Understanding COVID-19 Induced Responses for Individuals and Businesses: Changes in Human Mobility Patterns and Resilience Tactics by Small Food Businesses

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Abstract

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The COVID-19 pandemic has profoundly affected our daily lives, including the ways individuals access food, work, and carry out routine activities. From another perspective, small food businesses' operations have also been affected by the unprecedented indoor service restrictions and reduced customer foot traffic. Understanding how people and businesses adapted is essential for addressing the wider effects on urban mobility, food access, and resilience. This dissertation is driven by the overarching question: How has the COVID-19 pandemic reshaped individual's mobility patterns and affected their food access, as well as small businesses' resilience tactics?

To answer this, the study develops a comprehensive framework, combining advanced data modeling and empirical studies. First, the study introduces a modified Two-Step Floating Catchment Area (2SFCA) method to evaluate food accessibility through delivery services, addressing critical gaps in understanding disparities across regions and population groups. This methodology incorporates supply-demand interaction and the unique spatial characteristics of delivery services. Second, this dissertation investigates COVID and telecommuting-induced shifts in travel patterns using three waves of the Puget Sound household travel survey data and explores changes in the frequency, spatial and temporal distribution of maintenance and discretionary trips, as well as the resulting mode splits and vehicle miles traveled. Finally, this dissertation examines resilience strategies employed

by small food businesses during disruptions. Using first-hand, qualitative and quantitative data collected from businesses in Seattle's University District, it develops a mathematical optimization framework to evaluate and recommend effective strategies for coping with labor shortages, supply constraints, fluctuating demand, decreased production, and restricted capacity.

In sum, the study provides a comprehensive picture of how individuals and small businesses adapted during the unprecedented COVID-19 Pandemic. This work contributes to creating resilient and adaptive urban communities in the post-pandemic era.

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This marks the finish line of my PhD journey, but only the beginning of many new chapters—of growth, discovery, new questions to ask, and new ways to learn.

TABLE OF CONTENTS

LIST OF FIGURES

Understanding COVID-19 Induced Responses for Individuals and Businesses: Changes in Human Mobility Patterns and Resilience Tactics by Small Food Businesses

Chapter 1

INTRODUCTION

1.1 Background and Motivation

The COVID-19 pandemic presented unforeseen challenges to people's daily lives in multifaceted ways, ranging from work arrangements, and activity and travel pattern. Small businesses also were significantly affected. In March 2020, states and cities in the United States implemented extensive non-pharmaceutical interventions, such as reduced retail operation hours, social distancing mandates, and adopting telecommuting arrangements [1]. Aggressive and widespread lockdowns were implemented in 42 states and territories [2] and remained in effect in many states in the U.S. through the end of August 2020 [3]. COVID-19's impact has been unprecedented and complex [4], and the adaptations it prompted have continued to shape our lives well beyond the pandemic's end. People adapted to the adverse situation through the rapid adoption for food delivery services and information and communications technology that supported telecommuting, i.e. working from home (WFH). During the early stages of the COVID-19 pandemic, lockdowns, social distancing, and restrictions on indoor dining led customers to prefer contactless options for accessing prepared meals and groceries. A survey revealed that nearly 78.7% of more than the 300 U.S. respondents surveyed continued purchasing groceries online after the outbreak, and increase of 39% from before the pandemic. In parallel, telecommuting became essential and a routine arrangement for many. Before the pandemic, 5.7% of workers aged 16 and older primarily telecommute; in 2021, this number more than tripled to 17.9% and amounts to about 27.6 million based on the 2021 American Community Survey [5]. As of August 2024, 22.4% of workers aged 16 and older continued to telecommute [6].

The adaptation in food deliveries and telecommuting is likely to persist as part of a "new normal" [7, 8, 9] and has already manifested in our daily lives. Telecommuting eliminates commute trips and can also be seen as a way to reclaim personal time. A study surveying 27 countries about their working arrangements reported that telecommuting saved, on average, 72 minutes in commute time [10]. With commute trips gone, trips that are previously tied to commutes, (e.g. getting coffee right before work and dining at nearby restaurants during lunch breaks) disappeared. However, individuals still need to satisfy their household maintenance needs, such as getting food or groceries. Food delivery services became one of the means supporting those needs, and a study in Chicago founded that 39% of those ordered groceries online considered online ordering as the primary way of getting grocery during COVID-19 [11]. And reports from leading delivery platforms such as Grubhub and DoorDash revealed American tend to favor calorie-dense fast-food options when ordering online [12]. This observation triggers concern about whether there is an adequate amount of healthy food in the delivery-dominated COVID-19 era [13, 14].

Adapting to telecommuting and food delivery has impacts beyond personal travel patterns and accessing food – it also impacted the food businesses, especially the small businesses that once thrived in central business districts (CBDs). Telecommuting pulls workers away from CBDs where employment is concentrated [15]. As a consequence, food businesses that used to have a steady customer demand when people work on-site lost in-person traffic, regular patrons, and large group reservations [16]. They are also challenged in getting fresh produce, hiring employees, and maintaining indoor service under changing non-pharmaceutical interventions [17]. Because of the multi-faced challenges, food businesses struggled. Research has shown that businesses owners implemented a wide array of tactics: selling meal-kit products, using cooking and serving robots, and investing in online ordering and drive through services [18]. Even with tactics, rebounding from COVID-19 was particularly challenging for small and independent food businesses compared to large national restaurant chains [19].

The challenges brought by COVID-19 were unprecedented, as are the adaptations and their lasting implications in the post-COVID-19 era. Despite Amazon's recent announcement of a five-day office workweek starting in 2025, Forbes reported that hybrid work—combining working from home and office work—remained popular in 2024 [20]. In fact, the number of workers following a five-day on-site working schedule has decreased by six percent since

2023, according to a survey of 2,000 full-time workers in the United States [20]. And there are still questions to be answered about the implications beyond the adaptations in the post-COVID-19 era [21]. This dissertation examines how individuals and businesses have adapted during the COVID-19 pandemic. This study required a diverse array of data sources, including primary data collected directly from businesses and secondary data from government and regional agencies.

1.2 How Does Delivery Service Change Food Accessibility: A Modified 2-step Floating Catchment Area Method

Existing methodology on food accessibility predominately focuses on on-premise services, that is, dine-in and shopping at stores, which assumes a linear distance decay property of the closer, the higher accessibility. Access to delivery services is fundamentally different from that to on-premise stores. Stores with close proximity (within an inner boundary) are less desirable for delivery due to delivery fees, and there is an outer boundary beyond which deliveries are unavailable, both challenging the assumption of increasing impediment with distance. Accessing food on-premise versus through delivery also raises questions about whether food delivery can provide a level of accessibility comparable to that of on-premise food options [22]. For example, is there a correlation between neighborhoods with greater on-premise food accessibility and their access to delivered food?

The above question is important because United States Department of Agriculture (USDA) launched the Supplemental Nutrition Assistance Program (SNAP), the nation's largest nutrition assistance program to promote food access and a healthful diet for low-income Americans [23]. In 2022, SNAP announced its investment in SNAP online program, recognizing online shopping as a vital resource to improve access for SNAP participants [24]. SNAP online benefits continue to use income as the eligibility criteria: in Washington state, individuals and households should have monthly income (before taxes and reductions) under the gross monthly income standard listed in Washington Administrative Code. Since low-income households do not necessarily experience low-access, as about 41% of USDA defined low-income tracts are low-access, the income-alone criterion may not be appropriate. Furthermore, the criteria do not consider whether a household with limited access to on-premise shopping for food also faces limited access to delivered food. It is thus unclear how SNAP online benefits will affect food access, especially for low-income and low-access households.

As such, this study answers the following questions:

- How to incorporate the key features of delivery service into food accessibility quantification

- How does the increase in food accessibility brought by delivery services vary across different population segments and regions

- How is the population with low access to delivered fresh produce supported by Supplemental Nutrition Assistance Program online benefits?

To answer these research questions, this study developed a modified 2-step floating catchment area method and applied it to a Seattle case study. The contributions of this work are summarized as follows.

- The modified 2-step floating catchment area method incorporates the donut shape, accounts for both demand and supply, and examines the diversity of food options.

- The methodology satisfies the conservation property where supplies given out to the population equals the supplies received by the population.

- Delivery services increase restaurant and fast-food accessibility in areas where there is already good accessibility (e.g., downtown Seattle for restaurants and South Seattle for fast-food).

- With delivery services, more low-income or low-access households (those who live far from grocery stores) have better accessibility to fresh produce from grocery stores compared to the rest of the population.

- The Supplemental Nutrition Assistance Program (SNAP) online program appears to miss low-access households.

1.3 COVID-19, Telecommuting, and Changes in Travel Patterns in the Puget Sound Region

One enduring effect of the COVID-19 pandemic has been the popularity of telecommuting: To this day, 23% of the salaried workers continue to work from home, according to the U.S. Bureau of Labor Statistics. The adoption has significant implications, as telecommuting is closely tied to changes in travel demand and travel patterns [25]. Telecommuting has long been recognized as a Transportation Demand Management (TDM) strategy to reduce Vehicle Miles Traveled (VMT) and reliance on cars. Proponents argue that telecommuting has the potential to replace existing travel demand [26] while others note that time saved from the reduced trips will be re-allocated for traveling [27, 28]. These debates remained within a small circle of researchers prior to COVID, as only a small share of workers telecommuted (less than 5%). When individuals no longer need to commute to work on a regular basis, their travel behaviors are likely to change [29, 30, 31, 32, 33]. When there is a substantial number of telecommuters in the workforce, the sum of their travel behavior changes can have a significant impact on the transportation system, as well as have long-term implications for land use patterns and related transport policies.

Using three waves of the household travel survey data from 2017, 2019 and 2021 in the Puget Sound Region, WA, this study examines how telecommuting alters the rescheduling of maintenance and discretionary travels. Specifically, this work answers the following research questions:

- With respect to generation of trips, do telecommuters conduct fewer or more trips overall? What about maintenance and discretionary trips? And do telecommuters conduct simpler tours?

- How do telecommuters reschedule maintenance and discretionary trips spatially and temporally? Are those activities now clustered around home? Have the trip distances become shorter? Are activities now conducted throughout the day? Or are they clustering around certain time points, like mid-day or after work in the afternoon or early evening?

- What are the associated changes in the modes of transportation as well as VMT? It is expected that telecommuters likely conduct more vehicle-based travel. If so, will VMT increase as a result?

The highlights of the findings are listsed below:

- Telecommuting resulted in reduced number of trips and VMT.

- The number of maintenance and discretionary trips significantly increased but the effect is inelastic.

- Telecommuting led to simpler tours, shorter trips, fewer stops, and lower mode diversity.

- Spatially, telecommuters conducted flexible trips (maintenance and discretionary trips) closer to home; temporally, the departure times of these trips are more spread out with emerging peaks such as late morning, and mid-day.

1.4 Evaluation of Resilience Tactics for Food Businesses in Times of Disruption

During the COVID-19 pandemic, many businesses faced a series of challenges, and developing adaptation strategies to survive in a crisis environment has become a formidable task for operators. This challenge is particularly pronounced for local businesses that rely on foot traffic, especially small- and medium-sized enterprises like restaurants and cafes [34, 35]. How small and medium-sized enterprises (SMEs) can leverage data tools to make informed operational decisions to adapt to current technological trends is a subject worthy of study. Unlike large chains, these smaller restaurants face unique vulnerabilities during disruptions due to limited financial and operational resources.

Through in-depth interviews with managers of representative food businesses in Seattle's U District, we gathered insights on the operational and financial challenges faced by small restaurants during COVID-19 and identified five key disruptions:

(1) Employee Shock: This factor reflects the scarcity of available workers due to health risks, labor market fluctuations, or intensified competition for staff. This shortage forces small restaurants to operate with fewer employees, directly impacting service quality and customer satisfaction. Ensure each item is written in a parallel structure.

(2) Supply Shock: This factor captures challenges in securing essential supplies, such as fresh produce, meat, and other raw materials. Inconsistent supply leads to unpredictable costs and forced menu changes, affecting business stability and customer loyalty.

(3) Production Shock: Due to labor shortages and equipment limitations, many restaurants experienced a substantial decline in production capacity, struggling to reach pre-disruption output levels. In some cases, this resulted in slower service speeds, impacting revenue and customer retention.

(4) Capacity Shock: Capacity restrictions, such as limited seating or early closures, may arise from health regulations, natural disasters, or infrastructure issues, restricting the number of customers a restaurant can serve. For small restaurants relying on in-person dining, these limitations can severely impact revenue potential.

(5) Demand Shock: Customer demand dropped sharply as people avoided dining out for health reasons, especially during the peak of the COVID-19 pandemic. This demand shock was compounded by changing consumer preferences, such as a shift towards home dining, making it difficult for small restaurants to forecast and maintain typical demand levels.

We further conducted a comprehensive survey on 200 local restaurants that operated in U District in 2021. This endeavor will involve qualitative and quantitative data collection and mathematical simulation to assess the impact of three resilience tactics on restaurant performance: efficiency boosts, service quality adjustments, and capacity expansion. The following research questions are addressed in this study:

- What are the optimal resilience tactics small-scale restaurants can deploy to maintain stability under different types of disruptions?
- What measurable improvements in performance can these tactics provide? and
- Under what conditions should restaurants rely on external resources to sustain operations?

The study's core results are presented below.

- Food businesses deployed a wide arrange of short term adaptation strategies (adjust core operation, substitute supplies, and reassign labor) and long-term adaptation strategies (structural change in operation, large capital investments, and workforce development).
- Small-scale restaurants benefit significantly from tactics that improve productivity and diversify service capacity.
- When employee and supply are disrupted, small-scale restaurants are able to help themselves as opposed to disruptions in service capacity and customer demand.

The dissertation is organized as follows:

- **Chapter 2** examines how telecommuting affects the scheduling, timing, and location of trips in the Puget Sound Region. Household Travel Survey data from 2017 to 2021 wave were used to analyze changes in travel patterns.
- **Chapter 3** explores how food delivery services impact the quantification of food accessibility. An enhanced two-step floating catchment area method is introduced

to evaluate delivery-based food accessibility and investigate the consistency of food accessibility across different populations and regions.

- **Chapter 4** addresses challenges in data collection, sampling, and mathematical modeling for developing resilience strategies for food businesses. Using Seattle's University District as a case study, the chapter details the collection of qualitative and quantitative data to inform the optimization model.

- **Chapter 5** presents a quantitative model informed by qualitative insights to evaluate and recommend resilience strategies for food businesses during disruptions. Simulations of various shock scenarios identify effective strategies and optimal conditions for maintaining stability and profitability.

- **Chapter 6** explores interconnections between telecommuting, food accessibility, and business resilience, and discusses the implications of the findings.

Chapter 2

HOW DOES DELIVERY SERVICE CHANGE FOOD ACCESSIBILITY: A MODIFIED 2-STEP FLOATING CATCHMENT AREA METHOD

2.1 Introduction

Access to affordable and nutritious food has become a significant issue in many communities, particularly those with low-income populations [36]. United States Department of Agriculture (USDA) stated that approximately 11.5 million low-income individuals (with incomes at or below 200% of the Federal poverty threshold) have low access to food, with low-access defined as living more than one mile away from supermarkets or large grocery stores [36]. Among them, 1.9 million do not have access to a vehicle [37]. Low-access and lack of a vehicle likely lead to more barriers to accessing healthy food and increased health issues [38]. Existing research also found that low-income people spend more at fast-food, convenience stores, dollar trees, and drugstores compared to the population who live closer or are richer [39]. The reliance on fast-food is also a nationwide trend: U.S. spending on fast-food has risen from $6 billion to $110 billion over the last 30 years [40], making fast-food an alternative for people's food consumption choices. Similarly, the popularity of prepared meals from restaurants rose as 68% of the adults in the U.S. indicated prepared meals offered convenience over cooking at home [41], though prepared meals are less nutritious compared to cooking from fresh groceries.

USDA defines low-access, similar to the existing literature, using the distance from a population location, like the center of a census tract, to the nearest food establishment, such as grocery stores [42]. Other existing metrics include, for example, the number of food establishments within a pre-defined distance threshold from a population location [43, 44, 45], gravity-based metrics treating farther food establishments as less-accessible [46, 47], and utility-based metrics evaluating how much satisfaction one receives by purchasing from food establishments [48], etc. Each type of metric has its own strength and different use cases. Distance or time-based metrics, such as those based on proximity, offer simple interpretations: shorter distance or time means better accessibility. In contrast, gravity-based metrics require calibration of distance decay functions [49], and utility-based metrics consider people's preferences in purchasing food, food establishment quality, and characteristics, among others. These metrics assume that customers travel from a set location (like home or workplace) to buy food in person.

However, these metrics aren't easily applied to evaluating food access through delivery services, where food comes to the customer instead. Delivery services reduce the dependence on mobility (eliminate travel time) and proximity (distance becomes less significant), and this key feature can be further broken down into the following three aspects. First, food establishments too close to a population location are not necessarily more accessible, as delivery fees may apply regardless of the short distance. Second, with delivery service, people are no longer constrained by travel time to food establishments, opening a broader range of food choices. Third, existing food accessibility metrics focus solely on the supply side of food establishments [49], and with rising demand for delivered food, the metric should consider both supply and demand sides and competition when establishments can't meet demand or consumers have numerous food choices. There is a need to understand how to account for delivery in the methodology and our understanding of food access [50, 51]

To promote food access and a healthful diet for low-income Americans, USDA launched the Supplemental Nutrition Assistance Program (SNAP), the nation's largest nutrition assistance program [23]. In 2022, SNAP announced its investment in SNAP online program, recognizing online shopping as a vital resource to improve access for SNAP participants [24]. SNAP online benefits continue to use income as the eligibility criteria: in Washington state, individuals and households should have monthly income (before taxes and reductions) under the gross monthly income standard listed in Washington Administrative Code. Since low-income households do not necessarily experience low-access, as about 41% of USDA defined low-income tracts are low-access, the income-alone criterion may not be appropriate. Furthermore, the criteria do not consider whether a household with limited access to on-premise shopping for food also faces limited access to delivered food.

Thus, two observations can be made regarding food accessibility via delivery. First, no existing research has confirmed or refuted that people far from grocery stores (thus low-access) also have low-access to delivered groceries. Second, it would be of interest to evaluate whether the SNAP online program can indeed help individuals lacking access to fresh vegetables through food delivery. Low-income individuals may struggle with ordering delivery if online benefits do not cover fees and prefer pickup or on-premise purchasing, leading to unrealized SNAP online benefits. On the other hand, low-income individuals living within walking distance (e.g., a 15-minute walk to grocery stores) can also buy groceries on-premise. It is thus unclear how SNAP online benefits will affect food access, especially for low-income and low-access households.

In short, the rise of food delivery services motivated this study. More specifically, this study proposes a modified Two-step Floating Catchment Area (2SFCA) method that accounts for the unique features associated with delivery services, investigates how the emergence of delivery service changes the landscape of food access, and examines how the SNAP online program helps food access by low-income and low-access households with delivery service in mind. This study answers the following questions:

1. how to incorporate the key features of delivery service into food accessibility quantification

2. how does the increase in food accessibility brought by delivery services vary across different population segments and regions?

3. how is the population with low access to delivered fresh produce supported by SNAP online benefits?

2.2 The evolution of food accessibility metrics

Food accessibility, stemming from the widely explored work on accessibility, refers to the extent of potential opportunities for obtaining food [52]. People recognize the importance of food accessibility because enough and nutritious food options are critical for human survival and well-being. Past studies pointed out that people in rural areas [53, 54, 44, 36], having limited access to transportation [45, 36, 55, 56], and low-income and minority concentrated [57] communities have less access to food. Spatial factors, such as proximity to residential areas, population density, and service capacity of food establishments are also influential in determining food access [58, 56, 59].

Measurements for food accessibility started with a primitive form of the distance to the closest food establishment from a population location, for example, census tracts [42]. Longer distance to the closest establishment implies lower levels of food access. Later, the definition expands to the form of cumulative opportunity, which counts the number of food establishments within a given distance determined by travel time, mode, and speed from an origin or within a given area unit such as a census tract [43, 44, 45, 60, 61]. Commonly, these measurements involve a distance threshold from 0.5 to 15 miles [43, 54, 55, 62]. However, cumulative opportunity does not treat closer options as easier reach than farther options. Thus, gravity-based measures were proposed to discount opportunities that are farther away through distance decay functions [46, 47]. The discussion quickly evolves to incorporating personal characteristics because one might prefer one option over other options due to factors including income level and service quality [63, 64]. Under this branch, each food option is weighted by the utility, or the overall satisfaction one perceives, and consumers purchase food based on the random utility maximization principle [48]. Personal attributes like cultural preferences, service quality, and price sensitivity may lead individuals to opt for farther food establishments, which are challenging to be captured in gravity models. Understanding utility requires detailed data such as survey instruments to estimate preferences for qualitative and quantitative attributes of the food [48], which is more expensive and less accurate to collect compared to census tract and food establishment's coordinates.

Recent literature argue that the existing food accessibility measurements are compromised by focusing only on the supply side, i.e., the food establishments and overlooking supply-demand interactions [65, 66]. Simply speaking, given a set of food establishments, areas with higher population density will compete for food and receive less service quality compared with areas with lower population density. One step forward is calculating the density, or ratio of population to food establishments [67], to reflect how much competition for food exists within a place. However, this density metric usually treats all food establishments the same, despite varying capacities or the amount of service provided. A restaurant serving 100 customers simultaneously should be differentiated from other small-scale food stores serving only 10 customers.

To capture the intricacy of local competition between supply and demand, more literature in the last two decades began to explore the Two-step Floating Catchment Area (2SFCA) method, originally proposed by Luo et al. in 2003 [68]. 2SFCA begins with calculating a supply-to-demand ratio as the establishment's service capacity to the populations attracted to this establishment within a distance threshold. The accessibility of a population location is the sum of supply-to-demand ratios for establishments within this distance threshold. The original 2SFCA model counts every establishment equally like cumulative opportunity models and is later enhanced to incorporate distance decay functions including negative exponential function, power function, generalized logistic function, and kernel density forms such as gaussian, and generalized logistic function [47, 69, 70], to mimic the effect of higher accessibility of nearby services than those farther away in a gradually decaying fashion. A detailed discussion on the applicability and limitations of twenty-four distance decay functions can be found in Chen and Jia [66].

The service capacity for each food establishment is usually acquired using a store's square footages [71], sales volume ranges [72, 73], and the proportion of SNAP benefits used in one food category for all establishments belonging to that category [66, 49]. However, the use of different units for supply such as square footage units, monetary units, or percentages potentially making it challenging to interpret the supply-demand ratio and accessibility. For example, when monetary units are used, the supply-to-demand ratio will be in dollar per person. Thus, a high ratio of $1,000 per person could either result from the high monetary value associated with the supply or a low demand. Similar can be said about the proportion of SNAP benefits given that there likely exists large variations in how much SNAP benefits are used across different establishments. The use of square footages fares better than the other two and yet they are still in different units from the demand. Ultimately, it is desirable to use the same units for both supply and demand (both are in persons) and hence this is the approach adopted in this study.

The existing work on food accessibility is only oriented toward quantifying on-premise accessibility when individuals travel to the food establishment. Food incentive programs, such as SNAP, rely only on on-premise food accessibility findings, or simply by the income level of households to decide the eligibility status. Though a few analyze the SNAP program with spatial and supply-demand perspectives such as Chen (2019) [49], the effect of delivery on food accessibility remains unexplored, with one pointing out that rural, food insecure counties in Washington continue to lack access to grocery delivered to home [74]. The existing literature on food accessibility metrics often discuss either food quantity or diversity, and yet they can be very different from each other. High level of accessibility to one type of food can be associated with lack of diverse food options; a community may have an abundance of fast-food but lack access to fresh produce. Conversely, diverse food options may not meet population needs if quantity is insufficient. Most literature focuses only on the grocery category, leaving little room to discuss diversity. Some has argued the importance of examining both healthful and less-healthful (but affordable and convenient) food establishments to form a cohesive, comprehensive understanding of food access [75]. Hence, in our study, we look at three food categories: grocery stores, restaurants and fast-food, and examine accessibility in each category and their diversity.

2.3 Methodology

This study modified the 2SFCA method, originated from studies on the accessibility of physician services [68], to quantify and analyze food accessibility through a case study in Seattle, Washington. The modification contributes to the research questions by developing food accessibility metrics for on-premise and delivery services, accounting for supply vs. demand and quantity vs. diversity.

2.3.1 The original 2SFCA method

2SFCA first calculates the supply-to-demand ratio, R_j, for each physician location j. R_j serves as the physician's capacity (usually counted as the number of physicians) to serve the population in the vicinity. The population can only be served by a physician if the distance, d_{ij} between the population location i and the physician location j is less than a pre-defined distance threshold r. Suppose there are N population locations, and each location has a population size of P_i ($i = 1, \ldots, N$). There are M physician locations, each with one physician. Then, R_j is defined by equation 2.1[1]:

$$R_j = \frac{\text{supply at location } j}{\text{population within } r} = \frac{1}{\sum_{i \in \{N | d_{ij} \leq r\}} P_i}. \tag{2.1}$$

The second step of the 2SFCA formulation is to search all physician locations that are within the threshold r from population location i. Therefore, the accessibility to physician for a population location, A_i, is a sum of the supply-to-demand ratio:

$$A_i = \sum_{j \in \{M | d_{ij} \leq r\}} R_j. \tag{2.2}$$

2.3.2 Key features of delivery and their difference from on-premise options

To account for special features delivery, this work uses different catchment areas for food accessibility on-premise and through delivery. With delivery, customers are limited by travel time or distance, so one might enlarge the catchment area and increase the distance threshold for delivery scenario. However, drivers are reluctant to spend more than 15-20 minutes on the road, and prepared food loses taste after a long trip. Thus, delivery platforms consider 5 miles as a standard delivery distance [76]. Moreover, the impedance function for delivery service should discourage orders from service locations too close to the customer due to delivery fees. For example, Rodrigue proposed to modify the function to a straight-line function for e-commerce without delivery fee per order [77]. Given delivery apps' per-order fees, this study designs a donut-shaped catchment area, excluding food outlets too close to

[1] The numerator is set to 1 because each physician location only has one physician available.

the population center. A 1.5-mile distance threshold is set based on a survey indicating a preference for traveling to nearby establishments over ordering delivery [78]. Therefore, the donut-shaped catchment area has an inner and outer distance threshold of 1.5 miles and 5 miles, respectively. For on-premise food accessibility, literature has shown that the average distance traveled to food outlets varies depending on the type of the food outlets [79]. The outer radius for catchment area for grocery stores, fast-food outlets, and restaurants are set at 4.67, 4.96, and 6.10 miles, respectively, according to the finding from Kerr et al (2012)[79].

2.3.3 The modified 2SFCA method

The first modification is discounting the supply-to-demand ratio for food establishments further away from the population location or cost higher than others. Secondly, this study categorizes food establishments into full-service restaurants, quick-service restaurants, and groceries to analyze accessibility across categories and to examine competition, complementary effects, and the diversity of food choices. Originally conceptualized in the literature in the 1970s [80]. competition arises when customers have multiple service locations to choose from, potentially leading to demand dilution towards locations with lower costs. A recent work measuring job accessibility considers competition via a probabilistic model, comparing location attractiveness using a negative exponential decay function [81]. Third, service capacity can be estimated based on daily customer served, derived from seating capacity (the number of customers a food outlet can accommodate). Fourth, the demand for each food establishment should be carefully addressed to avoid demand and supply inflation, a phenomenon identified by several works [69, 82]. Demand inflation occurs if the 2SFCA method overestimates the potential population demand where multiple facilities are accessible to a population location. Supply inflation occurs if the 2SFCA assigns supply to all residents from a population location. To account for the above, equation (2.2) can be modified as follows:

$$R_j = \frac{\text{supply at location } j}{\text{population attracted to } j} = \frac{cap_j}{\sum_{i \in \{N | r_1 \leq d_{ij} \leq r_2\}} P_i \times p(d_{ij})}, \tag{2.3}$$

where cap_j $(j = 1, \ldots, M)$ being the supply capacity of j^{th} food establishment. r_1 and r_2 represent the inner and outer radius of the donut-shaped catchment area, respectively. Supply capacity, cap_j, is determined by multiplying seating capacity by daily operating hours, assuming customers spend up to one hour at the establishment. d_{ij} is the distance from population location i to food establishment j, which represents the cost for customers from location i to be served by j. The longer the distance, the higher the cost. The function $p(d_{ij})$ in the denominator is the fraction of the population i choosing location j out of a set of M available options, based on d_{ij}. So, the demand from location i to establishment j is not P_i but $P_i \times p\left(d_{ij}\right)$. Up to this step, the use of $p\left(d_{ij}\right)$ in calculating demand and R_j is the same as the row-normalization of the impedance matrix developed by Paez et al [82] and addresses demand inflation problem as noted by Paez et al [82]. The formulation of $p\left(d_{ij}\right)$ is discussed later in equation 5. An establishment with R_j value of less than 1 offers insufficient service to the demand.

Equation 2 is modified into a category specific food accessibility for location i, A_{ic}, to facilitate analyzing quantity and diversity:

$$A_{ic} = \sum_{j \in \{M | r_1 < d_{ij} < r_2 \ \wedge \ C_j = c\}} R_j \times p\left(d_{ij}\right), \ and \tag{2.4}$$

$$p\left(d_{ij}\right) = \frac{e^{-d_{ij}^2/\beta}}{\sum_q e^{-d_{iq}^2/\beta}}, \tag{2.5}$$

where $q = 1, \ldots, j, \ldots, M \wedge r_1 < d_{iq} < r_2$, and C_j represents the category of a food establishment j. Food establishments contribute to accessibility based on their relative importance, weighted by a fractional population from location i that will visit each food establishment j. We note that the above formulation defines the supply-demand ratio and category specific food accessibility via delivery. For on-premise establishments, the function $r_1 < d_{ij} < \ r_2$ should be changed to $d_{ij} < \ r_2$. Additionally, this study adopts the logit model with Gaussian function as the functional form of $p(d_{ij})$ and uses distance as the only input [2]. Gaussian function has been reported to outperform cumulative opportunity, inverse

[2] In a general form, other forms of costs such as travel time and monetary cost can also be included.

power-law, kernel density, and negative exponential decay functions. The decay parameter β is derived from the USDA Atlas finding that the maximum travel distance to purchase food is observed to be 20 miles. Therefore, Chen (2019) [66] believed that the critical value $e^{-20^2/\beta}$ equals 0.01 (the value for the Gaussian function approaching 0 [83]) and the decay parameter $\beta = -\frac{20^2}{ln0.01} = 86.9$.

$p\left(d_{ij}\right)$ in equation 4 calculates the food accessibility for location i as a weighted average of R_js, and the weight for each R_j equals the proportion of the population that visits the establishment j. This methodology addresses the supply inflation in that the supply from one establishment is only given to those who visits the establishment, not the entire population. Calculating food accessibility in this fashion, similar to Delamater (2013) [69], ensures the total supplies given out from the food establishments equals the total supplies received by the population, and thus the following equation holds: $\sum A_i P_i = \sum cap_j$ (see Appendix A for the proof). We note this is different from another line of literature that discusses preserving instead $\sum A_i = \sum R_j$, as proposed by Paez (2019) [82], and used by Pereira (2017) [84] and Desjardins et al [85].

Because customers can obtain food from one or more categories, the total food accessibility, , is the summation of all category-specific food options:

$$A_i = \sum_{c=1}^{C} A_{ic}. \tag{2.6}$$

The diversity of food accessibility comes into play through complementary effects using entropy [86], and higher diversity means a more balanced food accessibility. The diversity index D_i can be defined as:

$$D_i = -\sum_{c=1}^{C} \frac{A_{ic}}{A_i} \times ln\left(\frac{A_{ic}}{A_i}\right). \tag{2.7}$$

A_i and D_i are two key metrics that evaluate the census tract's food accessibility's quantity and diversity, respectively. Though much of the literature emphasizes accessing healthy foods from grocery stores in particular, a rising share of literature [87, 88] highlights the importance of diversity as an essential element of local food environment. And they suggest that a good food accessibility metric may not be the proximity to a single food source, albeit healthy, but the availability of different food sources in the residents' daily travel footprint.

2.4 Result

The analysis is carried out on a case study in Seattle, Washington, including 135 census tracts, 3,654 full-service restaurants (referred to as restaurants), 389 quick service restaurants (referred to as fast-foods), and 564 groceries. Before presenting the details, we first discuss the justification of selecting this region and data preprocessing.

2.4.1 Study area selection and data preprocessing

The study area is Seattle, Washington, and includes 135 census tracts with a total population of 779,200 reported in 2023. The sociodemographic data of the residents in the study area is collected from the American Community Survey (ACS) [89]. Additional characteristics such as low-income, low food access, and household SNAP participation rates are acquired from USDA Food Access Research Atlas and merged to ACS data based on census tract unique identifiers. According to the 2014-2018 ACS 5-year estimates, around 75% of Seattle's population consisted of individuals aged between 18 and 64. Additionally, 23.1% of the population are young adults aged 25 to 34. Nearly two-thirds of Seattle residents aged 25 years and older held a Bachelor's degree or higher, according to data collected between 2017-2021 [90]. Research has shown that regions with younger, more highly educated residents are more likely to have customers who patronize online food delivery services [91].

The 2019 data from the USDA Food Atlas and the Washington SNAP program indicated that, on average, each tract has 10% of the households participated in the SNAP program, while 50% of all tracts have a SNAP participation rate of less than 7%, which suggests that there are a small number of tracts relying heavily on the SNAP program. According to the Pareto principle, the wealth distribution typically ends up with 20% of the population using 80% of the resource. Hence, this study focuses especially on the tracts with participation rate greater than 16% (that is, the 20% of the population relying the most on SNAP benefit). Other than high SNAP participation rate, this study also adopts the same definition for low-

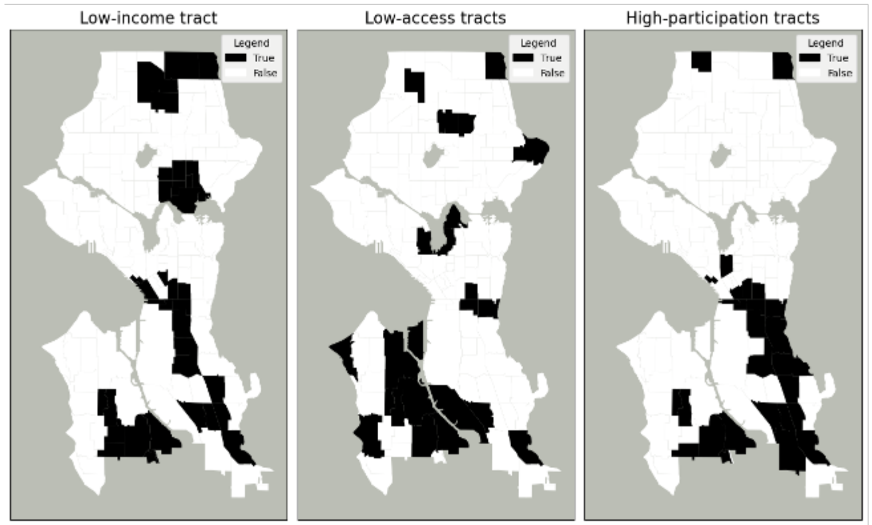


Figure 2.4.1: The distribution of low-income, low-access, and high SNAP participation tracts in Seattle.

income and low-access, following USDA Food Access Research Atlas's definition. There are 35 low-income tracts and 22 low-access tracts, with 9 tracts that falls into both categories. The spatial distribution of three types of census tracts is presented in Figure 2.4.1.

Data on food establishments are obtained from the King County Food Facilities Inspection data, which provides accurate latitude, longitude, category, and capacity information for food establishments. The food inspection data contains 10,000 food establishments such as grocery stores, restaurants, bakeries, etc. The food inspection data also includes food establishments such as school lunch program, bed and breakfast, and convenience stores and they are excluded in this study since they do not provide food to the public nor serve standard portion of meals. Among these establishments, about 85.5% of the food establishment are reported with a seating capacity of a range, e.g., between 0-12. This range of 0-12 means the food establishment can sit at most 12 customers. The seating capacity for the other 14.5% of food establishments is approximated using data from Safegraph and Google Place API. These two sources offer additional geometry information which delineates the occupied square footage of the establishment. For each type, there exist a recommended square footage per customer such that there is enough space to maneuver in case of fire. For example, restaurants should allocate 12-15 square feet per customer, whereas fast-food establishments should assign 11-14 square feet per customer [92]. The supply capacity, cap_j, is calculated as the number of customers this establishment can hold (i.e., the seating capacity) times the number of hours this establishment is open for service. This study assumes different hours of operations for different categories: restaurants open 8 hours, grocery stores open 14 hours, and fast-foods open for 18 hours, after surveying the food establishment near University of Washington's U-District, a vibrant community of food retailing.

After filtering, 4,607 food establishments in this case study are classified into three types: 3,654 full-service restaurants (referred to as restaurants), 389 quick service restaurants (referred to as fast-foods), and 564 groceries. Restaurants are defined as establishments offering table service, dining amenities, and waitstaff. On the other hand, fast-foods focus on a specific type of food, like burgers and pizza, and prioritize speed and convenience through counter or drive through ordering and payment. According to USDA, grocery stores are defined as food departments selling fresh fruits, vegetables, canned and frozen foods, fresh and prepared meats, fish, and poultry [93]. The spatial distribution of three types of food establishments is presented in Figure 2.4.2, overlapped with the Seattle Census tracts. Figure S2 demonstrates that restaurants cluster in downtown Seattle, but fast-food and grocery establishments cluster less and are more evenly distributed across the study area.

Supply-to-demand ratio

All food establishments have supply-to-demand ratio (R_j) greater than one, meaning that they provide excess supply compared to demand, regardless of the category or whether through on-premise or delivery service. However, the distribution of R_j is highly skewed to the right, so the mean value is much smaller and less reliable than the median (see Table 2.4.1).

Restaurants, fast-food, and grocery establishments have median of 27.00, 15.61, and 38.68, respectively. And the values are the same for delivery and on-premise services. This is due to approximating the seating capacity within a range (e.g., assuming an establishment can sit 6 individuals if the range is 0-12). Consequently, many food establishments have the

Figure 2.4.2: The distribution of food establishments by category in Seattle

Table 2.4.1: Summary statistics for food establishments supply-to-demand ratio through on-premise service (top) and delivery (bottom).

On-premise	**Mean**	**Median**	**Standard Deviation**
Restaurant	153.14	27.00	1,586.21
Fast-food	159.69	15.61	888.14
Grocery	115.23	38.68	906.48
Delivery	**Mean**	**Median**	**Standard Deviation**
Restaurant	69.29	27.00	540.54
Fast-food	159.69	15.61	888.14
Grocery	191.77	38.68	1,277.37

same capacity since 23.9% of the food establishments overall have a seating capacity between 0 and 12 and 31.2% of the food establishments overall have a seating capacity between 13-50. Therefore, many establishments will appear to share the same capacity, resulting in very similar supply-to-demand ratios. The food establishments in Seattle are providing excessive supply; however, this does not suggest residents are not competing for food. The supply capacity is calculated by counting on the hours of operation, where customers might only patronize at specific time of the day, for example, lunch breaks or hours after work. Some of the service capacity could be underutilized due to variations in customer demand patterns throughout the day. On average, fast-foods provide the most supply to residents through on-premise service, and grocery stores provide the most supply through delivery. Grocery stores provide the most supply observed from mean and median values, which suggests fresh produce are the main channel in food supply.

For on-premise services, restaurant's standard deviation is the largest among four categories. The conjecture for large standard deviation is that the seating capacity for restaurants has a wide spread. Investigating the food inspection data reveals that there are five intervals for seating capacity: 0-12 people, 13-50 people, 51-150 people, 151-250 people, and above 250 people; and there are 1437, 1099, 904, 133, and 81 food establishments that fall into those intervals, respectively. About 53% of restaurants sit less than 50 people, but other restaurants serve 51 to more than 250 customers. Such a variation in capacity leads to large standard deviation in its supply-demand ratio. With delivery, grocery stores provide the most supply, but its standard deviation is the largest. The reason for observing the large standard deviation can be inferred from the spatial distribution of the grocery stores. According to figure S1 in the case study section, grocery stores locate more evenly in the study area rather than clustered in downtown areas. Some grocery stores, therefore, serve less customers if they are not located in residential areas, resulting in high ratios. The number of residents who live within the catchment area varies more, thus affecting the supply-demand ratio calculation.

2.4.2 *How does the increase in food accessibility brought by delivery service vary across in the study area?*

Category-specific food accessibility

Figure 2.4.3 presents heat maps illustrating geographic variations in category-specific food accessibility. The 2x3 subplot distinguishes between on-premise vs. delivery and the category being plotted. A tract is shaded lighter if it has a smaller A_{ic} value compared to darker tracts. There is noticeable difference for the restaurant category comparing the first column. The heat map indicates that downtown Seattle has limited access to delivered restaurant food compared to peripheral areas. This pattern appears to contradict the high concentration of restaurants in downtown areas (bounded within the black rectangle in each subplot). However, it is consistent with the donut-shaped catchment area for delivery services, leaving the downtown area with fewer available food establishments to choose from. Since more restaurants are located in downtown, residents there are ensured to have enough food through dine-in option. Heatmaps for fast-food and grocery showed less discrepancy, possibly owing to a much smaller number of establishments. The heatmaps for grocery and fast-food establishments generally display a linear increase from north to south in the study area. Donut-shaped areas around downtown for these two types are less prominent than those for restaurants. Comparing the heatmaps for on-premise and delivery for fast-food and grocery stores respectively, several observations can be made. First, the south part has better accessibility than the north for both on-premise and delivery. Second, the difference between the north and south parts is more pronounced for fast-food compared to grocery stores. Third, adding the delivery option does not alter the overall pattern: it further enhances fast-food options in the south. Comparing on-premise and delivery heat maps shows increased restaurant food accessibility in the outskirts of downtown, although access to fresh produce is more subject to the number of establishments available in vicinity.

Table 2.4.2 reports the summary statistics of on-premise and delivery service's A_{ic}. In all categories, the mean and median of the delivery A_{ic} and on-premise A_{ic} are of simi-

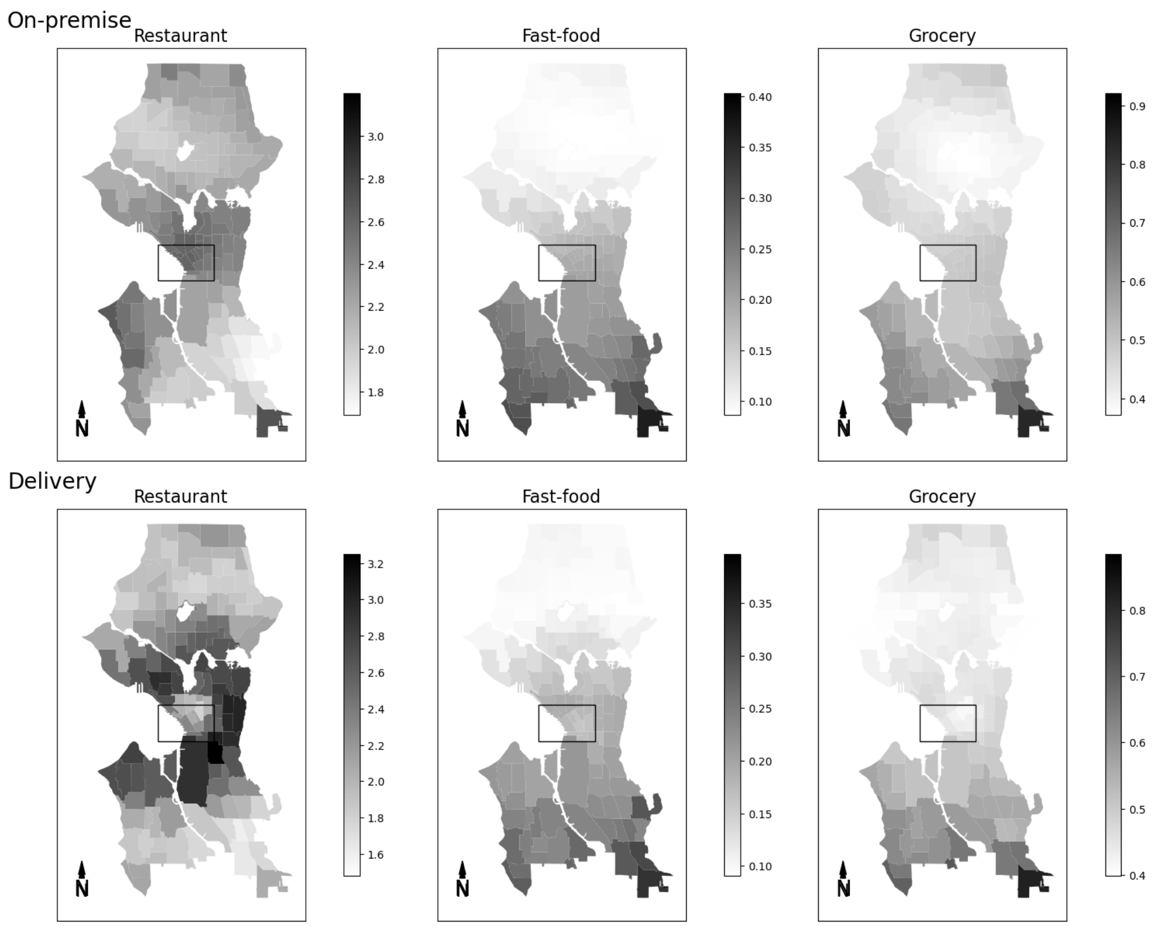


Figure 2.4.3: Heat maps for category-specific food accessibility in the study area. Top row: accessibility through on-premise service. Bottom row: accessibility through delivery service. Downtown Seattle is bounded within the black rectangle.

lar magnitude. Restaurant and grocery store's food access via delivery have medians that are slightly less than on-premise food access. In general, this indicates that if all food establishments exclusively offer delivery service (e.g. during strict social-distancing policy), customers would have equal amount of food to access compared to on-premise services. However, it is noteworthy that the standard deviation for restaurant-specific food accessibility is much higher than other categories in both delivery and on-premise cases, indicating greater variation in accessing cooked food from restaurants through delivery. The restaurant specific food accessibility is also considerably larger than other categories, due to the presence of 3,654 restaurants out of 4,607 establishments in the study area.

Table 2.4.2: Summary statistics for category-specific food accessibility through on-premise service (top) and delivery (bottom).

On-premise	**Mean**	**Median**	**Standard Deviation**
Restaurant	2.24	2.21	0.24
Fast-food	0.16	0.15	0.07
Grocery	0.48	0.47	0.09
Delivery	**Mean**	**Median**	**Standard Deviation**
Restaurant	2.23	2.11	0.39
Fast-food	0.16	0.16	0.06
Grocery	0.48	0.45	0.09

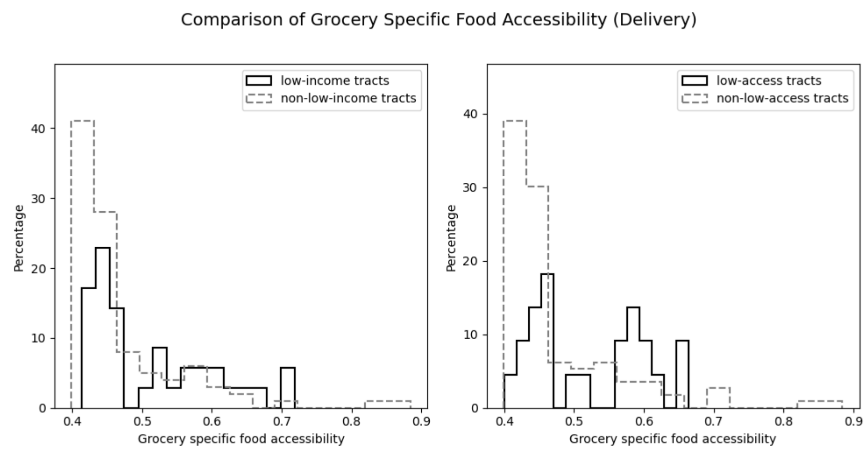
Further examining category-specific food accessibility for low-income/non-low-income and low-access/non-low-access (defined by USDA) reflects how delivery improves accessibility in different population segments. Figure 2.4.4a depicts the grocery specific food accessibility for low-income vs. non-low-income tracts and low-access and non-low-access tracts via delivery only. With delivery, non-low-income tracts have a wider range of grocery accessibility, ranging from [0.40, 0.89], whereas low-income tracts can at most have 0.72. Similarly, low-access tracts also have a lower upper-bound, with their maximum grocery access valued at 0.66 compared to 0.89 of the non-low-access tracts. However, the plots suggested that more of the low-income and low-access tracts have higher accessibilities compared to their counterparts. This implies that delivery services provide greater benefits to low-income and low-access areas by improving access to fresh produce and promoting a healthier diet.

Similarly, Figure 2.4.4b compares the restaurant specific food accessibility via delivery for the four types of census tracts. Two observations can be made. First, in general, with delivery option only, both low-income and low-access tracts have higher lower-bound values than their counterparts. Second, the upper bound value for low-income tracts is larger than the counterpart (non-low-income tracts) while the reverse is true for low-access vs non-low-access tracts. Multi-modal distributions exist for both low-income and non-low-income tracts (the former has three while the latter has two). This phenomenon is less pronounced for low-access and non-low-access tracts. Combing with the observations for Figure 2.4.4a for grocery store accessibility, the finding is that though delivery services do result in a good number of low-income or low-access tracts to have good accessibility (for both grocery stores and restaurants), there still exist a substantial number that have relatively low levels of accessibility.

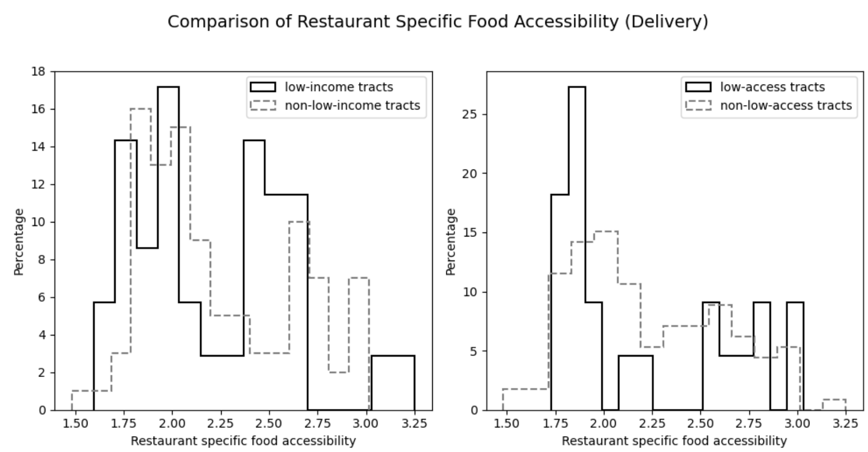
Diversity index measures the variety of food options in each census tract, and the heatmaps in Figure 2.4.5 revealed an increasing trend of diversity from north to south. As restaurants dominate the study area, increasing diversity could mean more healthy options from grocery stores and fewer cooked options from restaurants. Furthermore, with delivery, downtown area has higher diversity index compared to itself with on-premise service, which further confirms that delivery improves food accessibility diversity when the residents have less food establishments to choose from.

2.4.3 How are the population with low access to delivered fresh produce supported by SNAP online benefits?

The first three subplots in Figure 4 plots the low-income, low-access, and high-participation tracts, and the dark-colored tracts indicates the tract satisfies the definition. High-participation tracts refer to tracts with participation rate greater than 16% (that is, the 20% of the population relying the most on SNAP benefit). And the right-most subplot plots the total



(a) Probability density plot for grocery-specific food accessibility via delivery. Left: low-income vs. non-low-income tracts. Right: low-access vs. non-low-access tracts.



(b) Probability density plot for restaurant-specific food accessibility via delivery. Left: low-income vs. non-low-income tracts. Right: low-access vs. non-low-access tracts.

Figure 2.4.4: Comparison of probability density plots for grocery and restaurant-specific food accessibility via delivery.

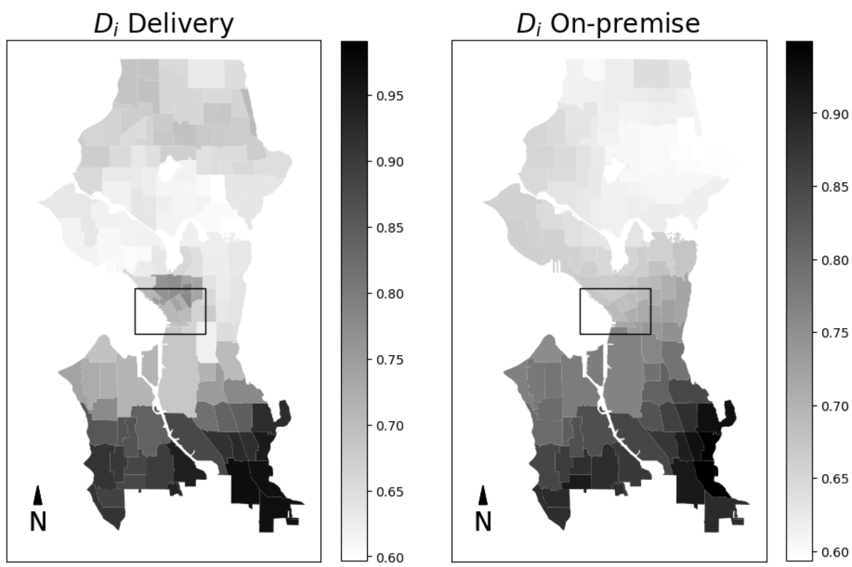


Figure 2.4.5: The diversity index, D_i, for delivery (left) and on-premise (right) for each tract in the study area. Darker shaded tracts have more diversified options for food compared to lighter shaded tracts. Downtown Seattle is bounded within the black rectangle.

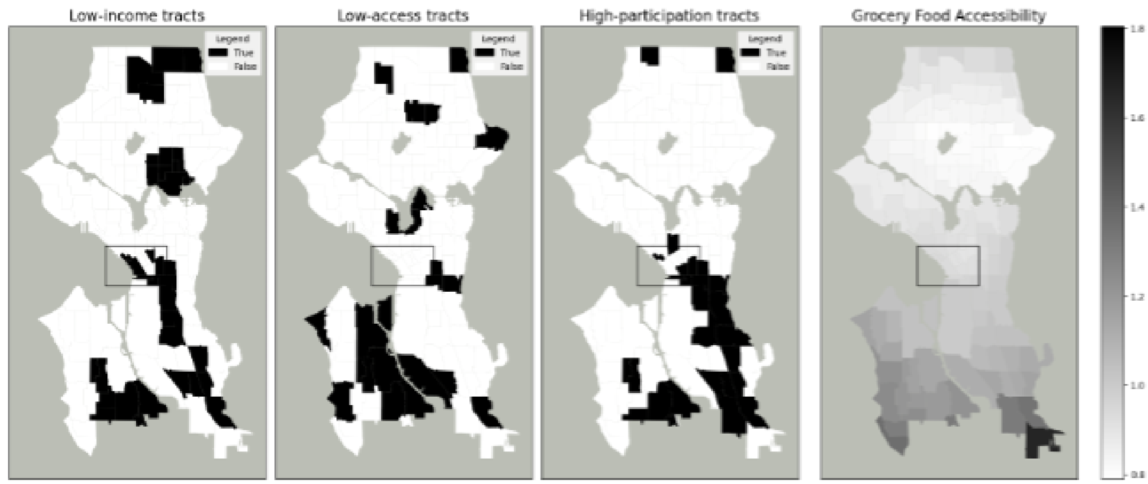


Figure 2.4.6: Maps indicating low-income, low-access, and high-participation, and grocery food accessibility (on-premise and delivery combined) tracts in Seattle. Downtown Seattle is bounded within the black rectangle.

grocery accessibility (on-premise and delivery). As expected, the pattern exhibited in the subplot for high-participation plots matches well with that for the low-income tracts, since SNAP eligibility is based on income alone. Between low-access tracts and high-participation tracts, the patterns seem to have just flipped: though both are in southern Seattle, low-access tracts primarily concentrate on the west side while high-participation ones are on the east side. This means that in Seattle at least, low-income tracts and low-access tracts capture two different populations. The last subplot shows the distribution of accessibility to grocery stores (both on-premise and delivery). Surprisingly, the South side in fact has better accessibility to grocery stores than the north side of the study area.

The first three subplots in Figure 2.4.6 plots the low-income, low-access, and high-participation tracts, and the dark-colored tracts indicates the tract satisfies the definition. High-participation tracts refer to tracts with participation rate greater than 16% (that is, the 20% of the population relying the most on SNAP benefit). And the right-most subplot plots the total grocery accessibility (on-premise and delivery). As expected, the pattern exhibited in the subplot for high-participation plots matches well with that for the low-income tracts, since SNAP eligibility is based on income alone. Between low-access tracts and high-participation tracts, the patterns seem to have just flipped: though both are in southern Seattle, low-access tracts primarily concentrate on the west side while high-participation ones are on the east side. This means that in Seattle at least, low-income tracts and low-access tracts capture two different populations. The last subplot shows the distribution of accessibility to grocery stores (both on-premise and delivery). Surprisingly, the South side in fact has better accessibility to grocery stores than the north side of the study area.

The mismatch between those in low-access tracts vs those in high SNAP participation tracts suggest that the SNAP online program, though capturing low-income tracts well, does misses low-access tracts. Additionally, overall, grocery store food accessibility (combining both on-premise and delivery only) fares better for South Seattle than for North Seattle, based on the rightmost plot in Figure 4, suggesting that the SNAP online program may miss pockets in North Seattle. Thus, relying solely on average household income as the criterion for SNAP eligibility may overlook critical factors such as the existing food accessibility landscape, the spatial distribution of establishments, and the competition among residents. In other words, those who actively participating in SNAP might not be the only population segment in great need of the benefit. Furthermore, regions with limited online grocery options, particularly the northern region, receive less SNAP benefit because it has only two tracts with high SNAP participation. Some regions, especially in the northern area, don't have enough online grocery options as shown by the lighter color (and lesser value) of the grocery food accessibility in the rightmost subplot in figure 4, suggesting that there are likely pockets where SNAP online benefits can be valuable.

2.5 Conclusions

Delivery challenges the long-adopted methodologies for calculating food accessibility in that delivery service are less reliant on proximity, excluding closer food choices, and rising competition between supply and demand. This work contributes to the literature by proposing a modified 2SFCA accessibility metric evaluating food accessibility for delivery and on-premise services that considers the above three features. The proposed methodology is also used to assess the efficacy of SNAP online benefits, considering that the current eligibility criteria rely solely on household income without factoring in food access.

This study raises interesting questions relating to how to improve people's access to fresh food as typically available in grocery stores, especially for the low-income people who are found to spend more at fast-food establishments. Our study shows that in the city of Seattle, the south part where low-income and low-access tracts concentrate, appears to have higher levels of accessibility to fresh food than the north part, due to more availability of grocery stores in the south part than those in the north. This suggests that while adding SNAP online benefits does improve accessibility to fresh food overall for the study area, other policies (in addition to making fresh produce more available) may be needed to increase people's consumption of fresh produce especially for the low-income people. One may point to the fact that while there is already vast availability of on-premise fast-food options (see Figure 2.4.3), adding delivering further enhances the accessibility to fast-food significantly, which may not be desirable. As such, one policy discussion is perhaps about how we can reduce accessibility to fast-food while at the same time improving access to fresh produce.

This work relies on annual food inspection data and assuming establishments recorded as operational in these datasets remain open which may not hold true post-pandemic due to significant disruptions in the food industry. This work assumes all food outlets, including restaurants, grocery stores, and fast-food establishments, have adopted delivery services due to the widespread availability of third-party delivery services like Instacart and DoorDash. However, adoption rates may vary across different types of establishments, potentially affecting the observed landscape of food accessibility. The study also does not explore how personal characteristics and preferences (affordability, daily work schedules, mobility, and cultural preferences, etc.) affect individuals' choices among available food outlets, thus limited the understanding of food accessibility determinants. Future research endeavors should consider incorporating these individual-level dynamics to provide a more comprehensive and nuanced exploration of the factors influencing food choices and accessibility through delivery.

Chapter 3

COVID & TELECOMMUTING-INDUCED CHANGES IN INDIVIDUAL ACTIVITY AND TRAVEL PATTERNS: EVIDENCE FROM THE PUGET SOUND REGION

3.1 Introduction

Telecommuting has long been recognized as a Transportation Demand Management (TDM) strategy to reduce Vehicle Miles Traveled (VMT) and reliance on cars. Proponents argue that telecommuting has the potential to replace existing travel demand [26] while others note that time saved from the reduced trips will be re-allocated for traveling [27, 28]. These debates remained within a small circle of researchers prior to COVID, as only a small share of workers telecommuted (less than 5%). This small percentage changed dramatically with COVID: the share of telecommuters jumped to 35.4 in the peak of May, 2020 and now still hovers around 23.0, as of March 2024 [5]. When individuals no longer need to commute to work on a regular basis, their travel behaviors are likely to change [29, 30, 31, 32, 33]. When there is a substantial number of telecommuters in the workforce, the sum of their travel behavior changes can have a significant impact on the transportation system, as well as have long-term implications for land use patterns and related transport policies. It is thus desirable to revisit the topic regarding the promise of telecommuting as a TDM strategy to potentially reduce VMT and reliance on cars.

Findings on this topic have been mixed, with findings for telecommuting to both substitute and complement travel demand. For example, telecommuting has been shown to increase both frequency and distance of non-work trips [94, 95], and travel farther and longer for those non-work trips [25]. Van Wee and Rietveld [96] found that travel time increased 8% with the 1975-2000 Dutch National Travel Survey and 26% with the Dutch Time Use Survey. On the other hand, Choo et al. [97] supported the substitution point of view– they found that telecommuting reduced total annual VMT in the U.S. by approximately 8%.

Ellder [26] also showed that telecommuters had a significantly lower personal-kilometers-traveled compared to commuters. The first aim of this paper is thus to obtain a holistic picture of how telecommuting changed people's daily travel patterns, including the generation of trips, temporal and spatial rescheduling, and changes in VMT and modes of transportation used.

In theory, we answer this question using Hagerstran's space-time prism framework [98]. In his now widely-cited paper "What about people in regional science?", Hagerstrand [98] proposed the concept of space-time prism, which explicitly recognizes the spatial and temporal constraints associated with traveling in terms of where, when, and mode of transportation used. In the prism, home and work are the anchor points because they are fixed spatially and temporally (most people have fixed home and work locations and the start and end times at workplace are often regulated by the employers). Trips surrounding those two anchor points are less fixed in space and time. In general, those trips are of two kinds: (1) maintenance trips that fulfill one's needs and necessity for living in a modern society, e.g., banking and meals; and (2) discretionary trips that enhance one's quality of life, e.g., social and recreational activities. Maintenance trips are less fixed in time and space than mandatory home and work trips but more so than discretionary trips. Maintenance and discretionary trips are often subject to spatial and temporal constraints placed by the anchor points. For example, a work-based tour, a sequence of trips that starts and end at the workplace, around noon for lunch must be finished within one's lunch break.

For telecommuters, workplace is no longer serving as an anchor point. When work is removed as an anchor point, Hagerstrand's framework [98] tells us that the consequent trip chaining (defined as a sequence of multiple trips in a chain) is likely altered. One can hypothesize several dimensions of changes that may take place. The first one concerns trip generation: does the removal of the workplace result in fewer trips made overall? Or are more trips made due to fewer spatial and temporal constraints? What about maintenance and discretionary trips previously associated with home and work? Do people simply forgo those trips or make more of them, with the relaxation of constraints previously placed by having a workplace outside home? What kinds of changes will occur to home-based tours:

do people simply form additional home-based tours or create more complex tours by adding stops to previously existing tours? Answers to those questions have important implications for understanding the potential impacts of telecommuting on the local economy in a region. Forgoing trips means lost businesses and revenue to the local economy while moving an activity (e.g., lunches) to a place closer to home means revenue re-distribution. A sufficient number of re-distributions could support the emergence of new local activity centers [99].

The removal of the workplace will inevitably result in rescheduling of one's activity and trip-making behavior. Spatially, with home as the only anchor, are maintenance and discretionary activities now clustered around home? Do people travel longer distance to maintenance and discretionary locations? Temporally, how do the start and end times of those trips change? Do people conduct those trips throughout the day while working at home? Or are they still clustered around certain time points, like mid-day around noon or after work in the early evening? Will people spend more or less time engaging in maintenance and discretionary trips? More because of the relaxed temporal and spatial constraints due to the removal of workplace and less because of no longer having a clear, designated lunch break. These questions constitute the second dimension of our inquiry in understanding how people re-organize their activities and travel spatially and temporally as the result of telecommuting. Answers to these questions not only lend insights in understanding how people reschedule their activity and travel patterns but also have implications in re-designing transportation service provision after COVID. America's transit system has long been operated as primarily serving commuters coming to major activity centers such as downtown. Now post-COVID, with the significant rise of telecommuters whose activity and travel patterns have changed, how can we re-orient our transit service to serve their needs better?

Another dimension is the associated changes in the modes of transportation used and vehicle miles traveled (VMT). Among the different kinds of trip purposes, transit mode share is the highest for home-based work trips [100]. If one takes transit to work, trips made around the workplace are often made by alternative modes such as walking. Now with home as the only anchor point, is there a shift towards automobiles in conducting those maintenance and discretionary trips? An additional thought is that even though working from home may result in reduced travel overall, the associated VMT could potentially increase if there were a shift toward vehicles for those trips that are flexible in nature. If so, there can be implications on societal outcomes such as congestion and emissions.

To summarize, this paper answers the key question: with workplace as an anchor point being removed, how do people reschedule their activity and travel patterns, especially with respect to those maintenance and discretionary trips that are previously associated with home and work? More specifically, we carry out our inquiries in three dimensions:

1. With respect to generation of trips, do telecommuters conduct fewer or more trips overall? What about maintenance and discretionary trips? And do telecommuters conduct simpler tours?

2. How do telecommuters reschedule maintenance and discretionary trips spatially and temporally? Are those activities now clustered around home? Have the trip distances become shorter? Are activities now conducted throughout the day? Or are they clustering around certain time points, like mid-day or after work in the afternoon or early evening?

3. What are the associated changes in the modes of transportation as well as VMT? It is expected that telecommuters likely conduct more vehicle-based travel. If so, will VMT increase as a result?

3.2 Data and Methodology

Three waves (2017, 2019, and 2021) of Household Travel Survey (HTS) data from the Puget Sound region were used to analyze the changes in travel behavior resulting from the removal of the workplace as an anchor point in one's activity and travel pattern. The first two waves (pre-pandemic) were used to identify a group of commuters who commuted to a workplace outside their home regularly, and the last wave (during pandemic) was used to identify a group of telecommuters who worked from home. This study is an observational study, where there is no intervention or manipulation of who telecommutes or the external factors affecting travel behavior. Therefore, many confounding variables, such as income level, household composition, and residential location, may influence travel patterns in addition to telecommuting itself. To rigorously compare the travel patterns of commuters and telecommuters, we created a quasi-experimental design in which telecommuting serves as the treatment. We controlled for various socio-demographic and built environment characteristics to ensure both groups were as similar as possible. This approach allows us to attribute observed differences in travel patterns more confidently to the effect of telecommuting.

Methodologically, we used propensity score matching technique (explained in section 3.2.3) to balance these characteristics between the telecommuting (treatment) group and the commuting (control) group. Although this approach does not completely eliminate selection bias, it significantly mitigates the bias. The limitations of this design and the potential impact of any remaining bias will be discussed in section 3.4.

The HTS data was collected by sending surveys to residents in the Puget Sound Region, including King, Pierce, Kitsap and Snohomish County, and Figure 3.2.1 shows the geographical extent of the survey study area. The Puget Sound Region includes 82 cities and towns with a total population of over four million people and approximately 1,602,953 households. The densely populated region is also a significant economic driver, with companies such as Microsoft, Amazon, and Starbucks. Besides tech giants, the region contains several regional growth centers and regional manufacturing/industrial centers (shown in Figure 3.2.2). From a transportation perspective, growth centers support mixed-use, walkable environments that integrate public transit, making it easier for residents to access work, amenities, and services without relying on personal vehicles. Regional manufacturing/industrial centers are locations for more intensive industrial activity, which requires high freight and logistics connectivity to maintain economic stability. PSRC prioritizes investments in transportation infrastructure and economic development within these centers to support efficient movement and regional resilience. In this context, understanding travel patterns in the telecommuting era becomes crucial for future planning and investments, as shifts in work locations may alter demand in transportation and regional growth.

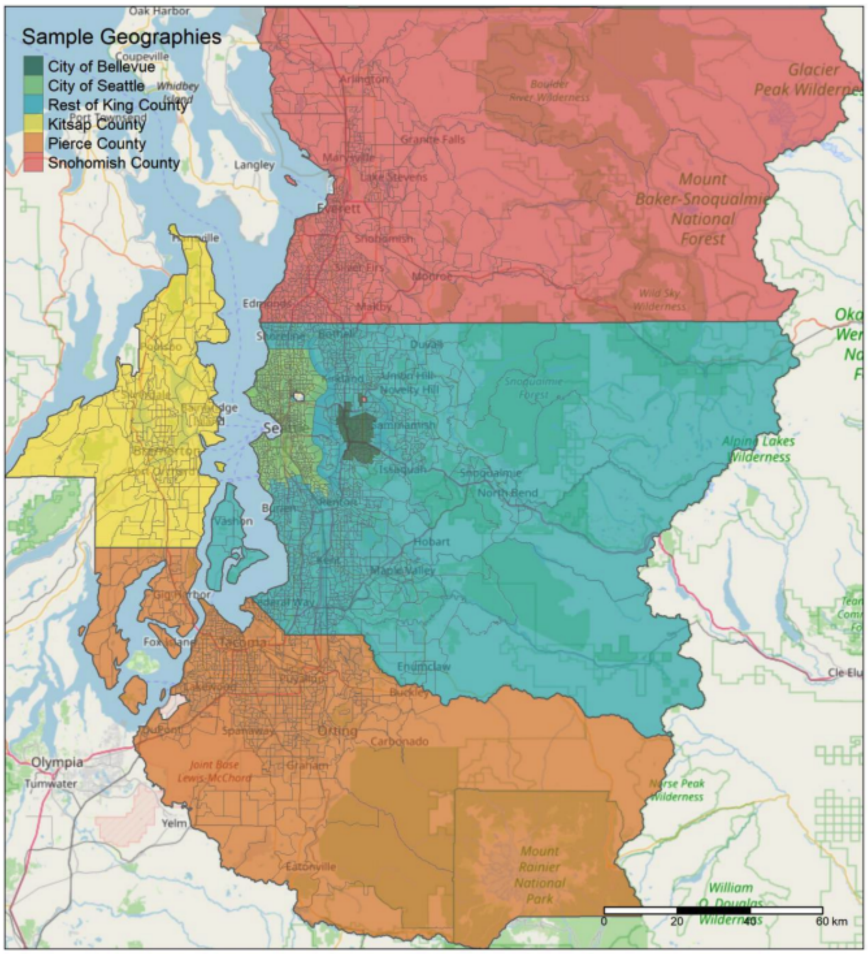


Figure 3.2.1: Puget Sound Regional Council's Household Travel Survey Study Area. Source: Puget Sound Regional Council (Credit: https://www.psrc.org/sites/default/files/2024-05/2023-Puget-Sound-Regional-Travel-Study-Final-Report.pdf)

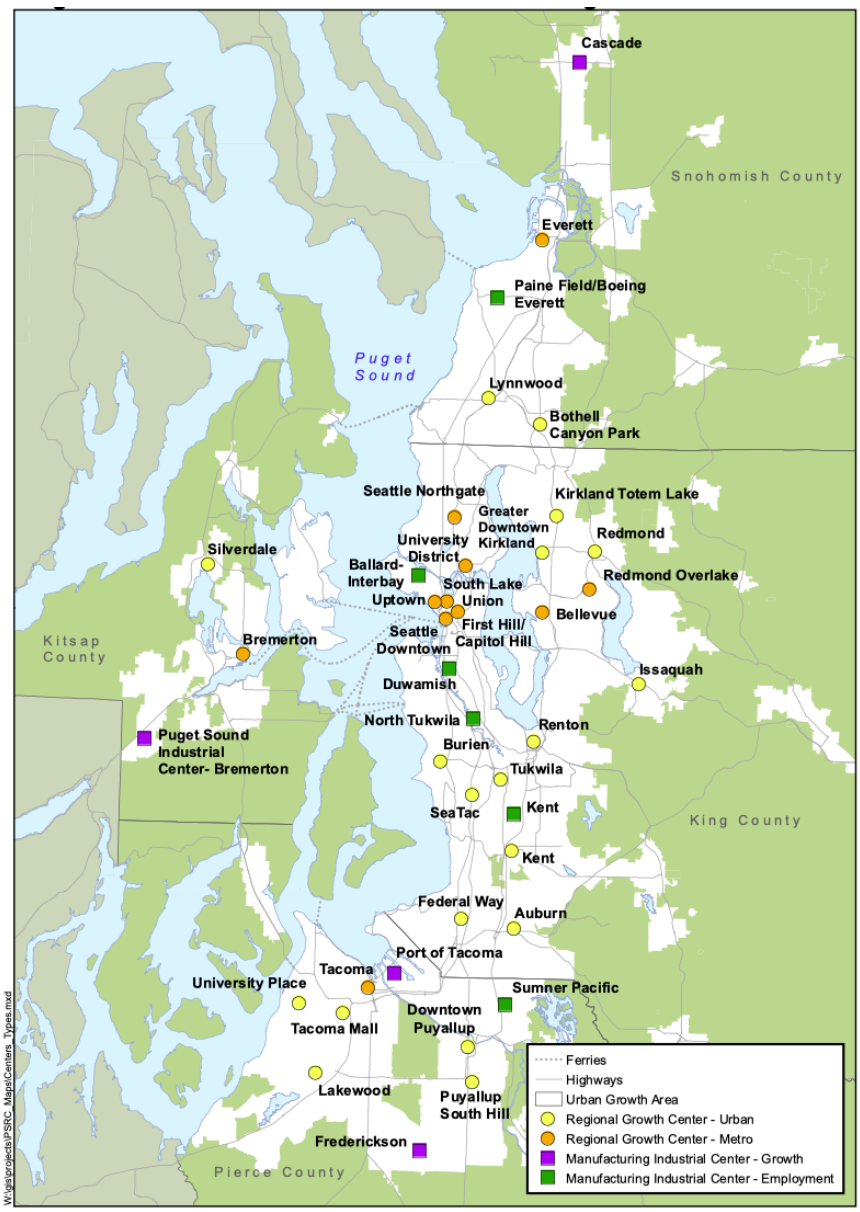


Figure 3.2.2: Regional Growth Centers and Manufacturing/Industrial Centers. Source: Puget Sound Regional Council (Credit: https://psrc.org)

The methodology for this study comprises five steps: 1) identifying a pool of commuters and telecommuters, 2) selecting relevant covariates, 3) applying propensity score matching to select telecommuters and commuters, 4) checking the distribution of covariates, and 5) defining travel patterns metrics. The implementation of each step is elaborated below.

3.2.1 Step 1: identifying a pool of commuters and telecommuters

The 2017, 2019, and 2021 wave of HTS dataset are used in this study. The dataset comprises household- and person-level activity and pattern information on a typical weekday within the Puget Sound Region. The data captures rich information about trips and individuals, including the purpose of the trip, start and end time of trips, mode of transportation, and frequency of telecommuting.

Telecommuters are defined as employed individuals working from home at least once per week, based on the answers to employment status and work mode in the HTS. And commuters are defined as employed individuals who never work from home. Specifically, HTS includes the following three questions (**Q1-Q3**) below [101]:

Q1: Primary type of employment as of today:

- Employed full-time (35+ hours/week, paid)
- Employed part-time (Fewer than 35 hours/week, paid)
- Self-employed
- Unpaid volunteer or intern
- Employed but not currently working (e.g., on leave, furloughed 100%)
- Homemaker
- Retired
- Not currently employed

Q2: Current work location?

- Only one work location outside of home
- Work at home ONLY (telework, self-employed)

- Telework some days and travel to a work location some days
- Work location regularly varies (different offices/jobsites)
- Drive/travel for work (driver, sales)

Q3: How many days worked from home or teleworked last week (instead of going to work that day)?

- 5+ days
- 3-4 days
- 1-2 days
- None

According to the US Bureau of Labor Statistics (BLS), a telecommuter is defined as who works for pay at home [102]. Thus, a person is considered a worker if one of the options of "Employed full-time (35+ hours/week, paid)", "Employed part-time (Fewer than 35 hours/week, paid)", and "Self-employed" is selected in the household travel survey. And one is a telecommuter if he is a worker and has selected either "Work at home ONLY (telework, self-employed)" or "Telework some days and travel to a work location some days" for the second question asking about home location, or has selected either "5+ days", "3-4 days" or "1-2 days" for the third question asking about days telecommuted last week. On the other hand, a commuter is a worker but selecting the counterpart options for question 2 and 3.

Next, we further exclude survey respondents who were under 18 years old, unemployed, or had missing data on their telecommuting frequency. Although the Bureau of Labor Statistics (BLS) collects telework data on workers aged 16 and older, the Puget Sound Regional Council's Household Travel Survey (PSRC HTS) age categories cut off at 18 years, with ranges for 'under 18' and '18-64' years. Therefore, we used 18 years as the age filter. Setting these filters ensures that the analysis focuses specifically on employed workers with clearly defined telecommuting or commuting status.

Additionally, respondents were excluded if they: (1) did not provide trip departure/arrival times, purpose, or mode; (2) reported trips outside of Washington State or exceeding 60 miles in length; or (3) commenced trips on weekdays but concluded them on weekends. The 60-mile threshold was selected to account for long commutes within the Greater Seattle Area to downtown Seattle, which typically span about 40 miles, with an additional 20-mile margin. These inclusion standards based on trip details were implemented to ensure that only representative, daily trips were analyzed.

3.2.2 Step 2: selecting relevant covariates

Studies on the impact of telecommuting indicate that selection bias may occur, as individuals who opt for remote work often differ systematically from those who do not. For example, employees who opt for telecommuting might have specific job roles, higher autonomy, or personal preferences that make them more inclined to work remotely. These inherent differences can affect variables such as work-life balance and productivity, making it challenging to attribute observed effects solely to telecommuting. Earlier studies on telecommuting often faced selection bias, as participants were volunteers, leading to overestimated productivity gains [103]. Increased productivity from telecommuting allows employees to reallocate the time saved from commuting into both work tasks and personal activities [104]. This reallocation leads to trips being scheduled differently, as employees can plan necessary travel at more convenient times outside of traditional peak hours. Fortunately, the pandemic has mitigated the susceptibility to selection bias, which allows a more accurate analysis on the impact of telecommuting [105].

To further minimize selection bias in this observational study, we will balance the distribution of socio-demographic and built environment characteristics reported in the HTS to reduce their influence on telecommuting and travel behavior. These characteristics are essential for the propensity score matching technique, explained in the following paragraph, which effectively controls selection bias and estimates average treatment effects in observational studies [106]. Socio-demographic attributes include household income, household size, and whether one is between 25-54 years old, and the built environment characteristics include number of jobs accessible within 45 minutes of transit travel, age, population density, accessibility to supermarkets, and accessibility to restaurants. These covariates are selected based on the existing literature suggesting telecommuters tend to be higher-income, white-collar, and highly educated workers [107, 108, 109, 110, 111, 112, 113, 114]. Easy access to regional shopping centers, the number of eating-out places nearby, and denser neighborhoods are also reported to increase the likelihood of working from home [115, 116]. This study identified the following covariates: income $100,000+, household size, level of accessibility to jobs, middle-aged (25-54 years), population density, level of accessibility to supermarkets, and level of accessibility to restaurants.

3.2.3 Step 3: applying propensity score matching to select telecommuters and commuters

Propensity score matching is a statistical technique used to estimate the causal effect of a treatment when treatment is not randomly assigned in observational studies [117]. It addresses the problem of selection bias, or systematic differences in the covariates between treatment and control groups through matching propensity scores, which represent the likelihood of receiving treatment based on observed covariates [118]. In this study, the word treatment means telecommuting or that workplace is no longer acting as an anchor point in one's activity and travel pattern. We are interested in knowing with telecommuting, what are the changes in people's activity and travel patterns, especially changes in trip generation and redistribution of maintenance and discretionary trips, mode share, and VMT.

There are two components in the propensity score matching process: logistic regression and nearest neighbor. For the logistic regression model, the dependent variable is a binary variable indicating whether the respondent is a commuter or telecommuter, and the above-described covariates were used as independent variables. The logistic regression model also yield the probabilities of belonging to the telecommuter group, which is considered as the propensity score. Next, the nearest neighbor algorithm [119] was used to match each telecommuter with its closest commuter, with "closest" defined as the smallest difference between the two propensity scores [120].

3.2.4 Step 4: checking the distribution of covariates

The quality of the matches is assessed by comparing the distribution of covariates between the two groups. To do this, we use statistical methods like t-tests and chi-squared tests, which evaluate whether any observed differences in characteristics between the groups are statistically significant or likely due to random chance (statistically insignificant). A key indicator in these tests is the p-value. P-value tells us the probability of seeing these differences if there is indeed no difference between the groups. Generally, a lower p-value, usually less than 0.05, suggests that the observed difference is likely meaningful rather than random, and the difference is statistically significant.

The t-tests on the continuous covariates and chi-squared test on the discrete covariates of the matched groups reported p values less than 0.05, which suggest that the covariates are not significantly different. We further visualized the distribution of covariates in density plot (see Figure 3.2.3). The solid and dashed curves represent the distribution of a specific covariate for telecommuters and commuters, respectively. Both curves show a similar overall trend, with comparable heights at each point along the distribution. This visual similarity suggests that treatment and control groups are similarly distributed in observed covariates. Table 3.2.1 shows distributions of socio-demographic and built environment attributes between the two groups, as well as the overall population distribution for the Puget Sound Region as a reference. Compared to the regional population, the study sample has similar household size and vehicle ownership, but slightly lower income and fewer number of households who are underrepresented (Black, Hispanic and other multi-race households).

Further, Figure 3.2.4 presents a map of the home locations of the commuters and telecommuters in the Puget Sound Region. It suggests that the two groups have comparable geographical distributions, and the matched individuals lived near the regional growth centers and manufacturing/industrial centers. Then, the matched groups were post-processed to further remove any individuals whose first trip of the survey day does not start from home or the duration between the departure of the first trip and arrival of the last trip exceeds 24 hours. These individuals were assumed to have unusual travel patterns because the trips were not completely diurnal, and the effect of home anchor is not significant.

After the four steps, our final sample includes 936 commuters and 950 telecommuters, and their responses in the HTS will be analyzed.

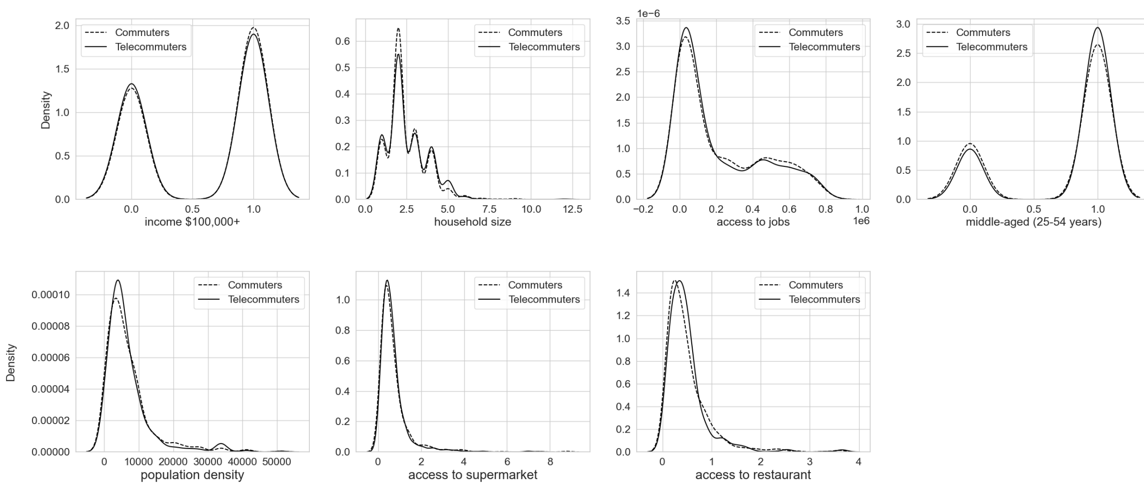


Figure 3.2.3: Balance check on the distribution of the covariates after propensity score matching.

3.2.5 Step 5: defining travel pattern metrics

Table 3.2.2 shows a summary of the outcome evaluation metrics used in this study. They are in three categories: trip generation, spatial and temporal redistribution, and mode and VMT changes. Within the trip generation category, in addition to trips, we also examine changes in the number and types of trip chains. Similar to Primerano et al. [121], we define a trip chain as a temporally ordered sequence of locations that start and end at home or work anchors (e.g., home-based tours or work-based tours). For home-based tours, we further define two types of trip chains: simple chains are those that originate at home, make a stop at another location, and then return home; complex chains are those that start at home but involve multiple stops at different locations (such as locations for shopping, escorting children, etc.) before returning home.

Table 3.2.1: Summary of socio-demographic and built environment characteristics of the matched individuals and the Puget Sound Region.

		Commuters		Telecommuters		Puget Sound Region	
		(2017-2019)		(2021)		(2023)	
		Share	Count	Share	Count	Share	Count
Sample Size	Individuals	-	936	-	950	-	4,244,197
	Households	-	785	-	814	-	1,671,727
Household Size	1 person	15.9%	149	18.4%	175	27.4%	485,333
	2 people	46.5%	435	40.9%	388	33.3%	588,612
	3 people	19.2%	180	19.2%	182	16.7%	296,160
	4+ people	18.4%	172	21.5%	204	22.5%	398,195
	Average household size[1]	-	2.40	-	2.44	-	2.34
Race	Asian only	11.9%	111	20.3%	193	13.2%	589,010
	Black only	3.0%	28	3.1%	29	5.5%	242,733
	Hispanic	4.2%	39	4.8%	46	9.9%	441,362
	Other, including multi-race	4.2%	39	4.1%	39	8.7%	388,522
	White only	69.6%	651	62.8%	597	62.7%	2,787,905
	No response	7.3%	68	4.8%	46	-	-
Vehicle Ownership (in household)	0 (no vehicles)	4.7%	44	6.8%	65	7.8%	129,069
	1 vehicle	29.5%	276	38.6%	367	31.0%	510,903
	2 vehicles	44.7%	418	41.4%	393	37.0%	609,875
	3+ vehicles	21.2%	198	13.2%	125	24.0%	396,377
	Average vehicle ownership[1]	-	1.83	-	1.61	-	1.77
Household Income	Under $25,000	3.6%	34	2.8%	27	10.6%	174,445
	$25,000-$49,999	7.4%	70	7.5%	71	13.4%	220,740
	$50,000-$74,999	10.6%	99	11.5%	109	14.9%	244,509
	$75,000-$99,999	10.0%	93	12.7%	121	12.7%	209,056
	$100,000-$199,999	46.7%	437	36.5%	347	31.5%	518,317
	$200,000 or more	12.2%	115	19.8%	188	17.0%	279,157
	No answer	9.4%	88	9.2%	87	-	-
	Average household income[1]	-	$91,935	-	$96,679	-	$109,192
Level of Access to Supermarket	0	11.9%	114	12.9%	123	-	-
	1	14.0%	134	12.7%	121	-	-
	2	19.2%	183	20.1%	191	-	-
	3	19.1%	173	24.5%	233	-	-
	4	36.8%	351	30.0%	282	-	-
	Average level of access[1]	-	2.57	-	1.61	-	-
Level of Access to Jobs via Transit	0	9.1%	87	6.8%	65	-	-
	1	13.8%	132	16.2%	154	-	-
	2	13.6%	130	11.4%	108	-	-
	3	22.0%	210	27.1%	257	-	-
	4	41.5%	396	38.5%	366	-	-
	Average level of access[1]	-	2.73	-	2.74	-	-

[1]: the value is calculated as a weighted average of the categories, where the weights corresponds to the percent share of each category. For categories "4+ people", "3+ vehicles", "Under $25,000", "$200,000 or more", the numerical values are interpreted as 4, 3, 25,000, and 200,000 respectively. And the the income categories denoted by ranges such as "$25,000-$49,999" are interpreted at the median value of the range, i.e. 37,449 in this case.

Table 3.2.2: Summary of travel pattern metric definitions.

Name	Definition
Trip Generation	
Trips (per person per day)	
Number of Trips	Number of times a trip is recorded
Number of Maintenance Trips	Number of times one goes to or arrives from locations for household related activities such as grocery shopping, banking service, or dropping off family members.
Number of Discretionary Trips	Number of times one participates in trips associated with non-maintenance and non-work purposes.
Number of Work Trips	Number of times one goes to workplace or work-related destinations from home, or goes from workplace or work-related destinations from home, or goes from one work-place to another workplace.
Trip Chains (per person per day)	
Number of Trip Chains	Total number of trip chains conducted per person per day.
Intermediate Stops within a Trip Chain	Number of intermediary stops in trip chain between initial and final home anchor.
Maintenance and Discretionary Trip Redistribution	
Spatial Redistribution	
Maintenance Trip Distance (network distance in miles)	The average distance for maintenance trips
Discretionary Trip Distance (network distance in miles)	The average distance for discretionary trips
Straight Line Distance from Home to Maintenance Destination	The average distance from the destinations for maintenance trips from home (miles)
Straight Line Distance from Home to Discretionary Destination	The average distance from the destinations for discretionary trips from home(miles)
Radius of Gyration[1]	The extent of one's travel around a point of interest.
Total Vehicle Miles (Driving) for Maintenance Trips	Total miles traveled via car in one day while participating in maintenance trips.
Total Distance Traveled for Maintenance Trips	Total miles traveled for all modes in one day while participating in maintenance trips.
Total Vehicle Miles (Driving) for Discretionary Trips	Total miles traveled via car in one day while participating in discretionary trips.
Total Distance Traveled for Discretionary Trips	Total miles traveled for all modes in one day while participating in discretionary trips.
Temporal Redistribution	
Trip Departure Time	Departure time of a trip.
Time Spent on Maintenance Trips (min)	Travel time for maintenance trips in minutes.
Time Spent on Discretionary Trips (min)	Travel time for discretionary trips in minutes.
Mode and Purpose	
Purpose Diversity	Diversity of destination purposes in one day.
Mode Diversity	Diversity of modes used in one day.
Total Time Spent on Walking Trips (min)	Total time spent on walking trips in one day.
Number of Walking Trips	Total number of trips completed by walking in one day.
Number of Driving Trips	Total number of trips completed by driving in one day.

[1]: see section 3.2.5 for more details.

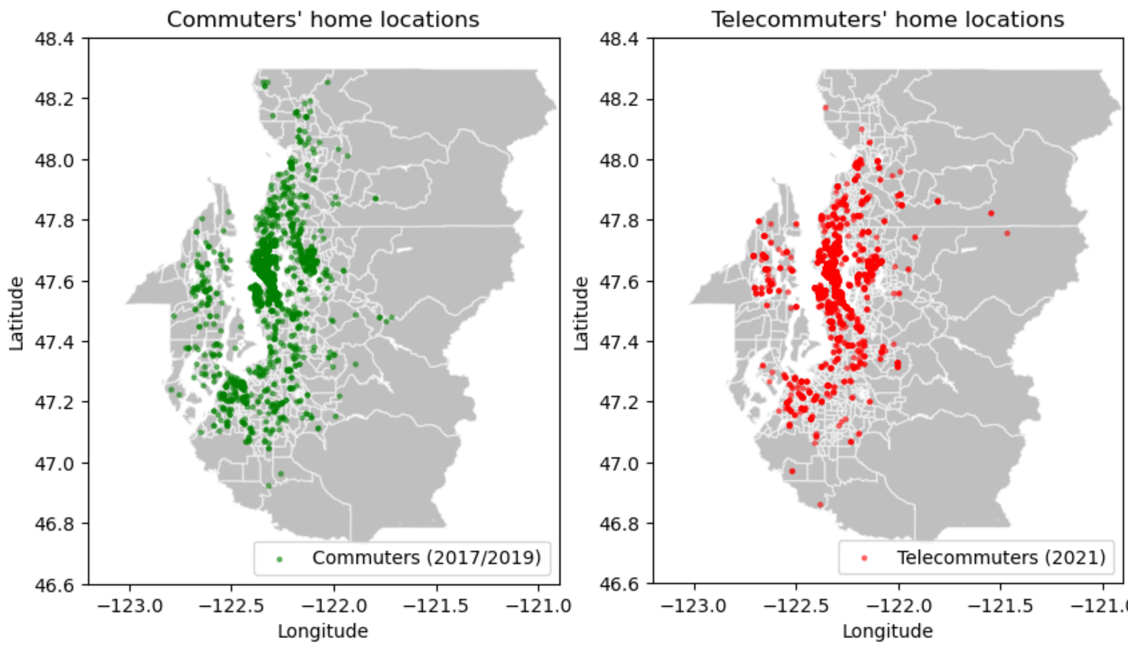


Figure 3.2.4: Comparison of home locations between commuters and telecommuters.

In the spatial redistribution category, one metric we use is radius of gyration (ROG), which quantifies the typical distance an individual travels from a point. It has been used to evaluate the spatial extent of an individual's movements, especially about whether an individual tends to have localized movement patterns or travels over larger areas [122, 123]. We calculate ROG as follows:

$$ROG = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {d_i}^2} \tag{3.1}$$

where d_i is the distance between the i^{th} location visited and the anchor point, and n is the number of locations visited by an individual.

To compare the impact of removing the workplace anchor in individuals' footprints, we computed the ROG around the workplace and home for commuters and the ROG around the home for telecommuters. We are interested in statistically testing the differences in home-based ROG between commuters and telecommuters, as well as between home-based ROG for telecommuters and work-based ROG for commuters. For the former, one may expect the home-based ROG for telecommuters may be larger since people now have more time to travel. For the latter, the underlying hypothesis is that there may exist an underlying budget in either distance or travel time in terms of how far people are willing to go for maintenance and discretionary trips. Comparing ROG around workplaces needs several preprocessing steps. First, for people who visited multiple workplaces or work-related locations, only the primary workplace (defined by HTS's purpose strictly as 'Work') was treated as the anchor point. Second, the latitudes and longitudes involved in ROG around workplace are coordinates of the destinations visited within a work-based tour, that is, a tour starting and ending at the primary workplace location. Destinations visited on the way from work to home were not considered, as these destinations are influenced by two anchor points, home and workplace, instead of workplace alone. For example, if a person's travel trajectory are: home, grocery store, home, work, bank, restaurant, work, fast-food, and returning home, work-bank-restaurant-work forms a work-based tour, in which case only the locations of bank and restaurant are counted towards the ROG around workplace. Similarly, home-grocery store-home is a home-based tour and ROG around home involves the grocery store but not others.

Last, for observing changes in mode choices and trip purposes, we are interested in understanding how the range of modes used varied when workplace no longer acted as an anchor point. Similarly, we want to capture the shifts in the diversity of trip purposes people undertake in a day. To quantify these two, we use the Shannon Diversity Index. The Shannon Diversity Index is widely used for calculating diversity of species in ecology systems [124], and has been adopted in transportation fields to study the diversity of land use, transportation options [125, 126]. The Shannon Diversity Indices for mode, H_m, and purpose ,H_p are calculated as follows:

$$H_m = -\sum_{m=1}^{M} (p_m * ln(p_m)), \tag{3.2}$$

$$H_p = -\sum_{p=1}^{P} (p_p * ln(p_p)), \tag{3.3}$$

where p_m is the proportion of total trips made with mode m, and p_p is the proportion of total trips made with purpose p. A diversity index of zero indicates only one mode or purpose was used in a day.

For every metric, we also calculated effect size and the associated confidence interval of effect size to gauze the magnitude of the differences between commuters and telecommuters. Effect size is computed as follows:

$$\text{Effect size}_M = \frac{\overline{M_T} - \overline{M_C}}{\delta_C} \tag{3.4}$$

where M is the metric to be evaluated, $\overline{M_T}$ is the average of telecommuters' metric, $\overline{M_C}$ is the average of commuters' metric, and δ_C is the standard deviation of the commuters' metric. Further, the standard deviation is calculated as:

$$\delta_C = \sqrt{\frac{1}{n_C - 1} \sum_{i=1}^{n_C} (M_{C_i} - \overline{M_C})^2} \tag{3.5}$$

The confidence interval is computed as follows:

$$\text{Confidence Interval}_M = \text{Effect size}_M \pm 1.96 \cdot \text{margin of error}_M, \tag{3.6}$$

where

$$\text{margin of error}_M = \sqrt{\frac{n_C + n_T}{n_C \cdot n_T} + \frac{\text{Effect size}_M}{2(n_C + n_T)}}, \tag{3.7}$$

and n_C and n_T are number of commuters in the control group and number of telecommuters in the treatment group, respectively. Here, 1.96 is the z-score corresponding to a 95% confidence level for a two-tailed test, which is a standard value for constructing confidence intervals assuming a normal distribution of the effect size estimates.

The effect size quantifies the difference between the two groups in terms of standard deviation units as a standardized measure of the magnitude of the difference. The confidence interval provides a range within which we can be 95% confident that the true effect size lies, which suggests precision and statistical significance of the estimated effect. By computing both the effect size and its confidence interval, we are able to not only quantify the magnitude of differences between commuters and telecommuters but also assess the reliability of these differences.

3.3 Results

Table 3.3.1 summarizes all travel pattern metrics' average value for the two groups, as well as the effect size, and the confidence interval of the effect size. The average values were calculated by taking the mean of each metric across all respondents within each group. Effect size and the confidence interval are calculated as outlined in the previous section. The effect size with a "(-)" sign means that telecommuting decreases the associated metric.

3.3.1 Trip generation

Telecommuting is observed to decrease the number of trips made for telecommuters significantly, compared to commuters. According to Table 3.3.1, on average, the total number of trips dropped from 3.94 to 3.37, which is a statistically significant decrease ($p < 0.05$). This decrease aligns with findings from Huang et al. [127], who analyzed Switzerland's travel patterns from September 2019 to October 2020 using longitudinal GPS data that tracked same individuals' mobility pattern over a year. Although our study is based on observational cross-sectional travel survey data, which lacks the temporal detail of longitudinal GPS datasets, our carefully structured quasi-experimental design mitigates these limitations. The alignment between our results suggests that our methodology effectively captures the impact of telecommuting on travel patterns, even with differing data collection approaches.

Breaking down the trips revealed that the reduction in the total number of trips is the sum of both a decrease in trips to and from workplaces and an increase in maintenance trips and discretionary trips. On average, telecommuters made 1.50 maintenance trips and 1.38 discretionary trips, compared to commuters' 1.30 maintenance trips and 1.13 discretionary trips ($p < 0.05$). These statistics suggest two observations. First, individuals reallocated the time saved from commuting toward conducting more discretionary and maintenance trips. Since the total number of trips is reduced for telecommuters, the increase in maintenance and discretionary trips with respect to the reduction in work related trips is inelastic, meaning that a 10% reduction in work trips will lead to a less than 10% increase in maintenance and

Table 3.3.1: Summary of metrics for trip generation, spatial redistribution, and temporal redistribution.

	Commuters (N=936) (2017-2019)	Telecommuters (N=950) (2021)	Effect Size	Confidence Interval
Trip Generation				
Trips (per person per day)				
Number of Trips	3.94	3.37	0.27 (-)*	[-0.35, -0.18]
Number of Maintenance Trips	1.3	1.5	0.11*	[0.02, 0.20]
Number of Discretionary Trips	1.13	1.38	0.16*	[0.07, 0.25]
Number of Work Trips	1.51	0.49	1.02 (-)*	[-1.10, -0.93]
Trip Chains (per person per day)				
Number of Trip Chains	1.39	1.33	0.08 (-)	[-0.17, 0.01]
Intermediate Stops within a Trip Chain	1.93	1.57	0.27 (-)*	[-0.35, -0.18]
Maintenance and Discretionary Trip Redistribution				
Spatial Redistribution				
Maintenance Trip Distance (network distance in miles)	2.24	2.10	0.04 (-)	[-0.13, 0.05]
Discretionary Trip Distance (network distance in miles)	2.24	2.51	0.06	[-0.03, 0.15]
Straight Line Distance from Home to Maintenance Destination (miles)	3.91	3.07	0.19 (-)*	[-0.32, -0.06]
Straight Line Distance from Home to Discretionary Destination (miles)	4.68	3.24	0.25 (-)*	[-0.38, -0.11]
Radius of Gyration (work-based)	4.24[1]	-	0.27 (-)*[2]	[-0.46, -0.07][2]
Radius of Gyration (home-based)	4.77[3]	3.00 0.34 (-)*	[-0.46, -0.21]	
Total Vehicle Miles (Driving) for Maintenance Trips	14.24 (10.45)[4]	11.02 (6.23)[4]	0.22 (-)*	[-0.35, -0.09]
Total Distance Traveled for Maintenance Trips (miles)	15.13 (11.07)[4]	11.72 (6.85)[4]	0.23 (-)*	[-0.36, -0.10]
Total Vehicle Miles (Driving) for Discretionary Trips (miles)	9.97 (4.96)[4]	8.25 (2.76)[4]	0.13 (-)	[-0.26, 0.00]
Total Distance Traveled for Discretionary Trips	12.16 (7.36)[4]	9.69 (4.25)[4]	0.18 (-)*	[-0.31, -0.06]
Temporal Redistribution				
Time Spent on Maintenance Trips (min)	19.06	16.57	0.22 (-)*	[-0.35, -0.09]
Time Spent on Discretionary Trips (min)	20.59	20.43	0.01 (-)	[-0.14, 0.12]
Mode and Purpose				
Purpose Diversity	1.4	1.21	0.45 (-)*	[-0.53, -0.36]
Mode Diversity	0.17	0.12	0.14 (-)*	[-0.23, -0.05]
Total Time Spent on Walking Trips (min)	4.50	6.90	0.10*	[0.00, 0.20]
Number of Walking Trips	0.58	0.90	0.26*	[0.17, 0.36]
Number of Driving Trips	3.24	2.41	0.38 (-)*	[-0.47, -0.28]

Note: Metric with '*' after the effect size means the difference between telecommuters and commuters are statistically significant at $p = 0.05$ level via t test for continuous metrics and chi-squared test for categorical metrics. [1]: There are 116 commuters who made work-based tours. [2]: Since telecommuters have workplace anchor removed, the effect size and confidence interval for commuter's work-based radius of gyration are calculated by comparing against telecommuter's home-based radius of gyration. [3]:There are 362 commuters who made home-based tours. [4]: The values in parentheses are the median value when the distribution of the metric is skewed.

discretionary trips. Second, as suggested by the effect size, the increase in the discretionary trips is more than that for maintenance trips, likely because not only discretionary trips are more flexible spatially and temporally but also there is more motivation for doing them compared to maintenance trips.

Analysis on home-based trip chains suggests that telecommuting did not affect the number of trip chains people made significantly (1.33 trip chains for telecommuters vs 1.39 trip chains for commuters). However, telecommuting is associated with simpler trip-chaining behavior. For telecommuters, the average number of intermediate stops per trip chain dropped significantly—from 1.93 stops for commuters to 1.57 stops for telecommuters. This difference is statistically confirmed by a chi-squared test on the distribution of simple chains (one stop) and complex chains (multiple stops), showing a significant result ($p < 0.05$).

We plotted the distributions of trip purposes for commuters and telecommuters in Figure 3.3.1 to visually illustrate the observed increase in maintenance and discretionary trips and the reduction in work-related trips. As expected, telecommuters made fewer number of trips to workplace and work-related destinations. In contrast, telecommuters had significantly more maintenance and discretionary trips across all categories except for school, including shopping, social and recreation, errands/others, escort, and meals. The higher frequency of trips returning home among telecommuters suggests the fact that these maintenance and discretionary trips typically conclude at home rather than a workplace. Additionally, the lower frequency of trips to school among telecommuters can be attributed to remote teaching arrangements adopted in the Puget Sound Region.

To further quantify the impact of telecommuting on trip generation, we developed four separate linear regression models. Each model aims at understanding how specific factors influence the number of trips or trips chains, or stops within a trip chain. We reported three key elements from the regression model in Table 3.3.2: dependent variable, confounding variables, and coefficient of treatment. The dependent variable is the main outcome we are measuring, and it varies from model to model, capturing different aspects of trip generation, such as the number of maintenance trips, discretionary trips, trip chains, and intermediate stops within a chain. Confounding variables are additional factors that might also influence

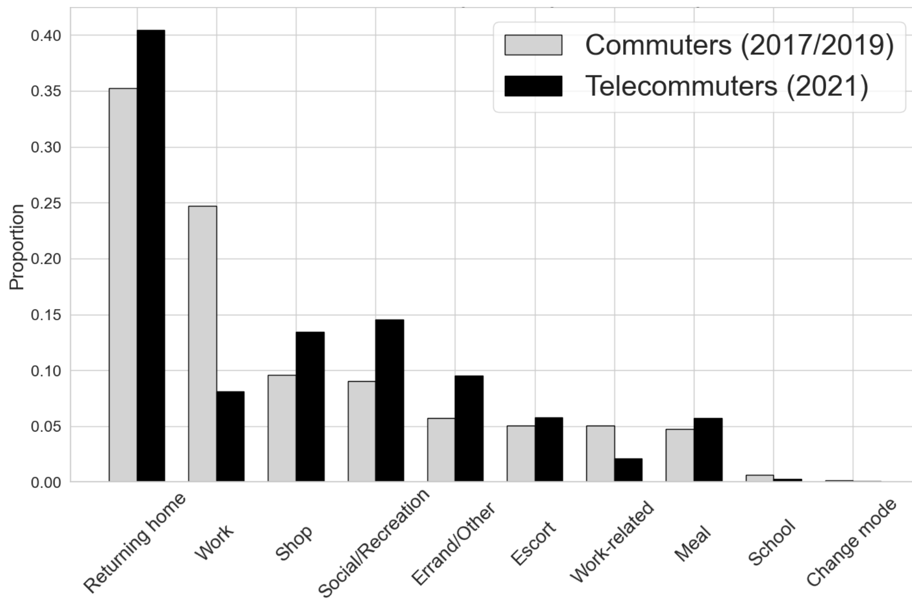


Figure 3.3.1: Distribution of trip purposes for all trips made by commuters and telecommuters.

trip generation—are included in each model. These confounding variables, such as household size, accessibility to supermarkets, gender, rural or urban residence, number of children, and number of workers in the household, are known to impact travel behavior and are summarized in Table 3.3.2.

The coefficient of treatment represents the effect of telecommuting itself. The coefficient of treatment will be multiplied to the treatment variable, which is a dummy variable set to 1 for telecommuters (indicating that they have no outside workplace) and 0 otherwise. The coefficient of treatment thus helps quantify how the absence of an external workplace affects each dependent variable. For example, we can examine the first and third rows in Table 3.3.2. In the model predicting the number of maintenance trips, a statistically significant, positive coefficient of treatment indicates that telecommuting tend to generate more maintenance trips, while a negative treatment coefficient in the number of trip chain model suggests that telecommuters typically make fewer trip chains.

In summary, these coefficients indicate that everything else being equal, removing an outside workplace result in an increase of 0.17 maintenance trips and 0.25 discretionary trips as well as a reduction of 0.06 trip chains and 0.36 stops per trip chain. These numbers reveal that telecommuters complete more maintenance and discretionary trips in less and simpler trip chains.

Table 3.3.2: Summary of regression models on trip generation metrics.

Dependent Variable	**Coefficient of Treatment**	**Confounding Variables**
Number of Maintenance Trips	0.17*	Household size*, accessibility to supermarket, female*, rural, number of children*, number of workers
Number of Discretionary Trips	0.25*	Household size, accessibility to supermarket, female, rural, number of children, number of workers*
Number of Trip Chains	-0.06*	Household size, accessibility to supermarket*, female, rural, number of children*, number of workers
Intermediate Stops within a Trip Chain	-0.36*	Household size, accessibility to supermarket*, female, rural, number of children*, number of workers

Note: The variables with * are statistically significant in the regression model.

3.3.2 Spatial and temporal redistribution

(1) spatial redistribution

It is hypothesized that telecommuting would redistribute maintenance and discretionary trips near home, due to the removal of the workplace anchor point. To quantify and understand the legitimacy of this hypothesis, Figure 3.3.2 plotted the distributions of distances from maintenance and discretionary trip destinations to home location. As shown in the figure, for telecommuters, the solid curves' peaks were both higher than and to the left of the commuters' dashed curves, meaning that telecommuters complete maintenance and discretionary trips not only closer to home but also more frequently than commuters.

A t-test was performed to evaluate whether the differences in the average straightline distances from maintenance trips' destination to home are statistically significance. The result showed that, on average, telecommuters complete maintenance distances closer to home (3.07 miles) compared to commuters (3.91 miles), and the difference is significant ($p < 0.05$). A similar observation can be made for discretionary trips, where telecommuters were on average 3.24 miles from home, whereas commuters were 4.68 miles from home ($p < 0.05$). This spatial redistribution of activities closer to the home for telecommuters aligns with the findings from Pendyala et al [128], who used two-wave panel data to study telecommuting impacts. Despite careful data collection, their study reported a decline in trip rates over time, likely due to panel fatigue, where repeated surveys may lead to underreporting. Our design, by contrast, uses matched control and treatment groups from observational data, which avoids panel fatigue and achieves similar conclusions on activity redistribution. This suggests that our quasi-experimental approach can reliably capture telecommuting impacts on travel behavior without the risk of underreporting associated with longitudinal data.

Connecting back to trip generation, telecommuters generated more maintenance and discretionary trips, though these trips were generally closer to home and covered shorter distances. For trip distances, telecommuters' maintenance trips measured along street network are significantly shorter than those of commuters (2.10 miles vs. 2.24 miles). However, telecommuters' discretionary trips are slightly longer on average (2.51 miles vs. 2.24 miles), though this increase is not statistically significant ($p > 0.05$).

We also looked at whether there is a difference in individuals' ROG of workplaces for commuters and that of home for telecommuters. This is motivated from two hypotheses: first, with an outside workplace removed from one's daily travel pattern, telecommuters may make longer-distance trips, since now they seemly have more time on hand. On the other hand, there may exist an internal threshold that limits how far people travel for maintenance and discretionary purposes. This internal threshold may be psychological or biological, working like the concept of travel time budget [129].

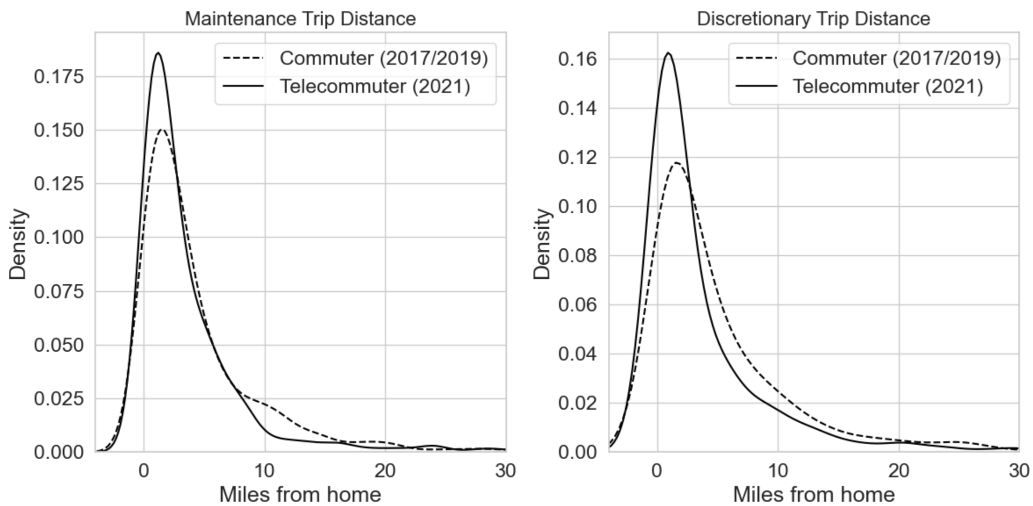


Figure 3.3.2: Density distribution of the distance from maintenance and discretionary trip destinations to home locations.

As outlined in Section 3.2.5, ROG for commuters completing work-based tours is computed around workplace, and ROG for telecommuters completing home-based tours is computed around home. Following the procedure described in Section 3.2.5, we identified 116 commuters (from a total of 936) who completed work-based tours, and 717 telecommuters (from a total of 950) who completed home-based tours. The average ROGs of workplace and of home are 4.24 miles and 3.00 miles, respectively, and the reduction in ROG due to telecommuting is statistically significant ($p < 0.05$). These numbers refute both hypotheses stated above: instead of expanding, telecommuters reduced their extent for maintenance and discretionary trips. One can also see from Table 3.3.1 that commuters' home-based ROG is also significantly larger than that of telecommuters.

Lastly, we computed the total person-miles traveled and vehicle miles by driving for commuters and telecommuters. Telecommuters are observed to travel fewer miles using cars (11.02 vs 14.24 for maintenance trips, and 8.25 vs. 9.97 for discretionary trips) or via all modes (11.72 vs. 15.13 for maintenance trips, and 9.69 vs 12.16 for discretionary trips). Within the telecommuter group, the difference between total person-miles and vehicle miles traveled was smaller ($9.69 - 8.25 = 1.44$ miles) than that of the commuter group ($12.16 - 9.97 = 2.19$ miles). This observation suggests a shift in mode choice and could be attributed to a sharp decrease in transit and a slight increase in driving and walking modes taken by telecommuters. A mode distribution plot (see Figure 3.3.5) in section 3.3.3 further illustrates this shift.

Like trip generation section, nine additional linear regression models were developed to further quantify the effect of telecommuting on spatial redistribution. The dependent variable, confounding variables, coefficient of treatment (a dummy variable indicating that the respondent is a telecommuter with an outside workplace removed) are summarized in Table 3.3.3. The estimated coefficients quantify the effect of removing an outside workplace on the corresponding dependent variables (shown in the leftmost column in Table 3.3.3). For example, examining the first and fifth rows in Table 3.3.3, we see contraction in telecommuters' spatial distribution of trips. In the model predicting average maintenance trip distance, a statistically significant negative coefficient indicates that telecommuters generally travel shorter distances for maintenance purposes compared to commuters. Similarly, the model for radius of gyration shows a significant negative coefficient for telecommuting, suggesting that telecommuters have a more limited travel radius in their daily activities, likely due to the absence of a centralized workplace.

In summary, all coefficients for treatment being negative and statistically significant indicate that for maintenance and discretionary trips, removing an outside workplace means shorter trips that are also closer to home and smaller footprint both in terms of total distance travelled and driving miles.

(2) temporal redistribution

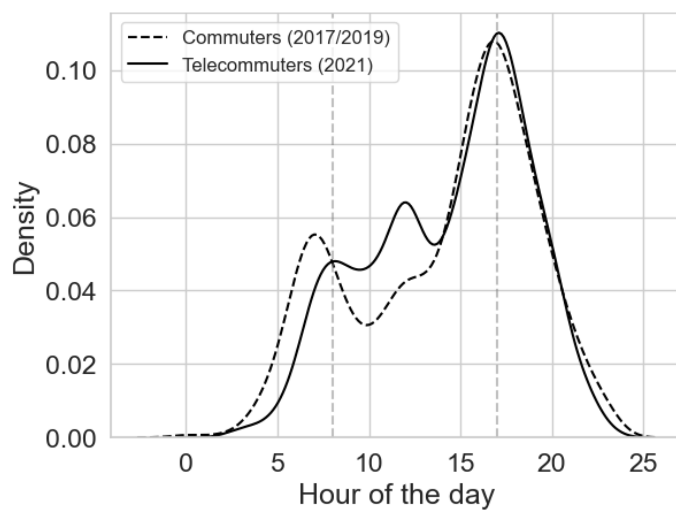
How trips are temporally redistributed will be visualized through the departure time distribution in Figure 3.3.3a and 3.3.3b. Two vertical dotted lines mark the peak hours: the first line represents the morning peak at 9:00 am, and the second line represents the evening peak at 5:00 pm. Figure 3.3.3a shows the departure time distribution of all trips for both commuters (dashed curve) and telecommuters (solid curve). Three observations can be made. First, with telecommuting, the morning peak is mitigated and delayed. Second, the evening

Table 3.3.3: Summary of regression models on spatial redistribution metrics

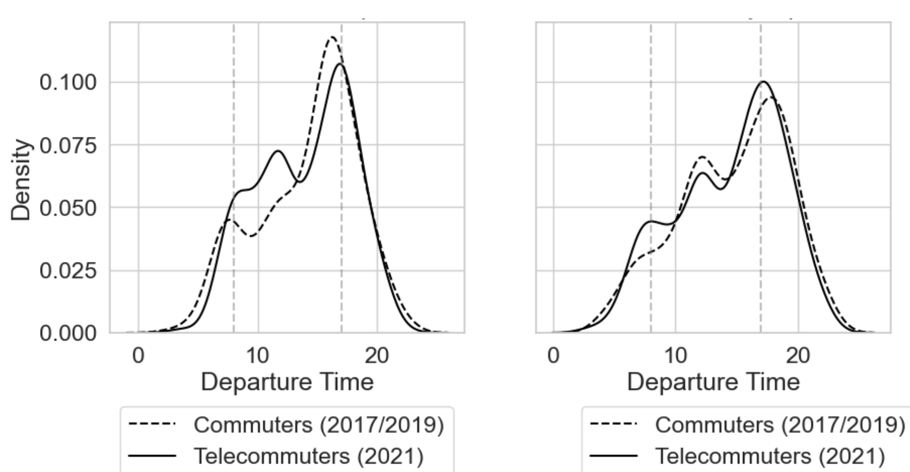
Dependent Variable	Coefficient of Treatment	Confounding Variables
Average Maintenance Trip Distance (network distance)	-1.23*	Household size*, accessibility to supermarket*, female, rural, number of children, number of workers
Average Discretionary Trip Distance (network distance)	-0.8*	Household size*, accessibility to supermarket*, female, rural, number of children*, number of workers*
Straight Line Distance from Home to Maintenance Destination	-0.83*	Household size*, accessibility to supermarket*, female, rural, number of children, number of workers
Straight Line Distance from Home to Discretionary Destination	-1.62*	Household size, accessibility to supermarket*, female, rural, number of children, number of workers
Radius of Gyration[1]	-1.35*	Household size, accessibility to supermarket*, female, rural*, number of children, number of workers*
Total Distance Traveled for Maintenance Trips	-3.46*	Household size, accessibility to supermarket*, female, rural, number of children, number of workers
Vehicle Miles (Driving) for Maintenance Trips	-3.22*	Household size, accessibility to supermarket*, female, rural, number of children, number of workers
Total Distance Traveled for Discretionary Trips	-2.68*	Household size*, accessibility to supermarket, female, rural, number of children, number of workers
Vehicle Miles (Driving) for Discretionary Trips	-1.97*	Household size*, accessibility to supermarket*, female, rural, number of children, number of workers*

Note: The variables with * are statistically significant in the regression model. The coefficients with * means the variable treatment (i.e. a dummy variable indicating telecommute) is statistically significant in the regression model.
[1]: commuters' radius of gyration is computed using stops visited in work-based tours, and telecommuters' radius of gyration is computed using stops visited in home-based tours (see section 3.2.5 for more details).

peak between the two groups is similar, with the one for telecommuters even slightly higher than that for commuters. Third, for telecommuters, there is a pronounced mid-day peak around noon.



(a) Distribution of departure times for all trips.



(b) Distribution of departure times for maintenance trips (left) and discretionary trips (right)

Figure 3.3.3: Comparison of departure times.

Figure 3.3.3b splits the distribution of all trips in Figure 3.3.3a into two: left one for maintenance trips and right one for discretionary trips. For maintenance trips, a delayed morning peak remains but greatly mitigated and there is also a pronounced mid-day peak for telecommuters. The evening peak is also both reduced and delayed. For discretionary trips, a distinct feature for telecommuters' distribution is that there exist three clear peaks: late morning, mid-day and evening: compared to commuters, telecommuters made significantly more discretionary trips in the morning, fewer around mid-day and more in the evening.

The maintenance trips were further divided into shopping, social/recreation, and escort, and the discretionary trips are further divided into meal and other. Under the "other" category, about 85% of trips are for personal businesses and medical appointments, and the remaining trips' purposes were not specified in the HTS. Figure 3.3.4 plotted the distribution of trips belonging to each subcategories. The dotted vertical curves represents the morning and evening peaks.

We observe temporal redistribution of all types of trips. Four types of trips, shopping, social and recreation, escort and others, had a redistribution from evening to late morning to mid-day. Meal related trips had an opposite redistribution: mid-day meal trips were moved to evening. We then computed the time spent on maintenance and discretionary trips as the time delta between arrival time and departure time derived from the HTS. Telecommuters are found to spend significantly less time on maintenance trips, but not for discretionary trips: the time spent in minutes dropped from 19.06 to 16.57 for maintenance trips and from 20.59 to 20.43 for discretionary trips. These findings are consistent with our earlier observation that the destinations for maintenance and discretionary trips are shorter and closer to home, and thus less time required to complete shorter trips.

Two regression models are built to quantify the effect of telecommuting on time spent on maintenance and discretionary trips. Table 3.3.4 is constructed similarly to previous Table 3.3.2 and 3.3.3 and reports the dependent variable, coefficient of treatment, and confounding variables. From Table 3.3.4, removing the workplace outside home decreased the travel time for maintenance trips by 2.64 minutes (statistically significant) and for discretionary trips by 0.3 minutes (not statistically significant). The results from the regression

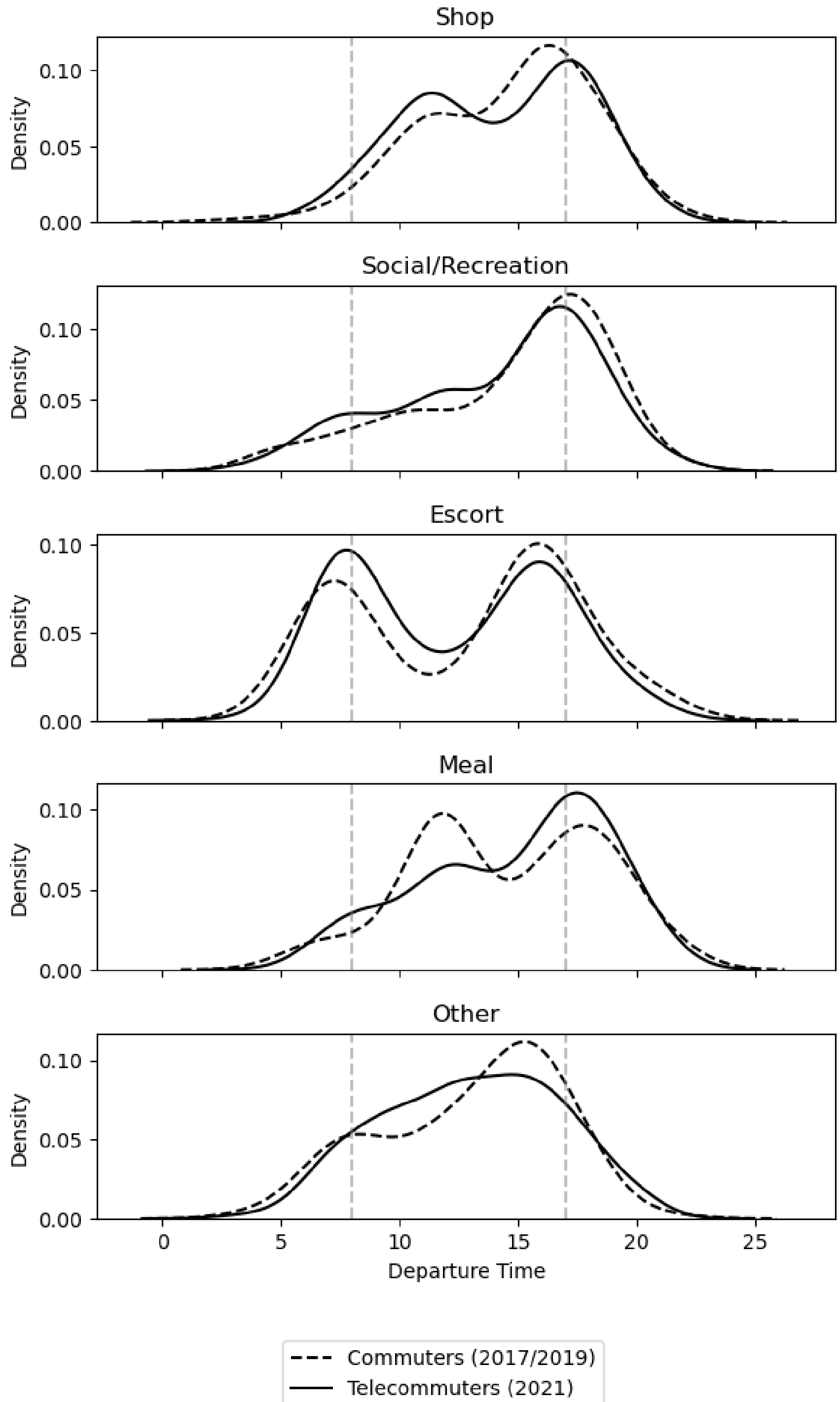


Figure 3.3.4: Distribution of departure times for maintenance and discretionary trips in detailed categories.

models indicate that telecommuting significantly decreased the time spent on maintenance trips but has a negligible effect on discretionary trips. The significance of these findings lies in demonstrating that telecommuting enables more efficient management of necessary errands without reducing participation in recreational activities, potentially enhancing overall quality of life and contributing to better work-life balance.

Table 3.3.4: Summary of regression models on temporal redistribution metrics.

Dependent Variable	**Coefficient of Treatment**	**Confounding Variables**
Time Spent on Maintenance Trips	-2.64*	Household size*, accessibility to supermarket, female, rural, number of children*, number of workers
Time Spent on Discretionary Trips	-0.3	Household size*, accessibility to supermarket, female, rural, number of children*, number of workers

Note: The variables with * are statistically significant in the regression model. The coefficient with * means the variable treatment (i.e. a dummy variable indicating telecommute) is statistically significant in the regression model.

3.3.3 Mode and Purpose

In terms of the modes of transportation used, there is a sharp decrease in transit, a slight decrease in driving and a significant increase in walking, comparing from commuters to telecommuters. Table 3.3.1 shows the average mode diversity for telecommuters is 0.12, which is significantly less than commuters' 0.17. And telecommuting increases the average number of walking trips from 0.58 to 0.9 and decreases the number of driving trips from 3.24 to 2.41. Then, we are interested in whether telecommuting encourages people to spend more time on walking. On average, telecommuters and commuters spent 6.9 and 4.5 minutes, respectively, for all walking trips and the difference is statistically significant with an effect size of 0.1. We note that these numbers are small as we also include those who made no walking trips.

The mode shift highlights that telecommuters tend to use fewer different modes of transportation. This reduction in mode diversity may reflect a simplification of travel patterns when commuting is eliminated. Telecommuters are more inclined to walk for their travel needs, possibly due to increased flexibility and proximity of activities when working from home. This shift towards walking not only has positive implications for individual health and well-being but also contributes to environmental benefits by reducing reliance on motorized transportation.

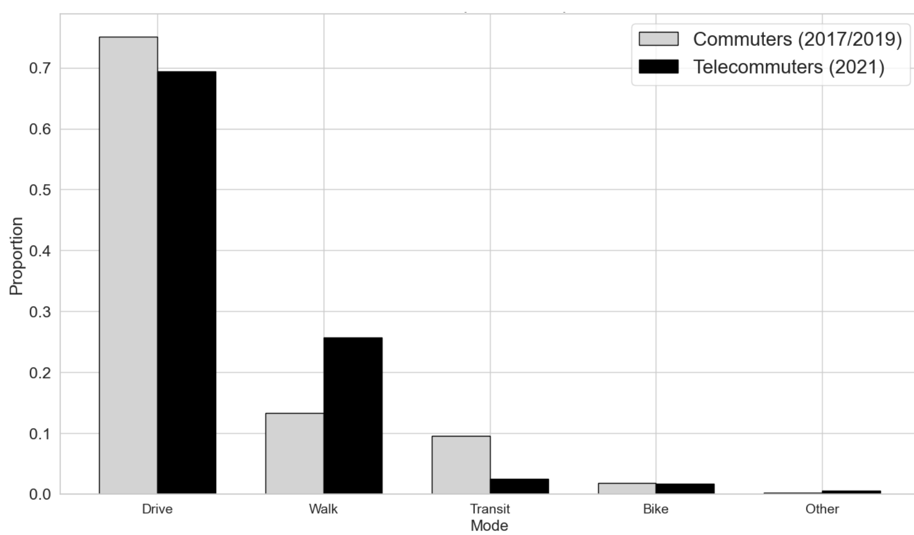


Figure 3.3.5: Mode usage for all trips

Telecommuters not only simplified their trip chains but also visited a smaller variety of destinations. The average purpose diversity score per person for all trips performed in a day dropped significantly (1.40 for commuters vs 1.21 for telecommuters, $t = 10.18, p < 0.05$). The effect size calculates to be 0.45, which is relatively large among all effect sizes reported in Table 3.3.1. What is interesting though is that the trip purpose diversity index at the aggregate level did not shrink at the aggregate level (Figure 3.3.1).

3.4 Conclusion and Policy Implications

Telecommuting has long been recognized a Transportation Demand Management (TDM) strategy to reduce Vehicle Miles Traveled (VMT) and reliance on cars. Prior to COVID, its effect has been minimal as only a small share of workers telecommuted (less than 5%). Findings of many studies have also been mixed, with telecommuting has reported to either substitute or complement travel demand. For example, telecommuting has shown to increase both frequency and distance of non-work trips [94, 95], and telecommuters were also argued to travel farther and longer for those non-work trips [25]. Van Wee and Rietveld [96] revealed that travel time increased 8% by observing the 1975-2000 Dutch National Travel Survey and 26% by observing the Dutch Time Use Survey. On the other hand, Choo et al. [97] supported the substitution point of view and found that telecommuting reduced total annual VMT in the U.S. by approximately 8%. Ellder [26] also showed that telecommuters had a significantly lower personal-kilometers-traveled compared to commuters.

COVID-19 changed the landscape of telecommuting dramatically: the share of telecommuters jumped to 35.4 in the peak of May, 2020 and now still hovers around 23.0, as of March 2024 [5]. With these many telecommuters all of sudden in the workforce, it is thus desirable to revisit the topic regarding the promise of telecommuting as a TDM strategy to reduce VMT and reliance on cars. In fact, it is desirable to obtain a holistic picture on how telecommuting changed people's daily travel patterns, including generation of trips, temporal and spatial rescheduling, changes in VMT and modes of transportation used. This is the aim of this study.

We use Hagerstrand's space-time prism framework to answer the question posted above. In Hagerstrand's time-space prism, telecommuting means having workplace removed, leaving home as the only anchor point in one's daily activity and travel pattern. This has several implications. The first is that commuting time would be saved. The question is thus: how did people reallocate their saved commute time, especially with regards to those trips that are relatively flexible such as maintenance and discretionary trips? The second question is how the removal of workplace related constraints spatially and temporally altered people's conduct of maintenance and discretionary trips? The last is the consequent changes in the modes of transportation used and the associated VMT.

Using three waves of the household travel survey data from the Puget Sound region (two pre-COVID-19 and one during COVID), we find that overall, telecommuting led to reduced number of trips. And yet, the overall reduction is the sum of elimination or substantial reduction of work-related trips and a significant increase in both maintenance (15% more) and discretionary trips (22% more). In other words, telecommuting did lead to significantly more maintenance and discretionary trips, but the effect is inelastic. Additionally, all three metrics measuring the extent of one's travel: total person miles, total VMT, and radius of gyration, decreased as the result of telecommuting. With home as the only anchor point, telecommuters conducted maintenance and discretionary trips closer to home and those trips are also shorter and simpler with less trip chaining. Temporally, except for meal related trips, the departure time distributions for maintenance and discretionary trips were more spread out with emerging peaks such as late morning, and mid-day. For meal related trips, the peak around lunch break for commuters was greatly reduced for telecommuters but there emerged a much higher evening peak. On modes of transportation used, as reflected in the drastic reduction in ridership nationwide, the use of transit was significantly reduced, accompanied with the increase in walking. These results suggest that the time saved from commuting are re-allocated throughout the day for telecommuters. Telecommuters no longer have designated breaks such as lunch breaks. Instead, they utilize short breaks throughout the day for more frequent but shorter trips, resulting in insufficient trip chaining and increased reliance on driving. Because the samples from which the study samples were drawn are probabilistic samples, the findings from the study can be generalized to the population in the Puget Sound Region, specifically the population that is characterized by the study sample (Table 3.2.1).

The transportation policy implications of the above findings are mixed and complicated. The positive news is that telecommuting can be an effective TDM strategy to reduce VMT. In addition, walk trips are increased. The answer to the question on whether it will also lead to reduced reliance on cars is less clear. Even though the share of driving trips is also reduced, there is also a reduction in the diversity of the modes of transportation used, suggesting that there may actually be more reliance on cars for trips beyond walking distance. The finding on the temporal re-distribution of maintenance and discretionary trips (especially with newly emerged peaks during the day) may mean reduction in concentrated congestion in morning and evening peaks (which is a welcoming news) but could also suggest a more spread-out congestion pattern that extends from morning to mid-day and to evening. Similarly, the spatial re-distribution of those trips around home can mean both reduced traffic on certain, previously crowded corridors (e.g., those to/from downtown) and emergence of increased traffic around residential areas. Both the spatial and temporal redistribution of those maintenance and discretionary trips pose grave challenges for our transit agencies, which has operated on a model that primarily served commuters between downtown and urban cores in a region and surrounding residential areas.

Methodologically, the study used propensity score matching to identify a control group (commuters) and a treatment group (telecommuters); there is a high level of similarity in socio-demographics and the built environment characteristics. This method is to address the self-selection bias that often exists in cross-sectional samples, in particular, on observed characteristics. The method cannot address self-selection bias that may also exist on the unobserved variables, e.g., motivation to telecommute. For example, Wang (2023) [130] found the existence of such bias on the unobserved variables for telecommuters but not for non-telecommuters. We suspect limited existence of the self-selection bias on the unobserved for two reasons. One, unlike prior to COVID where telecommuting was largely a choice of self-selection, telecommuting during COVID[1] was mostly not a result of self-selection but the result of government mandate. Second, the two groups: commuters and telecommuters, were drawn and matched from two independent household travel surveys (one prior to COVID and the other during COVID). This process mirrors a more desirable, sequential timeline where one was a commuter prior to COVID and become a telecommuter during COVID. In other words, if viewing telecommuting (or removal of the workplace as the an-

[1] 2021 was our study period for telecommuters. The largest hospitalization for COVID occurred in late 2020 and early 2021.

chor) as the treatment, this process has a clear timeline from observations before treatment, treatment, and observations after treatment. This is different from other studies that used a single cross-sectional dataset to split into two groups, i.e., Wang (2023) [130] used a more sophisticated technique (endogenous switching model, which essentially estimates the two choices: selection of being a telecommuter and VMT, simultaneously) to evaluate the effect of telecommuting.

There are also implications on local economy within a region. The significance of downtowns and urban cores in regions across America is not only marked by their tremendous concentration of workers (commuters) but also the vast number of service industries that those commuters supported: around workplaces, people shop, do errands and conduct social and recreational activities. The spatial re-distribution of those maintenance and discretionary trips suggests a substitution effect: the relocation of those trips from downtown to around residential areas. This relocation has grave consequences on America's downtown and regional urban cores but may also have spurred local economies in new areas.

With COVID as the biggest natural experiment in history for studying the effects of telecommuting, there are many future directions that aim to answer the same or similar questions. We discuss a few of them here. In one, there is a need to study consequent travel patterns for workers who work in downtown prior to COVID and those who relied on transit to get around. The former group is interesting as their consequent travel patterns post-COVID provided a detailed lens into the substitution effects of maintenance and discretionary trips from downtown to areas around their homes, as suggested by this study. The latter group is interesting because they faced additional constraints due to the lack of access to vehicles. In another, it will be interesting to study from a time use point of view, how the commute time saved is reallocated to other activities. The current study points to the reallocation toward maintenance and discretionary trips, since both of which experienced an increase in the numbers. However, on a per-trip basis, travel time decreased for these trips, so the time use reallocation will be more complex than suggested by this study.

Chapter 4

COLLECTING DATA, SAMPLING, AND PARAMETERS FOR BUSINESS RESILIENCE STRATEGY DEVELOPMENT

4.1 Motivation

Small and medium-sized food businesses have long been operating based on invaluable experience, and their operation strategies can be enhanced through data and mathematical modeling [131]. During the COVID-19 Pandemic, a plethora of literature has [34, 132, 133] qualitatively testified how the restaurant operators adapted by adopting delivery services [133, 18], servicing through robots [134, 18], offering meal-kits [18, 135], and implementing flexible work hours [135, 136]. Many researchers have pointed out the need for a combined qualitative and quantitative approach to better understand the challenges that restaurants face to survive and thrive [133]. This dissertation contributed to this effort by developing mathematical models to guide food businesses during disruptions and by engaging in direct discussions with restaurant managers for practical insights. These discussions guided the development of research questions focused on topics relevant to practitioners and helped establish mathematical models grounded in realistic assumptions.

The flow chart below (Figure 4.1.1) summarized four major components of this qualitative-quantitative data collection process:

(1) Defining Scope

(2) First Round of Interview

(3) Instrument Development and Sampling

(4) Defining Parameters

Each major component will be introduced in detail in the following subsections.

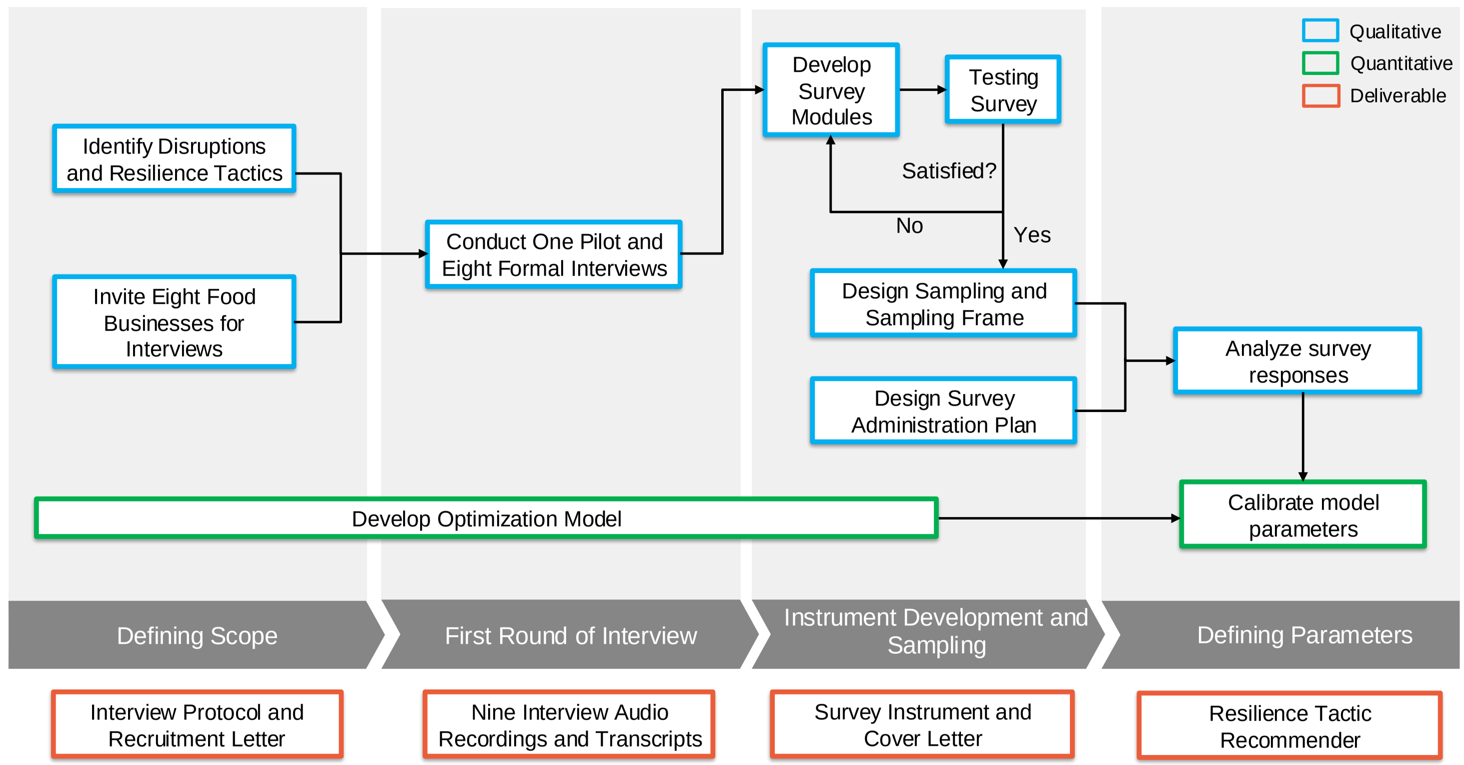


Figure 4.1.1: Flowchart of data collection, survey development, and resilience model optimization process

4.2 Defining Scope

Aiming to build a detailed and comprehensive understanding of the challenges, resources, and attitudes of businesses adapting to COVID-19, we designed a combination of face-to-face interviews and surveys to collect primary qualitative data. The first step involved identifying entities operating within U District and assessing how various types of outdoor spaces could adapt to disruptions. This initiative leveraged the help from a two-part studio course, URBDP 506 and 507, at University of Washington, College of Built Environment, Urban Design and Planning, where students investigate the policy environment for food businesses in U District. Recognizing these businesses operate at different scales, organization structures, cultural backgrounds, and resources (particularly outdoor spaces), we broadly categorized the businesses into seven categories: 1) full-service restaurants; 2) quick-service restaurants; 3) convenience stores; 4) large-scale grocery; 5) medium-scale grocery; 6) food banks; and 7) community gardens. These businesses either has a streatery (an outdoor dining area or eatery, usually located on sidewalks or in on-street parking) or are adjacent to surface paring lots. Our goal was to schedule interviews with representatives from each category to gain insights into their adaptation strategies.

During our initial outreach from October 30, 2022 to January 10, 2023, we contacted to 8 food businesses, including boba shops, restaurants, food banks, and convenience stores. Unfortunately, due to privacy concerns and non-disclosure agreements, large grocery chains such as Trader Joe's and Safeway and convenience store chains like 7-Eleven declined to participate. Concurrently, we developed an interview protocol featuring five hypothetical disruption scenarios: employee shortage, demand decrease, supply shortage, production decrease, and adaptation strategies. These scenarios were derived from literature review in section 5 focusing on the disruptions that food businesses have struggled to adapt. The literature review also identified key resilience tactics including boosting efficiency, adjusting quality, and adding capacity-that businesses have deployed in response to such challenges.

Parallel to inviting interviewees and developing interview protocols, we proposed a mathematical model that aims to recommend resilience strategies for food businesses to maximize profit during the above mentioned disruptions. The mathematical details about this model is discussed in length in section 5. Simply speaking, the model simulates the revenue earned by selling food, cost generated from hiring employees, purchasing raw materials, paying rent, and other expenses. Profit is equal to revenue minus costs. While modeling these aspects of daily operations, our model recognizes the presence of constraints – both those that naturally exist based on food business's resources, and those imposed externally during disruptions. For example, a restaurant can only serve as many customers as its room capacity allows, and excessive customers should wait to be served. And disruptions such as social distancing can further limit the number of customers served simultaneously. It becomes clear that making profits are more challenging for food businesses during disruptions. The mathematical model will then determine whether to implement resilience strategies, such as boosting efficiency or expanding capacity, and to what extent these tactics should be employed to maintain profitability.

As we developed the mathematical model, several key parameters, upper bounds and lower bounds of decision variables were not sufficiently addressed in the existing literature. Specifically, such parameters include employee wages, money spent purchasing raw materials, monthly rents, the number of employees, daily customer demand, how much revenue was lost during COVID-19, etc. The existing literature and government reports often reported these information on an aggregate level for the entire industry or a particular region. Applying aggregated statistics will incorrectly simulate the food businesses of interest in terms of operation status quo and the severity of disruption. While we had planned to actively collect these data through paper-based survey, we first incorporated targeted questions to test how comfortable operators are in sharing such granular details into our interview protocol (see Appendix C). For the purpose of illustration, several questions from the protocol are quoted below.

(1) "Do you have fewer customers than before the pandemic?"

(2) "Running your business involves purchasing many necessary supplies and ingredients. How do you usually estimate the amount of food supplies or products to buy for the

next month? What would you do if you were short of critical supplies? What kinds of substitutions are possible?"

(3) "How long did employee shortage last? If your business was unable to fill job openings but customer demand remained high, how would you respond? Could your business still operate if you lost half of your employees?"

Given that the proposed data collection plan involves human subjects, an application was submitted to the University of Washington's Office of Research, Human Subjects Division for Institutional Review Board (IRB) approval. The Human Subjects Division subsequently determined that this research is exempt from IRB review after examining the interview protocol. A recruitment letter (see Appendix D) was prepared from the researchers and the instructor of URBDP 506 and 507 to facilitate students' outreach effort.

4.3 First Round of Interview

The interviews are conducted in two groups: pilot group ($n = 1$) and formal group ($n = 8$). The goal of having a pilot group is to evaluate the clarity of the questions and willingness of restaurant owners to share information. Considering that the first interview might take longer when unclear questions leads to unexpected explanations, the pilot group participant was solicited through a personal relationship who can stay longer than scheduled. Though the participant's restaurant is not based in U District, the pilot interview helps obtain honest opinion about the interview process and not to waste any interviews with formal groups. The pilot interview received positive feedback form the participant, which validated the legitimacy of the interview protocol. The goal of interviews was to evaluate what questions were important from the business' perspective and thus should be included in the survey instrument. Each interviewee was compensated $50 Amazon gift card as an appreciation of their effort and time.

The eight interviews were carried out from January 10th, 2023 to May 26th, 2023, through in-person meetings or virtual meetings over zoom. Each interview group consisted of at least two students, with one leading and administering questions while the other(s) took high-level summary notes. At the beginning of each interview, the interviewees were presented with the recruitment letter and informed about the use of audio recordings for future transcription and analysis. The food businesses varied widely in scale, type of services, and resources, which influenced their responses and resilience strategies. For instance, quick-service establishments like BobaUp and Sweet Alchemy, which focus on high customer turnover and minimal dining space, adapted by shifting to online orders and social media marketing to reach customers during COVID-19. BobaUp noted that they relied "heavily on technology and social media to reach customers...COVID hit really hard...we couldn't just go with the standard (*indoor*) model." Similarly, Sweet Alchemy shifted operations, with the owner explaining, "we closed all lobbies and became a delivery pint shot; scoopers became pint packers to meet demand during lockdown". This flexibility in operations allowed these quick-service businesses to continue serving customers and maintain revenue despite pandemic restrictions.

In contrast, larger establishments such as H-mart, an Asian-American supermarket chain with a broad customer base, continued in-person services and relied on corporate supply chain support to manage disruptions. The manager at H-Mart stated that they "adapted to supply challenges with substitute products as needed, by we kept our focus on in-store shopping since we don't offer delivery". Moreover, smaller and independently operated grocery stores, like Joy Mini Mart, faced unique challenges in handling crime and safety concerns. Thus, the operator of Joy Mini Mart emphasized heavily on limited staffing and a high turnover rate. The operator shared that "the largest struggle has been crime, theft is common, and police responses are slow or absent, making it difficult to retain staff".

The scale of each business played a significant role in shaping their adaptability. Smaller businesses, like Sweet Alchemy and Joy Mini Mart, relied heavily on flexible staffing and rapid shifts in operation modes. The Sweet Alchemy owner described adapting to seasonal fluctuations, stating, "our sales rely heavily on the UW calendar; cakes and pints peak during summer and weekends, especially with local events". In contrast, larger businesses like H-Mart and the Food Bank had the resources to maintain a stable customer base and service offerings.

Across all interviews, a shared theme emerged: each business encountered significant operational challenges during the pandemic, such as fluctuating customer demand, rising supply costs, and adapting to evolving health guidelines. Many businesses adopted diverse strategies to navigate these challenges, and some emphasized the importance of community support. For example, Big Time Brewery viewed its brewpub as a community hub and explained that it was "a place where everyone feels welcome... you'll see birthday parties, business meetings, people studying." This strong community connection provided Big Time Brewery with a loyal customer base even through difficult periods. Similarly, the Food Bank adapted to increased demand during the pandemic, working with volunteers and mutual aid groups. Staff noted, "We saw a rise of mutual aid. . . neighbors recognized where there were others struggling, and mutual aid groups formed to support food access, shelter, and health needs."

Another important insight was restaurant operators were willing to share numbers about various aspects of their operations, including presumably sensitive topics such as revenue loss and money spent on hiring employee or restocking. This observation gave confidence of including similar questions into survey.

4.4 Instrument Development and Sampling

Survey development is central to this data collection process, as it transforms insights from interviews into targeted questions and directly informs the formulation of the optimization model. Based on our interviews, small and medium food businesses were challenged the most, and when challenged, they had more difficulties adapting compared to their counterparts. And interview also suggested the survey should be developed at the scale of the individual business entity, because despite commonalities, distinct challenges and solutions existed among food businesses. How the collected information will be incorporated into the optimization model will be discussed at length in section 5.

The survey development leveraged the help from the above-mentioned authors, members from Puget Sound Regional Council, and members of a NSF funded project, LEAP-HI: Re-Engineering for Adaptable Lives and Businesses for clarity and relevancy of the survey instrument. Mailing out paper-based survey is chosen given that the businesses can be located through a physical address, and email addresses are difficult to solicit and verify.

4.4.1 Survey Modules

The survey covers three main components: business operation, disruption preparedness and responses, and attitudes towards resource sharing. The first two components were crucial in developing the optimization model and the less time-consuming for respondent to recollect and fill-out. Placing them at the beginning maximized the chances of obtaining key information, even if respondents chose not to finish the entire survey. The resource sharing section is called for because many interviewees explicitly stated they engaged in community support. Further, recent literature has been exploring the willingness, and factors affecting the willingness to share resources in a disaster scenario [137]. The survey also included a background section to gather demographic information and responses to open-ended questions. Placing these questions at the end follows standard practice, as they may be perceived as less interesting or, at times, sensitive for respondents [138].

The survey was designed with a clear structure through four modules:

(1) Business Operations

This module begins with questions capturing essential operational details, including (1) what type of service is offered, e.g., full-service, quick-service, Grocery, Food-related retail, accommodations(such as motel, bed and breakfast); (2) how many hours of operation on weekdays, weekends, and holidays; (3) what are the primary transportation mode used by customers to reach the store; (4) whether the business has outdoor spaces for seating and dining, and (5) a series of fill-in-the blank questions about the number of employees hired, ideal number of employees, average hourly wage, and average work hours per week, the cost of using that outdoor space, if any.

The survey then branches off into two sub-parts, and the participants are guided to complete the first section if they selected full-service restaurant, quick service restaurant, or retail and complete second if otherwise. Both sections asks for how many customers are served through different operation modes (indoor, outdoor, delivery etc) and on average how much does customer spend per order. The wording of the questions are adjusted slightly to match the operation modes available for different types of businesses.

This module closes off with a series of questions asking profit margins by comparing in-store and third-party delivery orders, customer volume variations during peak and off-peak seasons, and additional customers serviceable without further investment. The questions also ask about average wait times during the busiest periods and weekly spending on restocking supplies. Furthermore, monthly expenditures on rent and utilities, as well as total operating revenue for the last month (excluding financial assistance), are gathered.

These questions ask respondents to recall a typical day-to-day operation with no disruptions and establish a baseline for comparing changes in business performance and resilience strategies under disruptive conditions.

(2) Disruption Preparedness and Responses

In this module, the survey asks respondents about their business's current cash reserves, minimum monthly profit needed to sustain operations, and perceived likelihood of receiving funding, such as grants or loans, during disruptive events like COVID-19. It also inquires about past experiences with funding applications, including the time required for preparing the application, and the amount received from grants, if applicable.

To further examine resilience, a mix-and-match questions was included where respondents will review a list of potential challenges, such as insufficient funds for essential goods or staffing, stock shortages, low customer demand, policy restrictions (e.g., social distancing), and neighborhood safety concerns related to crime or vandalism. For each challenge that has impacted their business during COVID-19, respondents are asked to select corresponding strategies that could help address the issue. Available strategies include adopting digital technologies, increasing service capacity, modifying management practices (such as employee multitasking), introducing or improving goods and services, and enhancing logistics, delivery, or distribution methods. Respondents can list multiple strategies per challenge and are also encouraged to suggest any additional tactics they believe would aid in overcoming these specific challenges.

This goal of this module is to understand at how long can the business stay in operation before the profit is driven to zero. And more importantly, what tactics are available for businesses to extend that period longer and even make more profit amid disruptions.

(3) Resource Sharing

The intent of this module is evaluating business operator's attitudes towards sharing resources with other local businesses, and in what way sharing is possible. Resources sharing refer to temporary borrowing or lending employees, cooking equipment, cooling/freezing equipment, utensils, sanitary supplies, outdoor space, or knowledge/expertise. It is understandable that operating a food business involve invaluable experience and capital, and the willingness to share could depend on who is the recipient. Therefore, the survey instrument proposed four tiers of recipient: any business in need, businesses within the same neighborhood, businesses operated by friends, families or relatives, or nobody.

(4) Background Information

The last module intends to gather respondents' demographic and background information, including U.S. birth origin, primary language, ethnicity, race, and gender identity. It also includes a question regarding whether the business qualifies as minority-owned, following the Small Business Association's definition, which includes both ethnic minorities and women-owned businesses. An open-ended section invites respondents to provide additional comments on the survey content, offering an opportunity to share further insights or feedback. This demographic information will support a richer analysis by contextualizing the experiences and challenges of diverse business owners.

4.4.2 Sampling and Sampling Frame

Sampling units were selected using a non-probabilistic sampling method, as it was feasible to locate all food businesses operating in the U District and the sampling frame could be small. Each sampling unit is either an owner or manager responsible for day-to-day decisions at small, medium, or large food establishments, including restaurants, cafes, convenience stores, and grocery outlets. The list of relevant businesses was compiled by combining data from two sources: King County Food Inspection Data [139] and the Google Maps Places API.

The King County Food Inspection Data, managed by the King County GIS Center, provides a comprehensive view of food facilities within the county's inspection area, with details such as name, address, zip code, seating capacity, and geographic coordinates. This dataset is updated periodically during inspections, typically conducted twice a year. However, since a business could close between inspection cycles, additional verification is needed. The Google Maps Places API was used as a supplementary source by querying for all points of interest within the U District. Manual inspection was required to filter relevant food businesses from this dataset. Business owners with Google My Business profiles are encouraged to update their information through API as frequently as needed. By cross-referencing and consolidating these two sources, we created a verified list of 178 businesses, including their names and addresses, to establish a comprehensive sampling frame.

4.4.3 Survey Administration

The survey instrument was pretested by inviting the pilot interview participant to assess completion time and identify any necessary adjustment to the wording. It was sent via email as a PDF to the same restaurant owner who participated in the pilot interview. The participant spent 35 minutes completing the survey, and based on their feedback, two questions—one regarding operating hours on weekdays, weekends, and holidays, and another about the impact of neighboring business closures—were refined for clarity.

The formal survey administration was scheduled in the week of March 15, 2023 to March

23, 2023. To facilitate the delivery, 178 businesses were grouped into 6 clusters through a clustering algorithm such that most members belong to the same cluster are closer to each other than another business outside of the cluster. The businesses are located between Roosevelt Way Northeast on west and 15th Avenue Northeast on east, NE 40th Street on south and Northeast Ravenna Boulevard on north (see Figure 4.4.1). Then, students from URBDP 506 and 507 also formed 6 groups, and each delivered a portion of the survey to one cluster. 160 out of 178 (89.9%) surveys were successfully delivered, and the failed delivery was due to temporary-closure or permanent closure of business, or incorrect address listed in both data sources.

The survey instruments were packaged in a letter-size envelope together with a pre-paid return envelope and a cover-letter (see Appendix F) introducing the goal of the survey, who was collecting the information, and how the data would be used. Both the cover-letter and the survey state that respondents will receive a $10 Amazon.com e-gift card upon completing and returning the survey to acknowledge the time and effort. A virtual gift card on a widely accepted e-commerce platform was chosen, considering that supplies (e.g., packaging materials, cleaning products, receipt paper roll) might be purchased for food business logistics operations.

4.5 Defining Parameters

Eight surveys were returned and analyzed to calibrate parameters for the optimization model. Specifically, the results are applied to parameters relating to employee, labor costs, customer demand, supply costs, operational capacity, and operational cost (see Table 4.5.1 for summary).

Survey results suggest that full-service restaurants reporting between 6 and 35 employees and quick-service restaurants reporting between 1 and 12 employees. These figures align with national data, which shows that 90% of restaurants employ fewer than 50 people. Wages reported from the survey ranged from $16 to $25 per hour, we set an average wage of $18 per hour for the optimization model's labor cost parameter. Given that all employees were assumed to work full-time, the model's lower and upper bounds for work hours were

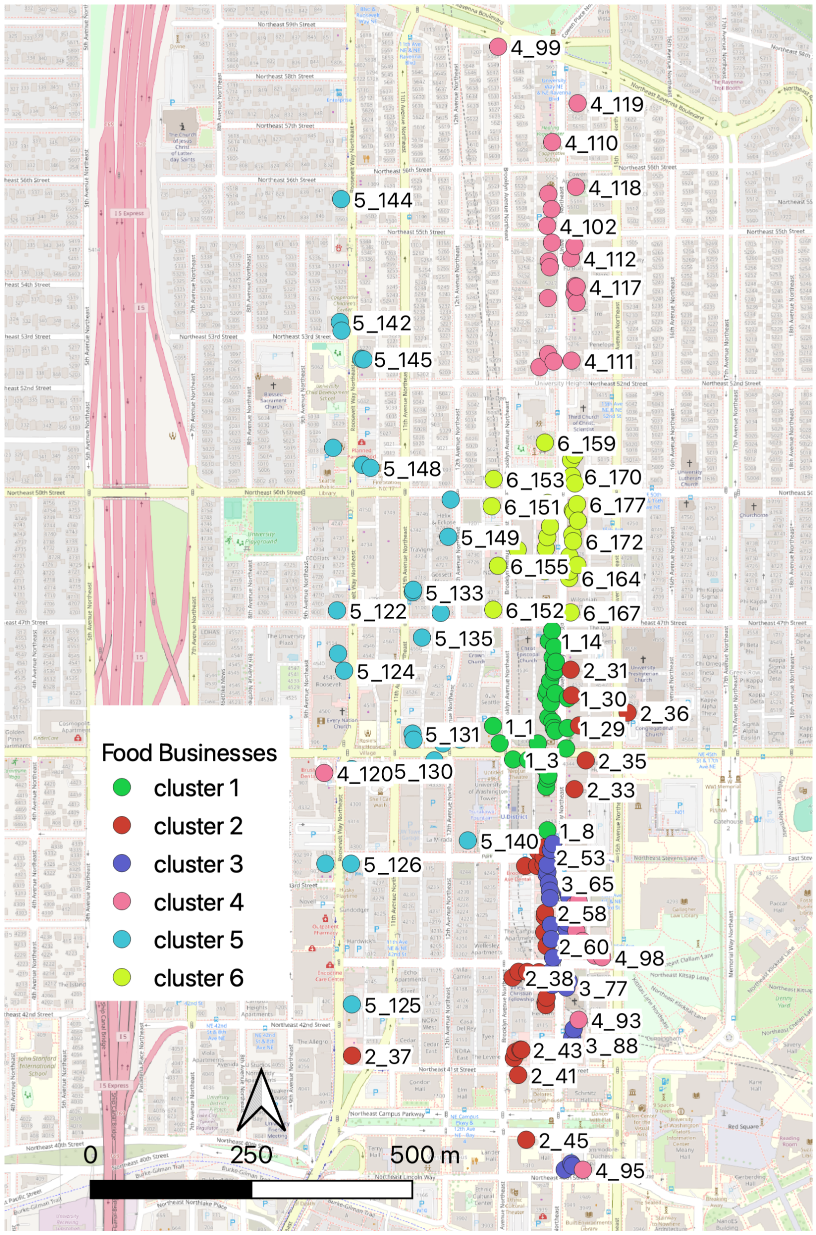


Figure 4.4.1: Locations of verified food businesses for survey delivery.

defined as 8 hours per day for a single employee and up to 480 hours in total for 60 employees.

Customer demand was calibrated through weekly customer counts collected in the survey for different service types, including indoor dining, outdoor dining, takeout, and delivery. For full-service restaurants, a majority of customers preferred on-premise dining, while quick-service restaurants handled a larger overall customer volume across all service types. Customer spending patterns also varied, with average expenditures ranging from \$10 to \$40 per visit. Takeout and delivery services tended to have higher average costs (\$20–\$40) than dine-in options (under \$20), enabling the model to set distinct demand and spending parameters for on-premise and off-premise services.

Supply costs were established based on restocking expenses reported in the survey. Full-service restaurants, serving between 560 and 700 customers per week, reported weekly supply costs between \$2,501 and \$4,000. Quick-service restaurants, which typically served a higher volume of approximately 3,150 customers weekly, spent between \$1,001 and \$1,500 on supplies. These costs were further refined by cross-referencing with USDA dietary guidelines, which estimate typical food preparation costs. As a result, per-customer supply costs were calculated as \$3.57 for full-service and \$0.32 for quick-service restaurants. Supply capacity was also determined through survey data, which estimated that full-service restaurants required a total of 14,832 cups (measuring unit for cooking) of ingredients per week, while quick-service restaurants needed 22,283 cups to meet customer demand.

Operational capacity was another critical parameter shaped by survey findings. Restaurants indicated they could serve an additional 15–75% of their existing demand without added investments in labor or supplies. Quick-service restaurants tended to operate closer to capacity, accommodating only a 15% increase, while full-service establishments had greater flexibility, accommodating up to 75% more customers. These insights were incorporated into the model by setting production capacity limits at 130% for quick-service and 150% for full-service restaurants, ensuring realistic bounds on operational expansion.

Fixed and operational costs were also informed by the survey. Establishing off-premise operations required a one-time setup cost, estimated at \$616.67, based on quarterly fees for outdoor space usage. Monthly utility and rent expenses ranged widely from \$2,500 to

$100,000. To standardize these findings, the model assumed an average daily operational cost of $333.33. These detailed, survey-informed parameters allow the model to accurately reflect the financial and operational realities of food businesses, offering valuable insights for resilience planning and decision-making during disruptions. How these parameters are incorporated into the optimization model will be discussed in detail in the next section.

Table 4.5.1: Survey-Informed Parameters for Food Business Model

Parameter	**Description**	**Survey Findings/Model Values**
Employee Count	Number of employees hired for full- and quick-service	Full-service: 6–35; Quick-service: 1–12
Work Hours/Wages	Average wage and daily hours	Wage: $18/hr; Hours: 8–480 (full-time)
Customer Demand	Weekly demand by service type	Full-service: on-premise; Quick-service: higher across types
Spending/Customer	Average spending per visit	On-premise: $10–$20; Takeout/Delivery: $20–$40
Supply Costs	Weekly restocking cost	Full-service: $2,501–$4,000; Quick-service: $1,001–$1,500
Supply Capacity	Weekly food supply needs	Full-service: 14,832 cups; Quick-service: 22,283 cups
Operational Capacity	Additional demand that can be met	Quick-service: 15% more; Full-service: up to 75% more
Fixed/Operational Costs	On/off-premise setup and operating costs	Off-premise setup: $616.67; Rent/Utilities: $2,500–$100,000; Daily ops: $333.33

4.6 Data Summary

Building on the methodological framework for data collection, this section analyzes the strategies enacted by small food businesses in the U-District to survive and revive from COVID-19. The food related enterprises that participated in the data collection process are of every kind - from full service restaurants and quick-service cafes to farmers' markets, mini-marts, and nonprofit food banks. The data collects are of two sorts: (1) paper-based survey responses highlighting the businesses' self-reported adaptations, and (2) interview recordings and transcripts revealing nuanced decision-making rationales.

Although the close-ended and semi-close-ended questions are mostly filled out by respondents, the open-ended questions have low response rates as expected. Thus, this section will rely on the interview transcripts to identify resilience strategies. Furthermore, the strategies are broadly classified as short-term if deployed as a temporary solution and expected not to continue as indoor dining restrictions relaxed, and long-term if expected to continue or has become part of their operations now.

Structurally, this section first maps short-term adaptations, then examines long-term policies and the possible ways to model long-term strategies, and finally discusses implications for post-pandemic resilience in small food businesses in U-District.

4.6.1 Short-term Adaptation Strategies

Although they faced different types of disruptions, the first resilience strategy adopted by many participants is to quickly adjust their core operation from indoor dining to grab-and-go. For example, several small restaurants eliminated indoor dining altogether when either labor shortages or COVID regulations made in-person service too risky or unmanageable. One full-service restaurants explained that they diverted nearly all their energy to fulfilling takeout and phone orders that require fewer staff interactions to avoid virus exposures. In parallel, a quick-service ice creamery shop shifted from scoop-and-serve model to a pint shop with pre-packaged online ordering. This rapid service adjustment was often supported by digital tools such as online platforms, even for relatively traditional entities such as farmers' markets and local food bank. According to the operator of one farmers' market, shoppers could place customized produce orders and prescriptions through the platform and then pick up sealed boxes from a pick up box stand. Similarly, the local food bank had their volunteers as "personal shoppers" selecting groceries according to stated preferences from customers who waited outside. Such immediate adjustments, although logistically taxing at the beginning, allowed businesses to continue operating under severe pandemic disruptions.

A second noteworthy short-term strategy is sourcing substitutions during supply chain issues. Full-service restaurants, as well as other cafés and mini-marts, described abruptly losing access to items like to-go packaging, nondairy milk powder, or glass jars. Their

Figure 4.6.1: The quick-service ice creamery shop switched from its signature scoop-and-serve approach and relaunched with fully pre-packaged products.

solutions were turning to neighbor restaurants, local supermarkets or Costco, or even cross to a different state to fill sudden gaps. A quick-service ice creamery recalled reaching to warehouses across multiple states to secure thousands of specialty pint jars once their regular supplier ran out. While improvising is expensive and time-consuming, these short-term substitutions ensured that critical menu items (such as bubble tea, pre-packaged ice cream, or convenience snacks) remained available.

A third short-term adaptation relates to labor reassignments in an immediate crisis. For family restaurants, staff simplification might mean an owner and one or two assistants taking on longer hours or suspending late-night service, if not completely closing certain days of the week. Multi-location businesses, such as the ice creamery owning four ice cream shops, have resorted to "hierarchy closures" whenever staff absences spike: they shut one store (typically with the lowest average walk-in customers) temporarily and redeploy employees to busier or flagship sites. Food banks facing a volunteer shortage push all available hands toward home delivery tasks or bagging groceries. Taken together, these abrupt adjustments illustrate the business's reliance on agility and improvisation in the face of disruption.

4.6.2 Long-term Adaptation Strategies

Many interviewees, besides immediate responses, also detailed larger, more permanent strategies intended to protect their operations from recurrent shocks. One of the most common was structural changes in operation. One quick-service business, for instance, increasingly combines its physical storefront with catering, farmers' market pop-ups, and online ordering systems. Similar trend also happened when farmers in the U District markets began new retail alliances with local bakeries or restaurants, ensuring that if one sales outlet disappeared, others could compensate. Specifically, the concept of "Farm to Food Bank" where PCC (Puget Consumers Co-op) paid farmers fair market rate and put their food into food banks has become a main food access platform. Similarly, family-run restaurants have learned to purchase from multiple suppliers rather than depending on a single entity for supplies.

Another recurrent strategy in these interviews was the decision on capital investment. One of the main benefit is to increase capacity. Food businesses can store or maintain a buffer stock of crucial supplies—an understandable response after struggling for months to find plastic cups, jar lids, and nondairy milks. Businesses that can afford it now keep surplus packaging or raw ingredients on hand, even if it raises storage costs and complicates cash flow. Food banks also mirror this pattern by drawing from numerous backup or donation channels; if grocery stores or major distributors are compromised, they still have relationships with smaller local producers or community resources. Stocking up in long-term prevents a single glitch from forcing closures or empty shelves. Another benefit, primarily for farmer's markets, is to install permanent infrastructures such as electric outlets on power poles, retracting bollards on streets. However, these usually requires a collaboration with the city and county, and the business operators have expressed the need for a public space liaison from the government to work with these installations.

Besides physical investment, a related long-term strategy involved deeper workforce development and staff cross-training. Where short-term measures focused on last-minute shift reassignments, a more sustainable approach calls for training employees to handle complementary tasks, like simultaneously managing front-of-house duties and basic kitchen prep. The ice creamery's hierarchical closure strategy is the short-term dimension of this, but more deliberate cross-training ensures that if a person calls out sick, others can step in. Having a thinner volunteer pool during COVID-19, food banks now cross-train helpers to drive delivery vans and to make bicycle drop-offs in neighborhoods where strict parking rules hinder truck loading and unloading.

The last but not least strategy is to establish stable partnerships with policymakers and municipal authorities. Restaurants burdened by sidewalk or street construction faced repeated revenue decreases but eventually sought permanent streatery permits for outdoor dining. Farmers' market managers took part in negotiations with the city health department to standardize safe, open-air selling requirements. Food banks described actively lobbying city officials for better cold storage infrastructure or easy load zones near their pantries. Thus, instead of retreating from civic channels, business owners increasingly learn to navigate or reshape local regulations to expand capacity and mitigate disruptions.

In the early months of COVID-19, food businesses relied on quick "stop-the-bleeding" measures—curbside service, ad-hoc supply swaps, and flexible staffing—to survive sudden capacity limits. Over time, these same instincts matured: temporary outdoor dining morphed into new operating modes, improvised substitutions prompted capital investment in storage and equipment, and improvised shift-swapping evolved into formal workforce-development programs. The purple Adapt band in Figure 4.6.2 highlights this bridge from short-term response to long-term strategy, providing a conceptual thread later formalized in the multi-period optimization model.

4.6.3 Contrasting Adaptation Across Different Types of Food Establishments

Although the above strategies appear frequently, each type of food business occupies a distinct position about how, when, and why the business deploy certain strategies. Full-service restaurants, with more elaborate dine-in experiences, often had to let go part of their brand and service identity during COVID and adopt minimalist takeout menus. Quick-service spots, including bubble tea shops and ice-creamery, found it simpler to toggle to

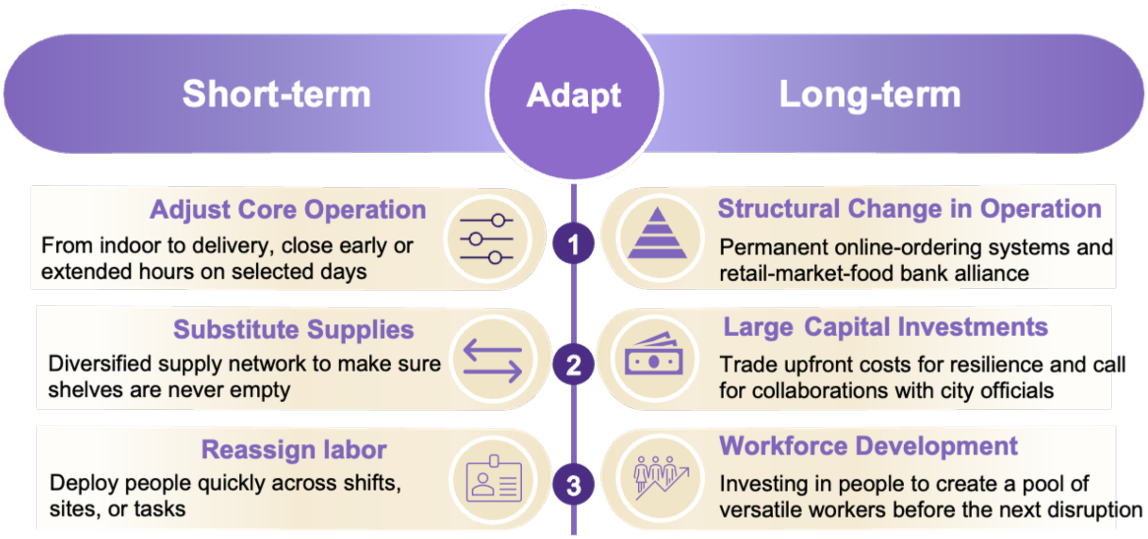


Figure 4.6.2: Comparison of short-term “stop-the-bleeding” tactics and their evolution into long-term adaptation strategies.

phone ordering or walk-in pickups because their clientele already prioritized convenience over dine-in ambiance. The farmers' market had a unique regulatory burden and collective identity to preserve: they could not simply trim half their vendors as easily as a single restaurant might trim its menu, so they improvised careful one-way foot traffic, six-foot spacing between stalls, and robust online prescription pre-order portals to keep farmer revenues flowing.

Nonprofit food banks experienced different limitations. Food banks have a unique motivation of reduce or eliminate barriers to accessing healthy food. They could not offset surging dairy or egg costs by raising retail prices or reducing the groceries on shelves. They had to launch expanded fundraising efforts, volunteer recruitment events to recruit more delivery person, and deepen partnerships with local clubs and libraries. A local Mini Mart, further along the convenience store spectrum, noted that crime and security overshadowed many COVID-related concerns mentioned by the other types of businesses. Facing minimal staff per shift before and throughout COVID, the store can only function if employees feel safe, leading them to clamor for enhanced policing or more visible security. Except for crime and theft, the operator reported COVID had small impact on their business, and their business was able to sustain supply chain shortage and even had revenue increased due to nearby Safeway being closed.

Taken as a whole, whether an enterprise thrives on restaurant ambiance, immediate convenience, a bustling open-air market vibe, or nonprofit mission delivery, each domain calls for a distinctive combination of short-term fixes and longer redesigns.

Chapter 5

ADAPTABLE BUSINESSES: RESILIENCE TACTICS IN THE FACE OF DISRUPTIONS

5.1 Introduction

Small-scale restaurants, typically defined as establishments with fewer than 50 employees or limited to single-location ownership, form a critical backbone of the restaurant sector and, by extension, the local economy [140]. These businesses represent a majority in the restaurant industry, driving employment and economic activity within their communities and supporting the livelihoods of millions of families. Unlike larger chains, these small-scale restaurants face unique vulnerabilities during disruptions due to their limited financial and operational resources. For example, during the COVID-19 pandemic, these small-scale establishments were disproportionately affected by challenges such as sudden supply chain disruptions, severe workforce shortages, and fluctuating customer demand due to health restrictions. Though larger restaurant chains could adapt by pivoting quickly to delivery models or securing bulk supplies, small-scale businesses often lacked the capital to invest in these rapid adaptations [34].

To gain an in-depth understanding of the unique challenges small-scale restaurants face during disruptions such as COVID-19 or other unexpected events, we directly engaged with local restaurant owners and managers. Our research began with a series of interviews with nine owners from both sit-down service and quick-service, counter-oriented establishments. These interviews provided critical insights into the operational and financial strains that small-scale restaurants endure, especially during high-impact disruptive events. Key challenges emerged around labor shortages, supply chain disruptions, and restrictive policies, all of which hindered daily operations. For instance, many owners reported difficulties maintaining staff levels, as the labor market was severely impacted, and others struggled to source consistent supplies of essential ingredients and materials during disruptions like COVID-19. While existing literature extensively documents the impacts of specific disruptive events on the restaurant sector, including earthquakes, hurricanes [141, 142], economic crises [143, 144], and pandemics [145, 146], there is limited research addressing a generalized framework for disruption scenarios. From these conversations with restaurant owners, we identified five key dimensions of disruptions that these small-scale restaurants experienced:

- Employee Shock: This dimension captures the scarcity of available workers due to factors like health risks, labor market fluctuations, or higher competition for employees. This shortage forced small restaurants to operate understaffed, which directly impacts service quality and customer satisfaction.

- Supply Shock: Many owners reported disruptions in obtaining critical supplies, such as fresh produce, meats, and other raw materials, often due to supply chain disruptions. This inconsistency in supplies created unpredictable costs and forced menu modifications, affecting both business stability and customer loyalty.

- Production Shock: Production capacity dropped significantly for several restaurants, as labor shortages and equipment constraints made it difficult to meet pre-disruption output levels. In some cases, this meant slower service that affects revenue and the ability to attract customers.

- Capacity Shock: Capacity limitations, such as restricted seating or early closures, can arise from various disruptions, like health regulations, natural disasters, or infrastructure issues, which restrict the number of customers a restaurant can serve. For small-scale restaurants that rely on in-person dining, these constraints can severely limit revenue potential.

- Demand Shock: Customer demand declined sharply as people avoided dining out due to health concerns, particularly during the peak of the COVID-19 pandemic. This shock was compounded by changing consumer preferences, such as a shift to home dining, which made it difficult for small restaurants to forecast and sustain their usual demand levels.

Given the critical role small-scale restaurants play in sustaining local economies, understanding how these businesses can adapt to and recover from various disruption types is essential. To explore effective strategies that help small restaurants survive during disruptions, we designed and distributed a comprehensive survey to around 200 local restaurants. The survey aimed to collect detailed information on each of the five disruption dimensions we identified. Respondents were asked to describe the specific tactics they employed to sustain operations and enhance resilience under these disruption scenarios. Based on the survey responses, we identified three primary resilience strategies frequently adopted by these restaurants: (1) boosting efficiency through streamlined processes, (2) adjusting quality, such as simplifying menus to reduce costs or adapting offerings to meet fluctuating demand, and (3) adding capacity, including strategies like outdoor seating or partnering with delivery services to offset indoor dining restrictions. These insights provide a foundation for developing adaptive strategies tailored to small-scale restaurant needs.

While existing literature provides valuable insights into the impacts of specific disruptions and identifies some resilience tactics to maintain operations, there is a noticeable gap in research that systematically integrates these resilience strategies into quantitative optimization models. Such models could provide a framework to guide restaurant owners in selecting the best resilience tactics based on their particular needs and constraints. Most current studies focus on qualitative assessments or isolated case studies [147, 148, 149, 150], which, while informative, limit our understanding of how resilience strategies can be systematically applied across the the small restaurant industry.

To address this need, our study develops a mixed integer nonlinear programming (MINLP) model specifically tailored to optimize small restaurant operations under disruption, with the integration of the resilience tactics identified through direct engagement with restaurant managers. Traditional optimization methods in the restaurant and hospitality sector have predominantly focused on stable conditions, addressing aspects like revenue management, employee scheduling, and inventory control through linear and mixed-integer programming [151, 152]. While effective under normal conditions, these models do not account for the volatility of disruptions. MINLP allows for a more complex, realistic representation of the operational challenges faced during disruptions. This modeling approach captures the nonlinearities inherent in restaurant operations during disruption events—such as the relationship between labor and productivity level. The flexibility of an MINLP model is essential for accommodating the range of disruption scenarios and variable conditions typical in small-scale restaurants, enabling the model to optimize decisions for cost reduction and resilience in a way that linear models cannot.

This research seeks to answer the following critical questions: (1) What are the optimal resilience tactics small-scale restaurants can deploy to maintain stability under different types of disruptions? (2) What measurable improvements in performance can these tactics provide? and (3) Under what conditions should restaurants rely on external resources to sustain operations? Through simulation analysis, the model evaluates multiple disruption scenarios — each representing a specific or combined disruption dimension — and assesses the impact of resilience tactics on production, profitability, and operational stability. This approach provides insights into how strategies such as efficiency boosts, service adjustments, and capacity expansion affect a restaurant's overall performance, from profit-making to break-even or crisis modes. By bridging theory and practice, this study offers a nuanced and actionable framework for managing disruptions, equipping small-scale restaurant owners with data-driven strategies to navigate complex and evolving challenges effectively.

5.2 Disruption and Resilience in Small Restaurant Sector

The small-scale restaurant sector is particularly vulnerable to a wide array of disruptions originating from both external and internal factors. External disruptions include natural disasters, economic crises, and public health emergencies like the COVID-19 pandemic, while internal disruptions may stem from management challenges, such as limited inventory control or reliance on a smaller labor force that may experience shortages during crises [153]. These disruptions create significant operational challenges for small-scale restaurants, which often lack the financial buffer and resources of larger chains to recover swiftly from such events, thereby increasing the risk of business closure or prolonged instability.

5.2.1 Understanding Disruptions in Small-Scale Restaurants

Disruptions in small-scale restaurants can manifest in numerous ways, including supply chain interruptions, labor shortages, and capacity restrictions due to health and safety regulations. For instance, natural disasters such as earthquakes and hurricanes may directly impact the physical infrastructure of small restaurants, resulting in immediate and often prolonged interruption in operation due to limited resources for repairs and recovery [141, 142, 154]. Similarly, public health emergencies like the COVID-19 pandemic revealed the heightened vulnerability of small-scale establishments, where government-imposed restrictions on indoor dining led to sharp declines in customer demand. These restaurants, without established delivery or takeout systems, were often forced to rapidly reconfigure their business models or risk closure [34, 146, 155].

Although research has extensively documented the impacts of disruptions to the restaurant sector in general, small-scale restaurants experience these effects more acutely because they have limited financial resources and operational flexibility compared to larger establishments. Moreover, studies show that full-service small-scale restaurants, which rely heavily on in-person dining, are significantly more vulnerable to disruptions than larger quick-service establishments that typically have established takeout and delivery services [156]. Additionally, disruptions in supply chains can severely affect these smaller businesses by limiting access to essential ingredients, which constrains their ability to offer a complete menu, often resulting in customer dissatisfaction and loss of revenue [35, 157].

5.2.2 The Role of Resilience in the Restaurant Industry

Resilience in the small-scale restaurant sector refers to the ability of businesses to withstand, adapt to, and recover from disruptions. The concept of resilience has gained significant attention in recent literature, with researchers focusing on various strategies that businesses can employ to mitigate the impact of disruptions. Resilience is often categorized into three primary areas: employee resilience, resilience in business models and processes, and proactive efforts to anticipate and respond to disruptions [158, 159, 160, 161, 162].

Employee resilience is crucial, as the workforce is often the most directly impacted by disruptions. For example, during the COVID-19 pandemic, many restaurants faced severe labor shortages due to health concerns and government restrictions. Cultivating employee resilience through training and support systems can enhance a restaurant's ability to adapt to changing circumstances [163]. For instance, Britt et al[164] and Lengnick-hall et al [165] proposed that cultivating employee resilience can be achieved through various approaches, including web-based training and developing key capabilities like cognitive, behavioral, emotional regulatory, and social networking skills, which are essential for adapting to disruptions.

Furthermore, resilience in business models plays a crucial role for small restaurants. Those with adaptable operations, such as flexible menus or diversified revenue sources, are better positioned to handle disruptions. For example, small restaurants that quickly implemented online ordering and partnered with delivery services during the pandemic were more resilient, as they could continue serving customers despite restrictions on in-person dining [155, 166].

Numerous resilience tactics have been identified to help small-scale restaurants proactively anticipate and respond to disruptions, such as strengthening supplier relationships and implementing flexible labor management practices. Strengthening relationships with multiple suppliers or local sources enables small-scale restaurants to maintain consistent stock levels and reduce dependency on single suppliers, which is especially useful during supply chain disruptions [157]. Flexible labor management, such as cross-training employees and using contingent labor pools, can also enhance resilience by allowing small restaurants to adjust quickly to workforce shortages [167, 168].

In this paper, we mainly consider three tactics that identified from the survey process. These include boosting efficiency, adjusting quality, and adding capacity. Boosting efficiency often involves leveraging technology to streamline operations, such as implementing advanced inventory management systems or automating customer service processes [169].

Adjusting the quality of service might involve simplifying the menu or using alternative ingredients when supplies are limited, thus allowing restaurants to maintain service levels even when their traditional supply chains are disrupted [135, 170]. Adding capacity, particularly in response to physical or regulatory constraints, is another critical tactic. During the COVID-19 pandemic, many restaurants added outdoor seating or converted indoor spaces to accommodate social distancing requirements. Such adaptations not only allowed businesses to continue operating but also provided new opportunities for growth [171].

5.3 Model Formulation

5.3.1 Preliminaries

This study proposes a mixed integer nonlinear programming approach to optimize the restaurants' day-to-day decisions under disruptions. There are 6 key decisions, including (1) which service modes, such as dine-in, takeout, or delivery, to offer each day, (2) the necessary amount of labor to meet daily production demands, (3) the quantity of inventory to purchase, (4) number of customers served for each service mode, (5) decides the production scaling, i.e., adjusting the level of production efficiency, and (6) service quality in terms of cost to purchase unit supply. These decisions are made based on anticipated profitability and resource limitations.

We consider the following five dimensions that are identified via interview, which can be challenged during disruptions: (1) employee shock; (2) supply shock; (3) production shock; (4) capacity shock; and (5) demand shock. When disruptions occur, businesses can implement strategies to help them recover and restore their performances [172, 173]. Key performance metrics include profit, revenue, and the number of customers served. In this study, a primary performance metric, profit, and a secondary performance metric,the number of customer served, are chosen as to evaluate restaurant performance. The model will maximize the primary metric, and the effectiveness of a restaurant's adaptation is measured by how well the restaurant can maximize its profit after applying resilience tactics. Analyzing the number of customers served will corroborate the effectiveness of these resilience tactics by demonstrating the restaurant's capacity to maintain or increase customer volume under disruptions.

Table 5.3.1: List of Notations for Optimization Model

Symbol	Description
Decision Variables	
x_i	Binary variable indicating if the restaurant opens operation mode i
v_i	Number of customers served in operation mode i
e	Total employee work-hours assigned
s	Amount of supplies to purchase
a	Total factor productivity
c	Adjusted cost of supplies when enabling tactic adjusting quality
Parameters	
P_i	Price per customer served in operation mode i
F_i	Fixed cost of operating mode i
W	Hourly wage for employees
Y	Default unit cost of supplies
D_i	Customer demand for mode i
U_i	Room capacity (as number of customers) for operation mode i
L	Maximum employee work-hours
C	Maximum storage capacity for supplies
α	Output elasticity of labor
A	Default total factor productivity
Δ_i	Ability of restaurant to operate in mode i
E	Quality-adjusted price elasticity of demand
B	Cost of each unit increase in productivity factor a

The objective is to maximize the total profit, which is calculated as the total revenue minus the operational, labor, and supply costs. We consider two operational modes for restaurant operations: on-premise (customers dine in-house and under the roof) and off-premise (including takeout, delivery, or any other service where customers consume food outside the restaurant's physical location). The restaurant can open some or all of the operations, and one customer is assumed to be served in one mode only. The list of notations used in the paper is summarized in Table 5.3.1.

5.3.2 Model setup

Mathematically, the model maximizes the profit earned in equation (5.1) under a series of constraints defined by equations (5.2), (5.3), (5.4), (5.5), (5.6), (5.7), (5.8), and (5.9). Specifically, the model is expressed as follows:

$$\max \quad f(x_i, v_i, e, s, c, a) = \sum_{i=1}^{N} P_i v_i - F_i x_i - We - cs - B(a - A), \tag{5.1}$$

$$s.t. \quad v_i \leq D_i(1 + E * \frac{c - Y}{Y}), \tag{5.2}$$

$$v_i \leq U_i x_i, \forall i = 1, \ldots, N, \tag{5.3}$$

$$\sum_{i=1}^{N} v_i \leq f(a, e, s), \forall i = 1, \ldots, N, \tag{5.4}$$

$$f(a, e, s) = a e^{\alpha} s^{1-\alpha}, \tag{5.5}$$

$$e \leq L \sum_{i=1}^{N} x_i, \quad e \leq L, \tag{5.6}$$

$$s \leq C \sum_{i=1}^{N} x_i, \quad s \leq C, \tag{5.7}$$

$$x_i \leq \Delta_i, \forall i = 1, \ldots, N. \tag{5.8}$$

$$v_i \geq 0, x_i \geq 0, e \geq 0, s \geq 0, a \geq 0, \forall i = 1, \ldots, N. \tag{5.9}$$

The objective function (5.1) calculates daily profit by first calculating the revenue earned as $\sum P_i v_i$ and then subtracting (1) fixed costs as $\sum F_i x_i$ for each operational mode, (2) labor costs as We, (3) supply costs cs, and (4) additional costs $B(a - A)$ incurred if production is boosted beyond its default level A incurred in the day. The fixed cost for a particular mode is positive and present in the objective function as F_i only if the model decides to open that specific mode. The labor cost is calculated by multiplying the number of employee work hours scheduled, e, to the hour wage parameter W. The supply cost is calculated by multiplying the units of supply purchased, s, to the cost per unit supply c. The additional cost due to increased production is calculated by first calculating the extend of increased productivity level, $(a - A)$, and multiplying the difference to the cost per unit increase parameter B. The variables and parameters in this model are constrained to non-negative values. Detailed bounds for variables and values for parameters will be discussed in the following section 5.4.1.

The model incorporates multiple constraints grouped into three main categories:

(1) *Customer Service Constraints*:

- *Demand Constraint* (5.2): Limits the number of customers served v_i to not exceed adjusted customer demand D_i, accounting for price elasticity: $v_i \leq D_i\left(1 + \mathrm{E} \times \frac{c-Y}{Y}\right)$.
- *Seating Capacity Constraint* (5.3): Ensures that v_i does not exceed the restaurant's seating capacity U_i when the operational mode is active ($x_i = 1$): $v_i \leq U_i x_i$.
- *Production Capacity Constraint* (5.4): Ensures the total number of customers served does not surpass the service capacity determined by the production function $f(a, e, s)$: $\sum_{i=1}^{N} v_i \leq f(a, e, s)$.
- *Production Function* (5.5): Defines the service capacity as a Cobb-Douglas function of labor e and supply s: $f(a, e, s) = ae^{\alpha}s^{1-\alpha}$, where α is the output elasticity of labor, indicating the percentage change in production in response to a change in labor input.

(2) *Resource Constraints*:

- *Labor Constraints* (5.6): Restricts labor e to zero when the restaurant is not operating and ensures it does not exceed the available labor L: $e \leq L \sum_{i=1}^{N} x_i$, and $e \leq L$.
- *Supply Constraints* (5.7): Restricts supply s to zero when not operating and ensures it does not exceed the maximum storage capacity C: $s \leq C \sum_{i=1}^{N} x_i$, and $s \leq C$.

(3) *Operational Feasibility Constraint*:

- *Operational Mode Constraint* (5.8): Allows the restaurant to operate in mode i only if it has the necessary resources and infrastructure ($\Delta_i = 1$): $x_i \leq \Delta_i$.

These constraints ensure that customer demand is met without exceeding capacity, resources are used efficiently to prevent over-hiring and overstocking, and operations are feasible given the available infrastructure and resources.

5.3.3 Modeling resilience tactics

This research defines three specific resilience tactics: boosting efficiency, adjusting quality, and adding capacity. Boosting efficiency is achieved by increasing the total factor productivity variable such that it exceed its normal value, A. Higher productivity means the restaurant can produce more output and serve more customers with the same number of employee hour assigned and number of supplies purchased. This model set the upper bound of a as 1.2 times A, meaning that the productivity can be at most increased by 20%. This number is derived from Gupta et al. [174] who found that the global gross domestic product growth has decreased from 2.9% to 2.4% (approximately an 20% decrease) during COVID-19. Thus, boosting efficiency by 20% can recover the restaurant's production level to its pre-disruption state. Nevertheless, increasing productivity incurs costs, such as employee training, upgrading online ordering systems, and upgrading cooking equipment, and this additional cost is subtracted from the objective function.

The tactic adjusting quality is integrated through the decision variable c. This variable enables equation (5.2) to capture the change in demand induced by changes in the quality and price of food. Adjusting quality can let the restaurant operate without a critical supply during supply shortage, at the risk of decreased customer demand. For instance, restaurants may buy cheaper materials used or use less material when preparing a dish, resulting in an adjusted product that may be disliked by customers. The relationship between reduced demand, price, and quality is established by the concept of quality-adjusted price elasticity, which was developed by Silver et al. [175] and Chung [176]. Specifically, Chung derived the adjusted price elasticity for various food categories, such as meat, grain, and vegetables, which correlates well with the model calculation of the number of material units used in a single dish. Thus, the revenue and supply cost in the objective function could be affected.

The tactic adding capacity is governed by the parameter Δ_i, which determines whether the restaurant can offer outdoor dining. If the restaurant lacks access to public space, the parameter Δ_i for outdoor dine-in is set to zero to disable this option. Otherwise, Δ_i is set to 1, enabling the restaurant to offer outdoor seating. During the COVID-19 pandemic, many government agencies expedited outdoor dining permits and waived fees, which reduce the application process to just 24 hours [171]. With Δ_i set to 1, the restaurant then has the flexibility to choose whether to implement this tactic by adjusting the corresponding x_i value.

5.4 Scenario Design and Model Calibration

The scenario design and model calibration in this study are grounded in practical insights obtained through extensive communication with restaurant owners, ensuring that the scenarios accurately reflect the real-world complexities and operational challenges faced by small-scale restaurants. The data collection followed a structured, multi-step process: (1) an initial review of literature and government reports to gather baseline statistics on the restaurant industry, (2) a first round of interviews with nine local restaurant owners to identify disruption scenarios relevant to small restaurant operations, (3) the design and distribution of survey instruments to collect detailed data on restaurant operations and resilience tactics to calibrate variables and parameters, and (4) a second round of interviews to present preliminary model results, conduct a "sanity check," and identify areas for model refinement. Collecting store-specific data through interviews and surveys is a standard practice in business management research, as evidenced by previous studies such as those by [177, 178, 179, 180]. The interviewees included owners or current operators of both full-service restaurants with sit-down services and quick-service restaurants that offer counter service. The second round of interviews was crucial in refining the model, and the changes will be elaborated upon in the results section.

5.4.1 Calibration in a disruption-free scenario

During our initial review of literature and first round of interviews, business operators usually compared business performance with respect to an anchor point, usually a disruption-free environment. For example, most interviewees refer to pre-COVID-19 as disruption-free, and stated what percent of profit or customer was lost compared to pre-COVID-19 level. In a disruption-free environment, the restaurant operates under normal, stable conditions without the need for extra adjustments in pricing, wages, or capacity. The calibration of the optimization model begins by setting up this baseline scenario, ensuring that all parameters are aligned with the standard operational metrics reported by restaurant operators during interviews and surveys. Four aspects of parameters are calibrated in this process: employee, customer demand and service capacity, supply, and operation. A summary of the calibrated values can be found in Table 5.4.1.

Employee

Our focus is on small-scale restaurants with fewer than 50 employees. This aligns with findings from our interviews and surveys, which revealed that full-service restaurants typically employ between 6 and 35 staff members, while quick-service restaurants have between 1 and 12 employees. The survey conducted in the previous section indicates that all employees work full-time; therefore, the model sets the decision variable for employee work hours, e, with a minimum of 8 hours per day (representing at least one full-time employee working 8 hours daily) and a maximum of 480 hours per day (assuming up to 60 employees each working 8 hours).

The interviewee and survey respondents commented that their employees typically get paid at or slightly above minimum wage, ranging from \$16 to \$25 per hour. And in the year of 2022, Seattle's minimum wage is \$17.27 if the employer does not pay towards the individual or the employee does not earn tips [181]. Thus, the hourly wage parameter W is calibrated at \$18.

Customer demand and room capacity

Customer demand, D_i, is calibrated using data collected through interviews and surveys, where restaurant operators provided weekly customer counts for indoor dine-in, outdoor dine-in, takeout, and third-party delivery services on a normal week. These data points are used to set the demand parameters for both on-premise (indoor) and off-premise (outdoor, takeout, and delivery) services. Survey results suggest the parameters for full-service restaurants and quick-service restaurants should also be estimated separately because they display different trends. For full service restaurants, they, on average, serve 171 customers through on-premise services and 65 customers off premise. For quick service restaurants, 571 customers order on-premise and 147 customers order off-premise. Since these numbers are provided when the respondents recollect on an normal week, these values are also treated as the room capacity, U_i, i.e., the number of customers allowed to serve.

It is important to consider potential limitations in the reliability of the quick-service restaurant figures. Field observations suggest that quick-service restaurants in the University District see high demand for off-premise options. This demand is likely driven by a largely mobile customer base, mainly students and faculty who frequently move between classes. Additionally, limited seating within many quick-service restaurants may further drive the preference for takeout and delivery options. This context suggests that the reported numbers for quick-service restaurants should be interpreted with caution, as off-premise data may be underrepresented, while on-premise data could be overrepresented. This discrepancy might stem from survey respondents potentially mixing up off-premise and on-premise services. Therefore, full-service restaurants will be the primary focus for modeling, but quick-service restaurants' parameters will also be discussed in this section.

On average, each customer spends about \$10 - \$40 per visit, with takeout and third-party delivery costs higher, ranging from \$20 to \$40, and dine-in costs being below \$20. Quick-service restaurants typically reported lower spending since they sell fast-food, sweets, and boba milk tea that are not in standard portion. Based on these observations, this study focused on data reported by full-service restaurants and decided that the average dollar spent per customer, p_i, is \$20 for on-premise and \$35 for off-premise.

Supply and supply cost

The default supply cost per customer, Y for full-service and quick-service restaurants are estimated separately because survey responses from the two types of restaurants exhibit different characteristics. First, full-service restaurants typically serve between 560 and 700 customers per week. And they reported spending between \$2,501 and \$4,000 on supplies. Then, the supply cost per customer is calculated by dividing the lower bound of the weekly supply cost (\$2,501) by the upper bound of customers served (700), which is approximately \$3.57 per customer. Similarly, quick service restaurants reported serving up to 3,150 customers weekly and spending between \$1,001 and \$1,500 on supplies. And the corresponding supply cost is computed at around \$0.32 per customer. This approach provides a conservative estimate of the supply cost per customer, reflecting the economies of scale achieved by quick-service restaurants through bulk purchasing and discounts on simple or preprocessed supplies.

These supply costs were cross-referenced with USDA's MyPlate dietary guidelines, which recommend daily intakes of fruit, protein, vegetables, dairy, and grains [182]. MyPlate recommends 2 cups of fruit, 5.5 ounces of protein, 2.5 cups of vegetables, 3 cups of dairy, and 6 ounces of grains (total 8.93 cups of food). Following the work from [182], the price for fruit, protein, vegetables, dairy, and grains are \$0.82/cup, \$0.21/cup, \$0.88/cup, \$0.27/cup, and \$0.21/ounce, respectively. And the estimated cost for raw material amounts to \$6.05 in 2015 dollors. Assuming each individual consumes one-third of these daily portions per meal (as people typically eat three meals a day) and that 40% of food is wasted [183], the average material cost for a single meal is estimated as $\$6.05/3 * 1.4 = \$2.82$. Adjusted for inflation between 2015 and 2022, the cost to prepare one customer's order is recalculated to \$3.48. The survey findings yielded an estimated cost of \$3.57 per customer, slightly higher than the estimated value of \$3.48 using MyPlate. This variation can be attributed to the inclusion of additional ingredients beyond the five categories defined by MyPlate. The comparison between these two values demonstrates the validity of the survey as a reliable data source for calibrating supply quantities and associated costs.

Supply capacity C is calculated by multiplying the cups per customer by weekly demand. For full-service restaurants, this equates to $8.93/3 * 1.4 * (171 + 65) = 983$. Quick-service restaurants, we assume that they use half of the quantities to prepare an order, which is 2.08 cups, and the supply capacity is estimated as 1496. The minimum value of C is the binding factor in the supply constraints because it sets the upper limit on supply s that the restaurant can use when operating. Increasing C beyond this minimum does not affect the optimal solution.

Operation

Three parameters, F_i, $alpha$, and A are estimated in this section. There are two assumptions before calibrating the value of F_i. First, each restaurant operation incurs a one-time payment when it switches from closed to open status, which covers the purchase of necessary permits, tables, chairs, cooking equipment, etc. And, second, this study assumes that the restaurant has the on-premise operation set as open but the off-premise operation set as closed. Thus, there should be fixed cost associated with switching on off-premise operation. The cost of off-premise operation is approximated by the cost of using outdoor space as seating area. Our survey indicates that restaurants pay $1,850 every quarter to agencies to use the outdoor space, therefore F_i equals $\$1850/3 = \$616.67$ for off-premise operation.

The Bureau of Labor Statistics recommends the elasticity of substitution α in equation (5.5) to be 0.7 [184]. Then we temporarily replace the decision variable a in the production function with the default total factor productivity A for this estimation. At this point, production function equation becomes $f(e, s) = Ae^{0.7}s^{0.3}$ Then A is calibrated by first setting a reasonable number on the left hand side of the production function equation, $f(e, s)$, then determining what units and values e and s should take, and lastly solving for A.

The survey asks whether the restaurants can accommodate more customers compared to their existing customer demand without additional investments in supplies or labor. The result suggests owners can serve an extra 15% to 75% percent of their existing customer demand. Quick-service restaurants tend to fall towards the lower end of this range, while full-service restaurants exhibit a higher capacity to the upper bound of this range. We interpret that extra percentage as the additional percentage of existing customer demand D_i that the business can serve given their current work hours and supply. From the modeling perspective, the left hand side of the production function (5.5) is assumed to be 130% and 150% of the customer demand for quick service and full service restaurants, respectively. For full-service restaurants, $f(e, s) = 354$.

This study assumed the maximum production level is achieved by setting the decision variables e and s at the calibrated values, 480 and 983, respectively. Since 480 is the upper bound for work hour and 983 is the minimum value, we aim to balance between overestimating and underestimating the default total factor productivity A. Dubina [184] confirmed that hours worked is an appropriate unit for e, but estimating the unit for s proved challenging. Therefore, we assume the unit of kilograms for s because α is reported at an aggregate industry level, and using a smaller unit like cups is not practical.

Consequently, the value of A is estimated as 1.64 for full-service restaurants. However, we acknowledge that this estimation has limitations due to potential discrepancies in units and scaling factors. The exact value of A may vary based on factors not captured in our calibration, such as variations in technology, efficiency, or measurement errors in input quantities. To address these uncertainties, our model emphasizes the percentage differences from the estimated value of A rather than its absolute value. By focusing on relative changes, we can more effectively analyze how variations in total factor productivity impact the restaurant's operations.

In addition to one-time fixed costs, the restaurant incurs monthly expenses for utilities and rent, which, according to the survey, range from \$2,500 to \$100,000. However, these costs are fixed and do not depend on any of the decision variables in our model. Since our optimization focuses on variables that influence operational decisions and vary with those decisions, including fixed costs like rent and utilities—which remain constant regardless of the choices made—will not affect the outcome of the optimization. Therefore, we have decided to exclude rent and utility costs from the model.

Table 5.4.1: Parameter definition and the calibrated value for full-service restaurants.

Symbol	**Description**	**Definition and Calibration**
P_i	Price per customer served in operation mode i	On-premise mode: \$20, Off-premise mode: \$35
F_i	Fixed cost of operating mode i	Off-premise mode: \$616.67
W	Hourly wage for employees	\$18
Y	Unit cost of supplies	\$3.57
D_i	Customer demand for mode i	On-premise: 171; Off-premise: 65
U_i	Room capacity for mode i	On-premise: 171; Off-premise: 65
L	Maximum employee work-hours	480
C	Storage capacity for supplies	983 cups
α	Output elasticity of labor	0.7
A	Total factor productivity upper bound	1.64
Δ_i	Ability of restaurant to operate in mode i	1 if mode i is feasible, otherwise 0
E	Quality-adjusted price elasticity of demand	0.41

5.4.2 The five dimensions of disruption

During the interview process, the interviewees prefer breaking down disruptions like COVID-19 into different components such as employee shortage, customer demand, supply chain, and operation. This study adopts the similar approach such that the model will be generic and applicable to disruptions other than COVID-19. The following five dimensions are considered in the scenario analysis: employee shock, supply shock, production shock, capacity shock, and demand shock. Each dimension changes the parameters' value, the bounds for decision variables, and/or constraint and will be discussed individually in the following sections. As disruption becomes more severe, the restaurant loses access to resources at a greater extend. For example, when social distancing rules dictate the indoor capacity to be 75% of its seating capacity, the restaurant loses 25% of room capacity resource. And the capacity shock is most severe when the social distancing prohibits any indoor dine-in operation, and the restaurant loses 100% of its indoor capacity. Additionally, each scenario will simulate the described disruption as outlined in the subsequent section. The simulation will be repeated 100 times, gradually increasing the severity of the disruption from 0% to 100% in increments of 1%.

This study proposes the following three bottlenecks: profit bottleneck, environment bottleneck, and operation bottleneck. Each bottleneck is the disruption severity that a specific status is first reached. Profit bottleneck is the disruption severity that first causes the profit to be negative, and environment bottleneck refers to the disruption severity that, in the past, caused most restaurants to shut down. The operation bottleneck is the disruption severity that the optimization model becomes infeasible and the restaurant cannot operate anymore. The order and the difference in which the three bottlenecks occur in the simulation shows how successful the tactics are helping the restaurant to adapt. When the presence of resilience tactics results in profit bottleneck greater than the other two bottlenecks, the restaurant is adapting and making money even during a period when the industry as a whole is facing challenges. Moreover, the longer the time gap between the profit bottleneck and the environmental bottleneck becomes apparent, the more successful the resilience tactic is deemed to be. The order and disparity among the bottlenecks may vary across different simulations of the five disruptive events, indicating that restaurants have different levels of resilience to different types of disruption.

Employee shock

During the employee shock period, the hiring capacity, L, will drop to reflect the limited number of workers available in the job market. Furthermore, government regulations such as the social distancing policy could result in less employees present at workplace. In March 2020, Washington's leisure and hospitality business employment lost 59.3% of its worker compared to January 2020, before the onset of COVID-19 [185]. The environment bottleneck is, therefore, set at 60% to reflect the restaurant industry's hardest time to survive in disruption. As restaurants experiencing employee shortage, restaurants raise wages and create more benefits to attract workers. This increase in wage was documented at 5.5%, suggested by Ansell et al [186], and the model parameter W will increase by 5.5% as severity increases from 0 to 100%.

Supply shock

When supply shock occurs, the supply capacity C decreases due to less available supplies in the market. It is reported that retailers prior to the pandemic had inventory that can support the business for 43 days, but during supply shortages, the inventory was dropped to 33 days as of November 2021 [187]. Thus, the environment bottleneck of supply shock was calibrated as (43-33)/43*100% = 23%. During supply shock, the restaurant is assumed to be a price-taker and has no power to negotiate the price with its supplier. According to USDA, food prices were 8.8% higher than in March 2021 [188]. Therefore, parameter Y will increase by 8.8% as severity increases from 0 to 100%.

Production shock

This study simulates production shock by decreasing the value of A, the upper bound of total factor productivity, in the production function, while keeping e and s the same. The pandemic hit the restaurant industry hard, and the Bureau of Labor Statistics reported the industry has lost 25.9% of the total factor productivity in 2020 [140]. The environment bottleneck of production shock is thus calibrated as 26%.

Capacity shock

Throughout the pandemic, indoor dining capacities were limited to 25% to 50% of their original capacity, with the strictest policies completely prohibiting on-premise dining when capacity was set to 0% [189]. As a result, the environmental bottleneck is calibrated at 100%, corresponding to a decrease in the utilization parameter U_i to 0 for on-premise operations.

Demand shock

During the pandemic, customer concerns about the risk of infection led to a significant decline in restaurant visits. According to the USDA, food away from home, which includes purchases made at restaurants, cafes, and other eating-out establishments, experienced a 48% drop from March to April 2020 [190]. Consequently, the environmental bottleneck for the demand shock is calibrated at 48%.

The scenarios can further be divided into two sets, an independent set where the scenarios are isolated from each other, and a combination set where scenarios are linked and changes in one will lead to changes in others. Employee shock, production shock, and capacity shock are considered as independent scenarios; and supply and demand shocks are associated. The combination scenario starts with a supply shock, which has been troubling the industry during COVID-19 pandemic.

When the availability of supplies in the market decreases, their prices naturally rise, leading to an increase in the per-dish cost. To maintain profit margins, restaurants typically increase their menu prices, which in turn makes customers less inclined to dine out. As a result, it is foreseeable that a supply shock could be followed by a demand shock, making the combination scenario both reasonable and realistic. Additionally, because the restaurant faces disruption on multiple fronts, the profit bottleneck is likely to occur earlier in this scenario compared to the independent scenarios.

5.5 Results

The optimization problem is solved using Gurobi, an optimization software designed to solve complex mixed-integer nonlinear programs. Total five disruptive scenarios following the definition in section 5.4.2 are modeled. For each scenario, two cases will be tested: 1) baseline case, where the restaurant does not deploy any strategies towards disruptions; 2) tactics-enabled case, where the restaurant can boost productivity, adjust quality, and add capacity. In each case, the disruption severity will increase from zero to 100% at an increment of 1%. This setup simulates a disruption that lasts 100 days, and situation degrades uniformly. Each time a new disruption severity is introduced, the model returns the maximized profit or a message indicating that no feasible solution exists. Thus, each test produces a profit trajectory, which is a series of profits as the disruption severity increases. The effectiveness of tactics can be observed by the additional increase in profit by comparing the baseline case and the tactic-enabled case. Further, the order and separation of the three bottlenecks are other signs of how effective the tactics are. In addition, the profit bottleneck is 20% in the baseline case. However, the business makes profit through out the simulation when tactics are enabled.

Figure 5.5.1 illustrates the profit trajectory, while Figure 5.5.2 presents the reported values of the decision variables derived from the employee shock simulation. In this simulation, the restaurant did not incorporate off-premise capacity due to associated additional costs and solely focused on on-premise operations. Thus, the restaurant did not increase its capacity and instead relied on the two other tactics. These figures demonstrate that by employing tactics to adjust quality and boost efficiency, the restaurant was able to generate profits even during a challenging period for the industry. This is evident from the profit bottleneck in the tactic-enabled case (77%) appearing after the baseline profit bottleneck (9%) and the environmental bottleneck (60%). Analyzing the upper-left subplot of Figure 5.5.2, we observe that tactics helped the business reduce the required work hours from over 80 hours to less than 10 hours. Then, the work hours remained relatively stable, given the difficulties associated with hiring employees.

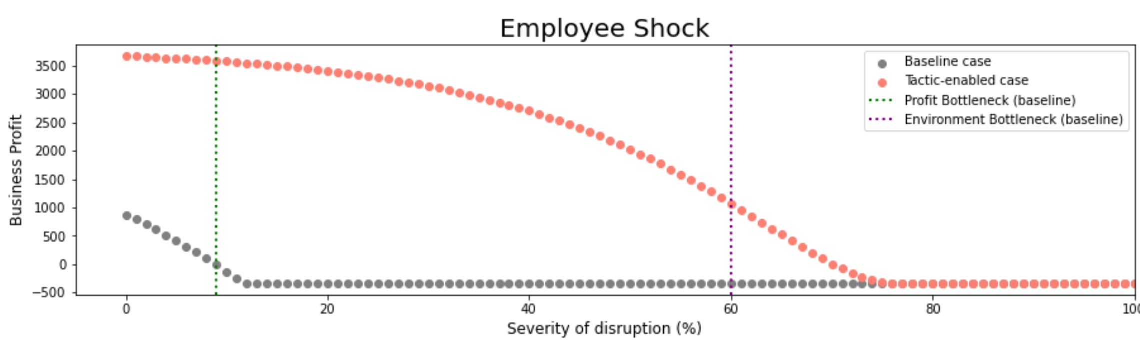


Figure 5.5.1: Profit trajectory during employee shock

During the employee shock, the restaurant opted to prioritize maximum efficiency when

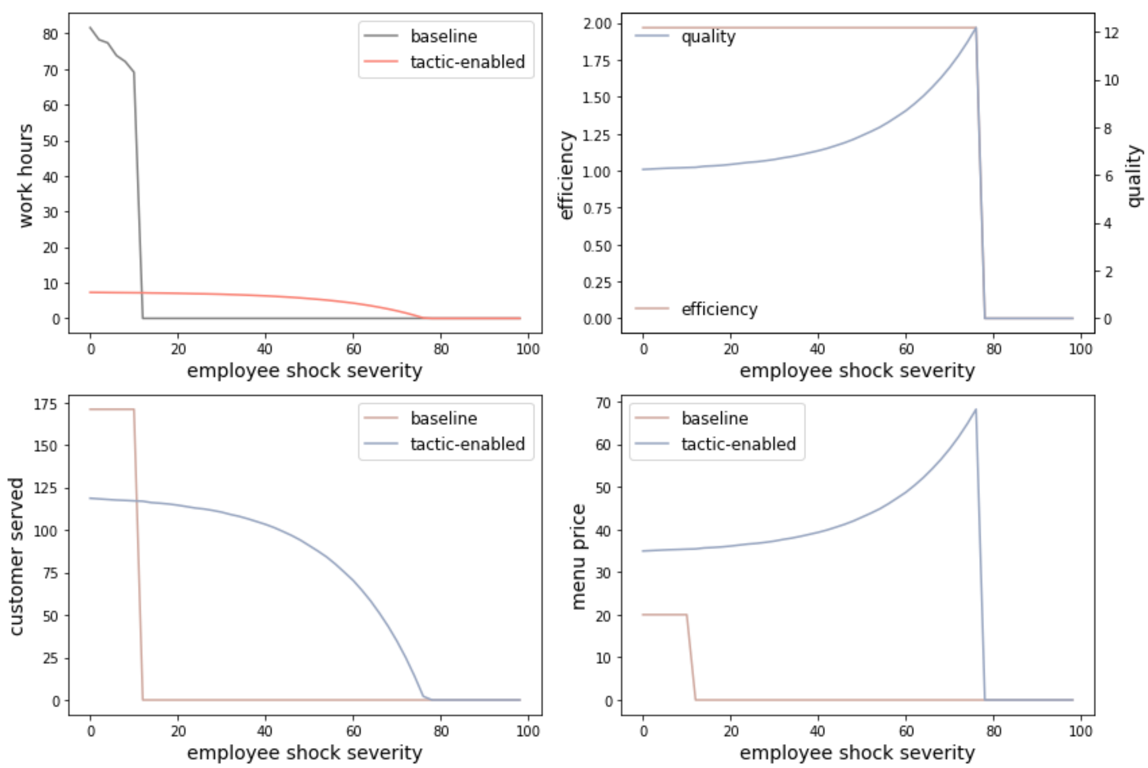


Figure 5.5.2: The value of decision variables and decision dependent parameters during employee shock. Upper left: employee work hours, e in baseline and tactic enabled cases. Upper right: total productivity factor a and quality, represented by the supply cost. Lower left: number of customer served, $v_{on\ premise}$ in baseline and tactic enabled cases. Lower right: menu price, $P_{on\ premise}$

the disruption was mild, gradually adjusting the quality as the severity of the disruption increased. Examining the upper-right subplot of Figure 5.5.2, we observe the behavior of two key variables. The total productivity factor, indicated by the pink line, initially started at its maximum value of 1.96 and maintained this level until 77% of the disruption severity. On the other hand, the quality of the product began at $6.23 per dish, which was lower than its default value of $8.93. As the disruption became more severe, the restaurant first slowly increased the quality back to $8.93 and then rapidly accelerated the rate of quality improvement. This acceleration in the increase of quality is evident from the slope of the blue line in the upper-right subplot.

Tactics play a crucial role in not only ensuring the profitability of a business but also in serving more customers during disruptive periods. Examining the lower left subplot, we observe that without tactics, the restaurant can serve 171 customers each day when the disruption is mild. However, the number of customers served rapidly drops to zero when the disruption reaches a severity of 7%. Although tactics may initially decrease the number of customers served during mild disruptions (as indicated by the blue line starting at 119), they enable the restaurant to continue providing food to residents even until 77% severity. It clearly demonstrates that tactics allow the restaurant to consistently offer food and meet the needs of local residents during challenging times. On the other hand, the restaurant also adjusts its menu prices (as shown in the lower right subplot) at an accelerating rate to compensate for increased quality. However, customers respond to these elevated prices by reducing their patronage of the restaurant.

During the capacity shock (Figure 5.5.3), tactics are less effective in providing assistance, comparing the ones under employee shock scenario, and resulting in the profit bottleneck being only delayed to 25% compared to the baseline case's 16%. Before the simulation, the environmental bottleneck for the capacity shock is set at 100%, indicating a point where it is anticipated that the industry will cease to operate. However, both the profit trajectory and the number of customers served demonstrate that the restaurant closes their business when the severity exceeds 40%, which is earlier compared to the employee shock scenario. The early plateauing of the profit trajectory reflects that capacity restrictions have a more disruptive impact on the business compared to employee shock.

As the disruption severity reaches 40%, the restaurant adopts a strategy to maximize quality. However, the quality remains constant at $6.24 per dish until the severity surpasses 7%. Beyond that point, the restaurant improves the quality at a decelerating rate, as depicted by the decreased slope in the upper right subplot of Figure 5.5.4. When comparing the cumulative number of customers served, it becomes evident that tactics are unable to accommodate more customers. This observation indicates that in the face of capacity reduction, restaurants have limited resources to navigate and provide services.

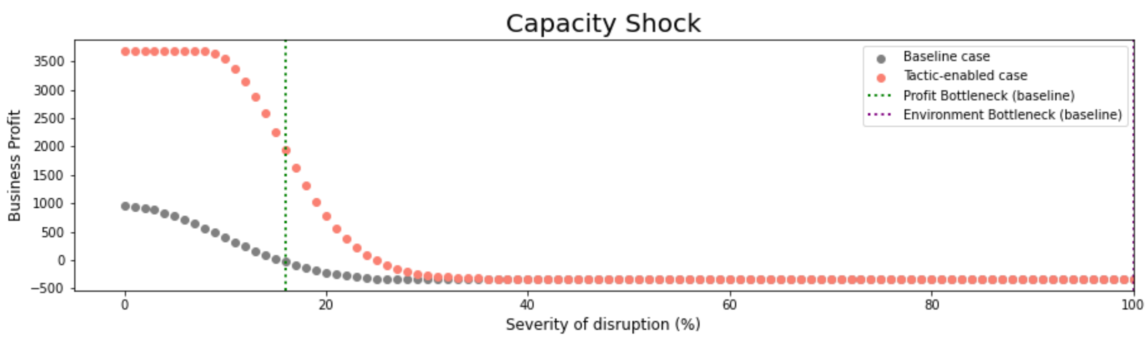


Figure 5.5.3: Profit trajectory during capacity shock

The simulation results for the fourth scenario, production shock, are presented in Figures 5.5.5 and 5.5.6. In this particular case, tactics demonstrate significant potential in assisting the business to avoid deficits until a severity of 97%. Among the five simulations conducted, the production shock scenario derives the greatest benefits from the incorporation of tactics.

As the severity escalates, the upper bound of the total productivity factor is reduced. Restaurants opt to invest in more employee work hours, as evidenced by the upward trend in the upper left subplot of Figure 5.5.6. With the implementation of tactics, the restaurant initially invests 7.3 hours, and this investment increases at an accelerating rate to compensate for the diminishing total productivity factor. Simultaneously, the restaurant strives to maximize productivity by targeting the upper bound value, despite its continuous decline. Additionally, the restaurant enhances quality at an increasing rate, starting at $6.24 and

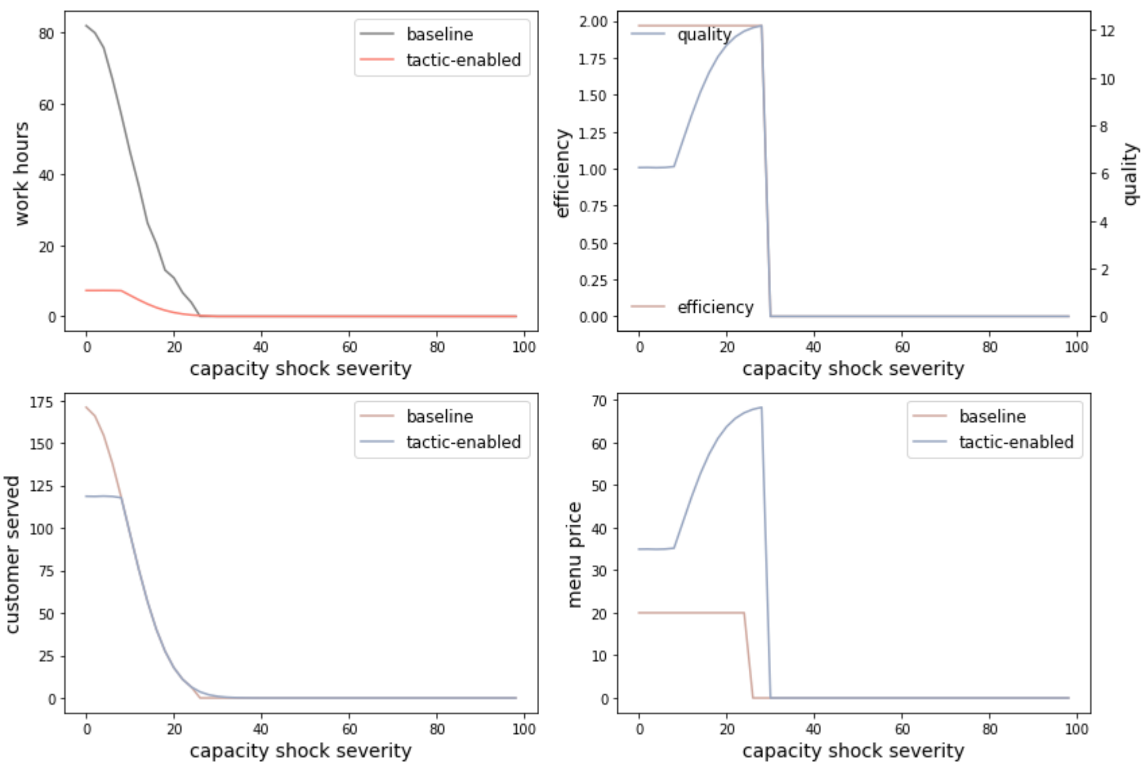


Figure 5.5.4: The value of decision variables and decision dependent parameters during capacity shock. Upper left: employee work hours, e in baseline and tactic enabled cases. Upper right: total productivity factor a and quality, represented by the supply cost. Lower left: number of customer served, $v_{on\ premise}$ in baseline and tactic enabled cases. Lower right: menu price, $P_{on\ premise}$

reaching a peak of \$12.10.

In the case of production shock, tactics continue to assist in serving more customers, as indicated by the greater area under the blue line in the lower left subplot of Figure 5.5.6 compared to the red line. Furthermore, the menu price does not experience a significant increase until the severity exceeds 80%. Consequently, more customers are willing to purchase food and continue their patronage.

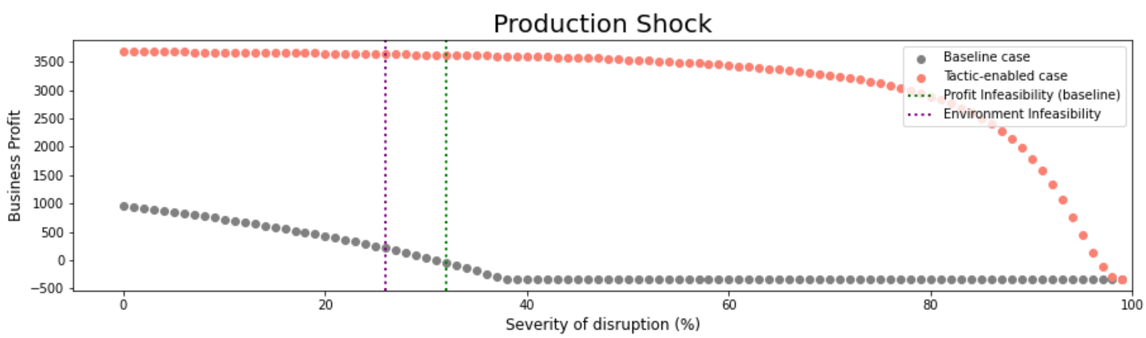


Figure 5.5.5: Profit trajectory during production shock.

5.5.1 Model Validation with a Local Restaurant Owner

To assess the practicality of the recommendations, a local restaurant owner was reach out as the second round of interview and presented with the findings from the optimization model. This restaurant, established in 1988, has served an university's neighborhood with traditional American cuisine, even during COVID-19 lockdown periods. Its longevity and resilience in the face of COVID-related challenges made it an ideal candidate for this interview. The owner is refered to as "Smith" for privacy protection. In summary, Smith affirmed that disruptions affecting capacity and customer demand were the most challenging, while he had effective strategies to address shortages in labor, supply, or production. Two specific tactics—boosting efficiency and adding capacity—proved particularly valuable for Smith's restaurant, whereas increasing quality did not yield the same benefits.

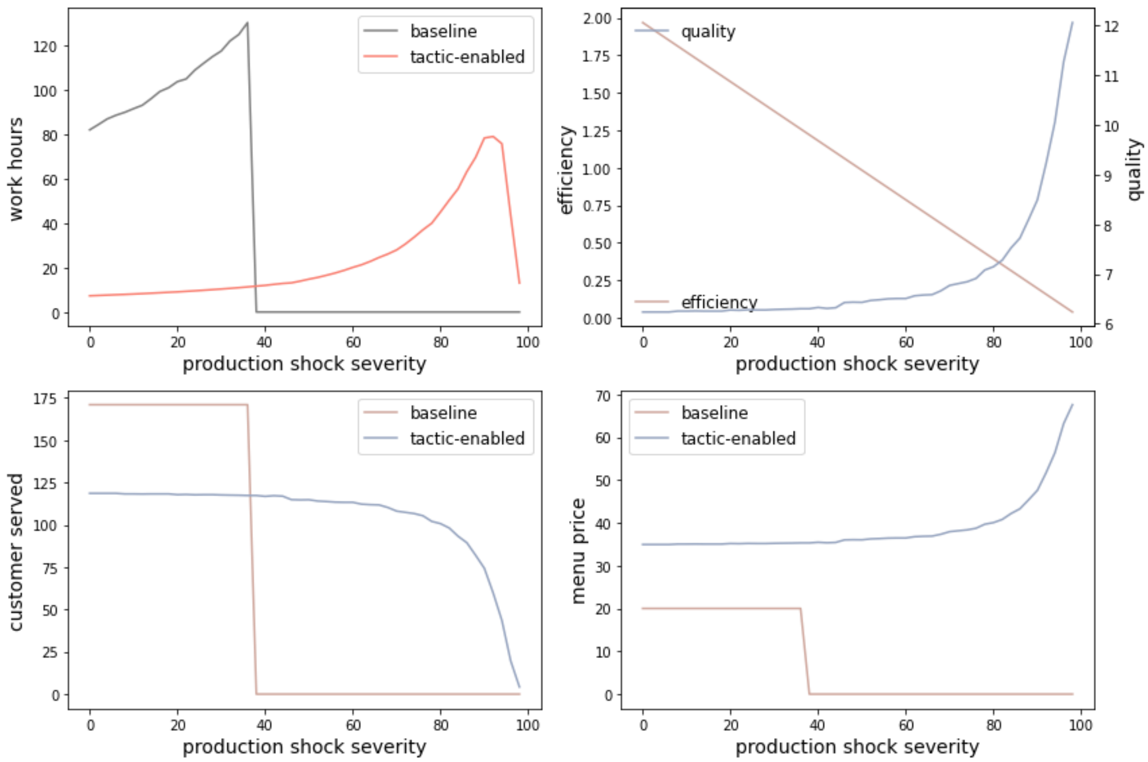


Figure 5.5.6: The value of decision variables and decision dependent parameters during production shock. Upper left: employee work hours, e in baseline and tactic enabled cases. Upper right: total productivity factor a and quality, represented by the supply cost. Lower left: number of customer served, $v_{on\ premise}$ in baseline and tactic enabled cases. Lower right: menu price, $P_{on\ premise}$

Among the five disruption scenario, Smith identified capacity decrease as the most challenging scenario. Smith's inability to find effective strategies to sustain profitability during capacity decreases confirmed the model's prediction that capacity reduction posed a greater challenge compared to supply, employee, and production shortages. Smith expressed frustration with the blanket ban on indoor dining and suggested that restaurants with proper ventilation systems should have the flexibility to maintain some indoor capacity.

There was nothing Smith could utilize to work around and maintain profit during capacity decrease scenario, which confirmed the model's prediction in that capacity decrease was more difficult to dealt with compared to supply, employee, and production decreases. Smith also confirmed the effectiveness of adding additional outdoor capacity. This restaurant built an outdoor seating patio and has been using the patio since then. However, the model did not recommend this tactic because it primarily simulated daily operations, and the one-time cost of adding outdoor seating outweighed the incremental profit it generated in the long run. But Smith emphasized that the patio investment was justified in the long run, as approximately 10% of customers still preferred outdoor seating.

The second most challenging scenario identified by Smith was demand decrease. During our interview, Smith emphasized how customer perceptions had dramatically changed throughout the course of the COVID-19 pandemic. For instance, in March 2020, they experienced a staggering 95% drop in customers as dining out was no longer considered safe. Even now, their revenue remains 30% lower than pre-COVID levels, making the task of regaining these customers more challenging than ever. Smith highlighted the significant loss of large party reservations, as fewer people are celebrating events like birthdays, retirements, and new recruitment. Changes in work schedules and locations due to telecommuting have become the norm, and customers have developed preferences for dining closer to their current residences. While Smith initially believed that nothing would work during the early stages of COVID, he now urges the need to bolster the sense of pride among the college students and the community. Smith's recommendation is to establish partnerships, offer discounts, or provide rewards in collaboration with the university and its associated organizations and clubs. This approach aims to foster stronger ties between local businesses and the university community, ultimately revitalizing the restaurant industry.

Smith took pride in the restaurant's resilience to disruptions affecting internal resources such as labor and supply, and appreciated the valuable suggestion provided by our model. Regarding employee shortage, the model predicted that a restaurant would starts to lose profit if it loses 60% of employee, even with tactics aimed at boosting efficiency and adjusting quality. Smith, however, considered this threshold to be overly optimistic and highlighted concerns with losing even 25% of the workforce. The overly optimistic estimate of 60% was derived from a national-level analysis, encompassing restaurants of various scales, including large, medium, and small establishments. Smith's suggestion of 25% underscored the vulnerability specifically faced by small- and medium-sized restaurants during disruptive periods. Smith argued that it was alarming to lose even 25%, and such a scenario would necessitate a reduction in operational hours from 12 to 8, resulting in overtime work for employees as shifts might change from 6 hours to 8 hours instead. In this case, Smith acknowledged the effectiveness of improving employee productivity, particularly by establishing reasonable work hours to maintain a healthy work-life balance and offering higher wages to compensate for lost tips from customers. However, Smith pointed out that multitasking was unfeasible in their restaurant due to the highly specialized nature of tasks. Training someone to multitask would be time-consuming and impractical.

Regarding supply shortage scenario, the model suggested that a restaurant could endure the disruption if it lost up to 40% of raw materials. Smith's perspective differed in that Smith believed the restaurant started losing profit and became hard to manage as soon as 5% materials were gone. This was primarily due to the specific cravings of customers, who, upon discovering their desired item was out of stock, would promptly leave the restaurant.

To address the overly optimistic scenarios, the model specifications were tested and refined. And the following changes were imbedded. First, the supply-demand combination scenario requires an additional logic: if the supply level is too low, no matter how high the quality of the supply is, no customer will want to buy food. This logic was implemented in two steps: (1) adding an upper bound on the supply cost, ensuring that quality improvements do not exceed a certain threshold appropriate for the restaurant's nature, equipment, and typical customer base. Since the quality improvement was then linked to demand, demand increase was also capped, ensuring the customer demand could not grow unlimited. (2) adding an upper bound on price, to mimic the fact that increasing price is only effective within a range. When the restaurant faced difficulties to attract customers, this adjustment prevented unrealistic spikes in demand or revenue, ensuring the model better reflected the limitations and challenges a restaurant might encounter in real-world scenarios. Second, the employee wage increase and unit price of price should increase steeper as the disruption becomes more severe. Previously, wages and unit prices increased linearly in response to severity. However, the rate of increase has now been adjusted to follow a nonlinear relationship: wages now increase sub-quadratically with an exponent of 1.3, and the unit price of supplies increases sub-quadratically with an exponent of 1.2. Then, the employee shock and supply shock scenarios were rerun, and the profit trajectories are presented below.

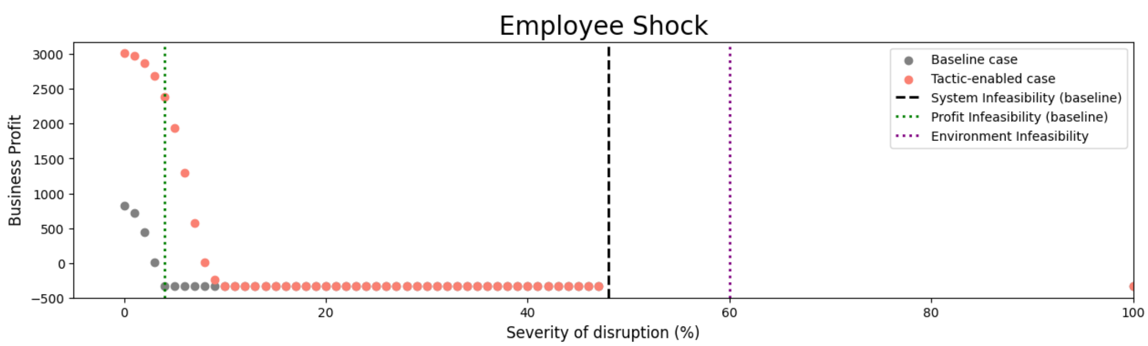


Figure 5.5.7: Modified employee shock profit trajectory

The profit trajectory in the tactic-enabled case in figure 5.5.7 was significantly less optimistic because the profit bottleneck happened around 10% severity, compared to 77% from the original model (see figure 5.5.1). Similarly,in figure 5.5.8, the profit bottleneck also happened early at around 8%, which was quite close to 5% indicated by Smith.

One disagreement arose during the interview, as Smith expressed doubt that increasing quality, thus consequently increasing price, would work for restaurants in the university district area. This area primarily consists of residents with limited food budget and are

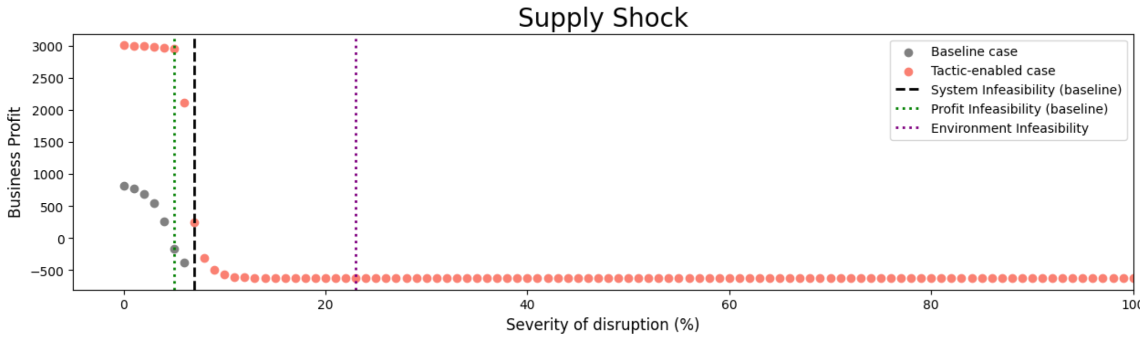


Figure 5.5.8: Modified supply shock profit trajectory

notably price sensitive. Establishments in this district like Smith's depend on high-volume sales. So Smith would try to keep the price as low as possible, even though COVID-19 led to drastic increase in cost of good sold. Smith clarified that this tactic, increasing quality, might be more suitable for higher-end restaurants offering fine-dining experiences. Smith also provided new perspectives to further help restaurants, regardless of area and types of customers served. For example, policies restricting indoor dining capacity should be more nuanced, taking into account the unique circumstances of each restaurant. Restaurants equipped with proper ventilation and air filtration systems, for instance, should be permitted to operate with higher indoor capacity or face restrictions only when indoor air quality reaches a concerning threshold. The determination of this threshold should be grounded in scientific assessments conducted by public health agencies.

This iterative process of consulting with real restaurant owners both during and after model development has polished our optimization model to recommend effective strategies. Additionally, the model has shown its flexibility to incorporate specific inputs and constraints from individual restaurants on a case-by-case basis, which highlight the usefulness of this model to formulate targeted strategies. And close interaction with restaurant owners is necessary as numbers and existing literature might deviate from reality and might also be too optimistic to reflect the struggles faced by small and medium sized businesses.

5.6 Conclusions

This study addresses the optimization of profit in restaurants in face with various disruptions, taking into account resource constraints such as labor, supply, capacity, production, and demand. Three resilience tactics — boosting efficiency, adding capacity, and adjusting quality — are introduced to effectively utilize available resources and mitigate the impact of disruptions. Comparing these tactics, it is observed that they are particularly effective when disruptions directly impact internal resources, including employees, raw material supplies, and production efficiency. On the other hand, seeking assistance becomes crucial when external resources such as customer demand and physical capacity are affected. Adjusting quality emerges as the most promising strategy among the tactics, with the rate of improvement varying depending on the type of disruption. Notably, adjusting quality leads to significant improvements in profitability. The study identifies accelerated improvements in quality for disruptions related to employee shock, supply shock, production shock, and demand shock. However, in the case of capacity shock, the rate of improvement in quality decelerates.

While this research provides valuable insights into maximizing profit in the face of disruptions, it is important to acknowledge its limitations. The data primarily focuses on local small restaurants, which may not fully capture the diversity and complexities of the broader food industry. Furthermore, the study's static nature primarily considers daily operational optimization and overlooks longer planning horizons and long-term returns. Additionally, the analysis assumes perfect knowledge, neglecting the uncertainties and incomplete information that real-world restaurants encounter during disruptions. Consequently, decision-making may vary when restaurants must assess risks with limited information.

These findings highlight the importance of adopting effective tactics tailored to specific disruption scenarios in order to maximize profit in the restaurant industry. By understanding the nature of the disruption and strategically implementing the appropriate tactics, restaurant owners and managers can navigate challenges and improve their financial performance. This study also quantitatively confirmed the qualitative reports on restaurant sector's adaptation during the COVID-19 Pandemic.

5.7 Incorporating Long-term Adaptations into Short-term Resilience Modeling Framework

A natural one-step-forward to refine the currently short-term optimization model is to adopt strategies that go beyond single-day. This rationale is confirmed by the interviews in the previous section, where interviewees have often adopted measures such as structural changes in operation modes, large capital investment, and workforce development. While the current model setup has its merits, several aspects could be reevaluated. This section discuss briefly how future work can be done to qualitatively incorporate the long-term strategies.

At the long-term level, investment decisions on purchasing equipment purchase or opening additional storefronts are made to increase the restaurant's capacity or service level over months or years. At the short-term level, day-to-day decisions include staffing each shift, purchasing supplies, and deciding how intensively to run each operational mode (e.g., dine-in vs. delivery). Early frameworks on operations management suggests that these decisions to be partitioned by time horizon and level of granularity. For example, Anthony [191] described that short-term decisions must operate within boundaries shaped by long-term capital or staffing choices. Conversely, long-term strategic decisions can benefit from detailed feedback about daily operations, e.g., whether a new product line or store location is generating the predicted revenue. Balancing the horizons can allow enough detail at the short-term level to guide good long-term strategic choices and not over-complicating the model to be unmanageable.

In general, long-term decisions can be incorporated into a single multi-stage large-scale optimization where each stage corresponds to a month or quarter, and each stage embeds or reference short-term operating decisions. Alternatively, a rolling-horizon approach may be employed, where only a certain number of upcoming periods are optimized in detail, then the horizon is moved forward in time as new information becomes available [192]. These approaches creates a feedback loop where long-term and short-term decisions have implications for each other. In the restaurant setting, a multi-stage model might allow for discrete decisions at the start of each quarter while also capturing weekly or daily staffing decisions within that quarter.

5.7.1 Large Capital Investment

Large capital investment, or capacity expansion, assumes that the value of a capital project depends on uncertain future demand and cost parameters [193, 194]. In a restaurant, decisions to expand kitchen capacity or storage involve high fixed costs but can reduce short-term labor or supply bottlenecks. The methodology of a long-term optimization model must therefore track the upfront investment versus ongoing benefits in terms of updated parameters (such as increased production efficiency, reduced labor hours needed) over many months. The model should also handle irreversible or partially reversible decisions, which could translate to impossible retract that upfront investment.

5.7.2 Workforce Development

From a theoretical standpoint, workforce development introduces complex dynamics such as learning curves and experience effects, where accumulated experience can lead to better coordination, reduced errors, and overall enhanced organizational performance [195]. There are also complexities associated with the benefit. For instance, training effects are uncertain. Some employees may leave after being trained, or not benefit as much as their peers, which makes it challenging to model the benefit deterministically. In this case, the model could assume different learning curves or varied levels of return after training.

5.7.3 Structural Changes in Operation Modes

Structural changes refers to efforts on opening new storefronts, launching delivery/catering services, or adopting new project lines. Launching a new channel can alter both the total volume of demand and its composition. In some cases, these expansions may cannibalize existing operations—for example, robust marketing of a new delivery platform might reduce dine-in attendance if the same customers opt for at-home convenience. Alternatively, they can be complementary if they tap into a largely separate market segment (e.g., wedding catering or corporate lunches that do not typically intersect with the dinner crowd). From a product portfolio perspective, managers must assess the net effect of adding each new channel or product line: whether it broadens overall market reach or dilutes their services. Strategically, this resembles technology adoption in that the restaurant must weigh upfront investment costs, training, and potential market uncertainty against the anticipated revenue streams from the new channel.

5.7.4 Working with Disruption and Uncertainty

In practice, restaurants do not operate in a vacuum of stable demand and guaranteed resources and may face sudden shocks in the long-term. One theoretical strategy is to augment the multi-period model with multiple scenarios for possible future states [196]. For instance, a restaurant might develop several macro-scenarios: normal supply vs. occasional shortages vs. major supply chain breakdown; or stable employee pool vs. moderate turnover vs. severe labor shortages. Each scenario is assigned a probability or considered equally likely. The long-term model then seeks a plan that on average, or in expectation, performs well across these different scenarios. However, enumerating many scenarios can increase computational burden, and real disruptions often do not neatly fall into pre-defined scenarios. Robust optimization attempts to find solutions that remain feasible and near-optimal under the worst-case realization of uncertain parameters (when labor capacity can drop to a known minimum) [197, 198]. This approach ensures less risk that a resilience strategy becomes infeasible if disruption is unexpectedly severe. But it can be conservative and makes a strategy appear suboptimal and more expensive if disruptions do not actually aggravate.

Instead of committing to an entire year's plan at once, the restaurant can adopt a rolling-horizon approach [192]. At the start of each month or season, the model can update forecasts by integrating new information or projection about labor availability, supply constraints, or policy changes. Then it re-optimize and solve the short-term subproblem on a daily basis within the broader context defined by the long-term strategies. Next, the daily decisions can be implemented in practice and the model moves forward by one horizon and repeat the process. This method is more agile in response to sudden shocks because the model does not rely on a single, fixed long-term forecast. Combined with robust optimization, each re-optimization step incorporates newly observed data on costs, labor availability, or demand. The uncertainty for these parameters can be approximated closer to the reality, or set uncertainty to be realistic for the near term future. But since each subproblem is a robust optimization, which itself can be more computationally demanding than a deterministic one, solving these repeatedly can be CPU-intensive in large-scale settings.

Chapter 6

CONCLUSION AND IMPLICATIONS

This dissertation explores the changes in travel patterns, food accessibility, and food business operations in response to COVID-19. In the Puget Sound region where Seattle lies, it was found that telecommuters travel in a shorter, more spatially localized and temporally scattered fashion compared to commuters. Their trips are no longer concentrated around traditional commute rush hours but spread to midday periods and within local neighborhoods closer to their homes. During COVID, the surge in food delivery services provides another option to access food. In the city of Seattle, it was found that delivery services increase restaurant and fast-food accessibility in areas where there is already good accessibility (e.g., downtown Seattle for restaurants and South Seattle for fast-food), while at the same time the accessibility to fresh produce from grocery stores is improved for low-income or low-access households (those who live far from grocery stores). The study on small and medium-sized restaurants found that they deploy both short-term (e.g., adjusting core operation modes, substitution of supplies, and labor reassignment) and long-term (e.g., structural change in operations, large capital investments, workforce development) adaptation strategies. These strategies are in response to disruptions in demand, labor supply, supply chain, and the indoor dining capacity restriction policy.

This chapter focuses on three interrelated policy domains in response to the observed changes: (1) the potential of shared and staggered use of public spaces, (2) the design of on-demand microtransit services and community-based delivery systems, and (3) the implications of more random and scattered travel on the current travel demand forecasting model for planning purposes.

6.1 *Staggered Use of Public Spaces*

The pandemic-induced changes in travel and activity patterns invite a closer look at staggered use of public space—time-based reallocation of the same curb or street segment for different functions. Results from our study on how telecommuters rescheduled their activity and travel patterns (Figure 3.3.4) show telecommuters making large numbers of maintenance and discretionary trips between roughly 10 a.m. and 2 p.m. Those hours fall between the surge demand for commercial freight deliveries in the morning [199, 200] and picking up restaurant delivery orders in the late-afternoon and evening [201]. Because freight/delivery vehicles need curb access mostly at dawn and around dinner, repurposing the same curb or travel lane for people-oriented uses at mid-day will not create significant scheduling conflicts. Telecommuters tend to make shorter trips and walk more often than commuters. During midday hours, when many of these trips occur, converting a lane into a pedestrian plaza or outdoor dining parklet can better align with this demand. These spaces offer safe and appealing environments at precisely the times people are already out walking, running errands, or eating lunch near home.

The staggered use of public space could be beneficial in promoting healthy food access. This dissertation provides evidence that with more grocery stores present, delivery service could enhance accessibility to fresh produce in low-income and low-access areas. As opposed to building new grocery stores from scratch, which is time and money consuming, having alternative uses of public spaces for pop-up grocery stands to sell or pick up fresh produce could also help in accessing healthy food. Food banks, farmers' markets, and local restaurants can all capitalize on a staggered schedule to expand food access without permanently surrendering curb space. Early-morning curb lanes that already accommodate freight deliveries on weekdays are typically idle on weekends; designating those same bays for Saturday-morning food-bank or mobile-pantry distribution would allow trucks to pull in, set up tables, and serve nearby residents while keeping heavy vehicles out of pedestrian periods.

Pilot projects have shown that flexible street configurations can increase economic activity without reducing vehicle throughput, and they support long-term resilience to climate and economic disruptions [202, 203]. A show case from National Association of City Transportation Officials (NACTO) provided an example where people reshape the streets by using their existing assets differently for essential trips and healthy activity. A wide variety of uses were being tested to serve other community needs. For example, the same curb side parking spaces can be converted into high-turnover pick-up or delivery zones, outdoor dining areas, and open markets on special or periodic occasions.

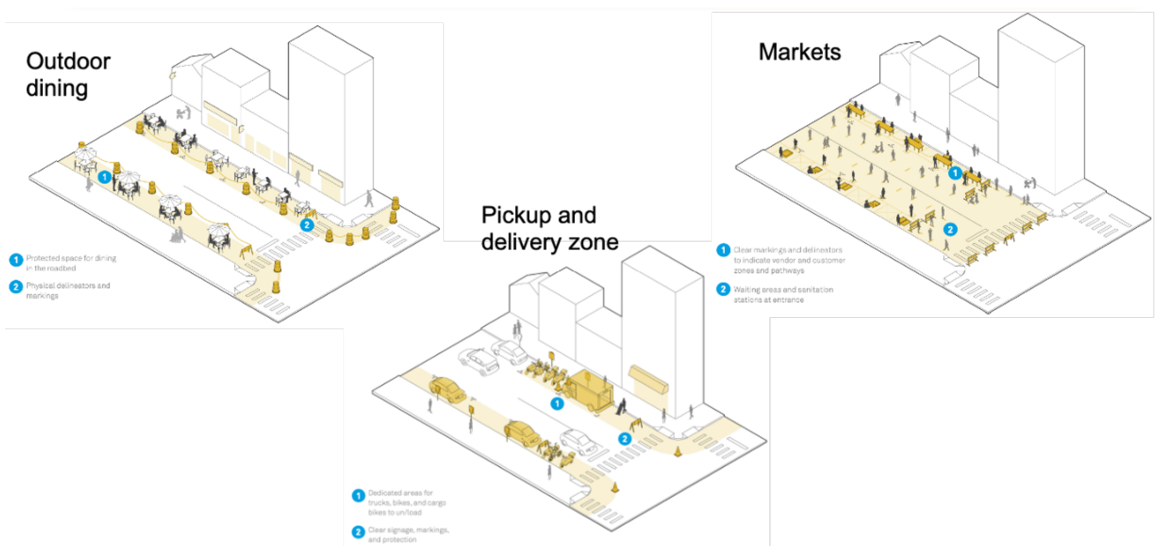


Figure 6.1.1: Examples of alternative street uses—curbside pickup, pop-up markets, outdoor dining, and playstreets—adapted from NACTO's *Streets for Pandemic Response & Recovery* (2020). Source: `https://nacto.org/wp-content/uploads/NACTO_Streets-for-Pandemic-Response-and-Recovery_2020-05-21.pdf`

There could be long-term implications for the regional planning policy if the changed travel patterns (more localized travel patterns around home) persist over time. If these patterns persist, do they still support the large infrastructure projects that were planned for the Puget Sound region years ago? The observed more localized travel patterns lend support to the 15-minute city idea, which focuses on access to amenities around the home: a person should be able to live, work, shop, go to school, access healthcare, and enjoy entertainment all in one neighborhood [204]. The 15-minute city idea, however, has long been viewed as too idealistic, as the reality of the current built environment often requires travel beyond home neighborhoods to reach these activities [205]. The results of this study suggest that without changes in the built environment, there is potential to achieve the 15-minute city idea by simply removing the work location as the anchor point via telecommuting, if the region decides that as a planning goal. And staggered public space usage could serve as a neighborhood-level response to the midday, home-centered travel pattern and a support to the 15-min city idea.

6.2 On-Demand Microtransit Services and Community-based Group Deliveries

Shifts toward hybrid work and telecommuting continue to reshape travel demand to a shorter, localized, more scattered outside conventional peak times pattern. This travel pattern might not be fully supported by the fixed-route public transit services that orient more towards serving commuters in morning and evening peaks. And food businesses that relied on food traffic and primarily served indoor dining services have been actively adapting to such changes through resilience strategies, especially large capital investment and structural shifts in operation modes (see section 4.6). New services are emerging or expanding to meet these changed patterns. Two such innovations are on-demand microtransit services, where rides are provided on a flexibly or on-demand basis [206], and community-based group deliveries, in which coordinated deliveries are scheduled collectively for neighborhoods [207].

On-demand microtransit services provides technology-enabled service that uses multi-passenger vehicles to provide on-demand services with dynamically generated routing [208]. These services offer viable alternatives to fixed-route transit, particularly benefiting individuals without regular commute schedules or in lower-density rural areas where fixed-route transit cannot be justified [209]. Telecommuters, who occasionally visit their workplaces, may find monthly transit passes or paying for parking their personal vehicles impractical. For them, dynamic, on-demand ride services represent cost-effective, convenient mobility solutions.

Currently, research on on-demand microtransit services has been focusing on its integration with Transportation Network Companies (TNCs), such as Uber and Lyft. Recent work shows promise as well as challenges. For example, TNCs are appreciated for its flexibility to dispatch drivers nearby within minutes, shorter waiting times, and guaranteed a seat [210, 209]. But taxis may have wheelchair accessible vehicles where TNCs generally do not, which makes TNCs less available for people who use wheelchairs [211]. Establishing partnerships with TNCs poses regulatory challenges, as publicly funded transit operators must comply with FTA's ongoing drug and alcohol testing requirements under 49 C.F.R. Part 655 [212], whereas TNCs are not subject to the same standards—an oversight flagged by the FTA in 2024 as a legal and reputational risk [213].

Community-based delivery is another service benefiting both the residents from local neighborhoods as well as food businesses during difficult times. In particular, groceries, medicine, and other critical services are organized and distributed collaboratively among a neighborhood [214]. Such collaborations also have environmental benefits of reducing carbon emission when delivery is aggregated by neighborhood [215]. Seattle neighborhoods have been testing this idea through the Seattle Neighborhood Delivery Hub pilot in Seattle Downtown areas, where e-cargo tricycle are leveraged as a last-mile delivery option complete deliveries. [207]. Beyond Seattle, a non-profit organization in New York that started as helping neighbors in need of grocery delivery during COVID has now engaged over 10,000 volunteers in delivering over $1,000,000 in groceries, medicine, and other necessities in the neighborhood [216]. This trend also echos with the interviews where a food bank manager steered their business towards recruiting volunteers from a local bicycle club for grocery deliveries to underserved neighborhoods on a weekly basis.

Local governments might implement incentive programs that encourage shared rides or deliveries, such as reduced registration fees for microtransit fleets serving off-peak hours, or tax rebates for companies and households participating in group-delivery cooperatives [217].

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6.3 Modeling Implications

The findings about telecommuting affecting travel patterns brings implications on the regional transit ridership and travel demand forecasting models, which serve as the basis for evaluating the potential of many mega-projects such as building highways and transit lines. Transit ridership models for example have long been developed as function of station-level factors, such as population and employment numbers and level of accessibility to stations [218, 219]. Those factors have not changed significantly since COVID but transit ridership has plummeted since COVID due to the disappearance of commute trips [220, 221]. This calls for rethinking and redevelopment of the long-standing transit ridership models. The regional travel demand forecasting models may be more resilient to the changes brought by COVID and telecommuting, especially if they are designed to capture individuals' entire day's travels (or so-called activity-based models). This is because these models are often constructed with a modeling sequence consistent with Hagerstrand's framework in that trips from/to anchor points (home and work) are developed first, followed by more flexible ones including maintenance and discretionary trips. Our study shows that Hagerstrand's framework continues to stand–flexible trips such as maintenance and discretionary trips are conducted with respect to anchor points and an anchor point is removed, those trips are redistributed around the remaining one (home) spatially and temporally.

And now, many companies – particularly tech companies – are calling employees back to the office, often on certain days of the week (Return-To-Offic, RTO policy). Consequently, full-time telecommuting is decreasing, but not yet returning to the five-day on-site level. Employees may commute only two or three days a week and work remotely on other days, which creates irregular travel demand with different peak patterns, especially when employees can choose which days to come to office. Furthermore, even on in-office days, employees are not strictly required to "clock out" at a specific time. This means that they can leave whenever they finish their tasks, resulting in a scattered return-home commute pattern throughout the afternoon and evening period. This adds uncertainty to modeling departure times from work as well as trips made around work and between home and work.

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Appendix A

2SFCA PROOF ON SUPPLY CONSERVATION

The methodology proposed in the manuscript ensures that the total supplies offered by the food establishment equals to the total supplies received by the population. And the conservation of supply is proved in this section. The following proof is prepared for the delivery accessibility; however, the proof can be adjusted to show that the preservation of supply holds for on-premise food accessibility by changing the function $r_1 < d_{ij} < r_2$ to $d_{ij} < r_2$. Further, assume all food establishments belong to category c.

Given:

$$R_j = \frac{cap_j}{\sum_{i \in \{N | r_1 < d_{ij} < r_2\}} P_i \times p(d_{ij})},$$

$$p(d_{ij}) = \frac{e^{-d_{ij}^2/\beta}}{\sum_q e^{-d_{iq}^2/\beta}}, where \ \ q = 1, \dots, j, \dots, M \wedge r_1 < d_{iq} < r_2,$$

$$A_i = \sum_{j \in \{M | r_1 < d_{ij} < r_2\}} R_j \times p(d_{ij}),$$

Prove:

$$\sum_i A_i P_i = \sum_j cap_j$$

Step 1: substitute R_j into A_i

$$A_i = \sum_{j \in \{M | r_1 < d_{ij} < r_2\}} \left(\frac{cap_j}{\sum_{i \in \{N | r_1 < d_{ij} < r_2\}} P_i \times p(d_{ij})} \right) p(d_{ij})$$

Step 2: multiply both sides of the equation in step 1 by P_i

$$A_i P_i = P_i \sum_{j \in \{M | r_1 < d_{ij} < r_2\}} \frac{cap_j p(d_{ij})}{\sum_{i \in \{N | r_1 < d_{ij} < r_2\}} P_i \times p(d_{ij})}$$

Step 3: sum over i on both sides for equation in step 2:

$$\sum_i A_i P_i = \sum_i P_i \sum_{j \in \{M | r_1 < d_{ij} < r_2\}} \frac{cap_j p(d_{ij})}{\sum_{i \in \{N | r_1 < d_{ij} < r_2\}} P_i \times p(d_{ij})}$$

Step 4: interchange the sign of summation on the right hand side of equation from step 3:

$$\sum_i A_i P_i = \sum_{j \in \{M | r_1 < d_{ij} < r_2\}} \frac{cap_j \sum_{i \in \{N | r_1 < d_{ij} < r_2\}} P_i \, p(d_{ij})}{\sum_{i \in \{N | r_1 < d_{ij} < r_2\}} P_i \times p(d_{ij})}$$

Let $\sum_{i \in \{N | r_1 < d_{ij} < r_2\}} P_i = \mathrm{D}_j$, which is the demand for food establishment j.

Step 5: substitute D_j

$$\sum_i A_i P_i = \sum_j \left(\frac{cap_j D_j}{D_j} \right) = \sum_j cap_j$$

Thus, the supply given from the food establishments, $\sum_j cap_j$, equals to the supply received by the population location, $\sum_i A_i P_i$.

Appendix B

COVID AND TELECOMMUTING SUPPLEMENTAL MATERIALS

B.1 Determining whether one telecommutes using Puget Sound Regional Council's Household Travel Survey Data

The Puget Sound Regional Council's household travel survey includes the following three questions [101] that will be used in this study to determine whether the respondent is a telecommuter or commuter. According to the US Bureau of Labor Statistics, a telecommuter is defined as who works for pay at home. Thus, a person is considered a worker if one of the options of "Employed full-time (35+ hours/week, paid)", "Employed part-time (Fewer than 35 hours/week, paid)", and "Self-employed" is selected in the household travel survey. And one is a telecommuter if he is a worker and has selected either "Work at home ONLY (telework, self-employed)" or "Telework some days and travel to a work location some days" for the second question asking about home location, or has selected either "5+ days", "3-4 days" or "1-2 days" for the third question asking about days telecommuted last week. On the other hand, a commuter is a worker but selecting the counterpart options for question 2 and 3.

Household travel survey question statements and options are copied below.

Q1: Primary type of employment as of today:

- Employed full-time (35+ hours/week, paid)
- Employed part-time (Fewer than 35 hours/week, paid)
- Self-employed
- Unpaid volunteer or intern
- Employed but not currently working (e.g., on leave, furloughed 100%)

- Homemaker
- Retired
- Not currently employed

Q2: Current work location?

- Only one work location outside of home
- Work at home ONLY (telework, self-employed)
- Telework some days and travel to a work location some days
- Work location regularly varies (different offices/jobsites)
- Drive/travel for work (driver, sales)

Q3: How many days worked from home or teleworked last week (instead of going to work that day)?

- 5+ days
- 3-4 days
- 1-2 days
- None

To explore potential differences among telecommuters, we recalculated the key metrics—trip generation, spatial redistribution, and temporal redistribution—separately for hybrid and full-time telecommuters. The 2021 household travel survey includes a question asking, “How many days worked from home or teleworked last week (instead of going to work that day),” with response options of 5+ days, 3–4 days, 1–2 days, and None. Based on this question, we identified approximately 133 out of 950 telecommuters who reported working from home 5 or more days a week and classified them as full-time telecommuters.

The results showed no statistically significant differences between the two groups for nearly all metrics. The only exception was the radius of gyration (ROG), where the sample size for full-time telecommuters (n = 6) was too small to draw meaningful conclusions. Table A1 below provides the summary of the metrics.

Table A1: Summary of metrics for hybrid and full-time telecommuters

	Hybrid telecommuters (N = 817)	**Full-time telecommuters (N = 133)**
Trip Generation		
Trips (per person per day)		
Number of Trips	3.39	3.26
Number of Maintenance Trips	1.50	1.47
Number of Discretionary Trips	1.39	1.35
Number of Work Trips	0.50	0.44
Trip Chains (per person per day)		
Number of Trip Chains	1.33	1.34
Intermediate Stops within a Trip Chain	1.59	1.46
Maintenance and Discretionary Trip Redistribution		
Spatial Redistribution		
Maintenance Trip Distance (network distance in miles)	2.12	2.00
Discretionary Trip Distance (network distance in miles)	2.59	2.05
Straight Line Distance from Home to Maintenance Destination (miles)	3.13	2.70
Straight Line Distance from Home to Discretionary Destination (miles)	3.33	2.72
Radius of Gyration (home-based)	3.03	7.16[1]
Total Vehicle Miles (Driving) for Maintenance Trips	11.29 (6.61)[2]	9.41 (5.11)[2]
Total Distance Traveled for Maintenance Trips (miles)	11.96 (7.28)[2]	10.28 (5.46)[2]
Total Vehicle Miles (Driving) for Discretionary Trips (miles)	8.25 (2.95)[2]	8.26 (0.90)[2]
Total Distance Traveled for Discretionary Trips	9.70 (4.56)[2]	9.67(3.31)[2]
Temporal Redistribution		
Time Spent on Maintenance Trips (min)	16.43	17.42
Time Spent on Discretionary Trips (min)	20.45	20.30
Mode and Purpose		
Purpose Diversity	1.21	1.18
Mode Diversity	0.12	0.14
Total Time Spent on Walking Trips (min)	6.40	8.41
Number of Walking Trips	0.88	0.98
Number of Driving Trips	2.45	2.22

Note: [1]: The fulltime telecommuters has a sample size of 6. [2]: The values in parenthesis are the median value when the distribution of the metric is skewed.

Appendix C

BUSINESS INTERVIEW PROTOCOL

Food Service Establishment Owner Interview Protocol

Instructions for Interviewers

Bold black headings such as **Introduction** are major topics to be covered in this interview.

Regular black paragraphs are the questions or statement prepared by the interviewer.

Content in square brackets such as [Follow up on **motivations**] are the goal of the question immediate to the brackets.

Content in *italics* indicates the potential answers expected from the interviewee. Consider following up on those italics points if the interviewee does not mention such information.

Blanks ___________ are places where the interviewer must fill out based on the interviewee's answer from the previous sections.

Interviewees should read through this protocol carefully and remember that the interviewee might already provide answers to what you are asking in earlier conversations. You should let the interviewee know that while this might happen, you will still ask the question(s) as sometimes a direct question elicits different responses than they got to from another question. If they feel like they've already answered the question, they can just tell you so.

Introduction (3 min)

Thank you for speaking with us today. We are University of Washington researchers studying how small businesses adapt to different disruptions. By disruptions, we refer to not just COVID-related ones, but also storefront constructions, extreme weather conditions, or other things you consider disruptive to the business. These disruptions can result in damage to our cities, like blockages on our roads, or lead to labor and supply shortages, like what you may have already experienced. We hope to develop tools that would help businesses make decisions to survive future disruptions.

We would like to hear about how your business responded to past disruptions and might respond to future ones. We will be asking you for some background information about your business, how you may adapt to some hypothetical and real disruptions, and your needs as a business operator during these disruptions.

Background information (30 min)

How would you describe your business, and can you give us a description of what your business does?

Notes: during this part, the interviewee might talk about the following points.

- *Motivations to open the business:*
  - *Serve food to those who need it for community welfare*
  - *An extra profit for the family*
- *Customer base:*
  - *Residents in the neighborhood*
  - *UW community*
  - *Local farmers*
  - *Others?*
- *Operational mode:*
  - *For grocery stores and farmer's markets: in-person shopping, curbside pickup, drop-off at doorsteps, etc.*
  - *For restaurants: indoor dining, outdoor dining, delivery, takeout, etc.*
- *Interviewee's responsibilities:*
  - *Hiring employees*
  - *Restocking materials*
  - *What to produce and how much to produce*
  - *Finding the right customer (meaning? Marketing? Advertising?)*
- *Difficulties experienced:*
  - *Esp. during COVID*
    - *Short staffed*
    - *Supply chain disruption*
    - *Customer decrease and perception of risk for dine-in*
    - *Policy restrictions such as social distancing*
    - *Difficult to apply and receive grants. (follow up if mentioned)*
    - *Uncertainties about the future*
  - *In general*
    - *Local construction projects*
    - *Safety concerns*
    - *Rent/utilities/other expenses*

[Follow up on **motivations**] You mentioned ___________ as your motivations in operating this business? Have they changed from before to after COVID-19?

- If so, how?

[Follow up on **customer base**] Who are your primary customers?

- What are your busiest times, by the hour of day and months of the year? [the answer might be correlated to the type of customers coming to the business]
- Do you know what percentage of your customers are coming to your place for delivery purposes vs sit-down service.
- Is your business open during off-peak times?

[Follow up on **operational mode**] I think your business does in-person shopping/dining, curbside pick-up/takeout, delivery, have I missed anything?

- Which of your service modes serves the most customers? Can you tell us roughly what percentage of customers are served in each mode?
- Why are some operations not available?

[Follow up about **public space use**] Did the interviewee use the sidewalk, street, or outdoor space during COVID? If so, how? If not, why not? Did they know this was an option? Do they share that space with another business? Is outdoor dining public or private? What was your experience with the permitting process? What trade-offs did they have to make (parking for example)?

[Follow up on **responsibilities**] Could you elaborate more on your responsibilities for the business?

- *Notes: during this part, the interviewee might talk about the following points.*
- *Managing employees*
  - *when to hire*
  - *how much to pay*
  - *Hard time finding employees*
- *Buying materials*
  - *How do you usually estimate the amount of food supplies or products to buy for the next month?*
  - *Where does the business get product/materials*
  - *How often they restock*
  - *What to do during supply chain shortages*

Disruption and Adaptation (20 min)

Thank you for sharing this information about your business and business operations. Now we will ask about some possible difficulties you might or have experienced, and more importantly, how you might respond.

[Follow up on **difficulties**] What do you worry about as a business owner?

- [Staffing shortage]
  - How often does employee shortage happen?
  - How long does the shortage last?
  - If your business was unable to fill job openings but customer demand remained high, how would you respond?
  - Could your business still operate if you lost half of your employees?
    - What is the minimum number of employees you must have?
- [Supply chain disruption]
  - What kinds of supplies do you need in the full scope of your business operation?
  - What are the most critical/important ones?
  - What would you do if you were short of critical supplies? What kinds of substitutions are possible?
  - How do you usually estimate the amount of food supplies or products to buy for the next month?
- [Customer decrease and perceptions of safety for dining-in]
  - Do you have fewer customers than before the pandemic?
  - Have you tried to bring customers back to your business? How?
- [Production decrease]
  - How often do you experience utility outages?
  - How long can you stay open without such utilities?
  - What backup plans do you have?

Bottlenecks and plans [7 min]

[what the business needs] What resources does your business require? Are there things the city or the U-District Partnership can do to help your business succeed? (Follow up with clarifying questions/probes)

Here we'd like to ask about the minimum thresholds of various business operations required for you to stay in business.

Is there a minimum profit level?

minimum number of employees?

Others we haven't discussed?

What might cause you to shut down your business?

Lastly, is there something you think we should have asked you about but didn't? Did we miss something that is a major concern to you?

Closing

Thank you for taking the time to speak with us, it has been a very helpful discussion. Before we end, do you have any questions or comments for us?

(Share the contact info—leave business cards or something similar)

Grace Jia: Research Assistant, gracejia@uw.edu

Cynthia Chen: Project Lead, qzchen@uw.edu)

This is our contact information if you would like to speak with us in the future. You can also contact us if you think of other people who might be interested in speaking with us.

Appendix D

INTERVIEW RECRUITMENT LETTER

UNIVERSITY of WASHINGTON
DEPARTMENT OF URBAN DESIGN AND PLANNING
College of Built Environments

January 23, 2023

Dear University District business owner:

We are writing as members of a University of Washington research team to ask about your experiences during times of business disruption. We know local businesses are the heart of neighborhoods like ours, but that they are also challenged by things outside their control, like the COVID pandemic, extreme weather conditions, or even local construction projects. Working with our partners in the U-District Partnership and the Seattle Department of Transportation, we hope to learn from local businesses to formulate business strategies and government policies that could help small businesses like yours through tough times.

We are requesting an interview with the business owner or operator who makes day-to-day decisions in your business. The interview will last approximately one hour, and as a token of our appreciation, we will send you a $50 Amazon.com e-credit for your participation. If you are interested, we will also share with you the results of our study.

Your responses are voluntary and will be kept confidential. Your name is not on any mailing list we hold, and your answers will not be associated with your business unless you so desire. Participants must be at least 18 years old and agree with the stated terms of the research. This study has been reviewed by the University of Washington Institutional Review Board.

By participating in this study, you will be adding to our understanding of the U-District's preparedness for disruptions, and you will help advance our research into business resilience in Seattle. We hope you will enjoy the conversation and we look forward to receiving your responses.

If you have any questions or concerns, you may contact either Principal Investigator, Professor Cynthia Chen (qzchen@uw.edu, (206) 543-8974) or Associate Professor Branden Born (bborn@uw.edu, (206) 718-5769).

Sincerely,

writing for:

Branden Born
Associate Professor
Urban Design and Planning

Cynthia Chen
Professor
Civil & Environmental Engineering

Grace Jia
Graduate Research Assistant
Civil & Environmental Engineering

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Appendix E

BUSINESS RESILIENCE SURVEY

BUSINESS RESILIENCE IN SEATTLE

A Study of Food Businesses' Disruption Adaptation and Resilience Strategies in Seattle

Welcome to the Seattle Food Business Resilience Survey. The University of Washington is seeking your help to understand the impact of recent disruptions, such as labor shortages, supply shortages, and public safety concerns on food businesses. Your participation in this survey is crucial in assisting policymakers, government officials, and neighborhood organizations to gain valuable insights during this challenging time.

This survey is designed for completion by business owners, operators, managers, or individuals who are in charge of running the business at this location. You will receive a $10 Amazon.com e-gift card upon completing and returning the survey.

Section 1: Business Operation

In this section, we are interested in understanding your normal business operations, as well as your opinions on growing your business.

1. What kind of business do you operate?

- ☐ Full-service food establishment (i.e., sit-down restaurant)
- ☐ Quick service food establishment (i.e., fast food, bar, café)
- ☐ Grocery
- ☐ Food-related retail
- ☐ Accommodations (i.e., hotel, motel, bed and breakfast)
- ☐ Other (please specify) ____

2. How long has the business been operating at this current location?

_______________ (years)

3. **During a typical week, what are your operation hours?**

    Weekdays from ___________________ to ___________________

    Weekends from ___________________ to ___________________

    Holidays from ___________________ to ___________________

4. **Which of the following modes of travel are important for your customers to reach your business? (Check all that apply)**
    - ☐ Walk
    - ☐ Bike
    - ☐ Bus
    - ☐ Light rail
    - ☐ Car or rideshare
    - ☐ They are all important
    - ☐ Others, please specify _______________

5. **In general, how easy it is to find a parking spot near your business?**
    - ☐ Difficult
    - ☐ Somewhat difficult
    - ☐ Neutral
    - ☐ Somewhat easy
    - ☐ Easy

6. **Does your business have access to an outdoor space that could be used as a seating area for service?**
    - ☐ Yes, we are currently using the outdoor space
    - ☐ Yes, but we are not using the outdoor space
    - ☐ No – Skip to question 9
    - ☐ Don't know – skip to question 9

7. **If you are currently using the outdoor space, how much is the permit cost to use this space each year?**

    $_______________

8. **If you are currently using the outdoor space, how many customers can be served outdoors?**

    ____

9. **How many employees does your business have?** ______________

10. **What is the ideal number of employees for your business?** ______________

11. **What is the average hourly wage for your non-management employees?** ______________

12. **What is the average number of hours non-management employees work per week?** _____________________

[Instruction: If you operate a full-service restaurant, a quick-service restaurant, or retail, answer Questions 13-14 and continue with Question 17. Otherwise, skip Questions 13-14. Continue at Question 15 on the next page.]

For **full-service restaurant, a quick-service restaurant, or retail** only

13. For each of the operations listed in the box below, please indicate whether your business currently has one by checking the box to the right of the operation. Next, on the line provided, please tell us how many customers your business serves through that operation each week. Then, next to the dollar sign, please indicate how much money you have to put down to start up that operation.

Operations	*Currently open*	*Number of customers served each week*	*Startup cost (Place an X on the line if you don't know)*
Indoor dine-in	☐	______	$______
Outdoor dine-in	☐	______	$______
Takeout	☐	______	$______
Third-party delivery	☐	______	$______
In-house delivery	☐	______	$______
Other, please specify ______	☐	______	$______

14. On average, how much do your customers spend per order in each of the following operation areas? Please select the range(s).

	Don't have	*Below $20*	*$21 - $40*	*$41 - $60*	*$61 - $80*	*Above $80*
Indoor dine-in	☐	☐	☐	☐	☐	☐
Outdoor Dine-in	☐	☐	☐	☐	☐	☐
Take out	☐	☐	☐	☐	☐	☐
Third-party delivery	☐	☐	☐	☐	☐	☐
In-house delivery	☐	☐	☐	☐	☐	☐
Other (please describe) ______	☐	☐	☐	☐	☐	☐

For grocery store, accommodation, and other food-related businesses only.

[Instruction: Begin at Question 15 if you operate a grocery store, accommodation, and other food-related businesses. Otherwise, if you operate a full-service restaurant, a quick-service restaurant, or retail, begin at Question 17 at the bottom of this page.]

15. For each of the operations listed in the box below, please indicate whether your business currently has one by checking the box to the right of the operation. Next, on the line provided, please tell us how many customers your business serves through that operation each week. Then, next to the dollar sign, please indicate how much money you have to put down to start up that operation.

Operations	*Currently open*	*Number of customers served each week*	*Startup cost (Place an X on the line if you don't know)*
On-premise shopping	☐	______	$______
Pickup orders	☐	______	$______
Delivery	☐	______	$______
Other, please specify ______	☐	______	$______

16. On average, how much do your customers spend per order in each of the following operation areas? Please select the range(s).

	Below $25	*$26 - $50*	*$51 - $100*	*$101 - $150*	*$151 - $200*	*$200+*
On-premise shopping	☐	☐	☐	☐	☐	☐
Pick up orders	☐	☐	☐	☐	☐	☐
Delivery	☐	☐	☐	☐	☐	☐
Others, please specify ______	☐	☐	☐	☐	☐	☐

17. If your business uses third-party delivery platforms, do you think your profit per delivery order is higher than the profit per in-store order?

If so, how much more? ______________

If not, how much less? ______________

18. How many customers come to your business at the following times?

	During peak seasons	*During off-peak seasons*
On a weekday	________	________
On a weekend day	________	________

19. Referring to the highest number of customers you answered in Question 18, how many more customers could your business serve without further investment in equipment or labor?

____

20. What is the average wait time before customers receive orders during your busiest times?

__________________ (minutes)

21. How much do you spend on restocking, such as ingredients for cooking or products for sale every week?

- ☐ $0-$500
- ☐ $501 - $1,000
- ☐ $1,001- $1,500
- ☐ $1,501 - $2,500
- ☐ $2,501 - $4,000
- ☐ More than $4,000

22. How much is your monthly expenditure on rent and utilities? $____________

23. In the last month, what were the total operating revenue/sales/receipts for this business, not including any financial assistance or loans?

- ☐ $0 - $500
- ☐ $501 - $2,500
- ☐ $2,501 - $5,000
- ☐ $5,001 - $15,000
- ☐ $15,001 - $50,000
- ☐ $50,001 - $125,000
- ☐ $125,001 - $200,000
- ☐ $200,001 - $500,000
- ☐ $500,001 or more
- ☐ Don't know

Section 2: Disruption Preparedness and Responses

In this section, we want to know about your disruption preparedness and responses, including how you would get supplies and operate during disruptive events (such as the COVID-19 Pandemic).

1. **How would you describe the current availability of cash on hand for this business, including any financial assistance or loans? Currently, cash on hand will cover business operations for:**
   - ☐ 0 days, no cash available
   - ☐ 1-7 days
   - ☐ 8-14 days
   - ☐ 15-29 days
   - ☐ 1-2 months
   - ☐ 3 or more months
   - ☐ Don't know

2. **What is the minimum profit per month your business needs to stay open?**

   $____________________

3. **How likely do you think you would be to receive any funding such as grants or loans in a disruptive event (such as COVID-19)?**
   - ☐ Extremely unlikely
   - ☐ Unlikely
   - ☐ Neutral
   - ☐ Likely
   - ☐ Extremely likely
   - ☐ I don't know

4. **If you have applied for any funding such as grants or loans in the past three years, how long did it take you to prepare the application and receive the decision? If you have never applied, check the "Never applied" box and go to Question 6 on the next page.**

   ____________________ weeks

   - ☐ Never applied

5. **If you have received a grant in the past three years, how much did you receive?**

   $____________________

6. **During the past three years, did you ever temporarily close your business?**
   - ☐ Yes
   - ☐ No

   If yes, for how long?

   ______________months

7. **Would your decision to keep your business open or close it during a disruption depend on whether neighboring businesses are remaining open or closing down?**
   - ☐ Yes
   - ☐ No

   If yes, how? ________________________

8. **For each of the challenges listed in the box below, please indicate whether this challenge has affected your business within the last three years by checking the box to the right of the statement. Then, on the line provided, please indicate which of the strategies listed in the column on the right might be used to help your business deal with that particular challenge. Each strategy can be used to address more than one challenge, and you can choose to list multiple strategies for dealing with each challenge.**

Challenges	***Affected my business***	***Indicate the strategies on that may help your business in this challenge***
Did not have enough money to purchase essential goods or hire employees.	☐	______________
The products I need are out of stock.	☐	______________
Not enough potential applicants for open employee positions.	☐	______________
Did not have enough customers.	☐	______________
Policy restrictions (i.e., social distancing).	☐	______________
Unsafe neighborhood due to drug use, crime, and/or vandalism.	☐	______________
Other disruptions, please specify ______________ ______________	☐	______________

Strategy description

A: Use digital technologies

B: Increase service capacities

C: Change the scope of the business

D: Change management practices, such as allowing employees to multitask

E: Introduce new goods or services

F: Improve existing goods or services

G: Improve production methods

H: Improve methods of logistics, delivery, or distribution

What other strategies not listed above might you use to help your business during the kinds of challenges described?

____

____

Section 3: Resource Sharing

In this section, we ask some questions about your attitude towards sharing resources with local businesses and also potential ways of sharing with them. Resources refer to employees, supplies, outdoor space, knowledge, and expertise.

1. If you need help for your business, where do you typically turn?

- ☐ Government-led programs
- ☐ Business organizations/associations
- ☐ Financial institutions/investors
- ☐ Other businesses
- ☐ Family, friends, and relatives
- ☐ Other, (please specify) ________________________

2. Have you ever shared resources with other businesses?

- ☐ Yes
- ☐ No

If yes, in what circumstances? ____

3. There are many reasons why you might not want to share some of your own resources with others. For example, you may need them for yourself, or perhaps you think neighboring businesses should have been more prepared themselves, or that others who have more than you should be the ones to share. So, honestly speaking, *with whom would you be willing to share the following kinds of resources during a pandemic?*

	Nobody	*Businesses operated by friends, families, or relatives*	*Businesses within the same neighborhood*	*Any business in need*
Employees	☐	☐	☐	☐
Cooking equipment	☐	☐	☐	☐
Raw materials	☐	☐	☐	☐
Cooling/freezing equipment	☐	☐	☐	☐
Utensils/linens	☐	☐	☐	☐
Sanitary supplies	☐	☐	☐	☐
Outdoor space	☐	☐	☐	☐
Knowledge/expertise	☐	☐	☐	☐

Section 4: Background Information

In this section, we ask some questions about you and your business. The answers you provide will help us to project the information from this small study sample to a larger population. Please be assured that the information collected through this survey will be kept confidential and used solely for the purpose of this research. Your business and personal identity will be kept completely anonymous at all times.

1. Were you born in the United States?

- ☐ Yes
- ☐ No
- ☐ Prefer not to answer

2. Is English your first language?

- ☐ Yes
- ☐ No

3. Are you of Hispanic, Latino, or Spanish origin?

- ☐ No, not of Hispanic, Latino, or Spanish origin
- ☐ Yes, Mexican, Mexican Am., Chicano
- ☐ Yes, Puerto Rican
- ☐ Yes, Cuban
- ☐ Yes, another Hispanic, Latino, or Spanish origin
- ☐ Prefer not to answer

4. What is your race?

- ☐ White
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Chinese
- ☐ Vietnamese
- ☐ Native Hawaiian
- ☐ Filipino
- ☐ Korean
- ☐ Asian Indian
- ☐ Japanese
- ☐ Other Asian
- ☐ Some other race
- ☐ Prefer not to answer

5. What is your gender identity?

- ☐ Female
- ☐ Male
- ☐ Other
- ☐ Prefer not to answer

6. **Do you identify this business as a minority-owned business?**

The Small Business Association defines "minority businesses" as small businesses owned in 51% or more by minority individuals (Black, African American, Indian American, Asian, Asian Indian, Asian Pacific, Latinx or Hispanic) or by economically and socially disadvantaged individuals. This survey includes women-owned businesses within the "minority-owned businesses" denomination.

☐ Yes ☐ No

We would value any additional comments you may have about the content of this questionnaire. Please write them in the space below, and/or attach another page.

____

____

____

____

____

____

____

____

____

____

Thank you for your participation!

If you are willing to be contacted further about this topic, please provide the following information. *__We will only use this information for the purposes you authorize.__*

You [the UW research team] may contact me for the following purposes: *select all that apply.*

- ☐ To send me a $10 Amazon gift credit for completing the questionnaire *(__you must include your email below__)*
- ☐ If you have any questions about this study
- ☐ For a follow-up interview
- ☐ To send me a report of the study results

How would you prefer to be contacted? *Please provide all that apply:*

Email address ____

Telephone ____

Business name ____

Business Address ____

Business website (if applicable) ____

If you would like to refer us to other businesses you know, please share our email address: uw4leap@uw.edu

Appendix F

SURVEY COVER LETTER

Dear University District Business owner,

The U District has been an important foothold that brings the community together and creates vitality. Local businesses like yours have supported the neighborhoods, but we are aware that many of you have been significantly impacted by disruptions: not just COVID-related ones, but also building construction, extreme weather conditions, or other uncertain events. We hope to learn from your experience and insights so that we can recommend policies that will assist businesses like yours through tough times.

Your business has been selected from Google Map listings to help in this effort. Your individual responses are voluntary and will be kept strictly confidential. Your name is not on our mailing list, and your answers will never be associated with your business. The unique code appearing on the survey is used solely for identifying which business completed the survey. Once the survey is collected, the code will be deleted to maintain your privacy. Participating in this survey implies that you are 18 years old or older and agree with the stated terms of the research. This study has been reviewed and approved by the University of Washington Institutional Review Board.

Please have the business owner or current operator who makes day-to-day decisions participate in this survey. The survey should take you about 30 minutes to complete. Please mail the survey back to us using the enclosed postage-paid envelope.

As a token of our appreciation, we will send you a $10 Amazon.com gift e-credit for your completed and returned survey. If you are interested, we will also share with you the results of our study. If you have any questions about this study, or if you would instead prefer to invite other business owners to participate, please contact us by email at uw4leap@uw.edu or by phone at 206-543-3870.

Sincere thanks,

Grace Jia, Graduate Research Assistant, Civil & Environmental Engineering, University of Washington,
261 Wilcox Hall, Seattle, WA 98195

Prof. Cynthia Chen, Civil & Environmental Engineering University of Washington, 201 More Hall, Box 352700 Seattle, WA 98195

Katy Ricchiuto, Urban Vitality Manager, U District Partnership, 1415 NE 45th St # 401, Seattle, WA 98105

Appendix G

FOLLOW-UP INTERVIEW PROTOCOL

Thrust 2 Follow-up Interview Protocol

Apr, 2023

Instructions for interview moderator

This protocol serves as a tool for interviewing U-District business owners who returned their surveys. The focus of this interview is two-fold:

1. To present Thrust 2 recommended actions to the owners and inquire whether they consider the recommendations feasible during various disruptive events.
2. Understand what businesses would like to do under disruptive events. Especially focusing on the following three aspects:
    a. under what condition do they think it is necessary to make a change to their business?
    b. how much cost would they like to pay such that the changes can take place?
    c. under what conditions do they think it is no longer worth it to implement the changes anymore?

The protocol should be revised on a case-by-case basis such that it is consistent with the interviewee's survey response. For example, the disruptions listed in the section "survey response" should match what they filled out on Page 7 of the survey.

Introduction

Thank you for agreeing to participate in this interview. We appreciate your effort in filling out the survey and agreeing to meet with us to further discuss how can our research team help your business. The purpose of this interview is to gather information on various actions that we think, and more importantly, you think will benefit your business. The interview will take approximately 30 minutes, and we will take notes/recordings to ensure we don't miss anything.

Before we begin, please provide your consent to participate in this interview. Your name and your business name will not be associated with your response. Your participation is voluntary, and you can withdraw at any time.

Survey response

We sent you a survey asking how your business makes decisions given different types of disruptions, especially, you answered that some scenarios had happened within the last three years, and you did something in response to that disruption scenario and helped your business adapt. We will use made-up numbers to represent costs, profits, and cash flows in this section, and if you feel our number does not make sense, or you do not know what we are referring to, we are happy to clarify at any time.

1. Did not have enough money to purchase essential goods or hire employees
2. The products you need are out of stock
3. Not enough potential applicants for open employee positions
4. Did not have enough customers

5. Policy restrictions (i.e., social distancing)
6. Unsafe neighborhood due to drug use, crime, and/or vandalism.

First, you mentioned you did not have enough money to purchase essential goods or hire employees. Suppose you have a cash flow in mind that is usually enough for you to restock and hire employees when there are no disruptions.

- So what do you mean by not having enough money? What percentage of profit did you lose that makes you consider you do not have enough money?
- You mentioned that you introduced new goods or services to overcome this difficulty, can you elaborate on what you did?
    - [Possible answers to look for are any changes in what operation mode they open, redesigned menu items]
    - [If they answered new menu items, ask about whether the price was lower such that the items are more attractive to customers]
    - Response:
- How much loss, in percentage, in the available cash flow will make you think it is necessary to implement this decision?
    - [be mindful that the business could be barely above water meaning that it can not withstand any loss in that available cash flow]
    - Response:
- Did you implement this tactic after all?
    - If implemented:
        - There would be a cost associated with actions you take in difficult times like this. How much is the cost associated with “introducing new goods or services”, if any?
            - If there isn’t a concrete number, can you tell us what percentage of your cash flow you would like to invest?
        - In return, how much profit does this decision bring you?
        - Other than benefits in profit, are there other benefits (for example, providing working opportunities, and serving the neighborhood in difficult times)
    - If not implemented, what are the reasons that you don’t want to implement it? [Follow up on the reasons if needed]

- Disruptions may be better the next day or worse the next day, it is difficult for us to know ahead of time. Let’s imagine a difficult situation where the disruption keeps getting worse, and your profit keeps decreasing no matter how hard you tried. How much loss in profit will make you consider temporarily closing your business?