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Restaurant Meals Consumption in California: Channel Shifts during COVID-19, Food Justice, and Efficient Delivery

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Restaurant Meals Consumption in California: Channel Shifts during COVID-19, Food Justice, and Efficient Delivery

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

Bumsub Park

Dissertation Committee:
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Professor R. Jayakrishnan (Jay)
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2023

DEDICATION

To

my family and UCI community

in recognition their support

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ABSTRACT OF THE DISSERTATION

Restaurant Meals Consumption in California: Channel Shifts during COVID-19, Food Justice, and Efficient Delivery

by

Bumsub Park

Doctor of Philosophy in Civil and Environmental Engineering

University of California, Irvine, 2023

Professor Jean-Daniel Saphores, Chair

This dissertation explores changes in the channels used for consuming prepared food (restaurant meals) and proposes optimization approaches for better managing a fleet of delivery vehicles. In the context of the COVID-19 pandemic, Chapter 1 examines how the consumption of prepared meals has evolved in California, with meal delivery gaining in popularity, dine-in experiences shrinking, and take-out witnessing marginal growth. I estimated heterogeneous ordered logit models to explain the frequency of consumption of restaurant meals before, during, and possibly after the pandemic for dine-in, take-out, and online orders with delivery using a broad range of explanatory variables, including components of the Social Vulnerability Index (SVI). My results show disparities in dine-in, take-out, and delivery frequencies, which affect equitable access to prepared meals.

Chapter 2 extends my investigation to meal delivery in California and contributes to the traditional Food-Away-From-Home (FAFH) literature. I estimate spatial Durbin models to explain the demand for monthly meal delivery at the census tract level in three major MSAs (Metropolitan statistical areas) in California before and during the pandemic. Unique dynamics in meal delivery behavior emerge across regions and time, with accessibility proving pivotal in driving demand. In particular, I find that meal deliveries benefitted marginalized communities, underscoring the role of meal deliveries in

enhancing food access. This chapter presents a holistic perspective, which encompasses business strategies and discusses policy implications.

Chapter 3 explores a fleet management framework based on graph theory optimization algorithms for meal delivery platforms. I identified critical parameters for meal delivery operations and measured platform performance metrics such as Vehicle Hours Traveled (VHT), Vehicle Miles Traveled (VMT), and fleet size by adjusting the parameters. The comparative analysis of the Hopcroft-Karp and Karp algorithms reveals trade-offs between cost minimization and computational complexity based on the algorithmic objects. My evaluation of Proposition 22's impact on platform costs underscores the importance of modeling legal constraints. This chapter provides practical insights for platform operators to optimize service efficiency. It also provides directions for future research for more realistic simulations, including a dynamic approach, vehicle repositioning strategy, and consideration of different modes.

Overall, this dissertation helps understand dynamic shifts in prepared meal consumption and delivery and shows the importance of modeling legal constraints when optimizing the size of a delivery fleet. Findings could guide equitable policy interventions by highlighting the influence of demographic, regional, and economic factors on the frequency of restaurant meal consumption. My research bridges academia and practices through its interdisciplinary approach, which helps promote informed decision-making for platform managers, restaurant owners, and equity-conscious urban planners.

INTRODUCTION

The COVID-19 pandemic has caused profound changes across the globe, including restaurant food consumption and its logistics. Lockdowns and social distancing measures reshaped traditional dining practices, causing a paradigm shift in food consumption and distribution mechanisms. Many restaurants, which used to be lively places for socializing, had to shut down onsite dining and invest in delivery and take-out services, prioritizing customer safety and business sustainability. This shift required adopting online ordering platforms and contactless delivery methods.

In this transformed landscape, meal delivery platforms like DoorDash, UberEats, and Grubhub emerged as vital lifelines for consumers and businesses alike by bridging the divide created by lockdowns motivated by health concerns. In addition, meal delivery platforms offered employment opportunities to vulnerable populations who were on the fringes of the traditional job market, such as retirees (Mulcahy, 2016), low-income workers (Lund et al., 2020), individuals with disabilities (Harpur & Blanck, 2020), and members from racial and ethnic minority groups (Gelles-Watnick & Anderson, 2021). Although these gig economy jobs are often perceived as “bad jobs” because of low pay, minimal benefits, and absence of unemployment insurance (Ton, 2014), they offer a stepping stone to better jobs and offer workers autonomy over their schedules and the freedom to pursue their passions (Mulcahy, 2016).

The pandemic-induced shift in dining habits extends beyond mere convenience, influencing food accessibility and the job market for gig drivers. However, as significant as these rapid changes are, research on our consumption of restaurant meals, the use of meal delivery services during the COVID-19 pandemic, and their logistics remain underexplored. Published research lacks a comprehensive understanding of long-term behavioral changes following COVID-19, and many studies have relied on non-probability samples, so their findings cannot be extrapolated to a target population. Furthermore, there is a lack of research that considers the operational efficiency of managing meal delivery platforms. Therefore, it is timely to investigate Californians’ changing restaurant meal consumption habits in the context of the pandemic and to comprehensively analyze the supply and demand of meal delivery from a logistics perspective. This dissertation starts addressing some of these gaps by analyzing dining-in, take-out, and delivery before, during, and after the pandemic. I also venture into the relatively unknown territory of analyzing some California transactions of a meal delivery platform. In addition, I assess the influence of key operational parameters on meal delivery platform operation to facilitate cost reduction and improvement of fleet management strategies. This multifaceted approach is instrumental in comprehending the diverse perspectives of stakeholders in the meal delivery market. As a result, this research can contribute to well-rounded and effective policy-making in the evolving food industry landscape.

In Chapter 1, I examine the impact of COVID-19 on the frequency of restaurant meal consumption in California before, during, and potentially after the pandemic. This study is novel in that it considers not only the characteristics of the respondents but also the characteristics of the neighborhood, including the four dimensions of social vulnerability, to understand food access disparities by food type during the phases of COVID-19 from the perspective of food justice. I estimate Heterogeneous Ordered Logit Models (HOLM) to analyze the frequency of restaurant meal consumption via three different channels: onsite dining, take-out, and online ordering with delivery. My data were collected during a random survey conducted by Ipsos in late May 2021 among California members of the KnowledgePanel©, the largest and oldest probability panel representative of the U.S. population. Across different service types, distinct patterns of change emerged during the different phases of COVID-19. Dine-in services, experiencing the most pronounced fluctuations, saw a significant decline in demand during the pandemic but are anticipated to recover after the pandemic. Take-out services exhibited relatively stable patterns throughout the pandemic. On the other hand, although initially having a lower frequency, delivery services witnessed heightened demand during the pandemic, and a new equilibrium is expected in the post-pandemic landscape. From the modeling work, I analyzed the factors that influenced Californians' food behavior, considering their demographics, residential characteristics, and the COVID-19 condition. In particular, I examine the interplay between regional vulnerability and restaurant food consumption. The results reveal a change in dining preference among Californians, with older demographics showing a growing interest in dine-in post-pandemic, while racial and cultural differences influence meal consumption patterns. Additionally, it underscores the impact of socioeconomic vulnerability on the frequency of take-out and meal delivery choices, highlighting the need for inclusive strategies to improve the accessibility of food services and the broader concept of food justice.

The increasing importance of meal deliveries during the pandemic and potentially after confirmed from Chapter 1 serves as a foundation to conduct deeper investigations to understand the demand for meal deliveries. Meal deliveries have received increasing attention since the pandemic. The studies I reviewed fall short of offering insights into local delivery market dynamics, and they predominantly focus on a single point in time, which limits their ability to understand how customer behavior evolved with COVID-19 comprehensively. Recognizing the limitations of online surveys that overlook regional considerations and temporal changes, I found the need to analyze local meal deliveries to inform the restaurant industry, meal delivery logistics managers, and policymakers.

In Chapter 2, I examine more in-depth the demand for meal deliveries at the census tract level by analyzing data collected by a marketing firm in three major metropolitan statistical areas (MSAs) in California: Los Angeles-Long Beach-Anaheim, San Francisco-Oakland-Berkeley, and Riverside-San Bernardino-Ontario. I utilize the Spatial Durbin model to effectively capture and analyze the intricate spatial interdependencies and temporal variations in meal delivery demand. I estimate spatial Durbin models for each MSA and each month of September from 2019 to 2022. This robust modeling approach is particularly adept at identifying and quantifying both direct and indirect effects, which consider the same geographical unit and neighboring areas. By incorporating these spatial dynamics, the model provides a comprehensive understanding of how factors like demographic and socioeconomic characteristics, the COVID-19 pandemic, and social vulnerability influence restaurant food delivery patterns across three California MSAs. The insight from this analysis should help meal delivery platforms identify market opportunities and foster region-specific service improvements. Furthermore, insights from this research could guide policymakers in shaping strategies that promote food accessibility and equity, particularly in serving vulnerable communities through collaborative efforts with delivery platforms.

In Chapter 3, I analyze the supply side of the meal delivery system. Flexible and efficient supply strategies are crucial to effectively manage the fluctuating demand triggered by external factors like COVID-19. To achieve optimal operations, I identified key parameters within the meal delivery process that meal delivery platforms can fine-tune. These parameters include the delivery time window, the allowance of order stacking, dispatch timing, and the vehicle operating hours. I employed well-established algorithms based on graph theory to demonstrate how varying these parameters can impact the performance of meal delivery platforms. I used algorithms proposed by Vazifeh et al. (2018), known as the Hopcroft-Karp algorithm (Hopcroft & Karp, 1973) and the Karp algorithm (Karp, 1980). Both algorithms are utilized to determine the minimum fleet size for meal delivery operations, but they exhibit different outcomes due to their varied objective: The Hopcroft-Karp Algorithm focuses on extending the sequence of deliveries for each vehicle, leading to fewer vehicles being required. In contrast, the Karp algorithm prioritizes route optimization, focusing on minimizing travel distance or duration. I use sampled transaction data from 2019 to define pickup and drop-off locations and the temporal distribution of demand to construct a set of hypothetical transactions through weighted random sampling. To measure the average performance of the algorithms, I create 50 virtual daily transaction sets. I adjust the operating parameters of the delivery platform to examine their impact on key metrics such as fleet size, vehicle miles traveled (VMT), vehicle hours traveled (VHT), and operating costs. My analysis sheds light on how these adjustments can lead to more cost-effective fleet management. Beyond optimizing operational expenses, I also explore the potential for integrating these platforms with other services, particularly delivery services of non-profit initiatives. This approach underscores the potential of meal delivery platforms to serve as versatile tools in addressing broader societal needs, demonstrating how technological advancements in logistics can be used for the greater good.

Finally, in Chapter 4, I summarize the main findings of this dissertation, outline some of its limitations, and propose avenues for future research.

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CHAPTER 1. RESTAURANT FOOD CONSUMPTION IN THE TIME OF THE PANDEMIC - Channel Changes and Social Vulnerability Implications

1.1. Introduction

Before the pandemic, restaurants played a special role in American society beyond merely serving meals. They functioned as vibrant social hubs where people from diverse socioeconomic backgrounds gathered, thus contributing to cross-class mixing and social cohesion (Tocqueville, 2023). Social distancing measures and lockdowns due to the COVID-19 pandemic disrupted this social function and profoundly altered the landscape of sourcing and consuming prepared meals. On March 9, 2020, Governor Newsom ordered Californians to stay home except for essential activities (Cowan, 2021). As a result, restaurant dining was banned statewide, limiting options to takeout and delivery, with sporadic outdoor dining until California reopened on June 15, 2021 (Cowan, 2021). During this period, approximately one-third of California's restaurants closed permanently, and a significant portion of restaurant workers faced temporary job losses (Thompson, 2021). Nationally, U.S. consumers spent 29.2 percent less on restaurant food in March-April 2020 than in 2019 (Marchesi & McLaughlin, 2022). Heal concerns, in addition to government restrictions, led diners to seek safer alternatives for consuming restaurant food (Gavilan et al., 2021; Truong & Truong, 2022)

As dine-in sales plummeted, takeout and delivery sales soared, with more than half of registered full-service restaurants shifting resources to these options (Klein, 2021). At the same time, food delivery platforms such as DoorDash, UberEats, Grubhub, and Postmates experienced unprecedented growth and industry consolidation. Despite these seismic shifts, research on restaurant-prepared food purchases in the U.S. remains relatively sparse. Although some studies have examined restaurant food consumption during COVID-19 (Ali et al., 2021; Ben Hassen et al., 2020, 2021; Gavilan et al., 2021; Mehrolia et al., 2021), their focus has often been on short time periods (one or two months) and predominantly on delivery. In addition, early studies have drawn from non-probability samples collected through online surveys, limiting the generalizability of their findings to broader populations.

This study addresses these gaps by examining a survey conducted with California members of KnowledgePanel © in late May 2021, renowned as the largest and oldest probability panel representative of the U.S. population. The primary aim is to explore the impact of the pandemic on Californians' frequency of consuming restaurant meals and to anticipate the potential evolution of these patterns in the post-pandemic. In an effort to test the hypothesis that Californians living in disaster-prone areas had greater difficulty accessing prepared meals during the pandemic, I added to my explanatory variables the components of the social vulnerability index (SVI) (Flanagan et al., 2011) to heterogeneous ordered logit models (HOLMs). Using this novel approach, I address the following questions: 1) what explains the frequency of meal purchases (dine-in, takeout, and delivery) in California, and how is it likely to change after the pandemic is over? 2) Did social vulnerability contribute to the observed changes in these purchasing patterns?

Guided by the Theory of Planned Behavior (TPB; Ajzen, 1985), this study concentrates on the intentions behind choosing various channels for restaurant food consumption. TPB suggests that intentions, which directly precede behaviors, are influenced by attitudes (i.e., the desirability of a behavior), subjective norms (i.e., social pressure from relevant people), and perceived behavioral control (i.e., perception of how difficult it is to adopt a behavior). The TPB has been widely used to explain various aspects of food consumption, including fast food (Dunn et al., 2011) and local food (Kumar and Smith, 2018).

The findings of this study have implications for restaurant managers, meal delivery platforms, and policymakers concerned with equity and public health. Restaurant operators adapting to new channels often require menu adjustments to maintain the intended flavors and textures of their offerings. This adaptation can be critical to maintaining customer satisfaction and loyalty in an environment where dine-in frequency may be declining. Meal delivery platforms are emerging as key players in the pursuit of food justice and public health. These platforms have the potential to improve food access for at-risk elderly populations. By partnering with social programs and implementing initiatives that prioritize affordability and accessibility, they can extend their reach to underserved communities. Policymakers can seek to support initiatives that bridge disparities in food access. Policies that encourage collaboration between meal delivery platforms and existing social programs can foster a more inclusive ecosystem in which companies voluntarily embrace social responsibility. Notably, research that incorporates social vulnerability remains sparse in the area of Food-Away-From-Home (FAFH). To my knowledge, this study represents the first attempt to account for local vulnerability in analyzing restaurant food consumption patterns.

In Section 1.2, I review the literature on FAFH and its consumption during COVID-19. Section 1.3 details the survey design and data collection process, leading to the data section covering survey design and data collection before motivating my choice of variables. In Section 1.4, I present my statistical framework, followed by a discussion of results and their implications in Sections 1.5 and 1.6. In Section 1.7, I summarize my findings, acknowledge some limitations of this work, and suggest avenues for future research.

1.2. Background and Literature Review

Long-term trends have shifted the percentage of meals Americans prepare and eat at home versus away from home. Previously, spending on Food-At-Home (FAH) outweighed that on FAFH. However, by 2010, the FAFH market share exceeded that of the FAH market for the first time (Saksena et al., 2018). Researchers have explored the factors that drive FAFH consumption, the nutritional quality of FAFH, and the health impact of their regular consumption.

The distinction between the various sources of FAFH in the literature is sometimes blurred due to different surveys defining terms differently. For example, the Consumer Expenditure Surveys (CES) (U.S. Bureau of Labor Statistics, 2015) and the National Household Food Acquisition and Purchase Survey (Food APS) (U.S. Department of Agriculture, Economic Research Service, 2016) define FAFH as foods obtained outside the home, consumed away from home, brought home, or delivered. In the National Health and Nutrition Examination Survey (NHNES), however, FAFH is limited to food consumed on-premise for immediate consumption (USDA, 2023). In their study of restaurant food consumption, Ben

Hassen et al. (2021, 2020) lumped takeout and delivery together. Although FAFH often includes food from restaurants, cafeterias, and food trucks, I focus here on restaurant food.

To inform my modeling framework, I reviewed empirical studies that analyze the effects of demographics and socioeconomic factors on FAFH consumption. I included a few older studies because of the relatively small size of this literature. Below, I first discuss FAFH studies published before the onset of the COVID-19 pandemic. Subsequently, I focus on studies investigating the pandemic's impact on FAFH. Then, I summarize papers on the customer characteristics of takeout and delivery services. Finally, I briefly review studies that analyze attitudes toward restaurant meal delivery services and the consumption of delivered food.

1.2.1. FAFH consumption before COVID-19

Prior to the COVID-19 pandemic, household income was a factor affecting FAFH. Households with higher incomes consumed FAFH more frequently and spent more on it. However, some low-income households, busy with their jobs and other responsibilities, rely on fast food (Saksena et al., 2018). Liu et al. (2013) discovered that household income had a positive relationship with consuming meals outside the home for all three daily meals. Meanwhile, eligibility for the Supplemental Nutrition Assistance Program, which is determined by household net income, negatively affected the consumption of FAFH.

Additionally, studies conducted before the COVID-19 pandemic consistently indicated that education has a similar impact on income, possibly due to the strong correlation between these two factors (Sullivan & Wolla, 2017).

According to the Household Production Theory, the time spent on food preparation is crucial in determining one’s decision to consume FAFH (Huffman, 2011). As a result, young adults consumed FAFH more often and spent more on it (Nagao-Sato & Reicks, 2022). On the other hand, older individuals were less inclined to eat restaurant-prepared food because they typically possess better culinary skills than their younger counterparts (Van der Horst et al., 2011). Moreover, the availability of time matters: Liu et al. (2013) found that with an increase in working hours, FAFH expenses increased for all daily meals.

According to Saksena et al. (2018), age and marital status have an interactive impact. Unmarried individuals below 45 typically consumed more FAFH, while the reverse held for older singles.

Significant effects were also found for race and gender. Non-Hispanic Whites had a higher likelihood of relying on FAFH in comparison to other groups (Nagao-Sato & Reicks, 2022; Saksena et al., 2018), and men were more likely than women to eat outside the home (Liu et al., 2013; Nagao-Sato & Reicks, 2022).

1.2.2. FAFH consumption during COVID-19

Several variables, including age, education, income, gender, and race, were used to explain FAFH before COVID-19 and continue to remain statistically significant in a few studies on FAFH during the pandemic (Codjia & Saghaian, 2022; Cohen et al., 2022; Dhakal et al., 2022); however, this is not always the case.

External factors related to various stages of the pandemic also influenced people's FAFH consumption (Ellison et al., 2021, 2022). During the early phase of the pandemic, or when the virus was spreading, the demand for indoor dining declined and was partially replaced by takeout (Ellison et al., 2021). Ellison et al. (2021) compared the frequency of indoor dining and takeout in three periods after the COVID-19 outbreak (September 2020, following the initial phases of panic buying and stockpiling; December 2020, which saw the first significant surge in COVID-19 cases; and March 2021, when the number of new cases was falling, and vaccines were administered). They found that eating out and takeout patterns reversed during the pandemic. In their takeout model, the pre-COVID-19 relationships between socioeconomic variables and FAFH expenditures were often no longer relevant. Specifically, they discovered that neither income nor age had explanatory power in their September 2020 model. In September 2020, the African-American variable showed a positive relationship with indoor dining. However, when the number of confirmed cases increased in December, it showed a negative relationship. For Whites, they found the opposite results regarding their frequency of fast food consumption.

According to Codjia and Saghaian (2022), the rising food costs during COVID-19 reduced FAFH consumption. Cohen et al. (2022) concluded that individuals who consumed fast food frequently were more likely to visit other restaurants after analyzing fast food and other restaurant usage during the pandemic. Their fast-food model did not show any significant impact on age and education.

1.2.3. Restaurant meal takeout and deliveries

The studies I reviewed above offer limited analysis of restaurant food takeout and deliveries as separate categories. To address this gap, I also examined the literature focusing on these services. Given the scarcity of relevant references, I did not impose geographical restrictions.

According to the National Restaurant Association (Riehle et al., 2021), the restrictions on dine-in services expedited the adoption of takeout and deliveries. This is especially factual for takeout: 68% of consumers reported a higher likelihood of purchasing takeout food from a restaurant than they previously did before the pandemic.

Furthermore, Ellison et al. (2021) reported that in April 2020, there was an increase in spending on takeout food while dine-in spending decreased. In addition, Ellison et al. (2022) discovered that the relationships between the use of takeout food, income, and racial characteristics were the opposite compared to the general characteristics of FAFH before COVID-19. In addition, income ceased to be statistically significant during the pandemic, and white Americans became more likely to consume takeout food than other ethnic groups.

Ben Hassen et al. (2021, 2020) conducted studies of the influence of the pandemic on food purchasing and consumption in Qatar and Russia based on non-probability samples obtained through social media. Their simple evaluations revealed that in both countries, gender, age, and income are influencing factors in relation to food consumption through takeout or delivery services during the pandemic.

Further research in this field has centered on user perceptions of food delivery services. Studies have shown that ordering restaurant meals via an online platform is affected by factors such as platform visibility, user-friendliness, and trustworthiness (Anbumathi et al., 2023; Dogra et al., 2023; Kumar et al., 2021; Kumar & Shah, 2021; Ray et al., 2019; Tandon et al., 2021; Uzir et al., 2021). Other studies have demonstrated that technical attributes are a key influence on app-based delivery services, as predicted by theoretical models (Gunden et al., 2020; Roh & Park, 2019; Uzir et al., 2021; Yeo et al., 2017).

1.3. Data

1.3.1 Survey

The data for this study were collected through a survey conducted by Ipsos in late May 2021. The survey involved a random selection of participants from KnowledgePanel© (KP), the largest and oldest probability-based online panel in the U.S. The KP panel's membership, numbering approximately 60,000 individuals, is large enough to be representative of the California population. Ipsos utilizes a patented approach that ensures that its samples behave as if they were generated via random sampling with the equal probability selection technique. This approach facilitates the extension of this study's findings to Californians aged 18 and over, which is my target population. Multiple studies have shown that internet surveys of probability samples produced more precise estimates than those of non-probability samples on the internet, even after poststratification weighting, as noted by Cornesse et al. (2020).

As most American households no longer use landlines (Blumberg & Luke, 2018), KP members are selected through address-based sampling, utilizing the Delivery Sequence File of the U.S. Postal Service. Extra measures are taken to engage harder-to-reach populations, including African Americans, Latinos, LGBTQ and non-binary individuals, Americans with disabilities, Veterans, rural residents, and households without internet or cell phone access. New panel members who do not have internet access get a tablet and a mobile data plan from Ipsos to connect them to the internet.

There are numerous advantages of surveying with KP. Firstly, it addresses the self-selection bias observed in online surveys because participants are chosen according to their recorded characteristics when they enroll, and these characteristics are kept updated every year. Secondly, conducting online surveys with KP members eliminates mode bias since all the questions are presented online. Thirdly, online surveys with KP members can help mitigate non-response bias by achieving cooperation rates that are typically close to 70% (i.e., ratios of the number of respondents to the number of KP members contacted). However, collecting data through KP has its drawbacks, namely the high cost of this approach and the inability to gather the exact location of participants.

The questionnaire was first written in English. It is composed of two sections. The first section queries participants' commuting behavior, telework preferences, and travel patterns before, during, and possibly after the pandemic. The second section investigates how they bought groceries and prepared restaurant meals before and during the pandemic and what they may do in the aftermath.

To validate the survey instruments, a pilot study was conducted in mid-May 2021 with 25 California-based KP members. Based on their feedback, the survey instrument was modified. To cater to Californians who prefer communicating in Spanish, a native Spanish speaker translated the questionnaire. The survey, in both versions, commenced on May 22, 2021. By the end of May 2021, 1,026 responses had been received. At this point, data collection stopped.

1.3.2 Dependent variables

The survey inquired about the frequency of prepared meal purchases (dine-in, takeout, and delivery) by the respondents before the March 2020 stay-at-home Executive Order, during the pandemic, and how often they intended to shop for prepared meals after the pandemic, by selecting one of six options ("Never," "Less than once a month," "1-3 times a month", "1-2 times a week", "3 or more times a week", and "I don't know").

1.3.3 Explanatory variables

The explanatory variables consist of socioeconomic characteristics, characteristics of the area within a 20-minute drive from the centroid of the respondents' ZIP Code on a typical weekday at 6:00 PM, COVID-19 severity, and a technology savviness index. 28 of the 1,026 respondents were dropped because of missing data. Summary statistics for the explanatory variables in my models can be found in Table 1.1

and Figure 1.1.

Table 1.1. Descriptive statistics for count and continuous explanatory variables

Variables (N=998)	Mean (Std. dev.)	[Min, Max]
Number of adults in the household	2.301 (1.065)	[1, 8]
Number of children (0-17) in the household	0.474 (0.925)	[0, 5]
Log_{10}(population in restaurant access area)	5.523 (0.624)	[2.708, 6.383]
Race diversity in the restaurant access area	1.185 (0.221)	[0.211, 1.598]
Land use (% residential in restaurant access area)	0.188 (0.172)	[0.000, 0.753]
Land use (% commercial in restaurant access area)	0.036 (0.037)	[0.000, 0.194]
Social Vulnerability Index		
SVI 1 – socioeconomic status	0.515 (0.194)	[0.000, 0.966]
SVI 2 - household composition & disabilities	0.393 (0.168)	[0.000, 0.904]
SVI 3 - minority status & language	0.749 (0.151)	[0.000, 0.991]
SVI 4 - housing type & transportation	0.568 (0.119)	[0.000, 0.829]
Technology savviness	0.228 (0.156)	[0.000, 1.000]
COVID-19 severity: $\log_{10}$(cumulative county deaths)	3.458 (0.718)	[0.699, 4.388]

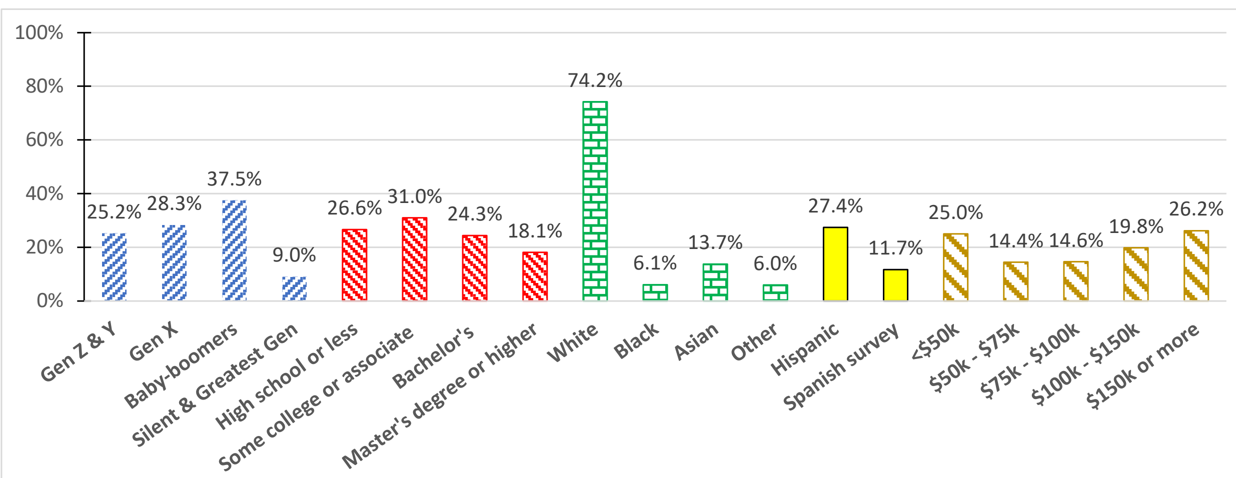


Figure 1.1. Summary statistics for categorical explanatory variables

1.3.3.1 Demographic/socioeconomic characteristics

Based on the literature review, I hypothesized that age impacts the consumption of restaurant meals. According to Huffman (2011), a household's productivity will likely increase due to its cooking efficiency and skills. Yang & Magrabi (1989) suggest that compared to younger households, older households are more likely to have an interest in and skills for preparing home-cooked meals. Thus, younger households are more likely to consume restaurant food than their older counterparts. An alternate explanation is that younger individuals are more comfortable with information and communication technology (ICT), so they are more likely to order meals online. To represent this generational disparity, generation variables were defined based on the Pew Research Center (Dimock, 2019) definitions, such as generation Z (born after 1996) and Y (born between 1981 and 1996), generation X (born between 1965 and 1980), Baby boomers (born between 1946 and 1964), and silent/greatest generations (born before 1946).

Furthermore, I assumed that households with a greater number of adult members are more adept at household production duties. Given a particular household size, time constraints may vary depending on the household structure. Therefore, I hypothesized that the frequency of eating at restaurants decreases as the number of adult household members increases.

In contrast, having children may diminish household productivity because of the childcaring responsibilities involved (Huffman, 2011). Therefore, I speculated that time restrictions posed by childcare contribute to an increased frequency of restaurant food consumption through delivery and takeout services. I anticipate the opposite for on-site dining, as it necessitates more child supervision at restaurants.

Previous FAFH studies suggest that race can influence the decision to eat out at restaurants. Research indicates that White households visit restaurants more than other groups (Nagao-Sato & Reicks, 2022; Saksena et al., 2018), especially Black households (Codjia & Saghaian, 2022; Dhakal et al., 2022). However, I did not expect to find similar differences in meal delivery and takeout based on race. I used typical racial binary variables to detect racial disparities based on respondents' self-identification. I also included a binary variable for Hispanics, and another to track the language the respondents used while taking the survey. These variables did not cause multicollinearity issues.

Higher education is expected to affect individuals' restaurant food preferences because they are more likely to have affluent parents, who may have exposed them to a broader range of restaurant foods

(Mayer, 2010).

According to household production theory (Huffman, 2011), income determines the opportunity cost of time and budget constraints in a household. Previous studies have consistently found a significant positive relationship between household income and FAFH consumption. Based on this, it can be conjectured that individuals with higher incomes tend to consume restaurant food more frequently, but not fast food.

1.3.3.2 Technology savviness

This survey contains questions that assess participants' inclination to adopt new technologies. According to Yeo et al. (2017), customers who are well-versed in IT tools and have had a positive service experience are more likely to re-engage with that service, partly due to the reduced effort involved. As a result, I hypothesized that customers with lower entry barriers who have some experience with online food ordering and delivery services are more likely to utilize these services regularly.

1.3.3.3 Restaurant access area

Studies conducted by Pinho et al. (2018) and Sharkey et al. (2011) have shown that having easy access to restaurants is associated with more frequent restaurant visits and a lower likelihood of home cooking. I defined the restaurant access area for each respondent as the area that can be reached within 20 minutes of driving at 6:00 PM on a typical weekday from the center of their ZIP Code area. Regrettably, I could not obtain information about the location of all restaurants in California. I relied instead on population size and diversity in the restaurant access areas for this study. This is based on the finding of Schiff (2015) that larger and denser areas have a greater number and variety of restaurants. The presence of diverse restaurants offers the public more choices when it comes to eating out or getting prepared meals. Mazzolari and Neumark (2011) have shown that more cultural diversity correlates with increased restaurant diversity. Population diversity was proxied using Shannon's diversity index (Shannon &

Weaver, 1949). For respondent "i," it can be calculated as

$$H_i' = -\sum_{r=1}^{R} p_{ir} \cdot ln\,(p_{ir}) \tag{1.1}$$

where p_{ir} is the proportion of people of race "r" in the restaurant access area of respondent "i."

The share of residential and commercial areas within each restaurant access area was also controlled because market geo-demographics plays a vital role in analyzing restaurant location (Y. Yang et al., 2017). For instance, fast food outlets are often positioned close to main arterials to attract a transient population of employees and consumers. In contrast, pizzerias tend to be in residential areas (Smith, 1985).

1.3.3.4 Social Vulnerability Index (SVI)

Social vulnerability relates to socioeconomic and demographic factors that may hinder a community's rapid recovery from a disaster, defined as an event causing emotional trauma, loss of life, severe physical injuries, and significant property damage. Given the pandemic's profound impact, marked by intense emotional distress and a high mortality rate, I used the most recent (2020) social vulnerability index (SVI) developed by the Center for Disease Control (CDC) and Prevention in collaboration with the Agency for Toxic Substances and Disease Registry (Flanagan et al., 2011).

The 2020 SVI has four components or themes. These are computed at the census-tract level by summing the percentile ranks of variables (in parentheses) from the 5-year American Community Survey (ACS) that make up each component: 1) Socioeconomic status (income, poverty, employment, and education); 2) Household composition and disability (age, single parenting, and disability); 3) Minority status and language (race, ethnicity, and English-language proficiency); and 4) Housing type and transportation (housing structure, crowding, and vehicle access). Ranking these sums gives a percentile between 0 and 1, where values closer to one represent greater vulnerability.

I hypothesized that individuals residing in more vulnerable areas face limited opportunities to enjoy restaurant food services. For instance, an area with a large proportion of low-income households is expected to have lower demand for restaurant food. Therefore, the number of restaurants in this area would decrease, as the study conducted by Yang et al. (2017) showed a positive correlation between household income and the number of local restaurants. Census tracts intersecting with restaurant access areas were selected, and SVIs were spatially combined. This allowed SVIs of a restaurant access area to be calculated by weighing the census tract SVI using their population size.

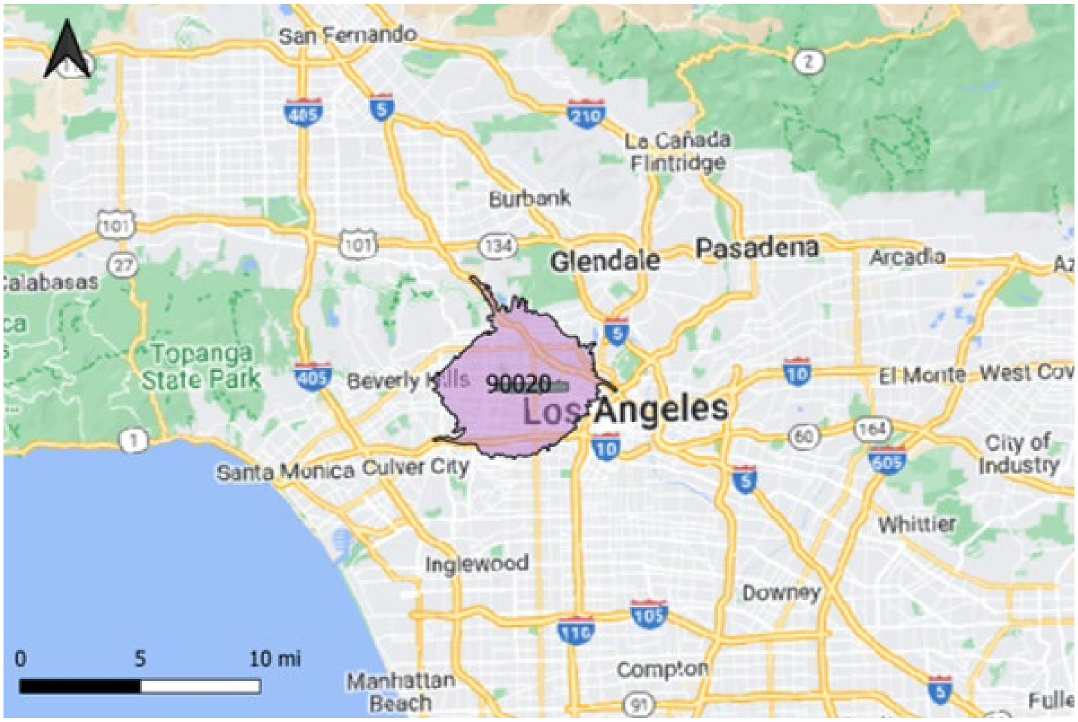
1.3.3.5 COVID-19 severity

Prior research demonstrated that heightened fear of illness alters dietary patterns (Mehrolia et al., 2021; Nam et al., 2019; Shen et al., 2020). Thus, I hypothesized that residents of counties that have experienced higher cumulative COVID-19 death counts would decrease their dining-in activities and increasingly adopt takeout or delivery meals.

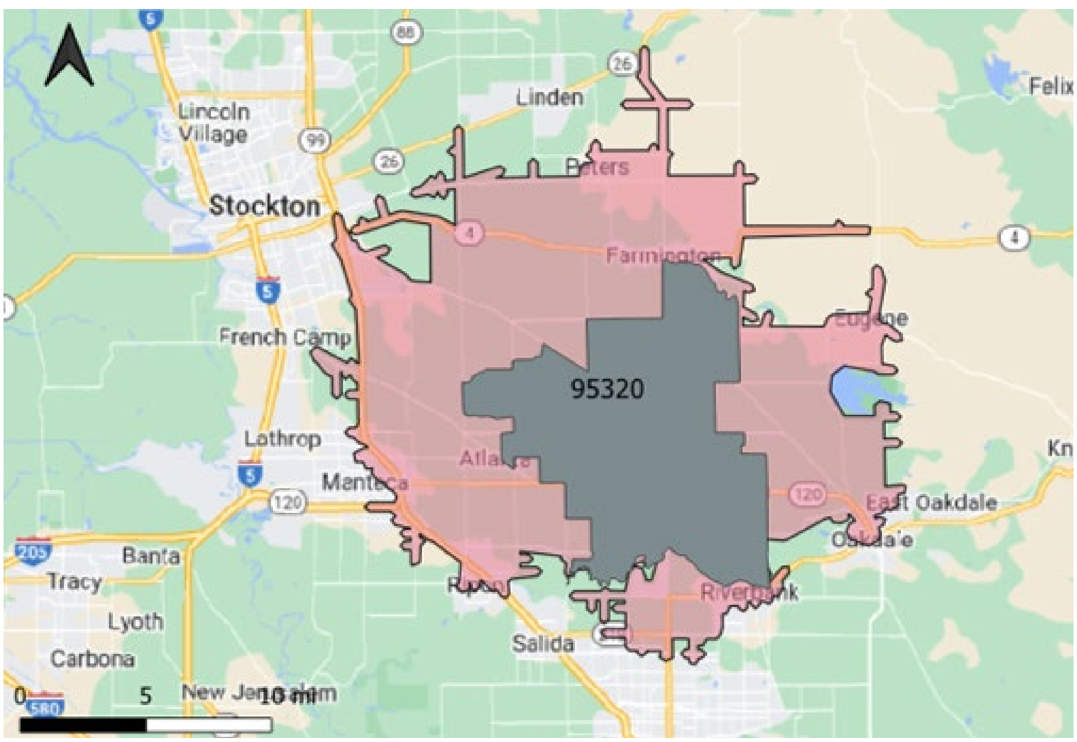
1.4. Methods

1.4.1 Restaurant access area

To determine the access area of each respondent to restaurant food, I identified a geographic area based on driving distance within a 20-minute range at 6:00 PM on a typical weekday from the centroid of their ZIP Code Tabulation Areas (ZCTA) (U.S. Census Bureau, 2022). This approach has been frequently applied in previous research (e.g., ElSamen and Hiyasat, 2017; Formánek and Sokol, 2022; O'Sullivan et al., 2000). To establish the boundaries of each restaurant access area, I relied on the Microsoft Bing Map Isochrone API. This API utilizes network distances and historical traffic conditions to generate accurate driving range polygons. Differences in geographical access to restaurants are displayed for two California ZIP Codes in Figure 1.2. Panel A and Panel B of Figure 1.2 show the restaurant access areas for a respondent living in downtown Los Angeles (ZIP Code 90020) and a resident of Escalon (ZIP Code 95320), which is a small town in California's Central Valley located in San Joaquin County.



Panel A. Downtown Los Angeles (ZIP Code 90020)



Panel B. Escalon (ZIP Code 95320)

Figure 1.2. Examples of restaurant access areas

Note: ZIP Code Tabulation Areas are shown as gray polygons. The restaurant access area is transparent.

1.4.2 Factor Analysis

This study adopts exploratory factor analysis (Kline, 2015) to summarize the responses to twelve questions that gauge respondents' attitudes towards communication technology using a four-point Likert scale (1 "Do not agree," 2 "Somewhat agree," 3 "Agree," 4 "Strongly agree").

It relied on the Kaiser criterion (Fabrigar & Wegener, 2011) to determine the number of factors. I obtained a single factor by retaining only factors associated with eigenvalues larger than one, and I characterized it as representing technology savviness. Question 10 ("I like to buy electronics or technology from a physical retail store") was excluded by only keeping factor components with loading greater than 0.3 (a common rule of thumb). Table 1.2 shows the remaining components. I normalized the savviness factor between 0 and 1 to make its interpretation easier.

I performed standard statistical assessments to evaluate the reliability and validity of the factor in questions. Initially, the Kaiser-Meyer-Olkin (KMO) index (Kaiser, 1974) was calculated, which ranges from 0 to 1. KMO metric evaluates the extent of shared variance among the variables. A higher KMO value, indicating a smaller proportion of variance, suggests greater suitability of the data for factor analysis. Generally, a KMO value less than 0.6 suggests that a factor is unsuitable, while values greater than 0.8 are desirable.

Table 1.2. Survey items for technology adoption propensity

Question number. Question	Factor loading
1. Others rely on me for advice about technology	0.57
2. I often buy a new technology or device as soon as it goes on sale	0.60
3. I like surfing the internet for fun	0.49
4. I tend to watch less TV on traditional television because I watch videos online	0.46
5. I like to post online video content that I create (such as on YouTube)	0.54
6. I use social networking to communicate with others more than email and instant messenger	0.52
7. I am fine with advertising on mobile phones	0.42
8. I would pay to watch a TV show or movie to avoid commercials	0.38
9. I have had to delay some technology purchases because I didn't have the money	0.43
11. I like to buy technology brands that are environmentally friendly	0.40
12. I always buy the lowest-priced electronics or technology	0.42

Note: I excluded Question 10 ("I like to buy electronics or technology from a physical retail store") because its factor loading was less than 0.3.

In addition, I performed a Bartlett test for sphericity (Bartlett, 1950) to determine if the variables in the factor analysis are independent by comparing the correlation matrix with the identity matrix. The null hypothesis posits that the correlation matrix equates to an identity matrix. For a factor to be suitable, this hypothesis needs to be rejected.

Finally, I used Cronbach's alpha to measure how closely related the variables in the model are (Cronbach, 1951). As a rule of thumb, an acceptable Cronbach's alpha coefficient value should be above 0.7. A coefficient lower than 0.6 suggests a weak association (Hair et al., 2019).

1.4.3 Heterogeneous ordered logit model

Ordered logit models (OLMs) are a common starting point for modeling ordinal dependent variables (Long & Freese, 2006) because they are simple to estimate and interpret. Given *J* categories, an OLM for a dependent variable y_i for observation $i \in \{1, \ldots \mathrm{N}\}$, which can take values in $\{1, \ldots, \mathrm{J}\}$, can be written:

$$\begin{cases} y_i = j \text{ if } \tau_{j-1} < y_i^* \leq \tau_j, \\ \quad y_i^* = X_i \alpha + u_i \ , \end{cases} \tag{1.2}$$

with $\tau_0 = -\infty$ and $\tau_{\mathrm{J}} = +\infty$. In the above, X_i is a $1{\times}k$ vector of explanatory variables; the u_is are independent and identically distributed (i.i.d) error terms that are assumed to follow a standard logistic distribution; and the τ_js refer to *J*-1 unknown threshold parameters that are jointly estimated with α, a vector of unknown coefficients with a dimension of $k{\times}1$.

In practice, some of the foundational assumptions of OLMs are commonly violated, leading to biased coefficients (Williams, 2010). For instance, heteroskedasticity may make the variance of u_i dependent on *j*, while the α coefficients in Equation (1.2) may not be independent to the value of *m*.

A generalized ordered logit model (Clogg & Shihadeh, 1994) offers more flexibility by allowing the alpha coefficients in Equation (1.2) to vary with *j*. However, this approach can generate a significant number of coefficients, which is tedious to interpret and can predict negative probabilities.

An alternative that does not have these drawbacks is a heterogeneous ordered logit model (HOLM) (Williams, 2009). It is obtained by estimating the system:

$$\begin{cases} y_i = j \text{ if } \tau_{j-1} < y_i^* \le \tau_j, \\ y_i^* = X_i\beta + \sigma_i u_i, \\ \sigma_i = \exp(Z_i\gamma) \end{cases} \tag{1.3}$$

where the second and third equations are the choice and variance equations (Williams, 2010). In the former, u_i has a standard logistic distribution. In the latter, Z_i is a 1×k' vector of explanatory variables for observation i (typically a subset of X_i), and γ is a k'×1 vector of unknown coefficients. The probability that respondent "i" selects an answer higher than $j \in \{1, \ldots, \text{J-1}\}$ is then:

$$Pr(Y_i > j) = \frac{\exp\left(\frac{X_i\beta' - \tau_j}{\sigma_i}\right)}{1 + \exp\left(\frac{X_i\beta' - \tau_j}{\sigma_i}\right)} \tag{1.4}$$

Marginal effects (the derivative of $Pr(Y_i > j)$ with respect to the explanatory variable x_m can help interpret results by providing insights into the rate of change of the probability of an outcome when x_m varies. The chain rule can be used to show that, for $j \in (1, \ldots, J\text{-}1\}$ and explanatory variable x_m:

$$\frac{\partial Pr(Y_i > j)}{\partial x_m} = \frac{\exp(z_{ij})}{\left(1 + \exp(z_{ij})\right)^2} * \frac{\beta_m - \gamma_m * \left(X_i\beta' - \tau_j\right)}{\exp(Z_i\gamma)}, \tag{1.5}$$

where

$$z_{ij} = \frac{X_i\beta' - \tau_j}{\sigma_i} = \frac{X_i\beta' - \tau_j}{\exp(Z_i\gamma)} \tag{1.6}$$

Equation (1.5) shows that $\frac{\partial Pr(Y_i > j)}{\partial x_m}$ has the sign of $\beta_m - \gamma_m * \left(X_i\beta' - \tau_j\right)$, which simplifies to β_m when $\gamma_m = 0$, but depends on $X_i\beta'$ otherwise. Moreover, except for $Pr(Y_i = 1)$ and $Pr(Y_i = J)$, the sign of the derivative of $Pr(Y_i = j)$ for $j \in \{2, \ldots, J\text{-}1\}$ with respect to x_m depends on an expression that contains explanatory variables and estimated coefficients/thresholds, so it is best explored numerically.

Like Williams (2010), I adopted stepwise selection to initially choose statistically significant variables for the variance equation. Despite being criticized for their atheoretical nature and the risk of capitalizing on chance, stepwise procedures are beneficial for producing alternative models that fit the data better (Williams, 2009). Following the selection of variance equation variables, iI applied stepwise selection to the choice equation to obtain more concise final models that explain the frequency of dining-in, takeout, and meal deliveries before, during, and possibly after COVID-19.

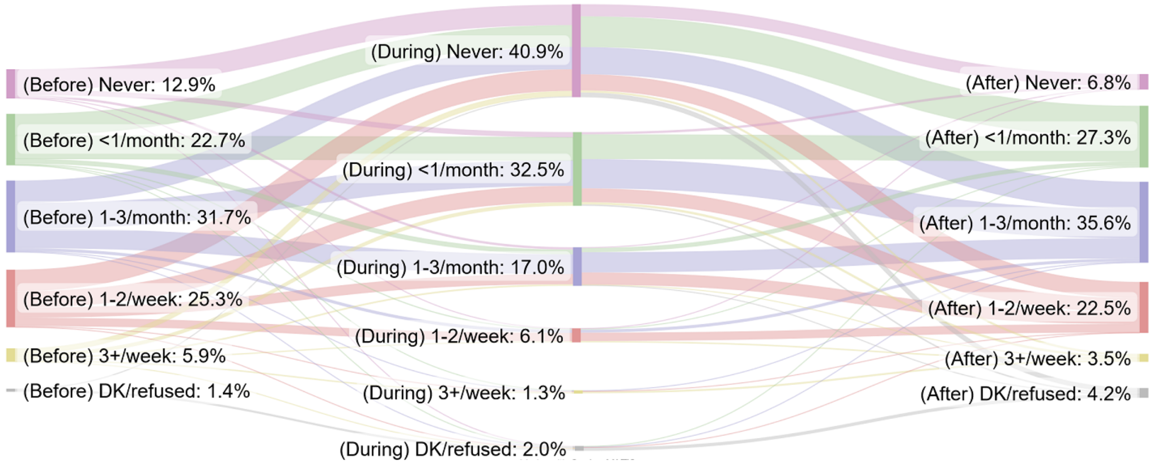
1.5. Results

1.5.1 Changes in restaurant meals consumption frequency

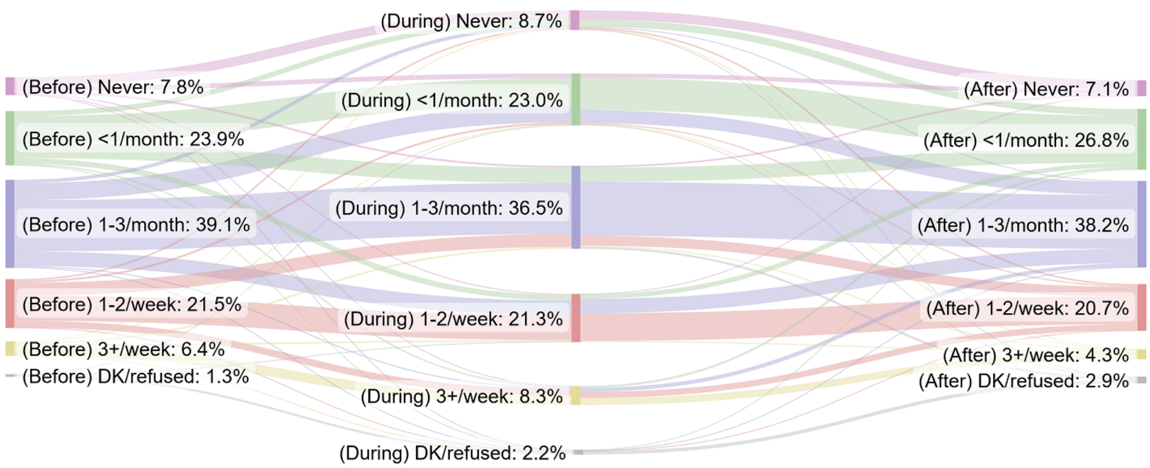
To match findings to Californians 18 and over (as the sampling process applied by Ipsos delivers the equivalent of a random sample), I weighted answers to the questions about dining in, getting takeout or delivery placed after online ordering, before and during COVID-19, and intentions for these three options when the pandemic is over. Ipsos employed raking to compute the weights by matching the sample to the 2019 American Community Survey's following distributions of Californians 18 and over: gender by age, race and Hispanic status, education, household income, and language proficiency (for English and Spanish). Results are shown in the Sankey diagrams of Figure 1.3.

1.5.1.1 Dine-in

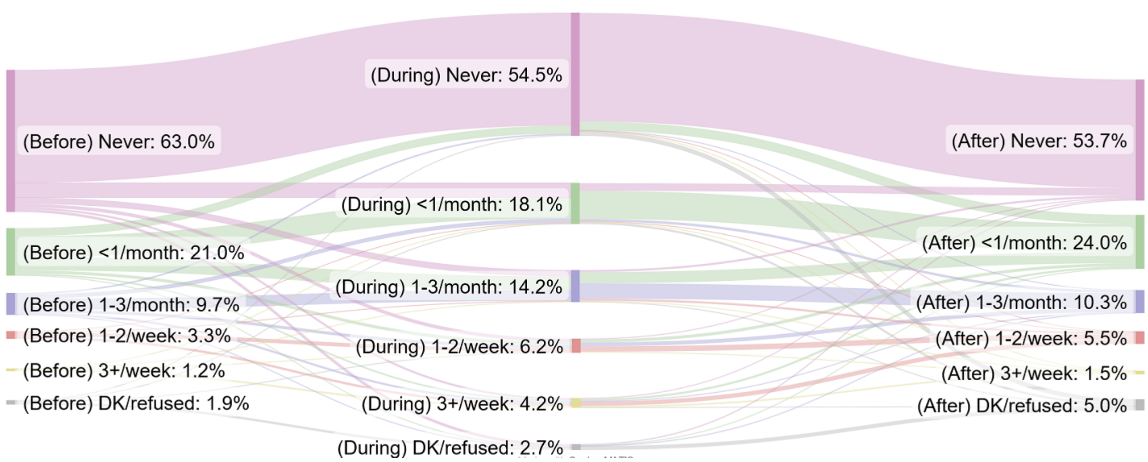
Panel A of Figure 1.3 displays a substantial change in the frequency of dine-in, with the percentage of Californians aged 18 and over who never dine-in, soaring to 40.9% during the pandemic, up from 12.9% before, a percentage that is expected to decline to 6.8% after the pandemic. Conversely, the percentage of Californians who eat in restaurants infrequently (less than once a month) increased during COVID-19, while all higher frequencies decreased. This is likely because of the mandatory dine-in restrictions and health concerns. However, after the pandemic, Californians could make less frequent visits to restaurants as the percentages for "Less than once a month" and "1 to 3 times per month" are higher compared to pre-pandemic, while values of higher frequencies are lower. I also observed a higher percentage of respondents who chose "don't know or refuse to answer" than before the pandemic (4.2% versus 1.4%), which reflects greater uncertainty after the pandemic.



Panel A. Dine-in



Panel B. Takeout



Panel C. Delivery

Figure 1.3 Changes in restaurant food consumption before, during, and after COVID-19

Note: “DK” stands for “I don’t know”

1.5.1.2 Takeout

In contrast to Panel A, Panel B of Figure 1.3 indicates insignificant changes in takeout, indicating slight increases at the upper and lower ends of the frequency spectrum, while the intermediate frequencies decline. During the pandemic, the percentage of Californians aged 18 and over who never ordered takeout increased from 7.8% to 8.7%. Those who ordered takeout three times or more a week increased from 6.4% to 8.3%. Compared to the pre-COVID-19 period, post-pandemic intentions slightly decrease for the higher frequencies. I conjecture that takeout did not become more popular because of inconvenience.

1.5.1.3 Delivery

The alternative that gained most in popularity during the pandemic is ordering restaurant meals for delivery. According to Panel C of Figure 1.3, the percentage of Californians aged 18 and over who never use this alternative has decreased from 63.0% before the pandemic to 54.5% during the pandemic, with an increase in all other frequency categories except “never” and “less than once a month” This increase in popularity is partially attributable to contactless food deliveries, which were adopted by major food delivery companies including DoorDash, UberEats, Grubhub, and Postmates (before its acquisition by UberEats) (Bratcher, 2020). Although the cost of this option is relatively high (typically 10% or more of an order), its popularity is likely to continue since the frequencies of usage after the pandemic range from “less than once a month” to “three or more times a week,” which is higher than the pre-pandemic period (but lower than during the pandemic). It is worth noting that the percentage of Californians aged 18 and over who do not intend to use this option post-pandemic is expected to be lower after the pandemic than it was during (53.7% versus 54.5%). Stiff competition and the rapid expansion of the availability of restaurant food deliveries (Ahuja et al., 2021) likely also played a role in the popularity gains of this option. Meanwhile, the level of uncertainty about the future has increased, with 5.0% of respondents choosing the “Don’t know/refuse” option, compared to 2.7% during and 1.9% before the pandemic.

1.5.2 Results from heterogeneous ordered logit models

The results were obtained using Stata 17.0. Before finalizing the models, I calculated variance inflation factors (VIF) and found that the highest VIF value is under 6, so multicollinearity is not an issue here.

Table 1.3 presents the estimated coefficients for the HOLMs for dine-in, takeout, and delivery before, during, and after COVID-19. The number of observations impacted the number of frequencies in the models: I considered all five frequencies shown in Figure 1.3 for dine-in before and after COVID-19 and for takeout before and during COVID-19, but only four ("Never," "<1 a month," "1-3 times a month," and "1+ times a week") for dine-in during COVID-19, takeout after COVID-19, and all delivery models because I did not have enough observations for "3+ times a week."

Each cell of Table 1.3 contains a combination of two numbers or "•" symbols. The first estimated coefficient is for the choice model (second equation of (1.3)), and the second estimated coefficient for the variance equation (third equation of (1.3)). Due to stepwise selection, not all explanatory variables appear in all models. The symbol "•" is shown instead of a numerical value when a variable is not in the final model (a few variables that were not significant at the end of the stepwise selection process are included.)

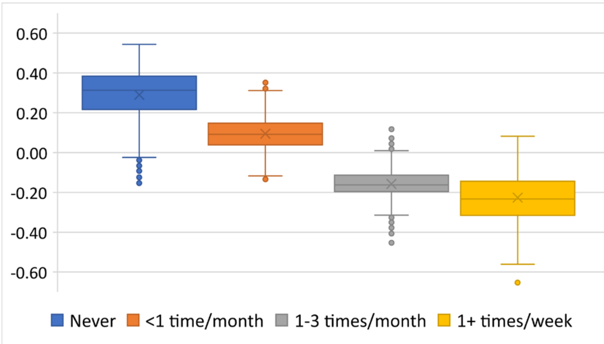
To gain a more in-depth understanding of the findings, I paid particular attention to three binary variables linked to the SVIs: Silent generation, African American, and Spanish survey, which have coefficients that frequently display statistical significance. I illustrate frequency patterns generated by the HOLMs. For each variable and each observation in the dataset, I computed the variations in the probability of each frequency (such as Silent Gen vs. Gen Y or Z) and plotted the corresponding box plot for dine-in, takeout, and meal deliveries before, during, and after the pandemic. Results are shown in Figure 1.4.

Table 1.3. Heterogeneous ordered logit results (second/third equation of (3))

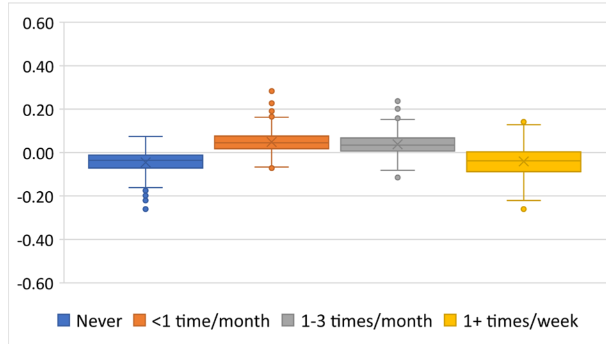
	Dine-in (N=957)			Takeout (N=969)			Delivery (N=946)		
Column #	I	II	III	IV	V	VI	VII	VIII	IX
Variable	**Before**	**During**	**After**	**Before**	**During**	**After**	**Before**	**During**	**After**
Generation (baseline=Gen Y and Z)									
Gen X	•/-0.193‡	•/•	•/-0.102	•/-0.155†	•/•	•/•	-0.975‡/•	-1.186‡/•	-0.704†/•
Baby boomer	•/•	•/•	•/•	-0.762‡/•	-0.505‡/•	-0.534‡/•	-2.937‡/•	-2.395‡/•	-2.127‡/•
Silent gen	-0.445†/•	•/•	•/0.197*	-1.440‡ /0.270†	-0.657†/•	-1.072‡/•	-3.652‡/•	-4.910‡/•	-3.299‡/•
# of HH adults	•/•	•/•	•/•	0.214‡/•	0.217‡ /-0.069†	0.101* /-0.090†	•/0.121‡	•/•	•/0.112‡
# of HH children	•/-0.101‡	•/-0.110‡	•/-0.092†	•/-0.096‡	•/•	•/•	-0.403‡/•	•/•	•/•
Race (Baseline=White)									
Black	-0.441*/•	0.482*/•	-0.605†/ -0.340†	•/•	0.398* /-0.356‡	•/•	1.488‡/•	1.353‡/- 0.442†	1.122†/•
Asian	•/•	•/•	•/•	•/•	•/•	•/•	•/•	•/•	•/•
Other	•/•	•/•	•/•	•/•	•/-0.283†	•/-0.281*	•/•	•/•	•/-0.294*
Hispanic	•/•	•/•	•/•	•/•	•/•	•/•	•/0.141	•/•	•/•
Spanish survey	-0.577‡/•	0.492†/•	-0.670‡/ -0.201*	-1.188‡/•	-1.099‡/•	-1.069‡ /-0.301†	0.770* /-0.485†	•/-0.424‡	•/•
Education (baseline= Some college)									
< High School	-0.245 /0.265‡	•/•	•/0.255‡	-0.464†/•	-0.301*/•	•/0.363‡	•/0.309†	•/•	•/•
BA / BS	•/•	•/•	•/-0.163†	0.104/•	•/•	•/0.200†	•/•	•/•	•/•
Grad./prof.	•/•	•/•	0.362*/•	-0.385†/•	•/-0.167†	•/•	•/•	•/•	-0.541*/•
Annual household income (baseline= $75k – $100k)									
< $50k	-0.478‡/•	•/•	-0.497†/•	•/•	-0.634‡/•	-0.459‡/•	•/•	•/•	•/•
$50k – $75k	•/•	•/•	•/•	•/•	•/-0.170*	•/-0.248†	•/•	•/•	•/•
$100k – 150k	0.313*/•	•/•	•/0.144*	•/•	•/•	•/•	•/•	0.602/•	•/•
>$150k	0.443‡/•	•/•	0.607‡/•	•/•	•/•	•/•	0.945‡/•	1.059†/•	1.156‡/•
Tech. savviness	1.060‡/•	•/•	1.057*/•	•/•	1.287†/•	•/-0.436†	3.145‡ /0.575*	4.299‡/•	4.068‡/•
Restaurant Access Area									
Population	•/•	•/•	•/•	•/•	•/•	•/•	0.241/•	•/•	•/•
Racial diversity	•/•	-0.729†/•	•/•	•/•	•/•	•/•	•/•	•/•	•/•

% Residential	•/•	-0.936*/0.571†	•/•	•/•	•/•	-0.829*/•	•/•	•/•	•/•
% Commercial	2.976†/•	•/•	3.967*/•	5.124†/•	•/•	•/•	•/•	•/-2.829*	•/•
Social Vulnerability Index									
SVI 1	•/•	•/0.763‡	•/•	1.658‡/0.361†	0.931†/•	•/0.616‡	•/•	•/•	•/•
SVI 2	•/•	•/•	•/•	•/•	•/•	0.745/•	-2.386†/•	-2.318‡/•	-3.450‡/0.589*
SVI 3	•/•	•/•	•/•	1.038*/•	•/•	•/•	•/•	2.042†/•	•/•
SVI 4	•/•	•/-0.694	1.278*/•	-1.610†/•	•/0.570†	1.120†/•	2.203*/•	•/•	•/•
COVID severity	NA	•/•	•/0.086*	NA	0.264‡/•	0.543‡/•	NA	•/0.223‡	0.404†/•
Thresholds									
τ_1	-1.803‡	-1.311‡	-2.236‡	-2.112‡	-0.912†	-0.339	2.479*	1.438*	0.957
τ_2	-0.325†	0.216	0.371	-0.071	0.895†	1.734‡	5.015‡	3.177‡	3.395‡
τ_3	1.088‡	1.700‡	2.483‡	1.910‡	2.634‡	3.652‡	7.290‡	5.380‡	5.155‡
τ_4	2.964‡	NA	5.731‡	4.037‡	4.522‡	NA	NA	NA	NA

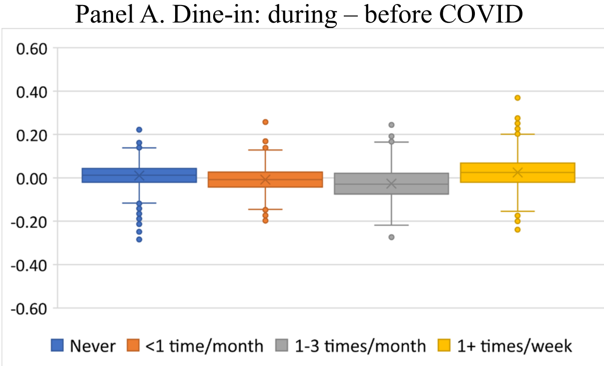
1. ‡: p-value < 0.01; †: p-value < 0.05; *: p-value < 0.10.
2. HH is a shortcut for "household."
3. SVI 1: socioeconomic status; SVI 2: Household Composition & Disability; SVI 3: Minority Status & Language; SVI 4: Housing Type & Transportation.
4. The first value/symbol in a cell is the estimated coefficient of the choice equation (second equation in (3)), and the second is the estimated coefficient of the variance equation (third equation in (3).



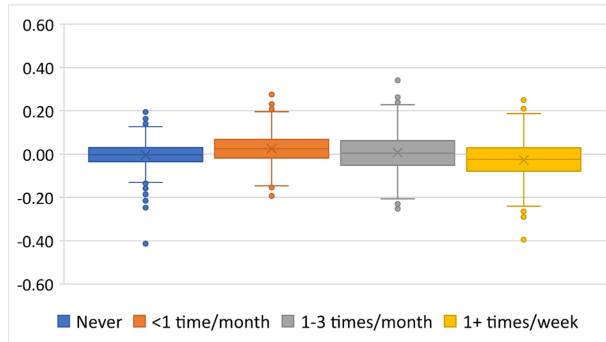
Panel A. Dine-in: during – before COVID



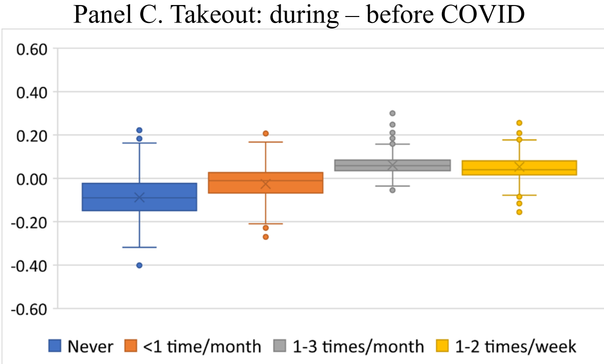
Panel B. Dine-in: after – before COVID



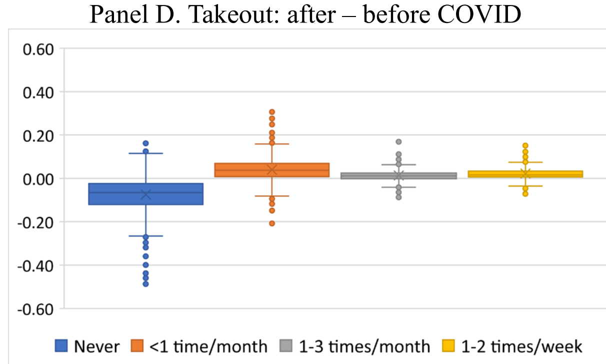
Panel C. Takeout: during – before COVID



Panel D. Takeout: after – before COVID



Panel E. Delivery: during – before COVID



Panel F. Delivery: after – before COVID

Figure 1.4. Change in probabilities of restaurant meal consumption frequency by channel

Consistent with expectations, Panel A of Figure 1.4 illustrates a sharp increase in dine-in frequency for "less than once a month" and especially "never" during the pandemic, while other frequencies dipped. The survey respondents expressed an increased desire to eat at restaurants more frequently after COVID-19 compared to pre-pandemic, according to Panel B. However, the highest frequency has decreased. Panels C and D indicate minor changes in takeout frequency during COVID-19, and intentions suggest only small frequency changes post-pandemic. Similarly, Panels E and F reaffirm the growing (yet somewhat limited) interest in meal deliveries.

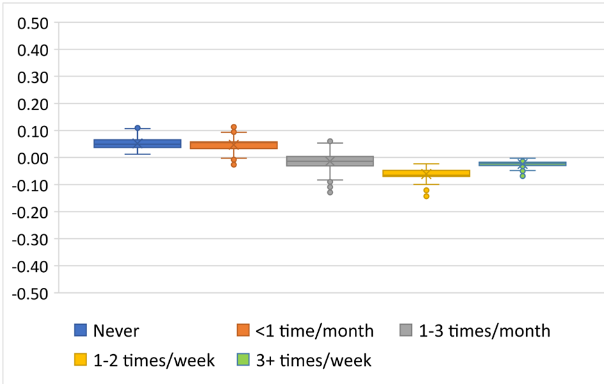
The strong correspondence between the changes in the weighted responses of the respondents, as shown in Figure 1.3, and the predictions generated by the models instills confidence in their aptitude for capturing fundamental characteristics of the dataset.

1.5.2.1 Dine-in (Figure 1.5)

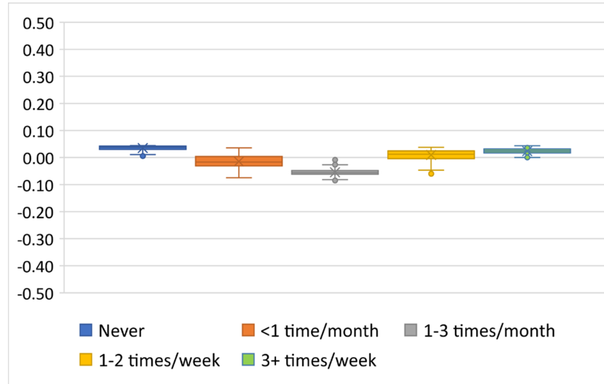
Panel A illustrates that, before the pandemic, Californians from the Silent Generation were slightly less likely to eat in a restaurant weekly compared to Gen Y or Z Californians and more likely to dine in less frequently ("less than once a month" or "never"). Although generational differences disappeared during the pandemic (shown in column II of Table 1.3), they are expected to reappear based on intentions after the pandemic. However, some heterogeneity appears in that group (Panel B). While some Californians from the Silent Generation may be more likely to dine in less frequently ("one to three times a month") or never dine in compared to Gen Y or Z Californians, others are more likely to dine in at least once a week.

Panel C-E indicates that the pandemic eliminated differences between Black and White Californians, consistent with the findings of Ellison et al. (2022). Before the pandemic, Black Californians dined in less frequently than otherwise similar White Californians. However, during COVID-19, Black Californians increased their relative frequency of dining in at restaurants. This may be because they did not alter their habits as much as Whites. Post-pandemic intentions (Panel E) indicate that Black Californians are more likely than Whites to dine in one to three times monthly or less than once a week. Longer box plots indicate greater uncertainty.

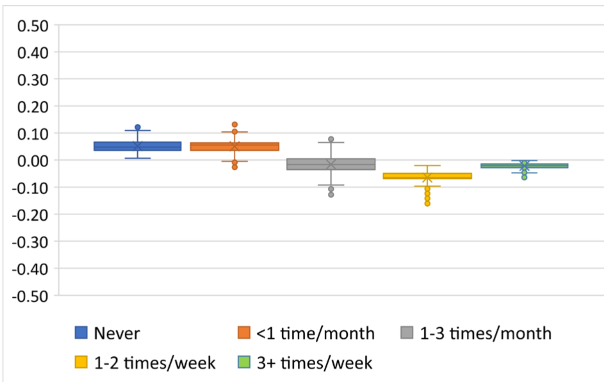
COVID-19 also reversed differences between primarily Spanish-speaking Californians and Californians who mainly rely on English. Before the pandemic (Panel F), the former group was less inclined to dine in than the latter, but the pandemic has swapped these differences (Panel G). Post-pandemic intentions suggest a return to pre-pandemic differences (except for "never"), while there remains a fair amount of uncertainty (Panel H).



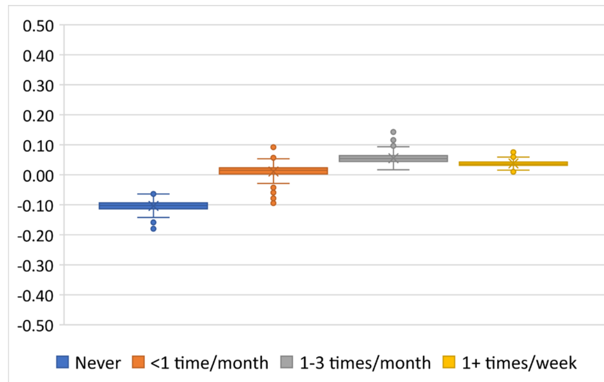
Panel A. Before COVID: Silent Gen vs. Gen Y or Z



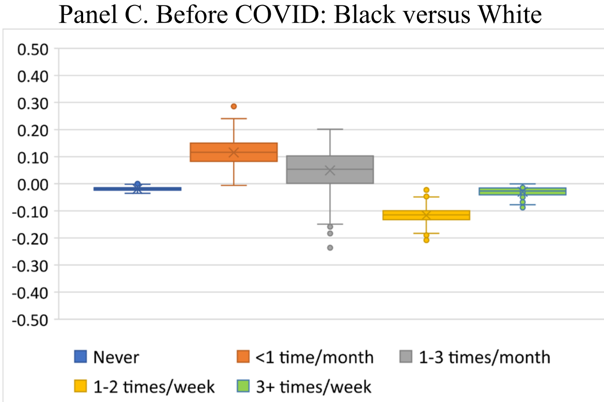
Panel B. After COVID: Silent Gen vs. Gen Y or Z



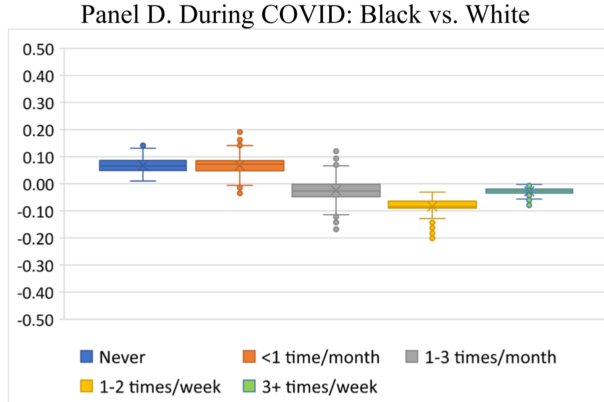
Panel C. Before COVID: Black versus White



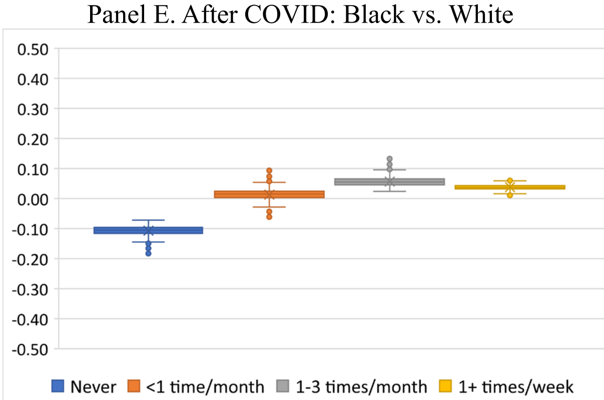
Panel D. During COVID: Black vs. White



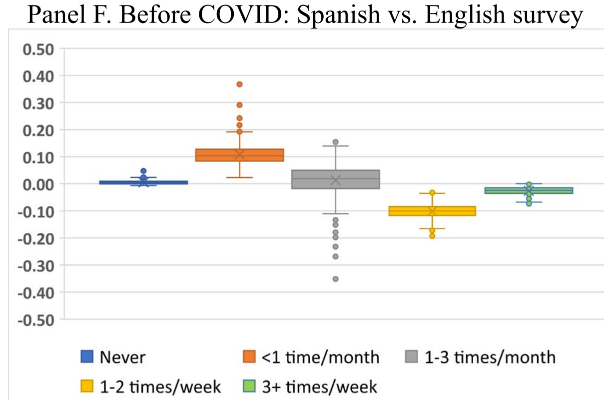
Panel E. After COVID: Black vs. White



Panel F. Before COVID: Spanish vs. English survey

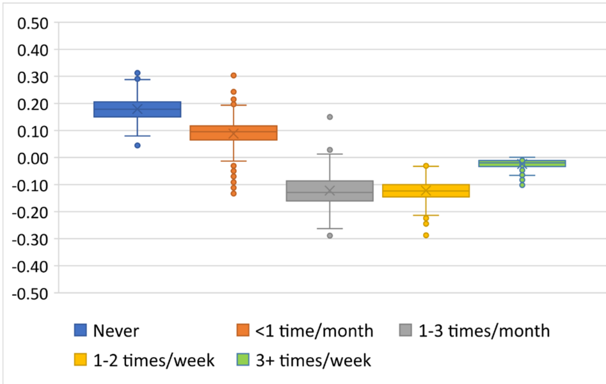


Panel G. During COVID: Spanish vs. English survey

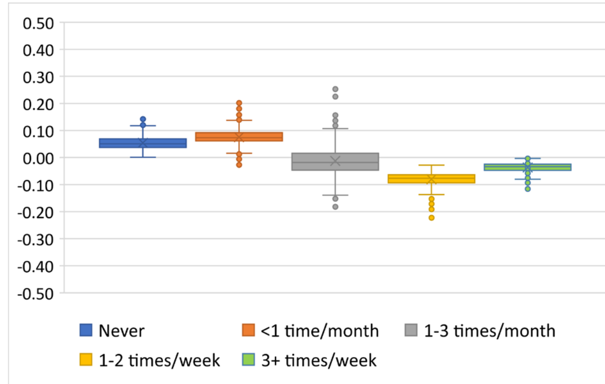


Panel H. After COVID: Spanish vs. English survey

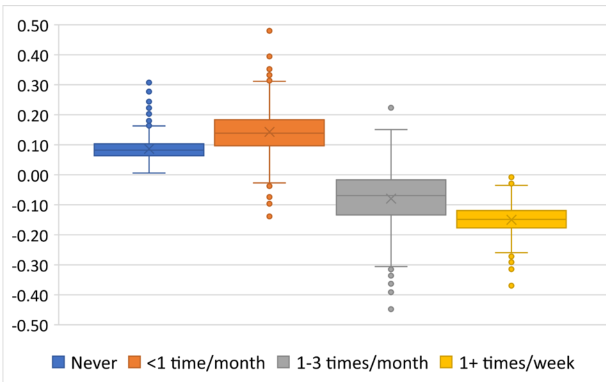
Figure 1.5. Change in probabilities of dine-in frequency



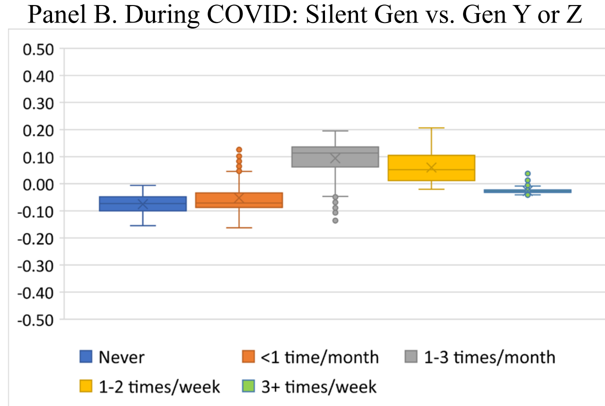
Panel A. Before COVID: Silent Gen vs. Gen Y or Z



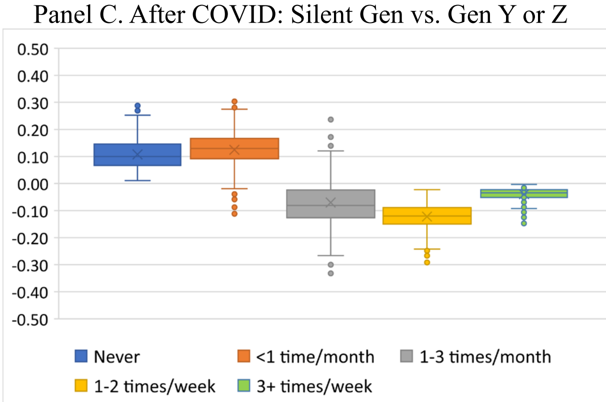
Panel B. During COVID: Silent Gen vs. Gen Y or Z



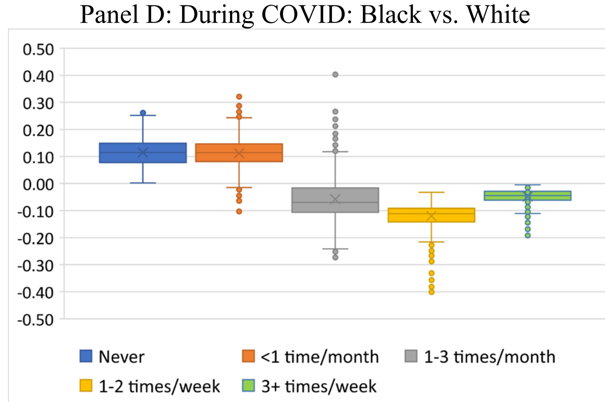
Panel C. After COVID: Silent Gen vs. Gen Y or Z



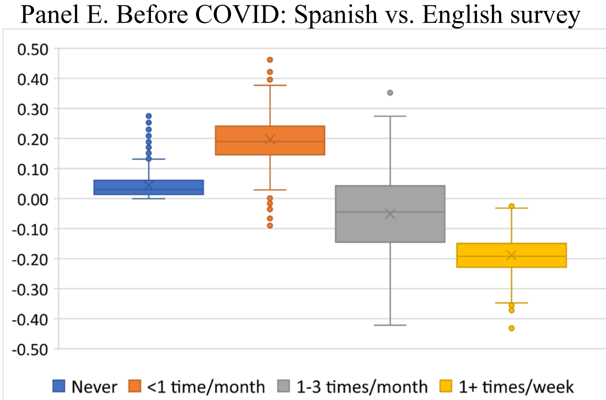
Panel D: During COVID: Black vs. White



Panel E. Before COVID: Spanish vs. English survey

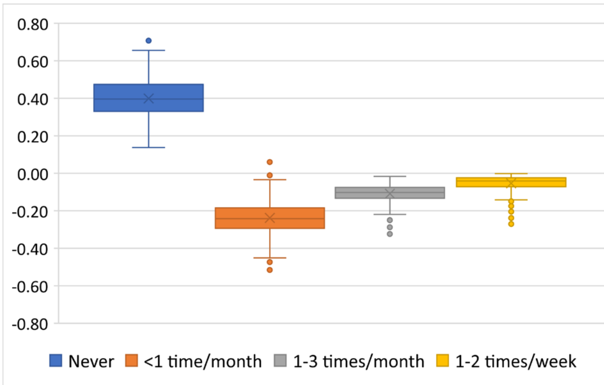


Panel F: During COVID: Spanish vs. English survey

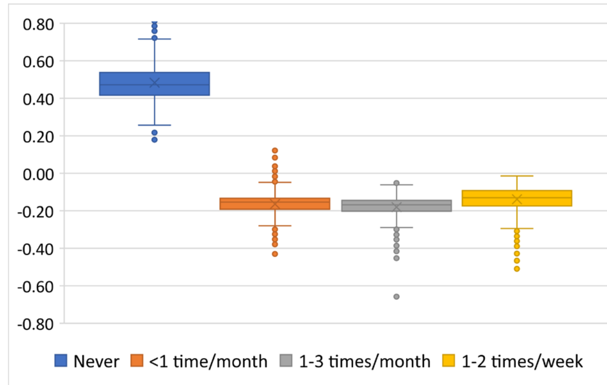


Panel G. After COVID: Spanish vs. English survey

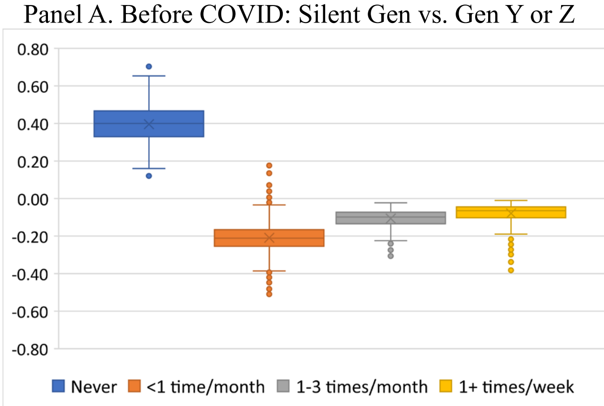
Figure 1.6. Change in probabilities of takeout frequency



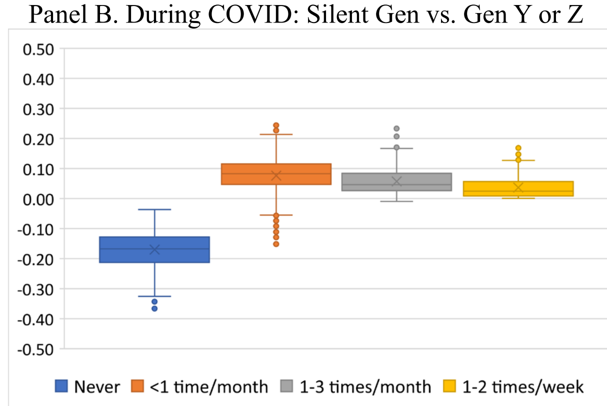
Panel A. Before COVID: Silent Gen vs. Gen Y or Z



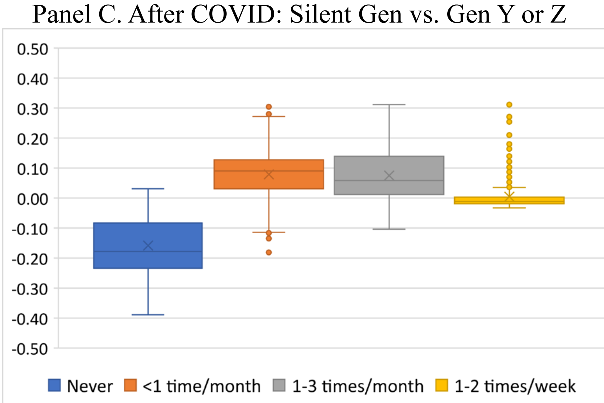
Panel B. During COVID: Silent Gen vs. Gen Y or Z



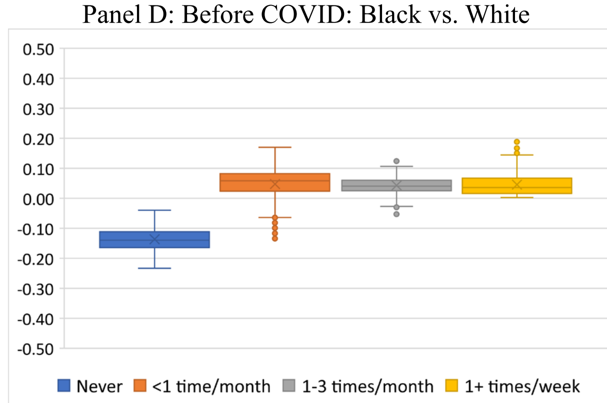
Panel C. After COVID: Silent Gen vs. Gen Y or Z



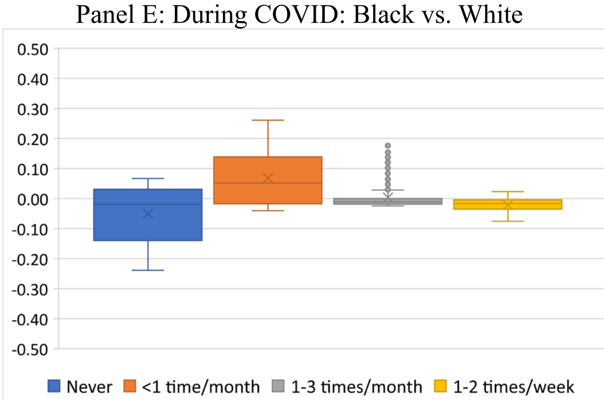
Panel D: Before COVID: Black vs. White



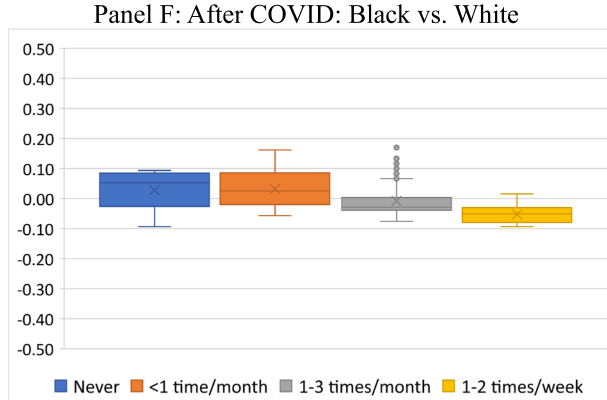
Panel E: During COVID: Black vs. White



Panel F: After COVID: Black vs. White



Panel G. Before COVID: Spanish vs. English survey



Panel H. During COVID: Spanish vs. English survey

Figure 1.7. Change in probabilities of delivery frequency

1.5.2.2 Takeout (Figure 1.6)

Panel A indicates that, before the pandemic, older Californians were less prone to order takeout compared to their Gen Y or Z counterparts, particularly for meal frequencies ranging from "one to three times a week" to "once or twice a week." Panel B illustrates that the pandemic decreased these differences but did not eliminate them, while intentions suggest that they may reappear after COVID-19 with more scatter (Panel C).

Of note, there were no differences in takeout frequency between Black and White Californians. Further, the intention for the post-pandemic era shows a return to that condition. However, during COVID-19 (Panel D), Black Californians were more likely to order takeout meals on a monthly or twice-weekly basis.

In contrast, the pandemic did not significantly change the difference in frequencies between primarily Spanish-speaking and English-speaking Californians, who tend to avoid takeout (Panel E-G).

1.5.2.3 Delivery (Figure 1.7)

Based on findings from Panel A-C, there were no significant shifts in generational delivery frequencies. Nevertheless, the pandemic elevated the probability that Californians from the Silent Generation would never receive restaurant food deliveries, unlike Gen Y or Z Californians. Additionally, it reduced the likelihood of more frequent food deliveries. These distinctions seem to persist after the pandemic (Panel C), with no significant increase in the variability of probabilities across different delivery frequencies.

In contrast to dine-in scenarios, prior to the pandemic, Black Californians were less inclined than Whites never to order restaurant food for delivery. They were also more likely to experience frequent meal deliveries (Panel D). These differences persisted during the pandemic (Panel E), with an increase in the spread between these two groups, although this variation is expected to diminish after the pandemic (Panel F).

A comparable pattern emerges for Californians who participated in the survey in Spanish compared to those who completed it in English (Panel G-H). The range of probability differences increased during the pandemic (although the number of outliers decreased), and these disparities are expected to fade post-COVID.

1.5.2.4 Social Vulnerability

To investigate the influence of SVIs on the likelihood of different frequencies for dine-in, takeout, and delivery before, during, and potentially after the pandemic, I computed these probabilities across the range of the four SVIs. For the remaining variables in the model (see Table 1.3), I selected the most probable values for the subset of 177 respondents whose four SVI scores are ≥0.5. This resulted in the following profile: Gen X (Baby Boomers with children under 18 are unlikely), White, in a household with two adults and one child, with a high school education, and an annual household income ≤ $50,000. Their tech savviness index is 0.246 (slightly above the overall mean). Their variables related to the restaurant access area (transformed as detailed in Table 1.1 and in the same order) are 5.2997, 1.1055, 0.0602, and 0.0116, and their COVID-19 severity variable is 3.2280. The outcomes are presented in Figures 1.8-1.11.

SVI_1 (socioeconomic characteristics) does not display statistical significance for dine-in before the COVID-19 outbreak. However, the likelihood diminishes during the pandemic as SVI_1 increases (as illustrated in Panel A of Figure 1.8). This trend is attributed to higher SVI_1 values elevating the probability of "Never" dining in, which dominates after SVI_1=0.6. At the same time, the probability of “Less than once a month” decreases, and other frequencies remain low.

Regarding takeout, SVI_1 is significant in several scenarios. Pre-pandemic (as shown in Panel B of Figure 1.8), the most probable scenario from the baseline is takeout one to three times a month. As SVI_1 increases, the probability of a weekly takeout frequency rises, while the likelihood of "less than once a month" occurrences decreases. Although these relationships do not qualitatively change during the COVID-19 period (Panel C), the different frequencies have much closer probabilities. After the pandemic (Panel D), expectations suggest two distinct groups for high values of SVI_1: one who never gets takeout and the second one who orders takeout weekly.

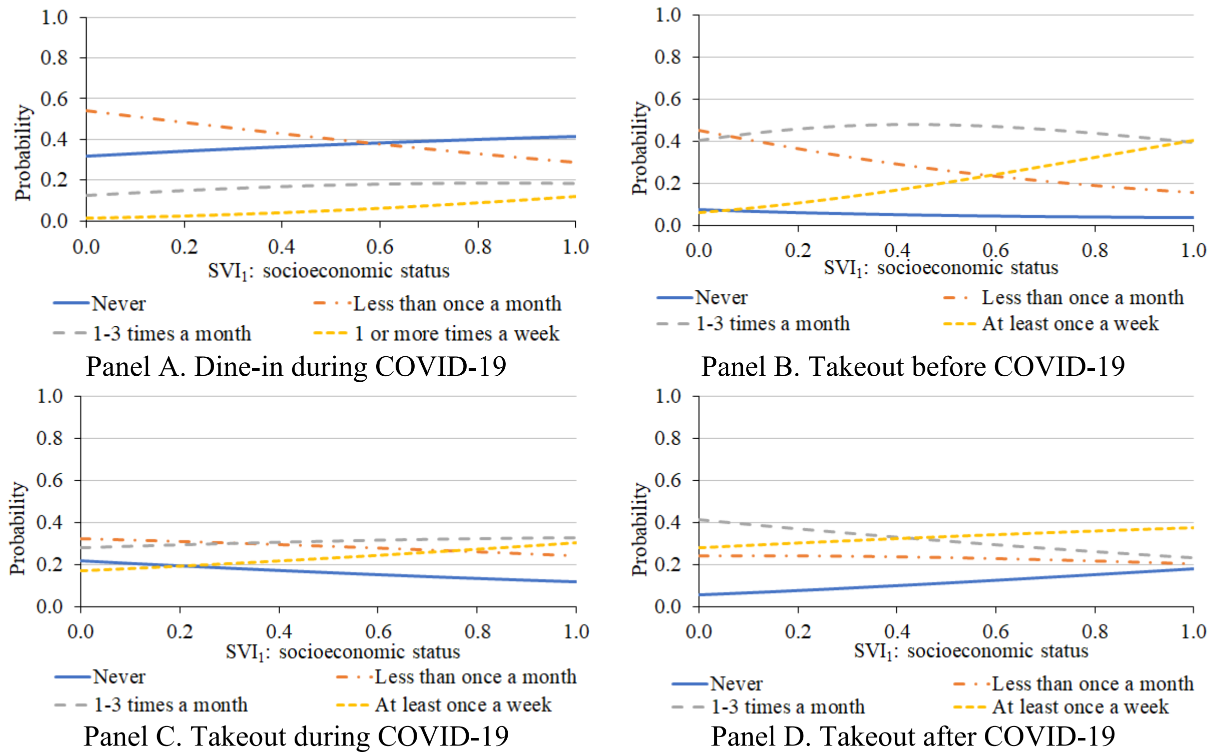
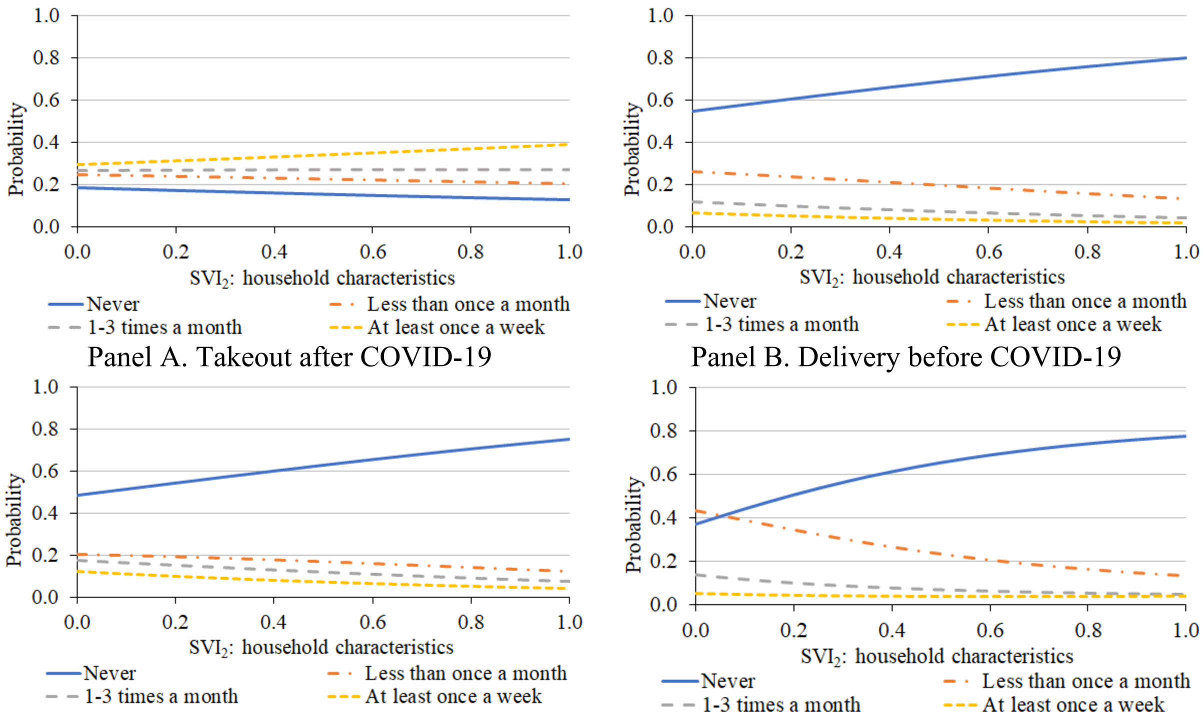


Figure 1.8. Probability of frequency changes vs. SVI_1 (socioeconomic status)

SVI_2 (household characteristics) exhibits significance for takeout after the pandemic (Panel A of Figure 1.9). For that case, as SVI_2 increases, the likelihood of a weekly takeout frequency also increases, accompanied by a drop in the probability of never using takeout, decreasing from 0.19 to 0.13. Additionally, SVI_2 shows significance for meal delivery. Across all three scenarios presented in Figure 1.9 (Panels B-D), as SVI_2 increases, the likelihood of engaging in delivery diminishes, and the probabilities of other frequencies decrease correspondingly. Notably, the probability of occasional delivery (less than once a month) remains above 0.4 for low SVI_2 values after COVID-19.

SVI_3 (racial and ethnic minority status) has a more limited role and is significant in only two instances. The first pertains to takeout patterns before the pandemic. As illustrated in Panel A of Figure 1.10, an increase in SVI_3 corresponds to a heightened probability of engaging in takeout at least once a week, coupled with a decrease in the probability of obtaining takeout less than once a month; the probabilities of other frequencies remain relatively stable.



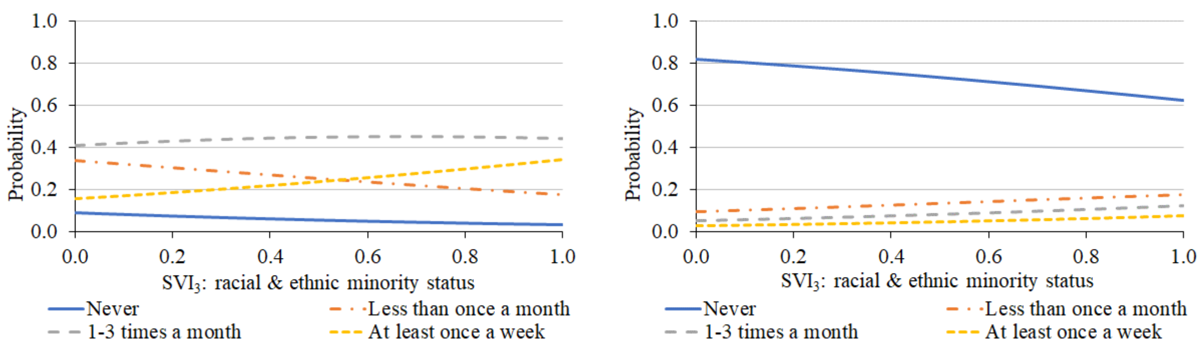
Panel A. Takeout after COVID-19

Panel B. Delivery before COVID-19

Panel B. Delivery during COVID-19

Panel D. Delivery after COVID-19

Figure 1.9. Probability of frequency changes vs. SVI$_2$ (household characteristics)



Panel A. Takeout before COVID-19

Panel B. Delivery during COVID-19

Figure 1.10. Probability of frequency changes vs. SVI$_3$ (racial & ethnic minority status)

The second case concerns meal deliveries during COVID-19. Panel B of Figure 1.10 illustrates that the likelihood of meal deliveries increases with SVI$_3$, although the probability of never getting deliveries remains above 60%. It is plausible that some members of racial and ethnic minorities in California predominantly turned to takeout and, on rarer occasions, to meal deliveries as a strategy to minimize exposure to COVID-19.

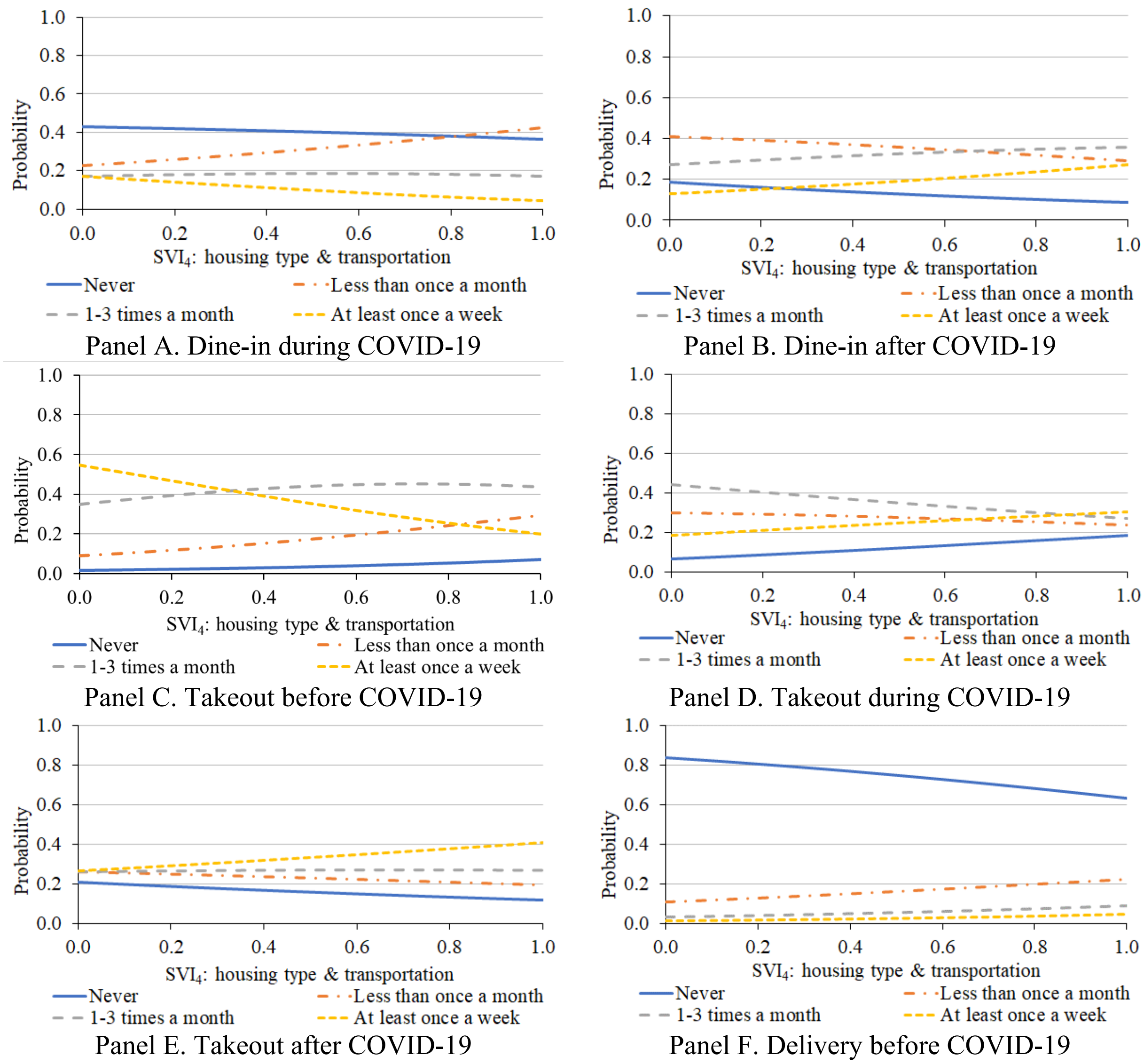


Figure 1.11. Probability of frequency changes vs. SVI_4 (housing type & transportation)

Lastly, the SVI component that is the most frequently significant is SVI_4 (housing type and transportation). For dine-in, it is significant both during and after COVID-19. During the pandemic, as depicted in Panel A of Figure 1.11, an increase in SVI_4 corresponds to a decrease in the likelihood of never engaging in dine-in and dine-in frequently (at least once a week). Concurrently, the probability of dine-in less than once a month rises. After COVID-19, an increase in SVI_4 is associated with diminished probabilities of never or rarely participating in dine-in experiences, alongside an increased likelihood of dine-in on a weekly basis.

The influence of SVI_4 on takeout behavior presents a distinct pattern. Before COVID-19, as SVI_4 increased, the probability of never or rarely using takeout (less than once a month) also increased, while the likelihood of engaging in weekly takeout decreased (Panel C). However, during the pandemic (Panel D), an increase in SVI_4 was associated with higher probabilities of both never getting takeout and ordering takeout on a weekly basis. After COVID-19 (Panel E of Figure 1.11), higher SVI_4 values are anticipated to coincide with a reduction in never using takeout and an increase in the likelihood of weekly takeout. Finally, for post-pandemic meal deliveries (Panel F), higher values of SVI_4 are linked to higher probabilities across all delivery frequencies except for "never." However, the probability of never receiving meal delivery remains notably high (over 60%).

1.6. Discussion

1.6.1 Will the post-COVID-19 era usher in a new normal for restaurant food consumption?

The landscape of restaurant food consumption in California underwent a transformation during the pandemic. Mandated policies and concerns about infection disrupted established patterns of FAFH consumption. Findings suggest a shift towards greater popularity of meal deliveries compared to the pre-pandemic period (Panel C of Figure 1.3), accompanied by a decline in higher dine-in frequency (Panel A of Figure 1.3). Meanwhile, takeout could experience only marginal growth (Panel B of Figure 1.3). The resilience of meal deliveries during the pandemic might be attributed to the minimal human interaction in the delivery process, which instills a sense of safety. In addition, some Californians seem to prioritize the convenience of doorstep meal deliveries over the associated costs.

However, these benefits are not equally distributed among all Californians. The primary beneficiaries of meal delivery services are more likely to be younger individuals (from Generation Y and

Z), African Americans, and those adept with technology. Additionally, they tend to have higher household incomes. Conversely, older individuals (especially from the Silent Generation) and those less comfortable with technology, along with those who prefer Spanish, are less likely to partake in the convenience of takeout and meal deliveries.

These findings emphasize implications for restaurant managers. They should recognize the growing popularity of meal deliveries in the post-pandemic era. Restaurant managers can tailor their marketing and menu offerings to cater to the preferences of different customer segments, considering factors like age, income, and technological proficiency. Developing user-friendly meal-ordering platforms and food applications is necessary while ensuring affordability. There is also potential to extend the reach of takeout and meal deliveries to a broader spectrum of Californians by offering services in languages beyond English, starting with Spanish.

1.6.2 Bridging Food Security Gaps for Seniors

My findings reveal a lower use of home delivery services among the Silent Generation, highlighting potential barriers, including financial constraints and technological challenges. Seniors facing health issues or limited mobility can fall into the food security gap (Administration for Community Living, 2022), where meal delivery platforms can support their well-being.

Existing welfare programs, such as the Older Americans Act (OAA) Title III C-2 Home-Delivered Nutrition program, are designed to provide in-home meal deliveries to frail, homebound, and isolated seniors. In 2021, over 1.5 million seniors nationwide benefited from home-delivered meals at a cost of $98.2 million. California alone had 105,422 seniors who participated (Administration for Community Living, 2023). Forecasts indicate this demand will surge, primarily because the 60+ age population will reach 93 million by 2030, with increasing racial diversity within this age group (Meals on Wheels America, 2023a). Meals on Wheels, a key OAA Nutrition Program component, reports a significant surge in demand, with 7 out of 10 local programs noting increased requests for home-delivered meals compared to the pre-pandemic period (Meals on Wheels America, 2023b). Challenges faced by these programs include volunteer recruitment and retention. To alleviate this, partnering with meal delivery platforms can bolster existing programs, leveraging their operational efficiencies and delivery networks. Such partnerships, supported by policy initiatives, can enhance the reach and effectiveness of welfare programs.

1.6.3. Food delivery logistics

As more consumers opt for the convenience and safety of meal deliveries, the demand for efficient food delivery logistics will continue to grow because it is critical to the financial viability and consumer satisfaction of food deliveries, as argued in the introduction. The share of online orders reached 35% of total restaurant revenue in 2022 in the U.S., with more than $76 billion generated in the meal delivery segment (Beyrouthy, 2023). However, this rapid growth exacerbates transportation externalities such as noise, air pollution, and greenhouse gas emissions. Last-mile delivery vehicles have also been competing for parking in inner-city areas, causing congestion as delivery drivers park in inadequate places.

To reduce the externalities of food deliveries in urban areas, planners and policymakers may consider removing obstacles to the establishment of dark kitchens in areas where restaurant deliveries are in high demand, which would then open the door to deliveries via cargo bikes or electric vans. As the latter are not currently widely available, in the short-term, local authorities should consider creating low and zero-emission zones where only cleaner delivery vehicles are allowed. Since these measures are only as good as their enforcement, cameras (including plate-reading cameras) could be installed in restricted areas. In parallel, authorities should encourage the consolidation of urban food deliveries when possible and revise regulations to allow experimenting with urban deliveries via drones or robots, not to mention automated fulfillment in smaller urban warehouses. As argued by Dablanc (2023), these developments are essential to make urban freight more efficient and more resilient.

To address the surging demand for urban curb from deliveries, bike-sharing, and ride-hailing, local governments could consider a range of alternatives. One particularly promising option is digitizing curb space to manage it more efficiently. For example, the City of Los Angeles plans to digitize all facility information related to curb space, including one million signs and 37,000 parking meters and curb paint 7,500 miles of city streets. This will allow the City to unlock new features for efficient curb management, such as guaranteed curb space and dwell time, fast reaction to public safety issues, and better pricing models (LADOT, 2020).

Digitized curb information would allow drivers to access real-time data on available loading zones, pricing, and regulations, resulting in a more efficient and streamlined delivery process. A flexible implementation would allow dynamically allocating curbside space to accommodate changing delivery demand throughout the day (Roe and Toochek, 2017). For example, during peak delivery hours, specific loading zones could be allocated for delivery vehicles near popular restaurants or retail establishments. As the demand for delivery services decreases during off-peak hours, some loading zones could be reallocated for other purposes, such as short-term parking or passenger pick-up/drop-off. Additionally, implementing a dynamic pricing strategy during peak hours would incentivize delivery drivers to use the designated loading zones more efficiently, with higher fees encouraging quicker turnover.

1.6.4. Restaurant service and food justice

The findings of this study indicate a positive association between higher household income and increased frequencies of both dine-in and meal delivery experiences. This underscores the influence of affordability in shaping an individual's food consumption behavior. In contrast, a higher degree of socioeconomic vulnerability (SVI_1) is linked to more frequent takeout food consumption. This observation implies that factors extending beyond individual attributes, such as the socioeconomic status of the residential area, exert an impact on the patterns of food consumption.

Moreover, the results revealed that regions characterized by higher vulnerability in household composition and disability (SVI_2) exhibit a reduced likelihood of having restaurant meal deliveries. This pattern was evident both before and during the pandemic, and intentions suggest it may persist. This issue became particularly critical during the pandemic when mobility restrictions and shortages of essential goods were prevalent. Online businesses such as DoorDash, Uber Eats, Grubhub, or Postmates delivered restaurant meals, and Amazon, Walmart, or Instacart delivered groceries and medication. Meal delivery would have been especially beneficial for vulnerable groups, including older adults and individuals with disabilities, so it is worrisome that these groups appear to rely less on such services compared to the broader population. Potential causes might include limited internet access, unfamiliarity with online platforms, or suboptimal user interfaces. Through collaborative investigations with community organizations, they should be improved to promote food security, enhance access to essential goods, and contribute to a more inclusive and equitable food landscape.

1.7. Conclusions

In this study, I analyzed data from a random sample of Californians from KnowledgePanel©, the oldest and largest probability panel in the U.S, to understand the frequency at which they consumed restaurant food for three different alternatives (dine-in, takeout, and delivery) before and during COVID-19, and their intentions about consuming restaurant food after the pandemic is over. My heterogeneous ordered logit models include a broad range of socioeconomic variables, a technology savviness factor, characteristics of restaurant access areas, a COVID severity variable, and the four components of the social vulnerability index. Each alternative exhibited distinct demand patterns and evolved differently throughout the pandemic.

My findings show that age (generational differences), race (specifically for African Americans), Hispanic status, education, technological familiarity, COVID severity, and social vulnerability all play important roles in understanding the variations in how frequently individuals consume restaurant food. These factors also shed light on how these consumption patterns shifted during the pandemic and how they might change in the future. On the other hand, household income only has a minor impact, primarily at the extremes of the income spectrum. Similarly, the characteristics of restaurant access areas, which act as indicators of restaurant availability and diversity, also have a limited influence.

One key takeaway is that the pandemic diminished socioeconomic disparities for dine-in and, to some extent, meal deliveries. However, this wasn't the case for takeout, despite minimal changes in takeout frequencies during the pandemic. Meanwhile, meal deliveries saw a significant increase, while dine-in experiences drastically declined in the initial year of the pandemic. Notably, older Californians were less inclined to dine in before the pandemic but expressed intentions to do so more post-pandemic. Nonetheless, they seem less likely to opt for takeout or meal deliveries compared to their counterparts.

I also noted distinct consumption patterns among racial (particularly for Black Californians) and cultural groups (Spanish-speaking Californians). These differences reflect historical disparities for the former and indicate important variations in restaurant food consumption for the latter.

Lastly, the results highlight the significance of social vulnerability in explaining restaurant meal consumption. For instance, higher vulnerability linked to socioeconomic status or housing and transportation was associated with reduced takeout frequency before the pandemic; and so did meal deliveries with an increase in vulnerability associated with household characteristics. Although the impact of each type of vulnerability is limited, it is important to keep in mind that the social vulnerability indexes are positively correlated. It underscores the practical importance of considering social vulnerability when designing strategies for enhancing access to restaurant meals. For instance, policymakers and restaurant managers could collaborate with local food banks or non-profit organizations to provide subsidized meal vouchers or discounts to individuals with lower socioeconomic status. This initiative would make restaurant meals more affordable and accessible to those who are socially vulnerable, promoting food security and equitable access to dining out experiences.

Recognizing the unique consumer behaviors for dine-in, takeout, and delivery underscores the significance of customizing experiences to align with customer preferences. Gaining insights into how consumer choices and behaviors evolve across various time frames holds immense value for policymakers and stakeholders. This understanding aids in developing impactful interventions and support structures, particularly for socioeconomically vulnerable communities. Such initiatives include equitable access to delivery services, enhancements in transportation networks to facilitate efficient last-mile deliveries, and efforts to address disparities in service availability.

One limitation of this study is that I examined restaurant food consumption on an individual basis rather than considering it as a household activity due to data constraints. Secondly, the availability of data on restaurant expenditures and food preferences, particularly distinctions between full-service and quick-service establishments, was limited. Thirdly, while the Theory of Planned Behavior (TPB) provides a robust framework for understanding how intentions influence behavior, it is essential to recognize that intentions do not always seamlessly translate into actions. Several factors, including external constraints, the availability of resources, and the regulatory and policy environment, can intervene in the process, leading to a gap between what individuals intend to do and what they actually do. Nonetheless, exploring intentions remains valuable as it provides insights into the motivations of customers and the underlying factors that shape decisions.

For future research, conducting a follow-up survey on restaurant meal consumption is valuable because it allows for tracking changes and trends over time, especially after COVID-19, when consumer preferences may continue to evolve. Another option for future work would be to analyze the specific food type and restaurant expenditures for dine-in, takeout, and delivery. Additionally, a valuable opportunity lies in conducting more investigations within specific MSAs, within California, across different states, or even internationally. It would allow for a comprehensive understanding of regional variations and cultural influences on dining behaviors, which can inform localized marketing and policy efforts.

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CHAPTER 2. RESTAURANT DELIVERIES IN THE TIME OF THE PANDEMIC - A California case study

2.1. Introduction

The restaurant meal delivery market has seen substantial expansion in recent years, primarily fueled by the surge in popularity of app-based delivery platforms and restrictions from the COVID-19 pandemic (Ahuja et al., 2021; Maze, 2020). The ease and adaptability of these app-based food delivery services have simplified the process of ordering food from preferred restaurants, particularly during the pandemic when contactless delivery options became popular (Li et al., 2022). Partly as a result, the U.S. meal delivery monthly gross sales surged more than 400% between January 2019 and January 2022. This surge continued well past the pandemic's early stages, with the market maintaining a steady growth trajectory (Perri, 2022).

The advent of the COVID-19 pandemic has changed how people live, although its influence varies across different phases. Since eating habits vary in different pandemic situations, restaurant meal delivery patterns have also varied over time. During the initial phases of the pandemic between April and June 2020, concerns about supply chain disruptions (e.g., reduced grocery store hours) and worries about food shortages (e.g., hoarding) propelled the expansion of meal delivery services (Lamy et al., 2022). When the government mandated shutdowns, numerous restaurants had to transition to pick-up or delivery-only models to mitigate the spread of the virus and keep their business alive (Luna, 2020). As vaccine availability expanded, there was a substantial rise in indoor dining (Ellison et al., 2022). As restrictions on food options eased after reopening following COVID-19 (on June 15, 2021, in California), delivery companies took steps to keep customers on their platforms (Durbin, 2021).

Despite the significant expansion of meal delivery services during the COVID-19 pandemic and the growing attention it has received from the academic community, research in this area remains relatively scarce. Published studies often rely heavily on data from convenience surveys collected online through social media. Many of these studies tend to be service-centric and neglect critical geographic considerations. Moreover, there is a notable lack of temporal analysis in this body of research. Many studies focus on a single time point or are limited to analyzing the early stages of the pandemic. Moreover, the FAFH studies of meal delivery I found are predominantly individual-focused and they do not consider a broader societal perspective and food justice.

The primary objective of this study is to examine the shifts in meal deliveries during COVID-19, with a particular emphasis on how these services have altered the landscape of food accessibility. This exploration covers the period that starts before the pandemic all the way to a phase characterized by higher levels of immunity that can potentially reduce viral deaths (Roush, 2023). My main focus is to explain restaurant meal delivery trends within three major MSAs in California across four distinct time frames: September 2019 (pre-pandemic), 2020, 2021, and 2022. I leveraged a dataset, sourced from NielsenIQ's online panel. It comprises over 26,000 customers and over 160,000 transactions (as of September 2019) to capture transactions from major market platforms. One advantage of this approach is that the data collection process is automated, which insulates it from recall errors, which are not unusual in survey-based approaches. A distinguishing feature of this study is that my unit of analysis is a census tract (individual orders are aggregated), which gives me a much richer set of explanatory variables and allows me to compensate for missing socioeconomic characteristics in my dataset. Another feature is my geographic analysis by MSA, which yields insights into regional variations, unlike most published studies. To explain the demand for meal deliveries, I estimated general spatial lag models, which consider the spatial dependence and the effects of characteristics of neighboring census tracts on meal deliveries.

Focusing on three major MSAs in California, I uncover how meal delivery services improved food accessibility during COVID-19 for vulnerable communities. The findings reveal a positive relation between meal delivery demand and lower socioeconomic status, indicating that these services were crucial in providing accessible food options in disadvantaged communities. Additionally, my results highlight the pivotal role of these services in enhancing food accessibility as a response to the pandemic and before in Riverside MSA.

This study contributes to the literature on FAFH by investigating the interplay between various factors, including the social vulnerability index (SVI; see Chapter 1) and changes in the COVID-19 pandemic's impact on the demand for restaurant meals. By incorporating SVI into my analysis, I assess the potential of meal delivery services to enhance food access, particularly for vulnerable populations. This is crucial in understanding the role of transportation and accessibility in shaping meal delivery trends during COVID-19. Policymakers can use these insights to develop targeted interventions that ensure equitable access to food in vulnerable communities. This study also underscores the responsibility of meal delivery companies in fostering an inclusive and equitable food delivery ecosystem by actively working to improve accessibility and affordability for these communities.

As meal delivery services heavily rely on curbside pickups and drop-offs, it is important for policymakers to better manage curbside activity. This research sheds some light on the implications of increased curbside activity associated with meal delivery services. The evolving patterns of meal delivery demand throughout the pandemic offer insight into the shifts in food behavior towards meal delivery services in the major MSAs in California.

In the next section, I review the literature on meal delivery before and during the COVID-19 pandemic. In the data section, I present the meal delivery transaction data, introduce my study area, and motivate my choice of variables before introducing my statistical framework. I then present my results and discuss their implications. In the last section, I summarize the contributions of this study, acknowledge some limitations of this work and suggest ideas for future research.

2.2. Literature Review

2.2.1. Food-Away-From-Home (FAFH)

Food delivery has emerged as a relatively recent focal point in research in the food service area. In the past, it was often encompassed within broader categories, FAFH to explore various aspects of eating habits (Codjia & Saghaian, 2022; Dhakal et al., 2022; Liu et al., 2013; Nagao-Sato & Reicks, 2022; Saksena et al., 2018). Many U.S. studies analyze national surveys, which allows for random sampling and representativeness of the characteristics of the American population. Common factors that have been found to influence FAFH patterns, such as food purchase frequency or expenditure, in existing FAFH research include income (+), race (White (+), Black (-)), education level (+), and age (-). However, it is important to note that the applicability of these relationships to individual regions cannot be assumed, given the vast geographical and cultural diversity of the U.S.

Some of these surveys, such as the Consumer Expenditure Surveys (CE) and National Household Food Acquisition and Purchase Survey (FoodAPS), consider delivered food as part of their discussion with dine-in and takeout options (Liu et al., 2013; Saksena et al., 2018). On the other hand, the National Health and Nutrition Examination Survey (NHANES) focuses solely on food consumed outside the home, excluding specific discussions on delivered food (Nagao-Sato & Reicks, 2022).

2.2.2. Online meal deliveries

The emergence of smartphone apps and the gig economy, a labor market characterized by temporary contracts and freelance roles rather than permanent employment, has significantly contributed to the rise of meal delivery services (Melián-González, 2022). Additionally, the COVID-19 pandemic heightened the significance of delivery as an alternative service type to dine-in, prompting increased attention from researchers. This discussion primarily focuses on literature published since 2019, incorporating more recent insights and developments in the field.

2.2.2.1. Demographic and socioeconomic factors

Several survey-based studies have examined the demographic factors associated with the use of meal delivery services. After analyzing data from a survey of 2,928 U.S. consumers aged 18 and above, Zion & Hollmann (2019) found that the younger age group (18-29 years old) and the lower-income group (< $24.9k) were the primary users of these services. Other studies have provided support for the robust relationship between age groups and the use of meal delivery services. They highlighted the positive influence of education on the adoption of meal delivery services, particularly during pandemic lockdowns

(Poelman et al., 2021; Vogel, 2020). Interestingly, in contrast to the findings of Zion & Hollmann (2019), studies conducted in other countries such as Qatar and Russia (Ben Hassen et al., 2020, 2021) found a positive relationship between income and meal delivery services. It suggests that in these specific cultural and economic contexts, higher-income individuals can afford and are more willing to invest in the convenience and benefits offered by meal delivery services.

2.2.2.2. Intention to utilize meal delivery services.

Various studies have shed some light on the factors that drive behavioral intention to use meal delivery services. Several studies outlined the importance of factors like ease-of-use and user-friendly interfaces in customers' intentions to use meal delivery platforms (Brewer & Sebby, 2021; Chotigo & Kadono, 2021; Gani et al., 2023; Lin et al., 2022; Ray et al., 2019). As expected, attitudes toward technology also influence the decision to use online food delivery services.

In addition to technical and system-related factors, various studies have identified other important factors influencing the demand for meal deliveries (Ali et al., 2020; Chotigo & Kadono, 2021; Leung & Cai, 2021; Lin et al., 2022). Hedonic motivation, the pleasure from the food delivery experience, plays a significant role in customers' decision to use meal delivery services (Lin et al., 2022). Favorable perceptions of meal delivery platforms, including optimism and innovativeness, also contribute positively to the intention to use these services (Ali et al., 2020). Trust is another critical factor (Chotigo & Kadono, 2021). Lastly, The COVID-19 pandemic has profoundly impacted attitudes toward food deliveries (Ali et al., 2020; Chotigo & Kadono, 2021; Leung & Cai, 2021; Lin et al., 2022).

2.2.2.3. Meal deliveries during COVID-19

Recent studies have investigated meal deliveries during the COVID-19 pandemic (Brewer & Sebby, 2021; Conger, 2021; Ellison et al., 2021; Hussey, 2020; Poelman et al., 2021). The pandemic has caused many restaurants to close or limit their in-person services, making delivery and carryout the only options for restaurant food (Conger, 2021). In a study of people's food buying patterns during the pandemic lockdown (Poelman et al., 2021), a significant proportion of existing food delivery customers (49.7%) continued to use meal-delivery services at their frequency during the lockdown, and 29.5% used meal delivery services more frequently. A majority of respondents said that they were getting groceries less often than usual during the lockdown. Furthermore, the fear of contracting the virus made many people reluctant to go out to eat, making delivery a safer option (Hussey, 2020). Brewer & Sebby (2021) suggest that heightened perceptions of COVID-19 risk have amplified the probability of utilizing online food delivery services, primarily by positively influencing the desire for food and the perceived ease of online food ordering.

Though these studies provide multiple insights into the consumption of delivery restaurant meals during COVID-19, most analyze only one point in time and, therefore cannot track the temporal dynamics of the demand for meal deliveries. One notable exception is Ellison et al. (2021), who examined FAFH in four rounds at the beginning of the pandemic: March 13 (Stocking Up), March 27 (Shelter-in-Place Orders), April 10 (CARES Payment Distribution), and April 24 (Reopening Plans Released). They observed significant changes—strengthening in the same direction—in grocery, corner store, dining out, and takeout spending across rounds. They were able to capture the drastic changes in the food environment during the early days of the pandemic and provided a benchmark for future research.

2.3. Data

In this study, I analyze customer transaction records obtained from restaurant meal delivery platforms, collected via NielsenIQ's online shopping panel that includes 1.1 million food delivery customers in the U.S. NielsenIQ obtains information by parsing the e-receipts of their app or service users. The panel has been selected to represent the demographics of the total U.S. online shoppers, encompassing factors such as age, ethnicity, gender, income, and geography. The transaction data used in this study was extracted from five main food delivery services, including DoorDash, UberEats, GrubHub, Postmates, and Caviar. Their combined market share during the study period is believed to be close to 100% (Perri, 2022), which suggests that the data obtained from these platforms is representative of food deliveries in California (in spite of missing data). The location of customers was coded at the 9-digit ZIP level, which allows locating each customer into a census tract. I used this location information to link transactions to a broad range of socioeconomic variables and overcome missing socioeconomic variables in my dataset.

2.3.1. COVID-19 timeline and timeframe of interest

Figure 2.1 displays the trend of COVID-19 cases reported by The New York Times (The New York Times, 2023) and the number of vaccinations from the CDC (CDC, 2023). The latter is the cumulative number of Californians who received at least the first dose of the vaccine, aggregated at the county level. Although there are instances where the number of individuals who received the first dose decreases compared to previous days, it is worth noting at what point the rate of increase is large and at what point it reaches a plateau. Table 2.1 presents key COVID-19 milestones in California, highlighting significant events that could serve as external factors influencing the meal delivery market, ranging from the COVID-19 outbreak to stay-at-home orders, vaccination timing, and variant outbreaks.

This study analyzes restaurant meal delivery transactions for each month at four time points in the context of COVID-19: September 2019 (before COVID-19); September 2020 (during the early stage of COVID-19); September 2021 (during vaccination); and September 2022 (as California was emerging from the pandemic).

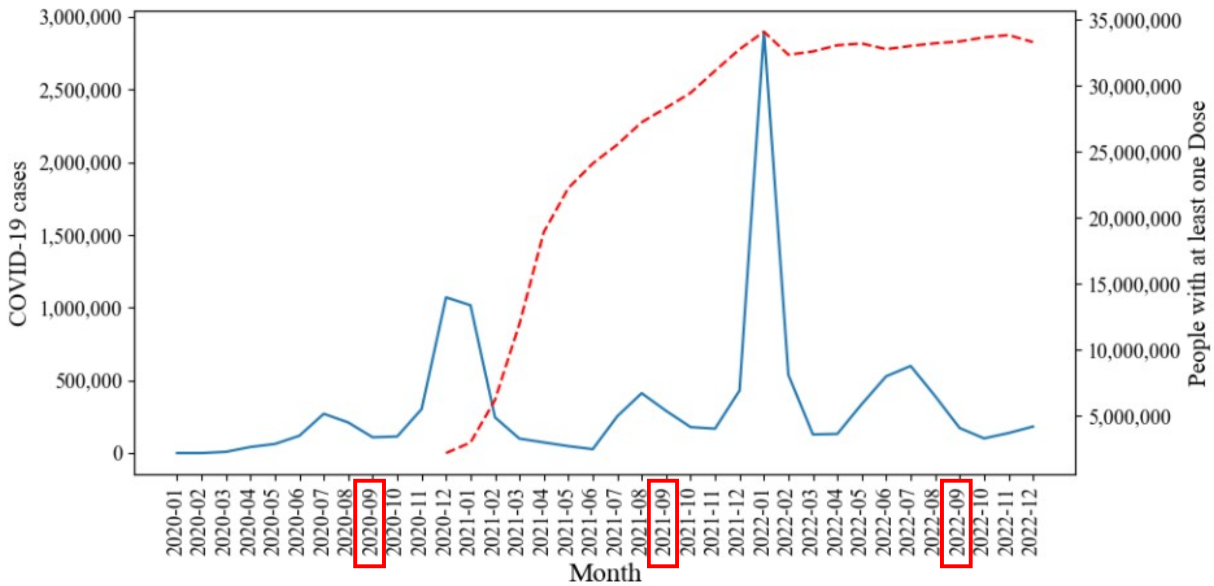


Figure 2.1. The trend of the COVID-19 cases and first dose vaccination rate[1]

Table 2.1. Major moment of COVID-19 in California

Date	Action
1/26/20	California's first case of coronavirus in Orange County.
3/4/20	State of emergency declared in California.
3/19/20	Statewide order to shelter-at-home, restricting all non-essential travel and activities outside the home.
6/12/20	Statewide, the following businesses are allowed to reopen: movie theaters, restaurants, wineries, bars, zoos, museums, gyms, fitness centers, hotels, cardrooms, racetracks, and campgrounds.
7/13/20	Statewide, all bars, indoor dining, indoor wineries and tasting rooms must shut down.
12/3/20	New stay-at-home order for California brings back many of the restrictions from March.
12/15/20	Coronavirus vaccinations begin in the Bay Area.
6/15/21	California reopens. Mask mandates are much looser and aligned with the CDC's guidelines. Social distancing requirements and business capacity limits are removed.
7/30/21	The Delta variant of coronavirus surging across the U.S. appears to cause more severe illness and spread easily.
11/26/21	Discovery of the "omicron" variant, which is highly transmissible.
2/16/22	California health officials lift statewide indoor mask mandate in public settings for vaccinated people.
4/1/22	Proof of vaccination or negative test are no longer needed for large indoor events in California.

[1] Data source: The COVID-19 cases (The New York Times, 2021) and vaccination rate (CDC, 2023)

2.3.2. Meal delivery transactions

The dataset analyzed in this study includes a large number of transactions, ranging from 163,143 in September 2019 to 511,429 in September 2021 in California (see Table 2.2). The data shows a significant increase in food delivery orders in California between September 2019 and September 2020. Specifically, the number of food delivery orders more than doubled in September 2020 compared to September 2019. This reflects a notable change in consumer habits, presumably influenced by the COVID-19 pandemic and associated safety precautions. The data also shows a significant decrease in delivery orders in September 2022 compared to the previous year, with a 48% drop. This likely reflects a shift towards eating out, as concerns about highly infectious COVID-19 variants decreased and indoor activity restrictions were lifted in California.

In September 2019, a total of 26,143 customers relied on food deliveries via the five platforms (DoorDash, UberEats, GrubHub, Postmates, and Caviar), with an average of 6.2 orders per customer. Following the outbreak of COVID-19, the number of customers increased significantly, and the average number of orders per customer rose. While the number of customers decreased in September 2021 compared to September of the previous year, the average number of delivery orders per customer continued to increase. However, in September 2022, both the number of users and the average frequency decreased, although the numbers were higher than pre-COVID-19 levels.

When considering users who have consistently used food delivery services for all four years and who have used delivery platforms prior to the pandemic, I found that they use delivery services more frequently than the average. These users had higher monthly usage frequency even before the pandemic, and their increase in usage frequency after the pandemic was greater compared to the overall average. Furthermore, as of September 2022, during a period of stabilization, these users still showed a higher growth rate (+36.4%) compared to pre-pandemic levels (Sep. 2019 vs. Sep. 2022) than the overall average (+9.7%), with their average monthly usage increasing from 8.8 to 12.0 orders (Table 2.2).

Table 2.2. Meal delivery transactions of users (5 platforms & ZIP+4)

	All Users			Users with a full 4-year history		
Month	Transactions	Users	Average number of transactions per user	Transactions	Users	Average number of transactions per user
Sep. 2019	163,143	26,143	6.2	40,328	4,606	8.8
Sep. 2020	435,682	40,323	10.8	84,709	4,606	18.4
Sep. 2021	511,429	39,891	12.8	105,778	4,606	23.0
Sep. 2022	266,784	38,984	6.8	55,070	4,606	12.0

I conducted a comparative analysis of the transaction data and the survey of Chapter 1 to assess the reliability of the survey data (and vice versa). It is important to note that due to the unique nature of the transaction data, certain frequency categories such as "never" and "less than once a month" are not present. Therefore, I focused on the remaining frequency categories: "1-3 times a month," "1-2 times a week," and "3 or more times a week." This approach allowed to examine the consistency of survey responses and transaction records. Another difference is that the survey from Chapter 1 and the dataset from this chapter cover different periods.

User frequency in transactional data tends to be higher than respondent frequency (Figure 2.2). For the highest frequency (3+ times per week), there was a consistent increasing trend during COVID-19 (September 2020 and 2021) and a decrease after September 2022. For the latter, although there was a large decrease in the number of transactions compared to the previous year, there was no dramatic decrease in the number of users (Table 2.2). It suggests that the delivery market, which grew rapidly during COVID-19, has reached a new equilibrium after COVID-19, as observed in the findings in Chapter 1, with a post-COVID-19 decline but not a return to pre-COVID-19 levels.

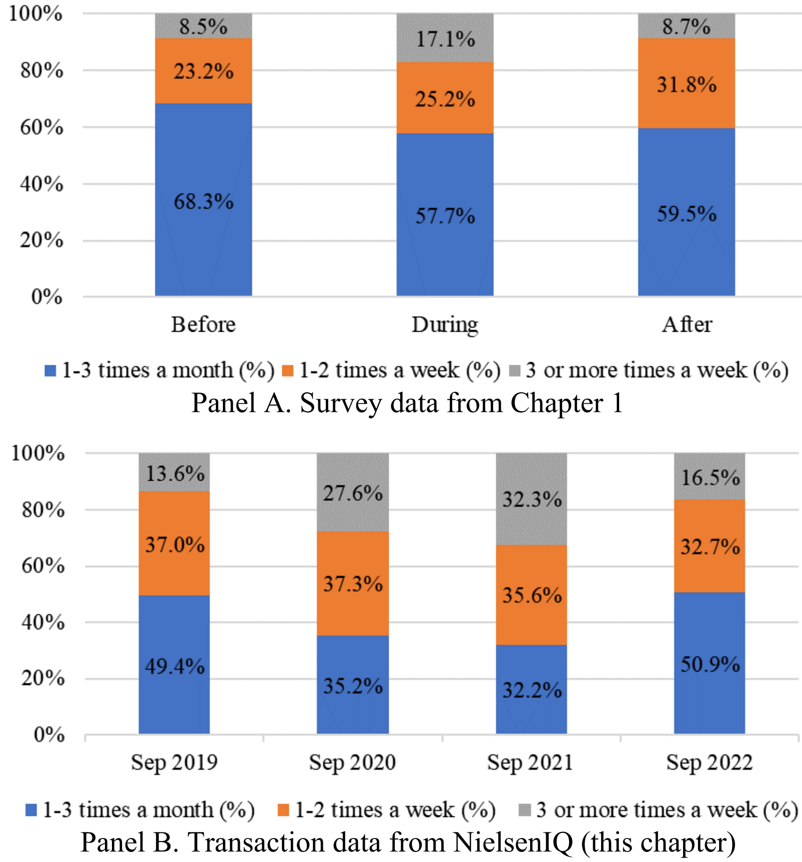


Figure 2.2. Comparison of frequencies of meal deliveries between the Ipsos survey of Chapter 1 and the NielsenIQ transaction data from this chapter

2.3.3. Census tract characteristics: Top 1% vs. zero-transaction tracts

I also analyzed census tract characteristics for subsets of the delivery data in September 2021. Based on the meal delivery density normalized by tract area, I compared the characteristics of the top 1% of census tracts with the highest meal deliveries to those with no meal delivery activity. I aimed to gain some insights into the distinct characteristics associated with high-meal delivery areas compared to those with no delivery activity. Out of 9,047 census tracts, the top 1% tracts amounted to 90 tracts, and there were 2,892 tracts with no meal delivery transactions.

Table 2.3 presents six characteristics of these census tracts: age, race, household income, education, household size, and urban/rural classification. The third bar in each panel presents the

California average based on the American Community Survey (ACS) 5-year data in 2021. I observed distinct differences between the two groups.

The characteristics of the top 1% tracts closely align with the variable relationships observed in previous studies regarding FAFH expenditure or FAFH frequency (Liu et al., 2013; Nagao-Sato & Reicks, 2022; Saksena et al., 2018). The top 1% tracts tend to have a higher proportion of Millennials, White residents, higher household income groups, higher education levels, and smaller household sizes than the ACS average.

In contrast, the zero-transaction tracts are close to the ACS average. Nonetheless, a noteworthy divergence was the significant share of rural areas in the urban/rural classification variable among the zero-transaction tracts. This finding suggests a strong association between the absence of meal delivery orders and the level of urbanization in an area. Furthermore, when examining the number of delivery restaurants in the delivery area (within a 15-minute radius from the center of each tract), the top 1% of tracts had an average of 2,400 delivery restaurants per tract, while the tracts with zero transactions had an average of 600 delivery restaurants. This discrepancy in the number of delivery restaurants highlights the relationship between the demand for meal delivery and the availability of delivery services.

2.3.4. Study area

Including the entire state of California in the analysis would mask regional differences. First, the presence of large urban areas geographically separated by sparsely populated regions can lead to a loss of spatial correlation in the analysis. Second, considering the vast size and heterogeneity of the state, modeling California as a single entity would overlook the distinct characteristics of different regions. I therefore selected three MSAs as my study area: Los Angeles-Long Beach-Anaheim, CA MSA (hereinafter the LA MSA), San Francisco-Oakland-Berkeley, CA MSA (hereinafter the SF MSA), and Riverside-San Bernardino-Ontario, CA MSA (hereinafter the Riverside MSA). Table 2.3 provides statistics related to the population and urban classification of the MSAs, while Figure 2.4 maps the MSA boundaries and displays meal delivery demand at the census tract level.

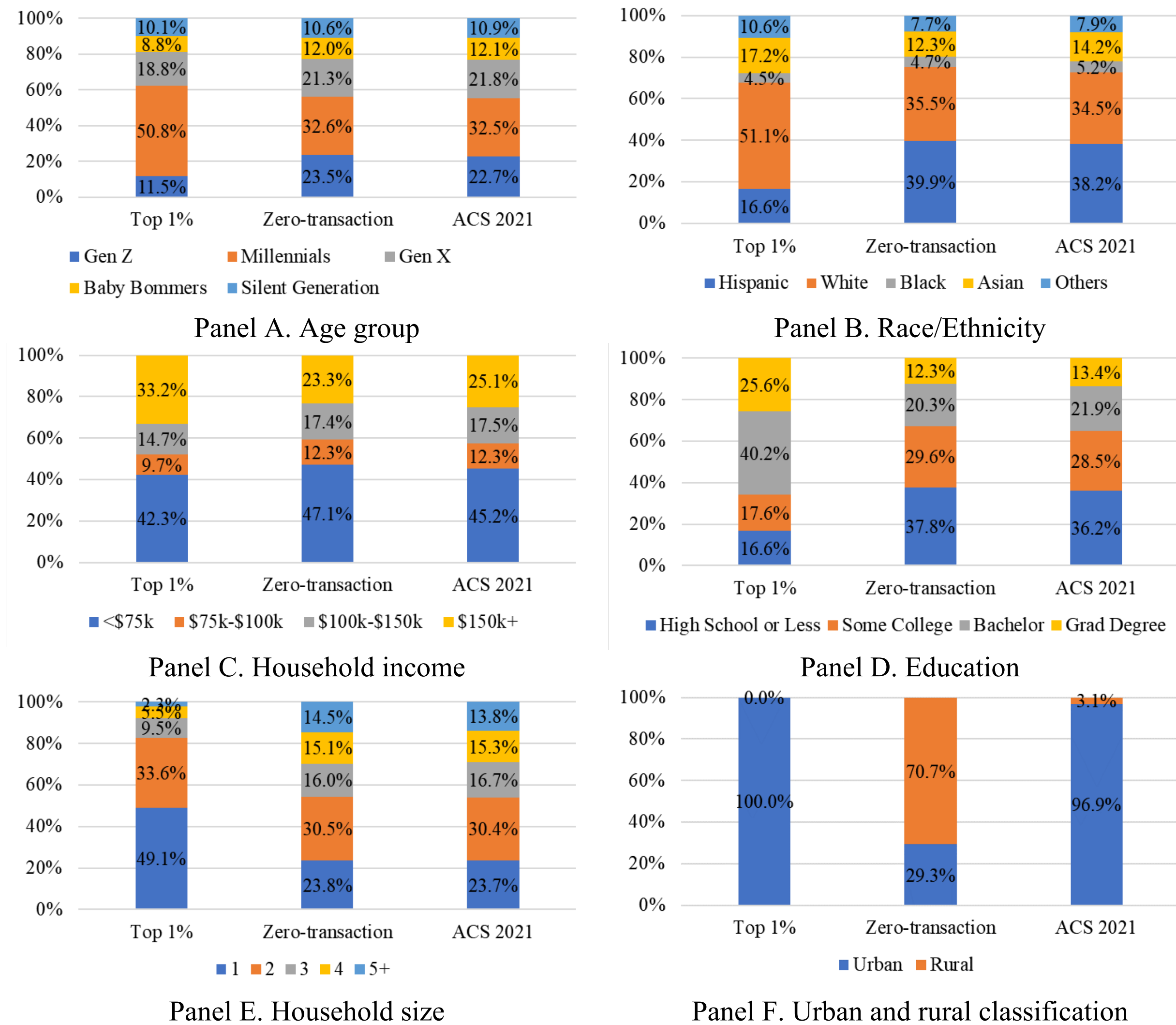


Figure 2.3. Comparison between the top 1% tracts and tracts with zero meal delivery transactions in 2021

Table 2.3. Key statistics of population and urban classification of the MSAs[2]

MSA	Population in 2020	Area (sqmi)	Pop. Density (people/sqmi)	Urban Area (sqmi)	Urban Area (%)
LA MSA	13,201,021	4,852.1	2,720.7	1,968.6	40.6
Riverside MSA	4,599,839	27,277.4	168.6	1,344.6	4.9
SF MSA	4,748,967	2,470.3	1,922.4	851.9	34.5

[2] Source – Census Bureau

The LA and SF MSAs are both highly urbanized and important in Southern and Northern California, respectively. The LA MSA boasts a large population and a high population density. As a result, it exhibits a higher demand for meal deliveries than the other MSAs (51% of all transactions in California in the data as of September 2022). The SF MSA, on the other hand, has a smaller population and a lower population density. Before COVID-19, it had a somewhat outsized share of the meal delivery market in California (27% in September 2019), partly because it was the home of meal delivery platform services like Uber Eats and DoorDash. However, its share shrank after the outbreak of the pandemic (17% in September 2022) as meal deliveries took off in other areas.

The Riverside MSA is adjacent to the LA MSA, but it has a distinct set of characteristics. Its area is more than five times larger than the LA MSA, but its population density is only around 6% that of the LA MSA. Additionally, while approximately 40.6% of the LA MSA is urban, less than 5% of the Riverside MSA belongs to that category. According to the data, it accounted for 4.8% of California meal deliveries as of September 2022. In this chapter, I aim to compare the characteristics of the meal delivery market in urban versus less urban areas, focusing on LA MSA and Riverside MSA.

2.3.5. Dependent variable

One goal of this study is to identify regional characteristics associated with the demand for restaurant meal delivery and understand who used meal deliveries in the context of food justice. Although the dollar amount of the order could have been used as the dependent variable, I prioritized understanding how meal delivery services improved food accessibility and impacted curbside traffic, and therefore, I selected order count as my dependent variable. The frequency of delivery orders was aggregated at the census tract level using customer location information.

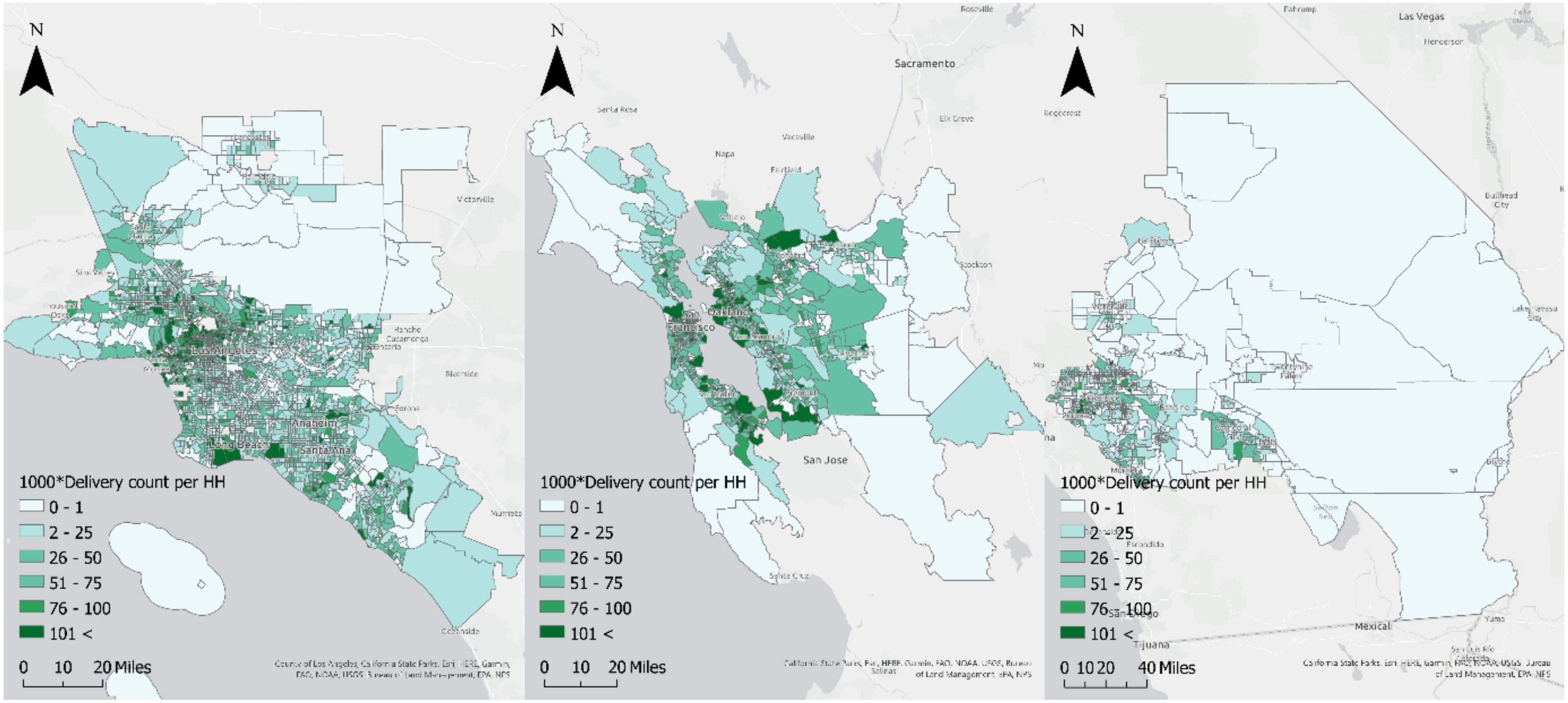
Among the non-overlapping and collectively exhaustive spatial units –county, tract, block group, and block— I consider census tracts to be the most suitable size unit identifying patterns at a fine-grained level because census tracts, which group between 1,200 and 8,000 people (U.S. Census Bureau, n.d.), are designed to be relatively homogeneous with respect to population characteristics. I normalized the frequency by the number of households in the census tracts to eliminate potential bias towards areas with a larger number of households. Also, I log-transformed the dependent variable to stabilize its variance, as the dataset exhibits a high degree of skewness in meal delivery count (See Figure 2.5).

The number of census tracts used in this analysis varies from year to year. There were geographical changes in the census tracts in the 2020 Census (9,129 tracts in California), which resulted in fewer tracts being available in the model for 2019 (8,057 tracts in California) based on the 2010 Census. Secondly, census tracts without households were excluded from the analyses. Table 2.4 summarizes the meal delivery count information aggregated by census tract.

2.3.6. Explanatory variables

My review informed the selection of my explanatory variables of the FAFH literature. Additionally, I included variables related to regional vulnerability, employment, restaurants offering deliveries, and COVID-19 from five distinct sources: the American Community Survey (ACS), the Centers for Disease Control and Prevention Social Vulnerability Index (CDC SVI), the Longitudinal Employer-Household Dynamics (LEHD), the California Health and Human Services Agency (CHHS), and DoorDash.

I used values corresponding to the relevant year to construct the explanatory variables, but as of September 2023, the 2022 census data has not yet been released. Therefore, the model for the year 2022 uses socioeconomic variables from 2021. In addition, for the variables of employment and delivery restaurants, the data is accessible only for a specific year. In this case, I assumed that the data for a given time represents the entire study period. An appropriate conversion process is necessary as there are inconsistencies between the Census 2010 and Census 2020 data. I overcome this issue using the 2020 census tract relationship files, which link 2020 census tracts to 2010 census tracts. The list of variables is presented in Table 2.5.



Panel A. LA MSA Panel B. SF MSA Panel C. Riverside MSA

Figure 2.4. Study area (three MSAs) and the geographical distribution of meal delivery transaction

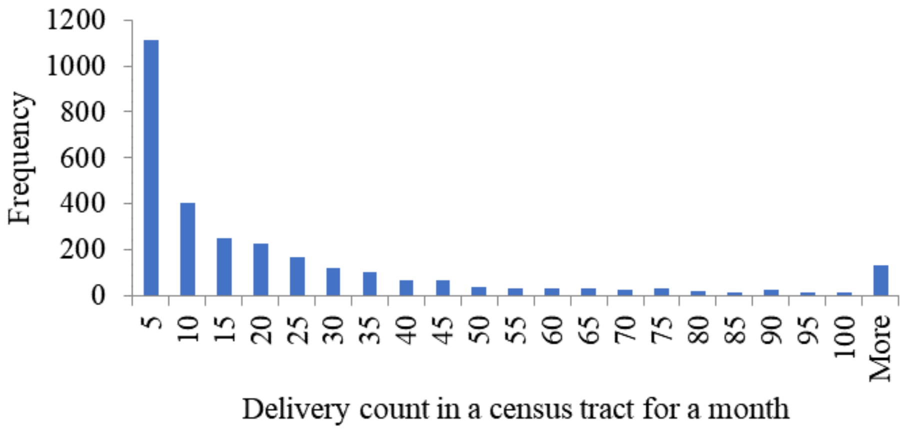


Figure 2.5. Histogram of the number of deliveries in a census tract over a month (LA MSA)

Table 2.4. Number of census tract and meal delivery transaction statistics by year and MSA

Year	LA MSA			SF MSA			Riverside MSA		
(September)	Census tracts	Meal delivery Mean	Std.	Census Tracts	Meal delivery Mean	Std.	Census Tracts	Meal delivery Mean	Std.
2019	2,930	15.8	92.3	1,006	26.2	36.7	786	4.0	5.8
2020	3,123	30.6	215.0	1,127	49.1	55.8	939	12.0	18.7
2021	3,123	42.2	173.8	1,127	43.2	80.7	940	15.7	25.7
2022	3,123	24.8	265.5	1,127	21.7	37.7	940	7.3	10.6

Note: Meal delivery transaction statistics are based on 1000*(meal delivery count/households in a census tract)

2.3.6.1. Demographic and socioeconomic characteristics

Demographic and socioeconomic variables, such as age, race, education, and income, are well-established predictors of FAFH consumer behavior (Codjia & Saghaian, 2022; Dhakal et al., 2022; Liu et al., 2013; Nagao-Sato & Reicks, 2022; Saksena et al., 2018). These variables were relevant for explaining variations in meal delivery demand in Chapter 1. As in Chapter 1, I also used the number of adults in the household and the same regional variables. I also considered the urban and rural classification as a crucial spatial variable. This classification categorizes areas based on factors such as housing unit density, geographical features, and employment size (Census Bureau, 2022). This variable is significant not only for its impact on meal delivery demand but also for its implications on road infrastructure and the availability of delivery personnel.

The demographic and socioeconomic variables are derived from ACS 5-Year data from the US Census Bureau. While ACS 1-Year data would be more appropriate for detecting recent changes in census tract characteristics, they are not available for 2020 due to data collection issues during COVID-19 (U.S. Census Bureau, 2021). As a result, I relied on demographic and socioeconomic variables from ACS 5-Year data. I initially also wanted to use household car ownership as an explanatory variable, but it had to be excluded because of multicollinearity.

2.3.6.2. Social Vulnerability Index (SVI)

As in Chapter 1, I included in my models the Social Vulnerability Index (SVI) developed by the Centers for Disease Control and Prevention to measure the social vulnerability of each census tract. The SVI is a composite index that considers factors such as poverty, unemployment, minority status, and housing and mobility quality and provides a measure of the overall social vulnerability of a given area. The inclusion of the SVI in this analysis is based on the premise that socially vulnerable populations may have different levels of demand for restaurant meal delivery compared to residents in more advantaged communities. For example, socially vulnerable populations may be more likely to experience food insecurity, which could also impact their demand for restaurant meal deliveries. In addition, people who have limited mobility may rely more on restaurant meal deliveries than those without mobility restrictions.

SVIs are variable for reflecting heterogeneity across census tracts because they encompass a wide range of census characteristics. By incorporating the diverse factors, SVIs provide a comprehensive view of the social vulnerability landscape within census tracts. On the other hand, it may not be the only variable needed to explain all aspects of heterogeneity within census tracts fully. I also consider it in conjunction with other relevant variables to provide a more complete picture of the factors influencing meal delivery demand in different areas.

I calculated the California SVI for each year, except for 2022, by referencing the method provided by the CDC. This exception was due to the unavailability of data for the year 2022. SVI_3, which represents Racial & Ethnic Minority Status, was excluded due to high multicollinearity.

2.3.6.3. Longitudinal Employer-Household Dynamics (LODES) Employment

I also included Longitudinal Employer-Household Dynamics (LODES) employment data to measure the employment characteristics of each census tract. Employment patterns can vary by census tract and contribute to capturing the heterogeneity of the area. Some tracts may have a high concentration of business and jobs, while others may be predominantly residential with limited employment opportunities. Employment is a fundamental driver of economic activity, such as higher income levels and greater consumer spending power. In addition, it can influence the accessibility of individuals to food options during work hours. Census tracts with numerous job opportunities may experience higher demand for meal deliveries as employees seek convenient meal solutions while at work. The LODES data is based on the Quarterly Census of Employment and Wages (QCEW) program, which collects data on employment and wages from employers in the United States. Since LODES data are only available for 2019, they do not capture changes in employment patterns resulting from the pandemic. Due to shutdowns and the spread of the virus, many individuals have transitioned to remote work or have experienced disruptions to their employment, which may impact the demand for restaurant meal deliveries.

2.3.6.4. COVID-19 characteristics

The COVID-19 pandemic has brought about substantial changes in food consumption. The number of COVID-19 cases and vaccination rates are key indicators of the level of concern and precaution within the areas. Higher case numbers may suggest increased health risks, potentially boosting the demand for contactless dining options like meal delivery. Similarly, vaccination rates can indicate the level of protection and comfort within a community, influencing the consumption of meal deliveries. I included COVID-19 statistics, such as the number of COVID-19 cases for 2020, 2021, and 2022 and COVID-19 vaccination rates for 2021 and 2022. However, a limitation of these COVID-19 statistics is that they may not fully capture the localized effects and variations within and between census tracts, as the pandemic's impact on meal delivery demand can vary significantly within a county.

2.3.6.5. Availability of meal delivery services

To capture the level of opportunities to consume restaurant meals, I included the count of delivery restaurants within a defined delivery area in my models. This delivery area was determined as a 15-minute driving distance using an isochrone from the centroid of each census tract. Areas with a higher concentration of delivery restaurants are likely to provide more choices, convenience, and ease of access to meal deliveries. Competition among meal delivery restaurants can also vary across census tracts. Areas with more delivery restaurants may experience more competition, potentially resulting in a wide range of options and competitive pricing, which can influence consumer demand. The data used in this study was limited to restaurants that were registered with DoorDash as of October 2022 because I do not have data for 2019-2021. Many restaurants closed or opened during the pandemic, but my dataset cannot fully capture this information.

Table 2.5. Summary of explanatory variables

Group	Variable	Description	Source
Demographic and socioeconomic characteristics	Population density	Population density of tracts (people/sqmi)	ACS 5-Year (B01001)
	Age group	Age group by generation (The Silent Generation, Baby Boomers, Gen X, Millennials, and Gen Z)	ACS 5-Year (B01001)
	Race	White, Black, Asian, and Others	ACS 5-Year (B02001)
	Education	High school graduate or less, Some college or associate degree, Bachelor's degree, Graduate or professional degree	ACS 5-Year (B15002)
	Household income	Less than \$75k, \$75k-\$100k, \$100k-\$150k, \$150k or more	ACS 5-Year (B19001)
	Household size	1, 2, 3, 4, 5+	ACS 5-Year (B15003)
	Urban and Rural	Urban-rural classification	Census Bureau
Social Vulnerability Index	SVI_1 (Socio-economic Status)	Below 150% poverty, Unemployed, Housing cost burden, No high school diploma, No Health insurance	Centers for Disease Control and Prevention (CDC) & ACS 5-Year
	SVI_2 (Household Characteristics)	Aged 65 & Older, Aged 17 & Younger, Civilian with a disability, Single-parent households, English language proficiency	
	SVI_3* (Racial & Ethnic Minority Status)	Hispanic or Latino (of any race), Black or African American, Not Hispanic or Latino Asian/American Indian or Alaska Native/Native Hawaiian or Pacific Islander/Two or more races/Other races	
	SVI_4 (Housing Type & Transportation)	Multi-unit structures, Mobile homes, Crowding, No vehicle, Group quarters	
LODES employment	Employment size	Total number of jobs	Longitudinal Employer-Household Dynamics (LEHD)
COVID-19 characteristics	COVID-19 statistics	COVID-19 cases (county level)	California Health and Human Services Agency (CalHHS)
	Vaccination statistics	COVID-19 1st dose vaccination rates (county level)	
Delivery restaurants	Count of DoorDash partner restaurants	Number of DoorDash partner restaurants (as of October 2022)	DoorDash

* Excluded in the models due to high multicollinearity

2.4. Methods

I estimated spatial Durbin models (SDM) to examine the meal delivery frequency, a choice driven by the model's capacity to account for the impact of neighboring areas on the explanatory variables. As explained above, my unit of analysis is a census tract, so SDMs model the spatial interdependencies between contiguous census tracts. This recognition is crucial because meal delivery events are not isolated within administrative boundaries but rather influenced by factors that transcend these boundaries.

One notable strength of the SDM is its ability to produce unbiased coefficient estimates regardless of whether the data generation process follows a spatial lag(error) model. This means that the GSM can provide consistent parameter estimates if the explanatory variables are right regardless of the underlying spatial relationship structure (Elhorst, 2010). Another strength of the SDM lies in its flexibility because it allows for the assessment of spatial spillover effects without pre-imposing constraints on their magnitude. This means that the model allows for both global and local spatial spillover effects, which can vary across different explanatory variables (Anselin & Le Gallo, 2006; Elhorst, 2010). The Spatial Durbin model can be written (Fischer & Wang, 2011):

$$y_i = \rho W y_i + X_i \beta + W \bar{X}_i \gamma + \varepsilon_i \tag{2.1}$$

$$\varepsilon_i = \mathcal{N}(0,\ \sigma^2 I) \tag{2.2}$$

where the subscript *i* refers to census "i". In the model, y is the dependent variable, the logged frequency of meal delivery orders at the census tract level, which is normalized by the number of households in each census tract. In the model, any census tract with zero households was excluded from the analysis. X denotes the matrix of explanatory variables, including a constant, $\bar{X}$ is X without a constant, β is an unknown coefficient vector, ε is the error term, and W is the spatial weight matrix. In Equation (2.1), the first $\rho W y_i$ captures the spatial lag of the dependent variable. It reflects the influence of neighboring observations on observation "i". The term $X_i \beta$ models the effects of the explanatory variables on the dependent variable, independent of spatial relationships. The third term, $W \bar{X}_\iota \gamma$, represents an influence of the spatially lagged explanatory variables on the dependent variable. The error term is assumed to be *iid* (Eq (2.2)).

Weight matrices (W) are key components of spatial models. As a starting point, I used an inverse distance weight matrix raised to the power of two to construct the spatial weight matrix:

$$W = \begin{cases} \frac{1}{d_{mn}^2} \; if \; d_{mn} \leq \text{threshold} \\ 0, \text{otherwise} \end{cases} \tag{2.3}$$

where d_{mn} is the distance in miles between census tract *m* and *n*. W is the row normalized to ensure the proportional weights, given there are an unequal number of neighbors across the observations. Dividing each weight value by the sum of all weights in the row can be interpreted as the relative contribution of neighboring tracts in shaping the meal delivery behavior (Dubin et al., 2009).

The choice of spatial weight matrix considers the food delivery context. Given the spatial constraints imposed by the coverage area of the food delivery service, I decided a distance-based approach is appropriate for constructing the spatial weight matrix compared to contiguity-based approaches or k-nearest neighbors. To determine the spatial weight matrix threshold, I employed a tailored approach for each MSA considered in this study. By evaluating the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, I identified the optimal threshold that best balanced model fit and complexity for each MSA. I developed 12 models, considering the combination of three geographic areas: the Los Angeles, San Francisco, and Riverside MSAs, along with four distinct time periods corresponding to September 2019, 2020, 2021, and 2022.

The interpretation of models that incorporate spatial lags of explanatory or dependent variables demands a more intricate approach compared to linear regression models that consist only of exogenous variables (Fischer & Wang, 2011). The spatial Durbin model incorporates information from neighboring regions or observations. To understand this effect, let us rewrite the SDM model as follows (LeSage & Pace, 2009):

$$(I_n - \rho W)y = X\beta + W\bar{X}\gamma + \varepsilon \tag{2.4}$$

$$y = \sum_{r=1}^{k} S_r(W)x_r + V(W)\varepsilon$$

$$S_r(W) = V(W)(I_n\beta_r + W\gamma_r)$$

$$V(W) = (I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots$$

To provide a clearer perspective on the significance of $S_r(W)$, let's examine the expansion of the data generation process outlined in equation (2.4) (Kim et al., 2003):

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \sum_{r=1}^{k} \begin{pmatrix} S_r(W)_{11} & S_r(W)_{12} & \cdots & S_r(W)_{1n} \\ S_r(W)_{21} & S_r(W)_{22} & & S_r(W)_{2n} \\ \vdots & & \ddots & \vdots \\ S_r(W)_{n1} & S_r(W)_{n2} & \cdots & S_r(W)_{nn} \end{pmatrix} + V(W)\varepsilon \tag{2.5}$$

Through equation 2.5, we can see the key difference between a simple linear regression model and the SDM: the derivative of y_i with respect to x_{jr} has the potential to be non-zero (equation 2.6), and is given by (LeSage & Pace, 2009).

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} \tag{2.6}$$

This relationship demonstrates how changes in the explanatory variable x_{jr} on the dependent variable y_i is intricately linked to the spatial relationships embodied in $S_r(W)$.

The derivative for the *i*th region (equation 2.7) quantifies the effect on the dependent variable observation *i* arising from a change in x_{ir}, the explanatory variable of that very region. In essence, $S_r(W)_{ii}$ encapsulates the direct influence of changes in x_{ir} on the dependent variable y_i (LeSage & Pace, 2009).

$$\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii} \tag{2.7}$$

LeSage & Pace (2009) present a method to simplify the complex array of impacts by adding up the effects along the rows or columns of the matrix $S_r(W)$, and then finding the average across all regions:

1) Average direct impact - The impact of a change in the explanatory variable x_{ir} on $y_i$could be measured by the average of diagonal elements of $S_r(W)$, $S_r(W)_{ii}$.

2) Average indirect impact – The average of the off-diagonal elements of $S_r(W)$, $S_r(W)_{ij}$ $(i \neq j)$. This commonly referred to as spatial spillovers.

3) Average total impact to an observation – The average of the row or column sums represent the total impact on individual observation y_i of changing the r^{th} explanatory variable.

2.5. Results

The COVID-19 pandemic has disrupted traditional dining patterns, leading to a significant increase in the demand for meal deliveries. This shift in behavior may have resulted in fundamental changes to the dynamics of the FAFH industry. Tables 2.6 to 2.8 present the spatial Durbin model estimation results for each of the three MSAs considered. These tables display the estimated coefficients of explanatory variables (β) for each year and the coefficients of the spatially lagged explanatory variables (γ), which typically do not have an intuitive interpretation. Tables 2.9 to 2.11 present the average direct impact (ADI) and average indirect impact (AII), which comprehensively assess the average effects that each region exerts on all other regions.

In each table, the coefficients are accompanied by significance levels denoted by ‡, †, and *, which indicate statistical significance at levels of 0.01, 0.05, and 0.1, respectively. Cases where variables are not statistically significant are represented by the symbol "·."

Across all three MSAs, a shared pattern emerged: in the year 2019, there was no evidence of a spatial lag in the dependent variable (ρ in Tables 2.6 to 2.8), whereas, following the onset of the COVID-19 pandemic, it showed consistent positive spatial lag effects in the dependent variable. This indicates that the pandemic induced important spatial changes in meal deliveries.

In addition, some variables, such as age, race, and income, which are known to influence FAFH behavior, do not carry the same weight in the demand for meal delivery. As a result, it is necessary to re-examine the drivers of consumer behavior in this evolving landscape. Rather than simply listing the variable relationships in the modeling results, I interpreted them by 1) comparing Southern and Northern California, 2) comparing urban and less-urban areas, 3) interpreting from the perspective of the delivery business environment, 4) discussing how the COVID-19 pandemic affected deliveries, and 5) exploring the value meal delivery created in California.

Table 2.6. Spatial Durbin model estimation results for Los Angeles-Long Beach-Anaheim, CA MSA

	2019 (N=2,940)		2020 (N=3,134)		2021 (N=3,134)		2022 (N=3,134)	
	β	γ	β	γ	β	γ	β	γ
Age group (baseline = Gen X (%))								
Gen Z (%)	0.978*	0.157‡	-0.067	0.052	0.269	0.044	0.193	0.062*
Millennials (%)	0.775	0.128‡	-0.988	0.060	-1.303*	0.037	-1.573‡	0.054
Baby Boomers (%)	-0.315	0.209†	1.296	0.030	1.172	-0.004	0.945	0.067
Silent Generation (%)	-2.324‡	0.110	-0.792	-0.016	-0.173	-0.056	-0.293	0.044
Race (baseline = White (%))								
Black (%)	0.451	0.002	0.139	-0.013	0.078	-0.021	0.007	-0.013
Asian (%)	-0.544†	-0.004	-1.255‡	0.035‡	-1.723‡	0.042‡	-1.396‡	0.022†
Others (%)	0.522†	-0.016	0.179	-0.016	0.002	-0.020	0.084	-0.013
Household Income (baseline = $75k - $100k (%))								
< $75k (%)	0.346	0.050	0.025	0.067	0.861	0.049	0.258	0.069
$100k -$150k (%)	-0.377	0.010	0.302	0.017	0.611	-0.029	0.471	-0.047
$150k + (%)	0.372	0.259‡	0.787	0.187‡	1.277†	0.216‡	0.678	0.204‡
Education (baseline = High school or Less (%))								
Some College (%)	-0.380	-0.011	1.891‡	-0.043	2.151‡	-0.038	2.172‡	-0.041
Bachelor (%)	0.940†	0.048*	1.596‡	-0.080‡	1.628‡	-0.086‡	1.689‡	-0.063†
Grad Degree (%)	1.818‡	-0.110‡	1.941‡	-0.032	1.958‡	-0.071*	2.080‡	-0.074†
Household Size (baseline = HH Size – 3 (%))								
HH Size -1 (%)	1.282‡	0.005	-0.002	0.025	0.036	0.027	-0.041	-0.014
HH Size -2 (%)	1.049†	-0.015	0.094	-0.081*	-0.105	-0.042	0.075	-0.070*
HH Size -4 (%)	0.816	0.025	0.487	-0.007	0.576	-0.057	0.708	-0.116†
HH Size -5+ (%)	-0.572	-0.065	-0.167	-0.101†	-0.305	-0.086*	-0.447	-0.085†
1000 · Pop Den	-0.021‡	-0.000	-0.013‡	-0.000	-0.012†	-0.000	-0.018‡	0.000
SVI 1	-0.055	0.018‡	0.134†	0.013†	0.190‡	0.010†	0.204‡	0.010†
SVI 2	-0.001	-0.001	0.011	0.004	-0.020	0.007†	-0.042	0.003
SVI 4	0.010	0.002	0.119‡	-0.000	0.137‡	0.000	0.098‡	0.001
Urban	0.984†	-0.171‡	1.536‡	-0.044	1.438‡	0.152	1.238‡	0.039
1000 · Job Count	0.011‡	0.000	0.004†	-0.000†	0.005‡	-0.000†	0.006‡	-0.000†
10 · DoorDash Restaurants	0.002‡	-0.000	0.003‡	-0.000‡	0.004‡	-0.000‡	0.004‡	-0.000‡
1000 · COVID-19 Cases	N/A	N/A	0.000	-0.000	-0.001	-0.000	0.002	-0.000
1st Vaccination rate (%)	N/A	N/A	N/A	N/A	0.044†	-0.003	0.022	-0.001
Constant	-0.805		-1.216		-4.254‡		-3.314†	
ρ (Global lag)	-0.000		0.010‡		0.010‡		0.010‡	

Table 2.7. Spatial Durbin model estimation results for Riverside-San Bernardino-Ontario, CA MSA

	2019 (N=804)		2020 (N=958)		2021 (N=959)		2022 (N=959)	
	β	γ	β	γ	β	γ	β	γ
Age group (baseline = Gen X (%))								
Gen Z (%)	0.299	0.152	-0.481	-0.106	0.598	-0.205	-0.407	-0.334
Millennials (%)	0.321	0.356	-1.862*	-0.558	0.108	-0.141	-1.207	-0.163
Baby Boomers (%)	0.469	-1.121*	-2.573*	-0.204	0.762	-0.212	-0.934	-0.771
Silent Generation (%)	-0.069	0.862†	-1.276	0.173	0.044	0.145	-1.357	0.504
Race (baseline = White (%))								
Black (%)	1.126*	0.018	-0.055	0.365*	-0.027	0.194	0.060	0.109
Asian (%)	0.332	-0.852‡	-1.518*	-0.467*	-1.570*	-0.064	-1.718†	-0.001
Others (%)	0.395	0.017	-0.308	0.020	-0.127	0.095	-0.245	0.010
Household Income (baseline = \$75k - \$100k (%))								
< \$75k (%)	0.464	0.287	1.986†	0.261	1.447	-0.167	1.254*	0.234
\$100k -\$150k (%)	0.978	0.347	3.565‡	0.264	4.348‡	0.369	3.194‡	0.354
\$150k + (%)	1.144	0.362	0.775	0.360	2.156†	0.480	1.241*	0.312
Education (baseline = High school or Less (%))								
Some College (%)	0.143	0.137	-0.778	0.131	-0.017	0.110	-0.023	0.063
Bachelor (%)	2.722‡	0.349	2.764‡	0.314	1.825*	-0.056	1.109	-0.108
Grad Degree (%)	-0.400	0.377	-1.748	-0.191	-0.894	0.040	-0.274	0.076
Household Size (baseline = HH Size – 3 (%))								
HH Size -1 (%)	-0.825	-0.033	-0.250	0.060	-0.348	0.042	-0.470	-0.012
HH Size -2 (%)	-1.681†	-0.500	-0.978	-0.152	-2.159†	0.155	-1.069	-0.086
HH Size -4 (%)	0.029	-0.222	-0.759	0.256	-1.421	-0.238	-0.827	-0.082
HH Size -5+ (%)	-0.718	-0.490	-2.078†	-0.362	-2.366†	-0.148	-1.821†	-0.225
1000 · Pop Den	-0.016	-0.004	-0.011	0.003	0.007	0.012*	-0.023	0.005
SVI 1	0.083	0.013	0.151	0.045	0.315‡	0.024	0.238‡	0.039
SVI 2	-0.115‡	0.011	0.028	-0.014	0.077	0.010	0.040	0.002
SVI 4	0.130‡	0.020	0.111†	0.063‡	0.093	0.056‡	0.102†	0.030†
Urban	0.442†	-0.090	0.925‡	-1.155†	0.750†	-0.107	0.744‡	-0.505
1000 · Job Count	0.012‡	0.002	0.018‡	-0.001	0.022‡	-0.002	0.020‡	-0.003
10 · DoorDash Restaurants	0.004†	-0.000	0.006*	0.000	0.009‡	-0.000	0.009‡	-0.000
1000 · COVID-19 Cases	N/A	N/A	0.016	0.065†	0.026	0.008	-0.020	-0.001
1st Vaccination rate (%)	N/A	N/A	N/A	N/A	-0.010	-0.009	0.004	0.006
Constant	-0.185		0.547		-1.079		0.231	
ρ (Global lag)	-0.015		0.026‡		0.032‡		0.027‡	

Table 2.8. Spatial Durbin model estimation results for San Francisco-Oakland-Berkeley, CA MSA

	2019 (N=1,006)		2020 (N=1,127)		2021 (N=1,127)		2022 (N=1,127)	
	β	γ	β	γ	β	γ	β	γ
Age group (baseline = Gen X (%))								
Gen Z (%)	2.925‡	0.019	-1.255	0.118*	-0.092	0.078	0.734	0.030
Millennials (%)	2.888‡	-0.026	-2.639†	0.075	-0.864	0.000	-0.126	-0.019
Baby Boomers (%)	-1.060	0.051	-1.130	0.002	0.027	-0.074	1.198	-0.073
Silent Generation (%)	0.320	0.204‡	-1.283	0.004	-1.093	0.025	-0.744	-0.021
Race (baseline = White (%))								
Black (%)	0.710	0.014	1.927†	-0.028	0.375	0.011	-0.107	0.005
Asian (%)	-0.076	-0.030	-0.425	-0.025	-0.525	-0.033	-0.774†	-0.028
Others (%)	1.086*	-0.038	0.409	-0.054	0.139	-0.071*	-0.048	-0.076†
Household Income (baseline = $75k - $100k (%))								
< $75k (%)	-0.986	0.068	1.243	0.250‡	1.172	0.315‡	0.044	0.291‡
$100k -$150k (%)	-0.633	-0.158*	-0.623	-0.003	0.442	0.020	-0.127	0.008
$150k + (%)	1.588†	0.039	0.978	0.033	1.357	0.110*	0.449	0.080
Education (baseline = High school or Less (%))								
Some College (%)	0.244	0.118†	-1.533	0.021	-2.265†	0.083*	-1.419	0.059
Bachelor (%)	1.116	0.124†	-0.731	-0.069	-0.733	-0.049	0.162	-0.034
Grad Degree (%)	-1.074	0.048	1.011	-0.094*	-0.118	-0.057	0.583	-0.040
Household Size (baseline = HH Size – 3 (%))								
HH Size -1 (%)	-0.079	-0.107	0.110	0.007	0.196	-0.045	0.263	-0.023
HH Size -2 (%)	0.008	-0.031	2.135†	-0.020	2.681‡	-0.060	1.380*	-0.040
HH Size -4 (%)	-2.301‡	-0.153	0.903	0.110	1.198	-0.039	0.315	-0.004
HH Size -5+ (%)	-1.472	0.087	-0.489	-0.195†	-1.038	-0.201†	-0.966	-0.125*
1000 · Pop Den	-0.016‡	0.000	-0.002	0.000	-0.007	0.000	-0.008	0.000
SVI 1	-0.150*	0.016*	-0.189	0.004	-0.095	0.018†	-0.095	0.014†
SVI 2	-0.032	-0.005	-0.047	0.002	0.028	-0.001	0.079	0.001
SVI 4	0.015	-0.009	0.122*	-0.011†	0.060	-0.007	0.106*	-0.010†
Urban	1.478‡	-0.003	2.358‡	-0.008	2.405‡	-0.346	1.690‡	-0.318
1000 · Job Count	0.006‡	0.000†	0.011‡	-0.000†	0.012‡	-0.000†	0.012‡	-0.000†
10 · DoorDash Restaurants	0.001	-0.000	0.004‡	-0.000	0.004‡	-0.000	0.002†	-0.000
1000 · COVID-19 Cases	N/A	N/A	-0.008	0.000	0.001	0.003*	0.042†	0.000
1st Vaccination rate (%)	N/A	N/A	N/A	N/A	0.028	0.004*	0.035*	0.004
Constant	-0.677		0.413		-2.775		-4.172*	
ρ (Global lag)	0.001		0.005‡		0.004‡		0.004‡	

Table 2.9. Spatial Durbin model average direct and indirect impact for Los Angeles-Long Beach-Anaheim, CA MSA

	2019 (N=2,940)		2020 (N=3,134)		2021 (N=3,134)		2022 (N=3,134)	
	ADI	AII	ADI	AII	ADI	AII	ADI	AII
Age group (baseline = Gen X (%))								
Gen Z (%)	0.978*	7.395‡	0.016	6.585	0.354	6.687	0.321	10.007
Millennials (%)	0.775	6.009‡	-0.906	6.492	-1.259*	3.452	-1.497†	5.915
Baby Boomers (%)	-0.316	9.846†	1.366*	5.549	1.187	1.101	1.099	12.038
Silent Generation (%)	-2.324‡	5.163	-0.831	-3.104	-0.278	-8.243	-0.211	6.382
Race (baseline = White (%))								
Black (%)	0.451	0.078	0.119	-1.561	0.041	-2.911	-0.019	-2.028
Asian (%)	-0.544†	-0.185	-1.219‡	2.846*	-1.679‡	3.442†	-1.381‡	1.140
Others (%)	0.523†	-0.772	0.156	-1.866	-0.035	-2.900	0.060	-1.834
Household Income (baseline = $75k - $100k (%))								
< $75k (%)	0.345	2.344	0.135	8.730	0.967	8.272	0.402	11.242
$100k -$150k (%)	-0.377	0.467	0.336	2.628	0.568	-3.339	0.386	-6.640
$150k + (%)	0.371	12.185‡	1.108†	25.285‡	1.697‡	32.89‡	1.1†	33.004‡
Education (baseline = High school or Less (%))								
Some College (%)	-0.380	-0.512	1.851‡	-3.110	2.122‡	-2.265	2.134‡	-2.925
Bachelor (%)	0.94†	2.243*	1.491‡	-8.312†	1.502‡	-9.921*	1.598‡	-7.121
Grad Degree (%)	1.818‡	-5.152‡	1.921‡	-1.581	1.865‡	-7.287	1.976‡	-8.171
Household Size (baseline = HH Size – 3 (%))								
HH Size -1 (%)	1.282‡	0.218	0.038	3.198	0.087	3.998	-0.071	-2.321
HH Size -2 (%)	1.049†	-0.696	-0.038	-10.4*	-0.183	-6.149	-0.064	-10.877
HH Size -4 (%)	0.816	1.158	0.484	-0.230	0.483	-7.311	0.490	-16.98*
HH Size -5+ (%)	-0.572	-3.035	-0.336	-13.35†	-0.468	-12.75*	-0.626	-14.032†
1000 · Pop Den	-0.021‡	-0.003	-0.013‡	-0.021	-0.012†	-0.024	-0.018‡	-0.016
SVI 1	-0.055	0.833‡	0.157†	1.797†	0.212‡	1.739†	0.228‡	1.898†
SVI 2	-0.001	-0.070	0.017	0.492	-0.009	0.908*	-0.037	0.342
SVI 4	0.010	0.100	0.121‡	0.117	0.14‡	0.257	0.103‡	0.380
Urban	0.984†	-8.021‡	1.489‡	-3.693	1.743‡	23.915	1.341†	8.095
1000 · Job Count	0.011‡	0.003	0.003†	-0.049†	0.005‡	-0.05*	0.005‡	-0.043*
10 · DoorDash Restaurants	0.002‡	-0.001	0.003‡	-0.003*	0.004‡	-0.005*	0.004‡	-0.007†
1000 · COVID-19 Cases	N/A	N/A	0.000	-0.031	-0.001	-0.008	0.002	-0.016
1st Vaccination rate (%)	N/A	N/A	N/A	N/A	0.04†	-0.339	0.021	-0.073

Table 2.10. Spatial Durbin model average direct and indirect impact for Riverside-San Bernardino-Ontario, CA MSA

	2019 (N=804)		2020 (N=958)		2021 (N=959)		2022 (N=959)	
	ADI	AII	ADI	AII	ADI	AII	ADI	AII
Age group (baseline = Gen X (%))								
Gen Z (%)	0.283	1.052	-0.514	-1.736	0.527	-3.276	-0.511	-5.249
Millennials (%)	0.283	2.498	-2.031*	-8.885	0.055	-2.437	-1.265	-2.971
Baby Boomers (%)	0.591	-8.023*	-2.649*	-3.964	0.690	-3.308	-1.173	-12.123
Silent Generation (%)	-0.163	6.144†	-1.237	2.054	0.100	2.583	-1.216	7.120
Race (baseline = White (%))								
Black (%)	1.126*	0.011	0.046	5.328*	0.047	3.423	0.09.	1.688
Asian (%)	0.425	-6.1‡	-1.66†	-7.414*	-1.614*	-2.022	-1.733†	-0.723
Others (%)	0.394	0.080	-0.305	0.184	-0.092	1.613	-0.244	0.049
Household Income (baseline = $75k - $100k (%))								
< $75k (%)	0.434	1.992	2.073†	4.569	1.401	-2.122	1.334*	4.074
$100k -$150k (%)	0.942	2.370	3.665‡	5.210	4.543‡	8.988*	3.326‡	6.703†
$150k + (%)	1.106	2.457	0.881	5.563	2.366‡	9.714	1.345†	5.260
Education (baseline = High school or Less (%))								
Some College (%)	0.129	0.961	-0.747	1.624	0.025	1.941	-0.005	0.947
Bachelor (%)	2.688‡	2.204	2.872‡	5.643	1.826*	0.048	1.085	-1.191
Grad Degree (%)	-0.441	2.727	-1.814	-3.462	-0.890	0.202	-0.253	1.050
Household Size (baseline = HH Size – 3 (%))								
HH Size -1 (%)	-0.822	-0.149	-0.235	0.791	-0.337	0.540	-0.478	-0.378
HH Size -2 (%)	-1.629†	-3.385	-1.028	-2.599	-2.126†	1.519	-1.103	-1.750
HH Size -4 (%)	0.053	-1.582	-0.693	3.475	-1.530	-5.011	-0.859	-1.585
HH Size -5+ (%)	-0.666	-3.412	-2.194†	-6.093	-2.452†	-3.962	-1.903†	-4.180
1000 · Pop Den	-0.015	-0.024	-0.010	0.034	0.011	0.21*	-0.021	0.067
SVI 1	0.082	0.081	0.164	0.715	0.328‡	0.607	0.252‡	0.688
SVI 2	-0.116‡	0.090	0.025	-0.193	0.082	0.218	0.041	0.051
SVI 4	0.128‡	0.127	0.13†	0.96‡	0.115†	1.036‡	0.112†	0.497†
Urban	0.453†	-0.689	0.609*	-16.585†	0.718	-1.467	0.598	-7.389
1000 · Job Count	0.012‡	0.011	0.018‡	-0.011	0.021‡	-0.030	0.02‡	-0.040
10 · DoorDash Restaurants	0.004†	-0.002	0.006*	0.005	0.009‡	-0.003	0.009‡	0.002
1000 · COVID-19 Cases	N/A	N/A	0.034	0.952†	0.030	0.154	-0.020	-0.017
1st Vaccination rate (%)	N/A	N/A	N/A	N/A	-0.014	-0.158	0.006	0.098

Table 2.11. Spatial Durbin model average direct and indirect impact for San Francisco-Oakland-Berkeley, CA MSA

	2019 (N=1,006)		2020 (N=1,127)		2021 (N=1,127)		2022 (N=1,127)	
	ADI	AII	ADI	AII	ADI	AII	ADI	AII
Age group (baseline = Gen X (%))								
Gen Z (%)	2.927‡	0.700	-1.073	6.677	0.025	2.371	0.789	1.089
Millennials (%)	2.885‡	-0.796	-2.538†	3.680	-0.869	-0.094	-0.159	-0.630
Baby Boomers (%)	-1.054	1.650	-1.136	-0.252	-0.084	-2.247	1.084	-2.239
Silent Generation (%)	0.344	6.756†	-1.288	-0.187	-1.061	0.629	-0.784	-0.777
Race (baseline = White (%))								
Black (%)	0.711	0.475	1.898†	-1.063	0.393	0.379	-0.099	0.154
Asian (%)	-0.079	-0.985	-0.470	-1.659	-0.578	-1.060	-0.827†	-1.025
Others (%)	1.082*	-1.239	0.324	-3.116	0.032	-2.143	-0.175	-2.505
Household Income (baseline = $75k - $100k (%))								
< $75k (%)	-0.978	2.237	1.664	15.429	1.654	9.737	0.533	9.586
$100k -$150k (%)	-0.651	-5.252*	-0.633	-0.357	0.475	0.660	-0.114	0.249
$150k + (%)	1.593‡	1.337	1.040	2.286	1.53*	3.498	0.586	2.679
Education (baseline = High school or Less (%))								
Some College (%)	0.258	3.902*	-1.512	0.750	-2.153†	2.268	-1.329	1.756
Bachelor (%)	1.131*	4.146†	-0.851	-4.394	-0.811	-1.572	0.106	-1.087
Grad Degree (%)	-1.069	1.574	0.867	-5.303	-0.205	-1.751	0.519	-1.243
Household Size (baseline = HH Size – 3 (%))								
HH Size -1 (%)	-0.092	-3.536	0.123	0.474	0.130	-1.342	0.225	-0.732
HH Size -2 (%)	0.005	-1.019	2.122†	-0.485	2.607‡	-1.500	1.322	-1.135
HH Size -4 (%)	-2.319‡	-5.130	1.092	6.929	1.146	-1.051	0.311	-0.084
HH Size -5+ (%)	-1.462	2.858	-0.814	-11.895	-1.348	-6.237	-1.182	-4.237
1000 · Pop Den	-0.016‡	0.007	-0.002	0.008	-0.006	0.005	-0.008	0.002
SVI 1	-0.149*	0.517*	-0.184	0.174	-0.069	0.522	-0.071	0.464
SVI 2	-0.033	-0.170	-0.044	0.125	0.027	-0.026	0.082	0.056
SVI 4	0.014	-0.288	0.105	-0.596	0.050	-0.208	0.090	-0.305
Urban	1.477‡	-0.050	2.365‡	0.258	1.897†	-10.245	1.166	-10.266
1000 · Job Count	0.006‡	0.011†	0.011‡	-0.015	0.012‡	-0.008	0.012‡	-0.007
10 · DoorDash Restaurants	0.001	-0.001	0.004‡	0.000	0.004‡	-0.001	0.002†	0.000
1000 · COVID-19 Cases	N/A	N/A	-0.008	0.006	0.006	0.096	0.042†	0.009
1st Vaccination rate (%)	N/A	N/A	N/A	N/A	0.035	0.128	0.041†	0.122

2.5.1. Regional differences: a comparative analysis of Southern California and Northern California

The LA MSA and the SF MSA are two of the most populous and economically important regions in California. These regions are geographically distant, and as such, I observed differences in the landscape of their meal delivery markets.

One of the most noticeable differences is the education variable. In the LA MSA (Table 2.9), higher levels of education exhibit a prevailing positive main effect and occasionally an adverse negative spillover effect (Bachelor AII=-8.312† (2020) and Grad Degree AII=-5.152‡ (2019) in Table 2.9) when compared to the baseline category of high school education or less. On the contrary, in the SF MSA (Table 2.11), educational factors seem to play a relatively minor role in meal deliveries. The impact of education level is generally not statistically significant, except for the positive AII in 2019 and a negative ADI for the "Some College" variable in 2021.

In the SF MSA (Table 2.11), before COVID-19, the highest income group had a positive direct impact (ADI=1.593‡ in Table 2.11). Following the onset of the pandemic, the income impact disappeared, except for some relationships significant at the 90% confidence level (ADI=1.53* in Table 2.11). This suggests a shift in dynamics: prior to the pandemic, food delivery appeared to be a convenience primarily enjoyed by higher-income areas, but with COVID-19, income differences have become an unimportant variable in food delivery. In contrast, for the LA MSA (Table 2.9), consistent positive AII was observed in areas with a higher concentration of affluent residents (AII=12.185‡ (2019); 25.285‡ (2020); 32.89‡ (2021); and 33.004‡ (2022) in Table 2.9). This may be due to the greater restaurant diversity and convenient accessibility to dining establishments in affluent neighborhoods. This study examines solely the number of orders, not the food type or food establishment type, making it challenging to refine my explanations.

Although some significant relationships were observed between race and meal delivery demand in the SF MSA, it is challenging to identify a consistent pattern. LA MSA (Table 2.9) shows a consistent negative ADI for Asians. This relationship became even stronger after the outbreak of COVID-19 compared to the pre-pandemic period (ADI=-0.544† (2019); -1.219‡ (2020); -1.679‡ (2021); and -1.381‡ (2022)). On the other hand, I observed a positive spillover effect (AII=2.846* (2020) and 3.442† (2021)), implying that a higher concentration of Asians in neighboring census tracts had a positive impact on the demand for meal deliveries. These contrasting effects between the ADI and AII underscore the importance of considering not only the characteristics of the census tract but also the influence of neighboring areas when examining the relationship between race and meal deliveries.

There are also different ADIs in the age group variables between the LA and the SF MSAs. The SF MSA has a positive relationship between meal deliveries and the proportion of younger generations before COVID-19 (ADI=2.927‡ in Table 2.11), whereas, in the LA MSA, the Silent Generation has a negative direct impact (ADI=-2.324‡ in Table 2.9). This echoes the findings of Chapter 1, where the younger the population, the greater the demand for food delivery. However, this is not necessarily the case when considering total effects. While the age effect was very clear in Chapter 1, the age distribution of the population at the census tract level does not necessarily indicate that there is a high demand for food delivery in neighborhoods with a younger population. Meanwhile, this effect has changed since the onset of the COVID-19 pandemic. The relationship in ADI for the Millennial age group changed from positive to negative (September 2020 model in SF MSA and September 2022 model in LA MSA), and all significant relationships for the other age group variables disappeared.

2.5.2. Comparison between the LA MSA and the Riverside MSA

While the LA MSA is highly urbanized with a large population and high population density, the Riverside MSA is more suburban in nature with a smaller population and a lower population density. According to the Census Bureau’s urban-rural classification, approximately 40.6% of the LA MSA's land area is classified as urban, while the Riverside MSA has only 5.0% of urban land. This difference in urbanization can lead to differences in meal delivery demand between the two regions. For example, in highly urbanized areas, consumers may have greater access to a variety of food options, including dine-in and take-out, which could affect their reliance on meal delivery services. In suburban areas, consumers may have fewer food options and may be more dependent on meal delivery services.

Compared to the LA MSA, the demographic and socioeconomic characteristics of census tracts in the Riverside MSA were not as influential before COVID-19 (Table 2.10). Instead, factors such as the number of jobs and the number of DoorDash partner restaurants had a significant impact on meal deliveries (ADI=0.004† in Table 2.10). This is likely because, prior to the maturity of delivery platforms, accessibility to the service had a greater impact than the residential characteristics of customers in areas outside the urban core.

One peculiarity is that population density is negatively related to meal delivery demand in the LA MSA (ADI=-0.021‡ (2019); -0.013‡(2020); -0.012†(2021); and -0.018‡(2022) in Table 2.9), while it is unrelated in the Riverside MSA. The high density of residential households in the LA MSA does not always translate into high demand for meal deliveries; quite the opposite. As population density increases, the number of households may also increase, resulting in a larger denominator in the dependent variable, the number of meal deliveries normalized by the number of households in the census tract. Thus, while an increase in population density may lead to a higher number of meal deliveries in a census tract, the demand per household may not increase.

In the Riverside MSA, the income variable showed a positive relationship with meal deliveries in higher-income groups following the onset of the pandemic (ADI = 2.366‡ (2021) and 1.345† (2022) in Table 2.10), whereas the relationship between income and meal delivery demand in the LA MSA was observed both in direct effect and spillover effects (Table 2.9).

2.5.3. Consistent patterns in meal delivery demand

To identify favorable environments for meal delivery across study areas and time periods, I examined the relationships that were consistently significant in Table 2.9-2.11. One of the key factors contributing to the high demand for meal deliveries is the urban classification of the census tract. Urban areas tend to have more diverse food options and greater demand for convenient food delivery services. In addition, the fast-paced lifestyles and busy work schedules of urban residents can make meal delivery an attractive option for those who value time and convenience. Therefore, it is not surprising that census tracts classified as urban tend to have higher demand for meal delivery than those in rural or suburban areas.

Second, my results show a positive relationship between the number of jobs in a census tract and the demand for meal deliveries. Areas with a high concentration of businesses may have more people working with less time to prepare meals or eat out. As a result, meal delivery may be a convenient option for busy workers who cannot afford to spend time preparing food or dining out during work hours. In addition, meal delivery may be more readily available in areas with a higher concentration of businesses due to the potential for a larger customer base even before COVID-19. In the LA MSA, the variable of job count (1000 · Job Count) has consistently shown a positive relationship with meal delivery demand, but the strength of the relationship weakened after the onset of the pandemic (ADI=0.011‡ (2019) vs. ADI=0.003† (2020) and 0.005‡ (2021 and 2022) in Table 2.9). This could be due to the increased prevalence of telecommuting after the pandemic or decreased workplace food consumption due to concerns about infection. On the other hand, in the Riverside (ADI=0.012‡ (2019); 0.018‡ (2020); 0.021‡(2021); and 0.02‡ (2022) in Table 2.10) and SF MSAs (ADI=0.006‡ (2019); 0.011‡ (2020); and 0.012‡(2021 and 2022) in Table 2.11), the strength of the relationship between the number of jobs and the demand for meal delivery has increased since the onset of the pandemic.

The third factor is the number of DoorDash partner restaurants in a census tract, which indicates delivery accessibility. A higher number of restaurants available for delivery corresponds to a higher demand for meal delivery. In areas where there are more DoorDash partner restaurants, customers are more likely to use the delivery service across the three MSAs, as it provides a wider range of options for their meals.

2.5.4. Impact of the COVID-19 severity

The result indicates a positive relationship between vaccination rates and meal delivery demand in LA MSA (ADI=0.04† (2021) in Table 2.9), which suggests this increased awareness may lead individuals to increase their reliance on food delivery instead of dining out to minimize the risk of exposure to the virus. This effect disappeared in the 2022 model (Table 2.9). The COVID-19 case variable did not display a distinct pattern in this analysis. This lack of consistent relationship may be because aggregating COVID-19 cases at the county level may limit the model's ability to capture spatial effects accurately.

2.5.5. Social Vulnerability and Meal Delivery Demand

From Tables 2.9, 2.10, and 2.11, I see that there is a statistically significant relationship between the log of the ratio of the number of census tract orders divided by the census tract population and SVI_1 (Socioeconomic Status) and SVI_4 (Housing Type and transportation).

The MSAs in Southern California have a positive relationship in SVI_1, suggesting areas with lower socioeconomic status exhibit higher demand for meal delivery services. In the LA MSA (Table 2.9), spatial spillovers are significant in all models (AII=0.833‡ (2019); 1.797† (2020); 1.739† (2021); and 1.898† (2022) in Table 2.9), and direct effects became prominent post-pandemic (ADI=0.157† (2020); 0.212‡ (2021); and 0.228‡(2022) in Table 2.9). The increasing strength of direct effects over time highlights the growing influence of a census tract's socioeconomic vulnerability on demand for meal delivery services. This trend suggests that areas with lower socioeconomic status are becoming significant drivers of meal delivery demand in LA MSA. The Riverside MSA has a significant coefficient for SVI_1 for 2021 and 2022 (ADI=0.328‡ (2021) and 0.252‡ (2022) in Table 2.10). The shift in significance in 2021 might be attributed to the changing dynamics brought about by the pandemic. As the pandemic unfolded, the MSA might have experienced economic shifts or altered social dynamics that intensified the relationship between lower socioeconomic status (SVI_1) and meal delivery demand.

Second, the positive relationship between meal delivery demand and SVI_4 suggests that communities with higher levels of housing and transportation vulnerability, such as lack of access to a vehicle or crowded housing conditions, may have greater demand for meal deliveries. Except for the 2019 model in the LA MSA, both the LA MSA and the Riverside MSA models consistently showed a positive relationship between SVI_4 and the dependent variable. However, the SVI variables were not significant in the SF MSA (Table 2.11), except for the SVI_1 variable, which is significant at the 90% confidence level in the 2019 model. This divergence could stem from varying population composition, lifestyle patterns, or other contextual factors unique to Southern and Northern California.

2.6. Discussion

From my results, variables that impact the demand for meal delivery in California offer an avenue for comparison with traditional FAFH consumption. Traditional FAFH studies have established robust associations with age, race, income, and education level (among key variables) (Liu et al., 2013; Nagao-Sato & Reicks, 2022; Saksena et al., 2018). Notably, the findings from the 2019 model provided support for certain of these relationships, such as the income effect observed in the SF MSA and the education effect identified in the LA MSA. However, there are cases where these relationships are not supported. This indicates that food consumption patterns are tied to regional characteristics, including economic disparities, cultural diversity, and food accessibility. Furthermore, since previous studies have primarily focused on general FAFH consumption, this study demonstrates that meal delivery behavior exhibits different patterns compared to dine-in options. These findings shed light on the unique characteristics of meal delivery behavior in relation to traditional FAFH patterns.

The result highlights the importance of modeling food delivery at the MSA level instead of for larger geographies to capture heterogeneity. For example, the negative relationship between the percentage of Asian residents and meal delivery demand in the LA MSA suggests the presence of underlying cultural and economic factors specific to census tracts with high Asian population densities that influence meal delivery demand. Though it is difficult to draw conclusions about the dietary patterns of Asian groups based on this variable alone, it is noteworthy that census tracts with higher proportions of Asian residents consistently show lower demand for food delivery compared to census tracts with higher proportions of White residents, regardless of COVID-19. Similarly, the consistent and significant relationship observed over time in the education level variable in the LA MSA and the income variable in Riverside MSA argues for estimating regional instead of statewide models.

However, I found some variables for meal delivery demand that are statistically significant regardless of region and time. These variables, including urban classification, the number of jobs, and the number of delivery restaurants within the delivery area, are primarily associated with service accessibility, which encompasses not only the availability of restaurants but also the delivery infrastructure. Meanwhile, the relationship to population density, which can be considered an indicator of demand size, is either negative or insignificant. This finding should be of interest to firms looking to enter the meal delivery market, as it suggests that accessibility may (at least initially) play a more significant role in determining meal delivery demand than population density.

This study contributes evidence of the impact of meal delivery services on vulnerable populations. My results show a consistent positive relationship between the demand for meal deliveries and the socioeconomic status (SVI_1) index in the LA and Riverside MSAs. This suggests the importance of meal delivery services in addressing food accessibility of vulnerable populations during COVID-19. Areas with lower socioeconomic status may face challenges in accessing traditional food options, and meal delivery service offers a convenient and reliable alternative.

In addition, significant relationships between meal delivery demand and housing type and transportation (SVI_4) in the LA and Riverside MSAs during COVID-19 indicate that meal deliveries played a crucial role in improving food accessibility. My findings also suggest that particularly in the Riverside MSA, with its suburban characteristics, meal delivery services contributed to improved food accessibility even before the pandemic.

The practical and policy implications of the findings are twofold. First, combining data on neighborhood characteristics enables delivery platforms to better understand different communities' unique needs and preferences. This strategy can enhance targeting and customization of delivery services, leading to increased customer satisfaction and market expansion. Secondly, policymakers can use these findings to develop policies and initiatives ensuring equitable food access through meal delivery services. This could involve developing support structures for meal delivery in underserved areas, incentivizing platforms to serve vulnerable communities, and implementing regulations that ensure fair pricing and service quality. Additionally, policies could focus on integrating meal delivery services into food security and public health missions, especially in regions with limited access to nutritious food options.

2.7. Conclusion

In this study, I conducted a spatial analysis of meal delivery demand across three MSAs in California using the Spatial Durbin model, focusing on how this demand has evolved over time and differed across regions. A key aspect of the research involved contrasting meal delivery demand with traditional FAFH consumption patterns, contributing to the current body of food behavior literature. My findings show the presence of heterogeneity in meal deliveries across different MSAs. For example, the demand in urban areas like the LA MSA shows distinct socio-demographic patterns compared to more suburban areas like the Riverside MSA. This variation underscores the influence of local demographics, economic conditions, and lifestyle preferences on meal delivery trends. Also, by identifying variables that are consistently related to meal delivery demand regardless of region and time, such as urban classification, the number of jobs, and the number of delivery restaurants, this study suggests potential directions for business growth and highlights the importance of factors in shaping meal delivery demand. This information can assist food businesses in making decisions regarding market expansion and resource allocation.

My findings also highlight the significance of SVI variables in understanding meal delivery demand. In areas with lower socioeconomic status, as indicated by SVI_1, there was a higher demand for meal delivery services in the LA and Riverside MSAs, suggesting that meal delivery services play a crucial role in enhancing food accessibility for socioeconomically vulnerable populations. Additionally, factors related to housing and transportation (SVI_4) showed a strong relationship with meal delivery demand, indicating that communities facing challenges in housing and mobility are more likely to rely on meal delivery services. Understanding the relationship between social vulnerabilities and demand for meal delivery offers policymakers and stakeholders a foundation for developing focused interventions to improve food access and address disparities in underserved communities. Such initiatives could focus on improving delivery infrastructure, supporting local businesses offering meal delivery options, and ensuring the affordability and availability of nutritious food choices.

This study also has a number of limitations. The first one is linked to the use of secondary data sources. For example, I used five-year averages due to a lack of data for the year 2022 and unreliable data quality for the year 2020. Moreover, LODES employment data is available only for the year 2019, so it does not capture changes in the employment landscape that occurred after the onset of the COVID-19 pandemic. Second, the limited availability of meal delivery restaurant data, which is available only for October 2022 data, may not provide a comprehensive view of the meal delivery landscape during earlier stages of the pandemic, considering the pandemic has had a profound impact on the food service industry. Third, there could be potential biases linked to the aggregation of COVID-19 variables at the county level, particularly in capturing the heterogeneity that exists between census tracts within a county because counties are typically large geographic areas that include diverse communities. Another limitation is that I only examine the frequency of meal deliveries without considering the types of food or restaurants. As a result, there is no clear connection between the consumption of unhealthy food and food delivery.

These limitations naturally point toward several areas for future research. First, recognizing the limitations of county-level data aggregation in COVID-19 variables, future research could explore variables at a finer level of granularity to reflect spatial heterogeneity within a county. Second, researchers could explore additional details related to deliveries, such as meal categories, restaurant attributes, and associated time and expense for delivery. A more comprehensive approach would yield a deeper analysis of the factors influencing consumer choices. For instance, a study examining the popularity of meal categories, such as vegan or ethnic cuisines, could shed light on evolving dietary preferences and cultural influences among various demographic groups. Third, analyzing the logistics of deliveries, including delivery times, distances, and cost structures, could offer an understanding of mobility patterns and logistics challenges in food delivery. Finally, shifting from aggregated spatial models by census areas to spatial panel models should be explored. Panel data models allow for eliminating variables that do not vary much. It would also be valuable to explore the motivations behind meal delivery demand to get a holistic view of how consumer behavior evolves, especially in response to external events like the COVID-19 pandemic. A richer understanding of meal delivery demand dynamics would be useful for targeted policies and interventions that aim at improving food accessibility.

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CHAPTER 3. OPTIMIZATION OF FLEET SIZE AND DELIVERY OPERATIONS IN MEAL DELIVERY PLATFORMS: A graph theory-based approach

3.1. Introduction

The last few years have witnessed a surge in the gig economy, i.e., services provided by people with flexible, temporary, or freelance jobs who are connected to firms by digital platforms. Enabling people to select when and where they work has proven particularly attractive to those seeking alternative employment structures, such as part-time workers, students, and retirees. For businesses, it provides a cheap way to outsource non-central functions. In the U.S. alone, in 2018, it was estimated that the gig economy involved approximately 5 million people and resulted in wage disbursements of $26.6 billion (Mastercard & Kaiser Associates, 2019). With a percentage of 57% of global gig economy wages, transportation-based services (ridesharing, carpooling, restaurant deliveries, and goods deliveries) make up the lion's share of the gig economy (Mastercard & Kaiser Associates, 2020). The proliferation of these digital platforms has fundamentally disrupted established transportation models and reshaped how people access rides and get their deliveries. I focus here on food deliveries, which made up 5.4% of global gig economy wages in 2018.

Over the past few years, restaurant food delivery has undergone a profound transformation. The conventional delivery model required customers to place orders directly with restaurants by phone or via a website. Restaurants would then manage the delivery process using their own resources. The emergence of online food delivery platforms has revolutionized this paradigm, enabling restaurants previously without delivery services to enter the delivery market (Hirschberg et al., 2016). Experts estimate that the online food delivery sector grew by 25% annually between 2015 and 2018, but the COVID-19 pandemic supercharged this growth, with an estimated 550% surge in January 2022 over January 2018 (Perri, 2022; Singh, 2019).

Although the gig economy has benefitted consumers, it is not without drawbacks. For workers, the large potential number of gig drivers creates intense competition, leading to a situation where drivers earn wages close to or below the minimum wage. As a result, there have been campaigns to reclassify gig drivers from contractors to employees (Irving & Maredia, 2022; Pettersson, 2023), which could create a significant burden for platforms. The driver surplus could also contribute to an increase in out-of-service vehicles, which would amplify externalities such as traffic congestion and air pollution (Erhardt et al., 2019). For platforms, ferocious competition is reducing profits and threatening the viability of this new industry. Surprisingly, there is a distinct lack of research on how to efficiently manage the fleet of delivery vehicles.

The purpose of this study is to start addressing these gaps. More specifically, I evaluate the ability of two algorithms—the Karp algorithm (Karp, 1980) and the Hopcroft-Karp algorithm (Hopcroft & Karp, 1973; Vazifeh et al., 2018)—to estimate the optimal fleet size across varying demand conditions in a realistic setting. I also assess metrics such as Vehicle Miles Traveled (VMT), Vehicle Hours Traveled (VHT), work duration, and driver wages, which emanate from the derived fleet sizes. To consider a realistic case study, I simulate the demand for meal deliveries using historical data from the San Francisco area, which I combine with the actual road network and historical travel time information. For added realism, my sensitivity analysis considers parameters like maximum delivery time, order stacking, vehicle dispatch timing, and fleet operating hours.

Findings from this research should be of interest to businesses by presenting a data-driven strategy to better manage delivery fleet sizes, which will enhance operational efficiency and increase customer satisfaction. By limiting externalities from meal deliveries, they should also be of interest to policymakers concerned with the sustainability of meal deliveries. More generally, this paper contributes to the broader discourse on gig economy labor practices by providing insights into the optimization of working conditions and earnings of gig drivers.

The background and literature review section motivates the importance of fleet size in the context of food delivery and the graph theory-based algorithms that form the basis of this study. The data section describes how the demand was generated, while the methods section describes the two algorithms used in this study, and details the parameters used in the sensitivity analyses. They are followed by the results and discussion sections, which precede the concluding section, which summarizes my main findings, outlines some limitations of this work, and proposes avenues for future research.

3.2. Background and Literature Review

3.2.1. Proposition 22 in California

Proposition 22, a significant piece of legislation in California, has been a focal point in the ongoing debate over the classification of gig workers. Passed during the 2020 election, this proposition effectively allows gig economy platforms like Uber, Lyft, DoorDash, and Instacart to maintain their treatment of workers as independent contractors instead of formal employees (Rosenbaum, 2020). The proposition emerged as a direct response to Assembly Bill 5 (AB5), a state law aimed at reclassifying gig workers as employees, affording them enhanced labor protections and benefits (Rapier, 2019).

Proposition 22 is touted as a means of preserving the flexibility that gig workers value. Companies argue that classifying workers as employees could potentially limit their freedom to choose their own schedules and work across multiple platforms (Irving & Maredia, 2022). However, critics argue that Proposition 22 deprives gig workers of essential labor rights and social benefits that come with employee status. These include guaranteed minimum wages, overtime pay, healthcare benefits, and the ability to engage in collective bargaining (O'Brien, 2020). After being approved by voters in 2020, Proposition 22 faced legal challenges. In the subsequent year, a trial judge ruled that it was in violation of the California Constitution due to its encroachment on the exclusive legislative jurisdiction to establish worker compensation laws. As of 2023, the California Supreme Court is on the brink of delivering its final verdict on this legislation. This impending decision holds significant implications for the gig economy's future and the ongoing debate surrounding the classification (Pettersson, 2023).

Delivery platforms compensate drivers based on Proposition 22. For an example of DoorDash, when operating as a Dasher in California, drivers receive at least 120% of minimum wage for active time on the platform, plus $0.34 per mile during active time, when driving a motor vehicle. Tips don't count toward the guaranteed earnings (DoorDash, n.d.). If, at the end of the week, the driver's earning is less than the guaranteed amount for the week, the platform pays the difference. Uber also ensures that drivers receive at least 120% of the minimum wage while giving rides or making deliveries. Additionally, they offer up to $424.76 per month as a healthcare stipend, along with a range of healthcare benefits within specific parameters (Irving & Maredia, 2022). As a result of this cost structure, the traditional model of low barriers of entry for drivers to meet demand through a large driver pool may not be as suitable anymore. This is because the addition of new drivers to the platform can lead to increased costs for the platform.

3.2.2. Pickup and delivery problems (PDPs)

The Pickup and Delivery Problems (PDPs) represent a well-established class of vehicle routing problems that have been extensively explored for over four decades across various domains, including passenger transportation, logistics, emergency medical services, and robotics (Berbeglia et al., 2007). To provide a clearer understanding of the research focus and methodologies in this field, PDP methods are often categorized based on two key criteria (Berbeglia et al., 2007, 2010):

A. Availability of Information: The categorization of PDP methods begins with the availability of information. This criterion distinguishes between three main problem types:

- Static Problems: These problems assume that all information is deterministic and fixed from the outset.

- Dynamic Problems: In dynamic problems, information is gradually revealed over time, allowing for adaptation and decision-making in real time.

- Stochastic Problems: Stochastic problems involve random generation of certain information using well-known probability distributions. This introduces an element of uncertainty into the problem.

B. Number of Origins and Destinations: The second criterion categorizes PDPs into three groups, differentiated by the nature of relationships between the origins and destinations of commodities:

- Many-to-Many Problems: In these scenarios, each vertex within the system has the potential to act as both a source and a destination for any commodity.

- One-to-Many-to-One Problems: In these problems, the flows of commodities involve goods originating from a central depot and destined for customer vertices, along with commodities available at customer locations that require transportation back to the depot.

- One-to-One Problems: These problems involve each commodity having a specific origin and a designated destination.

This classification framework serves to structure the diverse landscape of PDPs, enabling researchers to delineate the nature of the problem they are addressing and tailor their methodologies accordingly.

This study is dedicated to addressing static and one-to-one pickup and delivery problems, where each food order is associated with precisely one pickup restaurant and one predetermined delivery location. As classified by Berbeglia et al. (2007), this problem falls under the category of the multi-vehicle one-to-one routing problem with pickups and deliveries. Numerous approaches grounded in mathematical programming have been developed to tackle the Vehicle Routing Problem with Pickups and Deliveries (VRPPD) along with time window constraints (Cherkesly et al., 2015; Cordeau, 2006; Dumas et al., 1991; Ropke & Cordeau, 2009; Savelsbergh & Sol, 1998; Xu et al., 2003). However, it is worth highlighting that these algorithms have inherent limitations in terms of their capacity to effectively manage larger volumes of trips or vehicles.

Recognizing the practical need to manage larger-scale scenarios, several heuristic frameworks have been introduced to tackle this challenge. Researchers have proposed alternative approaches to address the size-related limitations of existing algorithms. Some of these frameworks include those developed (Bent & Hentenryck, 2006; Ropke & Pisinger, 2006; Wang et al., 2015). These heuristic techniques aim to strike a balance between computational efficiency and solution quality, making them valuable tools for solving real-world problems at a larger scale.

3.2.3. Graph-based approach

This study utilizes the graph-based approach for several reasons. First, the graph-based approach is particularly well-suited for addressing scenarios where each food package corresponds to a single pickup restaurant and a pre-designated delivery location, as is the case in this study. This characteristic aligns with the static and one-to-one pickup and delivery problems under investigation. Moreover, it offers advantages in terms of computational efficiency and scalability. Unlike some of the previously mentioned accurate methods and heuristic frameworks, which can face limitations when dealing with a larger number of trips or vehicles, a graph algorithm provides a more flexible framework that can effectively handle a broader scope of scenarios. This ability to manage larger-scale scenarios is vital for accommodating the complexities of real-world food delivery operations, where the volume of trips and vehicles can be substantial. Furthermore, the nature of the graph-based optimization process is conducive to minimizing the distance and time traveled by the vehicles while ensuring efficient pairing of pickups and deliveries. This directly aligns with the objectives of pickup and delivery optimization in the food delivery context.

Santi et al. (2014) introduce the innovative concept of “shareability networks” to address substantial vehicle-pooling challenges. This approach involves translating potential combinations of shared trips into a graphical representation. This representation can be effectively optimized using existing assignment algorithms. They demonstrate the applicability of this approach by revealing the potential for a significant portion of taxi trips (up to 80 percent) in New York City, USA, to be shared. Alonso-Mora et al. (2017) enhance the algorithm with pruning and insertion heuristics, thus enabling more computationally efficient solutions. They address the limitation of the previous study that the number of candidate taxis evaluated for each shared trip is limited by extending the scope of candidate taxis evaluated for shared trips. Additionally, their work introduces the notion of imposing maximum customer wait times as a constraint, which accelerates computational processes.

Vazifeh et al. (2018) similarly utilized the idea of a shareability network in solving the optimal fleet design problem. Vazifeh et al. (2018) leverage the Hopcroft-Karp algorithm, originally proposed by Hopcroft and Karp in 1973, to address the complexity of maximizing bipartite matching in a computationally efficient manner. This algorithm's time complexity of $O(n^{2.5})$ makes it well-suited for handling extensive datasets, such as the hundreds of thousands of ridesourcing trips encountered in New York City. The object of the research is to minimize fleet size to fulfill all service requests without any passenger delays. It presents that calculating the minimum fleet size is equivalent to the finding the number of paths in the minimum path cover which considered NP-hard for an arbitrary directed network. By constructing a directed graph and using the Hopcroft-Karp algorithm, the minimum fleet problem has been resolved efficiently and accurately. Following the pioneering study by Vazifeh et al. (2018), researchers have delved into investigating optimal fleet sizes across different mobility scenarios, such as taxis (Yu et al., 2023; Zhao et al., 2023), shared autonomous vehicles (Liu et al., 2022; Qu et al., 2022; Wang, 2020), electric buses (Wang et al., 2023), and shared autonomous scooters (Kondor et al., 2022). In the context of food delivery, Wang (2020) incorporates this approach specifically for optimizing the delivery service route with fixed pickup windows.

One notable characteristic of the Hopcroft-Karp algorithm is that it does not inherently consider edge weights. It focuses on finding maximum bipartite matchings based on the structure of the graph rather than the weights associated with the edges. This can be both an advantage and a limitation, as it simplifies the algorithm's implementation and reduces computational complexity, but it may not capture the characteristics that edge weights can convey. For instance, in situations where edges represent crucial factors like distances or costs, the algorithm's lack of attention to edge weights might hinder its accuracy in reflecting the real-world significance of these factors. This study leverages Karp's algorithm (Karp, 1980) while incorporating a strategy that takes edge weights into account, introducing a tradeoff in performance. Furthermore, I aim to conduct a comparative analysis between the methodology proposed by Vazifeh et al. (2018) and this approach.

3.3. Data

The ideal form of data for this research would be transaction records detailing who, when, and where orders are placed. However, such data is limited by the issue of personally identifiable information (PII). Including such extensive information risks identifying individuals from the data, even for research purposes. In addition, the ability to obtain data directly from platforms is limited, so most available data is sample-based rather than comprehensive. As a result, obtaining accurate local demand data is challenging. Given these limitations, it is important to recognize that it may be best to use less accurate but realistic data that may not be perfectly representative of real-world patterns. As such, this study acknowledges its limitations.

In this study, the data used for generating the realistic dataset are primarily from two sources: 1) meal delivery data for 251 restaurants in the city of San Francisco for a two-week period (April 17 to April 30) collected from Eat24.com in 2017 and 2) transaction data collected from the data platform for each September month from 2019 to 2022. The following is an explanation of how this study derived a realistic demand distribution. I used two datasets: statistics on meal delivery and company financial disclosures.

3.3.1. Demand

I use historical delivery data acquired from Eat24.com. This dataset provides the cumulative number of deliveries originating from partner restaurants in San Francisco. The dataset covers a span of two weeks, specifically from April 17, 2017, to April 30, 2017 (Figure 3.1). Eat24.com was a web-based food delivery service established in the Bay Area in 2008. In 2017, it was one of the main online food delivery companies in San Francisco, with a 22.2% market share (Recode, 2017). Although the dataset lacks information about factors such as order size, food type, and customer details, the count of delivery trips is useful for approximating the market size during that period from the logistics perspective. I extrapolated the forthcoming transaction volumes by leveraging the transaction data from Eat24 in 2017 and the Meal Delivery Sales Index (Figure 3.2). As a practical expedient, I have presupposed that the sales in January 2018 align with the average sales of 2017.

I estimated the demand size of Monday in San Francisco to be 6,060 orders as of April 2017, based on the fact that Eat24 held a 22.2% market share on Mondays, with a recorded demand of 1,345 orders. Furthermore, assuming a 210% to 220% growth compared to that period (Figure 3.2), the demand on Monday was projected to be 13,000 orders as of September 2019. Considering the acquisition of Eat24 by Grubhub, which held about 18% market share in 2019 (T. Kaiser, 2019), I set the demand size for experimentation at 2,300 orders. This demand size serves as the basis for investigating and analyzing various scenarios. The exact demand size isn't the most critical aspect of this study. As demand increases, more vehicles are needed, leading to longer delivery times and distances. The primary goal of this study is to shed light on how specific operational factors of food delivery platforms influence meal delivery performance.

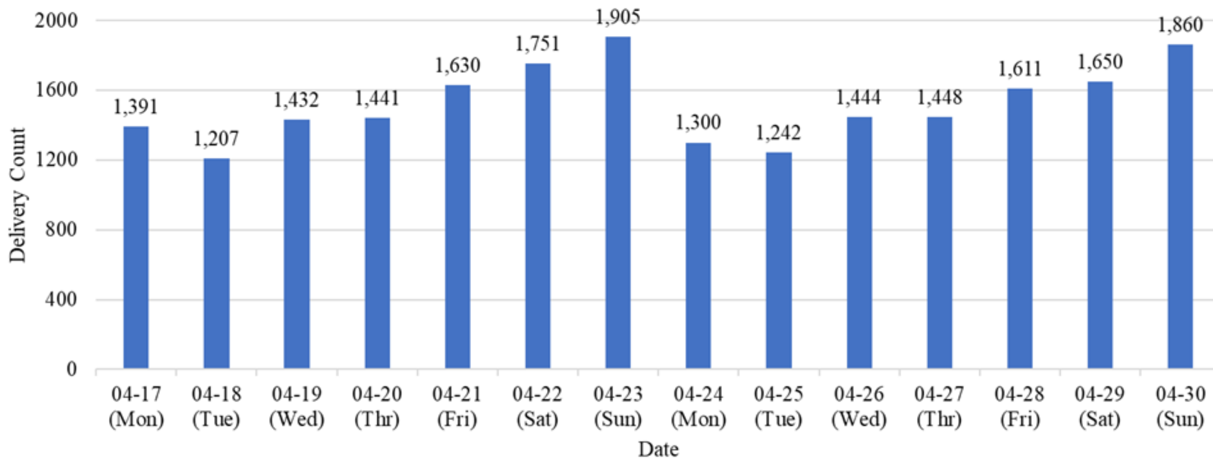


Figure 3.1. The number of Eat24 delivery orders in 2017

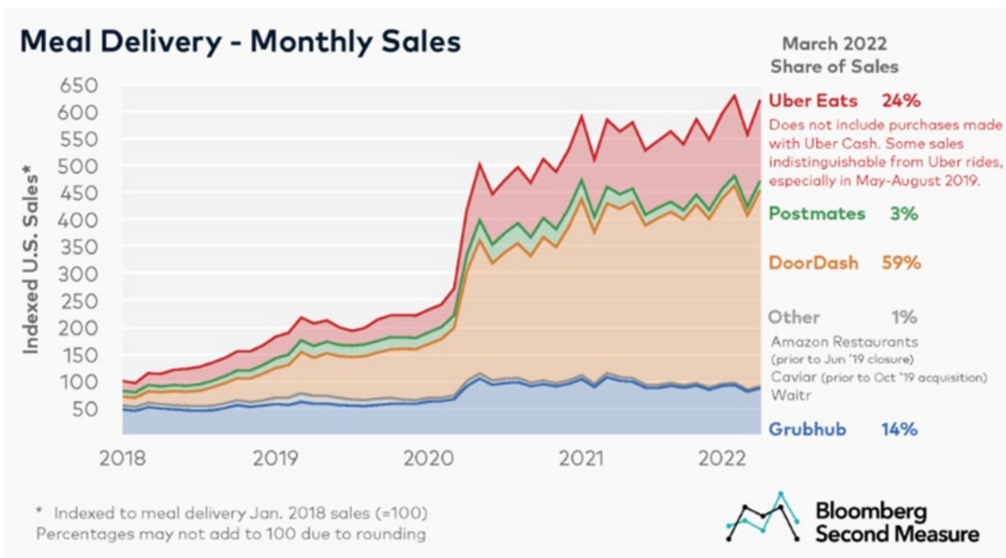


Figure 3.2. Monthly sales in the meal delivery market in the U.S

3.3.2. Spatial distribution

The spatial granularity of the meal delivery transaction data in this study is identified by the zip+4 code. Although the zip+4 system does not provide precise latitude and longitude coordinates for specific locations, it offers a detailed spatial unit for this study. The zip+4 refines a five-digit ZIP code region, delineating a more localized zone, such as a single side of a street, a specific building, or a smaller geographical subdivision (USPS, 2021). I leveraged a matching table between zip+4 codes and Census Blocks provided by the data source. This allowed me to convert the respective zip+4 locations to latitude and longitude coordinates using the center point of each Census Block. In an urban environment, a census block is generally equivalent to a city block encircled by streets on all sides (Rossiter, 2021). Given that the focus area is the city of San Francisco, this approach allows a reasonable representation of the geographical positions associated with the zip+4 codes. There were geographic changes in the 2020 Census, but I employ the 2010 Census geography to prevent any bias in the results of framework due to geographical changes.

The transaction data includes records where either the pickup, drop-off, or both locations are within San Francisco (See Table 3.1). There are 23,064 records in September 2019, 43,390 in September 2020, 38,168 in September 2021, and 24,633 in September 2022. These figures encompass scenarios where both the pickup and drop-off locations are within San Francisco, cases where one of them is within San Francisco while the other is outside, and instances where one location is within San Francisco while the other is missing. Out of these figures, 267 records in 2019, 631 in 2020, 950 in 2021, and 0 in 2022 have either a pickup or drop-off location outside of San Francisco. These cases have been excluded from the discussion. For missing locations, it is assumed for convenience that they are located within San Francisco.

Table 3.1. The number of transactions related to San Francisco

Year	2019	2020	2021	2022
Both in SF	8,685	12,610	116	6
Only pickup in SF	75	215	0	0
Only drop-off in SF	192	416	950	0
Pickup missing	11,959	27,301	35,877	20,279
Drop-off missing	2,153	2,848	1,225	4,348
Total	23,064	43,390	38,168	24,633

Overall, transactions where the drop-off location is missing are relatively small, while missing pickup locations are more prevalent, especially in the years 2021 and 2022. Furthermore, the availability of paired pickup and drop-off locations is not extensive. Considering these observations, I have chosen to adopt a multi-level approach for generating pickup and drop-off pairs for delivery routes. In this approach, rather than using the pairs of pickup and drop-off locations to directly create delivery routes, I generate an origin distribution based on the probability of pickup location for the given demand. Subsequently, I create a destination distribution within the delivery area using the probability of drop-off location.

3.3.2.1. Pickup (restaurant) locations

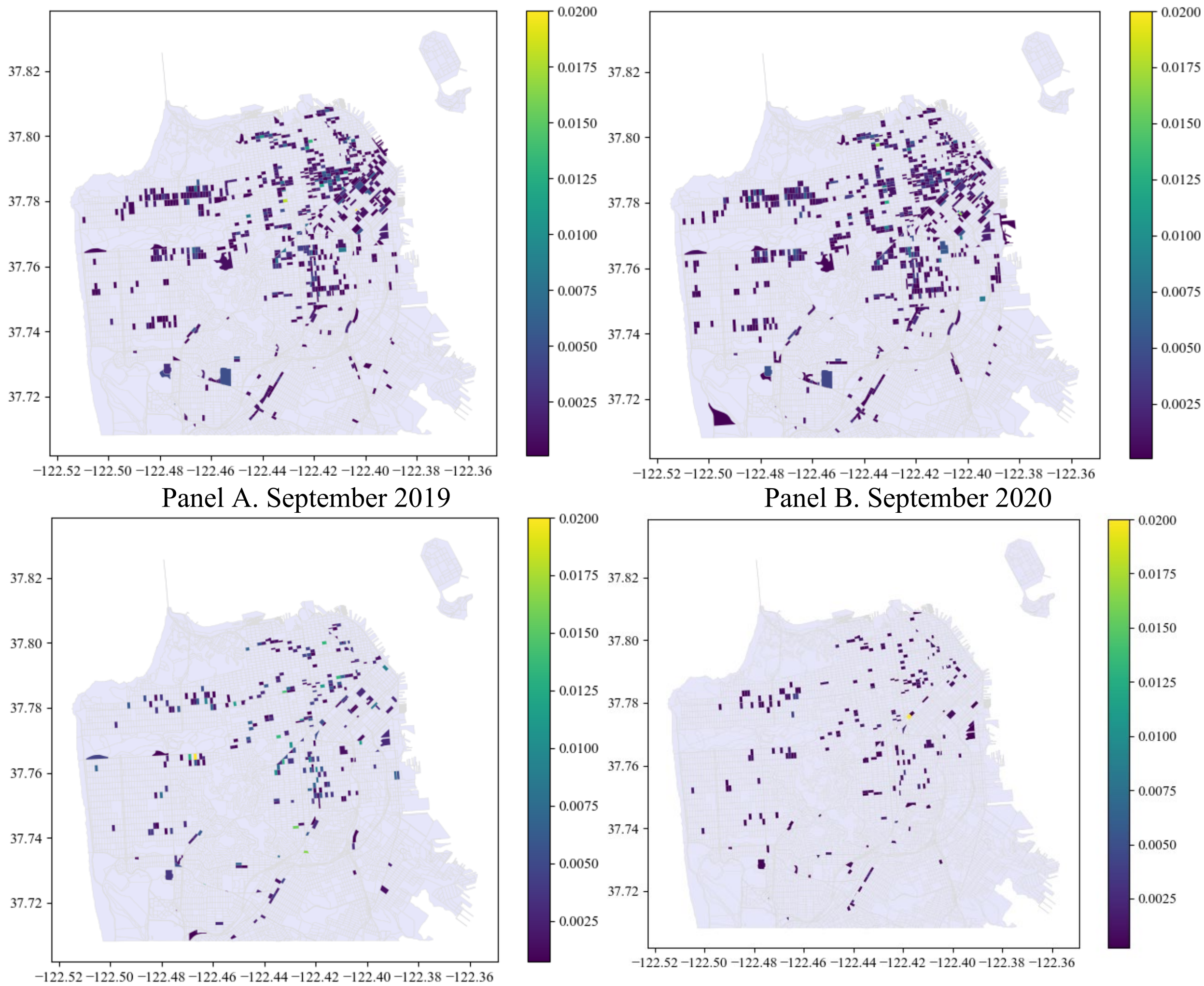
As mentioned above, the data doesn't include restaurant location information for all transactions. For instance, in 2019, 10,913 (47.3%) of transactions within San Francisco had restaurant location data available. In contrast, this proportion decreased to 36.1% in 2020, 3.5% in 2021, and about 17.7% in 2022. The platforms providing location information also changed; in 2019, four platforms (Grubhub, Doordash, Postmates, and UberEats) offered this data, whereas by 2021 and 2022, the number decreased to two (Grubhub and Postmates). For this reason, I consider it unreliable to utilize separate spatial distributions of restaurants for each year. In Figure 3.3, there are significantly more missing census blocks for the years 2021 and 2022 compared to 2019 and 2020. However, it's noteworthy that among the data points present, there is no substantial deviation in locations when compared to the years 2019 and 2020. As a result, I have concluded that while the spatial distribution of restaurants remains relatively consistent, the presence of missing data is primarily attributed to data collection factors.

3.3.3.2. Drop-off (Customer) locations

Conversely, drop-off location information is present for 90.3% of transactions in 2019, 92.9% in 2020, 96.8% in 2021, and 82.3% in 2022. Consequently, it can be deduced that the distribution of delivery destinations is estimable for each respective year. As previously mentioned, I aggregated the customer locations coded by each zip+4 to the census block level, tallying the number of transactions for each individual block (Figure 3.4).

3.3.3.3. Pickup and drop-off pair

Using the weighted probabilities derived from the aggregated counts of pickups at the census block level, I estimate the number of delivery orders made in each block based on the given total demand. For instance, if there were 1,000 delivery demands, I conducted 1,000 random choices weighted by the frequency. In contrast, for drop-off locations, I consider the practical delivery areas for each restaurant, as a restaurant may not be able to fulfill delivery orders across the entirety of San Francisco. Therefore, I identified realistic delivery zones for each restaurant to determine where their drop-off locations would be. Restaurants have the autonomy to define their respective delivery areas and set delivery fees. However, platforms, for example, Grubhub, recommend maintaining delivery times within 15 minutes to ensure the delivery of warm or fresh food and to prevent excessive customer waiting (Grubhub, 2016). I have considered factors such as parking, traffic conditions, and the distance between parking spots and restaurants. As a result, I assume a pure travel time of 10 minutes. I define the delivery areas for each restaurant based on historical traffic conditions, considering a typical Wednesday (14th) in September 2022 at 6:00 PM, which is a peak demand time (Figure 3.5). The Bing Map API was employed to generate the isochrones. The isochrone shapes for different areas would vary based on their unique geographical and urban characteristics.



Panel A. September 2019

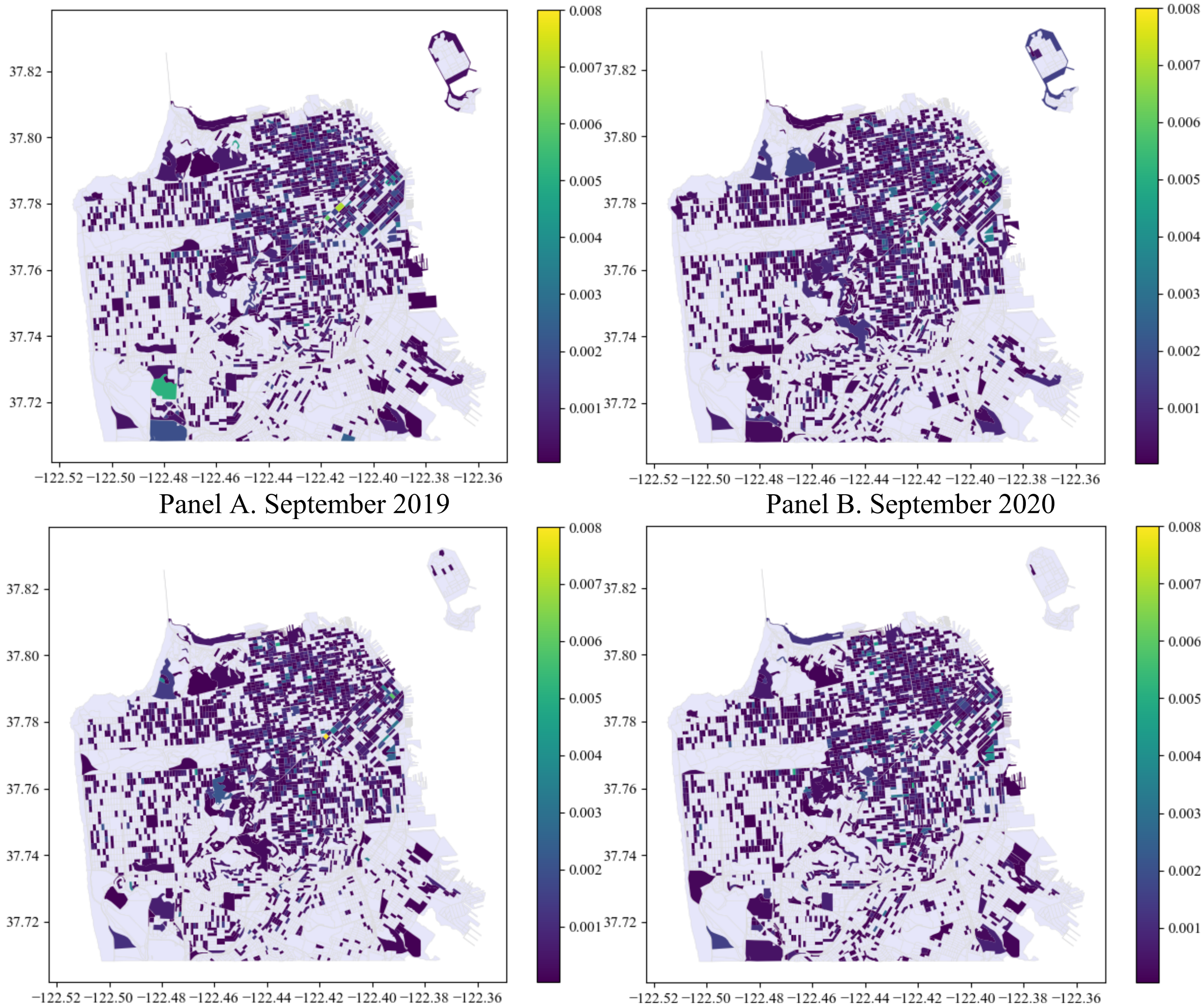
Panel B. September 2020

Panel C. September 2021

Panel D. September 2022

Figure 3.3. The spatial distribution of restaurants aggregated into census blocks.

Utilizing the defined delivery areas, I extracted the reachable blocks from each restaurant's location. This selection enabled the estimation of the probability of each block as a potential destination. Finally, I determine the destination for a delivery order by implementing a random choice process weighted by the transaction frequency.



Panel A. September 2019

Panel B. September 2020

Panel C. September 2021

Panel D. September 2022

Figure 3.4. The spatial distribution of customer locations aggregated into census blocks.

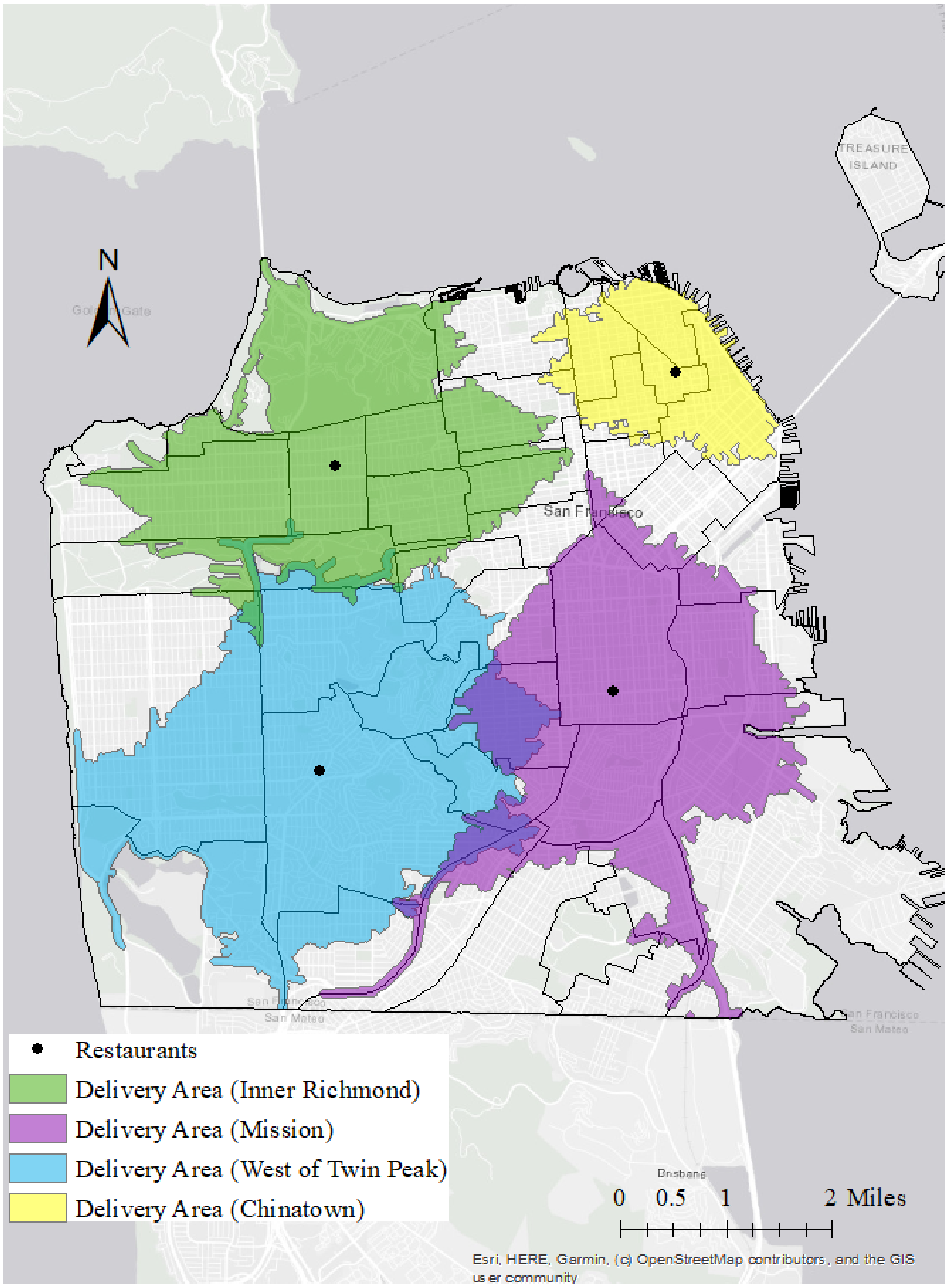
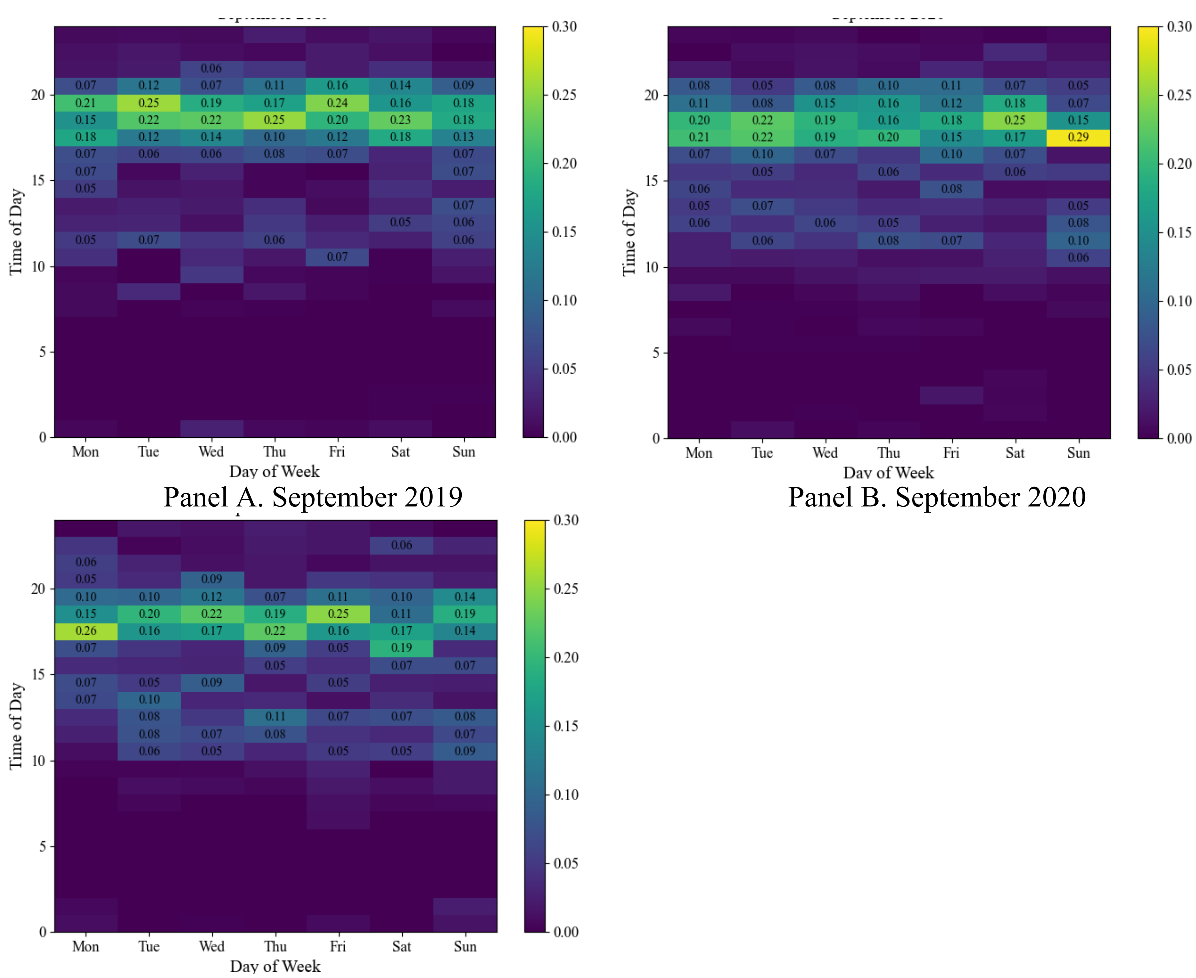


Figure 3.5. Examples of restaurant delivery areas represented by isochrones

3.3.3. Temporal distribution

The timing of deliveries, along with location, is a critical factor in delivery fleet planning. Unfortunately, the transaction dataset only provides order timing information for a limited subset: 3,274 records in 2019, 3,577 in 2020, and 2,669 in 2021. In 2022, this information is entirely absent for all San Francisco transactions. Consequently, the differentiation of order timing probabilities based on transaction types, such as restaurant-specific order timing, was not feasible. Instead, I generated temporal distributions representative of each year's September for each day of the week and time of day. The temporal distribution for the year 2022 has been excluded from Figure 3.6 due to the absence of data for that year.



Panel A. September 2019

Panel B. September 2020

Panel C. September 2021

Figure 3.6. The temporal distribution of orders by the time of day

3.4. Method

3.4.1. Shareability Network

This study aims to determine the optimal fleet size using the Hopcroft-Karp algorithm and the Karp algorithm and then compare their performance. To achieve this, I need to construct a "shareability network" (Santi et al., 2014) in the form of a bipartite graph, which serves as the common input for both algorithms. It captures all the feasible delivery route options, including the list of dispatchable vehicles at the restaurant and the potential combinations of stocked orders. Figure 3.7 provides a concise depiction of how the shareability network is constructed and utilized by the matching algorithm.

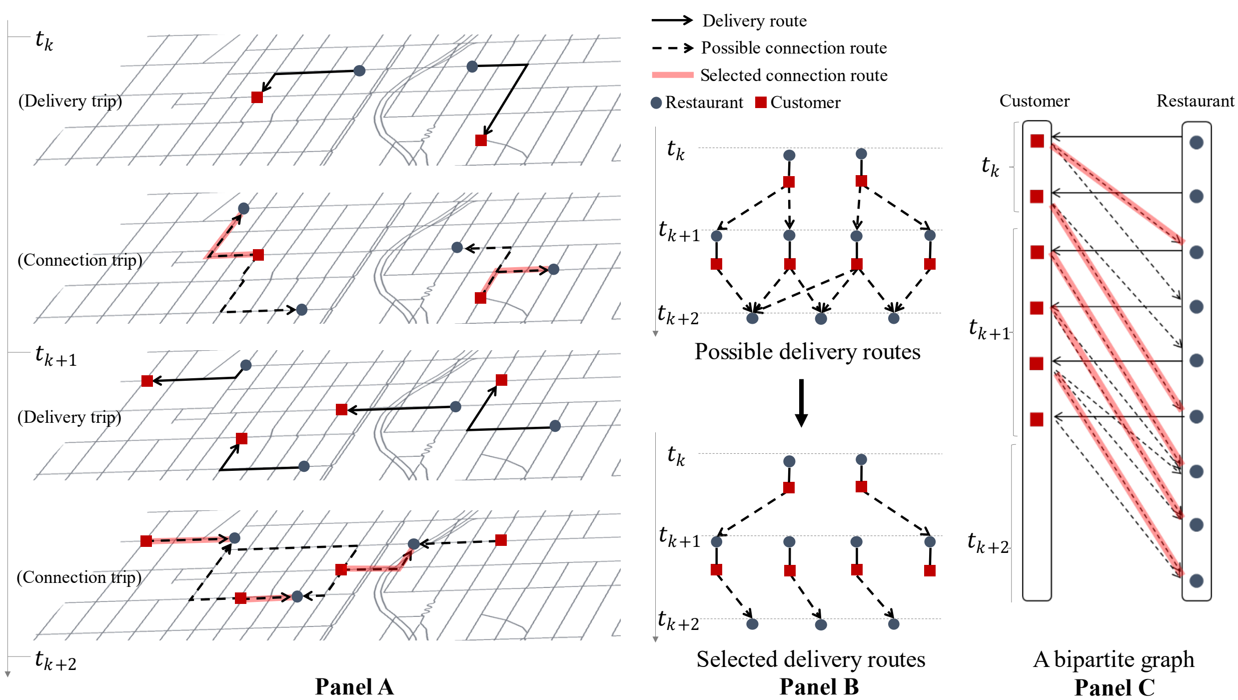


Figure 3.7. Example of a shareability network and bipartite graph

Given delivery orders $D_i \in D$ $(i = 1, 2, \dots, n)$, let a directed graph defined as G=(N, E), where a node $n_i \in N$ that corresponds to a pick-up (restaurant) location (l_i^p), $n_{n+i} \in N$ drop-off (customer) location (l_i^d) in delivery trip $D_i \in D$, the direct edges $(n_i, n_{n+i}) \in E$ (delivery route, solid lines in Figure 7), the direct edges $(n_{n+i}, n_j) \in E$ (connection route, dash lines in Figure 3.7), and t_{ij} the connection time between l_i^d and l_j^p. The connection routes satisfy the following two conditions: 1) a vehicle is required to reach the pick-up location (l_j^p), no later than the specified pickup time (t_j^p), $\left(t_i^d + t_{ij}\right) \leq t_j^p$ and 2) The connection time (t_{ij}) must not exceed the maximum allowable time (t_{max}), $t_j^p - t_i^d \leq t_{max}$. The directed graph (G) is acyclic by its very nature, as it has time and spatial constraints of delivery trips, prohibiting any possibility of time travel. The existence of a connection trip in the graph means that the two delivery orders can be consecutively served by one vehicle (See Panel B of Figure 3.7). Each path in the entire graph (G) represents a set of routes that a single vehicle can operate throughout the day.

Figure 3.8 illustrates the steps to create a shareability network. Orders are sorted chronologically in the data generation step. For each time (t_k), trips in the array of Predecessors find the possible pairs of connection trips fulfilling the two constraints: 1) a vehicle is supposed to arrive at l_i^p on or before t_i^p (line 15) and 2) the connection time is at most t_{max} (line 12). The array of Predecessors stores trips whose connection time is shorter than t_{max}. One can imagine that a vehicle in idle condition searches for possible pick-up orders and stops searching and its operation if it does not have any possible connection trip even until the waiting time exceeds t_{max}. When the last order of the day is added to the graph, it is ready to implement a matching algorithm.

Algorithm 1: Shareability Network

Input: Delivery trips (D) ($tuple(d, l^p, l^d, t^p, t^d)$)

Output: Bipartite graph (G) for daily delivery orders and Connection Trips (C)

$G(N, E) := (\emptyset, \emptyset)$

Connection trips (C) $\leftarrow$ [ ]($C_{ij} = tuple(d_i, d_j, l_i^d, l_j^p, t_i^d, t_j^p, t_{ij})$)

//Considering two consecutive orders, i is index for the first order trip and j is index for the second order trip.

Predecessors (P) $\leftarrow$ [ ]

Time set (T) $\leftarrow$ set(t^d) // Unique set of pickup times

foreach $t_k \in T$ **do**

  Get all deliveries at t_k

  Add nodes for the trips departing at t_k to G

  Add the trips to Predecessors P

  // trips in P are considered as D_i (the first trip of two consecutive trips)

  foreach D_i in P **do**

    if (t_{k+1}) - $t_i^d \leq t_{max}$ **then**

      // If connection time is smaller than the upper bound connection times

      foreach trips departing at t_{k+1} // D_j (the second trip of two consecutive trips) **do**

        if $t_i^d + \delta_i \leq t_j^p$ **then**

          // If the vehicle can arrive at the restaurant on or before food is ready

          Add $C_{ij} = tuple(d_i, d_j, l_i^d, l_j^p, t_i^d, t_j^p, t_{ij})$ into C

          Add an edge between D_i and D_j into G

      end

    else

      // connection time is larger than the upper bound connection time

      del p in P

    end

  end

end

Figure 3.8. Algorithm to produce the Shareability graph (G)

3.4.2. Hopcroft-Karp algorithm

The Hopcroft-Karp algorithm (Hopcroft & Karp, 1973) is a graph algorithm used for solving the maximum bipartite matching problem. In this problem, given a bipartite graph where nodes can be divided into two distinct sets, the algorithm aims to find the largest possible set of edges (matching) such that no two edges share a common node. The algorithm operates by iteratively improving the current matching. It starts with an initial matching and repeatedly augments it by finding augmenting paths in the graph. An augmenting path is a path that alternates between unmatched and matched edges and starts and ends with unmatched nodes. Through alternating along these paths, the algorithm enlarges the matching size. Hopcroft-Karp is known for its efficiency and has a time complexity of $\mathrm{O}(\sqrt{V} * \mathrm{E})$, where V is the number of nodes and E is the number of edges in the graph.

Figure 3.7 presents how the Hopcroft-Karp algorithm minimizes food delivery fleet size and vehicle deployment strategy. The figure showcases a series of delivery trips occurring between time t_k and t_{k+2} on the map (Panel A of Figure 3.7). At time t_k, two delivery requests are indicated. As depicted by the solid lines, two vehicles complete these deliveries. Following this, each vehicle searches for nearby restaurants that can be reached from their current locations to fulfill the next delivery pickups, considering the four requests available at time t_{k+1} (possible connection routes, dashed line). At time t_{k+1}, two additional vehicles enter to serve additional delivery requests. After fulfilling the four deliveries, the vehicles explore feasible connection routes to three pickup locations (restaurants) at time t_{k+2}. To implement the Hopcroft-Karp algorithm, the graph representation transitions to a bipartite structure, presented in Panel C of Figure 3.7. In this bipartite graph, each distinct set represents customer and restaurant locations, respectively, with edges indicating potential routes connecting these locations. The Hopcroft-Karp algorithm determines the size of the minimum path cover and establishes corresponding vehicle routes. These selected routes are represented in Panel B of Figure 3.7 or highlighted in red in Panels A and C.

3.4.3. Karp Algorithm

The goal of the Karp algorithm (Karp, 1980) is to find the path (P) and the associated quantities y(v). This optimization task is tailored to a scenario involving meal deliveries, where the input data consists of a directed graph G = <V, E>. The vertex set V is composed of nodes representing various locations, and edges in E represent potential routes between these locations. Two specific sets play a crucial role: S represents the set of start vertices, which correspond to the origins of meal deliveries, and T denotes the set of target vertices. The sets S and T are constructed to ensure that they do not overlap ($S \cap T = \emptyset$). Additionally, each edge <u,v> is associated with a nonnegative cost (c(u,v)), which quantifies the cost to traverse that edge. For every vertex $v \in V$, OUT(v) represents the set of edges directed out of v, and y(v) represents the minimum cost of a path from a vertex in S to a vertex in $T \cup \{v\}$. The algorithm iteratively calculates y(v) and the associated minimum-cost paths. In each iteration of the while loop, the set R denotes vertices for which y(v) has been determined. The set PATHSET contains the final edge of a minimum-cost path from S to vertices $v \in R\text{-}S$. The set EDGE comprises edges departing from vertices in R that have not yet been processed.

The algorithm predominantly focuses on operations concerning the EDGE set, where:

(a) When a vertex y is added to the set R, the algorithm performs the operation EDGE = EDGE $\cup$ OUT(y). This action indicates that y is now part of the process of finding the best path.

(b) An edge <x,y> is selected from EDGE to minimize y(x) + c(x,y), with c(x,y) representing edge cost.

The efficiency of these operations relies on the choice of the data structure for representing EDGE, with a priority queue that organizes items by value. The priority queue facilitates initialization, insertion, and deletion operations. The overall time complexity of EDGE operations during algorithm execution is $O(|E| \log|E|)$, considering priority queue operations for edge selection. Other operations, involving initializing, inserting, and deleting items contribute to an overall time complexity of $O(|V| + |E| \log|E|)$.

The computation of an optimal assignment involves executing the minimum-cost path algorithm |X| times. Each execution uses an augmentation digraph based on the current matching, with unoccupied sources as start vertices and unoccupied destinations as target vertices. Due to the augmentation graph's structure with $|X| + |Y|$ vertices and $|X|\bullet|Y|$ edges, each augmenting path computation takes $O(|X|\bullet|Y|\bullet\log|Y|)$ time. Consequently, the entire execution time of the assignment algorithm is $O(|X|^2\bullet|Y|\bullet\log|Y|)$.

By refining the algorithm's approach, the overall execution time is reduced. The modifications to the algorithm, including the handling of backward edges and the insertion of pairs <x,y> into EDGE, contribute to this reduction in time complexity. These changes optimize the algorithm's efficiency and reduce redundant operations, leading to the more favorable complexity of $O(|X|\bullet|Y|\bullet\log|Y|)$

3.4.4. Key parameters in meal delivery service

Figure 3.9 illustrates a cycle from when a customer accesses the platform to when they place an order and receive their food, with key events represented by key stakeholders. The cycle begins with the customer accessing the platform, which is the first point of contact between the customer and the meal delivery system. Once an order is placed on the delivery platform, the order is forwarded to the restaurant and food preparation begins. At the same time, delivery logistics are activated. The platform dispatches vehicles around the restaurant to assign deliveries. The assigned vehicles head to the restaurant to pick up the food, and when the food is ready, they drive to the customer's location to drop it off, completing one cycle of food delivery. The platform orchestrates this cycle, tracking the state of the stakeholders and passing messages between them.

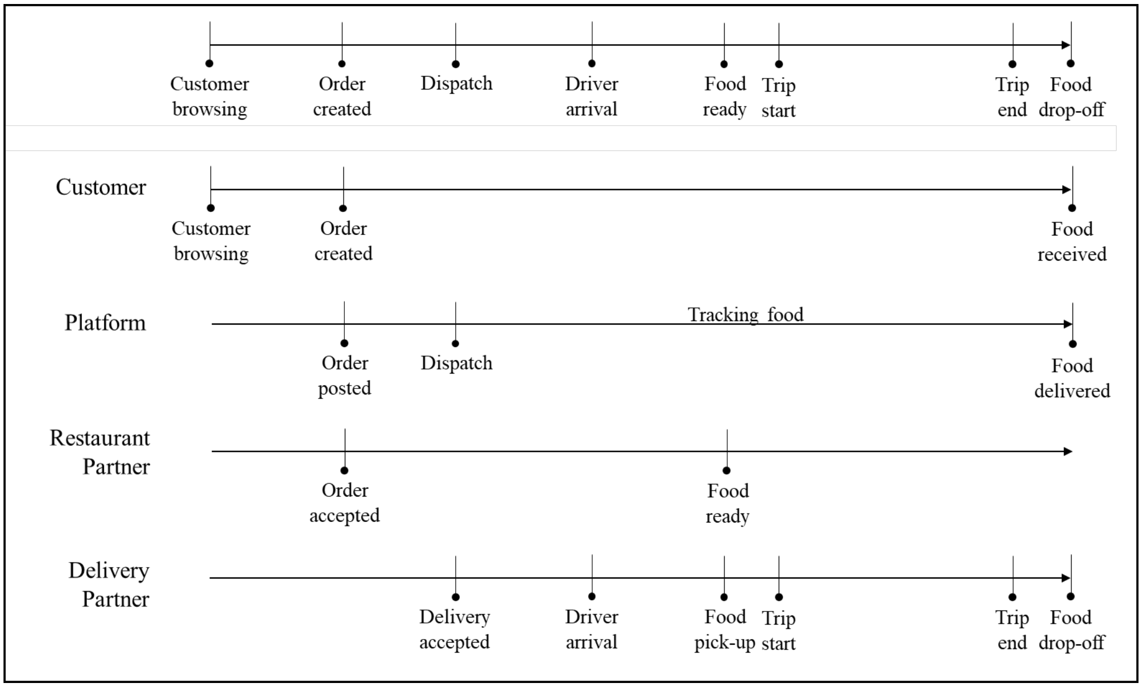


Figure 3.9. Summary of the meal delivery service cycle for key stakeholders

The platform's fleet operation plan may vary depending on the working conditions of the delivery partners and the platform's dispatching strategy. This research is focused on identifying the important factors that influence fleet operations and studying how the algorithm's results shift when these conditions change.

a. Stacked orders: Stacked orders refer to the practice of assigning multiple orders to a delivery driver for simultaneous delivery. If the platform can still guarantee timely delivery to customers even with stacked orders, it opens up the possibility of optimizing operations further. I aim to explore the differences between options that allow stacked orders and those that strictly adhere to one-to-one delivery.

b. Maximum delivery time: I define the delivery area based on the distance that a vehicle can reach within 10 minutes from the restaurant. However, what if the delivery time is extended to 15 minutes or more, and this doesn't affect the customer's satisfaction? In such a scenario, I could consider dispatching vehicles that are a bit closer to the restaurant if they can reach the customer within the extended time frame. Moreover, longer delivery times might also accommodate more stacked orders. This flexibility in delivery time could potentially lead to a more optimized allocation of resources. To investigate this, I conducted experiments for the scenarios of 1) immediate delivery without order stacking, with maximum delivery times of 2) 10 and 3) 15 minutes.

c. Dispatch timing: The timing of when to assign vehicles for delivery has an impact on the platform's costs. Under Prop 22, drivers are compensated based on both the time taken from accepting to completing an order and the distance during this time. Therefore, assigning drivers quickly can lead to higher costs, corresponding to the time spent. Conversely, if driver assignments are delayed excessively, it could result in delayed deliveries or even a shortage of available drivers. Meanwhile, dispatch timing might not be determined solely by fixed time intervals, but it could be influenced by the availability of drivers around the restaurant. Therefore, I conduct experiments by setting thresholds for both time – 1) 10 minutes in advance and 2) 15 minutes in advance – and the number of available drivers – 3) 5 drivers and 4) 10 drivers –.

d. Fleet operating hours: The operating hours of drivers significantly impact the size of the meal delivery fleet throughout the day. To simplify the scenario, I assume that all drivers have the same baseline working hours – 1) 4 hours, 2) 6 hours, and 3) 8 hours –. However, not all drivers strictly adhere to the designated working hours. Depending on the delivery situation, drivers might conclude their operations if no new orders are assigned to them after a certain period. A shorter waiting time could lead to a higher demand for drivers. I define this waiting time as 40 minutes and measure the fluctuation in the number of drivers based on the working hours.

3.5. Results

I investigate the impact of the four parameters (stacked orders, delivery time, dispatch timing, and fleet operating hours) on various stakeholders, including customers, drivers, and the platform. I measure key metrics such as fleet size, stacked order size, Vehicle Miles Traveled (VMT), Vehicle Hours Traveled (VHT), customer disutility, active time, and inactive time under different parameter settings. I calculate the delivery fees that the platform pays to drivers based on the distance and time spent during each delivery. Moreover, I compared the measurements of two algorithms: The Hopcroft-Karp algorithm and the Karp algorithm.

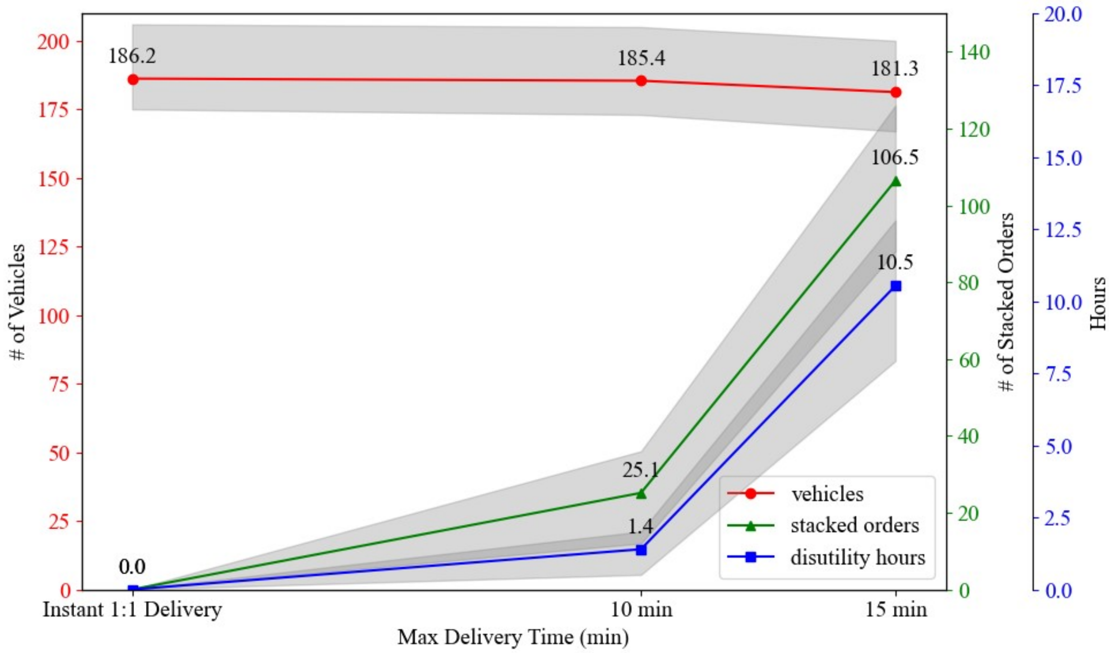
I conducted measurements for a total of 2,300 demand instances generated from weighted probabilities of location and time combinations within San Francisco restaurants. I randomly generated 50 sets of datasets for a comprehensive analysis of the platform's performance under various scenarios. To estimate the effects of individual parameters, I control the remaining factors. The default configuration featured 1) a maximum delivery time of 10 minutes, 2) the allowance of order stacking, 3) dispatch timing determined by the presence of 10 or fewer reachable vehicles to the restaurant, and 4) a fleet operating duration of 6 hours. In Figures 3.10, 3.11, and 3.12, the solid lines represent the average values of these measurements, and the gray shading highlights the range of variability, indicating the minimum and maximum values observed across the multiple datasets. Tables 3.2, 3.3, and 3.4 provide a cost analysis for both algorithms, delineating the variations in delivery fees as each parameter changes. The costs are categorized into distance and active time components based on the delivery fee policy of DoorDash's pricing policy adopted post-Proposition 22 (DoorDash, n.d.). Drivers can earn \$0.34 per mile during active time. Considering the minimum wage rate in San Francisco is \$18.07 per hour (City and County of San Francisco, 2023), this translates to approximately \$0.3614 per minute of active time.

3.5.1. Maximum delivery time and order stacking

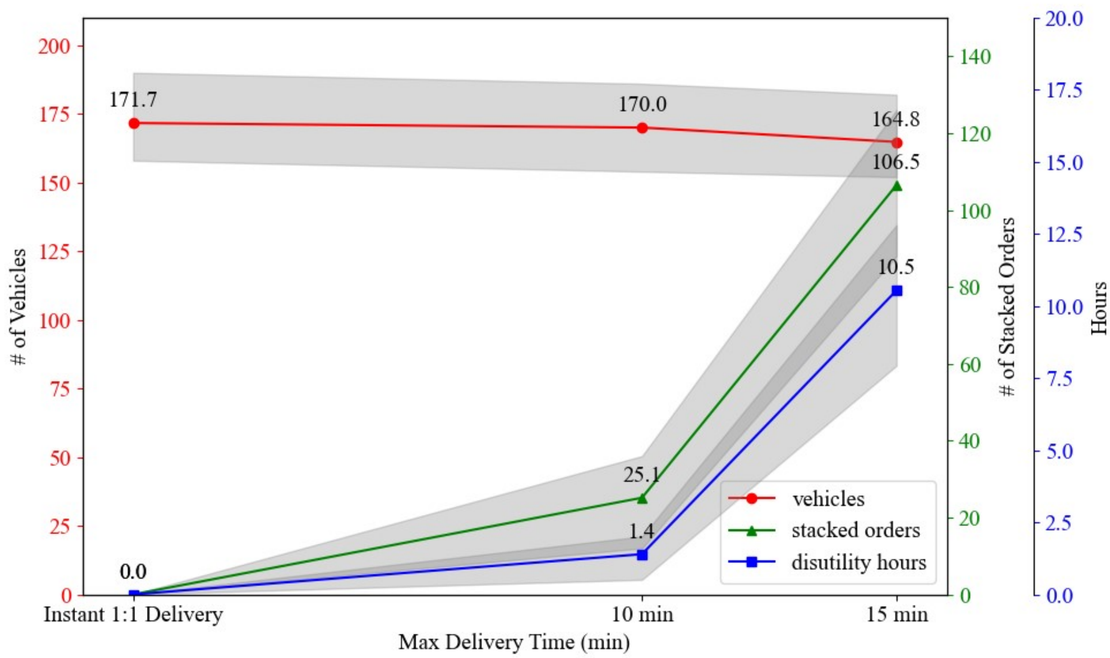
While there are differences in the numerical values between the two algorithms, the underlying patterns remain consistent. These patterns are particularly evident in key factors such as vehicle size, number of stacked orders, and customer disutility. In Figure 3.10, the initial value on the x-axis corresponds to scenarios where order stacking is limited and delivery is immediate with pickup. The delivery time of this case serves as a benchmark, with any delays beyond this baseline measured cumulatively as customer disutility at 10 minutes and 15 minutes maximum delivery time.

As the maximum delivery time is extended, the fleet size becomes smaller, and the number of stacked orders increases. A more generous delivery window enables better route optimization, allowing drivers to efficiently serve multiple customers with a smaller fleet. On the other hand, the increase in maximum delivery time leads to a rise in customer disutility hours. In scenarios where customers do not perceive a significant difference between a 15-minute delivery time and an instant delivery, opting for a longer time window could be strategic for the platform's operations. On the other hand, if customers do notice and value quicker delivery times, the platform must carefully balance the benefits of fleet size reduction and route optimization against the potential increase in customer disutility.

While the stacked order size and customer disutility between the two algorithms are the same, the fleet size shows an evident difference. The fleet size difference between the Hopcroft-Karp algorithm (Panel A of Figure 3.10) and the Karp algorithm (Panel B of Figure 3.10) is approximately 14.5 to 16.5 vehicles, which is equivalent to 7.8% to 9.1% of the vehicles of the Hopcroft-Karp algorithm case. Despite demanding a larger fleet, the Hopcroft-Karp algorithm achieves a 3.2% to 3.6% more cost-effective delivery cost than the Karp algorithm (Table 3.2). The difference can come from the distinct optimization objectives and methodologies employed by each algorithm. This distinction will be addressed in the discussion section.



Panel A. Hopcroft-Karp algorithm



Panel B. Karp algorithm

Figure 3.10. Impact of maximum delivery time and order stacking

Table 3.2. The cost table by algorithm based on maximum delivery time and order stacking policy

	Hopcroft-Karp algorithm time cost ($) (hours)	Hopcroft-Karp algorithm distance cost ($) (miles)	Hopcroft-Karp algorithm total cost ($)	Karp algorithm time cost ($) (hours)	Karp algorithm distance cost ($) (miles)	Karp algorithm total cost ($)
Instant delivery	10,021.5 (462.2)	2,504.2 (7,365.4)	12,525.8	9,838.3 (453.7)	2,283.5 (6,716.3)	12,121.8
10 minutes	10,031.2 (462.6)	2,474.2 (7,277.0)	12,505.4	9,827.4 (453.2)	2,271.0 (6,679.4)	12,098.4
15 minutes	10,065.1 (464.2)	2,399.9 (7,058.6)	12,465.1	9,774.8 (450.8)	2,235.7 (6,575.6)	12,010.5

3.5.2. Dispatch timing

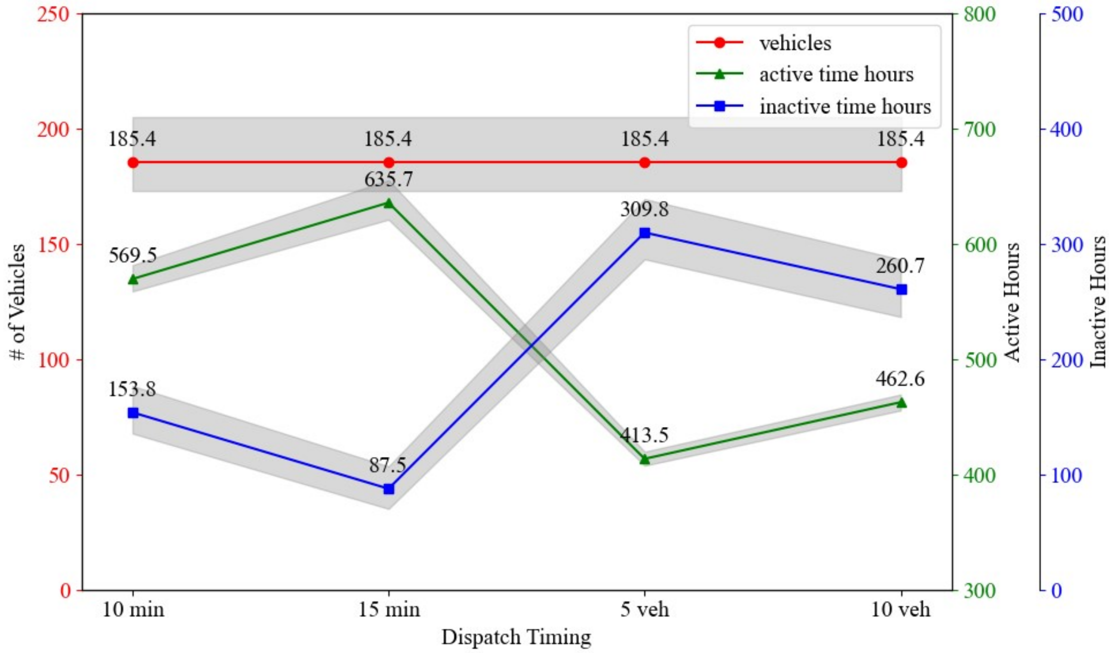
When changing a dispatch timing of 10 minutes before pickup to 15 minutes, there is a shift in the active time metric: the active time increases by 11.6% from 569.5 hours to 635.7 hours for the Hopcroft-Karp algorithm (Panel A of Figure 3.11) and by 8.2% from 525.3 hours to 568.6 hours for the Karp algorithm (Panel B of Figure 11). Similarly, waiting for the availability of 10 or fewer deliverable vehicles around the restaurant (an extended time window), compared to waiting for five or fewer vehicles (a tighter time window), resulted in an increase in active time for both the Hopcroft-Karp and Karp algorithms. Specifically, for the Hopcroft-Karp algorithm, the active time increased by 11.9%, rising from 413.5 hours to 462.6 hours. On the other hand, the Karp algorithm exhibited an active time increase of 10.8%, growing from 409.0 hours to 453.2 hours.

Dispatching vehicles earlier, with a larger time window, contributes to an extended period of driver activity. This suggests that as more time is allocated for drivers to commence their deliveries, the fees paid to drivers by the platform increase. According to the cost table (Table 3.3), there are significant variations in delivery fees, with differences of up to 29.3% for the Hopcroft-Karp algorithm and 23.7% for the Karp algorithm. On the other hand, the fleet size remained consistent for all scenarios, indicating that all demand was fulfilled without variation, with the only difference being in dispatch timing. Indeed, Table 3.3 reveals that there is no variance in cost from distance across the dispatch timing strategies. This suggests that by adopting a cautious yet efficient dispatch strategy—one that ensures the successful fulfillment of all demand—the platform can optimize its operational costs. However, this optimization in dispatch timing did not lead to an improvement of the entire system. What this implies is that while the platform managed to save on active time, there was a corresponding increase in drivers' inactive time. Inactive time refers to the period during which drivers are not engaged in delivering orders and are not compensated by the platform. It is the time between dropping off a previous order and accepting the next one, called connection time.

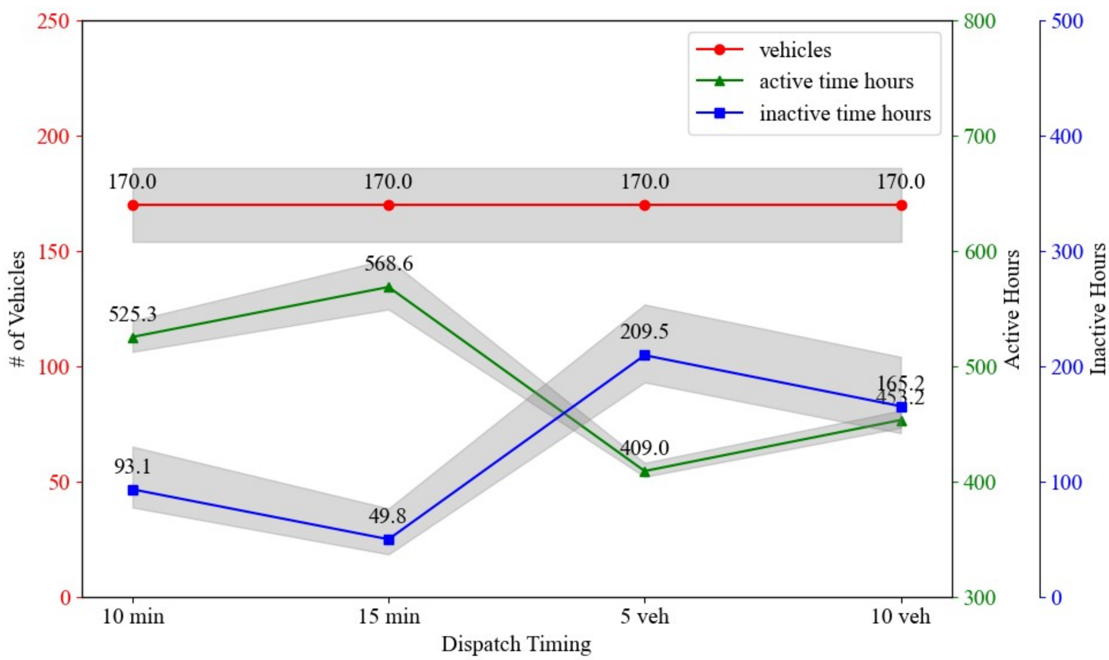
Comparing the Hopcroft-Karp algorithm (Panel A of Figure 3.11) with the Karp algorithm (Panel B of Figure 3.11), I observe discrepancies in fleet size, 15.4 vehicles between the two algorithms. Meanwhile, active time exhibits a range of difference ranging from 4.5 hours to 67.1 hours. Particularly, I observed significant differences in active time when applying time-based dispatch timing. This discrepancy can be attributed to the Hopcroft-Karp algorithm's emphasis on maximizing the number of matches without considering cost implications. On the other hand, in scenarios where vehicle count is considered, the Hopcroft-Karp algorithm demonstrates a higher degree of cost-effectiveness as the parameter itself focuses on local proximity.

Table 3.3. The cost table by algorithm based on the dispatch timing strategy

	Hopcroft-Karp algorithm			Karp algorithm		
	time cost ($) (hours)	distance cost ($) (miles)	Total cost ($)	time cost ($) (hours)	distance cost ($) (miles)	total cost ($)
10 minutes	12,349.1 (569.5)	2,474.2 (7,277.0)	14,823.2	11,390.5 (525.3)	2,271.0 (6,679.4)	13,661.5
15 minutes	13,785.6 (635.7)	2,474.2 (7,277.0)	16,259.7	12,330.3 (568.6)	2,271.0 (6,679.4)	14,601.3
5 vehicles	8,966.3 (413.5)	2,474.2 (7,277.0)	11,440.5	8,867.8 (409.0)	2,271.0 (6,679.4)	11,138.8
10 vehicles	10,031.2 (462.6)	2,474.2 (7,277.0)	12,505.4	9,827.4 (453.2)	2,271.0 (6,679.4)	12,098.4



Panel A. Hopcroft-Karp algorithm



Panel B. Karp algorithm

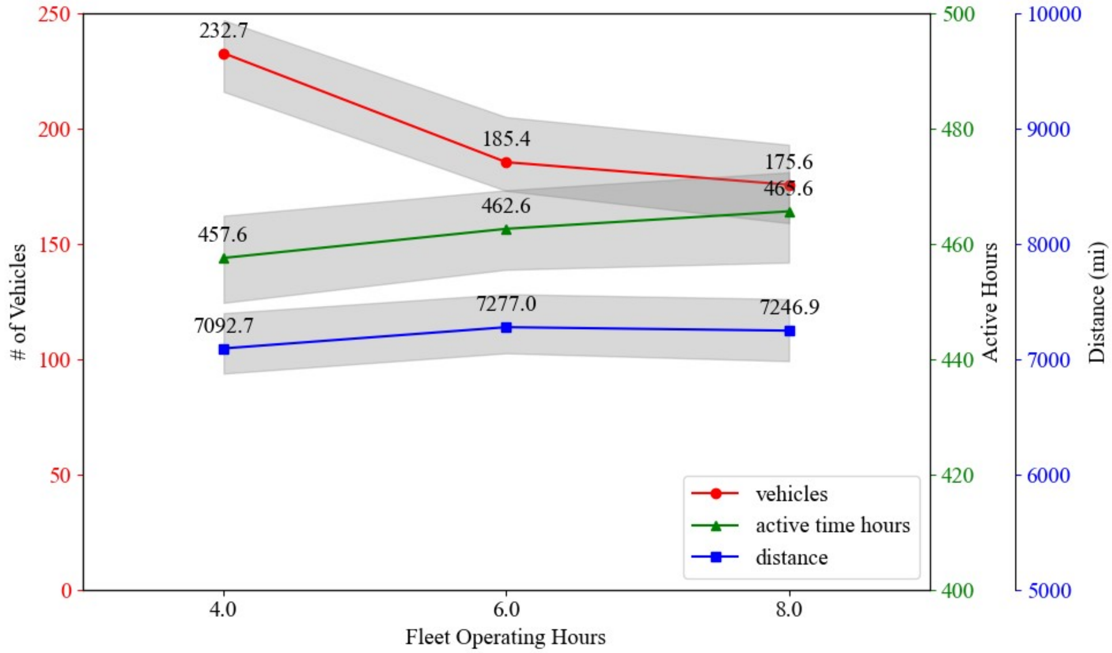
Figure 3.11. Impact of dispatch timing

3.5.3. Fleet operating hours

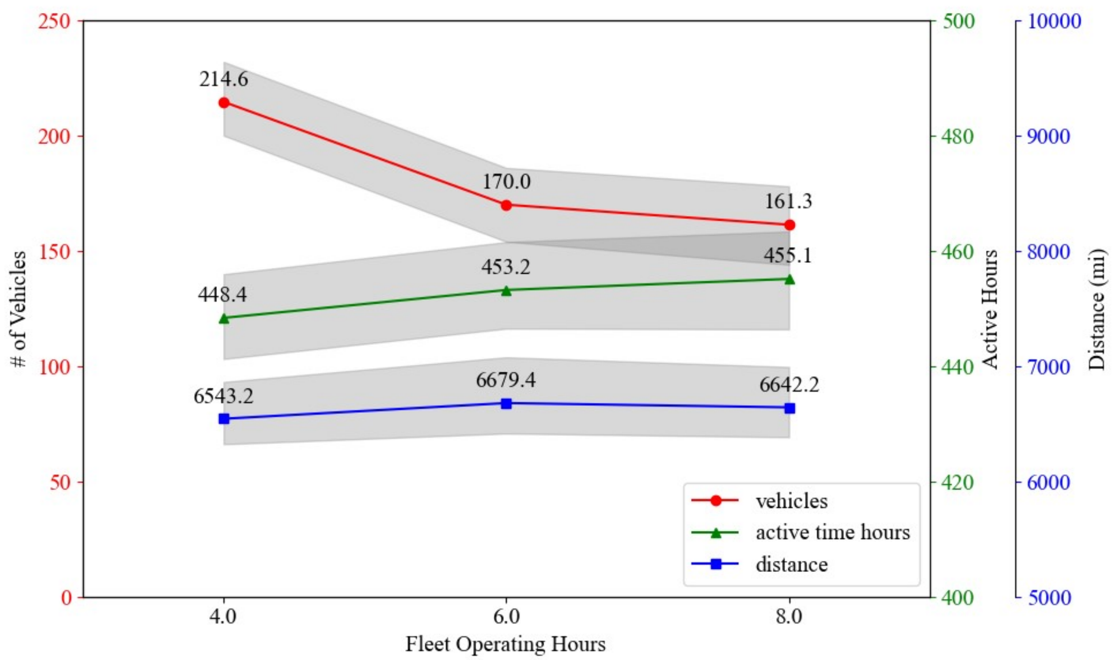
With an increase in fleet operating hours, there is a reduction in the required fleet size, aligning intuitively with the notion that longer working hours correspond to fewer shifts in a factory. However, this relationship does not follow a linear pattern. This deviation arises because not all vehicles strictly promise the designated working hours. A vehicle without orders to accept for a certain period (40 minutes in this experiment) concludes its operations. Moreover, meal delivery has heterogeneous spatial-temporal distribution of demand compared to the assembly-line process of a factory. Given that the delivery fee is proportional to both their active time and distance traveled, a 4-hour fleet operation could potentially be the most economically advantageous for the platform (Table 3.4). However, this assertion would not be the most effective when considering fleet size. This is primarily due to unaccounted factors, such as the platform's recruitment costs for additional drivers, idle trips that lead to extra expenses for drivers, and contribute to traffic congestion on a societal level. In this setting as well, the Karp algorithm demonstrates superior performance compared to the Hopcroft-Karp algorithm across key metrics, including fleet size (14.3 vs. 18.1 vehicles), active hours (9.2 hours vs. 10.5 hours), and distance traveled (549.5 miles vs. 604.7 miles) (Figure 3.12).

Table 3.4. The cost table by algorithm based on fleet operating hours

	Hopcroft-Karp algorithm			Karp algorithm		
	time cost ($) (hours)	distance cost ($) (miles)	total cost ($)	time cost ($) (hours)	distance cost ($) (miles)	Total cost ($)
4 hours	9,921.6 (457.6)	2,411.5 (7,092.7)	12,333.1	9,722.4 (448.4)	2,224.7 (6,543.2)	11,947.1
6 hours	10,031.2 (462.6)	2,474.2 (7,277.0)	12,505.4	9,827.4 (453.2)	2,271.0 (6,679.4)	12,098.4
8 hours	10,097.0 (465.6)	2,463.9 (7,246.9)	12,561.0	9,869.0 (455.1)	2,258.3 (6,642.2)	12,127.4



Panel A. Hopcroft-Karp algorithm



Panel B. Karp algorithm
Figure 3.12. Impact of fleet operating hours

3.6. Discussion

3.6.1. Striking the balance: Optimization Objectives and Methodology in Algorithms for Fleet Management

While the Hopcroft-Karp algorithm maximizes the number of matches, its sole focus on finding the longest paths may not always guarantee the minimum number of drivers required for the match. In the context of food delivery, the primary goal is to enable a vehicle to make as many deliveries as possible. To achieve this goal, the algorithm works to reduce the size of the fleet, although it cannot guarantee an absolute minimum. For example, if a vehicle delivering restaurant food in Area A finds greater potential for matches in Area B, it will shift its focus to Area B, even if there are remaining deliveries in its current Area A. This situation can result in the need for new vehicles to service the remaining deliveries in Area A. On the other hand, the Karp algorithm considers the edge weights, so it maximizes the number of matches by prioritizing nearby deliveries over long trips. As a result, instead of having newly introduced vehicles serve the remaining deliveries, the algorithm tends to address local deliveries first before moving on to areas with high match potential.

For this reason, results show the cost-effectiveness of the Karp algorithm in metrics like Vehicle Miles Traveled (VMT) and Vehicle Hours Traveled (VHT) by prioritizing nearby deliveries and minimizing the distances traveled. This not only influences the operational costs of the platform but also has an effect on fleet size. Meanwhile, from a computational efficiency perspective, the Hopcroft-Karp algorithm ($O(\sqrt{V} * E)$) demonstrates superiority over the Karp algorithm ($O(|V| + |E| \log|E|)$). Therefore, choosing the most suitable algorithm to determine fleet size should depend on factors such as the scale of the problem, the dimensions of the service area, and the distinct goals of the platform.

3.6.2. Adapting to regulatory landscape: implications from Proposition 22

The emergence of regulations such as Proposition 22 in the gig economy landscape has significant implications for platform operations. This regulatory framework necessitates platforms to reevaluate their compensation models and driver engagement strategies. Proposition 22's mandate for ensuring a minimum earnings threshold and benefits for gig workers has led to a recalibration of how platforms like DoorDash and Uber structure their driver compensation. The study's findings, which delve into the cost analysis of these platforms under Prop 22's guidelines, shed light on the complexities of aligning algorithmic dispatch and delivery fee structures with regulatory stipulations. As the legal environment evolves, this study provides a valuable lens through which to understand the financial repercussions of adapting to regulations and underscores the importance of incorporating legal constraints into the optimization process.

3.6.3. Navigating unforeseen challenges: the impact of external factors like COVID-19

While the study primarily focuses on algorithmic optimization and platform economics, it's important to acknowledge the dynamic influence of unforeseen external factors. The COVID-19 pandemic disrupted conventional service patterns, altering demand dynamics, driver availability, and traffic conditions. Examining how algorithms responded to these sudden shifts can provide insights into their adaptability and resilience in turbulent times. By considering the impact of such unpredictable events, the discussion can underscore the need for algorithms to be flexible, responsive, and capable of dynamically adjusting to unexpected changes in demand patterns. This aspect resonates not only with platform operators but also with policymakers and researchers seeking to create more robust and adaptable models for the gig economy in the face of uncertainties.

3.7. Conclusions

This study aims to uncover how two algorithms – the Hopcroft-Karp algorithm and the Karp algorithm– optimize fleet management for meal delivery platforms. I analyzed the performance of the algorithms under various conditions to understand their strengths and limitations. The findings highlight the importance of optimization objectives in these algorithms. While Hopcroft-Karp focuses on maximizing matches, it may not always guarantee the most efficient use of drivers. On the other hand, Karp prioritizes nearby deliveries, resulting in cost-effective outcomes like reduced distances traveled by vehicles and, ultimately, smaller fleet size. This study offers insights for both academic and practical purposes. It helps us understand the trade-offs involved in algorithm selection and how they impact fleet size, operational costs, and customer satisfaction. Platform operators can leverage these insights to fine-tune the supply-side strategies. For instance, they can make informed choices about which algorithm to adopt based on their specific operational goals and service area dimensions.

Meanwhile, it is important to acknowledge the study's limitations. I simulated various scenarios, but real-world conditions are more complex. The enforcement of uniform working hours among drivers and the omission of certain factors like vehicle charging, parking, and walking movements during operations may not fully capture the dynamic nature of real-world scenarios. Furthermore, the assumption of complete advanced knowledge of all order details could lead to over-optimization that might differ from actual service circumstances. While recognizing the study's limitations, there are promising directions for future research. First, by considering drivers' behavior, such as flexible working hours, preferred delivery areas, and modes other than cars, the simulations can become more realistic. Second, I can adopt a dynamic approach. Unlike static simulation, this dynamic approach processes delivery information in real-time as it becomes accessible without preexisting knowledge of complete order details. This strategy allows for adapting strategies on the fly and testing algorithms in situations that mimic the uncertainties and complexities of real-world meal delivery operations.

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CHAPTER 4. SUMMARY AND CONCLUSIONS

This dissertation comprehensively addresses the dynamics of restaurant meal demand, particularly focusing on restaurant meal delivery within the context of the COVID-19 pandemic. It offers a dual perspective, analyzing both the demand and supply side. On the demand side, the study employs statistical approaches to analyze the evolving landscape of restaurant meal consumption, segmented into dine-in, take-out, and delivery. It further investigates the relationship between meal delivery demand in three MSAs in California and their unique regional characteristics, utilizing meal delivery transaction records of meal delivery platforms. On the supply side, the focus shifts to optimizing the operational efficiency of meal delivery platforms in San Francisco, employing graph-based algorithms to optimize delivery fleet size and operational efficiency.

Chapter 1 explores the transformative impact of the COVID-19 pandemic on restaurant food consumption in California. The findings reveal shifts in preferences, with meal delivery gaining popularity, dine-in experiences declining, and take-out experiencing marginal growth during COVID-19. After the pandemic, while the trend for dine-in experiences displays resilience, the meal delivery domain is expected to maintain its momentum. However, a significant challenge looms for meal delivery platforms: despite the sector's growth, a majority of respondents indicate a reluctance to use meal delivery services even after the pandemic, with the percentage of respondents who indicated "never" using meal delivery services 63% before COVID-19, 54.5% during the pandemic, and 53.7% after the pandemic.

The statistical modeling underscores the influence of neighborhood vulnerability on the use of take-out and delivery services. It highlights the positive association of take-out food consumption to socioeconomic challenges (SVI_1), a negative association between meal delivery food consumption and household characteristics (SVI_2), and contrasting patterns of take-out and meal delivery service types in housing type and transportation limitations (SVI_4). This analysis suggests providing vouchers or discounts for different meal options, such as take-out and delivery, can enable vulnerable populations to access meals more affordably and conveniently, fostering equitable food accessibility and security.

This study primarily focuses on the frequency of restaurant food consumption, which limits its capacity to offer insights into food establishment types and food quality. Additionally, the investigation into the post-COVID-19 landscape relies on respondents' behavioral intentions, necessitating further research through supplementary surveys when concerns related to COVID-19 have subsided.

Chapter 2 extends the analysis to the demand for meal delivery, examining the unique dynamics over time across three MSAs in California. The study confirms and challenges traditional relationships established in FAFH studies. It reveals a more complex interplay of variables influenced by demographic and socioeconomic characteristics and food accessibility. Its regional lens reveals the diverse dynamics of delivery behavior. The relationships among variables, such as education, income, and race, differ between Southern and Northern California, and even within Southern California, they exhibit variations based on the degree of urbanization of the MSAs. Simultaneously, it uncovers enduring patterns that persist across time and region, such as urban classification, employment density, and the number of delivery restaurants. These elements underscore the central role of accessibility factors in shaping meal delivery demand. The study reveals the impact of meal delivery services on vulnerable populations. The positive association between meal delivery demand and socioeconomic status (SVI_1) underscores the service's role in improving food access for marginalized communities. In addition, the relationship between meal delivery demand and housing type/transportation (SVI_4) highlights the service's contribution to improving food mobility. The study's implications extend beyond business strategies; they extend to the realm of policy. The findings highlight the potential for meal delivery services to bridge food accessibility gaps for vulnerable populations, making them a crucial tool for policymakers aiming to address disparities in underserved communities.

This study faces limitations due to reliance on secondary data, including outdated employment data and incomplete meal delivery restaurant information, particularly during the early stages of the pandemic. Additionally, aggregating COVID-19 variables at the county level may overlook variations within counties and focus on delivery frequency without considering food or restaurant types, limiting insights into dietary health impacts.

Chapter 3 focuses on the operational efficiency of meal delivery platforms, exploring various parameters within delivery simulations to refine strategic approaches. It evaluates the performance of meal delivery platforms by focusing on metrics such as fleet size, VHT, VMT, the number of stacked orders, and inactive time. Another key aspect of this chapter is the comparative analysis of two key algorithms: the Hopcroft-Carp algorithm and the Karp algorithm. This approach allows us to understand how different parameters impact the efficiency of meal delivery services. While the Hopcroft-Karp algorithm excels at maximizing matches, it may fall short in ensuring the most efficient driver allocation. In contrast, by prioritizing minimizing costs, the Karp algorithm provides a significant advantage in metrics such as VMT and VHT. This, in turn, impacts operating costs and fleet size. Depending on the set of parameters, albeit varying, on average, the utilization of the Karp algorithm yielded a substantial reduction of approximately 8.2% in fleet size and 4.4% in platform costs compared to when the Hopcroft-Karp algorithm was employed.

The study, based on the revised cost structure established by California's Proposition 22, offers a practical model for estimating the actual costs of meal delivery platforms. Additionally, experiments with various parameter combinations enable platform operators to make informed decisions and strategically fine-tune their supply-side operations. The flexibility of this approach enables smooth integration across different platforms. Notably, its capacity to link with non-profit services can contribute to societal welfare. This demonstrates a dual commitment to social responsibility and operational efficiency. Nevertheless, it is important to note that this framework operates under the assumption of deterministic order information, which could potentially lead to over-optimization compared to real-world platform operations. Additionally, the simulations do not fully account for practical aspects like driver preferences, vehicle refueling, parking conditions, and unexpected delays, which are crucial in real-world scenarios.

This dissertation makes a significant contribution by providing a comprehensive understanding of the changes in restaurant food consumption patterns, the dynamics of meal delivery in different regions, and the strategic optimization methods. This research enhances our understanding of how individuals' eating habits changed during the COVID-19 pandemic and sheds light on the factors that shape their demand and usage patterns. In addition, exploring algorithms to optimize platform operations provides practical guidance to enable policymakers and industry stakeholders to navigate the landscape of meal delivery platforms more effectively. By bridging the gap between academic research and real-world application, this study provides valuable insights that can inform informed decision-making, promote improved policy frameworks, and drive the refinement of operational strategies in the field of restaurant food delivery and consumption. Nevertheless, this study has several limitations that should be noted in future research. In Chapter 1, I examined post-COVID-19 restaurant food consumption patterns and relied on respondents' behavioral intentions, requiring follow-up surveys to validate the findings. Chapter 2 relies on census tracts as the primary unit of analysis, which led to a notable omission of specific customer and restaurant information during the aggregation process. Consequently, future research endeavors should aim to conduct more detailed analysis at the individual customer or restaurant level, enabling a richer understanding of the meal delivery landscape. Additionally, in Chapters 1 and 2, it is still relevant to examine changes in patterns based on factors such as food type and establishment type, not just frequency. Chapter 3, which relies on a static model based on prior information, faces the inevitable challenge of over-optimization. Future research requires a dynamic approach, including the investigation of vehicle repositioning strategies and other auxiliary parameters, for more realistic platform operations.