. Standard errors clustered on state and month.

**Table 3.5:** Average Impacts on Stockpiling ($ per month) of Perishable Fruit and Vegetables, across Pandemic Phases

| | | Coefficient | Std. Err. | Avg. Impact on Stockpiling | Avg. Impact on SP per extra day |
|---|---|---|---|---|---|
| **Lockdown** | Food Supply Searches | 0.005 | (0.017) | 0.126 | |
| | Food Price Searches | -0.038 | (0.055) | -0.457 | |
| | COVID Mortality Searches | -0.024 | (0.015) | -0.310 | |
| | Extended Benefits Programs | -0.003 | (0.006) | -0.047 | -0.152 |
| | Lockdown Measures | -0.007 | (0.005) | -0.325 | -1.050 |
| | Mask Mandates | -0.004 | (0.004) | -0.038 | -0.202 |
| **Summer** | Food Supply Searches | -0.004 | (0.007) | -0.079 | |
| | Food Price Searches | -0.007 | (0.025) | -0.062 | |
| | COVID Mortality Searches | -0.014+ | (0.008) | -0.340 | |
| | Extended Benefits Programs | 0.006* | (0.003) | 0.562 | 1.814 |
| | Lockdown Measures | 0.001 | (0.002) | 0.005 | 0.017 |
| | Mask Mandates | -0.001 | (0.001) | -0.053 | -0.170 |
| **Winter** | Food Supply Searches | -0.015 | (0.018) | -0.318 | |
| | Food Price Searches | 0.011 | (0.014) | 0.113 | |
| | COVID Mortality Searches | -0.003 | (0.021) | -0.063 | |
| | Extended Benefits Programs | 0.002 | (0.002) | 0.110 | 0.353 |
| | Lockdown Measures | -0.000 | (0.004) | 0.000 | 0.000 |
| | Mask Mandates | -0.001 | (0.005) | -0.072 | -0.170 |
| **Vaccine** | Food Supply Searches | -0.007 | (0.008) | -0.136 | |
| | Food Price Searches | -0.019 | (0.020) | -0.256 | |
| | COVID Mortality Searches | 0.002 | (0.024) | 0.008 | |
| | Extended Benefits Programs | -0.000 | (0.002) | 0.000 | 0.000 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | -0.003 | (0.003) | -0.124 | -0.401 |
| **New Normal** | Food Supply Searches | -0.006 | (0.018) | -0.111 | |
| | Food Price Searches | 0.004 | (0.021) | 0.041 | |
| | COVID Mortality Searches | 0.01 | (0.022) | 0.066 | |
| | Extended Benefits Programs | -0.000 | (0.003) | 0.000 | 0.000 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | -0.000 | (0.002) | 0.000 | 0.000 |
| N | | 1742555 | | | |
| R2 | | 0.003 | | | |

*denotes statistical significance at $\alpha = 0.1$, ** at $\alpha = 0.05$, and *** at $\alpha = 0.001$.

**Table 3.6:** Average Impacts on Stockpiling ($ per month) of Non-Perishable Fruit and Vegetables, across Pandemic Phases

| | | **Coefficient** | **Std. Err.** | **Avg. Impact on Stockpiling** | **Avg. Impact on SP per extra day** |
|---|---|---|---|---|---|
| **Lockdown** | Food Supply Searches | 0.007 | (0.012) | 0.176 | |
| | Food Price Searches | 0.033 | (0.026) | 0.397 | |
| | COVID Mortality Searches | 0.018* | (0.008) | 0.232 | |
| | Extended Benefits Programs | 0.003 | (0.004) | 0.047 | 0.152 |
| | Lockdown Measures | -0.003 | (0.003) | -0.139 | -0.450 |
| | Mask Mandates | 0.001 | (0.004) | 0.009 | 0.051 |
| **Summer** | Food Supply Searches | -0.003 | (0.008) | -0.059 | |
| | Food Price Searches | -0.004 | (0.004) | -0.036 | |
| | COVID Mortality Searches | -0.003 | (0.006) | -0.073 | |
| | Extended Benefits Programs | -0.002 | (0.004) | -0.187 | -0.605 |
| | Lockdown Measures | -0.000 | (0.002) | 0.000 | 0.000 |
| | Mask Mandates | 0.002 | (0.003) | 0.105 | 0.340 |
| **Winter** | Food Supply Searches | -0.001 | (0.008) | -0.021 | |
| | Food Price Searches | 0.002 | (0.010) | 0.021 | |
| | COVID Mortality Searches | -0.002 | (0.021) | -0.042 | |
| | Extended Benefits Programs | 0.003 | (0.002) | 0.164 | 0.530 |
| | Lockdown Measures | 0.000 | (0.003) | 0.000 | 0.000 |
| | Mask Mandates | -0.000 | (0.002) | 0.000 | 0.000 |
| **Vaccine** | Food Supply Searches | -0.013 | (0.010) | -0.252 | |
| | Food Price Searches | -0.011 | (0.031) | -0.148 | |
| | COVID Mortality Searches | 0.024 | (0.048) | 0.100 | |
| | Extended Benefits Programs | -0.001 | (0.001) | -0.023 | -0.074 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | 0.002 | (0.002) | 0.083 | 0.267 |
| **New Normal** | Food Supply Searches | 0.002 | (0.005) | 0.037 | |
| | Food Price Searches | -0.005 | (0.008) | -0.051 | |
| | COVID Mortality Searches | -0.011 | (0.009) | -0.072 | |
| | Extended Benefits Programs | 0.002 | (0.002) | 0.007 | 0.023 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | 0.001 | (0.001) | 0.018 | 0.057 |
| N | | 1742552 | | | |
| R2 | | 0.01 | | | |

*denotes statistical significance at $\alpha = 0.1$, ** at $\alpha = 0.05$, and *** at $\alpha = 0.001$.

**Table 3.7:** Average Impacts on Stockpiling ($ per month) of Perishable Other Food, across Pandemic Phases

| | | Coefficient | Std. Err. | Avg. Impact on Stockpiling | Avg. Impact on SP per extra day |
|---|---|---|---|---|---|
| **Lockdown** | Food Supply Searches | 0.042 | (0.106) | 1.056 | |
| | Food Price Searches | 0.600* | (0.291) | 7.223 | |
| | COVID Mortality Searches | 0.343*** | (0.085) | 4.428 | |
| | Extended Benefits Programs | 0.085* | (0.042) | 1.332 | 4.295 |
| | Lockdown Measures | -0.075** | (0.027) | -3.487 | -11.248 |
| | Mask Mandates | 0.026 | (0.017) | 0.244 | 1.314 |
| **Summer** | Food Supply Searches | -0.081 | (0.068) | -1.593 | |
| | Food Price Searches | -0.069+ | (0.040) | -0.615 | |
| | COVID Mortality Searches | 0.033 | (0.049) | 0.801 | |
| | Extended Benefits Programs | -0.007 | (0.026) | -0.656 | -2.117 |
| | Lockdown Measures | -0.008 | (0.014) | -0.043 | -0.140 |
| | Mask Mandates | 0.017 | (0.022) | 0.895 | 2.886 |
| **Winter** | Food Supply Searches | -0.212** | (0.077) | -4.489 | |
| | Food Price Searches | -0.213 | (0.157) | -2.187 | |
| | COVID Mortality Searches | 0.163 | (0.154) | 3.410 | |
| | Extended Benefits Programs | 0.040+ | (0.023) | 2.191 | 7.068 |
| | Lockdown Measures | 0.003 | (0.013) | 0.007 | 0.052 |
| | Mask Mandates | -0.041* | (0.016) | 2.936 | -6.960 |
| **Vaccine** | Food Supply Searches | -0.076 | (0.078) | -1.474 | |
| | Food Price Searches | -0.066 | (0.233) | -0.890 | |
| | COVID Mortality Searches | 0.122 | (0.352) | 0.507 | |
| | Extended Benefits Programs | 0.002 | (0.006) | 0.046 | 0.147 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | 0.016 | (0.016) | 0.662 | 2.137 |
| **New Normal** | Food Supply Searches | -0.069 | (0.057) | -1.274 | |
| | Food Price Searches | -0.067 | (0.058) | -0.680 | |
| | COVID Mortality Searches | 0.046 | (0.097) | 0.302 | |
| | Extended Benefits Programs | 0.002 | (0.011) | 0.007 | 0.023 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | -0.002 | (0.005) | -0.035 | -0.114 |
| N | | 1742537 | | | |
| R2 | | 0.042 | | | |

*denotes statistical significance at $\alpha = 0.1$, ** at $\alpha = 0.05$, and *** at $\alpha = 0.001$.

**Table 3.8:** Average Impacts on Stockpiling ($ per month) of Non-Perishable Other Food, across Pandemic Phases

| | | **Coefficient** | **Std. Err.** | **Avg. Impact on Stockpiling** | **Avg. Impact on SP per extra day** |
|---|---|---|---|---|---|
| **Lockdown** | Food Supply Searches | 0.236 | (0.194) | 5.935 | |
| | Food Price Searches | 0.873* | (0.442) | 10.510 | |
| | COVID Mortality Searches | 0.624** | (0.224) | 8.056 | |
| | Extended Benefits Programs | 0.129+ | (0.069) | 2.021 | 6.519 |
| | Lockdown Measures | -0.151** | (0.052) | -7.020 | -22.645 |
| | Mask Mandates | 0.057* | (0.025) | 0.535 | 2.880 |
| **Summer** | Food Supply Searches | -0.112 | (0.093) | -2.202 | |
| | Food Price Searches | -0.109+ | -0.058 | -0.971 | |
| | COVID Mortality Searches | 0.086 | (0.077) | 2.087 | |
| | Extended Benefits Programs | -0.017 | (0.039) | -1.594 | -5.140 |
| | Lockdown Measures | -0.014 | (0.020) | -0.076 | -0.245 |
| | Mask Mandates | 0.021 | (0.030) | 1.105 | 3.565 |
| **Winter** | Food Supply Searches | -0.373+ | (0.214) | -7.899 | |
| | Food Price Searches | -0.348+ | (0.202) | -3.573 | |
| | COVID Mortality Searches | 0.257 | (0.228) | 5.377 | |
| | Extended Benefits Programs | 0.067+ | (0.038) | 3.670 | 11.838 |
| | Lockdown Measures | -0.073* | (0.035) | -0.162 | -1.277 |
| | Mask Mandates | 0.003 | (0.022) | 0.215 | 0.509 |
| **Vaccine** | Food Supply Searches | -0.138 | (0.145) | -2.676 | |
| | Food Price Searches | -0.003 | (0.359) | -0.040 | |
| | COVID Mortality Searches | 0.063 | (0.461) | 0.262 | |
| | Extended Benefits Programs | 0.004 | (0.013) | 0.091 | 0.295 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | 0.016 | (0.028) | 0.662 | 2.137 |
| **New Normal** | Food Supply Searches | -0.094 | (0.097) | -1.736 | |
| | Food Price Searches | -0.123 | (0.096) | -1.249 | |
| | COVID Mortality Searches | 0.060 | (0.169) | 0.394 | |
| | Extended Benefits Programs | 0.002 | (0.015) | 0.007 | 0.023 |
| | Lockdown Measures | N/A | N/A | N/A | N/A |
| | Mask Mandates | -0.006 | (0.011) | -0.106 | -0.341 |
| N | | 1742551 | | | |
| R2 | | 0.042 | | | |

*denotes statistical significance at $\alpha = 0.1$, ** at $\alpha = 0.05$, and *** at $\alpha = 0.001$.

## 3.9 Figures

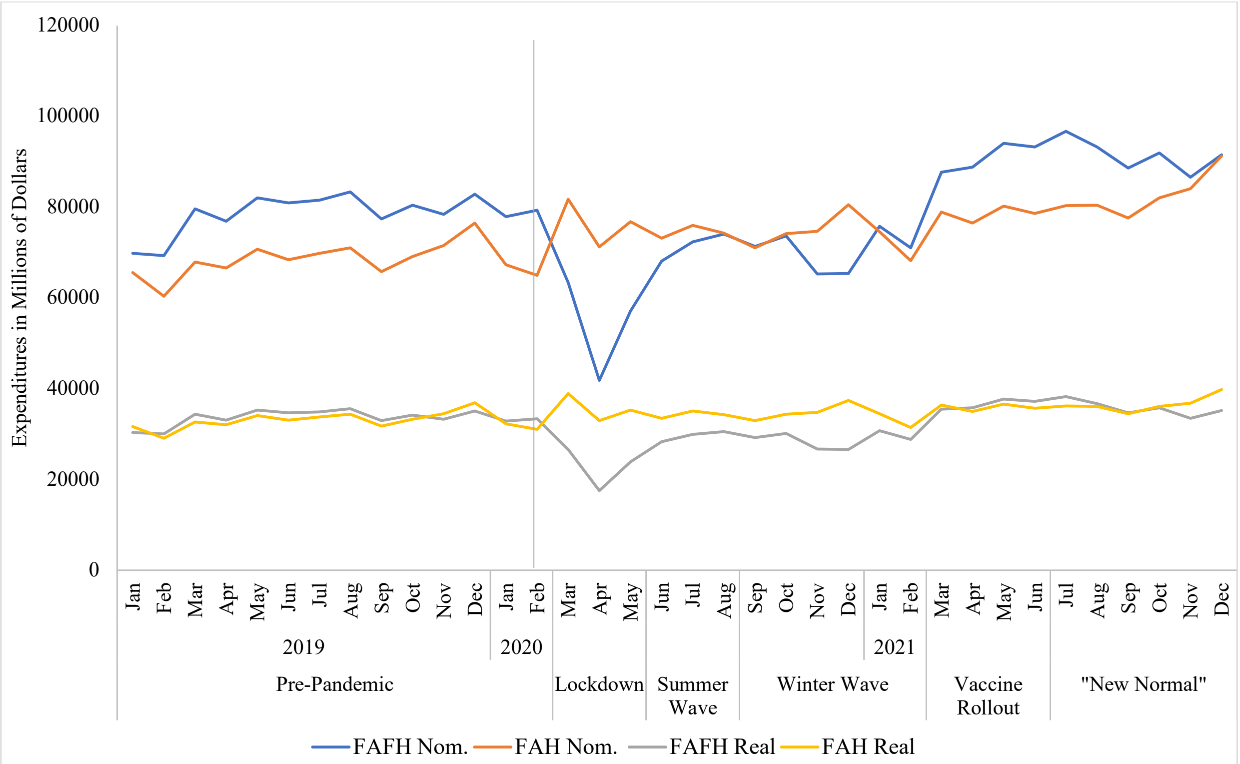



**Figure 3.1:** Observed food expenditures of aggregated FAH and FAFH, with real expenditures using base 1988. The data used in this figure is from US Census Retail Sales (United States Census Bureau, 2022).

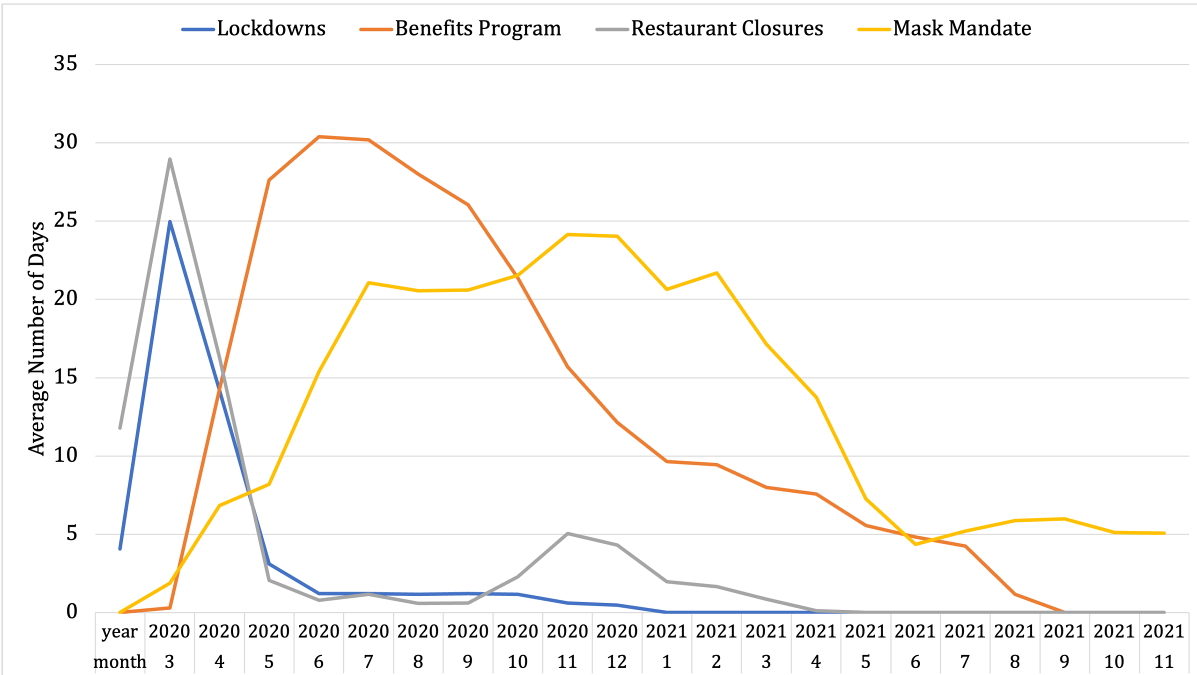



**Figure 3.2:** Average number of days policies were implemented in a given month from March 2020 to December 2021. Average was taken over all 50 US states. Source: CDC COVID Data Tracker (Centers for Disease Control and Prevention (CDC), 2022)

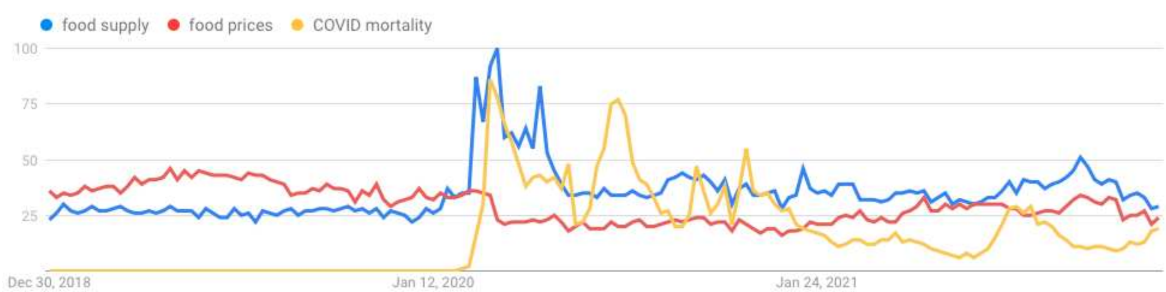



**Figure 3.3:** Google Trends data on various search terms related to food system uncertainty and pandemic-related fear from Jan. 2019 to Dec. 2021. Source: Google Trends (Google, 2024)

## 3.10 Appendix

### 3.10.1 Stockpiling Identification

**Identifying Stockpiling After Pandemic Shock**

Expected inventory, where:

$\hat{F}$ represents February (pre-pandemic) expenditures, $\hat{M}$ represents March expenditures, and $\hat{A}$ represents April expenditures. $\alpha$ is the coefficient estimating inventory change from previous month, and $\Delta P$ is the change in purchased goods from other influencing factors, like seasonality.

$\hat{A} - \hat{M} = \alpha(\hat{M} - \hat{F}) + \Delta P$

Identifying $A - M$:

Adding and subtracting A hat and M hat:

$A - \hat{A} + \hat{A} - M + \hat{M} - \hat{M}$

Simplifying, where $GAP$ represents difference in observed and expected purchasing for a given month:

$GAP_A + \hat{A} - GAP_M + \hat{M} = GAP_A - GAP_M + (\hat{A} - \hat{M})$

$A - M = (\hat{A} - \hat{M}) + GAP_A - GAP_M$

Inventory is now made up of the difference in predicted purchases from one month and the previous (lagged) month, and a term describing the difference in expected and observed purchases from one month and the previous month, or stockpiling. Thus, rearranging identifies stockpiling as:

$GAP_A - GAP_M = \delta(F_D^A - F_D^M) + \lambda(F_{Sto}^A - F_{Sto}^M)$

# Chapter 4

# Evaluating the Farmers to Families Food Box Program: Impact of Non-Traditional Eligibility Requirements on Vendor Participation and Success

## 4.1 Introduction

Soon after the onset of the COVID-19 pandemic, lockdown conditions in the US substantially affected the food system. Lockdown measures led to the closure of food-away-from-home (FAFH) outlets while demand for food-at-home (FAH) spiked, leading to supply chain disruption and panic buying (Chenarides et al., 2021a; Finck and Tillmann, 2022; Hobbs, 2020; Keane and Neal, 2021; Omar et al., 2021; Thilmany et al., 2021b). Simultaneously, many households experienced layoffs and reduced income, heightening the risk of a food insecurity crisis (US Bureau of Labor Statistics (US BLS), 2020; U.S. Census Bureau, 2020)[22]. In response, the federal government established the Farmers to Families Food Box (FFFB) program to move excess food supply originally destined for FAFH outlets to in-need households. Administered by the United States Department of Agriculture (USDA), the FFFB program contracted producers, wholesalers, and distributors to deliver food boxes to pantries and other community food assistance organizations. When designing this program, the USDA used small business set-asides to target "select" vendors; more specifically, awarded contracts were determined on the basis of "proposed pricing, box content, last mile delivery plans, means testing compliance, and support of small and local/regional food systems" (USDA Agricultural Marketing Service, 2020b). In doing so, policymakers aimed to simultaneously support vulnerable upstream suppliers whose regular distribution outlet was disrupted and also address increased demand for food assistance in under-served areas, termed "Opportunity Zones" (USDA

[22]The unemployment rate peaked in April 2020 at 50%, and the average percent of households experiencing food scarcity peaked at 11% in May 202 (US Bureau of Labor Statistics (US BLS), 2021; U.S. Census Bureau, 2020).

Agricultural Marketing Service, 2020a,2,2). While this program was intended as a temporary relief policy in response to an "urgent and compelling" emergency (USDA Agricultural Marketing Service, 2020a,2), this program presents an opportunity to evaluate the efficacy of a food procurement program aimed at remediating the disruption, or even loss, of food markets as a result of supply chain shifts. This paper provides an ex-post analysis of a temporary federal food procurement program by examining its impact on small businesses' performance during and after participation in the program, focusing on contracted vendors' employment trends as the outcome indicating effectiveness of the FFFB program. With uncertainty related to supply chains and food prices persisting into the current food environment (Murray, 2025), findings will be of interest to policymakers and food system stakeholders hoping to improve food system resiliency, or a food system's capability of upholding producers' well-being and food sufficiency through a crisis. Using FFFB shipment data matched to the National Establishment Time Series (NETS) data on employment levels, we leverage policy shifts within the FFFB program with a Difference-in-Difference model to understand whether the FFFB program's unique eligibility requirements led to differential employment impacts for small businesses.

Federal food procurement programs, like the FFFB, are designed to create market access opportunities for small businesses. Federal and state procurement programs for small and mid-size agricultural supply chains aim to leverage governments' stable and substantial demand for commodities[23] to support small, disadvantaged, and local food producers. Key federal programs that focus on local food procurement include the USDA's Patrick Leahy Farm to School grant program, which connects schools with local farmers to supply fresh, locally grown foods USDA Food and Nutrition Service (2025b). A recent study by Love et al. (2025) found that these policies are instrumental to school food authorities' participation in procurement programs (Love et al., 2025). Another federal food procurement program that prioritizes local food systems is the recently canceled Local Food Purchase Assistance (LFPA) program. After the pandemic, the Biden administration

[23] USDA Foods is an umbrella of commodity contracts that includes both domestic programs like the Commodity Supplemental Food Program and international programs like Food Aid - Food for Progress (USDA Food and Nutrition Service, 2025a).

implemented the LFPA program, which provided states and tribal governments with funds to purchase foods from underserved producers. This included both institutional contracts and food box assistance (USDA Agricultural Marketing Service, 2022b; USDA Press, 2024). By prioritizing small and underserved businesses in procurement decisions, federal efforts seek not only to diversify supply chains but also to strengthen regional food systems (USDA Agricultural Marketing Service, 2022b; USDA Food and Nutrition Service, 2025b). This includes initiatives that reduce barriers to entry, provide technical assistance, and promote equity in contracting opportunities (USDA Agricultural Marketing Service, 2022b; USDA Food and Nutrition Service, 2025b). There are many other federal food distribution programs that do not necessarily focus on local food, but do sometimes use small business set asides, including: The Emergency Food Assistance Program (TEFAP), Food Distribution Program on Indian Reservations (FDPIR), Commodity Supplemental Food Program (CSFP), and other school food procurement programs (National School Lunch Program, School Breakfast Program) (USDA Food and Nutrition Service, 2025a). The potential impacts of these programs extend beyond the direct contract payment, and may influence employment, business resilience, and longer-term market access. To our knowledge, the extent to which these procurement programs increase such outcomes has not yet been quantitatively measured. This gap in knowledge motivates our investigation.

A sub-objective of this investigation is to explore the trade-offs of federal investment in flexible supply chains by analyzing the FFFB program's impact on food system resilience. Food system resilience is broadly understood to describe a food system's ability to sustain food production and consumption during economic shocks (Hadachek et al., 2024a). In the wake of the pandemic and in recent discussions about the merits of tariff policy, literature debating the tradeoffs of food systems' resilience versus efficiency have come to light (Hadachek et al., 2024b; Hobbs and Hadachek, 2024; Stevens et al., 2024; Yenerall et al., 2024). The highly efficient, globalized food systems that have emerged due to economies of scale often lack adaptability and accessibility (Hobbs, 2021; Lusk, 2021). However during the pandemic, smaller growers and food businesses demonstrated greater adaptability and an ability to reach rural areas due to shorter local supply chains and strong social networks (Thilmany et al., 2021b). Previous research highlights the importance of flexibility in food systems, including the ability of producers to shift between market channels (Chenarides et al., 2021b). The FFFB program exemplified this type of flexibility, allowing small food businesses to reallocate supplies no longer flowing through channels negatively affected by disruptions toward food box production (USDA Agricultural Marketing Service, 2020b; Wallace, 2021). Findings from this investigation may determine whether federal procurement programs succeed in creating market opportunities and support for businesses that makeup the shorter, more flexible supply chains, which in turn may imply that such investments may also yield improvements for food system resilience.

We do not find measurable changes in firm-level employment in 2020 or 2021 from FFFB program participation. However, the null findings have notable implications for food procurement programs. The temporary nature of the FFFB program and its rapid implementation may have limited firms' ability or willingness to expand employment. Firms facing labor shortages or disrupted markets may have fulfilled contract obligations using existing capacity, while others may have chosen to engage with more familiar or streamlined support programs. Additionally, our findings provide important lessons for policy analysis in which multiple support programs may have been accessed simultaneously. Both FFFB vendors and control group firms had access to multiple overlapping federal relief programs, which may have diluted the detectable effects of any single initiative.

This paper contributes to several streams of literature. First, we contribute to the discussions on the efficacy of local and regional food systems by examining the tradeoffs between resilience and efficiency through the lens of the FFFB program outcomes. We provide empirical evidence on the program's impact on food system resilience by analyzing producers' performance, measured through comparative employment trends. This outcome offers a current perspective on how temporary relief programs can support vulnerable sectors during crises, while also investigating potential long-term benefits for market access opportunities and subsequent maintenance of (or even increases in) supply chain flexibility.

The current globalized food system emerged from the prioritization of efficiency; indeed, maximizing outputs and minimizing costs have been primary objectives in the development of the US food system, often at the expense of resilience (Hadachek et al., 2024b; Rude, 2021). Recent literature highlights this trade-off, suggesting that highly efficient systems can lack adaptability during shocks (Hobbs, 2021; Lusk, 2021; USDA Agricultural Marketing Service, 2022a). However, increases in the number of market disruptions have led to interventions like the FFFB program, which sought to reconcile losses from a supply chain disruption by providing a market access opportunity to selected food businesses (USDA Agricultural Marketing Service, 2020a). This goal, which differs from the aims of other types of commodity procurement programs in that it harnesses the adaptability of small food businesses, ensures market continuity in the face of disruptions. We build on the literature that discusses these tradeoffs by measuring impacts from the program for vendors, providing insights into how policies designed during emergencies can influence both short-term recovery and longer-term market access and food system resilience.

Secondly, we contribute to the literature on labor market policy. U.S. labor market policy has historically incorporated a range of mechanisms aimed at promoting job security during periods of economic crisis, reflecting a commitment to stabilizing employment and supporting household income. During downturns such as the Great Recession and more recently, during the COVID-19 pandemic, the federal government deployed expansive policy tools, including enhanced unemployment insurance benefits, Paycheck Protection Program (PPP) loans to incentivize firms to retain workers, and temporary expansions of eligibility for public assistance programs (Blanchard et al., 2014; Coibion et al., 2020; Gerard et al., 2020; Hubbard and Strain, 2020; Michaelides and Mueser, 2020). These interventions are designed to mitigate the adverse effects of sudden job loss, smooth consumption, and preserve firm-worker matches. While the U.S. lacks a comprehensive short-time work scheme like those implemented in many European countries (Crépon and Van Den Berg, 2016), recent crises have seen the temporary adoption of similar measures, underscoring the government's adaptive approach to labor market stabilization. Nevertheless, debates continue regarding the long-term efficacy and equity of these responses, particularly in terms of their reach across diverse sectors and populations.

Lastly, we contribute to the literature on policy implications that can be learned from the dynamics of the COVID-19 pandemic. This case study of the FFFB Program is particularly timely as states consider how to address the recent cancellation of Local Food Purchasing Assistance Cooperative Agreements (LFPA) and Local Farm to School (LFS) Cooperative Agreements Brown (2025). If policymakers hope to maintain the interest of local and regional food producers who rely on the market access points that are established when they participate in governmental food procurement programs, future changes to such policies require thoughtful consideration. Furthermore, as food systems face persistent disruptions— whether from pandemics, global trade conflicts, extreme weather events, or technological changes— there is a growing need for policies that enhance small businesses' market access opportunities and increase food systems' ability to respond to supply chain disruptions.

The remainder of the paper proceeds as follows: Section 2 presents details of the FFFB program and our conceptual framework. In Section 3, we provide a detailed description of our data sources and econometric models. Section 4 presents results, reflecting on both short- and long-term impacts of the program. Section 5 discusses policy implications, particularly in the context of ongoing investments in local food systems. Finally, Section 6 concludes with lessons learned and recommendations for future policy design.

## 4.2 Conceptual Framework

### 4.2.1 Details of the FFFB Program Implementation

The FFFB program was implemented to address two simultaneous challenges during the COVID-19 pandemic: surplus agricultural goods caused by the closure of FAFH outlets, and rising demand for food assistance in underserved areas (USDA Agricultural Marketing Service, 2020b,2). To meet these challenges, USDA contracted vendors to supply food boxes, creating a temporary market for surplus goods. Vendors assembled excess foodstuffs into household-size boxes and delivered them directly to recipient organizations. The USDA also relaxed traditional vendor eligibility requirements for procurement programs and implemented set-asides for small businesses so that local and regional food businesses, known to have the most flexible supply chains and sometimes located in more remote areas, could take advantage of the FFFB program (USDA Agricultural Marketing Service, 2020a,2). These adjustments allowed many smaller food businesses to participate in federal contracts for the first time (U.S. Government Accountability Office (GAO), 2021). According to the Wallace Center, 55% of FFFB vendors in the first two rounds were associated with local and regional farms, receiving over $84 million in contracts (Wallace, 2021). These contracts provided much-needed revenue for small producers, who otherwise faced significant disruptions due to the loss of their usual regional downstream markets.

The program included five rounds of food box deliveries between May 2020 and May 2021: Round 1 (May 15–June 30, 2020), Round 2 (July 1–September 18, 2020), Round 3 (August 24–October 31, 2020), Round 4 (November 1–December 31, 2020), Round 5 (January 19–May 31, 2021). Initially, vendors supplied five types of boxes: fresh produce, milk, dairy, ready-to-eat meat, and combination boxes. Starting in the third round, only combination boxes were offered, reflecting an effort to simplify logistics and improve efficiency (U.S. Government Accountability Office (GAO), 2021). This change was in response to logistical challenges that emerged during the early rounds. Some vendors failed to fulfill contracts or delivered food boxes that expired before distribution, creating additional burdens for recipient organizations (Charles, 2020; U.S. Government Accountability Office (GAO), 2021). In response, the USDA reevaluated the program in late summer 2020. Eligibility requirements were tightened- vendors were required to cover all production, transportation, and delivery costs. These changes introduced barriers for many small businesses and shifted participation toward larger vendors capable of meeting cost and efficiency demands. The reevaluation also prioritized deliveries to "economically distressed communities" and resulted in greater reliance on processed goods suppliers rather than fresh produce vendors (Marchesi, 2022; U.S. Government Accountability Office (GAO), 2021).

The average price per box paid to the vendor also varied substantially across the rounds of the program. Early rounds paid higher prices, reflecting the government's urgency to stabilize food systems by supporting a select subset of food system participants (U.S. Government Accountability Office (GAO), 2021). This is evidenced by the "Justification for other than full and open competition" document that the USDA filed in order to explain the need for this policy intervention (USDA Agricultural Marketing Service, 2020a). The USDA cited that without the FFFB program, there would be a *"(a) Failure to meet agency mission related to creation of domestic opportunities for U.S. producers of food (b) Catastrophic losses to agricultural producers that were impacted by supply chain disruption of COVID-19 pandemic (c) Failure to supply vital food assistance resources to non-profit entities that experienced dramatic demand increases in underserved ares of the United States and to the people those entities serve"* (USDA Agricultural Marketing Service, 2020a).

Figure 4.1 shows a table from the GAO report on the FFFB program, which illustrates the shifts in average prices paid per box, quantities delivered, and dollar value of contracts in each round (U.S. Government Accountability Office (GAO), 2021). For example, vendors in Round 1 received an average price of $63 per combination box, while prices dropped to $32 per box by Round 5 (U.S. Government Accountability Office (GAO), 2021). These pricing changes highlight a shift in program priorities—from maximizing vendor support, including by offering prices that would be acceptable to vendors with smaller capacities, to cost efficiency and targeted food assistance in later rounds. This evolution in program design highlights the tradeoffs involved in balancing adaptability, efficiency, and equity in federal interventions. The annual nature of the employment data used in this study limits the capability of a model to capture the FFFB policy change that occurred in September 2020 (after the second round). However, differences of vendor characteristics before and after the program's reevaluation is explored in the Stylized Facts section 4.3.2. The timeline of the FFFB program's logistical changes highlights the uniqueness of the way in which the program sought to temporarily support small businesses whose supply chains may have been disrupted in the earlier rounds. This paper provides insights into whether temporary support policies that redirect market supply result in positive outcomes when accounting for the alternative outcome, as demonstrated by businesses that were eligible for small business set-asides but did not participate in the FFFB program.

### 4.2.2 Pandemic-era Support Programs Available to Small Businesses

The FFFB was not the only program available to available to small businesses during this time period. Businesses that would have been eligible for FFFB were also eligible for other programs. Table 4.1 lists the legislation passed by Congress that were offered to small businesses. The Paycheck Protection Program (PPP), administered by the Small Business Association, was an important program that was expanded over the course of the pandemic. It offered forgivable loans to small businesses (and nonprofit organizations, other businesses) for economic injury that resulted from the pandemic (Lindsay et al., 2023). As small businesses makeup about 47% of all employers, this legislation sought to support US labor markets by providing funds for payroll and other eligible expenses (Kapinos, 2021). A criticism of this program is that it may have been manipulated by some businesses which chose to close and thus mitigate many expenses, then receive a forgivable loan for lost revenue rather than stay open. One study sought to understand whether the PPP actually yielded negative side effects on small business activity, and found evidence that increased access to PPP loans was associated with fewer open small businesses Kapinos (2021). Given these concerns about the PPP, it is important to examine how other programs like the FFFB influenced small business outcomes and whether they addressed similar gaps related to businesses' decisions during the pandemic, or whether they generated different effects.

### 4.2.3 Testable Hypotheses

To empirically evaluate the short-term and long-term impacts of the FFFB program, we develop two testable hypotheses that follow from the theoretical expectations outlined above. Specifically, we examine whether participation in the FFFB program influenced vendors' labor retention during and after participation in the program. These outcomes are indicators of the program's effectiveness in achieving its stated objectives of supporting producers' economic viability during the crisis and meeting the USDA mission of creating domestic opportunities for food producers (USDA Agricultural Marketing Service, 2020a).

**Hypothesis 1: Employment Effects During FFFB Participation**

The first hypothesis examines whether the FFFB program helped vendors sustain or increase employment levels during participation in the FFFB program (2020). By contracting vendors who lost access to FAFH markets, the program provided a revenue source that could offset potential labor reductions. The USDA claimed that the FFFB program was needed in order to avoid losses to producers that were impacted by supply chain disruption (USDA Agricultural Marketing Service, 2020a). Yet, the opportunity cost of participating in the FFFB program is unclear. It may have been true that vendors' non-participating peers were able to adapt to shifting consumer demand in other ways, such as via direct-to-consumer sales. This hypothesis compares employment levels of FFFB small businesses to non-participating peers (defined in the following section) that would also have been eligible for small business set-asides. In doing so, we evaluate whether the FFFB program achieved its aim of sustaining businesses during a crisis, and that this policy provided a necessary relief.

One consideration is the time frame of these effects. If the FFFB program's impact was temporary as intended (USDA Agricultural Marketing Service, 2023), we would expect to see employment gains *only during* the program years (2020 and 2021), but no lasting difference once the program ended. As our data is annual, we exclude round 5 participants, who participated in the Spring of 2021. Thus, our treatment period is 2020 only.

- Null Hypothesis ($H_0$): FFFB program small business vendors experienced equal or worse employment outcomes in 2020 compared to non-participating or low-participating peers.
- Alternative Hypothesis ($H_A$): FFFB program small business vendors experienced more positive employment outcomes in 2020 compared to non-participating or low-participating peers.

Figure 4.2 shows examples of the Null and Alternative cases for Hypothesis 1.

**Hypothesis 2: Employment Effects Beyond FFFB Participation**

Another stated goal of this program was to uphold the USDA mission of providing domestic opportunities to food producers (USDA Agricultural Marketing Service, 2020a). If the FFFB program had structural effects on market access opportunities— such as strengthening vendor relationships with USDA or improving operational capacity— we might expect employment gains to persist beyond the program into 2021. Thus, the positive effects from the FFFB programs that increased market access (bring in new USDA vendors) in the short term may have effects that ripple beyond the implementation of the program.

- Null Hypothesis ($H_0$): FFFB program small business vendors experienced equal or worse employment outcomes in 2021 compared to non-participating or low-participating peers.
- Alternative Hypothesis ($H_A$): FFFB program small business vendors experienced more positive employment outcomes in 2021 compared to non-participating or low-participating peers.

Figure 4.3 shows examples of the Null and Alternative cases for Hypothesis 2.

## 4.3 Methods

### 4.3.1 Data

We rely on three datasets to evaluate the FFFB program and its outcomes. These datasets provide complementary information about vendors' participation in the FFFB program, business characteristics, and outcomes over time.

The first dataset is FFFB Program Box Shipment data, constructed by a team at the USDA Economic Research Service (Marchesi, 2022). The data was originally collected by the USDA Agricultural Marketing Service. This shipment data contains specific information about FFFB program contracts, including: vendor names and addresses, contract quantities and values for all FFFB rounds, shipment dates, and unique numeric identifiers such as internally coded USDA vendor IDs (Marchesi, 2022). This dataset allows us to track vendor participation across FFFB rounds and to quantify the contract sizes.

The second dataset is the National Establishment Time Series (NETS) database, which provides annual census-like information on all US businesses. Because the dataset is structured as a time series, we can track businesses over time to observe variables of interest before, during, and after the FFFB program. We extract time-varying data from 2018 to 2021 to observe pre- and post-program trends for vendors. NETS data include a numeric identifier “duns number", NAICS industry codes, employee counts, annual revenue, FIPS codes used to match U.S. Census regions and core-based statistical areas (CBSAs), company names, and zip codes. The NETS data are particularly valuable for providing employment information for businesses that both participated and did not participate in the FFFB program, which facilitates the construction of the control group.

Third, we used the online Dun and Bradstreet Duns number lookup tool to find DUNS numbers, or unique business IDs for all federally registered companies, to each vendor. This is the numeric identifier used to match FFFB shipment information to the employment data. We then match the datasets using DUNS numbers as the primary identifier, supplemented by business names and addresses when necessary. This matching process ensures accuracy in matches across datasets and allows us to construct a comprehensive dataset for analysis. Table 4.2 describes the variables used in this analysis, including the data source for each variable.

The outcome variable of interest is firms' employment level in each year. The covariates used to create a balanced control, which will be described in more detail in the following sections, included industry, as defined by the three digit NAICS code, U.S. Census division, Metropolitan status of county, and the quartile classification of a firm's annual revenue within the larger sample (as a proxy for business size).

**Restricting Data**

The research question is whether vendors who received FFFB contracts maintained or increased employment at higher rates compared to similar firms who did not participate in the program, and we narrow the scope of this question to the most vulnerable (smaller) food businesses. Therefore, and put more simply, we are concerned with comparing the employment outcomes of small businesses that did and did not participate in the FFFB program. To achieve this, the final dataset was restricted to only include businesses that would have been classified as a small business by the small business administration. The industry size standards, which are established by the Small Business Association administrator, are defined by employee and revenue rules that are specific to certain NAICS codes (US SBA Office of Size Standards, 2023). These size standards, combined with the NAICS codes, employee counts, and revenue in the final matched data, were used to restrict the analysis to businesses that were eligible for small business contracts.

Other restrictions imposed on the final dataset were that the businesses were required to have reported employee data from 2017 through 2019. This was done in order to ensure that the data sample was restricted to established businesses. Finally, the final data was restricted to only include businesses whose six-digit NAICS code was included in the list of contracted FFFB vendors. These restrictions ensure that we only considered established businesses that would have been eligible for small business contracts, and that the control group consisted businesses within the same industries as the FFFB program vendors.

Table 4.3 describes the summary statistics of variables in the final dataset that are used in this analysis. FFFB vendor characteristics are contrasted with the broader pool of non-participating vendors to highlight how the FFFB vendors differed from other USDA contractors. Overall, FFFB vendors had fewer businesses in the crop and animal production, food and beverage retailing, and food services industries, and more businesses in the food manufacturing and merchant wholesale industries. Distributions across US Census divisions were relatively similar between the treatment and control groups, but FFFB vendors contained more businesses located in metropolitan statistical areas. This is likely a result of the program's effort to distribute food to populations in need, which are inherently more densely located in metropolitan areas. Finally, the FFFB vendors' annual revenue exhibited notably higher distribution in the highest revenue quartile compared to non-participants.

### 4.3.2 Stylized Facts

**Stylized Fact 1: Earlier rounds contained more new-to-USDA vendors**

As shown in figure 4.4 below, there is preliminary evidence that the FFFB program created market access opportunities by contracting vendors who had not previously been contracting with USDA Foods. 181 vendors in round 1 & 2 had not contracted with USDA from 2017 to 2019, along with 17 vendors in round 3, 3 vendors in round 4, and 5 vendors in 5. This reflects positively on the USDA's stated goal to provide market access opportunities for US food producers with the FFFB program (USDA Agricultural Marketing Service, 2020a). However, many of these vendors exited the program after its reevaluation following rounds one and two. The FFFB program's reevaluation after Round 2 (ending September 18, 2020) increased capacity requirements for vendors, required assembly and delivery of combination boxes to the final distributor, and resulted in lower price-per-box offerings compared to earlier rounds (U.S. Government Accountability Office (GAO), 2021). Figure 4.4 illustrates the way in which the FFFB program reevaluation affected the pool of contracted vendors. To understand how vendor characteristics and contract sizes changed over the course of the FFFB program, the following stylized facts compare FFFB vendors in the first two rounds, before the program reevaluation, to those in the last three rounds. Whether the participation in rounds one and two was sufficient to sustain employment levels of small businesses remains to be seen. Additionally, it is possible that vendors exited the program in order to take advantage of alternative adaptation strategies. Comparing FFFB vendors' performances to their non-participating peers will shed light on whether the FFFB program was truly needed.

**Stylized Fact 2: Later rounds of the FFFB program shifted toward larger and more urban vendors**

After the program's reevaluation, the FFFB contracts were made with vendors that had higher revenue and more employees compared to earlier vendors. The t-tests in table 4.4 show that vendors in rounds 3-5 had higher mean revenue compared to vendors in rounds 1-2, though this difference was not found to be statistically significant. Additionally, seven of the eight vendors who entered into the FFFB program after the re-evaluation were in the wholesale foods industry, implying that they had larger capacities. This preliminary summative evidence indicates that the program's reevaluation, which tightened eligibility requirements, favored vendors with larger operational capacities.

In rounds one and two of the FFFB program, for which the USDA AMS sought to achieve the dual objectives of mitigating food insecurity while also supporting food businesses that lost their markets from the initial pandemic shock, contracted vendors included a mix of those in rural, suburban, and urban areas. Table 4.5 shows the percent of vendors in each round that reside in a given Rural-Urban Commuting Area (RUCA) code (USDA Economic Research Service, 2010b). The first row of the cross-tabulation illustrates that the majority of vendors were located in core metro areas (RUCA code 1). Yet, there is a marked difference after round two of the FFFB program, when the focus shifted towards decreasing food insecurity (toward areas with higher population density) rather than supporting vulnerable food businesses (which are more commonly found in rural areas). When the focus shifted, almost all contracted vendors resided in RUCA codes one and two, the most metropolitan categories, and only three vendors were contracted in the other eight RUCA codes, representing non-metro codes from moderate commuting to an urban center to the most rural classification. This is substantially less than the number of vendors that resided in RUCA codes 2-8 in the first two rounds of the program.

**Stylized Fact 3: Earlier rounds contained more vendors eligible for small business set-asides**

Table 4.6 conveys select differences between FFFB vendors classified as small businesses and those that were not (analyzed before the non-small businesses were dropped from the sample).

This table provides preliminary evidence that the support for small businesses may have been prioritized in the first two rounds of the FFFB program. This could explain some of the differences in the types of vendors that participated before and after the program's reevaluation. For example, the average contract size in the first two rounds was smaller for small businesses, but more small businesses were contracted. Also, all small businesses that participated after the program's reevaluation were in the wholesale industry. The following section explains the empirical approach used to understand whether this temporary support for small businesses led to differential impacts on employment when comparing FFFB participants to those who did not participate in the program.

### 4.3.3 Empirical Approach

To test Hypotheses 1 and 2 described in Section 4.2.3, specifically the impact of the FFFB program on vendors' employment levels compared to peers (1) in 2020 and (2) in 2021, we use a Difference-in-Difference (DiD) framework. The sample is restricted to established businesses that would have been eligible for small business contracts, and were within the subset of industries exhibited by FFFB program vendors.[24]

The outcome variable of interest is annual employment, as NETS data is collected annually. Then, the treatment variable is a binary variable that represents participation in the FFFB program in 2020. While this data limitation largely simplifies the complex story of program reevaluation that occurred, it also ensures that relatively simple two-way fixed effect (TWFE) model can be used to achieve unbiased DiD estimates.[25]

Advances in the economic literature highlight several limitations of the two-way fixed effects (TWFE) approach when applied to settings with continuous treatments, or treatments of varying sizes. In traditional binary-treatment DiD models, like the one used in this analysis, TWFE es-

[24]To achieve this, we eliminated firms that reported greater than zero revenue in any year from 2017 to 2022, used the revenue/employment and NAICS code criteria from the SBA that defines eligibility for small business set-asides, and required the first three digits of NETS firms' NAICS codes to be within the list of the first three digits of FFFB vendors' NAICS codes.

[25]If data were not annual, a model with staggered treatment timing or an approach that allows for continuous treatment variable would capture nuanced effects of FFFB round participation or contract size differences, respectively. This may be a potential question investigated in future research.

timates the difference in outcomes between treated and untreated units while controlling for unit and time fixed effects. The TWFE model performs well in this simplified circumstance (Callaway and Sant'Anna, 2021). However, for continuous treatments, TWFE may introduce bias. Primarily, when treatment effects vary across treatment intensities, TWFE fails to account for the selection bias of every varying treatment level, leading to unreliable estimates (Borusyak et al., 2024; Callaway et al., 2024; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). In the setting where a continuous treatment variable is used, such as FFFB contract size, a TWFE model would require strong parallel trends assumptions due to the selection bias that may be introduced when a business receives a specific contract size. In their working paper, Callaway et al. (2024) suggest non-parametric solutions to this problem. However, the traditional TWFE model used in this investigation simply requires the classic parallel trends assumption.

The standard parallel trends assumption is the keystone of DiD methods. It assumes that, in the absence of treatment, there is no difference in the outcome between treatment and control groups. In other words, there are no unobserved factors that affect the outcome of interest which systematically differ across the treatment and control groups over time. By "systematically differ", we mean the rate of change differs; the levels can be different. Formally, where the dosage D is the binary participation in the FFFB program:

For dosages d,

$[\Delta Employment_t(0)|D = d] = [\Delta Employment_t(0)|D = 0]$

ATT(d|d) $= [\mathrm{Y}_t(d) - Y_t(0)|D = d]$

$= [Y_t(d) - Y_{t-1}(0)|D = d] - [Y_t(0) - Y_{t-1}(0)|D = d]$

$= [Y_t(d) - Y_{t-1}(0)|D = d] - [\Delta Y_t(0)|D = 0]$

$= [\Delta Y_t(d)|D = d] - [\Delta Y_t(0)|D = 0]$

This states that, in the absence of treatment, the expected change in employment over time for treated units would have followed the same trend as those with zero treatment.

To ensure that the treated and control groups are balanced with respect to propensity to receive and FFFB contract and other characteristics, we use a propensity score matching approach. The matching method indirectly ensures that the parallel trends assumption holds, as we theoretically expect that groups with equal propensity to receive the FFFB contract, equal geographic distribution across the US, equal distribution across metropolitan areas, and equal distribution of business size quartiles (as captured by revenue quartiles) would exhibit the same pre-treatment trends in employment.

### 4.3.4 Creating a Valid Control Group with Propensity Score Matching

Due to the very large number of non-participating FFFB businesses that exist in the NETS database, even after restricting the sample to reflect small businesses within FFFB vendors' industries, it was necessary to create a subset of the control group that was comparable in size to the sample size in the treated group so that our model had sufficient power. Additionally, for the control group to be regarded as true peers of the FFFB businesses, the control group needed to have equal likelihood of receiving an FFFB contract. Thus, prior to estimating the DiD models, we match treated and control units based on baseline (pre-treatment) covariates using propensity score matching. A logit model was used to estimate the propensity scores, or the likelihood of receiving an FFFB contract.

Let $D_i$ denote the binary treatment level for unit $i$, and $X_i$ be a vector of observed covariates. $X_i$ consists of: a 3-digit NAICS code specifying the industry, U.S. Census division, Metro/Non-Metro status, and revenue quartile (capturing categorical business sizes).

We estimate the propensity score for each unit, where $P$ stems from the logistic density function:

$$e(X_i) = \mathbb{P}(D_i = 1 \mid X_i)$$

Using Nearest Neighbor Matching (NNM), we match each treated unit to one or more control units with the closest propensity scores. This is done using only the pre-treatment period (2019) to avoid post-treatment bias. Post-matching balance was assessed using standardized mean differences and visual inspection of propensity score distributions. After the nearest-neighbor matching is performed and validated, the two-way fixed effect DiD models were then analyzed on the matched dataset.

### Propensity Score Matching Validation

The propensity score matching technique was done for two primary reasons- first, to mitigate the otherwise large difference in sample sizes between FFFB vendors and non-participants in the NETS database, and second, to ensure that the treatment and control group had an equal distribution of businesses that were likely to receive the FFFB contract. The logit model estimating this propensity was included the dummy variables listed in table 4.3 as covariates. The covariates included in the logit model were the variables in the NETS database that provided information about the businesses which may be related to the FFFB vendor selection criteria. These covariates capture the 3-digit NAICS industry code of a business, the US Census division, the metro or non-metro status as defined by the US Census[26], and the categorical size of the business as represented by the revenue quartile.

Table 4.3 illustrates the differences in means of these covariates between the FFFB vendors and the non-participant control group before the propensity score matching occurred. Before matching, FFFB vendors are more concentrated in food manufacturing and wholesale industries, with fewer firms in production agriculture, retail, and food service compared to non-participants. While geographic distribution across US Census divisions was similar between groups, FFFB vendors are more often located in metropolitan areas. Additionally, FFFB vendors are disproportionately represented in the highest revenue quartile. However, as a reminder, the entire dataset was limited to those businesses eligible for small business contracts, as defined by the Small Business Administration. Without the propensity matching technique or a similar method, we would expect that the disparities in covariate distributions across the treatment and control groups would result in a violation of the parallel trends assumption due to selection of vendors into the FFFB program.

---

[26] Metropolitan statistical areas are defined as areas with a population of 50,000 or greater (U.S. Census Bureau, 2019).

However, after the groups are balanced on covariate means (and on the mean propensity to receive an FFFB contract), we can assume that the parallel trends assumption holds.

Table 4.7 describes the covariate means of the treated and control groups after the nearest-neighbor propensity matching was completed. The covariate means are equal across the treated and control groups, implying that the nearest neighbor matching technique successfully found non-participant businesses that were close matches, with respect to the listed covariates (including estimated propensity to receive an FFFB contract), for the FFFB vendors. Employment level was not included in the matching scenario. However, employment means did become less different between the treated and control groups after the matching technique. Figure 4.5 illustrates the balancing of mean differences between the treated and control groups before and after the propensity score matching. Lastly, after finding “neighbors" of the FFFB vendors to make up the control group, the sample size of the control and treated groups were the same. Thus, the TWFE DiD models can be estimated with confidence that mismatched sample sizes and covariate imbalances are not biasing results and/or leading to a violation of parallel trends.

### 4.3.5 TWFE models estimating differences in employment levels from FFFB Program participation

Two TWFE models are carried out to test each hypothesis. The only difference between the two models is the year of the outcome measure; the first model tests the difference in employment levels of the groups from 2019 to 2020 (Hypothesis 1) and the second tests the differences across the treatment and control from 2019 to 2021. [27]

The TWFE models will include fixed effects for time (year), and unit (the business). This will control for common shocks or trends affecting all units at a given time, and will also control for time-invariant differences between units. Equation 4.1 describes the TWFE model.

$$Y_{it} = \alpha + \delta D_{it} + \gamma_i + \tau_t + \epsilon_{it} \tag{4.1}$$

[27] For robustness, we also test this hypothesis from 2019 to 2022.

Where $Y_{it}$ represents a business $i$'s employment in a given year $t$. $D_{it}$ represents participation in the FFFB program (0 or 1) and its associated coefficient, $\alpha$ is the intercept, $\gamma_i$ represents unit fixed-effects, controlling for time-invariant business characteristics, $\tau_t$ represents year fixed effects, controlling for time trends common to all businesses, and $\epsilon_{it}$ is the error term.

Our coefficient of interest is $\delta$, which represents the average treatment effect of participating in the FFFB program in a given year (2020 or 2021).

## 4.4 Results

We carry out equation 4.1 to recover the estimate of FFFB program participation on firm-level employment for 2020 and 2021, separately. As shown in Table 4.8, the estimated treatment effects are small and statistically insignificant for both years. Specifically, FFFB participation is associated with a 0.071-unit increase in employment in 2020 (SE = 1.542) and a 0.117-unit increase in 2021 (SE = 2.692). With confidence intervals that include zero, we are unable to reject the null hypothesis that the FFFB program is associated with positive outcomes for employment levels during the program (with respect to Hypothesis 1, in 2020) or beyond the program (with respect to Hypothesis 2, in 2021). Or put more succinctly, these results suggest no measurable impact of FFFB program participation on employment levels during the study period.

There are several potential explanations for these null findings. First, the FFFB program may not have generated employment effects at the firm level if vendors used existing capacity or reallocated resources rather than hiring additional staff. Second, the temporary and uncertain nature of the program could have limited firms' willingness to make longer-term employment commitments. Third, any employment impacts may have been offset by broader labor market disruptions or constraints during the COVID-19 pandemic, such as labor shortages or supply chain issues. Lastly, it is possible that employment effects were muddled by other support programs that occurred during the study period, such as the Paycheck Protection Program. While both the control and treatment group may have accessed such programs, it may be true that potentially eligible vendors may have chosen to participate in other support programs rather than apply for an FFFB contract. The following section discusses further policy implications from these findings.

## 4.5 Discussion

The null results from this study suggest that participation in the FFFB program did not coincide with measurable changes for participating enterprises in firm-level employment during 2020 or 2021. While this finding may initially appear to indicate limited impact of the FFFB program, it is important to interpret the results within the broader context of the COVID-19 policy response landscape. During the pandemic, firms— both FFFB vendors and non-participants that made up the control group— had access to a wide array of federal relief programs, including the Paycheck Protection Program (PPP), Economic Injury Disaster Loans (EIDL), and other USDA supports[28]. These overlapping initiatives may have diluted the observable employment effect of any single program, including the FFFB program.

Furthermore, the temporary nature of the FFFB program and the short implementation associated with each round of the program may have shaped participation and employment outcomes. For example, already vulnerable firms whose retail market was disrupted at the beginning of the pandemic, and who may also be facing pandemic-related labor constraints, may have opted to meet FFFB contract obligations without expanding their workforce. Similarly, some potentially eligible vendors may have prioritized more familiar or administratively simpler relief programs over FFFB participation, further blurring differences between treatment and control groups. However, the assertion that such assistance programs do not expand employment levels should not be broadly applied to other federal food procurement or even state-level procurement programs, since such programs are generally not temporary in nature as was the case for the FFFB program.

On the other hand, the concept that temporary programs may lead to more resilient businesses in the long term may be relevant to policymakers that are considering the cancellation of such programs. For instance, the Biden Administration started the Local Food Purchase Assistance

[28]Table 4.1 lists the federal relief programs available to small businesses during the COVID-19 pandemic.

(LFPA) Cooperative program and its extension, the LFPA plus program that together allocated $900 million for local food procurement (USDA Agricultural Marketing Service, 2022b; USDA Press, 2024). However, the cancellation of allocated LFPA funds, along with the Local Food for Schools Cooperative Program (Brown, 2025), may erode the willingness of small businesses to invest their trust and resources into federally-funded supply chains when doing so has proven to be a risky endeavor. In turn, this implies that the previously discussed contributions of such programs, including both their direct impacts on market access opportunities and indirect contributions to US food systems' resilience, is lost.

These findings can help to inform several policy considerations. First, evaluating food assistance programs solely on traditional economic indicators like employment may miss other critical outcomes—such as improvements in supply chain resilience, firm liquidity, building business capacity to participate in public procurement programs, or community-level food access. Second, effective targeting and communication of program benefits are crucial in ensuring vendor uptake, especially among small and mid-sized firms. Finally, future iterations of such programs might benefit from integrating longer-term capacity-building components that could yield more persistent employment and business development outcomes.

### 4.5.1 Limitations

Several limitations should be noted when interpreting these findings. First, while the use of a difference-in-differences (DiD) framework helps address time-invariant unobserved heterogeneity by observing impacts of program participation for individual businesses, the TWFE approach may still mask treatment effect heterogeneity that is more granular than the annual level of data provided by the NETS database. If monthly employment data is available, future work could incorporate alternative specifications such as event-study or staggered treatment effect models to explore dynamic or subgroup-specific effects. For example, the Callaway and Sant'Anna "did" package in R may be used to add covariates to the TWFE models and/or to test staggered treatment adoption.

Second, the analysis relies on administrative and commercial data that, while rich in firm characteristics, may have measurement error in employment reporting or incomplete linkage across datasets. In particular, employment levels may not capture temporary or contract labor commonly used during high-demand periods, such as the pandemic. Another consideration with regard to the reliability of the employment data is that while the NETS employment data has been found to be closely aligned with other sources of employment data overall, the data for smaller businesses is more likely to be imputed, and may therefore be less reliable Barnatchez et al. (2017). Future analysis may consider evaluating the efficacy of the FFFB program with a different outcome variable or data source. While the control group was carefully constructed with nearest neighbor matching on covariates and propensity score, there may be residual differences between treated and non-treated firms— capacity, networks, or motivations to pursue federal contracts— that could influence outcomes and limit causal interpretation.

Understanding the broader economic implications of these findings requires examining other potential outcomes beyond employment, such as revenue changes, firm survival rates, and regional economic effects. Future work integrating more granular firm-level financial data, beyond employment levels, as well as participation in other federal relief programs that occurred during this time, could provide a more comprehensive evaluation of the FFFB program's economic impact and inform more effective policy design for future food assistance programs.

## 4.6 Conclusion

This study contributes to the growing body of research evaluating ways to craft food procurement policies that stabilize food systems and/or provide market access opportunities to underserved food businesses. We examine firm-level impacts of the Farmers to Families Food Box (FFFB) program. Although we find no statistically significant employment effects from program participation, these null results must be interpreted within the broader context of pandemic-era policy overlaps, labor constraints, and the temporary nature of the program itself. Firms likely engaged with the

FFFB program using existing capacity or chose to participate in alternative federal relief initiatives, which may have dampened observable outcomes.

Despite the absence of measurable employment gains, our findings highlight critical considerations for the design and implementation of emergency food procurement programs. The positive impact of temporary interventions that provide market access opportunities, such as the FFFB program, may not be evident when alternative market opportunities are taken into account. We expect that this finding may be due, in part, to the temporary nature of such programs; small food businesses may not want to make long term resource allocation commitments when the program implementation is relatively short. While future research is needed to compare temporary relief programs to more permanent local food procurement programs, our results may suggest that if procurement programs are to serve as tools for building a more resilient and inclusive food system, they must be designed with long-term commitments, predictable funding, and accessible administrative processes. This consideration is particularly relevant in light of recent cancellations of local food procurement programs. Future research should continue to explore not only firm-level impacts but also broader supply chain and community-level effects of such interventions.

## 4.7 Tables

**Table 4.1:** Pandemic Era Support Programs Available to Small Businesses

| Legislation | Name | Description |
|---|---|---|
| P.L. 116-123 | Coronavirus Preparedness and Response Supplemental Appropriations Act | Allocated disaster assistance funds and classified injury from the pandemic as eligible for disaster loans |
| P.L. 116-136 | Coronavirus Aid, Relief, and Economic Security (CARES) Act | Allocated funds for lending programs, including the Paycheck Protection Program (PPP) that offered forgivable loans to small businesses and other organizations |
| P.L. 116-139 | Paycheck Protection Program and Health Care Enhancement Act | Allocated additional funds for lending |
| P.L. 116-142 | Paycheck Protection Program Flexibility Act | Lengthened the forgiveness period for PPP loans |
| P.L. 116-147 | Paycheck Protection Program Flexibility Act, cont. | Allocated additional funds for PPP commitments |
| P.L. 116-260 | Economic Aid to Hard-Hit Small Businesses, Nonprofits, and Venues Act | Lengthened PPP authorizations and authorized additional funds for lending |
| P.L. 117-2 | American Rescue Plan Act of 2021 | Allocated additional funds for PPP loans, small business association programs, and a restaurant revitalization program. |
| P.L. 117-6 | PPP Extension Act of 2021 | Lengthened time available for PPP applications. |

Source: Congressional Research Service (Lindsay et al., 2023).

**Table 4.2:** Data source and description of variables

| Variable Name | Data Source | Variable Description |
|---|---|---|
| PON | FFFB Shipment Data | A numeric identifier that is specific to a vendor's FFFB contract in a given round of the program. |
| Year | FFFB Shipment Data | Year of the FFFB contract |
| Total Contract Quantity | FFFB Shipment Data | Total quantity of boxes shipped for a contract |
| Total Contract Value | FFFB Shipment Data | Total value (p*q) of boxes shipped for a contract |
| Duns Numbers | Dun and Bradstreet | A numeric identified specific to a vendor, also used in NETS data. |
| Treatment | FFFB Shipment Data | Dummy indicating whether FFFB vendor was an FFFB Vendor in a given year |
| Year | National Establishment Time Series (NETS) | Year of observation |
| NAICS code | NETS | NAICS code, from which industry is discerned |
| Company Name | NETS | Company Name |
| Zipcode | NETS | 5 digit zip, used to match to Census region and metro designation |
| Employment | NETS | # of employees |
| Sales | NETS | Annual revenue |
| Division | U.S. Census | U.S. Census Division in 2020 |
| Metro/Micro | U.S. Census | U.S. Census Core-Based Statistical Area Code |

**Table 4.3:** Statistical summaries of numeric variables

| **Variable** | **Means of FFFB-Vendors** | **Means of Non-Participant Control** |
|---|---|---|
| *Outcome Variable of Interest* | | |
| Employment 2020 | 11.353 | 24.587 |
| Employment 2021 | 10.987 | 24.312 |
| *Dummy Variables (0/1)* | | |
| Crop Production Industry | 0.073 | 0.178 |
| Animal Production and Aquaculture Industry | 0.008 | 0.023 |
| Food Manufacturing Industry | 0.114 | 0.009 |
| Merchant Wholesalers, Nondurable Goods Industry | 0.642 | 0.053 |
| Food and Beverage Retailing Industry | 0.081 | 0.147 |
| Food Services Industry | 0.081 | 0.588 |
| US Census Division ENC | 0.155 | 0.133 |
| US Census Division ESC | 0.065 | 0.052 |
| US Census Division MA | 0.187 | 0.140 |
| US Census Division MW | 0.049 | 0.071 |
| US Census Division NE | 0.024 | 0.046 |
| US Census Division P | 0.203 | 0.166 |
| US Census Division SA | 0.163 | 0.197 |
| US Census Division WNC | 0.065 | 0.086 |
| US Census Division WSC | 0.089 | 0.108 |
| Metro Area | 0.951 | 0.826 |
| Revenue Quartile: Lowest 25% | 0.057 | 0.207 |
| Revenue Quartile: 26-50% | 0.041 | 0.126 |
| Revenue Quartile: 51-75% | 0.049 | 0.325 |
| Revenue Quartile: Highest 25% | 0.854 | 0.343 |
| N | 123 | 908645 |

Non-participant control consists of small businesses whose industry (defined by the three-digit NAICS code) is included in the FFFB vendor subset.

**Table 4.4:** T-Test of Vendors' Revenue Means Pre- and Post-FFFB Reevaluation

| | Mean (Rounds 1-2) | Mean (Rounds 3-5) | Mean Difference | t-Statistic | p-value |
|---|---|---|---|---|---|
| **Revenue ($)** | 39,020,812 | 48,513,030 | -9,492,218 | -0.779 | 0.437 |

**Table 4.5:** Count of Vendors' RUCA Codes Across Rounds

| RUCA Code | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 | Total |
|---|---|---|---|---|---|---|
| **1** | 59 | 82 | 23 | 12 | 25 | 201 |
| **2** | 9 | 16 | 0 | 2 | 3 | 30 |
| **3** | 0 | 1 | 0 | 0 | 0 | 1 |
| **4** | 1 | 4 | 1 | 1 | 0 | 7 |
| **5** | 2 | 1 | 0 | 0 | 0 | 3 |
| **6** | 0 | 3 | 0 | 0 | 0 | 3 |
| **7** | 2 | 2 | 0 | 1 | 0 | 5 |
| **8** | 1 | 2 | 0 | 0 | 0 | 3 |
| **9** | 0 | 2 | 0 | 0 | 0 | 2 |
| **10** | 4 | 7 | 1 | 0 | 0 | 12 |
| **Unknown** | 1 | 0 | 0 | 1 | 1 | 3 |
| **Total** | 79 | 120 | 25 | 17 | 29 | 270 |

**RUCA Code Descriptions:**
1: Metropolitan core (urbanized area with more than 50,000 residents).
2: High commuting to an urban core.
3: Moderate commuting to an urban core.
4: Micropolitan core (urban cluster with 10,000–49,999 residents).
5–6: Areas with commuting ties to micropolitan cores.
7: Small town core (urban cluster with 2,500–9,999 residents).
8–9: Areas with commuting ties to small town cores.
10: Rural areas with minimal or no commuting to urbanized areas.

**Table 4.6:** Comparison of Small Business and Not-Small Business FFFB Vendors Before and After Program Reevaluation

| Variable | Small Business Designation | Rounds 1 & 2 | Rounds 3-5 |
|---|---|---|---|
| Avg. Contract Size | Small Businesses | $ 18,551,813.00 | $ 38,143,440.00 |
| | Not Small Businesses | $ 22,057,699.00 | $ 22,329,859.00 |
| Total Vendor Count | Small Businesses | 98 | 38 |
| | Not Small Businesses | 15 | 4 |
| Percent in Metro Area | Small Business | 93.90% | 100% |
| | Not Small Business | 93.30% | 100% |
| Agriculture Industry Count | Small Business | 10 | 0 |
| | Not Small Business | 8 | 2 |
| Food Manufacturing Industry Count | Small Business | 14 | 0 |
| | Not Small Business | 1 | 0 |
| Wholesale Industry Count | Small Business | 61 | 38 |
| | Not Small Business | 6 | 2 |
| Food Retail Industry Count | Small Business | 7 | 0 |
| | Not Small Business | 0 | 0 |
| Food Services Industry Count | Small Business | 7 | 0 |
| | Not Small Business | 0 | 0 |

**Table 4.7:** Statistical summaries of numeric variables of dataset after nearest-neighbor propensity score matching

| **Variable** | **Means of FFFB-Vendors** | **Means of Non-Participant Control** |
|---|---|---|
| *Outcome Variable of Interest* | | |
| Employment 2020 | 11.353 | 11.353 |
| Employment 2021 | 10.987 | 10.98 |
| *Dummy Variables (0/1)* | | |
| Propensity to Receive FFFB Contract* | 0.0019 | 0.0019 |
| Crop Production Industry | 0.0732 | 0.0732 |
| Animal Production and Aquaculture Industry | 0.0081 | 0.0081 |
| Food Manufacturing Industry | 0.1138 | 0.1138 |
| Merchant Wholesalers, Nondurable Goods Industry | 0.6423 | 0.6423 |
| Food and Beverage Retailing Industry | 0.0813 | 0.0813 |
| Food Services Industry | 0.0813 | 0.0813 |
| US Census Division ENC | 0.1545 | 0.1545 |
| US Census Division ESC | 0.065 | 0.065 |
| US Census Division MA | 0.187 | 0.187 |
| US Census Division MW | 0.0488 | 0.0488 |
| US Census Division NE | 0.0244 | 0.0244 |
| US Census Division P | 0.2033 | 0.2033 |
| US Census Division SA | 0.1626 | 0.1626 |
| US Census Division WNC | 0.065 | 0.065 |
| US Census Division WSC | 0.0894 | 0.0894 |
| Metro Area | 0.9512 | 0.9512 |
| Revenue Quartile: Lowest 25% | 0.0569 | 0.0569 |
| Revenue Quartile: 26-50% | 0.0407 | 0.0407 |
| Revenue Quartile: 51-75% | 0.0488 | 0.0488 |
| Revenue Quartile: Highest 25% | 0.8537 | 0.8537 |
| Matched N | 123 | 123 |
| Unmatched N | 0 | 908522 |
| Discarded | 0 | 0 |

*Likelihood measured from logit model during propensity score matching technique, where all other dummy variables were covariates.

**Table 4.8:** Results from the TWFE DiD Estimations of Employment Levels from Participation in the FFFB Program

| | Hypothesis 1:<br>2020 Employment Impacts | Hypothesis 2:<br>2021 Employment Impacts |
|---|---|---|
| FFFB Vendor == 1 | 0.071 | 0.117 |
| | (1.542) | (2.692) |
| Unit Fixed Effects | X | X |
| Year Fixed Effects | X | X |
| N | 487 | 484 |
| R2 | 0.987 | 0.973 |
| R2 Adj. | 0.974 | 0.945 |
| AIC | 3538.6 | 3928.4 |
| BIC | 4577.3 | 4965.6 |

*Note: Standard errors calculated by unit (duns number of business).

## 4.8 Figures

**Table 8: Price per Food Box, by Type, for USDA's Farmers to Families Food Box Program, by Round**

| Food box type | | Round 1 | Round 2 | Round 3 | Round 4 | Round 5 |
|---|---|---|---|---|---|---|
| Combination | Maximum | $150.00 | $150.00 | $99.00 | $64.95 | $105.00 |
| | Minimum | $10.30 | $10.30 | $34.95 | $32.61 | $27.79 |
| | Mean | $63.09 | $63.25 | $45.23 | $38.89 | $31.90 |
| | Median | $76.05 | $67.18 | $44.39 | $38.90 | $31.25 |
| | Contract obligations | $258,797,740 | $476,266,382 | $916,478,455 | $485,649,656 | $1,416,651,915 |
| | Number of food boxes specified in contracts | 4,102,321 | 7,529,684 | 20,260,689 | 12,488,297 | 44,402,739 |
| Dairy | Maximum | $85.20 | $93.60 | | | |
| | Minimum | $5.00 | $7.00 | | | |
| | Mean | $34.01 | $34.81 | | | |
| | Median | $29.22 | $29.00 | | | |
| | Contract obligations | $140,163,233 | $231,078,363 | | | |
| | Number of food boxes specified in contracts | 4,121,474 | 6,637,849 | | | |
| Fresh fruit and vegetable | Maximum | $90.00 | $580.00[a] | | | |
| | Minimum | $9.70 | $9.70 | | | |
| | Mean | $23.41 | $22.73 | | | |
| | Median | $22.25 | $21.95 | | | |
| | Contract obligations | $438,062,085 | $817,116,197 | | | |
| | Number of food boxes specified in contracts | 18,711,212 | 35,946,172 | | | |
| Milk | Maximum | $35.05 | $35.05 | | | |
| | Minimum | $1.35 | $1.35 | | | |
| | Mean | $4.38 | $4.04 | | | |
| | Median | $3.79 | $3.55 | | | |
| | Contract obligations | $95,610,611 | $111,470,845 | | | |
| | Number of food boxes specified in contracts | 21,838,452 | 27,615,258 | | | |
| Precooked meat | Maximum | $149.01 | $180.00 | | | |
| | Minimum | $17.65 | $17.65 | | | |
| | Mean | $52.11 | $54.75 | | | |
| | Median | $42.55 | $45.66 | | | |
| | Contract obligations | $179,319,800 | $313,073,866 | | | |
| | Number of food boxes specified in contracts | 3,441,058 | 5,717,887 | | | |

Source: GAO analysis of U.S. Department of Agriculture (USDA) data. | GAO-21-353

**Figure 4.1:** Average prices paid per box, quantities delivered, and dollar value of contracts in each round. Source: US GAO Report to Congressional Committees, GAO-21-353

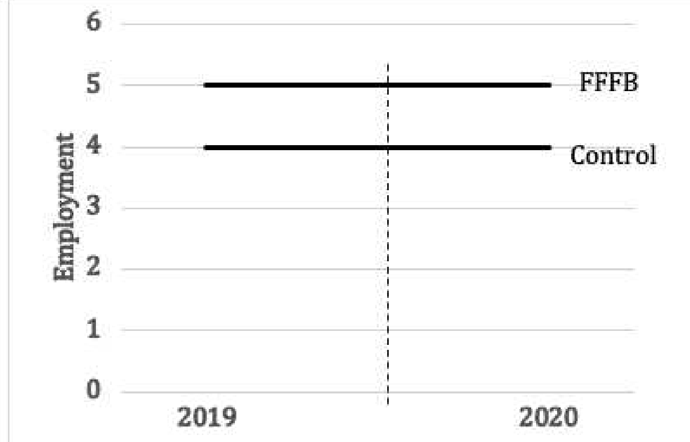
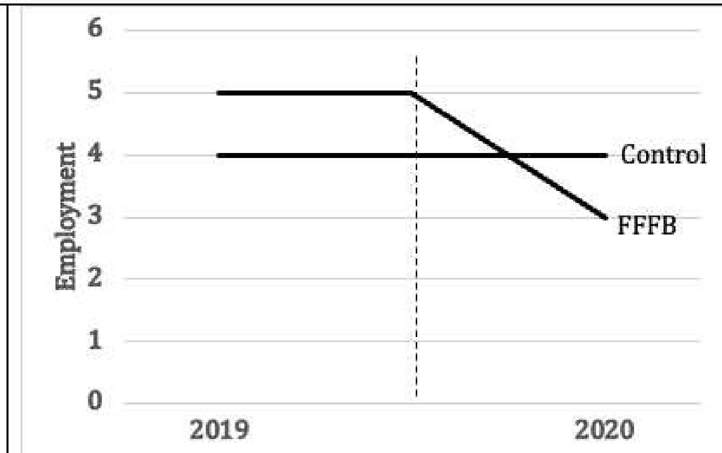
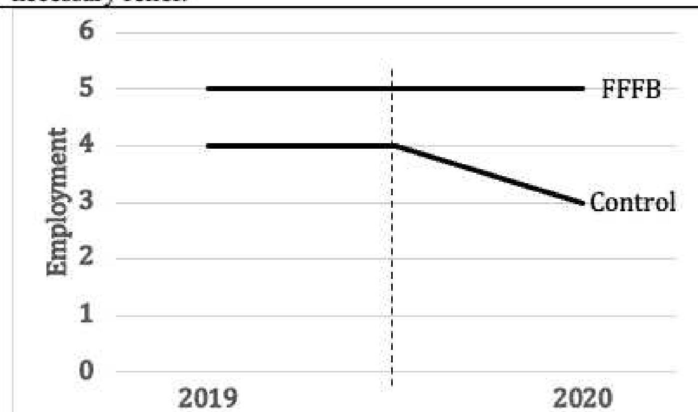
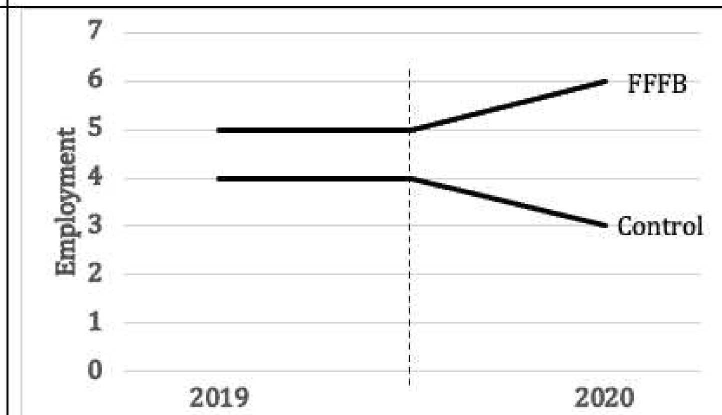
| | | |
|---|---|---|
| $H_0$ |  |  |
| | FFFB participation did not result in positive employment outcomes. There is no evidence that the program was a necessary relief. | FFFB participation resulted in negative employment outcomes. There is no evidence that the program was a relief. |
| $H_A$ |  |  |
| | FFFB participation resulted in sustained employment outcomes. There is evidence that the program was a temporary and necessary relief. | FFFB participation resulted in positive employment outcomes. There is evidence that the program was a temporary and necessary relief. Note: this would also have been true if the Control's employment levels stayed constant. |

**Figure 4.2:** Hypothesis 1 - Examples of Null and Alternative Hypotheses.

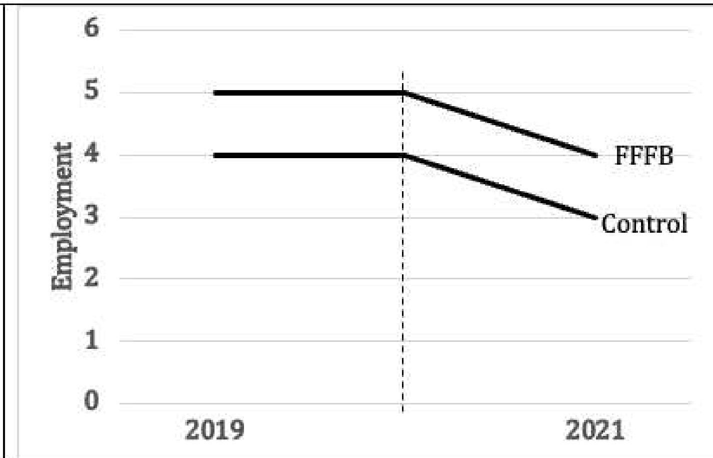
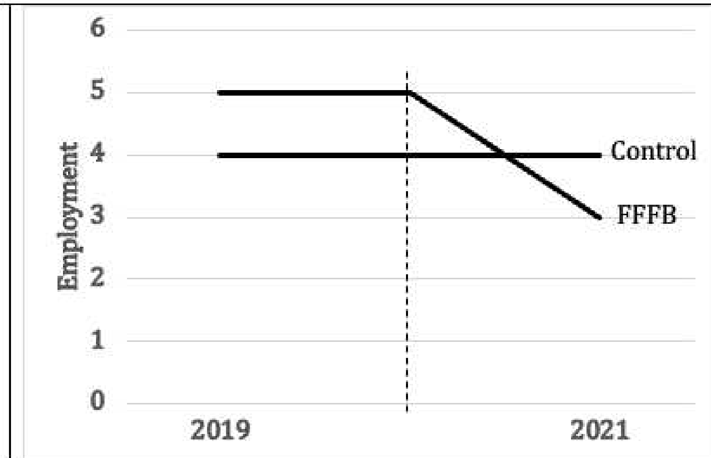
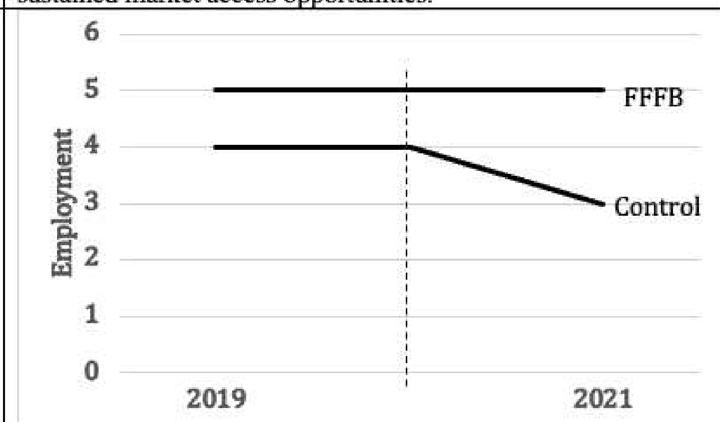
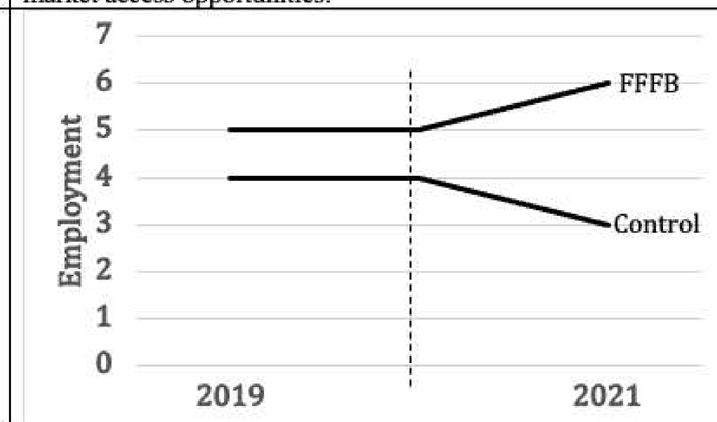
<table>
<tr><td>H<sub></sub>$H_0$</td><td></td><td></td></tr>
<tr><td></td><td>FFFB participation did not result in positive employment outcomes. There is no evidence that the program resulted in sustained market access opportunities.</td><td>FFFB participation resulted in negative employment outcomes. There is no evidence that the program resulted in sustained market access opportunities.</td></tr>
<tr><td>$H_A$</td><td></td><td></td></tr>
<tr><td></td><td>FFFB participation did result in sustained positive employment outcomes. There is evidence that the program resulted in sustained market access opportunities.</td><td>FFFB participation resulted in positive employment outcomes. There is evidence that the program resulted in sustained market access opportunities. Note: this would also have been true if the Control's employment levels stayed constant.</td></tr>
</table>

**Figure 4.3:** Hypothesis 2 - Examples of Null and Alternative Hypotheses.

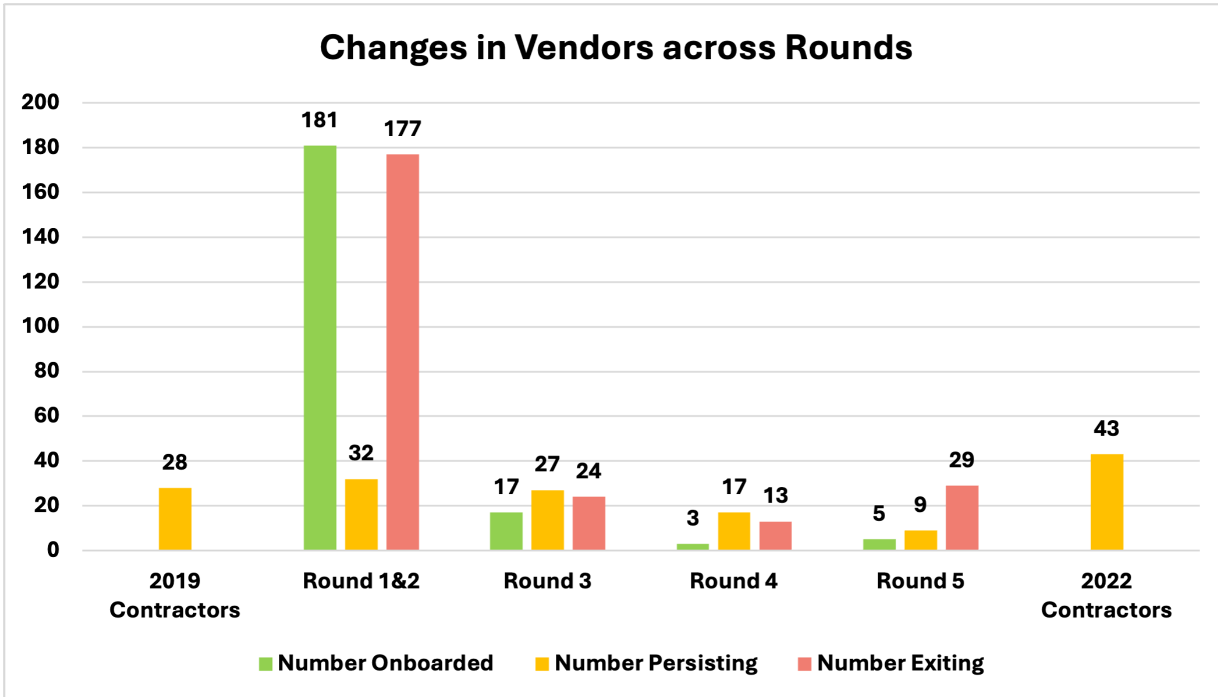
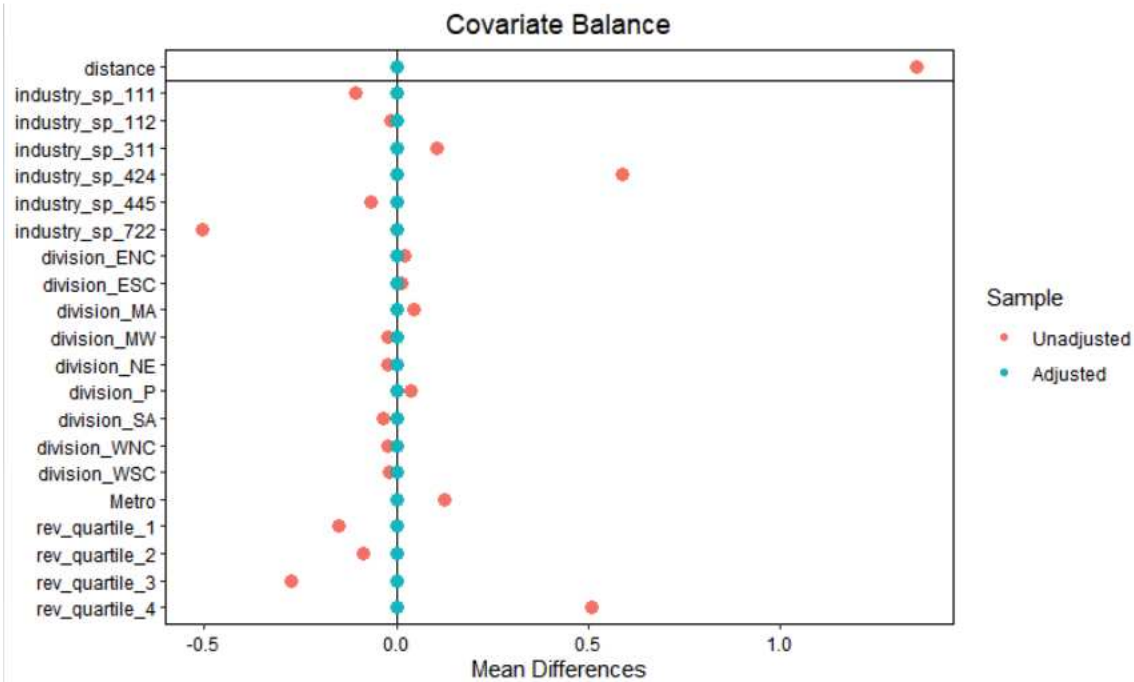



**Figure 4.4:** Rounds 1 and 2 brought in many vendors who had not contracted with USDA in 2019. However, a large portion of these new vendors appear to have exited the program before round 3

**Figure 4.5:** Balance of covariate distribution before and after propensity score matching




Note: Distance represents propensity to receive an FFFB contract, and the sample refers to the NETS control group of non-FFFB participants.

# Chapter 5

# Conclusion

## 5.1 Implications for Food System Resilience

Collectively, the findings from these three essays describe just a small set of the multitude of dynamics that influence food supply chains. By considering several of the strategies to adapt to such dynamics, we contribute to the discussion of how various business and policy levers may contribute to food system resiliency. Within the setting of the COVID-19 pandemic, we consider three important aspects of the food system including consumer usage of marketing channels, stocking up purchasing strategies across food categories, and also, the efficacy of governmental policies to redirect food to mitigate supply chain disruptions.

We contemplate the phrase “food system resiliency" as a measure of the capability of a food system to uphold food security and producer well-being when facing unexpected disruptions and/or uncertainty. A food system resiliency lens helps to frame how all of this work examines market, consumer, and policy responses to heterogeneity of consumer preferences, a changing landscape across food markets and products, and government responses intending to improve outcomes for food system stakeholders. Using diverse data sources and methodological approaches to capture various dimensions of the larger market response, these essays examine three specific supply chain scenarios that occurred within the U.S. food system during, or in response to, the COVID-19 pandemic. While survey data is used to understand nuanced details related to changes in market behavior, actual expenditure data conveys more aggregate representation and revealed purchase behavioral shifts in consumers’ shopping in various phases of the pandemic, and finally, food box (FFFB) shipment data is used alongside businesses’ performance data to understand the efficacy of a pandemic-era policy response.

Using latent class analysis of market selection based on food value preferences, the first essay of this dissertation underscores the importance of accounting for heterogeneity of consumers’ preferences when analyzing the dynamics of shopping patterns. This concept is further highlighted in the second essay, when we consider how underlying fears and other policy shifts may lead to differences in stockpiling behavior of perishable and non-perishable food across various phases of the pandemic. When we consider these takeaways in the greater context of the ability of the food system to uphold food security, it becomes evident that the diversity of consumers' preferences, which led them to respond to shortages and fears in a variety of ways, likely mitigated the severity of food shortages at major retailers. For example, the existence of consumers who did not perceive COVID-19 to be a major threat (and did not change behaviors) and/or consumers who were motivated to support local food businesses (rather than retailers who were not prepared for the large shift to food-at-home) meant that those shortages at major food retailers were not as exacerbated as they would have if consumers all responded uniformly.

It is important to note that heterogeneity of consumers' food preferences can only exist in a food system that offers access to a variety of markets and products. Another complementary theme of essays one and two's findings is that a food system with many different product offerings and available food markets implicitly requires diverse supply chains, which increases the ability of a food system to find alternative food supply sources during shortages or even market closures (e.g. FAFH during pandemic lockdowns). This complementarity of local, regional, and national markets was exemplified by food systems during the COVID-19 pandemic, in which the existence of many market channels, with a variety of buyers and sellers, including those with smaller capacities and shorter supply chains meant that the food system was more able to adapt to changing demand (Chenarides et al., 2021b; Hobbs, 2021). Extending this concept to the broader food system, findings from chapters two and three illustrate one form of food system resiliency: the existence of relatively diverse supply chains allowed consumers to shop at alternative retailers (e.g. small and independent markets, discount stores) or switch across perishable and non-perishable products in the face of uncertainty surrounding food supply and prices.

The third essay in this dissertation conveys another important way in which the US food system was able to adapt during the COVID-19 disruption- through a federal policy response, that subsequently catalyzed block grants to states to invest in similar, more localized responses. The Farmers to Families Food Box (FFFB) program was a policy response that embodied both components of the food system resiliency definition - food security and producer (or food supply chain enterprise) well-being. While the efficacy of the program with respect to food security outcomes has been previously analyzed (U.S. Government Accountability Office (GAO), 2021), essay three's findings provide preliminary insights about whether this program mitigated the challenges to vulnerable food businesses and allowed them to remain afloat through the loss of their their common institutional buyers during the height of COVID lockdown measures.

The common linkage between the three essays which focus on consumer choices relates to the importance of having diverse markets. Had vulnerable small food businesses not survived the pandemic, the diversity of retail types they contributed would have been lost, potentially accelerating market consolidation beyond what would have occurred without the COVID-19 disruption. Moreover, loss of intermediaries in food supply chains would also lower access of producers to buying markets. Thus, the FFFB program contributed to resiliency both via direct support to food businesses (and therefore food supply) and by indirectly supporting the diversity of markets, which is necessary to support the heterogeneity of consumer responses throughout this dissertation.

## 5.2 Limitations

The investigations included here are empirically tested using data collected during a pandemic. This potentially inhibits the generalizability of findings. The COVID-19 pandemic was a unique point in time, in which many factors affecting food systems shifted simultaneously. These studies take this into account by focusing on the market responses to overarching trends that that have either persisted and/or are more likely to reoccur in response to future disruptions (shifts to online, stockpiling, policy levers to manage mismatched supply chain and demand). Still, while the pandemic offers a valuable lens through which to understand food system vulnerabilities and adaptations, caution should be taken when extending these insights to non-pandemic contexts or assuming similar patterns would emerge in future disruptions.

When considering implications for local and regional food systems, another limitation common across these studies are a lack of available granular data that reflects local food system dynamics and policy efficacy. Many existing datasets are either too aggregated to capture region-specific trends or are released with significant time lags, making it difficult to assess how local food systems are responding to shocks or evolving over time. This limitation is particularly relevant when examining consumer behavior shifts or market adaptations during rapidly changing periods, such as the COVID-19 pandemic. Without timely, location-specific data, researchers and policymakers face challenges in identifying which strategies are most effective for building resilient local food networks. As a result, the ability to make informed decisions or generalize findings across different local contexts is constrained. This dissertation both provides an example of ways in which current data can be leveraged to estimate potential implications for local and regional food systems, but also its limitations underscore the need for improved data infrastructure and reporting mechanisms focused on regional food systems.

Additionally, the specifics of food system resiliency, and the factors that enhance it, remain poorly defined in both academic and policy contexts. This ambiguity complicates efforts to measure and compare resiliency across regions or time periods. On the other hand, this limitation also opens up important areas for future research, including the development of more nuanced definitions and metrics for resiliency in local and regional food systems. The observed consumer tendency to explore alternative food markets—such as farmers markets, CSAs, or direct-to-consumer channels—during the pandemic suggests promising regional dynamics worth further investigation. Understanding the extent to which these behavioral shifts persist post-pandemic could offer valuable insights into providing the market environment and/or policy tools which could support more adaptive and diversified food systems.

# References

Acciai, F., Srinivasan, M., and Ohri-Vachaspati, P. (2021). Sugar-sweetened beverage consumption in children: the interplay of household SNAP and WIC participation. *American Journal of Preventive Medicine*, 61(5):665–673.

Adjemian, M. K., Arita, S., Meyer, S., and Salin, D. (2024). Factors affecting recent food price inflation in the United States. *Applied Economic Perspectives and Policy*, 46(2):648–676.

Alaimo, L. S., Fiore, M., and Galati, A. (2020). How the COVID-19 Pandemic Is Changing Online Food Shopping Human Behaviour in Italy. *Sustainability*.

Alakaam, A. A. H. and Lemacks, J. L. (2015). Fruit and vegetable consumption, fat intake, and physical activity participation in relation to socio-demographic factors among medically underserved adults. *AIMS Public Health*, 2(3):402.

Alemu, M. H. and Olsen, S. (2019). Linking consumers' food choice motives to their preferences for insect-based food products: An application of integrated choice and latent variable model in an african context. *Journal of Agricultural Economics*, 70(1):241–258.

Andersen, A. L., Hansen, E. T., Johannesen, N., and Sheridan, A. (2022). Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data. *The Scandinavian Journal of Economics*, 124(4):905–929.

Anderson, J. E. (2011). The gravity model. *Annual Review of Economics*, 3(1):133–160.

Anderson, J. E. (2016). The gravity model of economic interaction. *Boston College and the National Bureau of Economic Research (NBER)*, 3:391–397.

Arnold, S. J., Oum, T. H., and Tigert, D. J. (1983). Determinant attributes in retail patronage: seasonal, temporal, regional, and international comparisons. *Journal of Marketing Research*, 20(2):149–157.

Arora, V. S., McKee, M., and Stuckler, D. (2019). Google trends: Opportunities and limitations in health and health policy research. *Health Policy*, 123(3):338–341.

Aslihan-Nasir, V. and Karakaya, F. (2014). Consumer segments in the organic foods market. *Journal of Consumer Marketing*, 31(4):263–277.

Atkins, K. G., Kumar, A., and Kim, Y.-K. (2016). Smart grocery shopper segments. *Journal of International Consumer Marketing*, 28(1):42–53.

Awijen, H., Zaied, Y. B., and Nguyen, D. K. (2022). COVID-19 vaccination, fear and anxiety: Evidence from Google search trends. *Social Science & Medicine*, 297:114820.

Babbitt, C. W., Babbitt, G. A., and Oehman, J. M. (2021). Behavioral impacts on residential food provisioning, use, and waste during the COVID-19 pandemic. *Sustainable Production and Consumption*, 28:315–325.

Bachas, N., Ganong, P., Noel, P. J., Vavra, J. S., Wong, A., Farrell, D., and Greig, F. E. (2020). Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data. *National Bureau of Economic Research Working Paper*, (No. w27617).

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020). How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *The Review of Asset Pricing Studies*, 10(4):834–862.

Balagtas, J. V., Cooper, J., McLaughlin, P., and Qin, F. (2023). Consumer demand for food at home and food away from home: Understanding economic linkages during the pandemic. *Applied Economic Perspectives and Policy*, 45(3):1604–1617.

Barnatchez, K., Crane, L. D., and Decker, R. A. (2017). An assessment of the national establishment time series (NETS) database. *Finance and Economics Discus- sion Series*.

Beatty, T. K., Shimshack, J. P., and Volpe, R. J. (2019). Disaster preparedness and disaster response: Evidence from sales of emergency supplies before and after hurricanes. *Journal of the Association of Environmental and Resource Economists*, 6(4):633–668.

Beatty, T. K. and Tuttle, C. J. (2015). Expenditure response to increases in in-kind transfers: Evidence from the supplemental nutrition assistance program. *American Journal of Agricultural Economics*, 97(2):390–404.

Béné, C. (2020). Resilience of local food systems and links to food security–a review of some important concepts in the context of COVID-19 and other shocks. *Food security*, 12(4):805–822.

Berjan, S., Vaško, Ž., Ben Hassen, T., El Bilali, H., Allahyari, M. S., Tomić, V., and Radosavac, A. (2022). Assessment of household food waste management during the COVID-19 pandemic in Serbia: A cross-sectional online survey. *Environmental Science and Pollution Research*, pages 1–12.

Bimbo, F., Russo, C., Di Fonzo, A., and Nardone, G. (2021). Consumers' environmental responsibility and their purchase of local food: evidence from a large-scale survey. *British Food Journal*, 123(5):1853–1874.

Bina, J. D., Tonsor, G. T., and Briggeman, B. C. (2023). COVID-19 federal aid and household food expenditures. *Journal of Agricultural and Applied Economics*, 55(4):567–608.

Biondi, B., Capacci, S., and Mazzocchi, M. (2021). Food purchasing behavior during the COVID-19 pandemic: Evidence from Italian household scanner data.

Blanchard, O. J., Jaumotte, F., and Loungani, P. (2014). Labor market policies and IMF advice in advanced economies during the Great Recession. *IZA Journal of Labor Policy*, 3:1–23.

Blattberg, R. C., Eppen, G. D., and Lieberman, J. (1981). A theoretical and empirical evaluation of price deals for consumer nondurables. *Journal of marketing*, 45(1):116–129.

Bonanno, A., Gill, M., and Thilmany, D. (2025). Counterfactual Food Expenditures, Quantity Purchased and Price Paid during the COVID-19 Pandemic. *Working Paper, Under Review*.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting event-study designs: robust and efficient estimation. *Review of Economic Studies*.

Bougherara, D., Grolleau, G., and Mzoughi, N. (2009). Buy local, pollute less: What drives households to join a community supported farm? *Ecological Economics*, 68(5):1488–1495.

Brand, C., Schwanen, T., and Anable, J. (2020). 'Online Omnivores' or 'Willing but struggling'? identifying online grocery shopping behavior segments using attitude theory. *Journal of Retailing and Consumer Services*, 57:102195.

Brandt, E. J., Silvestri, D. M., Mande, J. R., Holland, M. L., and Ross, J. S. (2019). Availability of grocery delivery to food deserts in states participating in the online purchase pilot. *JAMA Network Open*, 2(12).

Brown, M. (2025). USDA cancels $1b in local food purchasing for schools, food banks. *Politico*.

Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., and TuYe, H.-Y. (2020). COVID-19 and remote work: An early look at US data. *National Bureau of Economic Research (NBER)*, (No. w27344).

Cadwallader, M. (1981). Towards a cognitive gravity model: The case of consumer spatial behaviour. *Regional Studies*, 15(4):275–284.

Callaway, B., Goodman-Bacon, A., and Sant'Anna, P. H. C. (2024). Difference-in-differences with a continuous treatment.

Callaway, B. and Sant'Anna, P. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Carneiro, H. A. and Mylonakis, E. (2009). Google trends: a web-based tool for real-time surveillance of disease outbreaks. *Clinical infectious diseases*, 49(10):1557–1564.

Cavallo, A., Cavallo, E., and Rigobon, R. (2014). Prices and supply disruptions during natural disasters. *Review of Income and Wealth*, 60:S449–S471.

Centers for Disease Control and Prevention (CDC) (2022). CDC COVID data tracker.

Chang, H.-H. and Meyerhoefer, C. D. (2021). COVID-19 and the demand for online food shopping services: Empirical evidence from Taiwan. *American Journal of Agricultural Economics*, 103(2):448–465.

Charles, D. (2020). How Trump's Food Box Initiative Overpaid and Underdelivered. *National Public Radio*.

Chen, L. A. and House, L. (2022). Food lifestyle patterns among contemporary food shoppers. *International Journal of Consumer Studies*, 46(3):944–963.

Chenarides, L., Grebitus, C., Lusk, J. L., and Printezis, I. (2021a). Food consumption behavior during the COVID-19 pandemic. *Agribusiness*, 37(1):44–81.

Chenarides, L., Manfredo, M., and Richards, T. J. (2021b). COVID-19 and food supply chains. *Applied Economic Perspectives and Policy*, 43(1):270–279.

Ching, A. T. and Osborne, M. (2020). Identification and estimation of forward-looking behavior: The case of consumer stockpiling. *Marketing Science*, 39(4):707–726.

Chronopoulos, D. K., Lukas, M., and Wilson, J. O. (2020). Consumer spending responses to the COVID-19 pandemic: An assessment of Great Britain. *Available at SSRN 3586723*.

Chryssohoidis, G. M. and Krystallis, A. (2005). Organic consumers' personal values research: Testing and validating the list of values (LOV) scale and implementing a value-based segmentation task. *Food Quality and Preference*, 16(7):585–599.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). Labor markets during the COVID-19 crisis: A preliminary view. *National Bureau of Economic Research*, (No. w27017).

Conlin, M., Harris-Lagoudakis, K., Jung, S. Y., Haughey, C., and Wich, H. (2024). The new normal: Grocery shopping behavior changes before and after the COVID-19 vaccine. *Applied Economic Perspectives and Policy*, 46(3):1241–1264.

Correia, R. A. and Mammola, S. (2024). The searchscape of fear: A global analysis of internet search trends for biophobias. *People and Nature*, 6(3):958–972.

Cosgrove, K., Vizcaino, M., and Wharton, C. (2021). COVID-19-related changes in perceived household food waste in the united states: A cross-sectional descriptive study. *International Journal of Environmental Research and Public Health*.

Crawford, A. (2018). High-dimensional inventories and consumer dynamics: demand estimation for fast moving consumer goods. *Working Paper*.

Crépon, B. and Van Den Berg, G. J. (2016). Active labor market policies. *Annual Review of Economics*, 8(1):521–546.

CSA Innovation Network (2020). August 2020 impact assessment.

Currim, I. S. and Schneider, L. G. (1991). A taxonomy of consumer purchase strategies in a promotion intensive environment. *Marketing Science*, 10(2):91–110.

Davis, G. C. and You, W. (2010). The time cost of food at home: general and food stamp participant profiles. *Applied Economics*, pages 2537–2552.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

Dickins, T. and Schalz, S. (2020). Food shopping under risk and uncertainty. *Learning and Motivation*, 72:101681.

Dunn, A., Hood, K., Batch, A., and Driessen, A. (2021). Measuring consumer spending using card transaction data: lessons from the COVID-19 pandemic. In *AEA papers and proceedings*, volume 111, pages 321–325. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Edmondson, H., Gill, M., Jablonski, B., Ladd, J., Rossi, J., Schaffstall, S., Thilmany, D., and Woods, T. (2021). U.S. Consumer Food Insights During the COVID-19 Pandemic. *Local and Regional Food Systems Response to COVID*.

Edmondson, H. E. (2021). Exploring local food purchasing patterns during COVID-19: insights from a nationwide consumer survey: Masters of science thesis. Master's thesis, Colorado State University.

El Baba, W. and Fakih, A. (2023). COVID-19 and consumer behavior: Food stockpiling in the US market. *Agribusiness*, 39(2):515–534.

Ellison, B. and Kalaitzandonakes, M. (2020). Food waste and COVID-19: Impacts along the supply chain. *Farmdoc Daily*, 10(164).

Ellison, B., McFadden, B., Rickard, B. J., and Wilson, N. L. (2021). Examining food purchase behavior and food values during the COVID-19 pandemic. *Applied Economic Perspectives and Policy*, 43(1):58–72.

Erdem, T., Imai, S., and Keane, M. P. (2003). Brand and quantity choice dynamics under price uncertainty. *Quantitative Marketing and Economics*, 1:5–64.

Etumnu, C. E., Foster, K. A., Widmar, N. O., Lusk, J. L., and Ortega, D. L. (2019). Drivers of online grocery shopping. *Selected Paper prepared for presentation at the 2019 Agricultural*

*Applied Economics Association Annual Meeting, Atlanta, GA, July 21 – July 23*.

Etumnu, C. E. and Widmar, N. O. (2020). Grocery shopping in the digital era. *Choices*, 35(2):1–8.

Fabusoro, O., Singleton, C. R., Terán-Garcıa, M., and Lara-Cinisomo, S. (2023). Predictors of food and water stockpiling during the COVID-19 pandemic among Latinos and Non-Latino Black People. *Disaster Medicine and Public Health Preparedness*.

Farag, S., Krizek, K. J., and Dijst, M. (2006). E-Shopping and its Relationship with In-store Shopping: Empirical Evidence from the Netherlands and the USA. *Transport Reviews*, 26(1):43–61.

Farag, S., Schwanen, T., Dijst, M., and Faber, J. (2007). Shopping online and/or in-store? a structural equation model of the relationships between e-shopping and in-store shopping. *Transportation Research Part A: Policy and Practice*, 41(2):125–141.

Finck, D. and Tillmann, P. (2022). Pandemic shocks and household spending. *Oxford Bulletin of Economics and Statistics*, 84(2):273–299.

Finkelstein, A., Kocks, G., Polyakova, M., and Udalova, V. (2024). Heterogeneity in damages from a pandemic. *Review of Economics and Statistics*, pages 1–45.

Fox, M. K., Hamilton, W. L., and Lin, B.-H. (2004). Effects of food assistance and nutrition programs on nutrition and health: Volume 4, executive summary of the literature review. *Food Assistance and Nutrition Research Report*, (19-4).

Ganesh, J., Reynolds, K. E., Luckett, M., and Pomirleanu, N. (2010). Online shopper motivations, and e-store attributes: an examination of online patronage behavior and shopper typologies. *Journal of Retailing*, 86(1):106–115.

Gao, X., Shi, X., Guo, H., and Liu, Y. (2020). To buy or not buy food online: The impact of the COVID-19 epidemic on the adoption of e-commerce in china. *Plos One*.

Gerard, F., Imbert, C., and Orkin, K. (2020). Social protection response to the COVID-19 crisis: options for developing countries. *Oxford Review of Economic Policy*, 36(Supplement_1):S281–S296.

Ghosh, S. (2011). The Gravity Model in International Trade. Advances and Applications - Edited by Peter A.G. Van Bergeijk and Steven Brakman. *Review of International Economics*, 19(5):979–981.

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., and Brilliant, L. (2009). Detecting influenza epidemics using search engine query data. *Nature*, 457(7232):1012–1014.

Goldman, A. and Hino, H. (2005). Supermarkets vs. traditional retail stores: diagnosing the barriers to supermarkets' market share growth in an ethnic minority community. *Journal of Retailing and Consumer Services*, 12(4):273–284.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Google (2024). Google trends data. Web-scraped state granularity via python.

Griffith, R., Leibtag, E., Leicester, A., and Nevo, A. (2009). Consumer shopping behavior: how much do consumers save? *Journal of Economic Perspectives*, 23(2):99–120.

Hadachek, J., Ma, M., and Sexton, R. J. (2024a). Market structure and resilience of food supply chains under extreme events. *American Journal of Agricultural Economics*, 106(1):21–44.

Hadachek, J., Ma, M., and Sexton, R. J. (2024b). Market structure and resilience of food supply chains under extreme events. *American Journal of Agricultural Economics*, 106(1):21–44.

Hagenaars, J. (2002). *Applied Latent Class Analysis*. Cambridge University Press.

Hansen, T. (2007). Determinants of consumers' repeat online buying of groceries. *International Review of Retail, Distribution, and Consumer Research*, 16(1):93–114.

Hansen, T. (2008). Consumer values, the theory of planned behaviour and online grocery shopping. *International Journal of Consumer Studies*, 32(2):128–137.

Harris, P., Dall'Olmo Riley, F., Riley, D., and Hand, C. (2017). Online and store patronage: a typology of grocery shoppers. *International Journal of Retail & Distribution Management*, 45(4):419–445.

Harris-Lagoudakis, K. (2022). Online shopping and the healthfulness of grocery purchases. *American Journal of Agricultural Economics*, 104(3):1050–1076.

Haynes-Maslow, L., Hardison-Moody, A., Patton-Lopez, M., Prewitt, T. E., Byker Shanks, C., Andress, L., Osborne, I., and Jilcott Pitts, S. (2020). Examining rural food-insecure families' perceptions of the supplemental nutrition assistance program: A qualitative study. *International Journal of Environmental Research and Public Health*, 17(17):6390.

He, W. and Jia, S. (2024). Exploring multigenerational co-residence in the united states. *International Journal of Housing Markets and Analysis*, 17(2):517–538.

Hendel, I. and Nevo, A. (2006a). Measuring the implications of sales and consumer inventory behavior. *Econometrica*, 74(6):1637–1673.

Hendel, I. and Nevo, A. (2006b). Sales and consumer inventory. *The RAND Journal of Economics*, 37(3):543–561.

Hendel, I. and Nevo, A. (2013). Intertemporal price discrimination in storable goods markets. *American Economic Review*, 103(7):2722–51.

Hernández-Vasquéz, A., Visconti-Lopez, F. J., and Vargas-Fernández, R. (2022). Socio-economic inequalities in the consumption of fruits and vegetables in Peru between 2014 and 2019. *Public Health Nutrition*.

Hertz, R., Mattes, J., and Shook, A. (2021). When paid work invades the family: Single mothers in the COVID-19 pandemic. *Journal of Family Issues*, 42(9):2019–2045.

Hobbs, J. E. (2020). Food supply chains during the COVID-19 pandemic. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 68(2):171–176.

Hobbs, J. E. (2021). Food supply chain resilience and the COVID-19 pandemic: What have we learned? *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 69(2):189–196.

Hobbs, J. E. and Hadachek, J. (2024). The economics of food supply chain resilience. *Annual Review of Resource Economics*, 16.

Houghtaling, B., Haynes-Maslow, L., Andress, L., Hardison-Moody, A., Grocke-Dewey, M., Holston, D., Patton-López, M., Pradhananga, N., Prewitt, T., Shanks, J. D., Webber, E. J., and Shanks, C. B. (2023). Food insecurity among households with children during the early months of the COVID-19 pandemic. *Journal of Agriculture Food Systems and Community Development*.

Hubbard, R. G. and Strain, M. R. (2020). Has the paycheck protection program succeeded? Technical Report No. w28032, National Bureau of Economic Research.

Jablonski, B. B., Bauman, A., and Thilmany, D. (2021). Local food market orientation and labor intensity. *Applied Economic Perspectives and Policy*, 43(3):916–934.

Jacobsen, G. D. and Jacobsen, K. H. (2020). Statewide COVID-19 stay-at-home orders and population mobility in the United States. *World Medical & Health Policy*, 12(4):347–356.

Jaller, M. and Pahwa, A. (2020). Evaluating the environmental impacts of online shopping: A behavioral and transportation approach. *Transportation Research Part D: Transport and Environment*, 80:102–223.

Jensen, K. L., Yenerall, J., Chen, X., and Yu, T. E. (2021). US consumers' online shopping behaviors and intentions during and after the COVID-19 pandemic. *Journal of Agricultural and Applied Economics*, 53(3):416–434.

Jones, J. (2022). SNAP spending reached record high of $113.8 billion in fiscal year 2021. *Charts of Note, USDA Economic Research Service*.

Kapinos, P. (2021). Did the paycheck protection program have negative side effects on small-business activity? *Economics Letters*, 208:110045.

Keane, M. and Neal, T. (2021). Consumer panic in the COVID-19 pandemic. *Journal of econometrics*, 220(1):86–105.

Kilders, V., Caputo, V., and Lusk, J. L. (2024). Consumer preferences for food away from home: Dine in versus delivery. *American Journal of Agricultural Economics*, 106(2):496–525.

Klumpp, T. (2021). Stockpiling and shortages:(the "toilet paper paper"). *Working Paper: University of Alberta, Faculty of Arts, Department of Economics*.

Konuş, U., Verhoef, P. C., and Neslin, S. A. (2008). Multichannel shopper segments and their covariates. *Journal of Retailing*, 84(4):398–413.

Kuan, I.-H., Liu, Y., Jones, J. W., and Zhou, P. (2025). SNAP online purchasing and the healthfulness of food purchases. *Applied Economic Perspectives and Policy*.

Li, J., Hu, W., Qing, P., and Chavas, J.-P. (2024). On household food stock and waste under risk. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 72(1):23–44.

Liboredo, J. C., Amaral, C. A. A., and Carvalho, N. C. d. (2022). Food delivery before and during the COVID-19 pandemic in brazil.

Lindsay, B. R., Levin, A. G., and Blackford, C. R. (2023). COVID-19 relief to small businesses: Issues and policy options. Technical Report R46284, Congressional Research Service.

Lo, A., Duffy, E. W., and Ng, S. W. (2021). Who's grocery shopping online and why: Cross-sectional analysis of a nationally-representative sample since the pandemic. *Current Developments in Nutrition*, 5:231.

Long, J. C., Delamater, P. L., and Holmes, G. M. (2021). Which definition of rurality should I use?: The relative performance of 8 federal rural definitions in identifying rural-urban disparities. *Medical Care*, 59(10 Suppl. 5):S413.

Love, E., Jablonski, B. B., McFadden, D. T., and Bellows, L. (2025). A roadmap for modeling institutional and values-based procurement decisions in food supply chains. *Agricultural and Resource Economics Review*, pages 1–29.

Low, S.A. et al. (2015). Trends in U.S. Local and Regional Food Systems: A Report to Congress. *U.S. Department of Agriculture, Economic Research Service*, (Administrative Publication 068):89.

Lusk, J. L. and Briggeman, B. C. (2009). Food values. *American Journal of Agricultural Economics*, 91(1):184–196.

Lusk, J.L., T. G. S. L. (2021). Beef and pork marketing margins and price spreads during COVID-19. *Applied Economic Perspectives and Policy*, 43(1):4–23.

Marchesi, K. (2022). FFFB Shipment Data from USDA Agricultural Marketing Service. *USDA Economic Research Service*.

Marchesi, K. and McLaughlin, P. (2024). Food Spending Shifted in Response to Pandemic; Changes for Food Away From Home Continued Through 2022. *Amber Waves*.

Martinez, C. E., Ritchie, L. D., Lee, D. L., Tsai, M. M., Anderson, C. E., and Whaley, S. E. (2022). California WIC participants report favorable impacts of the COVID-related increase to the WIC cash value benefit. *International Journal of Environmental Research and Public Health*, 19(17):10604.

Mavragani, A., Ochoa, G., and Tsagarakis, K. P. (2018). Assessing the methods, tools, and statistical approaches in Google Trends research: A systematic review. *Journal of Medical Internet Research*, 20(11):e270.

McElrone, M., Zimmer, M. C., and Steeves, E. T. A. (2021). A qualitative exploration of predominantly white non-Hispanic Tennessee WIC participants' food retail and WIC clinic experiences during COVID-19. *Journal of the Academy of Nutrition and Dietetics*, 121(8):1454–1462.

McFadden, B. R., Malone, T., Kecinski, M., and Messer, K. D. (2020). Covid-19 induced stigma in u.s. consumers: Evidence and implications. *American Journal of Agricultural Economics*, page ajae.12188.

Mela, C. F., Jedidi, K., and Bowman, D. (1998). The long-term impact of promotions on consumer stockpiling behavior. *Journal of Marketing research*, 35(2):250–262.

Melis, K., Campo, K., Lamey, L., and Breugelmans, E. (2016). A bigger slice of the multichannel grocery pie: when does consumers' online channel use expand retailers' share of wallet? *Journal of Retailing*, 92(3):268–286.

Melnick, E. M., Ganderats-Fuentes, M., and Ohri-Vachaspati, P. (2022). Federal food assistance program participation during the COVID-19 pandemic: participant perspectives and reasons for discontinuing. *Nutrients*, 14(21):4524.

Melo, G. (2020). The path forward: US consumer and food retail responses to COVID-19. (Special Section: COVID-19 and the agriculture industry: labor, supply chains, and consumer behavior.). *Choices. The Magazine of Food, Farm, and Resources Issues*.

Meuwissen, M. P., Feindt, P. H., Spiegel, A., Termeer, C. J., Mathijs, E., De Mey, Y., Finger, R., Balmann, A., Wauters, E., Urquhart, J., et al. (2019). A framework to assess the resilience of farming systems. *Agricultural Systems*, 176:102656.

Michaelides, M. and Mueser, P. (2020). The labor market effects of us reemployment policy: lessons from an analysis of four programs during the great recession. *Journal of Labor Economics*, 38(4):1099–1140.

Miller, V., Yusuf, S., Chow, C. K., Dehghan, M., Corsi, D. J., Lock, K., Popkin, B. M., Rangarajan, S., Khatib, R., Lear, S. A., Mony, P., Kaur, M., Mohan, V., Vijayakumar, K., Gupta, R., Kruger, A., Tsolekile, L., Mohammadifard, N., Rahman, O., Rosengren, A., Avezum, , Orlandini, A., Ismail, N. H., López-Jaramillo, P., Yusufali, A., Karşıdağ, K., Iqbal, R., Chifamba, J., Oakley, S. M., Ariffin, F., Zatońska, K., Poirier, P., Li, W., Bo, J., Chen, H., Liu, X., Bai, X., Teo, K., and Mente, A. (2016). Availability, affordability, and consumption of fruits and vegetables in 18 countries across income levels: Findings from the prospective urban rural epidemiology (pure) study. *The Lancet Global Health*.

Mokhtarian, P. L., Ory, D. T., and Cao, X. (2009). Shopping-related attitudes: a factor and cluster analysis of Northern California shoppers. *Environment and Planning B: Planning and Design*, 36(2):204–228.

Murphy, B., Benson, T., McCloat, A., Mooney, E., Elliott, C. T., Dean, M., and Lavelle, F. (2020). Changes in consumers' food practices during the COVID-19 lockdown, implications for diet quality and the food system: A cross-continental comparison. *Nutrients*.

Murray, B. (2025). Bloomberg trade uncertainty index soars to new record. *Bloomberg Newsletter: Supply Lines*.

Naito, T., Tomata, Y., Otsuka, T., Tsuno, K., and Tabuchi, T. (2022). Did children in single-parent households have a higher probability of emotional instability during the COVID-19 pandemic? a nationwide cross-sectional study in Japan. *International journal of environmental research and public health*, 19(7):4239.

Neslin, S. A., Henderson, C., and Quelch, J. (1985). Consumer promotions and the acceleration of product purchases. *Marketing science*, 4(2):147–165.

Noda, S. and Teramoto, K. (2024). A dynamic model of rational "panic buying". *Quantitative Economics*, 15(2):489–521.

Nuti, S. V., Wayda, B., Ranasinghe, I., Wang, S., Dreyer, R. P., Chen, S. I., and Murugiah, K. (2014). The use of Google trends in health care research: a systematic review. *PloS one*, 9(10):e109583.

Nylund, K. L., Asparouhov, T., and Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural equation modeling: A multidisciplinary journal*, 14(4):535–569.

O'Connell, M., De Paula, Á., and Smith, K. (2021). Preparing for a pandemic: Spending dynamics and panic buying during the COVID-19 first wave. *Fiscal Studies*, 42(2):249–264.

Ogundijo, D. A., Tas, A. A., and Onarinde, B. A. (2021). Exploring the impact of COVID-19 pandemic on eating and purchasing behaviours of people living in England.

O'Hara, J. and Low, S. (2020). Online sales: A direct marketing opportunity for rural farms? *Journal of Agricultural and Applied Economics*, 52(2):222–239.

Omar, N. A., Nazri, M. A., Ali, M. H., and Alam, S. S. (2021). The panic buying behavior of consumers during the COVID-19 pandemic: Examining the influences of uncertainty, perceptions of severity, perceptions of scarcity, and anxiety. *Journal of Retailing and Consumer Services*, 62:102600.

Osborne, M. (2018). Frequency versus depth: How changing the temporal process of promotions impacts demand for a storable good. *The Japanese Economic Review*, 69:258–283.

O'Neill, V., Hess, S., and Campbell, D. (2014). A question of taste: Recognising the role of latent preferences and attitudes in analysing food choices. *Food Quality and Preference*, 32:299–310.

Palardy, N., Costanigro, M., Cannon, J., Thilmany, D., Berning, J., Bayham, J., and Callaway, J. (2023). Beer sales in grocery and convenience stores: a glass half-full for craft brewers? *Regional Studies*, 57(10):1981–1994.

Palma, M. A., Ness, M. L., and Anderson, D. P. (2017). Fashionable food: a latent class analysis of social status in food purchases. *Applied Economics*, 49(3):238–250.

Parker, J. R. and Lehmann, D. R. (2011). When shelf-based scarcity impacts consumer preferences. *Journal of Retailing*, 87(2):142–155.

Prentice, C., Quach, S., and Thaichon, P. (2022). Antecedents and consequences of panic buying: The case of COVID-19. *International Journal of Consumer Studies*, 46(1):132–146.

Rathke, B. H., Yu, H., and Huang, H. (2023). What remains now that the fear has passed? Developmental trajectory analysis of COVID-19 pandemic for co-occurrences of Twitter, Google Trends, and public health data. *Disaster Medicine and Public Health Preparedness*, 17:e471.

Restrepo, B. J. and Zeballos, E. (2020). The effect of working from home on major time allocations with a focus on food-related activities. *Review of Economics of the Household*, 18(4):1165–1187.

Richards, T. J., Hamilton, S. F., Gomez, M., and Rabinovich, E. (2017). Retail Intermediation and Local Foods. *American Journal of Agricultural Economics*, 99(3):637–659.

Rocker, S., Kropczynski, J., and Hinrichs, C. (2022). Using social network analysis to understand and enhance local and regional food systems. In *Food systems modelling*, pages 231–256. Elsevier.

Roe, B. E., Bender, K., and Qi, D. (2021). The impact of COVID-19 on consumer food waste. *Applied Economic Perspectives and Policy*, 43(1):401–411.

Rohm, A. J. and Swaminathan, V. (2004). A typology of online shoppers based on shopping motivations. *Journal of business research*, 57(7):748–757.

Roos, J. M. (2024). Personality traits and stockpiling in the united kingdom during the COVID–19 pandemic. *European Journal of Psychology Open*.

Rude, J. (2021). Resilience versus efficiency: The feasibility of small local meatpacking plants in Canada. *The Canadian Agri-Food Policy Institute*.

Sadus, K., Göttmann, J., and Schubert, A.-L. (2023). Predictors of stockpiling behavior during the covid-19 pandemic in Germany. *Journal of Public Health*, 31(10):1717–1733.

Salop, S. and Stiglitz, J. E. (1982). The theory of sales: A simple model of equilibrium price dispersion with identical agents. *The American Economic Review*, 72(5):1121–1130.

Schmidt, C., Goetz, S., Rocker, S., and Tian, Z. (2020). Google searches reveal changing consumer food sourcing in the COVID-19 pandemic. *Journal of Agriculture, Food Systems, and Community Development*, 9(3):9–16.

Schmidt, R. C., Westbrock, B., and Hoegen, H. (2023). A simple model of panic buying. *Journal of Economic Behavior & Organization*, 216:268–286.

Schumacher, A. and Micheli, L. (2024). Anticipated scarcity and stockpiling during the COVID-19 pandemic: The role of perceived threat, childhood ses and materialism. *Plos One*.

Seo, J. (2024). An empirical investigation of online grocery shopping behaviors based on different generations. *International Journal of Business and Management*.

Severn, V., Washburn, L., Frisk, R., and Conway, K. (2023). Child nutrition program operations during the COVID-19 pandemic, march through september 2020: School meals operations study year 1 report. *USDA, Food and Nutrition Service, Office of Policy Support*.

Shamim, K., Ahmad, S., and Alam, M. A. (2021). COVID-19 health safety practices: Influence on grocery shopping behavior. *Journal of Public Affairs*, 21(4):e2624.

Shonkwiler, J. S. and Yen, S. T. (1999). Two-Step Estimation of a Censored System of Equations. *American Journal of Agricultural Economics*, 81(4):972–982.

Sim, K., Chua, H. C., Vieta, E., and Fernandez, G. (2020). The anatomy of panic buying related to the current COVID-19 pandemic. *Psychiatry research*, 288:113015.

Smith, H. (2004). Supermarket choice and supermarket competition in market equilibrium. *The Review of Economic Studies*, 71(1):235–263.

Smith, N. and Thomas, S. J. (2021). Doomsday prepping during the COVID-19 pandemic. *Frontiers in Psychology*.

Stevens, A., Tealb, J., Court, C., DiGiacomod, G., Millere, M., Peterson, F., and Hikaru, H. (2024). Predicting firm diversification in agri-food value chains. *Food Distribution Research Society*, 55(3):43–64.

Subramaniam, S. and Chakraborty, M. (2021). COVID-19 fear index: does it matter for stock market returns? *Review of Behavioral Finance*, 13(1):40–50.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Taylor, A. W., Coveney, J., Ward, P. R., Henderson, J., Meyer, S. B., Pilkington, R., and Gill, T. K. (2012). Fruit and vegetable consumption–the influence of aspects associated with trust in food and safety and quality of food. *Public health nutrition*, 15(2):208–217.

Tekle, F. B., Gudicha, D. W., and Vermunt, J. K. (2016). Power analysis for the bootstrap likelihood ratio test for the number of classes in latent class models. *Advances in Data Analysis and Classification*, 10:209–224.

Tendall, D. M., Joerin, J., Kopainsky, B., Edwards, P., Shreck, A., Le, Q. B., Krütli, P., Grant, M., and Six, J. (2015). Food system resilience: Defining the concept. *Global food security*, 6:17–23.

Thilmany, D., Brislen, L., Edmondson, H., Gill, M., Jablonski, B. B., Rossi, J., Woods, T., and Schaffstall, S. (2021a). Novel methods for an interesting time: Exploring us local food systems' impacts and initiatives to respond to covid. *Australian Journal of Agricultural and Resource Economics*, 65(4):848–877.

Thilmany, D., Canales, E., Low, S. A., and Boys, K. (2021b). Local food supply chain dynamics and resilience during COVID-19. *Applied Economic Perspectives and Policy*, 43(1):86–104.

Thompson, G. D. (1998). Consumer demand for organic foods: what we know and what we need to know. *American Journal of Agricultural Economics*, 80(5):1113–1118.

Timoneda, J. C. and Vallejo Vera, S. (2021). Will i die of coronavirus? Google Trends data reveal that politics determine virus fears. *Plos one*, 16(10):e0258189.

Trude, A. C., Lowery, C. M., Vedovato, G. M., Ali, S. H., and Dudzik, J. M. (2025). Changes in grocery shopping behaviour among low-income households during the COVID-19 pandemic. *Public Health Nutrition*, 28(1):e26.

Tsao, Y.-C., Raj, P. V. R. P., and Yu, V. (2019). Product substitution in different weights and brands considering customer segmentation and panic buying behavior. *Industrial Marketing Management*, 77:209–220.

United States Census Bureau (2022). Monthly state retail sales, P-7506880.

US Bureau of Labor Statistics (US BLS) (2020). Changes in consumer behaviors and financial well-being during the coronavirus pandemic: results from the U.S. Household Pulse Survey. *Monthly Labor Review*.

US Bureau of Labor Statistics (US BLS) (2021). The Employment Situation - April 2021. Technical report, News Release.

U.S. Census Bureau (2019). Micropolitan America. Technical report, U.S. Department of Commerce.

U.S. Census Bureau (2020). 2020 Census and Household Pulse Survey. U.S. Department of Commerce.

U.S. Department of Agriculture National Agricultural Statistics Service (USDA NASS) Census of Agriculture (2020). Local Food Marketing Practices Survey.

U.S. Government Accountability Office (GAO) (2021). USDA FOOD BOX PROGRAM Key Information and Opportunities to Better Assess Performance. Report to Congressional Committees GAO-21-353.

US SBA Office of Size Standards (2023). Small business size standards. Technical report, US Small Business Administration (US SBA).

USDA Agricultural Marketing Service (2020a). Awards under Delivery Order Competition/Bilateral Modifications AG-12-3J14-20-B-0588 - October Delivery Farmers to Families

Food Box Program. Technical report, USDA Agricultural Marketing Service Commodity Procuremnt Program.

USDA Agricultural Marketing Service (2020b). Public notice. Technical Report 12-3J14-20-G-0588, USDA Agricultural Marketing Service Commodity Procuremnt Program.

USDA Agricultural Marketing Service (2022a). Agricultural competition: A plan in support of fair and competitve markets. *USDA's Report to the White House Competition Council*.

USDA Agricultural Marketing Service (2022b). Local Food Purchase Assistance Cooperative Agreemant Program. *Selling Food to USDA*.

USDA Agricultural Marketing Service (2023). USDA Farmers to Families Food Box.

USDA Agricultural Marketing Service, Colorado State University, University of Kentucky, and others (2023). Local and Regional Food Systems Response to COVID Project.

USDA Economic Research Service (2010a). The impact of food away from home on adult diet quality. *Economic Research Report*, (90).

USDA Economic Research Service (2010b). Rural-Urban Commuting Area Codes. *U.S. Department of Agriculture Economic Research Service*. Data Products.

USDA Economic Research Service (2023). Food Expenditure Series. *U.S. Department of Agriculture Economic Research Service*.

USDA, Economic Research Service (2025). Rural classifications. Technical report, Topics: Rural Economy  Population.

USDA ERS (2020). Food Environment Atlas. *U.S. Department of Agriculture, Economic Research Service*. Data Products.

USDA Food and Nutrition Service (2023). State guidance on Pandemic EBT. *FNS Responds to COVID-19*.

USDA Food and Nutrition Service (2024). Supplemental Nutrition Assistance Program (SNAP). *Programs*.

USDA Food and Nutrition Service (2025a). Food distribution  emergency assistance. Technical report, US Department of Agriculture.

USDA Food and Nutrition Service (2025b). Patrick Leahy Farm to School Grant Program.

USDA Press (2024). USDA Invests $1.7 Billion to Support Farmers, Deliver Nutrition Assistance, and Bolster Rural Economies. *Press Release*, (Release No. 0185.24).

Van Droogenbroeck, E. and Van Hove, L. (2017). Adoption of online grocery shopping: personal or household characteristics? *Journal of Internet Commerce*, 16(3):255–286.

Ver Ploeg, M. and Wilde, P. E. (2018). How do food retail choices vary within and between food retail environments? *Food Policy*, 79:300–308.

Verdon, J. (2020). How local stores are moving to selling online. *U.S. Chamber of Commerce*.

Verhetsel, A., Beckers, J., and Cant, J. (2022). Regional retail landscapes emerging from spatial network analysis. *Regional Studies*, 56(11):1829–1844.

Vermunt, J. K. (2002). Latent class analysis of complex sample survey data: Application to dietary data. *Journal of the American Statistical Association*, 97(459):736–737.

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, 18(4):450–469.

Vermunt, J. K. and Magidson, J. (2002). Latent class cluster analysis. *Applied Latent Class Analysis*, 11(89-106):60.

Volpe, R., Jaenicke, E. C., and Chenarides, L. (2018). Store formats, market structure, and consumers' food shopping decisions. *Applied Economic Perspectives and Policy*, 40(4):672–694.

Wahdat, A. Z. and Lusk, J. L. (2024). Understanding the determinants of consumer grocery stockpiling behavior. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 73(1):17–31.

Wallace (2021). Farmers to Families Food Box Research Findings. *Wallace Center at Winrock International*.

Wang, E. and Gao, Z. (2021). The impact of COVID-19 on food stockpiling behavior over time in china. *Foods*, 10(12):3076.

Wang, E., Rojas, C., and Colantuoni, F. (2016). Heterogeneous behavior, obesity, and storability in the demand for soft drinks. *American Journal of Agricultural Economics*, 99(1):18–33.

Wang, M.-C., Deng, Q., Bi, X., Ye, H., and Yang, W. (2017). Performance of the entropy as an index of classification accuracy in latent profile analysis: A monte carlo simulation study. *Acta Psychologica Sinica*.

Wang, Q., Yang, X., Song, P., and Sia, C. L. (2014). Consumer segmentation analysis of multi-channel and multistage consumption: A latent class mnl approach. *Journal of Electronic Commerce Research*, 15(4):339.

Wang, Y., Xu, R., Schwartz, M. B., Ghosh, D., and Chen, X. (2020). COVID-19 and retail grocery management: Insights from a broad-based consumer survey. *Ieee Engineering Management Review*.

Watson, P., Wilson, J., Thilmany, D., and Winter, S. (2007). Determining economic contributions and impacts: What is the difference and why do we care? *Journal of Regional Analysis & Policy*, 37(2):140–146.

Weden, M. and Zabin, L. (2005). Gender and ethnic differences in the co-occurrence of adolescent risk behaviors. *Ethnicity and Health*, 10(3):213–234.

Weller, B. E., Bowen, N. K., and Faubert, S. J. (2020). Latent class analysis: a guide to best practice. *Journal of Black Psychology*, 46(4):287–311.

Wilson Sinclair and Eliana Zeballos (2025). From holiday feasts to new-year savings, U.S. food sales shift with the seasons. *Data Products: Charts of Note*.

Xaba, T. and Dlamini, S. (2020). Factors associated with consumption of fruits and vegetables amongst adults in the Alfred Duma Local Municipality, Ladysmith. *South African Journal of Clinical Nutrition*.

Yenerall, J., Muhammad, A., DeLong, K., and Malone, T. (2024). Navigating the challenges of building a more resilient infant formula industry. *Applied Economic Perspectives and Policy*, 46(2):499–513.

Zeballos, E. (2023). Food retailing market concentration increased more at national level than county level over past three decades. Technical report, USDA Economic Research Service. Charts of Note.

Zeballos, E. and Dong, X. (2022). The effect of COVID-19 on food sales. *Applied Economic Perspectives and Policy*, 44(4):2131–2144.