

Eating-out Behavior across Different Restaurant Segment Types: Implications for Transportation, Public Health, and Food Service Sectors

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ABSTRACT

This paper investigates the factors shaping dining-out preferences, focusing on the allocation of monthly weekday dinner occasions across four key restaurant segments: quick-service restaurants (QSRs), coffeehouses (CHs), casual-service restaurants (CSRs), and full-service restaurants (FSRs). The paper employs a Multiple Discrete-Count Extreme Value (MDCNTEV) modeling approach to analyze the data obtained from an online survey conducted in Texas in 2022. The findings reveal the compromises and considerations consumers make when determining their dining habits. Model estimation results indicate that frequent restaurant diners are white, affluent, single men, own multiple vehicles, and work full-time from a physical workplace location. There are also notable differences in those who tend to patronize different restaurant segments. QSRs attract younger, non-white, low-income individuals living with roommates, and residing in QSR-dense areas. CHs primarily draw in younger, non-white, working individuals. CSRs are favored by older individuals, single white women, car-less individuals, and residents of high-restaurant-density areas. FSRs are popular among non-white, high-income individuals. Our findings highlight the multifaceted interactions of demographic, socioeconomic, lifestyle, and location factors influencing consumer dining behavior, offering valuable insights for the transportation and urban planning, public health, and food service sectors.

Keywords: Consumer dining behavior; Teleworking; Built Environment; Multiple Discrete-Count Extreme Value model; Count model

1. INTRODUCTION

The past two decades have witnessed a significant shift in public sentiment toward eating out at restaurants. Previous research has shown that consumers prefer dining out not only because it is a convenient option, but also because it is a social and cultural activity that contributes to the overall well-being of individuals. In 2021, households spent 55% of their food budget on meals consumed outside of the home, resulting in the restaurant and food service industry earning over \$799 billion in sales (National Restaurant Association, 2022, U.S. Department of Agriculture, 2021). As the restaurant industry continues to grow, and as individual preferences pivot toward more dining out, restaurant choices are becoming more sophisticated and complex.

In today's market, consumers are presented with a range of restaurant segments, each offering distinct attributes, services, and environments that meet varying customer needs and expectations. These segments include fast-food restaurants (referred to as quick-service restaurants, or QSRs), casual service restaurants (or CSRs), and fine dining restaurants (referred to as full-service restaurants, or FSRs). In addition to selecting among the many restaurant segments, consumers also have to consider the different channels through which meals can be consumed, including in-person dining, in-person pickup, and delivery (see, for example, Dias et al., 2020, and Kim and Wang, 2021). Over the past decade, the popularity of pickup and delivery channels has increased tremendously due to the development of technology platforms, such as Uber Eats, DoorDash, and Grubhub. The COVID-19 pandemic in early 2020 further accelerated this growth due to restaurant closures, lockdowns, social distancing measures, and fear of infection (Ahuja et al., 2021, Shi and Xu, 2021).

Despite the decrease in demand for eating out during the height of the pandemic, in-person dining has mostly rebounded in the past couple of years to pre-pandemic levels. Extensive data collected between February 2020 and December 2022 reveals a sharp decrease in the percentage of in-person diners, with the lowest point occurring between April and May of 2020. However, this trend began to reverse gradually after the widespread administration of COVID-19 vaccines in 2021. Notably, since early 2022, the percentage of in-person diners has consistently matched that of 2019, the year preceding the pandemic (OpenTable, 2022). At the same time, Yelp's data corresponding to the first quarter of 2022 shows a remarkable 6,360% increase in online searches for indoor dining at restaurants compared to 2019 when indoor dining was the norm (Yelp, 2022). While Yelp's data represents consumer online search activity rather than actual dining behavior, the desire to eat out is clear. Overall, these industry and consumer statistics highlight the resiliency of in-person restaurant dining and further suggest that consumers still value the full restaurant experience, including social interaction, ambiance, and table service.

The renewed intensity of in-person restaurant dining (which we will also refer to as the "eat-out" channel in the rest of this paper), while clearly showing movement back toward pre-pandemic levels, has not been uniform across all restaurant segments. In particular, QSRs have recovered back to pre-pandemic level sales, but FSR and CSR sales have yet to fully recover. This discrepancy reflects dissimilarities across restaurant segments (Marchesi and McLaughlin, 2022), based on the unique experience afforded by each restaurant segment in the cognitive mind space of consumers. In this regard, both hedonic and utilitarian motives serve as a foundation to determine the overall value of the dining experience (Kim and Chung, 2011, Ryu and Han, 2010, Shin et al., 2019). Hedonic motives are pleasure-oriented and relate to the enjoyment derived from eating out, while utilitarian motives are function-oriented and associated with the cost, convenience, and accessibility of eating out (Kim and Chung, 2011, Ryu and Han, 2010, Shin et al., 2019). Of course, the precise boundary between hedonic and utilitarian motives may be blurred

in the sense that the motives may be characterized as a continuum in the mental map of consumers. In this continuum, QSRs appeal to utilitarian motives for dining out, through their emphasis on affordability, efficiency, and productivity rather than necessarily ambiance and other hedonic motives (Parsa et al., 2020). Accordingly, QSRs are typically chains that limit their menus to specific products that are prepared in a standardized manner to enable quick production (Canziani et al., 2016). At the other end of the spectrum, FSRs appeal more to the hedonic motives of individuals more so than mainstream utilitarian considerations, through their offering of the highest quality of service, ingredients, and atmosphere (Harrington et al., 2011, Canziani et al., 2016, Parsa et al., 2020). Menus are carefully designed by professional chefs and typically provide a large selection of alcoholic drink choices (Parsa et al., 2020, Walker, 2017). The service involves highly trained wait staff who are often formally dressed. In return, patrons are expected to maintain a certain dress code and cover a high check (Hwang and Ok, 2013, Parsa et al., 2020). Between the utilitarian and hedonic ends, lies the appeal of CSRs, which offer full-service dining with servers placing and serving the orders of seated diners. CSR prices are moderate and the atmosphere is informal, friendly, and laid-back (Hwang and Ok, 2013). Their menus are often diverse and include comfort foods, tried and true items, and limited alcohol options (Parsa et al., 2020, Walker, 2017). This segment includes a vast range of restaurants, such as ethnic, family, and midscale casual (Walker, 2017).

Clearly, each restaurant segment offers a distinct mix of utilitarian and hedonic stimulation through associated attributes, as also summarized in Table 1. At the same time, consumers too continually shift and adjust their desired mix of utilitarian and hedonic desires. This behavior is supported by the theory of “optimal arousal”, which suggests that repeated experiences in similar restaurant types can result in diminishing satisfaction due to decreasing marginal utility (Chua et al., 2020; Foxall, 1993, Lee et al., 2020). In fact, Jung and Yoon (2012) suggest that even highly satisfied customers still exhibit an intention to switch to other restaurants due to a variety-seeking orientation. Further, because different individuals will, in general, have different preferences for their respective utilitarian and hedonic desires, there will be heterogeneity across individuals in the intensity of variety-seeking (Ha, 2020). Furthermore, variety-seeking behavior persists across different financial situations. While some studies suggest decreased variety seeking among financially constrained individuals (see Fan et al. 2020), others have found evidence of consumer resilience and adaptive strategies. For instance, research has shown that consumers with low socioeconomic status who perceive low economic mobility may actually seek more variety as a coping mechanism to compensate for their low sense of personal control (see Yoon and Kim, 2018, and Hamilton et al., 2019). Overall, consumers patronize a “portfolio” (or bundle) of restaurant segments that, over a period of time, provide them optimal utility in their quest for fulfilling both utilitarian and hedonic desires. Such variety-seeking behavior also would imply that an exogenous variable that increases the choice of one particular segment while pulling away from other segments may also have a “push” effect. For example, an increase in the number of fast food restaurants in an individual’s residential neighborhood may increase fast food consumption, at the expense of consumption at other restaurant segments due to a “pull-based” substitution effect. But, because fast food restaurants are typically lower cost than other segments, and because of variety seeking, there may be an increase in total eat-out count. That is, a combination of income and variety-seeking effects can increase total eat-outs and “push” consumption toward other segments. Thus, in this situation, while the consumption of fast food will necessarily increase, the consumption of other segments may increase or decrease.

Motivated by the preceding discussion, in this paper, we estimate an individual-level portfolio choice model of restaurant segments over the period of a month as a function of individual/household demographics, employment characteristics, and residential built environment (BE) attributes while accommodating variety seeking and the bundled nature of the dining-out consumption behavior. Specifically, we develop a multivariate count model that produces as output the total monthly weekday dinner eat-out occasions (referred to as “total eat-outs”) of an individual as well the total eat-outs broken down by restaurant segment. The restaurant segments include (1) QSR (including food trucks), (2) coffee houses (CH), (3) CSR, and (4) FSR. The CH segment, while not discussed earlier, is considered a fourth segment, given the growing popularity of CHs.

The rest of this paper is structured as follows. The next section provides a brief overview of earlier relevant studies and positions the current study. Section 3 discusses the objectives and contributions of this research. Sections 4 and 5 present the methodology for the survey data collection process and modeling. Section 6 presents the estimation results. Section 7 discusses the magnitudes of impacts of variables on the outcomes and discusses policy implications related to transportation systems, urban planning, public health, and social equity. The final section concludes by summarizing our findings and discussing policy implications.

2. RELEVANT BACKGROUND

The past two decades have experienced a surge in research dealing with restaurants and eat-out activities, though not in the transportation field. DiPietro (2017), Rodríguez-López et al. (2020), and Rejeb et al. (2022) have recently conducted comprehensive bibliometric analyses of the related published academic research. Through a comprehensive review of the existing literature, we are able to group earlier studies into five distinct paths of analysis (A through E), as presented in Figure 1 and discussed below.

In general, almost all earlier studies examine factors that influence consumers' perceptions of restaurant-specific attributes (such as price, food quality, service quality, menu variety, and location in relation to the residential/work office location). Such relationships, which expressly consider the effects of consumer characteristics (that is, consider the individual-attribute link represented by Path C in Figure 1), and also sometimes control for event type (Path A) and restaurant segment (Path B), are estimated (imputed) from the choice of restaurant from a larger set of unlabeled restaurant alternatives, each with specific attributes (that is, by using the restaurant choice as the endogenous outcome; see bottom of Figure 1). The endogenous outcome itself in the studies may be in the form of the last eat-out occasion (see Chua et al. (2020) and Ha and Jang (2013)), typical eat-out occasion (see Harrington et al. (2011, 2013) and Olise et al. (2015)), or revisit intention when already at a restaurant (see Rajput and Gahfoor (2020), and Ryu and Han (2010)). A few studies have also used stated choice experiments, presenting two to three unlabeled restaurant alternatives with specified restaurant-specific attributes and asking respondents to pick one alternative (see, for example, Jung et al. (2015)).¹ Almost all these earlier studies, however, either consider (a) all restaurant segment categories together without distinguishing among

¹ Some studies in Paths A and B with restaurant choice as the endogenous outcome do not examine individual-level heterogeneity in the relative sensitivities across individuals in restaurant attributes. Similarly, there are studies that directly ask individuals to rank the importance of attributes they consider in making their restaurant choice, but do not consider heterogeneity in attribute selection/priority across individuals (that is, these studies ignore Path C -- the individual-attribute link; see, for example, Jang and Namkung, 2009 and Chua et al., 2020). We do not review such studies here, which tend to be descriptive rather than predictive. We only consider those studies that expressly consider Path C (that is, controlling for individual characteristics) as they study Paths A and B.

restaurant segments (that is, ignore Path B entirely – Group 1 studies), or (b) focus on only one specific restaurant segment (thus acknowledging the Path B “segment-attribute link”, but not modeling the choice of restaurant segment as a horizontal choice of all restaurant segments at once – Group 2 studies).²

2.1. Studies Ignoring Path B Entirely (Group 1)

An example of a study that did not differentiate restaurant segments is Choi et al. (2009), who reported significant differences based on consumer characteristics in the ranking of restaurant attributes. Specifically, Choi et al. (2009) revealed that taste, cleanliness, service quality, and menu healthiness were attributes that exhibited significant differences based on gender, with women expressing a stronger preference. Additionally, higher-income individuals placed greater emphasis on service quality and ambiance compared to lower-income consumers. Choi et al. also reported that the availability of healthy meals was significantly more important to older consumers. Another similar study by Alonso et al. (2013) also identified significant discrepancies in restaurant attribute preferences by gender and age. In particular, women placed more emphasis on service timeliness and the health aspects of menu items compared to men. Additionally, consumers aged 40 to 49 showed less sensitivity to the attribute of “A feeling of openness and space in a restaurant” compared to other age groups. However, income and education levels were not found to significantly impact restaurant attribute preference in the study. More recently, a 2016 survey in the U.S. found that younger individuals earning less than \$35,000 a year and living in a single-person household placed more emphasis on price, while older individuals earning a high income and residing in urban and suburban areas indicated a higher influence of service quality (Statista, 2016). Nevertheless, all consumers ranked food quality as the most significant restaurant attribute.

2.2. Studies Considering a Single Restaurant Segment (Group 2)

Another group of studies evaluated the effect of consumer characteristics on the importance levels of restaurant attributes for different restaurant segments separately. For example, Harrington et al. (2013) studied the importance of the various attributes in the context of QSRs by asking survey respondents to rank the importance of several selection factors. They found that younger individuals tend to place higher importance on price, value, and convenience, while older individuals prioritize food quality and ambiance to a greater extent (Harrington et al., 2013). In the context of CSRs, Duncan et al., (2015) classified older consumers as “Functional Feasters” who prioritize restaurant cleanliness and location over the quality of service and ambiance. Additionally, Harrington et al. (2011) found that gender and age significantly influence the importance of restaurant attributes in FSR settings. Women rated price, quality, and dietary attributes as substantially more important than men when selecting an FSR. Regarding age, older consumers placed a higher emphasis on reputation, quality, and ambiance factors rather than price, compared to their younger counterparts. Similarly, Ma et al. (2014) concluded, also in the context of the FSR segment, that women tend to assign higher ratings to factors such as food quality, service quality, and image compared to men. In contrast, Lee and Hwang (2011) did not find

² We are not aware of a study of restaurant attribute selection that considers consumer characteristics (that is, accommodates Path C effects), while also considering event type effects on restaurant attribute type choice (that is, Path A) or even restaurant segment choice (that is, Path D). Besides, from a predictive standpoint, considering event type in a model would require that event types themselves be predicted, which can be challenging given the vagaries of life events. So, in the rest of this review and paper, we will not focus on the effect of event type choice on restaurant attribute ranking (Path A) or restaurant segment choice (Path D).

significant gender differences in attitudes toward service quality at FSRs. However, their conclusion regarding age aligned with Harrington et al. (2011). Furthermore, Lee and Hwang investigated the effect of income on attitudes toward service quality attributes and found that low-income consumers generally hold more negative attitudes toward overall service quality at luxury restaurants, a distinction not examined by Harrington et al. (2013).

2.3. Critical Analysis of Existing Literature

The preceding sections have underscored the importance of distinguishing among restaurant segments when considering consumer heterogeneity in restaurant attribute preferences (that is, highlighting the importance of considering Paths B and C together). However, according to Ha and Jang (2013), given the overwhelming number of restaurant choice possibilities, consumers actually engage in a more rationally-bounded two-stage process when selecting restaurants in ways that align with their desired values. They initially identify and choose a specific segment that caters to their needs, preferences, and situational factors. Once a segment is chosen, consumers evaluate the attributes of the restaurants within that segment, with the evaluation process potentially varying based on the consumers' individual characteristics. This emphasizes that individual-level characteristics have a first precursor impact on restaurant segment choice (Path E in Figure 1 or the individual-restaurant segment link), and then, given the choice of a restaurant segment at any point in time (Path B), affect restaurant attribute preferences (Path C) leading up to a specific restaurant choice within the restaurant segment. This points to the importance of modeling Path E before moving to Paths B and C.

Surprisingly, there is little literature on Path E (the individual-restaurant segment choice link), which will be the focus of the current study. And the few studies that examine path E confine their attention to the QSR segment. For instance, Athens et al. (2016) and Moore et al. (2009) examined the influence of consumers' proximity to QSRs on the weekly frequency of fast-food dining, consistently finding a significant positive association between residential density/accessibility of QSR restaurants and QSR patronage. The Athens et al. study considered the self-reported weekly count of fast-food restaurant visits, while the Moore et al. study categorized the self-reported weekly count into the three categories of "never," " <1 time/week", and " ≥ 1 time/week". The former study did not investigate variations in dining frequency based on consumer demographic characteristics, while the latter found that white, higher income, and more highly educated participants were less likely to be influenced by proximity effects in their fast food consumption frequency. Similar to Athens et al. and Moore et al., AlTamimi et al. (2022) also used a categorical measure of fast food consumption, but in the form of two binary variables: whether or not there typically is a fast food intake one or more times a month, and whether or not there is a fast food intake one or more times in a day. AlTamimi et al. confined their analysis to younger adults between the ages of 20-35 years in the population of men in Saudi Arabia, and reported increased fast food consumption among older age individuals living with family, and with high education and income levels. In contrast to AlTamimi et al., Hidaka et al. (2018) examined weekly QSR patronage frequency, but specifically in the week prior to the survey (rather than in a typical week), in the three categories of "None," "Once a week", and " ≥ 2 times a week." While AlTamimi et al. focused on younger adults, Hidaka et al. confined their analysis to a sample of older (50-79 years of age) low-income adults. Their results revealed a positive association between highly educated employed women and their weekly fast-food consumption. The authors attributed these findings to the time poverty experienced by women because of their typically asymmetric share of domestic responsibilities.

The studies above have provided important insights regarding QSR patronage over either a week or a month. However, no study that we are aware of has focused on predicting the frequency of CSR and/or FSR visits. The general emphasis on the QSR restaurant segment in the literature is ostensibly because QSR is the restaurant category most tied to health-related concerns. However, from a broader transportation, public health, and restaurant service perspective, it is important to consider participation in each type of restaurant segment. Besides, as discussed in Section 1, each restaurant segment offers a distinct mix of utilitarian and hedonic stimulation, and so there is a clear need to recognize the “portfolio” (or bundled) nature of restaurant segment choices over a period of time, such as a month, rather than as a series of single discrete-choice decisions at each eat-out occasion.

3. OBJECTIVES AND CONTRIBUTIONS

This research introduces a novel approach to modeling individual dining behaviors. We develop an individual-level portfolio multivariate count model that estimates two key aspects of an individual's dining-out patterns: the total number of weekday dinner eat-out occasions per month, and how these occasions are distributed across different restaurant segments. The proposed model is explicitly based on the “optimal arousal” process underlying dining consumption. This, combined with the unique utilitarian/hedonic mix offered by each restaurant segment, leads to our formulation of the dining choice process as a deliberate “at-once” horizontal choice of a portfolio of restaurant segment participation occasions over a period of time. To do so, we employ the Multiple Discrete-Count Extreme Value (MDCNTEV) modeling approach recently proposed by Bhat (2022). The primary data for this study is obtained from a 2022 online survey collected in Texas and includes information on individuals’ food service venue choices for their eat-out dining occasions, as well as individual and household characteristics.

To our knowledge, this is the first study to consider the frequency of participation in each restaurant segment, while also accounting for variety-seeking and joint portfolio choice. In doing so, we acknowledge the heterogeneity across individuals in the preference for each segment, as well as in the variety-seeking behavior across segments. Also, in contrast to a multivariate count model that would mechanically stitch the counts of participation across different types of segments without considering variety seeking or complex income/substitution effects, we develop a model that accommodates both of these issues. In doing so, our study incorporates four key considerations. First, it expressly focuses on the eat-out (that is, dine-in at the restaurant) counts, because of the clear passenger travel demand and restaurant service impact of eat-outs. Second, it considers a monthly count of eat-outs by segment, which is better able to model the cardinal count of actual eat-outs rather than force the analyst to employ a bracketed representation of eat-outs when considering a weekly time period (because of the relatively few weekly episodes of eat-out). Third, the study implements the Multiple Discrete-Count Extreme Value (MDCNTEV) modeling framework (Bhat, 2022). This two-stage method initially addresses multiple discreteness by viewing consumer choice as a portfolio choice made within a specified time frame. Following this, the second stage assesses total demand as a cumulative count, representing the aggregation of all consumption events. Specifically, we focus on examining consumers’ discrete restaurant segment decisions over a single month, along with the number of their total monthly eat-out occasions. Fourth, in addition to presenting model estimates, our study extends the analysis to include “what-if” scenarios, quantifying the effects of variations in essential built-environment and sociodemographic variables on the overall frequency of dining out at restaurants and the distribution of restaurant visits across different segments. By conducting these analyses, we gain

insights into the implications of dining choices for the transportation and urban planning, public health, and food service fields. Specifically, from a transportation and urban planning perspective, it is important to understand that travel demand is fundamentally derived from the need to participate in activities distributed across space and time. Eating out is one such activity that generates significant travel demand. Consequently, models forecasting the total eat-out count by restaurant segment type can be used along with land-use models of restaurant locations by restaurant segment to better characterize the generation of eat-out trips as well as the location of eat-out trips. These models can be integrated into activity-based models that, for the most part, today either use an aggregate social/recreational activity purpose or an aggregate eat-out purpose without disaggregation by restaurant segment type. In addition, we consider the effects of a substantially changed landscape of work arrangements, as well as residential BE effects, on eat-out activity patterns. The consideration of BE effects provides insights into land-use and zoning policies. From a public health perspective, non-home-cooked meals are generally associated with poorer diet quality than home-cooked meals (see Wellard-Cole et al., 2022 for an extensive review). This is especially so for QSRs that typically offer affordable, but calorie-rich and nutrient-poor meals. Thus, the number of eat-outs and the patronage patterns by restaurant segment have implications for physical health. Models such as the one estimated here can, therefore, uncover health disparities, particularly among specific groups such as dual-earner couples, single mothers, individuals with lower income, and racial/ethnic minorities. From a food services standpoint, particularly after the onset of the pandemic, it is critical that restaurateurs and food service professionals understand the factors that drive consumers to eat out and influence their restaurant segment selection, so they can cater to their customer base and implement effective marketing strategies (Chua et al., 2020, Ha and Jang, 2013). Such insights, to be accurate, need to accommodate satiation effects in restaurant type choice, recognizing that decisions regarding segment choice are not single discrete choice occasions in a vertical process over time, but constitute a deliberate “at-once” horizontal choice of a portfolio of restaurant segment participation occasions over a period of time.

4. THE DATA

4.1. The Survey

The data for our analysis is obtained from a 2022 online survey undertaken between mid-February and mid-March in the state of Texas, U.S. The survey was restricted to Texas residents, and was promoted via e-mail to several chambers of commerce across the state of Texas, alongside other businesses, professional organizations, and media outlets, as well as a database of roughly 55,000 Texas residents’ email addresses. The survey collected detailed information about respondents’ individual and household socio-demographics, residential characteristics, employment arrangements, and perception of the threat of COVID-19, in addition to revealed preferences (RP) regarding weekday dinner eat-out activity participation over one month. Specifically, the survey asked the following questions to solicit the total count of monthly weekday dinner eat-out occasions (i.e. total eat-outs) and the count of eat-out occasions at each of the four different restaurant segments. The relevant survey questions include the following:

- In the past month, across weekdays (that is, not counting weekend trips), how many times did you go out to eat for dinner?
- Please break down your eat-out dinner occasions by restaurant type:
 - Fast food/food truck
 - Café/coffee shop

- Casual sit-in restaurant
- Fine/luxury dining restaurant

A total of over 1,479 responses were obtained through the survey effort. However, 387 individuals did not respond to the dining-related questions or provided a count that exceeded the number of weekdays in a month and/or did not provide information on basic socio-demographics and job-related questions. The final sample included 1,092 individuals.

4.2. Endogenous Outcome Variables

The endogenous outcome variables correspond to the monthly weekday dinner counts of eat-out by each of the four restaurant segments: QSR, CH, CSR, and FSR. Table 2 presents the distribution of total eat-outs for each of the four restaurant segments. The table shows that, among the 1,092 individuals in the sample, 284 (26.0%) individuals did not engage in any dinner eat-out activities over the course of the month prior to the survey. The statistics also reveal that irrespective of the total count of eat-outs (the x-axis in Table 2), the CSR segment is the most popular corresponding, on average, to 65% of eat-out activities, followed by the QSR segment, which, on average, accounts for 19% of the eat-out occasions.

Table 3 highlights the multiple discreteness in the data by examining the distinct number of different restaurant segments visited by individuals who eat out at least one time per month. Individuals who eat out frequently are more likely to diversify their restaurant choices and visit multiple segments. For example, 41.88% of those who eat out twice a month choose to visit two different restaurant segments, rather than always going to the same segment. While not shown in Table 3, the most visited restaurant segment pair among those who eat out twice a month corresponds to CSRs and QSRs. Additionally, people who eat out more than twice a month tend to spread their visits across a greater variety of restaurant segments. For example, people who eat out 11 or more times a month tend to visit at least three different restaurant segments, as indicated by the last two rows in Table 3. This is because individuals seek variety in their dining experiences, and want to explore different cuisines and styles of restaurants.

Given the retrospective nature of our survey, we acknowledge the potential for recall bias in reporting monthly weekday dinner eat-out occurrences across restaurant segments. However, we implemented several measures to mitigate this bias, aligning with established survey methods (see Groves et al., 2009, and Babbie, 2010). In this study, we focused on dinner eat-out occasions, which tend to involve more conscious decision-making between cooking at home versus eating out and are often for special occasions rather than simply fulfilling a biological need (Cadario and Morewedge, 2022). Therefore, it is likely that monthly dinner eat-out occasions would be easier to recall than other types of meals. Our survey also used precise language, asking about “times did you go out to eat for dinner” and included prompts for different restaurant types to aid memory retrieval. This approach, which asks about frequency for each restaurant segment separately, aligns with the recommendation by Groves et al. (2009), who provide an example of effective memory prompts: “The NCVS item on shopping tries to offer respondents help in remembering by listing various kinds of stores they may have visited (‘drug, clothing, grocery, hardware, and convenience stores’)....The best cues are the ones that offer the most detail, provided that the specifics in the cue match the encoding of the events.” By focusing on the “last month,” we aimed to minimize recall bias compared to longer retrospective periods or open-ended questions about general dining habits (as is the case in most published surveys). Additionally, to ensure the reliability of our data, we implemented rigorous quality control measures. This included removing responses submitted within two minutes of starting, based on a pilot experiment indicating a typical completion time

of 15-20 minutes. Additionally, we incorporated internal consistency checks in our survey, excluding responses where the reported number of meals fell outside the expected range of 1 to 22 (the number of weekdays in a month), ensuring consistency and reliability in our dataset.

Lastly, our findings align with national trends, though direct comparisons are not strictly possible due to survey data administration differences and national data not necessarily reflecting Texas-specific data. Our average of 3.42 dinner eat-outs per month is consistent with a 2022 survey reporting 3 dinner-time eat-outs per month (USFOODS, 2023). Furthermore, other surveys from 2016 and early 2022 found that 22% and 23.4% of Americans, respectively, never eat out at restaurants (see Statista, 2016, and YouGov, 2024). These figures are comparable to our 26% finding. While we cannot eliminate recall bias entirely, our approach incorporates several strategies recommended in the literature to mitigate its effects. Future research could consider complementary data collection methods, such as real-time logging or receipt collection, to further validate and enhance data accuracy.

4.3. Exogenous Variables

Several categories of exogenous variables are considered in our analysis. Individual-level demographics (gender, age, race/ethnicity, and education level), household characteristics (annual income, motorized vehicle ownership level, and household structure), employment status/job characteristics (not employed/part-time employed/full-time employed based on employment status and hours of work per week, self-employed or not, number of days of work per month, commute duration, and the fraction of work undertaken from a third workplace location and home), and COVID-19 threat/perspective variables were obtained directly from the survey responses.

The built environment (BE) factors of the residential location included three different sets of variables. The first set was obtained from the survey and involved the classification of residential neighborhoods into urban, suburban, or rural categories, as self-reported by respondents. A second set of BE variables was developed based on the home location zip code, which was recorded in the survey. These zip codes were mapped to census block groups (CBG), and then bestowed with built-environment (BE) attributes as obtained from the U.S. Environment Protection Agency (EPA) Smart Location Database (or SLD; see Chapman et al., 2021, and Ramsey and Bell, 2014). This second set of BE variables included employment and residential density, a walkability index (ranging from 0 to 20, based on a combination of intersection density, proximity to transit stops, and jobs-housing balance mix), and the proportion of employment in five sectors (retail (Ret), office (Off), industrial (Ind), service (Srv), and entertainment (Ent)). The latter employment-related variables were used to calculate a land-use mix diversity index ranging between 0 (low land-use diversity) and 1 (high land-use diversity), based on Bhat and Gossen (2004). The actual form of the land-use index is:

$$LUDI = 1 - \frac{\left| \%Ret - \frac{1}{5} \right| + \left| \%Off - \frac{1}{5} \right| + \left| \%Ind - \frac{1}{5} \right| + \left| \%Srv - \frac{1}{5} \right| + \left| \%Ent - \frac{1}{5} \right|}{\frac{8}{5}} \quad (1)$$

Finally, a third set of residential BE attributes was developed by the authors using a web-scraping approach to create a comprehensive database of restaurants across the state of Texas, along with their location and restaurant category from Yelp. From this compiled list, the total number of restaurants and the proportion of quick-service restaurants (QSRs), coffee houses (CHs), casual service restaurants (CSRs), and fine service restaurants (FSRs) were computed for

each zip code area. Our methodology involved compiling a list of all Texas cities and towns and then using the Yelp API to search for restaurants in these locations. We extracted zip codes and tags related to restaurant price and type. The categorization was as follows: Restaurants tagged as “Fast Food” were classified as QSRs; establishments tagged as “Coffee,” “Coffee & Tea,” or “Coffee Roasteries” were categorized as CHs; restaurants with more than three dollar (\$\$\$) signs in their pricing were considered FSRs; and all other restaurants not falling into the above categories were classified as CSRs. For more information, readers can refer to the Yelp API documentation (Yelp, 2024). Additionally, data scraped from Areavibes.com was used to assess the livability and amenities of each zip code area (AreaVibes, 2023). The Livability Score, which ranges from 0 to 100, assesses the quality of an area based on amenities, cost of living, crime rates, employment density, housing affordability, school quality, and general public ratings. Higher scores indicate a better quality of life. It is important to note that this score was not calculated by the authors but were obtained directly from the AreaVibes platform.

Table 4 presents the socioeconomic and demographic characteristics of the sample. The table also provides statistics corresponding to the State of Texas to compare the analysis sample to the general population demographics. The population statistics are obtained from the five-year estimates from the 2021 American Community Survey (ACS) and the 2020 Texas Census. In cases where the State of Texas values are not readily available, there is a “--” in the table. The data in the table illustrates that certain demographic groups are overrepresented in our sample, including women, individuals aged 50 or older, white individuals, those with higher levels of education, and those from households with high income and high motorized vehicle ownership (in the rest of this paper, we will use the label “vehicle ownership” to refer to motorized vehicle ownership). The sample also includes a higher proportion of couples without children. Regarding employment status, our sample's non-employment rate (21%) closely mirrors the non-employment rate of the Texas population (24%). On the other hand, our sample includes a lower percentage of part-time employees (4.6% in our sample versus 14.9% in the Texas population) and a higher percentage of full-time employees (74.4% in our sample versus 61.1% in the Texas population).³ Despite these differences, our sample's average commute time to work (22.8 minutes) and average number of work days per month (21.5 days) are comparable to the corresponding population averages of 26.6 minutes and 22 workdays, respectively.⁴

It is unsurprising that certain sociodemographic groups are overrepresented in the sample. This may be attributed to the survey being distributed online and through professional organizations, which will attract individuals who are highly educated, have high incomes, and are part of the full-time workforce. Additionally, selection bias is also likely to have played a role, as individuals with strong opinions on the survey's main topic (the impact of COVID-19 on workplace choices) may be more inclined to participate. These individuals are expected to have white-collar jobs that offer workplace flexibility and are associated with higher education and income levels. Given the deviation from population statistics, caution should be exercised when generalizing descriptive statistics for endogenous outcome variables. However, our objective is not to estimate descriptive statistics for the population of Texas, but rather to determine how changes in exogenous factors related to demographics, households, work, COVID-19 perspectives,

³ Part-time workers are those who work 30 hours or less per week, while full-time workers are those who work more than 30 hours per week.

⁴ The commute time here refers only to those employed individuals with a designated out-of-home work office (or simply “office” for short from hereon) that they commuted to at least occasionally in the month. The Texas mean of 26.6 minutes also refers to only those who had a designated office and commuted at least occasionally to that office.

and built-environment affect dining behavior outcomes. Moreover, within the exogenous variables used in our analysis, there is substantial variability in the demographic categories such that each segment of the population is reasonably represented. Therefore, for our case where we estimate causal effects using data obtained through exogenous sampling (that is, not based on endogenous sampling as would be the case if our survey were administered among patrons at restaurants), an unweighted estimation procedure is appropriate (see Wooldridge, 1995 and Solon et al., 2015 for an extensive discussion of this point).

Lastly, Table 5 summarizes the descriptive statistics for the BE variables included in our analysis. The majority of these variables are continuous, and for these, we report the mean, standard deviation, minimum, and maximum values. For the residential area type categorical variable, we provide the frequency and relative frequency of respondents living in rural, suburban, or urban areas.

5. METHODOLOGY

In this paper, we employ an “at-once horizontal choice” approach recently proposed by Bhat (2022). This approach, originating from a utility-theoretic framework, is based on the notion that consumers seek a social-psychological sense of “optimal arousal” in restaurant food consumption patterns based on stability (psychological security) as well as change (novelty). Accordingly, the model structure includes two components. The first component is a total count model, framed within a generalized ordered-response (GOR) framework. A linking function from the second fractional split multiple discrete-continuous (MDC) model component appears in this total count model. This linking function allows for the total count of eat-outs to increase in response to an increase in the preference for any single restaurant segment, as discussed earlier. In the second MDC model component, the discrete component corresponds to whether or not an individual has a non-zero eat-out occasion at each restaurant segment, and the continuous component refers to the proportion of eat-out occasions allocated to QSRs, CHs, CSRs, and FSRs, over a specific time period.

5.1. Reverse Gumbel MDCEV Model of Fractional Split Model (RG-MDCEV)

The RG-MDCEV model represents the second stage of the two-stage budgeting framework. For an individual with a positive count of eat-out occasions, the amount of occasions allocated to each alternative k (i.e. restaurant segment) is modeled using the following functional form for utility (Bhat, 2022):

$$U(\tilde{\mathbf{f}}) = \sum_{k=1}^K \gamma_k \psi_k \ln \left(\frac{\tilde{f}_k}{\gamma_k} + 1 \right) \quad (2)$$

$$s.t. \sum_{k=1}^K \tilde{f}_k = 1$$

In the above function, we suppress the index for individuals. $U(\tilde{\mathbf{f}})$ is a quasi-concave, increasing, and continuously differentiable utility function, and $\tilde{\mathbf{f}} = (\tilde{f}_1, \dots, \tilde{f}_K)'$ is a $(K \times 1)$ -vector representing the fraction of the total eat-out count allocated to each restaurant segment k with $0 \leq \tilde{f}_k \leq 1$ for all k . In the context of this paper, $K=4$ for the four restaurant segments of QSR, CH, CSR, and FSR. The ψ_k parameter ($\psi_k > 0$) represents the baseline marginal utility at the point of zero eat-outs at restaurant segment k , while the γ_k parameter allows for corner solutions (zero

patronage for restaurant segment k) as well as accommodates satiation effects. The baseline marginal utility, ψ_k , is parameterized as follows:

$$\psi_k = \exp(\boldsymbol{\beta}'\mathbf{z}_k + \varepsilon_k) = q_k \exp(\varepsilon_k), \text{ where } q_k = \exp(\boldsymbol{\beta}'\mathbf{z}_k), \quad (3)$$

and \mathbf{z}_k is an $(L \times 1)$ -vector which includes the individual-specific attributes (including a constant) that are relevant in the individual's evaluation of alternative k , and $\boldsymbol{\beta}$ is a corresponding $(L \times 1)$ -vector of coefficients to be estimated. ε_k is an error term representing idiosyncratic (unobserved) characteristics impacting the baseline utility of alternative k , assumed to follow an independent and identical distribution (across individuals and alternatives) with a reverse Gumbel $(0, \kappa)$ distribution.⁵ The exponential form is utilized to ensure the positivity of baseline utility.

We also consider heterogeneity in the MDC satiation parameters (the γ_k parameters) by parameterizing as follows:

$$\gamma_k = \exp(\boldsymbol{\mu}'\boldsymbol{\omega}_k), \quad (4)$$

where $\boldsymbol{\omega}_k$ is a vector of decision maker-related characteristics and $\boldsymbol{\mu}$ is a vector to be estimated (note that $\gamma_k > 0 \forall k$). A positive element in $\boldsymbol{\mu}$ implies that an increase in the variable has the effect of increasing the γ_k parameter and decreasing satiation (that is, increasing repeat visits of the individual to restaurant segment k), while a negative parameter has the effect of decreasing the γ_k parameter and increasing satiation (that is, decreasing repeat visits of the same individual to restaurant segment k). To determine the optimal distribution of consumption across restaurant segments, we employ a mathematical optimization approach. This involves constructing the Lagrangian function and deriving the first-order equations based on the Karush-Kuhn-Tucker (KKT) conditions. In our model, we designate one restaurant segment (let's call it segment 1) as a baseline, assuming it receives some non-zero fraction of consumption. This assumption is valid because our second-level model is predicated on a positive eat-out count. In particular, designate restaurant segment 1 as a purpose to which the individual allocates some non-zero fraction of consumption (at least one restaurant segment must be chosen for consumption because this second-level model is contingent on a positive eat-out count). The fractional consumption of the first alternative is automatically determined from that of other inside alternatives as $\tilde{f}_1^* = 1 - \sum_{k=2}^M \tilde{f}_k^*$.

Then, the probability expression for the fractional allocation pattern with the first M restaurant segments being consumed at levels \tilde{f}_k^* ($k = 2, 3, \dots, M$) and the remaining restaurant segments see zero patronage; i.e., $\tilde{f}_k^* = 0$ ($k = M + 1, M + 2, \dots, K$); is (see Bhat, 2022):

⁵ Unlike the prior formulation in Bhat (2022) where the scale of the error terms in the baseline preference parameters was normalized to one, in this paper, we relax the scale parameter to be freely estimated. This results in superior model performance in terms of goodness-of-fit measures and forecasts.

$$\begin{aligned} & \text{Prob}[\tilde{f}_2^*, \tilde{f}_3^*, \dots, \tilde{f}_M^*, 0, 0, \dots, 0] \\ &= \frac{|J|(M-1)!}{\kappa^{(M-1)}} \left[\frac{\exp\left(\sum_{i=1}^M \left(\frac{V_k}{\kappa}\right)\right)}{\left(\sum_{k=1}^M \exp\left(\frac{V_k}{\kappa}\right)\right)^M} + \sum_{D \subset \{M+1, M+2, \dots, K\}, |D| \geq 1} (-1)^{|D|} \frac{\exp\left(\sum_{i=1}^M \left(\frac{V_k}{\kappa}\right)\right)}{\left(\sum_{k=1}^M \exp\left(\frac{V_k}{\kappa}\right) + \sum_{k \in D} \exp\left(\frac{V_{k0}}{\kappa}\right)\right)^M} \right] \\ & \text{where } |J| = \left(\prod_{i=1}^M c_i\right) \left(\sum_{i=1}^M \frac{1}{c_i}\right), \text{ where } c_i = \left(\frac{1}{\tilde{f}_i^* + \gamma_i}\right), \text{ and} \end{aligned} \quad (5)$$

$$V_k = -\beta' \mathbf{z}_k + \ln\left(\frac{\tilde{f}_k^*}{\gamma_k} + 1\right) \quad (k = 1, 2, 3, \dots, K), \text{ and } V_{k0} = -\beta' \mathbf{z}_k \quad (k = 1, 2, 3, \dots, K).$$

D in the above equation represents a specific combination of the restaurant segments appearing in parenthesis, and $|D|$ is the cardinality of the specific combination D . The probability that all the inside restaurant segments see some patronage at fractional levels $\tilde{f}_2^*, \tilde{f}_3^*, \dots, \tilde{f}_K^*$ is:

$$P(\tilde{f}_2^*, \tilde{f}_3^*, \dots, \tilde{f}_K^*) = \frac{|J|(M-1)!}{\kappa^{(M-1)}} \frac{\exp\left(\sum_{i=1}^K \left(\frac{V_k}{\kappa}\right)\right)}{\left(\sum_{k=1}^K \exp\left(\frac{V_k}{\kappa}\right)\right)^K} \quad (6)$$

The probability that none of the restaurant segments, except the first one, are consumed is:

$$P(0, \dots, 0) = 1 + \sum_{D \subset \{2, \dots, K\}, |D| \geq 1} (-1)^{|D|} \frac{e^{\left(\frac{V_{10}}{\kappa}\right)}}{\left(e^{\left(\frac{V_{10}}{\kappa}\right)} + \sum_{k \in D} e^{\left(\frac{V_{k0}}{\kappa}\right)}\right)}. \quad (7)$$

The model's estimation process involves determining the values of three sets of parameters: the β vector, the $\gamma = (\gamma_1, \gamma_2, \dots, \gamma_K)$ vector, and the κ scalar. Since the MDCEV fractional model shares some parameters with the total budget model, we defer a detailed discussion of the estimation procedure to Section 5.4.

5.2. Linking with the Fractional Split Model

Linking the fractional split model, which is concerned with the allocation of goods (i.e. restaurant segments) within the commodity group of interest (i.e. eat-outs), with the total eat-outs count model in a single framework requires a specialized function that reconciles the theoretical and empirical preliminaries of both these model components in a utility consistent manner. Bhat (2022) derives the appropriate structure of this link function, which takes the following form (see Bhat, 2022 for details of this derivation):

$$\Lambda = \kappa \ln \left[\sum_{k=1}^K \left[q_k^{1/\kappa} \exp(\tau_k) \right] \gamma_k \right], \quad (8)$$

where τ_k is another set of standard reverse Gumbel stochastic terms allowing unobserved heterogeneity (across individuals) in the linkage function (we use a different set of error terms τ_k

above than the error terms ε_k in Equation (3) to obtain a closed-form integrated model by avoiding unobserved correlations across the MDC fractional split model and the total count model discussed in the next section).

5.3. The Total Count Model

The modeling framework used for analyzing individuals' monthly eat-out frequency takes the form of a Count Model proposed by Castro et al. (2012) (also see Bhat et al., 2015). Castro et al. (2012) show that a Poisson count regression model can be considered a special case of a Generalized Ordered-Response Probit (GORP) that allows for more flexibility compared to the ordinary Poisson model. This section discusses the mathematical formulation for the Multivariate Count Model and formulates the linkage with the fractional split model.

Let ℓ ($\ell = 0, 1, 2, \dots, \infty$) be the frequency of total monthly eat-outs for an individual. The utility maximization process underlying the fractional split model gets linked to the count model by embedding the Λ linkage function from Equation (8) into the latent continuous stochastic propensity y^* that is associated with the count variable (see Bhat, 2022):

$$y^* = \theta\Lambda - \zeta, \quad y = \ell \text{ if } \Theta_{\ell-1} < y^* < \Theta_\ell, \quad \Theta_\ell = f_\ell(\mathbf{x}) + \sum_{j=0}^{\ell} \alpha_j, \quad \ell \in \{0, 1, 2, \dots, \infty\} \quad (9)$$

In the above equation, y^* is a latent continuous stochastic propensity variable associated with the count variable that maps into the observed count ℓ through the Θ vector (which is a vertically stacked column vector of thresholds $(\Theta_{-1}, \Theta_0, \Theta_1, \Theta_2, \dots)'$; $\Theta_{-1} = -\infty$; $-\infty < \Theta_0 < \Theta_1 < \Theta_2 < \dots$). θ is the linking parameter. ζ is a random error term assumed to be reverse Gumbel distributed with scale $\theta\kappa$. $f_\ell(\mathbf{x})$ is a non-linear function of a vector of individual-specific variables \mathbf{x} (\mathbf{x} includes a constant), and the α terms are threshold shifter parameters to be estimated to accommodate high or low probability masses (spikes and dips) for specific count outcomes without the need for using zero-inflated or related mechanisms in multi-dimensional model systems ($\alpha_{-1} = -\infty$ and $\alpha_1 = 0$

for identification). Also, let $f_\ell(\mathbf{x}) = -S_\zeta^{-1} \left(e^{-\lambda(\mathbf{x})} \sum_{j=0}^{\ell} \frac{[\lambda(\mathbf{x})]^j}{j!} \right)$, where $S_\zeta^{-1}(\tilde{t}) = \theta\kappa \{ \ln[-\ln(\tilde{t})] \}$ is

the inverse survival function of the reverse Gumbel with scale $\theta\kappa$, and $\lambda(\mathbf{x}) = e^{\boldsymbol{\varpi}'\mathbf{x}}$ ($\boldsymbol{\varpi}$ is a coefficient vector to be estimated). Accordingly, the thresholds in Equation (9) take the following form:

$$\Theta_\ell = -S_\zeta^{-1} \left(e^{-\lambda(\mathbf{x})} \sum_{j=0}^{\ell} \frac{[\lambda(\mathbf{x})]^j}{j!} \right) + \sum_{j=0}^{\ell} \alpha_j, \text{ with } \alpha_j = 0 \text{ if } j > L^*, \quad (10)$$

where L^* represents an appropriate count level, which is determined based on the empirical context of the study.

By incorporating Λ from Equation (8) in y^* in Equation (9), we get:

$$y^* = \theta\kappa \ln \left(\sum_{k=1}^K (q_k^{1/\kappa} \exp(\tau_k)) \gamma_k \right) - \zeta = -\theta\kappa \left[\zeta^* - \ln \left(\sum_{k=1}^K a_k \exp(\tau_k) \right) \right], \quad a_k = q_k^{1/\kappa} \gamma_k, \quad (11)$$

where ζ^* is now a standardized reverse Gumbel distributed variable. A normalization needs to be made in the above count model specification because the scale $\theta\kappa$ is not identified (that is, it can be set to any value). But the scale of the MDC error term κ is estimable from the fractional split model. In this paper, we achieve identification by setting the linking parameter $\theta = \exp(1) = 2.718$. Also, Bhat (2022) derived the properties of the error term distribution of $\delta = \theta\kappa \left[\xi - \ln \left(\sum_{k=1}^K a_k \exp(\tau_k) \right) \right]$, which he labeled as a minlogistic distribution. Based on this minlogistic distribution, the probability of an individual with a count value of ℓ is:

$$\begin{aligned} \text{Prob}[y = \ell] &= \text{Prob}[\Theta_{\ell-1} < (-\delta) < \Theta_{\ell}] \\ &= \text{Prob}[-\Theta_{\ell-1} > (\delta) > -\Theta_{\ell}] \\ &= \left[\frac{1}{\prod_{k=1}^K \left(1 + a_k e^{-\left(\frac{\Theta_{\ell}}{\theta\kappa}\right)} \right)} \right] - \left[\frac{1}{\prod_{k=1}^K \left(1 + a_k e^{-\left(\frac{\Theta_{\ell-1}}{\theta\kappa}\right)} \right)} \right]. \end{aligned} \quad (12)$$

The expression is dependent on both the fractional split model as well as count model parameters (the fractional split parameters are embedded in a_k ; $a_k = q_k^{1/\kappa} \gamma_k = \exp\left(\frac{\mathbf{b}'\mathbf{z}_k}{\kappa}\right) \gamma_k$).

5.4. Estimation

As mentioned in the previous section, using τ_k instead of ε_k in the linking function results in the independence of error terms in the total count and the fractional split models. Consequently, the likelihood function for an individual with a count value of g ($g > 0$), and consuming the first M goods at levels \tilde{f}_k^* ($k = 2, 3, \dots, M$), may be obtained from Equations (5) and (12) as follows:

$$\begin{aligned} L(\mathbf{\beta}, \mathbf{\mu}, \mathbf{a}, \mathbf{w}, \kappa) &= \text{Prob}[y = g, \tilde{f}_2^*, \tilde{f}_3^*, \dots, \tilde{f}_M^*, 0, 0, \dots, 0], g > 0 \\ &= \left\{ \text{Prob}[y = g] \times \text{Prob}[\tilde{f}_2^*, \tilde{f}_3^*, \dots, \tilde{f}_M^*, 0, 0, \dots, 0] \right\}, g > 0 \end{aligned} \quad (13)$$

Similar likelihood expressions may be derived for the case when all K restaurant segments are consumed, and none of the restaurant segments except the first are consumed. For the case of zero total eat-outs, the likelihood function is:

$$L(\mathbf{a}, \mathbf{w}, \kappa) = \text{Prob}[y = 0] = \left[\frac{1}{\prod_{k=1}^K \left(1 + a_k e^{-\frac{\Theta_0}{\theta\kappa}} \right)} \right]. \quad (14)$$

6. EMPIRICAL RESULTS

In the empirical specification process, we investigated different functional forms and combinations of explanatory variables. For variables in bracketed form (age and income) and those naturally discrete (gender, race/ethnicity, education level, motorized vehicle ownership level, household

structure, employment status, self-employed status, and urban/suburban/rural residential living, count of workdays per month, and COVID perspectives/threat variables), dummy variables were created in the most disaggregate form possible, and progressively combined based on statistical tests to yield parsimonious specifications. For variables in continuous form (commute duration, fraction of work days worked from home, fraction of work days worked from a third workplace, residential and employment density, walkability index, land-use diversity index, number of restaurants by type per square area in the zip code of the respondent's residence, and fraction of fast food eateries), various functional forms were tested, including a continuous linear form, a continuous logarithm form, a piece-wise linear form, and a set of dummy variables for different ranges. But the non-linear dummy variable form outperformed the linear form in terms of data fit, except for the fraction of workdays from home, land-use mix, walkability index, restaurant density, and proportion of restaurant segments. Further, we examined a number of interaction effects across variables, including single women interacted with children of different age groups and employment status of adults in the household interacted with children. However, none of such interaction effects turned out to be statistically significant, even at a t-statistic threshold of 1.00 to retain variables (corresponding to a 0.32 level of significance or 68% confidence level).

The final linked model specification is presented in Table 6. As may be observed from the table, not all variables included in the model are statistically significant at a 95% confidence level. This is to acknowledge the relatively small sample size of our estimation that may have led to the marginal significance of some of the variables, which nonetheless can provide valuable insights for future investigations with larger sample sizes. Also, we use the label “na” in Table 6 to indicate that the corresponding endogenous outcome alternative is the base category when representing the effects of exogenous variables. In contrast, a “—” is used to signify that a variable is not statistically significant for a given alternative. Finally, an exogenous variable affecting the baseline preference or satiation for any alternative in the MDC model also indirectly affects the total count of eat-out through the linking function. In addition, the same exogenous variable may also have an additional direct effect through inclusion in the count model.

The exogenous variables in the model are arranged vertically in Table 6, while the parameters of the baseline utility and satiation components of the MDC model, and the count model parameters, are organized in columns. The parameter estimates for the MDC baseline marginal utility present the impact of variables on the logarithm of the baseline preference (that is, represent elements of the β vector), and accommodate heterogeneity across individuals in the baseline preference function. The satiation model estimates (elements of the μ vector), which allow for heterogeneity in the MDC satiation parameters, are also presented in Table 6. The exogenous effects in the count model correspond to the non-constant elements of the ω vector. These represent direct effects on the count model, after accommodating any indirect effects through the linking function. In terms of the direct effects, a positive coefficient in ω shifts the threshold toward the left of the propensity scale, which has the effect of reducing the probability of the zero-eat-out outcome (increasing the overall probability of the non-zero eat-out outcome).⁶ A negative coefficient, on the other hand, shifts the threshold toward the right of the propensity

⁶ Note that $f_i(\omega) = -S_\zeta^{-1} \left(e^{-\lambda} \sum_{j=0}^{\ell} \frac{\lambda^j}{j!} \right)$, with $\lambda = e^{\omega'x}$. Thus, if an element of ω is positive, it decreases $e^{-\lambda} \sum_{j=0}^{\ell} \frac{\lambda^j}{j!}$, increases $S_\zeta^{-1} \left(e^{-\lambda} \sum_{l=0}^{\ell} \frac{\lambda^l}{l!} \right)$, and therefore decreases $f_i(x)$.

scale, which has the effect of increasing the probability of the zero eat-out outcome (decreasing the overall probability of the non-zero outcome).

The bottom of Table 6 provides the constant estimate in the $\boldsymbol{\omega}$ vector, and the elements of the threshold shifter terms (elements of the $\boldsymbol{\alpha}$ vector) embedded in the thresholds of the count model. The constant does not have any substantive interpretation, except for mapping the latent propensity optimally to the observed counts, given the coefficients on other variables embedded in the threshold function. Similarly, the threshold shifter elements of the vector $\boldsymbol{\alpha}$ also do not have any substantive interpretation, though they provide flexibility in the count model to accommodate high or low probability masses for specific outcomes. In the current empirical analysis, the best specification was reached with eight threshold shifter terms that are listed toward the bottom of Table 6. The large positive value for the first threshold reflects the large share of individuals who have zero monthly eat-out occasions. Also, the large negative threshold between the counts of 14 and 15 adjusts for the small share of individuals reporting 14 eat-out occasions and a rather large share reporting 15 eat-out occasions (potentially due to rounding in recollection and/or self-reporting). Finally, the linking function coefficient is normalized as discussed in Section 5.3, and the scale of the error terms in the MDC model is estimated. These are provided toward the bottom of the table. Note that, because of the linking coefficient, a shift in a variable that positively impacts the baseline preference or the satiation parameter of any MDC alternative (that is, increases the consumption of any MDC alternative) has the effect of increasing total eat-out count too, an effect we discuss further in Section 7.2. In the rest of this section, we discuss the effects of exogenous variables on the baseline preference/satiation components of the MDC model and on the total eat-out count model (to conserve on space, and also because the model estimates themselves did not show too much differences between the linked and unlinked models, we relegate the table containing the unlinked model estimates to Appendix A; however, we briefly discuss the different implications of the linked and unlinked models toward the end of Section 7.2).

6.1. Exogenous Variable Parameter Estimates

6.1.1. Individual Demographics

Based on the MDC component results in Table 6, middle-aged (49-64 years) and senior adults (65 years or older), relative to their younger peers, generally exhibit a reduced preference for quick service restaurants (QSRs), coffee houses (CHs), and casual service restaurants (CSRs), a relationship that is consistent with earlier studies (see, for example, Fryar et al., 2018, Slack et al., 2021, and Wolfson and Bleich, 2015). For instance, Fryar et al. (2018) examined fast food consumption in American adults using National Health and Nutrition Examination Survey (NHANES) data between the years 2013 and 2016 and found that 44.9% of younger adults aged 20-39 reported consuming fast food, compared to 37.7% of middle-aged adults, and only 24.1% of older adults aged 60 and over. Possible reasons for this age-related effect include concerns over health and nutrition (Hiza et al., 2013), as well as a preference for higher quality and more socially-oriented dining experiences (Harrington et al., 2011). Additionally, our results regarding CH preferences align with the findings of the National Coffee Association, which indicate that younger generations are more interested in specialized coffee houses that offer innovative and premium coffee products compared to older generations (National Coffee Association, 2020). In addition to offering food and beverage, CHs also serve as a popular third workplace location (Ferreira et al., 2021). Interestingly, middle-aged and senior adults have less satiation in CSR consumption (higher CSR monthly participation occasions) if they partake at all in CSR consumption. In terms of the total eat-out count model, the absence of a direct association between age and the frequency of

eating out may be indicative of dining out becoming an integral part of modern-day life for individuals, irrespective of age (Haddad et al., 2023).

The race-based effects reveal a lower inclination to dine out at the CSR segment for people of color compared to white individuals. But, when the walkability of the residential neighborhood is interacted with race, we find that the overall negative effect for CSR preference among people of color, while still existent, gets tempered (note that that range of the walkability index/100 variable is between 0 to 0.2). One explanation is that walkable neighborhoods are generally associated with good CSR dining options (see Baobeid et al., 2021), as well as good racial diversity in the resident population. Thus, while several ethno-racial studies have reported biased treatment of racial minorities at restaurants (Billingsley, 2016, Brewster and Heffner, 2021), as also suggested by the lower participation of non-white individuals in total eat-outs from our count model results in Table 6, the combination of good CSR dining options and racial diversity in areas of good walkability may provide a more positive dining environment for all individuals. These results highlight the intricate interplay of race, exposure, and cultural factors in shaping restaurant preferences and the frequency of eating out.

Formal education degree attainment has no effect on restaurant segment choice, but indicates more zero total eat-outs among those who have attained a graduate degree, consistent with the results from Mills et al. (2018) and Haddad et al. (2023). Many previous studies have reported that higher educational attainment leads to higher food literacy and heightened health consciousness, leading to more home-cooked meal consumption relative to non-home-cooked meal consumption (Krause et al., 2018, Nogueira et al., 2016).

6.1.2. Household Characteristics

While educational attainment does not directly influence individuals' preferences for specific restaurant segments, income is a key factor that drives such preferences. Overall, the many income-related coefficients indicate a strong preference for the FSR restaurant segment among those with an annual household income of \$100,000 or more, a clear sign of hedonic pursuits associated with a desire for (and projection linked to) luxury, exclusiveness, sophistication, and power signaling of social status and wealth (Kraus et al., 2017, Sung and Huddleston, 2018). The satiation and total count model specifications also demonstrate a direct positive and consistent association between income and the extent of eating out, attributable to the greater purchasing power of high-income individuals and their inclination to invest in the added convenience and time-saving benefits offered by non-domestically prepared meals (Clifford Astbury et al., 2020, Spurlock et al., 2020).

Vehicle ownership is another significant factor in determining restaurant segment preferences, though not total eat-out count. Households owning two or more vehicles have a higher baseline reference for QSRs and CHs for weekday dinners, compared to those with less than two vehicles. Households with more vehicles may prioritize speed and convenience in their general lifestyle, including in their meal choices, consistent with the attribute offerings of QSRs and CHs (see Table 1).

In terms of household structure, relative to single men, women and those from multiple related adult households (including two-adult and other types of joint families, but mainly two-adult households) appear to be less satiated (more participation occasions conditional on participation) in the CSR restaurant segment (for women) and the QSR segment (for those from multiple related adult households). Also, both single women and those from multiple adult households are less likely to have eat-out episodes than single men. The latter result is consistent with earlier studies. Women tend to eat less outside the home (and more home-cooked meals)

because of their greater health and diet consciousness, attributable in part to a higher body shape/image emphasis placed by society on women as well as women's higher priority to mental, emotional, physical, and spiritual well-being (Bärebring et al., 2020, Marques-Vidal et al., 2015, Pop et al., 2021). Furthermore, single women may feel particularly vulnerable dining out alone in the evening (Brown et al., 2020, Lahad and May, 2017). The finding that individuals living in households with multiple related adults tend to eat out less has also been reported in earlier studies, and ascribed to the cultural norm of viewing the dinner meal as an in-home family gathering event (Fulkerson et al., 2011) and/or to the time-cost efficiency gains of cooking at home by collectively allocating income, time, and market goods and services (see Stewart and Yen, 2004). Also, the results in Table 6 reveal that individuals from households composed of two or more unrelated adults (e.g., roommates) are more likely than individuals from other (related adult or single adult) households to dine at QSRs, though satiation effects seem to set in sooner among such individuals for QSRs. Financial constraints may be responsible for the QSR baseline preference, as individuals living with roommates typically have limited resources and may be looking for a more affordable option for dining out. At the same time, such individuals may also be seeking more variety in restaurant segments because of the diversity in their social dining company, resulting in a distribution of dinner eat-out meals across multiple restaurant segments. Regardless of restaurant segment preference, individuals from unrelated adult households, not surprisingly, are more likely to partake in eat-outs, presumably due to the social lifestyle and lifecycle associated with roommate living (see Cho et al., 2019, Kenyon and Heath, 2001).

Finally, the presence of children has important effects on eat-out preferences and frequency, particularly in the context of QSRs, with households with children exhibiting a strong preference for QSRs. Children are often attracted to fast food establishments for several reasons, including the availability of salty and sweet meal options, and the promise of fun and novelty with on-site playgrounds and toys with their meals (Ipatenco, 2012, Thomas, 2018). Interestingly, these findings contradict previous research suggesting that parents prioritize their children's dietary intake and so refrain from potentially unhealthy food options for the children (Jones, 2018, Petersen et al., 2014). However, it appears that this parental care for children's health is more focused on the frequency of eating out as a whole rather than the choice of a restaurant segment, a finding that is also supported by Kim and Kim (2021) and Haddad et al. (2023). This suggests that, while parents may be mindful of their children's nutrition, they do not seem to perceive QSRs as providing particularly unhealthy options.

6.1.3. Employment Status/Job Characteristics

Several employment and job characteristics are examined. The intensity of work can be described either by the number of workdays per month or the number of work hours per week (with part-time being characterized as 30 hours or less per week and full-time being more than 30 hours per week). Our analysis reveals that both of these job characteristics affect dining behaviors and preferences, though in distinct ways.

The number of work days per month does not affect restaurant segment preference but positively influences eat-out participation. However, there is a tempering of this latter effect as the fraction of workdays from home grows. The net result is that eating out is a more common occurrence among those working many days per month rather than fewer days, and this is especially the case for those working primarily from their in-person workplace (rather than from home). Work-related activities contribute to time constraints (see Bernardo et al., 2015, and Giurge et al., 2020), resulting in increased instances of dining out. Also, as individuals work more from

their office and are already outside the home, there is greater accessibility and convenience to visit restaurants on the work-to-home evening commute. Moreover, individuals who work frequently from home may have a general lifestyle preference for eating in the comfort and familiarity of their homes (Xiao et al., 2021) due to a frame of body and mind that may be linked to the psychological theory of homeostasis (see Marks, 2022).

While the number of workdays (and working from home) affects eat-out participation but not restaurant segment preference, the reverse holds for the number of work hours per week (see the results under “employment status” in Table 6). Specifically, relative to those not employed, employed individuals (regardless of part-time or full-time) have a predisposition toward CHs, perhaps due to the professional-social atmosphere offered by such establishments, which may be conducive to networking outside the office environment (Ferreira et al., 2021). Further, employment status also affects the extent of QSR consumption (conditional on positive QSR consumption). Specifically, individuals who are employed tend to visit QSRs more frequently compared to their unemployed counterparts, with this effect being particularly strong for those employed part-time. While time poverty and a quest for efficiency may explain the reason for frequent QSR participation (that is, less satiation for the QSR segment), the reasons for the lower QSR satiation among part-time workers (relative to full-time workers) need further study and exploration.

Interestingly, commute duration to the in-person workplace did not turn out to be a significant predictor of the frequency of eating out or preference for any particular restaurant segment, even for those individuals who always traveled to the office on each work day.

6.1.4. Residential Location BE Factors

Our analysis identified four residential location factors that significantly influence dining choices and eating-out frequency, including the walkability index, land-use diversity index, restaurant density, and proportion of QSRs. Based on the results in Table 6, customers are less likely to visit QSRs in more walkable areas (this is a main effect, separate from the race and walkability interaction effect discussed earlier), potentially because those living in walkable areas are generally health-conscious and avoid QSRs (see Lamb et al., 2020). Residents in high land-use diversity residential neighborhoods, on the other hand, have an elevated preference for CSRs, even though there is also higher satiation for CSRs among such individuals. Mixed land-use areas offer multiple attractions to explore and tend to be more vibrant and culturally diverse (Yue et al., 2017). In such areas, CSRs may be particularly popular because their ambiance, menu, and overall atmosphere often reflect the unique culture and character of the neighborhood. For the same reason, a higher residential land-use diversity is associated with higher satiation in terms of visits to CSRs, indicating a more diverse segment portfolio. Restaurant density and exposure to various restaurant segments also affect dining preferences as well as the frequency of eating out. As expected, individuals exposed to a high number of QSRs (as a fraction of the total restaurants in their residence area) are more likely to dine at fast food restaurants (Athens et al., 2016, Bell et al., 2020, Burgoine et al., 2018), and individuals residing in high-density restaurant neighborhoods generally eat-out more (Haddad et al., 2023, Wang and He, 2021).

6.1.5. COVID-19 Perspectives

The COVID-19 pandemic has significantly impacted the restaurant industry and has caused shifts in consumer behavior and attitudes toward dining out. Our study reveals that “being immunocompromised or having an immunocompromised loved one” (simply

“immunocompromised” for short) significantly reduces the appeal of CHs. Unlike the other three restaurant segments, which primarily focus on providing food services, CHs are typically viewed as socialization or working spots where food is considered to be a secondary service. As a result, individuals who are immunocompromised may be more likely to avoid CHs as well as eating out altogether. Also, individuals who perceive that their “well-being was or still is at risk during the pandemic” tend to be more predisposed to CSRs and reticent to be patrons of QSRs. The latter result may be traced to the relatively crowded nature of QSRs. Not surprisingly, those immunocompromised and/or worried about their well-being are more likely to have zero eat-outs, though older individuals with a heightened worry about their well-being appear to be less risk-sensitive than their younger peers.

6.2. Goodness of Fit

Goodness-of-fit statistics are computed to compare the constant and threshold shifters (CT)-only model (all parameters set to zero, except the constants and the threshold shifter terms in the count model), unlinked MDCNTEV model, and the linked MDCNTEV model. The different models can be compared using the Bayesian Information Criterion (BIC) statistic $[= -L(\hat{\Theta}) + 0.5 (\# \text{ of model parameters}) \log (\text{sample size})]$ for the linked and unlinked models ($L(\hat{\Theta})$ is the log-likelihood at convergence with the estimated parameter vector denoted by $\hat{\Theta}$).⁷ A lower BIC statistic implies better model performance. The linked and non-linked models can also be compared using a non-nested likelihood ratio test. The adjusted likelihood ratio index $\bar{\rho}^2$ is calculated as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\Theta}) - M}{L(c)} \quad (15)$$

where $L(\hat{\Theta})$ and $L(c)$ are the log-likelihood functions at convergence and for the CT-only model, respectively, and M is the number of parameters (excluding the constants and thresholds) estimated in the model. If the difference in the adjusted likelihood ratio indices for the linked (subscript 2) and unlinked (subscript 1) models is $(\bar{\rho}_2^2 - \bar{\rho}_1^2) = \tau$, then the difference between the two models is considered to be statistically significant at level p if $\Phi\{-[-2\tau L(c) + (M_2 - M_1)]^{0.5}\} < p$.⁸

In addition to likelihood-based performance, we evaluate the performance of the models intuitively and informally using the average probability of correct prediction statistic for the observed multivariate count outcome.

Table 7 presents the results of these disaggregate likelihood-based goodness-of-fit statistics. It is evident that both the linked and unlinked model log-likelihood values outperform the constants-only model, as confirmed by the nested likelihood ratio test. Furthermore, the BIC and the results of the non-nested likelihood ratio test comparing the linked and unlinked models demonstrate that the linked model exhibits a better fit compared to the unlinked model. Also, the

⁷ The linked and non-linked models are non-nested (see Bhat, 2022), because the kernel error term distributions are different between the two models. While many measures have been suggested in the literature to evaluate model fit among non-nested models (see Dziak et al., 2020), the BIC-based measures demand a higher strength of evidence to add complexity than do the other measures, and thus the BIC-based measure favors more parsimonious models.

⁸ The $L(c)$ values differ for the unlinked and linked models because of the different count component error structures in the two models. For consistency and comparison purposes between the unlinked and linked models, in all computations in the current section, we use the $L(c)$ value for the unlinked model.

average probability of correct prediction at the multivariate count level is 0.098 for the unlinked model and 0.105 for our proposed linked model. This average probability may also be computed separately for the zero counts and for the non-zero counts. The average probability of correct prediction for zero counts is 0.300 for the unlinked model and is 0.326 for the linked model. The corresponding average probability of correct prediction for non-zero counts is 0.027 for the unlinked model and 0.028 for the linked model.

To complement the disaggregate-level goodness-of-fit outcomes, we also evaluated the data fit of the linked and unlinked models at the aggregate level. For clarity and manageability, we focused on the univariate count of visits to each restaurant segment (rather than considering the 234,256 possible multivariate eat-out count combinations). Table 8 presents the results of this assessment, comparing the predicted and observed values for each restaurant segment in terms of the (a) number of individuals with zero consumption, (b) number of individuals with positive consumption, and (c) total number of visits to each segment. We used two metrics for comparison, including the average absolute percentage error (APE) and the weighted APE (WAPE), which is obtained by multiplying the APE with the observed share in the data for each restaurant segment. The linked model demonstrates significantly better performance, particularly in predicting the number of individuals with zero consumption (WAPE of 8.34% for the linked model versus 12.72% for the unlinked model) and the number of individuals with positive consumption (WAPE of 18.79% for the linked model versus 28.21% for the unlinked model). Both models perform reasonably well in predicting the total number of visits across segments.

Overall, all the goodness-of-fit statistics demonstrate the importance of linkage from a data fit perspective. However, based on the discussion in Bhat (2022), it is the linkage implications from a behavioral perspective that are even more important, as further discussed in Section 7.2.

7. MAGNITUDE EFFECTS OF VARIABLES

7.1. Analysis Preparation

The estimation results in the previous section do not provide information on the actual effects of the variables on eat-out frequency by restaurant segment, nor do they provide a sense of the relative magnitudes of impacts of different variables. To determine directionality and magnitude effects, the estimates need to be translated to actual outcome effects. But unlike the model coefficients in Table 6, the effect of any variable change on the count outcomes will vary based on the current level of the variable as well as the levels of other variables. However, an average effect of a change in a variable may be computed across individuals, assuming the levels of other variables are fixed for each individual at those currently in the sample. Specifically, for each exogenous variable, we consider all sample individuals to be at each specific state of the exogenous variable. For example, we consider all individuals to be in the youngest age category (18 to 29 years old). Then, using the forecasting procedure discussed in detail in Bhat (2022), we compute the expected counts in each restaurant segment as well as the total eat-outs for each individual, and compute the average across all individuals. Next, we consider all individuals to be over 65 years old, and repeat the procedure above. Finally, we compute the percentage ATE change in trip-making per capita at the total eat-out level as well as separately for each restaurant segment due to a change in age from 18-29 years to over 65 years.

The above procedure can be applied to compute the ATE for the change from any state of a variable to any other state. But, for presentation simplicity, we only report the ATEs for a change between a specific pair of states for categorical variables that can take more than two states. Specifically, we consider the following pair of states for each individual/household demographic

variable: age (change from 18-29 years to 65 years and older), race (change from white to non-white), education degree attainment (from less than graduate degree to graduate degree), household income (from <\$25,000 to >\$150,000), vehicle ownership (from zero/one vehicle to ≥ 3 vehicles), and household structure (from the state of single men to single women, multiple unrelated adults to multiple related adults without children, and multiple related adults without children to multiple related adults with children). For employment status/job characteristics, we only consider the case of a change of being unemployed to working from the office every day, to working from home 60% of the days (3 days a week), to working from home every day (that is, a change in the fraction of work days from home from 0 to 1 for those employed, while keeping all other job-related variables at their current values). Finally, for the continuous residential location/BE factors, we change the variable from the 10th to the 90th percentile to compute an ATE measure.

Table 9 provides a summary of the computed Average Treatment Effects (ATEs) for each variable. To illustrate, let us consider the interpretation of the first numeric row corresponding to the age variable. If all sample individuals were adults in the 18 to 29 years old age category, they are estimated to make a total of 3,237 weekday monthly dinner eat-out trips (an average of 2.96 monthly eat-out trips per individual). Out of these trips, 22.2% are allocated to QSRs, 15.8% to CHs, 48.7% to CSRs, and 13.3% to FSRs (fourth broad column of Table 9). In contrast, adults who are 65 or more years old (treatment level) make a total of 3,266 eat-out trips (an average of 2.99 monthly eat-out trips per individual), with 15.3% allocated to QSRs, 3.7% to CHs, 67.8% to CSRs, and 13.2% to FSRs (fifth broad column of Table 9). In terms of net effect on total eat-outs and individuals segment eat-outs, one has to multiply the proportions with the total eat-outs in each of the base and treatment cases, and then get the percentage ATE. Thus, according to the results, older adults are estimated to have 0.9% more monthly eat-outs compared to the base younger age group, with 30.4% lower QSR eat-outs, 76.4% lower CH eat-outs, 40.5% higher CSR eat-outs, and 0.1% lower FSR eat-outs (last broad column of Table 9). Similar interpretations can be made for all other variables reported in the table.

7.2. ATE Results

The ATE findings in Table 9 generally align with our expectations and are consistent with the model results. The outcomes suggest that individuals who frequently eat out (see the percentage ATE shift in the last broad column under “total eat-outs”) tend to be young, white, have an educational attainment below a graduate degree, enjoy a high income, own three or more motor vehicles, are single men, are couples or other related adults without children, work full-time from an office, and those who perceive less personal risk due to COVID-19 and are not immunocompromised. The income effect is particularly strong, dominating over other variables. Additionally, our analysis reveals distinctive demographic groups for QSR, CH, CSR, and FSR dining. The demographic groups that are particularly conspicuous in the QSR and CH segments include individuals who are younger than 30 years and not white, have a formal education degree that is below a graduate degree with low income levels, have three or more motorized vehicles, are single men and full-time employees (especially if working only from the office). Not surprisingly, those residing in areas with a high fraction of QSRs are also likely to be QSR patrons. For the CSR segment, the demographic groups that stand out include young, white individuals from high income households, individuals living with multiple-unrelated adults, and full-time employees with no work from home. Meanwhile, in the FSR segment, the prominent demographic groups are individuals who are from high income households, single men, multiple-unrelated

adults, and full-time employees with no work from home. Overall, in terms of demographics, there is much more commonality between frequent patrons of QSRs and CHs on the one hand, and CSRs and FSRs on the other.

An important observation from Table 9 is that variables that only directly affect the fractional splits among the different restaurant segments (without directly affecting the total eat-out count) still do indirectly affect the total eat-out count through the composite linkage from the segment model to the total eat-out count model. For instance, consider the effect of three or more vehicles (versus zero or one), full-time employed and working all days from home (versus unemployed), and the fraction of QSR restaurants in a residential neighborhood. All these variables positively affect one or both of QSR and CH patronage, but do not directly impact the total eat-out count. However, through the composite linkage (that is, a combination of income and variety seeking effects) in our linked model, all these variables lead to an overall increase in total eat-out count too. Besides, our linked model also increases the eat-outs at some other restaurant segments. For example, consider the effect of being full-time employed and working from home every day (versus being unemployed). This increases the fractions of QSR/CH eat-outs and the total eat-outs, but also increases patronage at the CSR (12.1% increase) and FSR (2.7% increase) segments because of the increased total eat-outs (see the last two entries in the final row of Table 9). On the other hand, the unlinked model necessarily (and incorrectly) estimates that full-time employees working from home every day, while having a higher fraction than their peers of QSR/CH eat-outs, also reduce their patronage of CSR and FSR restaurant segments. This shows the kind of complementary effects across restaurant segments that are possible in our linked model, rather than the strictly substitutive relationship that would be imposed by a more naïve unlinked model.

7.3. Implications

The ATE results point to several important implications, emphasizing the multidisciplinary nature of eating-out behavior and revealing the intricate interplay between transportation systems, urban planning, public health, and social equity.

First, there is no substantial difference in total eat-outs based on age, though there are clear age effects based on restaurant segments, with elevated visits to QSRs and CHs among young individuals relative to their older counterparts. This does suggest lower vehicle miles of travel among the younger individuals (because QSRs and CHs are closer to places of residence than CSRs and FSRs), but also does not portend too well from a public health standpoint, given the typically low nutrient value of foods and snacks at QSRs and CHs relative to CSRs and FSRs. While reduced vehicle miles align with transportation sustainability goals, the increased consumption of less nutritious food conflicts with public health objectives. Policymakers must navigate this trade-off, potentially by incentivizing healthier options at QSRs and CHs or improving public transit or active transportation mode access to CSRs and FSRs. Additionally, public health policy efforts need to highlight the strong connection between healthy eating and healthy living among this younger adult group are warranted. Also, nutritional programming and education at high schools and even earlier for the upcoming generation of adults would be beneficial and can put a stop to the inter-generational poor meal sourcing domino effect.

Second, there are strong racial disparities in the total eat-outs and CSR eat-outs, as can be observed from the last column panel of Table 9. But, interestingly, the relative proportions of the allocation of eat-outs to different restaurant segments are affected by the walkability of the area (even though the ATEs in the last column panel do not show much variation between high and low walkability areas based on race). In less walkable built environments, individuals of color allocate

27.4% of their restaurant visits to QSRs and 45.0% to CSRs, while, in high walkable built environments, individuals of color allocate a reduced 20.9% to QSRs and an increased 49.6% to CSRs. Overall, the findings consistently validate that individuals of color exhibit lower rates of eating out, but also reflect a higher propensity for consuming relatively unhealthy fast food. While this may imply fewer trips generated from a travel perspective as the US population continues to diversify, it also portends a widening health disparity gap based on race, as well as an unhealthier population, unless appropriate interventions are designed and implemented (note that the ATEs in the last column of Table 9 are consistently higher for the QSR and CH segments among people of color relative to white individuals). For instance, the presence of enhanced walkability fosters an inclusive and diverse dining environment, effectively reducing the health disparity gap based on race. This suggests that building walkable environments not only has transportation and active lifestyle-based public health benefits but can also help a more equitable playing field in terms of the nutrient quality of food consumption. By advocating and prioritizing walkable environments, policymakers can stimulate a diverse culinary ecosystem, promote healthier dining practices, and mitigate racial disparities tied to the distribution of visits to healthier dining establishments. In this regard, future studies should focus on the effect of studying specific urban design features that promote walkability, such as safe pedestrian crossings, well-lit streets, and attractive walking routes. Also, policymakers can further promote healthy diets and better access to ingredients for healthier meal preparation by launching free diet and nutrition clinics that provide nutritional education, resources, and personalized guidance.

Third, income appears to be the strongest determinant of eating out behavior and preference as evident from the high ATE values associated with both the overall frequency of dining out and the distribution of visits across various restaurant segments (especially in the CSR and FSR segments). These findings highlight the profound influence of income disparities on eating behaviors, with individuals in lower income brackets displaying a significantly greater reliance on the unhealthy meal options provided by QSRs (20.1% of eat-outs are allocated to QSRs among low income individuals, relative to 11.3% for high income individuals, as can be observed from the “base level” and “treatment level” columns for the income variable). This tends to be the case because healthy food options are often more expensive than processed and unhealthy alternatives, causing low-income individuals to prioritize cheaper, calorie-dense, and nutrient-poor foods. Access to affordable, nutritious food options in underserved areas through initiatives such as community gardens and pantries, farmers' markets, and subsidized grocery programs can help promote healthy eating habits among low income individuals.

Fourth, an increase in the number of vehicles (typically correlated with high income) also increases overall eat-out trip-making, though, interestingly, much of this additional trip-making is targeted at QSRs and CHs, with an increase by 85.3% for trips to QSRs and 73.4% to CHs. The availability of personal vehicles, a key component of the transportation system, clearly influences not only the frequency of eat-out trips but also the types of restaurants visited. While convenient for car owners, the easy access to drive-throughs and ample parking at QSRs engendered by car availability may contribute to a sedentary lifestyle and poorer dietary choices, potentially leading to increased obesity and related health problems. In contrast, the findings emphasize the potential benefits of having a walkable environment, and promoting walking as a transportation mode across all individuals, which can not only have a direct walkability-based benefit to transportation and public health as discussed earlier, but also an indirect benefit to both transportation and public health through a reduced vehicle ownership effect. The close linkage between transportation, urban design, and public health brought about by a walkable environment becomes clear here through

(a) reduced motorized trip-making, (b) a higher level of walking and physical activity, (c) inexpensive and ready walk mode access to healthy eating environments, and (d) a direct negative effect on relatively unhealthy food consumption. Building on these findings, further research is needed to understand the complex relationship between transportation systems and eating-out behavior. Studies on the length of eat-out trips, their spatial-temporal patterns, and the modes of transportation used could provide valuable insights. While our results show increased eat-out trips with higher vehicle ownership, particularly to QSRs and CHs, there is a need in the future to examine how alternative transportation options might influence eat-out patterns, issues that have not been considered in the current research. For instance, enhanced public transportation accessibility could counteract the increased visits to QSRs and CHs associated with higher vehicle ownership. Further, the role of ridesharing and micro-mobility services in eat-out trip patterns, especially in areas with high vehicle ownership, merits investigation. Lastly, analyzing how parking availability and costs in different urban contexts impact decisions to dine out could offer additional insights. This could help explain the higher prevalence of QSR and CH visits among vehicle owners and inform strategies to promote healthier eating-out behaviors across different transportation contexts.

Fifth, the impact of employment and workplace location on dining habits also deserves attention, especially given the disruption in work location arrangements engendered by the pandemic. There has been substantial debate in the transportation literature about whether teleworking from home for a few days will lead to urban sprawl and even reduced commute vehicle miles traveled (VMT). In a recent paper by Asmussen et al. (2024), the authors indicate that, while some sprawl is inevitable as people choose residential locations that are not necessarily proximal to their work location due to the flexibility of teleworking, commute VMT over a period of a month also reduces as long as teleworking is in the order of two days per week or more (teleworking one day a week or less often actually increases commute VMT, based on their analysis, due to the increased commute distance more than making up for the one-day reduction in commuting). The results here suggest that teleworking, especially at high levels, also has the benefit of reducing non-commute eat-out trip-making (see also Caldarola and Sorrell, 2022). In particular, working from home three days a week for workers who work five days a week (corresponding to 60% work from home in the table) cuts down eat-out trip-making from an average of 3.83 per capita (for employees working all days from an office) to 3.10 per capita (see the total eat-outs per capita within the treatment column panel), constituting a 19% decrease in eat-out trip-making. This total eat-outs per capita further reduces by 30% for those who work all days from home relative to those who work all days from the office. While teleworking may increase other non-work travel relative to not teleworking, our results do indicate that, at least in the context of eating out, there is a net and clear benefit in trip reduction associated with eat-outs. As importantly, the results also indicate that the allocation across the many restaurant segments stays relatively fixed regardless of teleworking or not teleworking (see the percentage allocations across the three employment rows in the treatment level column panel of Table 9), suggesting that telework, while having benefits in terms of transportation, does not adversely impact public health considerations in terms of the nutrient quality of food consumption.

Sixth, built environment measures (land-use mix, exposure to QSRs, and restaurant density) all play a role in shaping individuals' dining patterns, though land-use mix and restaurant density have relatively little effect on dining choices. However, the fraction of QSRs does have a more tangible positive effect on overall eat-out trip-making, and particularly on visitations to QSRs. These findings indirectly reflect the influence of transportation systems on eating-out

behavior. For instance, areas with high restaurant density are likely to have more developed transportation networks, potentially increasing eat-out trips via various modes. The accessibility of QSRs, often designed with car-centric transportation in mind (e.g., drive-throughs, ample parking), appears to have both negative implications for transportation as well as for public health, highlighting the importance of managing restaurant density and diversity to cultivate a balanced and healthier dining landscape. Policymakers may want to consider these insights when developing zoning regulations that limit restaurant density and the concentration of QSRs within residential zones, especially in areas with a high population of low-income individuals. This approach, combined with investments in walkable environments and alternative transportation options, can nudge individuals towards healthier choices and reduce reliance on car-dependent fast food.

Finally, dining behaviors are notably affected by perceived pandemic risk, with overall eat-outs decreasing and preference shifting towards CSRs.

Overall, this discussion highlights the complex and nuanced interplay between transportation systems, urban design, public health outcomes, and socioeconomic factors in shaping eating-out behavior. It also demonstrates that interventions aimed at improving community well-being cannot be siloed within a single domain. Instead, effective and sustainable policies must consider the existing interactions across sectors. For instance, transportation decisions influence not just mobility, but also dietary choices and public health outcomes. Similarly, urban planning affects both the physical landscape and the health equity of communities. By recognizing and leveraging these interconnections, policymakers can collaborate across sectors to develop more holistic and effective strategies that simultaneously address multiple aspects of community well-being, from transportation efficiency and environmental sustainability to public health and social equity.

8. CONCLUSIONS AND LIMITATIONS

The results of this study contribute to the existing literature on dining choices by demonstrating the significant role of individual demographics, household characteristics, employment status/job characteristics, residential location BE factors, and COVID-19-related perceptions in determining the frequency of eating out and preferences for different restaurant segments for weekday dinner meals. The study recognizes the unique utilitarian/hedonic mix offered by each restaurant segment, leading to a formulation of the dining choice process as a deliberate “at-once” horizontal choice of a portfolio of restaurant segment participation occasions over a period of time.

The study has implications for multiple fields, including transportation and urban planning, public health, and food services, as discussed in the previous section. From a transportation and urban planning perspective, in particular, there is little literature on travel-related behaviors for eat-out activity. Indeed, in all trip-based models as well as in all activity-based models that we are aware of, there is no specific eat-out activity purpose, with eat-out being aggregated within a broader social-recreational category or a non-work category. At the same time, in the aftermath of the onset of the pandemic, it is becoming increasingly important to consider eat-out as a category of its own. In particular, our results, as discussed earlier, suggest a strong relationship between employment/telework arrangements and eating-out choices, with individuals working from the office on all days of the week having a strong positive effect on the total number of eat-out episodes. The implication is that there is a good bit of activity chaining of eat-out activities during the evening commute of employed individuals, reinforcing the need for an activity-based modeling approach that considers eat-out as a stand-alone activity purpose. The model proposed in this study addresses this gap by forecasting monthly weekday dinner eat-outs (by restaurant segment type)

as a function of socio-demographics. Importantly, we diverge from traditional practice models by considering a suite of BE measures, identifying four such measures significantly impacting dine-out activity generation. These BE measures can now be incorporated within the activity generation step of travel demand models, enhancing their accuracy and relevance. Although our model primarily focuses on monthly weekday dinner eat-outs, it can be modified for today's travel demand models that rely on one-day "average" weekday forecasts. This modification includes transforming our monthly eat-out forecasts into the probability of participating in an eat-out activity on any given weekday. This probability can then be integrated into typical agent-based daily activity-based travel model frameworks. The results also emphasize the need for future activity-travel surveys to incorporate detailed questions related to eat-outs, as well as telework arrangements. Then, by predicting the frequency of eat-outs and the allocation to different restaurant segments, it becomes possible to estimate the number and characteristics of trips people will take to restaurants. This information can be used to identify areas with high transportation demand during peak dining hours, facilitating optimal route planning and resource allocation. In addition, integrating the models into activity-based travel demand models can help identify areas with high demand for parking near restaurants during peak dining hours. Moreover, the outputs of our models, in conjunction with activity-based travel models, can be used to predict the impact of changes in restaurant availability on travel patterns and to identify areas where new restaurants may have the most significant impact on travel demand. Additionally, incorporating information on the allocation of visits to different restaurant segments can help identify which types of restaurants are likely to generate the most traffic and at what times, leading to more effective transportation planning and resource allocation.

The implications of our results from a public health perspective have already been discussed in the previous section. From a food service sector perspective, our findings emphasize the importance of understanding individual demographics, household characteristics, and employment status in shaping restaurant preferences. Restaurants can tailor their offerings and marketing strategies to cater to different age groups, income levels, and household structures more effectively. Age-related factors, for instance, reveal a higher consumption of meals at CSRs by older individuals. As a result, CSRs may consider offering early-bird specials, menus with larger font sizes, and easily accessible facilities to accommodate older adults. At the same time, our results reveal that the CH segment is not particularly appealing to older patrons. To broaden their appeal, CHs could diversify their offerings, incorporating a range of food and beverage options that cater to the unique preferences and dietary requirements of older individuals. Furthermore, it would be beneficial to cultivate an inviting atmosphere that resonates with an older demographic. This could entail providing ample and suitable seating options, integrating softer furniture for increased comfort, and ensuring good lighting. Additionally, our results unmask cultural barriers that appear to discourage racial minorities from eating out. To tackle these barriers, restaurant operators can regularly conduct anti-bias training for their employees. These measures can contribute to fostering a more inclusive and welcoming dining environment for individuals of all racial backgrounds. Household structure also plays an important role in shaping dining habits. For instance, the presence of children significantly increases the preference for QSRs and decreases the inclination to visit CSRs. To counteract this trend, CSRs could attract families by organizing family-friendly events, providing childcare services, or offering dedicated play areas. Finally, the restaurant industry must adapt to the shift in dining patterns with increased remote work. Remote workers eat out less frequently than those working from the physical workplace, showing a higher reliance on delivery and pick-up services (Haddad et al., 2023). This shifting landscape indicates

an urgent need for restaurants to be prepared to partner with reliable delivery services or develop and maintain their own ordering platforms. This will ensure that the restaurants can meet the evolving demand while maintaining accessible and convenient service for all consumers, irrespective of their work arrangements.

Although the results of this study contribute to a richer understanding of dining choices, there are important avenues for further research. A more comprehensive consideration of additional factors and dimensions affecting/characterizing eat-out episodes, including the mode of transport used to reach restaurants, travel distance and location, dining companions and occasion, duration spent, and expenditure, is essential for accurately identifying and addressing changing travel patterns. Unfortunately, our dataset did not provide this level of detail. In addition, data concerning preferences for delivery and pickup services across different restaurant segments were unavailable. As delivery and pickup services are growing trends in the food service industry, a comprehensive understanding of these aspects could enhance our understanding of changing consumer behaviors. Further, our analysis was focused only on weekday dinner meals, not considering lunch and weekend meals. Eat-out behavior and choices during these other meal periods may differ substantially and warrant further investigation. Finally, eat-out decisions are likely a combination of individual-level preferences and the preferences of other individuals in the household. Thus, a hybrid individual-household level analysis would be a good direction for further exploration.

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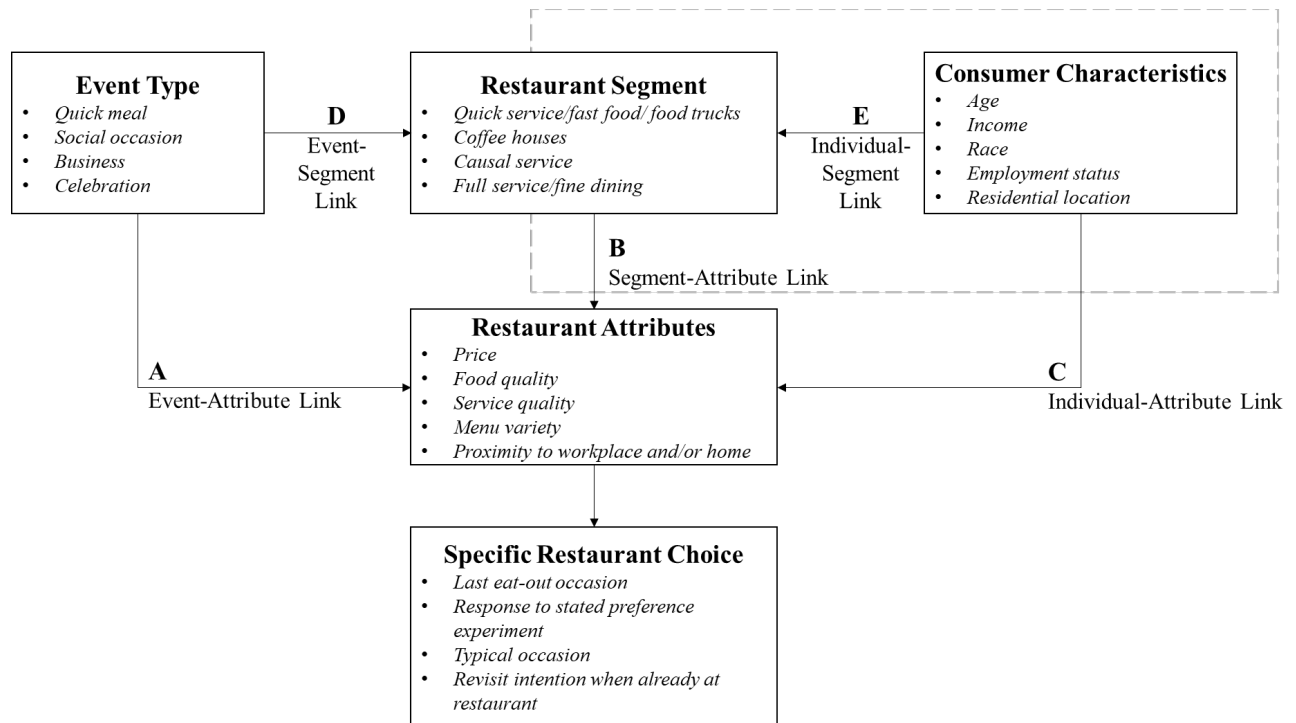


Figure 1. Illustration of analysis paths in restaurant selection literature

Table 1. Restaurant segments and their attributes and the utilitarian/hedonic motives they satisfy

Restaurant Segment	Restaurant Attributes	Utilitarian/Hedonic Motives
Quick Service (QSR)	Fast service	Utilitarian
	Low prices	Utilitarian
	Convenience	Utilitarian
	Limited menu options	Utilitarian
Casual Service (CSR)	Good value	Utilitarian/Hedonic
	Variety of menu items	Utilitarian/Hedonic
	Relaxed atmosphere	Hedonic
	Good service	Utilitarian/Hedonic
Full Service (FSR)	High-end cuisine	Hedonic
	Luxurious atmosphere	Hedonic
	High-quality service	Hedonic/Utilitarian
	Extensive wine list	Hedonic

Table 2. The relationship between the frequency of monthly weekday dinner eat-outs and the distribution to different restaurant segments

Number of Eat-outs	Observed Number of Individuals	Distribution Across Segments			
		QSR	CH	CSR	FSR
0	284	0.0%	0.0%	0.0%	0.0%
1	140	13.6%	4.3%	70.0%	12.1%
2	160	16.6%	5.3%	66.9%	11.3%
3	79	19.4%	9.7%	63.3%	7.6%
4	117	15.8%	7.3%	66.9%	10.0%
5	96	16.3%	6.0%	64.4%	13.3%
6	39	15.4%	8.1%	68.8%	7.7%
7	12	26.2%	4.8%	60.7%	8.3%
8 to 9	46	20.4%	8.0%	60.6%	11.0%
10	67	26.0%	9.6%	55.5%	9.0%
11 to 15	29	28.6%	4.2%	63.1%	4.2%
16+	23	12.5%	6.7%	70.6%	10.2%

Table 3. Distribution of eat-out trips across multiple restaurant segments

Number of Eat-outs	Number of Individuals	Percentage of Individuals Visiting (X) Restaurant Segments			
		(1)	(2)	(3)	(4)
1	140	100.00%	0.00%	0.00%	0.00%
2	160	58.13%	41.88%	0.00%	0.00%
3	79	37.97%	45.57%	16.46%	0.00%
4	117	41.03%	40.17%	17.09%	1.71%
5	96	39.58%	40.63%	14.58%	5.21%
6	39	35.90%	35.90%	17.95%	10.26%
7	12	41.67%	25.00%	33.33%	0.00%
8 to 9	46	25.85%	41.95%	30.98%	1.22%
10	67	14.93%	52.24%	25.37%	7.46%
11 to 15	29	16.67%	25.69%	54.86%	2.78%
16+	23	15.61%	28.18%	44.77%	11.44%

Table 4. Descriptive statistics for individual/household-level and employment status/job variables

Variable	Sample		Texas	Variable	Sample		Texas
	Count	%	%		Count	%	%
Individual-Level Demographics				Motorized vehicle ownership level			
<i>Gender</i>				0	18	1.6	5.2
Male	466	42.7	49.7	1	244	22.4	32.3
Female	626	57.3	50.3	2	501	45.9	40.1
<i>Age</i>				3 or more	329	30.1	22.4
18 to 29	64	5.9	29.9	Household structure			
30 to 49	353	32.3	36.3	Single male	84	7.7	13.3
50 to 64	408	37.4	15.8	Single female	147	13.4	19.6
65 or more	267	24.4	18.0	Couples without children	549	50.3	31.2
<i>Race</i>				Couples with children	196	17.9	23.2
White	944	86.4	68.6	Multiple related adults	80	7.4	6.9
Not White	148	13.6	31.4	Multiple unrelated adults	36	3.3	5.8
<i>Education level</i>				Presence of children	415	38.0	36.2
No degree	11	1.0	15.7	Employment Status/Job Characteristics			
High school	87	8.0	46.2	Employment status			
Technical degree	104	9.5	7.4	Not employed	229	21.0	24.0
Undergraduate	377	34.5	19.9	Part-time employee (≤ 30 hours per week)	50	4.6	14.9
Graduate	513	47.0	10.8	Full-time employee (> 30 hours per week)	813	74.4	61.1
Household Characteristics				Self-employment			
<i>Annual income</i>				Self-employed	104	9.5	6.7
Under \$24,999	38	3.4	17.1	Variable			
\$25,000-\$49,999	81	7.4	20.2	Mean			
\$50,000-\$74,999	148	13.6	17.3	SD			
\$75,000-\$99,999	176	16.1	12.7	Texas			
\$100,000-\$149,999	313	28.7	16.2	Commute duration			
\$150,000-\$249,999	231	21.2	9.2	Commute (minutes)	22.8	14.3	26.6
\$250,000 or more	105	9.6	7.3	Number of work days per month			
				Number of days	21.5	9.2	22
				Workplace location			
				Percentage of workdays from home in the past month	44.8	38.3	--

Table 5. Descriptive statistics for built-environment variables

Variable	Mean or Proportion or Frequency	Standard Deviation (Relative Frequency)	Minimum	Maximum
Residential area type – frequency				
<i>Rural</i>	208	19.1%	--	--
<i>Suburban</i>	628	57.5%	--	--
<i>Urban</i>	256	23.4%	--	--
Employment density (jobs per acre)	2.277	4.948	0.000	109.052
Population density (people per acre)	4.440	4.006	21.289	8.890
Walkability index (/100)	0.093	0.031	0.018	0.180
Proportion of employment by type:				
<i>Retail</i>	0.141	0.086	0.000	0.548
<i>Office</i>	0.110	0.084	0.000	0.946
<i>Industrial</i>	0.227	0.167	0.000	0.915
<i>Service</i>	0.386	0.152	0.003	0.940
<i>Entertainment</i>	0.136	0.073	0.000	0.643
Land-use diversity index	0.622	0.142	0.067	0.909
Restaurant density (number of restaurants/100 square acres)	0.017	0.046	0.000	0.395
Proportion of restaurants by type:				
<i>QSR</i>	0.136	0.122	0.000	0.600
<i>CH</i>	0.029	0.034	0.000	0.333
<i>FSR</i>	0.015	0.028	0.000	0.250
Livability score	75.406	8.305	53.000	93.000

Table 6. Model estimation results

Variables	Baseline Marginal Utility Component of MDC Model								Satiation Component of MDC Model								Count Model	
	QSR		CH		CSR		FSR		QSR		CH		CSR		FSR		Eat out	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Exogenous Variables																		
Individual Demographics																		
<i>Age (base: 18 to 29 years old)</i>																		
30 to 49 years old	—	—	-0.163	-1.77	—	—	na	na	—	—	—	—	—	—	na	na	—	—
49 to 64 years old	-0.085	-2.00	-0.163	-1.77	—	—	na	na	—	—	—	—	0.635	4.47	na	na	—	—
65 and older	-0.090	-1.75	-0.247	-2.22	-0.171	-2.09	na	na	—	—	—	—	1.244	4.97	na	na	—	—
<i>Race (base: White)</i>																		
Not White	—	—	—	—	-0.253	-1.71	na	na	—	—	—	—	—	—	—	—	-0.064	-1.79
Not White × (Walkability Index/100)	—	—	—	—	0.203	1.52	na	na	—	—	—	—	—	—	na	na	—	—
<i>Educational level (base: below graduate degree)</i>																		
Graduate	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	-0.061	-2.51
Household Characteristics																		
<i>Income (base: <\$25,000)</i>																		
\$25,000 - \$49,999	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.184	2.12
\$50,000 - \$99,999	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.214	2.53
\$100,000 - \$149,999	-0.148	-2.63	-0.139	-2.39	—	—	na	na	—	—	—	—	—	—	na	na	0.306	3.10
>\$150,000	-0.320	-3.17	-0.229	-2.83	-0.117	-2.38	na	na	1.082	3.07	—	—	—	—	na	na	0.306	3.10
<i>Vehicle ownership (base: zero or one vehicle)</i>																		
Two vehicles	0.095	1.95	0.104	1.83	—	—	na	na	—	—	—	—	—	—	na	na	—	—
Three or more vehicles	0.138	2.30	0.118	1.90	—	—	na	na	—	—	—	—	—	—	na	na	—	—
<i>Household structure (base: single male)</i>																		
Single female	—	—	—	—	—	—	na	na	—	—	—	—	0.500	2.61	na	na	-0.098	-1.99
Multiple related adults	—	—	—	—	—	—	na	na	0.423	1.18	—	—	—	—	na	na	-0.064	-1.52
Multiple unrelated adults	0.212	1.84	—	—	—	—	na	na	-1.573	-3.16	—	—	—	—	na	na	0.202	2.59
Presence of children	0.049	1.28	—	—	—	—	na	na	—	—	—	—	—	—	na	na	-0.060	-1.98
Employment Status/Job Characteristics																		
<i>Number of workdays per month</i>																		
Number of workdays	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.573	2.85
<i>Workplace location</i>																		
Fraction of work days from home in the past month	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	-0.124	-2.97
<i>Employment status (base: not employed)</i>																		
Part-time	—	—	0.134	2.14	—	—	na	na	1.179	2.35	—	—	—	—	na	na	—	—
Full-time	—	—	0.134	2.14	—	—	na	na	0.601	1.57	—	—	—	—	na	na	—	—
Residential Location BE Factors																		
<i>Land-use</i>																		
Walkability (/100) (range 0-0.2)	-0.764	-1.37	—	—	—	—	na	na	—	—	—	—	—	—	na	na	—	—
Land-use Diversity Index (range 0-1)	—	—	—	—	0.271	1.49	na	na	—	—	—	—	-1.173	-2.33	na	na	—	—
<i>Restaurant density</i>																		
Fraction of QSR restaurants (range 0-0.6)	0.265	1.83	—	—	—	—	na	na	—	—	—	—	—	—	na	na	—	—
Restaurant density (number of restaurants/100 square acres) (range 0-0.4)	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.620	2.12

Table 6. Model estimation results (contd.)

Variables	Baseline Marginal Utility Component of MDC Model								Satiation Component of MDC Model								Count Model	
	QSR		CH		CSR		FSR		QSR		CH		CSR		FSR		Eat out	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Exogenous Variables																		
<i>COVID-19 Perspectives</i>																		
I or someone I live with or frequently visit is immunocompromised	—	—	-0.103	-2.28	—	—	na	na	—	—	—	—	—	—	na	na	-0.062	-2.27
My personal well-being was or still is at risk during the pandemic	—	—	—	—	—	—	na	na	-0.443	-1.52	—	—	0.258	3.203	na	na	-0.104	-2.37
My personal well-being was or still is at risk during the pandemic × Age 50 and older	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.042	1.23
<i>Constant</i>	na	na	0.107	-0.94	0.337	2.12	-0.174	-1.89	1.293	2.68	0.916	2.75	0.350	0.70	1.382	4.45	3.425	9.71
Threshold Shifters																		
0 1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	4.213	17.55
1 2	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.022	1.43
2 3	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.050	2.45
4 5	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.051	2.46
10 11	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.370	3.22
12 13	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.685	2.07
14 15	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	-2.351	-3.34
20 21	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.299	2.29
Linking	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	2.718	—
Scale (κ)	0.270 (t-statistic of 3.680)																—	—

Table 7. Likelihood-based data fit measures

Summary Statistics	Linked Model	Unlinked Model
Log-likelihood at convergence	-3704.91	-3728.09
Number of parameters	66	66
Bayesian Information Criterion (BIC)	3935.77	3958.95
Constants and threshold-shifters (CT) only log-likelihood*	-3876.63	
$\bar{\rho}^2$	0.031	0.025
Nested likelihood ratio test: Linked/Unlinked model versus constant-only model	LR=325.08> $\chi^2_{(50,0.05)}=67.505$	LR=297.08> $\chi^2_{(50,0.05)}=67.505$
Non-nested likelihood ratio test: Linked model versus Unlinked model	$\Phi(-6.22) <<< 0.0001$	

* The value refers to the (CT) only log-likelihood of the unlinked model.

Table 8. Aggregate fit measures

Aggregate Goodness of Fit Measure	Restaurant Segment	Observed	Linked Model Predictions			Unlinked Model Predictions		
			Predicted	APE (%)	WAPE (%)	Predicted	APE (%)	WAPE (%)
Number of individuals with zero consumption for each restaurant segment	QSR	810	910	12.35	8.34	959	18.39	12.71
	CH	936	1005	7.37		1008	7.65	
	CSR	378	424	12.17		474	25.42	
	FSR	887	923	4.06		953	7.45	
Number of individuals with positive consumption for each restaurant segment	QSR	282	181	35.82	18.79	133	52.82	28.21
	CH	156	86	44.87		84	45.91	
	CSR	714	667	6.58		618	13.46	
	FSR	205	168	18.05		139	32.24	
Number of visits to each restaurant segment	QSR	744	540	27.42	10.94	446	40.03	10.60
	CH	272	192	29.41		268	1.34	
	CSR	2454	2353	4.12		2432	0.89	
	FSR	370	405	9.46		453	22.53	

Table 9. Average Treatment Effect (ATE) for all exogenous variables

Variables	Base Level	Treatment Level	Base level					Treatment level					ATE (% shift)				
			Total eat-outs per capita	Allocation to restaurant segment (%)				Total eat-outs per capita	Allocation to restaurant segment (%)				Total eat-outs per capita	Number of visits to restaurant segment			
				QSR	CH	CSR	FSR		QSR	CH	CSR	FSR		QSR	CH	CSR	FSR
Individual Demographics																	
Age	Less than 30 years	More than 65 years	2.96	22.2	15.8	48.7	13.3	2.99	15.3	3.7	67.8	13.2	0.9	-30.4	-76.4	40.5	0.1
Race	White and low walkability (10th percentile=0.05)	Not White and low walkability	3.36	17.1	5.2	66.7	11.0	2.27	27.4	9.2	45.0	18.4	-32.3	8.3	18.4	-54.3	13.4
	White high walkability (90th percentile=0.14)	Not White high walkability	3.19	13.0	5.7	69.2	12.1	2.13	20.9	9.8	49.6	19.7	-33.3	7.1	13.2	-52.2	9.1
Educational level	Below graduate degree	Graduate degree	3.46	15.4	5.5	67.5	11.6	2.90	15.2	5.5	67.6	11.7	-16.2	-17.3	-16.5	-16.0	-15.7
Household Characteristics																	
Income	Less than \$25,000	More than \$150,000	1.57	20.1	7.5	64.7	7.7	3.36	11.3	4.4	66.7	17.6	114.5	20.9	26.1	120.8	391.7
Vehicle ownership	0 or 1 vehicles	3+ vehicles	2.94	11.1	4.0	71.2	13.7	3.33	18.1	6.1	65.2	10.6	13.4	85.3	73.4	3.9	-12.9
Household composition	Single man	Single woman	3.58	13.8	5.8	68.2	12.2	3.16	10.5	4.1	76.2	9.2	-11.6	-32.1	-37.1	-1.3	-33.9
	Multiple unrelated adults	Multiple related adults without children	5.53	15.8	6.1	67.2	10.9	3.25	15.0	5.5	67.4	12.1	-41.2	-44.1	-46.8	-41.1	-35.0
	Multiple related adults without children	Multiple related adults with children	3.25	14.9	5.5	67.5	12.1	2.85	17.9	5.1	65.6	11.4	-12.3	4.8	-18.7	-14.6	-17.5
Employment Status/Job Characteristics																	
Employment status and workplace location	Unemployed	Full-time employees with no work from home	2.29	13.6	3.1	70.1	13.2	3.83	15.6	6.1	66.9	11.4	67.4	93.3	225.1	59.8	44.0
	Unemployed	Full-time employees with 60% workdays from home	2.29	13.6	3.1	70.1	13.2	3.10	15.3	6.1	67.1	11.5	35.7	53.6	161.4	29.9	18.3
	Unemployed	Full-time employees with 100% workdays from home	2.29	13.6	3.1	70.1	13.2	2.67	15.2	6.0	67.2	11.6	17.0	31.1	124.5	12.1	2.7

Table 9. Average Treatment Effect (ATE) for all exogenous variables (contd.)

Variables	Base Level	Treatment Level	Base level				Treatment level				ATE (% shift)						
			Total eat-outs per capita	Allocation to restaurant segment (%)				Total eat-outs per capita	Allocation to restaurant segment (%)				Total eat-outs per capita	Number of visits to restaurant segment			
				QSR	CH	CSR	FSR		QSR	CH	CSR	FSR		QSR	CH	CSR	FSR
Residential Location BE Factors																	
Land-use mix index	0.40 (10th percentile)	0.80 (90th percentile)	4.88	15.7	5.5	67.3	11.5	3.17	15.4	5.6	67.3	11.8	-1.7	-4.0	2.6	-2.0	0.9
Fraction of QSR restaurants	0.00 (10th percentile)	0.30 (90th percentile)	3.10	12.9	5.8	69.0	12.3	3.31	17.9	5.2	66.0	10.9	6.5	46.7	-4.8	2.0	-5.0
Restaurant density (number of restaurants/100 square acres)	0.00 (10th percentile)	0.03 (90th percentile)	3.09	15.5	5.4	67.5	11.6	3.26	15.5	5.4	67.5.5	11.6	5.5	6.0	5.5	5.5	5.2
COVID-19 Perspectives																	
I or someone I live with or frequently visit is immunocompromised	No	Yes	3.41	15.2	6.4	67.1	11.2	2.80	15.9	3.6	68.3	12.2	-17.8	-14.0	-53.5	-16.3	-10.9
My personal well-being was or still is at risk during the pandemic	No and age is less than 50 years	Yes and age is less than 50 years	3.50	24.2	16.8	44.8	14.2	2.50	19.6	14.6	53.3	12.5	-28.3	-42.2	-37.6	-14.8	-36.4
	No and age is more than 50 years	Yes and age is more than 50 years	3.23	11.4	4.3	68.9	15.4	2.78	9.5	4.0	72.7	13.8	-13.8	-28.3	-22.2	-8.9	-22.3

Appendix A.

Table A.1. Unlinked model estimation results

Variables	Baseline Marginal Utility Component of MDC Model								Satiation Component of MDC Model								Count Model	
	QSR		CH		CSR		FSR		QSR		CH		CSR		FSR		Eat out	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Exogenous Variables																		
Individual Demographics																		
<i>Age (base: 18 to 29 years old)</i>																		
30 to 49 years old	—	—	-0.888	-4.50	—	—	na	na	—	—	—	—	—	—	na	na	—	—
49 to 64 years old	-0.780	-7.56	-0.888	-4.50	—	—	na	na	—	—	—	—	0.692	2.62	na	na	—	—
65 and older	-0.467	-3.10	-1.568	-7.25	-0.202	1.59	na	na	—	—	—	—	1.046	2.63	na	na	—	—
<i>Race (base: White)</i>																		
Not White	—	—	—	—	-0.623	-1.09	na	na	—	—	—	—	—	—	—	—	-0.199	-2.52
Not White × (Walkability Index/100)	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	—	—
<i>Educational level (base: below graduate degree)</i>																		
Graduate	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	-0.114	-2.47
Household Characteristics																		
<i>Income (base: <\$25,000)</i>																		
\$25,000 - \$49,999	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.447	2.91
\$50,000 - \$99,999	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.527	3.84
\$100,000 - \$149,999	-0.805	-6.49	-0.722	-6.36	—	—	na	na	—	—	—	—	—	—	na	na	0.579	4.15
>\$150,000	-2.357	-11.80	-1.358	-10.53	-1.050	-7.57	na	na	0.846	2.06	—	—	—	—	na	na	0.579	4.15
<i>Vehicle ownership (base: zero or one vehicle)</i>																		
Two vehicles	0.322	2.13	0.172	1.52	—	—	na	na	—	—	—	—	—	—	na	na	—	—
Three or more vehicles	0.436	2.67	0.156	1.45	—	—	na	na	—	—	—	—	—	—	na	na	—	—
<i>Household structure (base: single male)</i>																		
Single female	—	—	—	—	—	—	na	na	—	—	—	—	0.845	2.87	na	na	-0.170	-1.94
Multiple related adults	—	—	—	—	—	—	na	na	-0.244	-1.12	—	—	—	—	na	na	-0.117	-2.40
Multiple unrelated adults	0.741	1.74	—	—	—	—	na	na	-1.669	-2.95	—	—	—	—	na	na	0.360	2.38
Presence of children	1.019	9.71	—	—	—	—	na	na	—	—	—	—	—	—	na	na	-0.081	-1.50
Employment Status/Job Characteristics																		
<i>Number of workdays per month</i>																		
Number of workdays	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	1.295	4.51
<i>Workplace location</i>																		
Fraction of work days from home in the past month	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	-0.325	-4.11
<i>Employment status (base: not employed)</i>																		
Part-time	—	—	0.778	5.62	—	—	na	na	-0.550	-1.94	—	—	—	—	na	na	—	—
Full-time	—	—	0.778	5.62	—	—	na	na	-0.550	-1.94	—	—	—	—	na	na	—	—
Residential Location BE Factors																		
<i>Land-use</i>																		
Walkability (/100) (range 0-0.2)	-1.720	-1.03	—	—	—	—	na	na	—	—	—	—	—	—	na	na	—	—
Land-use Diversity Index (range 0-1)	—	—	—	—	1.742	2.51	na	na	—	—	—	—	-2.710	-3.08	na	na	—	—
<i>Restaurant density</i>																		
Fraction of QSR restaurants (range 0-0.6)	0.716	1.81	—	—	—	—	na	na	—	—	—	—	—	—	na	na	—	—
Restaurant density (number of restaurants/100 square acres) (range 0-0.4)	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.969	1.63

Table A.1. Unlinked model estimation results (contd.)

Variables	Baseline Marginal Utility Component of MDC Model								Satiation Component of MDC Model								Count Model	
	QSR		CH		CSR		FSR		QSR		CH		CSR		FSR		Eat out	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Exogenous Variables																		
COVID-19 Perspectives																		
I or someone I live with or frequently visit is immunocompromised	—	—	-0.942	-9.89	—	—	na	na	—	—	—	—	—	—	na	na	-0.214	-2.87
My personal well-being was or still is at risk during the pandemic	—	—	—	—	—	—	na	na	0.460	2.55	—	—	0.536	3.91	na	na	-0.086	-1.92
My personal well-being was or still is at risk during the pandemic × Age 50 and older	—	—	—	—	—	—	na	na	—	—	—	—	—	—	na	na	0.119	1.66
Constants	na	na	-0.944	-2.64	2.482	4.94	-1.377	-4.87	-0.873	-2.48	-1.714	-8.30	-1.986	-3.20	-1.827	-10.98	2.003	14.32
Threshold Shifters																		
0 1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	2.118	32.43
1 2	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.117	3.38
2 3	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.196	5.42
4 5	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.208	5.01
10 11	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1.364	5.85
12 13	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	2.525	2.45
14 15	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	-8.208	-7.32
20 21	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0.717	1.87
Goodness of Fit																		
Log-likelihood at convergence	-3728.09																	
Bayesian Information Criterion (BIC)	3958.95																	
$\bar{\rho}^2$	-3876.63																	
Constants and threshold-shifters (CT) only log-likelihood*	0.025																	
Nested likelihood ratio test: Unlinked model versus constants and threshold-shifters only model	LR=297.08 > $\chi^2_{(50,0.05)}=67.505$																	

* The value refers to the (CT) only log-likelihood of the unlinked model.