Eat-in or Eat-out? A Joint Model to Analyze the New Landscape of Dinner Meal Preferences

Angela Haddad
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: angela.haddad@utexas.edu

Aupal Mondal
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: aupal.mondal@utexas.edu

Chandra R. Bhat (corresponding author)
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Tel: 1-512-471-4535; Email: bhat@mail.utexas.edu
and
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

ABSTRACT

In this paper, we examine the non-domestically cooked meal (NDCM) preferences of individuals for their dinner meal by studying the monthly count of NDCM meals by channel type: eat-out, eat-in takeout, and eat-in delivery. Data from a 2022 online survey collected in Texas is employed to estimate a multivariate joint model. Model estimation results indicate that the most frequent customers of the eat-out channel are white individuals, individuals from 3+ motorized vehicle owning households, those in non-joint families, those in households with no children, full-time employees who never work from home or do so only for a small fraction of their workdays, and those residing in areas with a high density of restaurants. The distinct consumer segments for the eat-in takeout channel include young individuals, those with high household incomes, those working from home all their workdays or a substantial fraction of their workdays, and urban residents; the most enthusiastic consumers of the eat-in delivery channel are white individuals, those with less than three vehicles in the household, individuals with children, urban residents, and those worried about pandemic-related personal health risks. Older individuals, non-white individuals, individuals with a graduate degree, individuals in fewer motorized vehicle-owning households and in joint families, those with children in the household, and rural residents constitute the most committed population segments of the domestically cooked meal (DCM) consumption channel. The results suggest the important impact of workplace location on dining channel choice. The results also show clear evidence of complementary and substitution effects at play; the delivery channel complements eating out but substitutes takeout. Similarly, eat-out has a substitution effect on eat-in takeout. These effects have important implications for activity-travel behavior due to emerging technology-based ordering options for dining choices, especially so in the aftermath of the onset of the COVID pandemic.

Keywords: Dinner choice, pick-up, delivery, takeout, dine-in, COVID-19.

1. INTRODUCTION

Food expenditure outlays constitute the third leading category of household budget expenditures in most countries of the world, along with housing and transportation outlays (Bureau of Labor Statistics, 2020). In the U.S., it has been estimated that about 12.5% of the average U.S. household budget is spent on food, almost evenly distributed between non-domestically cooked meals (for simplicity for the rest of the paper, NDCM) and domestically cooked meals (DCM) (U.S. Department of Agriculture, 2021). Furthermore, until the COVID-19 pandemic, there was a steady 5% annual increase in NDCM consumption, especially eating meals outside the home at a commercial catering establishment (U.S. Department of Agriculture, 2022). The increased expenditures on NDCM resulted in record-high restaurant sales totaling $864 billion in 2019, reflecting an average annual household expenditure of $3,526 (Kelso, 2022, Statista, 2020). This cultural shift away from DCM preparation and toward NDCMs has been attributed in food sociology studies (see, for example, Holm, 2013; Smith et al., 2013; Venn et al., 2017; and Warde et al., 2007) to multiple factors, including (a) increasing participation of women in the workforce and the resulting time rebalance to accommodate this remunerative pursuit, (b) growing acceptance in society that cooking is not primarily the women's responsibility, (c) rising affordability of NDCMs due to the industrialization of the food industry, (d) delinking of DCMs from its symbolic social, cultural and/or religious significance as a family gathering event, (e) viewing NDCMs as an opportunity to socialize, or an opportunity to experience different cuisines, or an escape from routine, and (f) signaling cultural capital and social distinctiveness.

The increasing expenditure on NDCM over the years, while primarily associated with eat-out activity, may also be associated with eat-in NDCM (that is, take-out from an eatery or delivery of fully/partially-prepared meals to the home). To be sure, there was a rise in the e-commerce spurred eat-in NDCM even before the COVID-19 pandemic (Ma et al., 2021). And there is little doubt that the COVID-19 pandemic accelerated eat-in NDCM frequency (for ease in presentation, we will refer to such eat-in NDCM food consumption simply as "eat-in", distinctly different from the traditional in-home eat-in of domestically-cooked meals or DCMs). Such eat-in arrangements, facilitated by the widespread adoption of information and communication technologies (ICT), are resulting in a boom in the total food delivery market's worth, with delivery sales projected to increase from $107 billion in 2019 to $154 billion in 2023 (Business Research Company, 2021; Ahuja et al., 2021). In another survey of 10,000 consumers, OpenTable revealed that the pandemic resulted in a 72% increase in the proportion of Americans picking up NDCM at least once a week and a 62% increase in the proportion of individuals ordering food deliveries (Terenzio, 2020). This is because, during the pandemic, some individuals who never had an eat-in episode before have become more experienced with ordering food online, and have become aware of the benefits of eat-in as another NDCM channel, including (a) convenience and efficiency to busy consumers through a reduction in ordering, waiting, and payment time, (b) enhanced comfort and safety to those who might not want to venture out while continuing their activities in-home, and (c) a greater variety of restaurants and menu options to customize from and dip into. In particular, eat-in has the appeal of the familiar home-related ambiance of socialization and familiarity and does not need

extra grooming preparation. These considerations have led to optimism among food industry insiders about the future of eat-ins. A study by Gunden et al. (2020) supports such optimistic industry assessments.

However, as the world continues to readjust as the impacts of the pandemic recede, uncertainty about post-pandemic dining choices remains. A recent consumer tracker survey of 3000 U.S. consumers by Deloitte (see Renner et al., 2021) suggested that NDCM consumption may not return to the pre-pandemic levels because of a resurgence of DCMs. This renewed movement back toward DCMs may be attributed to several reasons, including (a) the social-psychological coping mechanisms associated with the pandemic that may have made some individuals comfortable in their isolated being, (b) a focus on personal change and well-being leading to a desire for more control over the ingredients going into a meal, (c) delighting and embracing a new interest in one's own cooking skills, (d) the rise in financial worries, and (e) the increased frequency of teleworking. Indeed, Oblander and McCarthy (2022), using credit/debit card transaction data, found evidence of the persistence of such pandemic-acquired DCM-oriented food consumption habits, months after vaccinations and other preventive measures have reduced the deadly effects of the pandemic. In contrast, however, the National Research Association of the U.S. indicates that, since January, eat-out and drink-out places witnessed a real sales gain of 10%, after accounting for menu-price inflation effects.[1] Additionally, a study by Giambattista (2020) suggests that consumers will indeed increase their eat-out NDCM activities as COVID's effects fade. In yet another study, Shi and Xu (2021) examined the split of restaurant visits between dine-in and takeout before, during the peak of COVID, and after dining capacity restrictions were lifted. They found that the takeout proportion of the total restaurant foot traffic ranged between 50% to 60% before the pandemic, spiked to 100% with the enforcement of dine-in restrictions during COVID, and dropped back to about 65% after society made significant progress in protecting against COVID. This may indicate a "return to normal" in terms of eat-out tendency, though eat-in appears to have gained an increased share of the NDCM market.

The preceding discussion highlights the importance of studying each (and all) of the different food consumption channels jointly. This is especially so because adding eat-in channels can result in "cannibalization" from the eat-out channel (see Collison, 2020), leading to a substitution effect among the different NDCM channels (especially the eat-in delivery and eat-out channels). But eat-in and eat-out can also reinforce each other through exposure to time savings and convenience effects that lead to an overall complementary tendency for NDCM across different channels, which can then increase overall travel. Or an increase in DCM tendency can lead to a reduction in all forms of NDCM. Which of these effects hold? Does one effect dominate over the other? Do these effects vary by consumer demographic and work characteristics? By COVID threat levels? At the heart of these questions related to e-commerce-modified travel patterns (with also implications for other sectors) is a need to understand and characterize

[1] See https://restaurant.org/research-and-media/research/economists-notebook/analysis-commentary/consumer-spending-in-restaurants-continued-to-rise-in-may/, accessed June 17, 2022.

demographic and other individual/household-level factors that affect the portfolio choice related to the use, and intensity of use, of the different NDCM channels.

Motivated by the discussion above, in this paper, our emphasis is on better understanding the new terrain in NDCM activity choices from a consumer perspective. Specifically, using survey data collected in Texas between February middle to March middle of 2022, we attempt to gain insights regarding self-reported actual NDCM choices at a time when all channels of NDCM food consumption (including dine-in at restaurants) have largely opened up. While we admit that longer-term equilibrium in multiple NDCM channel consumption trends may be somewhat different from the choice behavior at the current time, it should be pointed out that the current situation of multiple NDCM channel options has been in existence for already sometime after vaccinations became widely available; besides, the deadly effects of COVID have been substantially reduced from even a year before this survey was administered. Thus, our analysis should provide a reasonable indication of the new landscape in NDCM choices. Different from many studies in the past two years that have examined potential workplace choices in a post-COVID future, to our knowledge, this is the first study to jointly examine NDCM channel choices and the count of channel-specific NDCM episodes. As such, our analysis should be of interest to transportation planners, health professionals, as well as food services specialists, as discussed in turn in the subsequent paragraphs.

From a transportation planning perspective, which constitutes the primary disciplinary emphasis of this paper, there is little literature and consideration of the nuances and interplay of decisions among in-person and ICT-based online food service purchasing options as a function of individual and household demographics, the built environment, and employment status/job characteristics. NDCM behavior, in most travel models, is folded in within the general category of "leisure" or "recreation" or "non-work" activity, and even so focused on the destination and related dimensions of eat-out activity with no consideration of the ICT-assisted eat-in channels. On the other hand, eat-in channels also have repercussions on travel, either through the household itself generating a trip to pick-up food or through another individual delivering the food to the home. In this context, the overall portfolio of NDCM choices becomes important, not just the individual-specific channel choices, because of the possible presence of substitution or complementarity across the counts of occurrences within each channel. For example, a change from working at home to working from the office may increase the probability of eat-out activity as it becomes more convenient to visit restaurants as part of the individual's commute, but also decrease the frequency of eat-in as the individual spends less time at home. Conversely, the frequency of eat-in activities may also increase due to the additional time crunch and tiredness created by commuting to the workplace. Thus, it is important to understand the interplay of participation in the different NDCM channels to examine how they, together, contribute to reshaping urban activity-travel patterns.

From a health standpoint, NDCM meals have been generally associated with poorer diet quality, with cascading impacts on health problems such as obesity, type II diabetes, and cardiovascular disease. The typically poorer diet quality of NDCM meals originates from higher

contents of fat, salt, sugar, and calories, and lower contents of fruits/vegetables, compared to traditional DCMs (see Goffe et al., 2017; Tumin and Anderson, 2017; and Wellard-Cole et al., 2022 for an extensive review). This issue is exacerbated by the fact that the eat-in service business model intrinsically favors high-calorie-serving fast-food restaurants that had already invested in food distribution digital infrastructure and drive-through windows. Traditional exclusive "sit-in" restaurants, while having more ability to customize food to suit the diet quality desired by patrons, have not been able to adapt as quickly to the new pandemic-engendered food consumption landscape. Besides, dual-earner couples, single mothers, the poor, and members of racial/ethnic minorities tend to be particularly time poor, creating further health inequities (see, for example, Devine et al., 2006; Djupegot et al., 2017; Oostenbach et al., 2022; and Okumus, 2021). In this regard, the current study can provide additional insights for health policies through the analysis of joint NDCM consumptions across all channels, as opposed to previous studies in the area that consider a single aggregated NDCM outcome across all channels or focus on a singular channel (mostly eat-out).

From a food services standpoint, particularly after the onset of the pandemic, expanding to provide an eat-in channel for NDCM has gained substantial currency (literally and figuratively), as restaurants and food service providers navigate the new competitive market to increase revenue and profitability (and, in some cases, to survive in the short run). According to the National Restaurant Association, 68% of consumers indicate that they use the two eat-in channels (takeout and delivery) more so than before the pandemic, and 53% indicate that the eat-in channels have become essential to their way of living.[2] But adding eat-in channels has not always been successful, especially the delivery-based eat-in option. This is because of potential cannibalization effects, as discussed earlier. The net result is that, while total revenue may increase, profitability does not always follow revenue trends because of the investments needed in establishing and maintaining an eat-in option. The underlying issue here again is the interplay between resource investment needs for eat-out at the restaurant and the eat-in options. If a higher frequency of eat-ins takes away from eat-outs, this may reduce profitability. But if the higher frequency of eat-ins leads to more eat-outs, then it can be profitable. There has been little empirical investigation into such cross-channel effects at the individual consumer level, the focus of the current paper.

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 methodology for both the survey data collection process and the modeling. Section 4 presents the estimation results, while Section 5 computes the magnitude effects of variables. The final section concludes with a discussion of implications and future research directions.

2. RELEVANT LITERATURE

The earlier literature on food consumption behavior has focused on (1) supply-side restaurant/service characteristics, (2) NDCM consumption motivations, and (3) consumer-level

[2] https://www.producebluebook.com/2021/01/26/nras-state-of-the-restaurant-industry-report-shows-massive-losses/#, accessed June 17, 2022.

considerations. Supply-side research focuses on studying the effect of service-related factors such as price, quality, and ambiance on consumers' NDCM eat-out decision-making (such as Jung et al., 2015; Sulek and Hensley, 2004; Ubeja et al., 2021). Other supply-side studies have evaluated the impact of information quality and credibility, ease of use, system trust, convenience, design, and other online delivery service-related factors on the frequency of purchasing delivered meals (see Cho et al., 2019; Gunden et al., 2020; Hong et al., 2021; Kang and Namkung, 2019; Ray and Bala, 2021; and Roh and Park, 2019). Such studies are mainly undertaken in the food services and hospitality fields, as they inform restauranteurs how to prioritize service improvements. For our study, though, it is the latter two demand-side aspects of NDCM consumption motivations and consumer-level considerations that are of more relevance, as the emphasis is on understanding overall individual-level NDCM preferences rather than specific restaurant or delivery mechanism features. In this regard, the second group of NDCM consumption motivation studies tends to be theoretical or descriptive in nature. Undertaken primarily in the food services and health fields, such studies broadly investigate the hedonic and utilitarian drivers for NDCM consumption. Hedonic value relates to enjoyment, satisfaction, celebrating special occasions, fulfillment, and pleasure, while utilitarian value integrates more cognitive aspects, such as cooking stress, cost-effectiveness, and time savings (Jones, 2018; Josiam and Henry, 2014; Kertasunjaya et al., 2020; Kim and Kim, 2021; Ma et al., 2021; Namin et al., 2020; Okumus, 2021; Yeo et al., 2017). These studies, while certainly providing useful insights regarding factors that drive NDCM behavior, are not the best suited for transportation planning purposes or to inform the targeting and tailoring of public health/food service positioning interventions. However, they can provide insights for the results obtained later in this study.

For our current study, it is the third category of studies on consumer-level considerations that is most relevant. Within this category, some studies focus on a specific instance of eat-out NDCM participation. Such studies analyze the venue (such as fast food outlets, pizza houses, and sit-down restaurants) or the cuisine type (such as by ethnic categorization or other categorizations such as vegetarian versus non-vegetarian) or specific restaurant choice, based on a combination of consumer characteristics, day of week and season of the year, and restaurant service characteristics. But, these studies investigate the characteristics of a specific eat-out NDCM participation occasion rather than on the count of the eat-out episodes over a period of time such as a week or a month. The studies do not also consider individuals who never eat out. In the rest of this section, we will confine attention to earlier consumer-level studies of the frequency of NDCM consumptions (including non-participations) over a period of time, based on revealed choice behavior. We categorize these consumer-level studies by the NDCM channel considered.

2.1. Eat-Out Studies

Warde et al. (2020) suggested that determinants affecting the frequency of eating out have been consistent across the years. Individuals with higher income, men, those younger and with higher educational attainment, and belonging to white ethnicity are more frequent NDCM eat-out consumers than their corresponding peers, while low-income earners, older individuals, and

families with children tend to eat at home more frequently (see also Zang et al., 2018). Household structure and dynamics also have been noted to influence the frequency of eating out. Sonneveld (2019) and Zang et al. (2018) suggested that unmarried individuals eat out almost twice as much as those who are married. This trend is consistent with previous findings suggesting that couples living together are likely to monitor each other's health, which results in healthier DCM consumption (Malon et al., 2010; Umberson, 1992). Within married couples, Sonneveld (2019) suggested that individuals with employed spouses consumed 0.9 more meals out of the home in a week compared to individuals with unemployed spouses. The presence of children is generally associated with lower eat-out NDCM consumption. Overall, the need for family connectedness, spending quality time with family members, and financial stress are commonly reported factors to eating together at home (Appelhans et al., 2014; Bowen et al., 2014; Fulkerson et al., 2011; Robson et al., 2016).

2.2. Eat-In Studies

Most earlier studies have focused on the NDCM eat-out channel; there is relatively scant literature in the area of the two eat-in channels, especially in the context of directly examining consumer-level demographic and employment-related effects. So, we combine an overview of earlier studies of both the eat-in channels in this section and relate general findings in earlier studies to possible demographic correlates. Overall, saving time and effort has been found to be an important motivator for using online food deliveries (see Yeo et al., 2017 and Roh and Park, 2019), which may be correlated with time-poor individuals, such as those with children, single parents, those financially-challenged, or those with high incomes and busy schedules. Additionally, online NDCM consumers benefit from the ability to compare prices between different restaurants to pick the one that offers the lower price for a comparable quality level (Chiu et al., 2014; Ray and Bala, 2021; Yeo et al., 2017). This may make delivery orders more appealing to low and middle-class individuals who are looking into the most effective ways to spend their income. Technological savviness and technology acceptance, which typically are positively associated with younger individuals, are also recognized as important influencers of food delivery purchase decisions (Paenchan and Kookkaew, 2022). Recently, research has found that the propensity for eat-in NDCMs increased in response to perceived COVID threats (Bouarar et al., 2021; Hong et al., 2021; Shi and Xu, 2021; Yang et al., 2020). Lavieri et al. (2018), who examined eat-in food deliveries, reported that the presence of children in the household, identifying as female, and individuals from households with high income are more likely to have food deliveries, while age has a negative effect on food deliveries.

2.3. Joint Eat-Out and Eat-In Studies

Three studies in the literature model eat-out and eat-in jointly. Two of these studies have been published in the transportation field in the context of emerging technology impacts on travel, while the third has health and nutrition as its focus. The first study by Dias et al. (2020) examined interactions between meal delivery to the household (eat-in delivery channel) and eat-out, as part

of a larger multidimensional framework that also studied non-grocery shopping and shopping activity behavior. The outcomes used in this study were the number of days in a week that had at least one meal delivery (for the eat-in dimension) and the number of days in a week that had at least one eat-out episode. The study found no unobserved correlation between the eat-in delivery and eat-out channels but found that eat-in delivery does reduce eat-outs, suggesting an overall cannibalization effect (though this effect was indirect through recursive effects on in-person and online non-grocery shopping). Individuals from high-income households, with multiple adults and children, who rented their homes, and lived in high-density neighborhoods tended to have more eat-in and eat-out outcomes than their corresponding peers. Individuals from multiple worker-households had a higher propensity for eat-out, while those from no worker-households had more eat-in, but not eat-out. The analysis was undertaken using a 2017 Puget Sound household travel survey with 705 households and employed a multivariate ordered probit modeling methodology.

More recently, Kim and Wang (2021) built on the Dias et al. (2020) study by using additional person-related attributes in the analysis. In the context of food deliveries, using data from a 2018 New York City Department of Transportation citywide mobility survey, the study examined the determinants of food deliveries (as part of a trivariate ordered-response model of deliveries for grocery and non-grocery items), followed by two separate bivariate ordered-response models related to NDCMs - one of which examined food deliveries and eat-outs by walk, and the second of which analyzed food deliveries and eat-outs by driving. The eat-in delivery outcome corresponded to an ordinal variable of the frequency of food deliveries (a few times a year or less, once a month, a few times a month, once a week, and several times a week), while the eat-out was a simple binary variable of whether the respondent had an eat-out episode by walk or driving on the specific survey day. The results indicated that men, younger individuals, non-Asians, higher-income individuals, those with children in the household, and those living in dense Manhattan had a higher propensity for eat-in deliveries. Those with a higher propensity to have eat-in food deliveries had a higher propensity to eat out by walking. They also found that single individuals have a lower propensity to drive to eat out, while those with more cars in the household had a higher propensity to drive to eat out and a lower inclination to walk to eat out.

Another relevant study is that of Mills et al. (2018), though that study has health and nutrition as its focus. As they state, “few studies to date have specifically identified the sociodemographic characteristics of those currently engaging in different meal sourcing patterns, which is important to inform targeting and tailoring of public health interventions”. The authors use a large cohort study that recruited adults 29-64 years of age between 2005 and 2015 and asked the specific source of the food consumed for the main meal of the day (the interpretation of what the “main meal” was left to the respondent). The source (channel) of consumption included (1) home-cooked meals, (2) ready-to-eat pre-prepared eat-in delivery meals, (3) takeaways, and (4) eat-out meals. A binary variable was created with “two times per week or less” and “more than two times per week” for the home-cooked and two eat-in channels, and “less than once per week” and “one or more per week” for the eat-out channel. Separate binary models (using logistic regressions) are estimated for each of the four channels. Their results indicate that men are more

likely than women to partake in all the three non-home-cooked channels (that is, equivalently, women are more likely to consume home-cooked meals); individuals who are white, working overtime, highly educated, and earning high-income levels tend to eat-out more often relative to their peers; those who are white and with high incomes are particularly unlikely to order takeaways or have food delivered to their homes; and, interestingly, those at the highest income levels and high education levels are more predisposed to having home-cooked meals than any other kind of meal.

2.4. The Current Study

Earlier studies have provided important insights regarding NDCM behavior. But most studies focus on a singular channel for NDCMs, which does not capture the potentially complex interplay in the human decision-making process related to eat-out and eat-in behaviors. The three studies in Section 2.3 that investigate more than one NDCM channel have all been undertaken before the pandemic, which has clearly shifted overall eat-out and eat-in behaviors. These earlier studies also use outcomes that are relatively short-term (such as weekly behavior) and are not always coordinated on a uniform time scale (such as a day for eat-out and a week for eat-in behavior in Kim and Wang (2021), or a binary indicator of less than twice per week versus twice a week or more for eat-in but less than once per week versus once a week or more for eat-out in Mills et al. (2018)). Besides, unlike Dias et al. (2020) and Kim and Wang (2021), we disaggregate eat-in into "delivery" and "takeout", and unlike Mills et al. (2018), we examine all the NDCM channels jointly with attention to the interplay among the channels.

Overall, in the current study, a first to our knowledge in the field after the onset of COVID, we use a monthly timeframe for analysis, with a consistent temporal scale across the NDCM channels. Further, to do away with the ambiguity that may arise in reporting and analysis, we specifically ask respondents about NDCM behavior related to dinner meals on weekdays.[3] Specifically, our outcomes correspond to the following:

- Count of weekdays with an eat-out dinner occurrence in the last month (eat-out)
- Count of weekdays with a takeout dinner occurrence in the last month (eat-in takeout)
- Count of weekdays with a food delivery dinner occurrence in the last month (eat-in delivery)

The uniformity in scale and the direct use of counts as the dependent variables (as opposed to the use of an ordinal scale or a binary scale in previous studies) facilitates a more accurate picture of substitution and complementarity effects in activity behavior for weekday dinner NDCMs. Also, to be noted is that, in our joint model, the count of home-cooked meals is implicit, and arises as a zero count in all the three channels identified above. Other salient aspects of our study are as follows. First, we use a joint multivariate ordinal-response modeling approach, which is

[3] Weekend NDCM behavior is quite different from weekday NDCM behavior (see, for example, Venn et al., 2017), and breakfast/lunch are typically more associated with place of work and individual consumption decisions. On the other hand, the end-of-the-day dinner meal tends to be a stable meal of the day, and more of a family affair and a collective family decision.

particularly suited for the current analysis because the count values for each NDCM channel are capped in a way that the sum of the count values across all NDCM channels cannot exceed the number of weekdays in the month (which we assumed to be 22 days, based on the survey responses we received where the maximum of the sum was 22 days).[4] Second, through our joint modeling, we are able to control for unobserved factors that lead to associations among the counts of the three channels before estimating any substitution/complementary effects of one channel on another. For example, if an individual is a Foodie (has an ardent and refined interest in food, and variety in food), they may be pre-disposed to consuming NDCMs through all three channels. A methodology that ignores the resulting correlation due to this individual unobserved factor (being a foodie), and simply introduces eat-in delivery count as an explanatory variable for eat-out count (or vice versa), would overestimate the complementary effect between these two channels of participation, while our methodology that controls for such correlation would estimate the "uncorrupted true causal" complementary/substitution effects across channels. Third, in joint limited dependent variable models, only recursive effects of one endogenous observed variable on the underlying propensity of another endogenous variable are allowed, due to logical consistency considerations (see Bhat, 2015 for a detailed discussion). Thus, as part of our joint count system, we estimate alternative directions of recursivity among the three count outcomes (for a total of six possible recursive configurations) and obtain the one that outperforms the others based on data fit considerations (more on this in Section 3.3). The final recursive configuration provides important insights into the pathway effects of substitution and complementarity across the three NDCM channels.[5] Fourth, in addition to individual and household attributes that have been considered in earlier consumer-level studies related to NDCMs, we also include a richer set of residential zip-coded built environment variables (including the density of residential location, land-use mix, number of restaurants per capita, and fraction of fast food restaurants). Such built environment factors reflect accessibility conditions, exposure opportunities, and the food environment, which have been shown in the past to be important determinants of delivery-based food consumption and general out-of-home activity participation decisions (see, for example, Lee et al., 2017, and Wang

[4] Note that an ordered-response model is perfectly suited for positive discrete values when there is a clear upper bound on the count values. It is also quite parsimonious when that upper bound is not very large. While a multivariate count model may also be considered, the problem with the multivariate count model is that it allows count values from zero all the way until infinity. In fact, in our empirical analysis in the paper, we estimated both a multivariate count model as well as a multivariate ordered-response model. The former was estimated using the reframing of count models as a generalized ordered-response model (see Castro et al., 2012). Such a framework provides more flexibility than a traditional count model, and also facilitates introducing jointness across multiple counts. In addition, it offers an elegant way of estimating count models with zero-inflations as well as spikes/dips at any other count value. However, in our empirical analysis, the multivariate ordered-response model outperformed the multivariate count model in terms of data fit, even though both models provided similar directions of effects of variables.

[5] On this issue, Kim and Wang (2021) do not actually consider substitution/complementarity effects, because they do not consider the effect of an observed endogenous variable on the latent propensity of another endogenous variable (which is what provides the actual pathway effects of one observed variable on another observed variable). Rather, Kim and Wang use the latent propensity underlying an observed endogenous variable on the latent propensity of another, which is essentially the same as a model with error correlation and all exogenous variables affecting all underlying propensities. But this insightful model does not have the interpretation of one count affecting another count variable as in our model.

and He, 2021). By including these variables within our joint model of different NDCM channels, we are better able to understand how the built environment affects different channels of NDCM participation. Fifth, to our knowledge, this is the first study to evaluate the effect of workplace location choice (that is itself witnessing change through the pandemic; see Asmussen et al., 2022) and an individual's perception of the risk of COVID-19 on NDCM activity. On the latter point, we include variables related to risk perceptions of the COVID-19 virus on an individual's personal well-being as well as the well-being of their loved ones.

3. METHODOLOGY

3.1. The Survey

The primary data for our current study is drawn from a Qualtrics-based revealed preference (RP) online survey, deployed across Texas, U.S., in February-March 2022. Before the final survey deployment, multiple rounds and subsequent revisions were undertaken through pilot survey efforts with a sample of friends, coworkers, and other members of the Austin community. The final administration for data collection, coordinated with the Texas Department of Transportation, involved a suite of communication and information recruitment strategies, including promotion 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. Survey access was restricted to individuals who were residents of the state of Texas at the time of the survey.

A total of over 1,479 responses were collected through the survey effort. However, 387 individuals did not respond to the NDCM frequency or provided a count across all the NDCMs that exceeded the number of weekdays in a month and/or did not provide information on related relevant information such as job and workplace-related questions. The final sample included 1,092 individuals. The survey was deployed at a time when the Omicron variant was past its peak in Texas (and the U.S.), and restrictions and safety measures in-place for the pandemic were on the decline to non-existent in Texas.

3.2. Exogenous Variables

In this study, we consider 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 fraction of work undertaken from a third work place location and home), residential location built environment (BE) factors, and COVID-19 threat/perspective variables. All of the variables listed above were obtained directly from the survey, except for the residential BE variables. In this residential BE group of variables, one set of variables was obtained directly from the survey by asking respondents to characterize their residence neighborhood in one of three categories: urban, suburban, and rural. These were used as dummy variables in the specifications. A second set of

BE variables were 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). Since the area corresponding to one zip code overlaps with multiple CBGs, the BE data from SLD was aggregated from the CBG to the zip code level. The SLD database includes employment and residential density, a walkability index (that is a function 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 (Srvc), and entertainment (Ent)). The last set of variables was translated into a land-use mix diversity index ranging between 0 and 1, based on Bhat and Gossen (2004), as follows:

$$\text{Land-use Mix} = 1-\left\{\frac{\left|\%\text{Ret} - \frac{1}{5}\right| + \left|\%\text{Off} - \frac{1}{5}\right| + \left|\%\text{Ind} - \frac{1}{5}\right| + \left|\%\text{Srvc} - \frac{1}{5}\right| + \left|\%\text{Ent} - \frac{1}{5}\right|}{\frac{8}{5}}\right\} \quad (1)$$

Residential areas with high values of the land-use mix diversity index indicate a richer land-use mix than residential areas with low values. Finally, a third set of residential BE attributes associated with the number of restaurants in the zip code of residence and the proportion of fast-food restaurants in the zip code of residence were obtained by the authors through a systematic web-scraping effort from https://everyrestaurantinthecity.com/, which provides a national restaurant directory of restaurants in the U.S.

Table 1 presents the distribution and descriptive statistics of the survey respondents for the individual/household-level variables and employment status/job characteristics variables. The table also presents statistics corresponding to the whole State of Texas to compare the analysis sample to the general population demographics, which are obtained from the 2020 Texas Census (Texas Demographic Center, 2022), in addition to other sources. In cases where the State of Texas values are not readily available, there is a "--" in the table. The table clearly indicates an over-representation of women, middle-aged and senior (those 50 years or over) individuals, white individuals, the highly educated, and those from households with high income, high car ownership levels, more than a single adult, and high presence of children. In terms of employment status, our sample indicates a non-employment rate of 21%, which is close to the non-employment rate of 24% in the population of Texas. But our sample underrepresents part-time employees (4.6% of the total sample compared to 14.9% of the overall Texas population) and overrepresents full-time employees (74.4% of the total sample versus 61.1% of the Texas population).[6] The sample also slightly over-represents those who are self-employed (9.5% of the sample relative to 6.7% self-employed in Texas as identified in the 2020 Texas Census). But, in terms of commute times to the

[6] A part-time employee is defined in the survey as an individual who works for 30 hours or less per week, while a full-time employee is an individual who works more than 30 hours per week.

work office, the average one-way commute time in Texas is 26.6 minutes, while our sample's average commute time to the work office is 22.8 minutes.[7] Similarly, the average number of days an employee works in a month is 22 days, and our sample reported working an average of 21.5 days.

While the over-representation of women in our sample is interesting, the skew in the other socio-demographic variables is to be expected since this survey was administered online and disseminated, in part, through professional organizations that employ a highly educated and high-income full-time workforce. Additionally, the discrepancies may be attributed to selection bias where individuals with a particular interest in the topic of COVID effects on work patterns and dining patterns are more inclined to participate. Of course, the implication of the divergence of our sample characteristics from the Census population is that caution needs to be exercised in generalizing the descriptive statistics of the sample NDCM patterns to the Texas population NDCM patterns. However, the objective of this paper is to investigate individual-level causal relationships between exogenous variables and NDCM behavior (that is, how changes in exogenous characteristics impact NDCM behavior), and there is no reason to believe that such causal relationships would not apply to the larger Texas population. For example, NDCM behavior may vary across individuals of different age groups, but such demographic heterogeneity is considered through the exogenous "age" category variables. Thus, as long as there is adequate variation in the age variable in our sample to test a variety of functional forms across different age ranges, it is really immaterial whether our sample is exactly representative of the Texas population age distribution. Importantly, because our sampling strategy itself is not based on the endogenous variables (that is, our sample corresponds to the case of exogenous sampling where the sample collection process itself is not predicated on participation (and the intensity of participation) in NDCM), an unweighted estimation approach provides consistent estimates as well as yields more efficient estimates relative to a weighted procedure (see Wooldridge, 1995 and Solon et al., 2015 for an extensive discussion of this point).

3.3. Main Outcome Variables

The model framework requires that there be at least one individual (and, more generally, a reasonable number of individuals) who select each count value; otherwise, the thresholds for each NDCM channel and the entire multivariate model cannot be estimated. In this context, the first occurrence of a zero value for eat-out corresponded to the count of 11, with most of the specific count values above the value of 11 also having zero individuals participating. Thus, we assigned a count value of 10 for those whose eat-out count value was higher than 10. Similarly, there was a substantial drop in the count of individuals at the value of 7 (with only two individuals selecting

[7] The sample includes individuals who worked 100% from home and did not commute to the work office at all (and many of these individuals did not even have a work office). So, the commute time here refers only to those employed individuals who had a regular work office that they went to at least occasionally during the month. The Texas mean of 26.6 minutes also refers to only those who had a regular work office and commuted at least occasionally to that work office. For those who always worked from home (143 individuals of the 996 employed individuals in our sample), the commute time takes the value of zero.

the value of 7 for eat-in takeout and only three individuals selecting the eat-in delivery channel, with zeros for most higher categories). So, we assigned a count value of 6 for those whose count value exceeded 6. Implicitly, this also helps in model prediction because the model will predict non-zero probabilities for all combinations of count values across the three NDCM channels, and our construction above ensures that the maximum possible value of prediction from the data is no more than the count of weekdays in a month (=22 days). As indicated earlier, we focus only on the count of NDCMs for dinner meals on weekdays over the month. For ease of presentation, in the remainder of this paper, we will use the more concise label of "monthly NDCM count" to refer to the more precise label of "dinner-related NDCM count over the 22 weekdays in the month."

Table 2 presents the distribution of the weekday monthly counts of dinner-associated NDCM behavior by channel type: eat-out, eat-in take-out, eat-in delivery.[8] The statistics clearly reveal that the eat-out channel is more commonly used than the eat-in channels, with only 25.92% of individuals who do not partake in the eat-out channel during the month relative to 66.85% of individuals (57.05% of individuals) not using the eat-in takeout (eat-in delivery) channel.

3.4. Framework for Jointly Modeling Count Outcomes

The modeling framework used for analyzing individuals' monthly frequency of NDCM consumption takes the form of a multivariate ordered-response probit (MORP) model system that appropriately accounts for the discrete as well as the capped nature of the counts.

3.4.1. Model Structure

Let c be the index for the NDCM channel type (c = 1, 2,…, C; C=3 in our case). Define a latent propensity y_c^* underlying the count variable y_c for channel c and consider the following structure:

$$y_c^* = \boldsymbol{\beta}_c' \mathbf{x} + \varepsilon_c,\ y_c = k_c \text{ if } \psi_{c,k_c-1} < y_c^* < \psi_{c,k_c}, \tag{2}$$

where $\mathbf{x}$ is a $(L \times 1)$ vector of exogenous variables (not including a constant), $\boldsymbol{\beta}_c$ is a corresponding $(L \times 1)$ vector of channel-specific coefficients to be estimated, and ε_c is a random error term assumed to be standard normally distributed (the scale of ε_c is not identified and so is arbitrarily set to one). k_c represents a specific value of y_c, which can range from the value of 0 to a maximum of K_c in the sample ($y_c \in \{0,1,2,...,K_c\}$. The latent count propensity y_c^* is mapped to the observed count variable y_c by the thresholds ψ_{c,k_c}, which should satisfy the ordering conditions $(k_c = 0,1,2,...,K_c;\ \psi_{c,-1} = -\infty; -\infty < \psi_0 < \psi_1 < ... \psi_{K_c-1} < \infty)$ in the usual ordered-response fashion.

[8] The count value at 10 is high with 119 individuals for eat-out, but 68 individuals had the value of 10, leaving only 51 individuals (less than 4.67% of the overall sample) with a value higher than 10. Similarly, 20 individuals had the value of six for eat-in takeout, leaving only 43 individuals (less than 3.94% of the overall sample) with a value higher than six. For eat-in delivery, 13 individuals had the value of six, leaving 29 individuals (less than 2.66% of the sample) with a value higher than six.

Next, vertically stack the C latent variables y_c^* into a $(C \times 1)$ vector $\mathbf{y}^*$, and the C error terms ε_c into another $(C \times 1)$ vector $\boldsymbol{\varepsilon}$. Let $\boldsymbol{\varepsilon} \sim MVN_C(\mathbf{0}_C, \boldsymbol{\Xi})$, where $MVN_C(\mathbf{0}_C, \boldsymbol{\Xi})$ represents the C dimensional multivariate normal distribution with mean vector $\mathbf{0}_C$ (a $(C \times 1)$ vector of zeros) and a correlation matrix of $\boldsymbol{\Xi}$. The off-diagonal terms of $\boldsymbol{\Xi}$ capture the error covariance across the underlying latent continuous propensities of the different NDCM consumption channels; that is, they capture the effect of common unobserved factors influencing the propensity of monthly weekday counts in each NDCM channel. If all correlation parameters (i.e., off-diagonal elements of $\boldsymbol{\Xi}$) are identically zero, the model system collapses to independent ordered response probit models for each activity type. For future use, also define the vector of thresholds for each channel c as: $\tilde{\boldsymbol{\psi}}_c = (\psi_{c,0}, \psi_{c,1}, \ldots \psi_{c,K_c-1})'$, and further vertically stack all the $\tilde{\boldsymbol{\psi}}_c$ vectors into a single $\tilde{\boldsymbol{\psi}}$ vector.

Let an individual under consideration be observed to have the count values of k_c $(c = 1, 2, ..., C)$. Accordingly, stack the lower thresholds ψ_{c,k_c-1} $(c = 1, 2, ..., C)$ corresponding to the observed count values of the individual into a $(C \times 1)$ vector $\boldsymbol{\psi}_{low}$, and the upper thresholds ψ_{c,k_c} $(c = 1, 2, ..., C)$ into another $(C \times 1)$ vector $\boldsymbol{\psi}_{up}$. Also, define $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, ..., \boldsymbol{\beta}_C)'$ [$(C \times A)$ matrix]. With these notational preliminaries, the latent propensities underlying the multivariate count outcomes may be written in matrix form as:

$$\mathbf{y}^* = \boldsymbol{\beta}'\mathbf{x} + \boldsymbol{\varepsilon}, \ \boldsymbol{\psi}_{low} < \boldsymbol{y}^* < \boldsymbol{\psi}_{high}, \text{ where } \mathbf{y}^* \sim MVN_C(\boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Xi}). \tag{3}$$

Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = \left(\left[\text{Vech}(\boldsymbol{\beta})\right]', \tilde{\boldsymbol{\psi}}', \left[\text{Vechup}(\boldsymbol{\Xi})\right]' \right)'$, where the operator "Vech(.)" row-vectorizes all the non-zero elements of the matrix/vector on which it operates, and the operator Vechup(.) row-vectorizes the upper diagonal elements of a matrix. Then the likelihood function of a single individual may be written as:

$$\begin{aligned} L(\boldsymbol{\delta}) &= \Pr\left[\boldsymbol{\psi}_{low} < \mathbf{y}^* < \boldsymbol{\psi}_{high} \right], \\ &= \int_{D_r} f_C(\boldsymbol{r} \mid \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Xi}) d\boldsymbol{r}, \end{aligned} \tag{4}$$

where the integration domain $D_r = \{\boldsymbol{r} : \boldsymbol{\psi}_{low} < \boldsymbol{r} < \boldsymbol{\psi}_{high}\}$ is simply the multivariate region of the $\mathbf{y}^*$ vector determined by the upper and lower thresholds. $f_C(\boldsymbol{r} \mid \boldsymbol{\beta}'\mathbf{x}, \boldsymbol{\Xi})$ is the MVN density function of dimension C with a mean of $\boldsymbol{\beta}'\mathbf{x}$ and a correlation matrix $\boldsymbol{\Xi}$. The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions defined in Equation (4).

The likelihood function in Equation (4) involves the evaluation of C-dimensional rectangular integrals for each decision-maker, which can be computationally expensive. However, Bhat's

(2018) matrix-based approximation method for evaluating the multivariate normal cumulative distribution (MVNCD) function was employed to evaluate this integral, which provides an efficient and tractable formulation to approximate the integral.

3.4.2. Endogenous Effects Specification

The model framework discussed above accommodates jointness in the count of participation across the three NDCM channels through the correlation matrix $\boldsymbol{\Xi}$. But, after accommodating such associations through the correlations, we can also obtain causal effects of one NDCM count variable on the others by including the observed count for one channel as an embedded endogenous explanatory variable in the $\mathbf{x}$ vector with a non-zero coefficient in the specification of the latent propensity for another endogenous variable. However, as discussed in detail in Bhat (2015), in multivariate model systems with limited dependent variables (that is, when one or more dependent variables are not observed on a continuous scale, such as the joint system considered in this paper that has count endogenous values), such a structural effect of one limited-dependent variable on another can only be in a single direction due to logical consistency considerations. Further, cyclical relationships are also not possible where observed endogenous variable A affects the underlying latent propensity for variable B, then observed endogenous variable B affects the underlying latent propensity for variable C, and observed variable C affects the latent propensity for variable A; see Maddala, 1986 and Bhat, 2015 for a detailed explanation). Taking these issues into account, six possible endogenous pathway specifications are possible, as shown in Figure 1. All six possible structures were estimated, along with the effects of other exogenous variables. The final specification involved the first causal structure, which will be the one discussed in the next section.

4. MODEL ESTIMATION RESULTS

The final model specification was developed through a systematic process of analyzing a number of alternate combinations of explanatory variables while removing statistically insignificant ones. The individual demographics and household variables are in either bracketed categories (age and income), or are naturally discrete (gender, race/ethnicity, education level, motorized vehicle ownership level, and household structure). Within the group of employment status/job characteristics variables, the employment status and self-employed status variables are naturally discrete. Among the residential BE variables, respondents were asked to characterize their household location in the three categories of urban, suburban, and rural neighborhoods. The COVID perspectives/threat variables were obtained either on an ordinal scale or as a simple binary variable.[9] The effects of all these variables were tested as dummy variables in the most disaggregate form possible, and progressively combined based on statistical tests and intuitive

[9] These COVID threat/perception variables were obtained in the survey as a response to the following statements/questions: (a) Covid-19 was/is still a threat to my loved ones, (b) My personal well-being was or still is at risk during the pandemic, (c) Would you consider yourself immunocompromised?, and (d) Would you consider someone you live with or frequently visit immunocompromised? Individuals could provide a response to the first two statements on a five-point Likert scale from strongly disagree to strongly agree, and were asked to provide a response to the latter two questions on a binary scale of "yes" or "no".

reasoning to yield parsimonious specifications. For the non-discrete job characteristics variables (number of work days per month, commute duration, fraction of work days worked from home, and fraction of work days worked from a third workplace) and residential BE variables (residential and employment density, walkability index, land-use diversity index, number of restaurants per square area, 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. Further, we examined interaction effects across many sets of variables, though few of these came out to be statistically significant.

The final model specification is presented in Table 3. Five points of note before we proceed to a detailed discussion of the results. First, as can be observed, the effects of all the non-discrete job characteristics and BE variables appearing in the final specification turned out to be best represented in continuous linear form. Second, not all the included variables are statistically significant at a 95% 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 help inform future investigations with larger sample sizes. Third, the parameters represent the elements of the $\boldsymbol{\beta}_c$ vector for each NDCM channel c; that is the effect of the variable on the underlying propensity y_c^* for participation in the NDCM channel c. Fourth, whenever the same coefficient appears for more than one variable for an NDCM channel, it implies that the two corresponding variables were found not to have differential effects on the NDCM channel propensity. Also, a '--" for a variable-NDCM channel combination represents a null effect of that variable on the NDCM channel, and the absence of a variable from Table 3 (but listed in Table 1) implies that the variable was not even marginally significant in explaining any of the three NDCM channel propensities. Finally, as we will show later in Section 5.1, the results also implicitly provide information about the monthly DCM count. This is because the consumption count of DCMs for any individual may be computed as the difference of 22 (the number of weekdays in a month) and the sum of the predicted values of count for the NDCM channels. Thus, if a variable coefficient on one NDCM channel is positive (with the corresponding variable coefficients on other NDCM channels being zero) or the coefficients on a variable on more than one NDCM channel are <u>all</u> positive, this would generally imply a negative effect of the variable on the DCM count. On the other hand, if a variable coefficient on one NDCM channel is negative (with the corresponding variable coefficients on other NDCM channels being zero) or the coefficients on a variable on more than one NDCM channel are <u>all</u> negative, this would generally imply a positive effect of the variable on the DCM count.

The model results are discussed next by exogenous variable category, followed by the correlation effects and endogenous variable parameter estimates.

4.1. Exogenous Variable Parameter Estimates

<u>Individual Demographics</u>

The individual demographics effects in Table 3 indicate that women have a lower propensity to eat out, but only if they are living alone without a partner (while this variable is technically a

combination of an individual-level variable and a household structure variable; that is, a woman living alone; we categorize it under the label of individual demographics for presentation convenience). The implication is that the propensity for eat-out episodes is not different between men and women once they are in a partner relationship or in living arrangements with other individuals. This latter result may be an indication of inter-individual influences when living with others to the point where gender differentials tend to fade. But sans any influence from other adults in close living quarters, there is literature in the food and health fields that women intrinsically tend to not only eat more healthy, but also are much more open to vegetarianism (see, for example, Rosenfeld and Tomiyama, 2020). Such diet consciousness among women may be attributed in part to a higher body shape/image concern and a higher priority on mental, emotional, and spiritual well-being (Bärebring et al., 2020; Pop et al., 2021), which in turn leads to less consumption of NDCMs (that are generally associated with poorer diet quality than DCMs).

In terms of age, adults over 30 years of age have a generally reduced inclination toward eat-out and eat-in pick-up compared to their younger peers. This reduced NDCM consumption inclination (and, therefore, increased inclination for DCMs) with age may be attributed to several physical and psychosocial factors. Older individuals, especially those 65 years and older, are typically over the peak of their life cycle and career responsibilities, leaving more pre-occupation-free time for preparing DCMs. That is, even though we have controlled for lifecycle and intensity of work characteristics, older individuals may just not feel the same time and mental pressure as their younger peers (see, for example, Neubauer et al., 2019 and Luong and Charles, 2014). Also, the human development literature indicates that as humans get older, there is more resistance to change in established life rhythms, in part because change is perceived as a loss of control that leads to anxiety and stress (Duque et al., 2019). Thus, being accustomed to DCMs for a good part of their lives, it is only natural that older individuals save NDCMs for those occasional celebratory events rather than as a routine affair. In addition to habituation factors, the hedonic benefits of eating out decline with age. In particular, younger adults strive to have expansive social networks and have a greater desire to signal cultural capital/social distinctiveness, which can lead to more episodes of NDCMs. On the other hand, as humans get older, there is a higher preference for compact social networks and a less perceived need for signaling of any kind (Soh, 2019). Finally, the negative effects of age on the propensities for eat-in take-out and delivery are not surprising, given that the use of these NDCM channels requires a certain level of technological proficiency and adeptness, which decreases with age (Ali et al., 2020; Faverio, 2022).

Racial minorities (non-whites) have a lower propensity for eat-out and food delivery relative to white individuals. This result is consistent with the findings of Mills et al. (2018) and Li et al. (2017), though Li et al. observe that the eat-out differences between white and Black individuals diminish after controlling for income and education. Our results on racial differences, however, remain even after controlling for income, education, and other variables in Table 3.[10]

[10] Li et al. differentiate between white and Black individuals in their study, while our study differentiates between whites and non-whites. Our survey collected information on race in multiple categories, including white, Black, Native

The lower tendency of minorities to eat-out may be, at least in part, due to the discriminatory treatment that racial minorities tend to experience at restaurants. For example, ethno-racial studies have indicated that minorities, on average, wait longer for a table at a restaurant, and also longer for the food after ordering (see Billingsley, 2016 and Brewster and Heffner, 2021). A similar reason may be behind the disinclination among minorities for food delivery. Specifically, while the intention to use online delivery services is positively influenced by vendor, transaction, and delivery trustworthiness (Jung et al., 2015), minorities are known to exhibit more misanthropy (less trust) than members of the majority, attributable in part to historical and contemporary discrimination (Smith, 2010; Wilkes and Wu, 2018).

Individuals with graduate (i.e., Master's or Doctoral) degrees have a lower propensity for eat-out and eat-in takeout than those with less than graduate education. This finding is somewhat in disagreement with the findings presented in a few earlier studies, which suggest that adults with a higher educational attainment are more likely to eat-out due to time-saving and convenience factors (see, for example, Zang et al., 2018). Mills et al. (2018) also find higher educational attainment to be positively associated with eat-out (unlike our result), though also distinctly and strongly negatively associated with eat-in takeout (similar to our result). However, consistent with our study, Mills et al. (2018) report that individuals with higher educational degrees have a higher tendency for DCMs (note that the negative coefficients on both eat-out and eat-in takeout in Table 3, with no effect on eat-in delivery, implicitly point to the positive association between educational attainment and the likelihood to partake in DCMs). An explanation for this last result is that higher educational attainment leads to higher food literacy and heightened health consciousness, leading to more DCM consumption (Krause et al., 2018; Nogueira et al., 2016). In summary, the heterogeneous results about the impact of education level on food consumption patterns deserve additional attention in future studies, with better accounting for context-specific factors (such as time-pressure, convenience, and health consciousness).

Household Characteristics

The results from Table 3 suggest, consistent with the findings in the literature (see, for example, Kim and Wang, 2021, and Unnikrishnan and Figliozzi, 2021), that individuals from high-income households ($100,000 of annual income or more) are positively predisposed to NDCM consumption through the eat-out and eat-in takeout channel. This is generally attributed to the greater purchasing power of high-income households, though also may serve as a means to signal social capital and distinctiveness. Also, higher income allows time-poor individuals to invest in the additional time-saving and convenience provided by NDCM consumption (Clifford et al., 2020, Spurlock et al., 2020).

Individuals from households with three or more vehicles appear to have a higher propensity for eating out, which is not surprising as more vehicles imply better accessibility to restaurants of

American, Asian or Pacific Islander, and Other. But there were too few individuals in each individual non-white category to separately tease out disaggregate racial effects. Kim and Wang (2021) report a lower propensity for food deliveries for those of Asian and other races, but no statistically significant difference between white, Hispanic, and Black individuals.

different kinds and cuisines. Also, individuals from households with two or more vehicles have a generally higher proclivity for eat-in delivery, a result that warrants more attention in future studies. One reason may be that high vehicle ownership is generally a reflection of a luxury-oriented lifestyle; individuals from such households may place a high premium on comfort and convenience, and so may be predisposed toward food delivery services (while not being as predisposed to eat-in takeout).

A number of interactions of individual demographics and household structure were considered, including single women interacted with children of different age groups and employment status of adults in the household interacted with children (the latter to consider work-family spillover and the ensuing competing demands for parents' time and energy; see, for example, Devine et al., 2006). But the final specification turned out to have a relatively simple specification with no interaction effects. The results in Table 3 indicate the reduced tendency of joint families to eat-out, strongly supporting the notion that eating choices in joint families are fundamentally driven by a social-cultural norm of viewing the dinner meal as a "sacred" in-home family gathering event (see Fulkerson et al., 2011). However, another possible explanation originates from home production theory, which postulates that households attempt to optimize "production" utility through their joint allocation of income, time, and market goods and services (Stewart and Yen, 2004). From this standpoint, through collaboration in the cooking process (or specialization in the cooking process) and the basic cost economies of scale, eating at home can be a far more time-cost efficient mechanism to fulfill biological needs.

Households with children (regardless of the age of children or other household structure characteristics, which were tested through disaggregation by age groupings of children and interaction effects) have a lower propensity to participate in eat-out and eat-in takeout (particularly the former), presumably attributable to financial stress from the lack of disposable income, feelings of guilt associated with exposing children to unhealthy food, and the generic worry about having to handle the behavior of children in public places (Kim and Kim, 2021). Especially in the context of monitoring their children's weight and diet, parents (especially mothers) feel a "gatekeeping" responsibility for their children's food choices, to the point of viewing their children's dietary intake as a "quality of parenting" performance measure (Petersen et al., 2014 and Jones, 2018). This may result in avoiding NDCMs in favor of DCMs when children are present in the household, given that NDCMs are generally associated with poorer diet quality. However, this tendency for lower intensity for NDCMs in the presence of children does not seem to extend to food deliveries, which perhaps reflects the fine balance families with children find themselves having to maintain between healthy parent-cooked DCM meals and the time-pressure coping mechanism of ordering food (Spurlock et al., 2020).

Employment Status/Job Characteristics

A number of employment status/job characteristics variables were considered, but only those related to employment status (not employed or part-time employed or full-time employed), number of work days per month, and fraction of work days from home turned out to be influential. It should

be noted that part-time or full-time employed status refers here to the number of work hours per week (respondents were asked to self-report, with part-time being characterized as 30 hours or less per week, and full-time being more than 30 hours per week).

For the eat-out channel, only the number of work days per month turned out to be influential. That is, the effects of part-time and full-time status, relative to not being employed at all, were completely overshadowed once the number of work days per month was included (and the best specification for number of work days turned out to be the linear form). This is an interesting finding. The suggestion is that two individuals, one working part-time for 20 hours in the week, but on all five days of the week, and another working full-time for 40 hours in the week, again on all five days of the week, do not have differential eat-out propensities (after controlling, of course, for other observed and unobserved factors). That is, our result suggests that it is not the intensity of the work day, but the number of work days that influences eat-out propensity. In this context, work-related activities have been known to contribute to time poverty (or at least the perception thereof; see, for example, Giurge et al., 2020 and Bernardo et al., 2015). This time poverty generally translates into more eat-out activities (see Oostenbach et al., 2022). What is interesting from our results though is that individuals view the opportunity cost of work time (or, equivalently, time poverty) more in the context of number of days of work rather than the actual daily intensity of work. Why this is the case certainly deserves more attention in the future. From a survey collection standpoint, our observations also underscore the need to capture multiple dimensions of work arrangements (including number of days of work per month, number of days per week, and number of work hours on a typical work day), not just part-time or full-time (as done in many data collection efforts). As we highlight further below, it is also important to start considering hybrid work arrangements, especially in a post-COVID world.

In terms of the effect of the number of work days per month on eat-out propensity, the positive sign of the number of work days needs to be considered together with the strong negative sign of the fraction of work days working from home. The magnitudes of the coefficients on these two variables indicate that it is only for those who work less than 4.3% [=(0.025/0.585)×100] of their work days from home that the positive eat-out propensity holds, which basically implies that the higher propensity of eat-out applies pretty much only to those who do not work from home at all (or do so on that occasional day of the month) and who travel to their in-person work office almost every working day. Indeed, this result makes sense, as the accessibility and convenience to visit restaurants are greatly enhanced when an individual is already outside home on their work-to-home evening commute. On the other hand, individuals who work more than an occasional day from home have a lower tendency to eat-out, relative to both those who travel in to work regularly as well as those who are not employed. It is possible that those who work more from home may have a general preference to be "homebound" not only for work but also for other non-work activities, including eating out (Xiao et al., 2021). Interestingly, commute duration to the in-person workplace did not turn out to be an even marginally significant predictor of eat-out propensity, even for those individuals who always traveled to the work office on each working day.

For eat-in takeout and eat-in delivery, part-time workers have the highest propensity, followed by full-time workers.[11] The higher propensity of part-time workers for eat-in may be tied to more time availability. Also, in a flipped situation relative to the case of eat-out, it appears that time scarcity perceptions get filtered through the lens of the daily intensity of work for eat-ins rather than the number of days of work (given that part-time and full-time status influences the eat-in propensities rather than number of work days per month). This further calls for how time scarcity perceptions get formed in the context of NDCM consumption decisions, and reinforces the need to obtain a more complete characterization of work arrangements. Finally, in the group of employment status/job characteristics, the higher propensity of those who work more from home for the eat-in channels is not surprising.

Residential Location BE Factors

A number of residential location BE factors were developed using the SLD database and through web-scraping, as discussed earlier. Three of these turned out to be drivers of NDCM behavior in our analysis.[12] Individuals dwelling in urban and suburban neighborhoods (relative to those in rural neighborhoods) are more disposed to order food takeouts and deliveries, perhaps because such services are more commonly offered in non-rural areas than in rural areas (see Wang and He, 2021). Additionally, urbanized areas are associated with higher population density, which improves the reliability and reduces the price of delivery services (Kim and Wang, 2021). However, in addition to density (as captured by the urban/suburban/rural classification), land-use mix also appears to play a role. Our analysis, the first to our knowledge to introduce land-use mix in the context of eat-in NDCM behavior, suggests that those living in areas with a richer land-use mix have a particular disinclination toward food delivery services, The third BE variable pertains to "Number of restaurants per square mile area" in the zip code of residence. As the number of opportunities for eating-out increases beyond a threshold of 20 (in the typical size of a suburban zip code in Texas, this translates to about 280 restaurants), there is a higher eat-out tendency, which can be ascribed to the higher exposure and improved accessibility to eateries.

COVID-19 Threat/Perception Variables

Of the four COVID-19 threat/perception variables, responses to two statements; "COVID-19 was/is still a threat to my loved ones", and "My personal well-being was or still is at risk during the pandemic", were sought on a five-point Likert scale in the survey from strongly disagree to strongly agree, as discussed at the beginning of this section. In our analysis, the best specification for representing these two variables corresponded to a binary classification where the "somewhat

[11] Those not employed are most unlikely to pursue eat-ins and NDCMs in general, possibly because of financial uncertainty and worry about the future, even though current household income earnings has been controlled for.

[12] This result suggests either that food choices are more driven by demographics/job characteristics rather than residential BE, or that there is a natural residential self-selection process at play wherein specific demographic segments of the population locate themselves in specific neighborhoods such that residential BE factors get, to a good extent, implicitly accounted for through resident demographics. It would be interesting in future studies to attempt to disentangle these two possible explanations.

agree and strongly agree" responses were collapsed into a single "Yes" category, and the other three were combined into the "No" category.

The results in Table 3 reveal that eat-out propensity appears to be particularly influenced by the concern about other individuals as opposed to personal concerns. Typically, eating out is viewed as a social activity with family or friends which may pose a health risk to loved ones due to the increased public exposure. The two other variables related to personal considerations; "I am immunocompromised" and "My personal well-being was or still is at risk"; were highly correlated, and the latter turned up being more influential in the specification. The result suggests that the concern for one's own health and well-being is likely to encourage pursuing contactless services that can be accomplished through food pick-up and delivery (Mehrolia et al., 2021).

Thresholds

The elements of the $\tilde{\boldsymbol{\psi}}_c$ vector for each channel in Table 3 (these represent the upper bounds for each count) do not have any substantive interpretations. They serve to map the underlying propensity to the actual observed count. These elements are important for predicting the actual count combination for each individual, but, by themselves, do not have any meaning.

4.2. Endogenous Variable Parameter Estimates

Table 3 also presents the estimates of the endogenous variable parameters for the first pathway specification structure in Figure 1. Both continuous functional forms for these endogenous effects, as well as categorical forms of the effects, were attempted. In the latter case, we introduced the endogenous counts in the most disaggregate dummy variable form, but progressively constrained the count category effects based on the results. The final specification included a non-linear dummy variable form for the eat-in delivery effect on eat-out and for the eat-out effect on eat-in takeout. But the linear continuous form outperformed the non-linear form for the eat-in delivery effect on eat-in takeout. Also, since the jointness among the endogenous variables due to unobserved correlation effects (discussed later in this section) is accounted for, the recursive effects capture the "true" causal effects of one NDCM channel count on the propensity for another.

The prevailing causal structure indicates that the chain of recursive effects starts with decisions related to eat-in delivery. Individuals who order food delivery for dinner meals more frequently have a progressively higher propensity to eat-out, and also are less predisposed to order through the takeout channel. These results imply a complementary relationship between food delivery and dining out, but a substitutive relationship between food delivery and takeout. Our research adds to the ongoing discourse on the relationship between eating out, takeout, and delivery. For example, Kim and Wang (2021) and Ma et al. (2021) report a complimentary effect where adding delivery services increases restaurants' revenue and dine-in visits due to the advertising effect of online delivery platforms, while Collison (2020) and Dias et al. (2020) suggest a substitution (cannibalization) effect where expenditures on food delivery draw away from restaurant dine-in expenditures. Perhaps the reason behind the contradictory findings is the sensitivity of the effect of delivery on eat-out to the type of restaurant and the overall market (Ma

et al., 2021; Weltevreden and van Rietbergen, 2009). However, unlike the previous studies that investigated the relationship between delivery and eat-out, this study is undertaken in a transitory post-COVID landscape when things started opening up rapidly and Texans, for the most part, started going about their lives. In this context, during the pandemic, many consumers used the delivery channel for the first time, while others increased their consumption and solidified their delivery ordering habits. After the end of the lockdown restrictions, individuals might have been eager to visit the restaurants they ordered from online during the pandemic, which may explain the complementary effect. Also, it is not surprising that as we come out of the pandemic, it is the eat-in NDCM channel that drives and affects the other channels.

The substitutive relationship between eat-in delivery and eat-in takeout is also not surprising (even though, to our knowledge, this is the first study to examine the inter-relationship between these two eat-in NDCM channels). Delivery and takeout are clear competitors because they both satisfy eat-in meals. For a similar reason, eat-out also has a substitutive relationship with eat-in takeout propensity. In Section 5, we further study the magnitude of such effects on the actual counts of each NDCM channel.

4.3. Error Correlation Matrix

The error correlation matrix at the bottom of Table 3 shows a statistically significant negative error correlation between the eat-out and eat-in delivery propensities, and a marginally positive correlation between the two eat-in NDCM channel inclinations (the correlation between eat-out and eat-in takeout is also negative, though statistically insignificant). These results are to be expected, as unobserved lifestyle preferences and attitudinal variables are likely to simultaneously affect the propensity of the NDCM options. In particular, individuals who may be introverted, or like to eat their meals in the privacy of the familiar surroundings and ambiance of their home (while also enjoying the convenience of consuming food from the outside), or fear risks of contracting COVID in ways beyond what has been captured through the COVID-19 threat/perspectives variables, are intrinsically likely to adopt the two eat-in channels and avoid the eat-out channel. Importantly, though, these error correlations in the underlying propensities of the channels are in opposite directions of the causal effects of the eat-in delivery channel count on the propensity of the other two channels. The implication is that if these error correlations were ignored, it would incorrectly underestimate the complementary effect of delivery on eat-out (and potentially also can completely overturn the complementarity effect into a substitutive one), and would inaccurately also underestimate the substitutive effect of delivery on takeouts, as discussed further below.

To be sure, in any population, there are going to be individuals who generically prefer eating in the privacy of their homes (leading to higher propensities of both the eat-in channels with less preference for the eat-out channel, as captured by the error correlations). Now, consider that we want to examine the effect of deliveries on eat-outs from a sample of this population. For presentation simplicity, consider the question of how a single delivery instance will shape future eat-outs. We may do so by examining the number of eat-outs in the week following a delivery instance in the sample. Among the group of those who prefer the privacy of their homes when eating, individuals would be loath to eating out after the delivery instance. But this reticence

toward eating out is not reflective of the tendency of a random individual (who will have much more of an adventurous and variety-seeking nature) to eat out after experiencing a delivery instance (say from the restaurant from where the delivery was placed). More generally, the unobserved "privacy-in-eating" tendency of a select group in the sample will corrupt (lower) the "true" effect of delivery on eat-out tendency, unless that "privacy-in-eating" effect (unobserved correlation effect) is controlled for. Similarly, if the study was to examine takeout tendency after a delivery instance, the higher-than-normal tendency of the "privacy-in eating" group to takeout following the delivery instance will temper the "true" negative impact of delivery on take-outs in the general population, underplaying the substitutive tendency between the two eat-in channels.

4.4. The Goodness-of-Fit Measures

The joint model used in modeling the frequency of NDCMs through the three different channels provides important insights on the different factors influencing individuals dining preferences. But it is also important to consider the data fit provided by such a model relative to a naïve independent model that completely ignores jointness (i.e. the correlations) among the three dimensions as well as the endogenous effects. The two models can be compared using a simple nested likelihood ratio test because the independent model is a nested (and restricted) version of our proposed joint model.

We also evaluate the data fit of the joint and the independent models intuitively and informally at both the disaggregate and aggregate levels. At the disaggregate level, for the joint model, we compute an average (across individuals) probability of correct prediction of the observed monthly count combination level. A similar disaggregate measure is computed for the independent model. At the aggregate level, we first compute, at the individual level, the multivariate probability prediction for each of the 539 multivariate combination outcomes of the three channels of NDCM (total possible combinations=$11 \times 7 \times 7 = 539$). Then, we can aggregate these counts across individuals for each of the 539 combinations and compare our model-predicted aggregate values with the actual number of individuals in each of these combinations. But, this presentation would be cumbersome; besides, many of the 539 combinations will have zero observed entries. So, for presentation compactness, we aggregate the number of individuals based on three bins for eat-out (0, 1-3, and >3), three bins for eat-in takeout (0, 1-2, and >2), and three bins for eat-in delivery (0, 1-2, and >2). We then compare the observed and model-predicted numbers of individuals in each of the resulting 27 combination bins, to compute a weighted absolute percentage error (WAPE) value (the weighting here is based on the actual observed share of individuals in each of the nine combination bins).

The results of the data fit evaluations are provided in Table 4. The likelihood-based fit measures and the average probability of correct prediction from the joint model indicate the better fit relative to the independent model (see top row panel of Table 4). Note that while the difference in adjusted rho-bar squared and average probability of correct prediction between the two models may seem marginal, these differences are actually quite substantial given the 539 combinations possible. To provide a sense of this, note that the average probability of correct prediction of an equal share model would be 0.00186, so each decimal point of improvement in the disaggregate

metrics is not trivial. In terms of aggregate data fit too (see bottom row of the panel), for each of the 27 combination bins, the numbers predicted by the joint model are better than those predicted by the independent model. Overall, across the 27 combinations, the weighted average (weighted on the observed shares) of the absolute percentage error is 13.19% for the joint model and 16.62% for the independent model, once again highlighting the superior fit of the joint model.

5. MAGNITUDE EFFECTS OF VARIABLES

5.1. Analysis Preparation

The results provided in Section 4.2 do not provide information on the actual effects of the variables on NDCM frequency by channel, nor do they provide a sense of the relative magnitudes of impacts of different variables. In fact, even the directionality of the effect of a variable on the underlying propensity does not provide a sense of how the variable may actually impact counts in each channel. Besides, with the unobserved correlation effects and endogenous effects, the variable effects get even more challenging to quantify from the model estimates.

To determine directionality and magnitude effects, the estimates need to be translated to actual outcome effects, which however will vary across individuals because of the non-linear nature of our model. But an average effect of a change in the variable on the monthly count of each of the three NDCM channels (and, implicitly, then, also the monthly count of DCM meals over the 22 weekdays) can be computed, using average treatment effects or ATEs.

The ATE computation procedure is as follows. First, similar to the computation of the aggregate data fit measures in Section 4.4, we compute, for each individual, the multivariate predictions for each of the 539 multivariate combinations of possible outcomes for the three channels of NDCM. Then, for each individual, we compute the expected count for each univariate channel as the appropriate weighted sum of the specific count value combination with the probability of the count combination. Thus, let the index of counts be r (r=0,1,2,…,10) for the eat-out channel, s (s=0,1,…,6) for the eat-in take-out channel, and t (t=0,1,…,6) for the eat-in delivery channel. Let the ordered outcomes be y_{EO}, y_{TO}, and y_{DE} for eat-out, eat-in takeout and eat-in delivery channels respectively. Let $P(y_{EO}=r, y_{TO}=s, y_{DE}=t)$ be the multivariate probability for a specific combination of r, s, and t, and for a specific individual, computed using our model estimates. Finally, let $\bar{f}_{EO}$, $\bar{f}_{TO}$, and $\bar{f}_{DE}$ be the expected univariate monthly count for the individual for the three NDCM channels,

$$\bar{f}_{EO} = \sum_{r=0}^{11} r \left(\sum_{s=0}^{6} \sum_{t=0}^{6} P(y_{EO}=r, y_{TO}=s, y_{DE}=t) \right) \tag{5}$$

$$\bar{f}_{TO} = \sum_{s=0}^{6} s \left(\sum_{t=0}^{6} \sum_{r=0}^{11} P(y_{EO}=r, y_{TO}=s, y_{DE}=t) \right) \tag{6}$$

$$\bar{f}_{DE} = \sum_{t=0}^{6} t \left(\sum_{r=0}^{11} \sum_{s=0}^{6} P(y_{EO}=r, y_{TO}=s, y_{DE}=t) \right) \tag{7}$$

Finally, for each individual, we can then compute the expected count of DCM, $\overline{f}_{DCM}$ as:

$$\overline{f}_{DCM} = 22 - \overline{f}_{EO} - \overline{f}_{TO} - \overline{f}_{DE} \quad (8)$$

The average of these quantities across all the individuals provides the expected monthly count for the entire dataset. Using this procedure, we compute the average treatment effects (ATEs; see Heckman and Vytlacil, 2000) for all pairwise changes from a specific level to another specific level for each variable. The ATE computes the impact on a downstream posterior variable of interest due to a treatment that alters the state of an antecedent variable from *A* to *B*. For example, if the intent is to estimate the "treatment" effect of age on the NDCM channels, *A* can be the state where an individual is less than 30 years and *B* can be the state where the individual is 65 years or above. To quantify the impact of this change in state, all individuals in the dataset are set to state *A*, and the expected univariate monthly count of individuals in each channel is computed as just discussed. Then, all the individuals in the dataset are set to state *B*, and the expected univariate monthly counts are again computed. A percentage change can be computed for going from state *A* to state *B*, which provides the magnitude and direction impact of the antecedent variable.

The above procedure can be applied to compute the ATE for the change from any state of a variable to any other state. For example, in the context of age, we can quantify the impact of age from the state of being less than 30 years to 30-49 years of age, or from the state of less than 30 years to 50-64 years, or for any other pairwise combination of states. But, for presentation simplicity, we only report the ATEs for a change between the two extreme categories for each variable (for example the effect of a change from being less than 30 years of age to being 65 years or older).

Table 5 summarizes the computed ATEs for each variable. For example, the interpretation of the first numeric row corresponding to the "single female" variable is as follows. A single male (the base level demographic) is estimated to make, on average, 3.72 eat-outs, 1.00 eat-in takeouts, 1.09 eat-in deliveries, and 16.20 DCMs on a monthly basis (see fourth broad column of Table 5). In comparison, with all other variables being the same, a single female is estimated to make, on average, 3.35 eat-outs, 1.04 eat-ins, 1.09 eat-in deliveries, and 16.52 DCMs (see fifth broad column of Table 5). Thus, a randomly picked single female is estimated to make 9.79% fewer monthly eat-outs, 3.43% more monthly eat-in takeouts, 0% more monthly eat-in deliveries, and 2.03% more monthly DCMs (last broad column of Table 5). Similar interpretations can be made for all other variables reported in the table. To be noted here is that, in terms of employment status variable effects in Table 5, we examine the effect of not being employed (base level) versus being employed full-time and for 22 work days (almost all full-time employees worked 22 work days or more per month, which is the treatment level). We will label such employed individuals as "full time-22ers" from here on. In addition, because "fraction of work days from home" has an opposite direction of effect on eat-out relative to number of work days (see Table 3), we computed ATEs for four categories of full time-22ers: (1) those never working from home on for all workdays (percentage of work days from home=0), (2) those working from home for 33% of their workdays, (3) those

working from home 66% of their workdays, and (4) those working all days from their home (percentage of work days from home=100%).

5.2. ATE Results

It is important to note that, from a policy perspective, it is the ATEs that are more insightful than the model results themselves. The model results, on the other hand, are more useful if the intent is to employ the joint model in an agent-based modeling framework, where each unique individual's count of NDCMs and DCMs can be predicted in a disaggregate manner using the estimates. On the other hand, the ATEs are more of summary aggregate measures that represent overall "average" (across all individuals) shifts in the channel counts for each individual variable, though these shifts are after controlling for other variables at the model estimation stage. Besides, as indicated earlier, the non-linear nature of the joint model, along with the correlations across channels and the endogenous effects, implies that the estimates themselves do not provide full information. For example, consider the effect of a joint family. The model estimates indicate that individuals in a joint family have a lower underlying propensity to eat-out (see Table 3), but with no impact on the underlying propensities for eat-in takeout and eat-in delivery. However, this does not mean there will be no change in the eat-in channels between an individual not in a joint family and another observationally identical individual in a joint family. This is clearly observed in the positive ATE effect of being in a joint family on both the eat-in channels. This is because of the negative endogeneity effect of eat-out on eat-in takeout, so that as eat-outs decrease, eat-in takeouts increase. At the same time, an increase in eat-in takeouts also increases eat-in delivery through the positive unobserved error correlation between these two eat-in channels, leading to a positive increase even in eat-in. Similar nuances play out because of correlation effects, the non-linear variable effects, and the endogeneity effects for other variables.

Overall, though, the ATE results (focusing now only on the last broad column of Table 5) are consistent with, and follow from, the model results, with some nuances as just discussed. The most frequent customers of the eat-out channel are white individuals, individuals from 3+ motorized vehicle owning households, those in non-joint families, those in households with no children, full-time22ers who never work from home or do so only for a small fraction of their workdays, and those residing in areas with a high density of restaurants. The distinct consumer segments for the eat-in takeout channel include young individuals, those from high household incomes, those working from home all their workdays or a substantial fraction of their workdays, and urban residents; the most enthusiastic consumers of the eat-in delivery channel are white individuals, those with less than three vehicles in the household, individuals with children, urban residents, and those worried about pandemic-related personal health risks. The results suggest the important impact of work place location on dining channel choice. Indeed, the predicted swing from an almost 73% increase in eat-out (16.46% increase in eat-in takeout) among full time-22ers never working from home (relative to those not employed) to only a 10.20% increase in eat-out (74.78% increase in eat-in takeout) among those working always from home is remarkable, as is the predicted swing from an almost no change in eat-in delivery for full time-22ers never working

from home to a 43.53% increase in eat-in delivery for full time-22ers always working from home. These results reveal the importance of studying work place location (WPL) hybridization patterns into the future (see Asmussen et al., 2022 for such a recent study).

The percentage shifts for DCMs are generally lower in Table 5, but this is just an artifact of the high number of DCMs per month at the base level. Older individuals, non-white individuals, individuals with a graduate degree, individuals in fewer motorized vehicle-owning households and in joint families, those with children in the household, and rural residents constitute the most committed segments of the DCM consumption channel. Of course, the DCM ATEs also provide insights into the net effect of variables on travel related to dining through the cumulative effect on the total of all NDCMs, which is nothing but the reverse of the effect on DCMs (the percentage change in total NDCMs would not be the negative of the value in the DCM column, because of a different base level for all NDCMs; but the substantive implications are the same as that presented by the DCM ATEs). Thus, all those not included above as being most DCM-oriented constitute the ones that would generate the most travel.

An additional observation from Table 5 is that, except for the "presence of children", the effect of all other variables shows clear complementarity in eat-out and eat-in delivery (though, in some few cases, there is a neutral effect on eat-in delivery with a clear impact on eat-out, as for single women and individuals with a graduate degree). The results also reveal that, while there are some population segments for which there is a distinct positive increase in all NDCM channels at once: young individuals less than 30 years of age, full-time 22ers with a non-zero fraction of time working from home, and urban residents; other segments and BE factors have opposite effects between eat-in delivery and eat-in takeout, as well as between eat-out and eat-in takeout. This indicates the complex interplay among the many NDCM channels.

In terms of COVID risks, the results again reinforce the notion that eat-out propensity is influenced by the concern about being a COVID messenger to loved ones than risk to oneself. In fact, there is a small increase in eat-out tendency among individuals with personal health concerns, spurred by the substantial increase in eat-in delivery that permeates apparently into the temptation to eat out those occasional times and also break the home isolation these individuals may otherwise impose on themselves. But this small increase in eat-out is dwarfed by the substantial increase in eat-in takeout and eat-in delivery within this segment of individuals with personal COVID concerns. Finally, the endogenous effect ATEs represent "true" effects after accommodating for any "spurious" effects through the error correlations. The endogenous effects more directly indicate the strong complementarity between eat-in delivery and eat-out, as well as the strong substitution between the other two pairwise channels.

6. DISCUSSION AND CONCLUSIONS

In this paper, we have examined NDCM preferences of individuals by studying their monthly count of NDCM meals by channel type: eat-out, eat-in takeout, and eat-in delivery. This research is a novel effort to understand NDCM consumption using data from a 2022 online survey collected in Texas. A multivariate ordered probit model was estimated to understand the interplay among

the in-person dining out option and ICT-assisted (and COVID pandemic-accelerated) eat-in options. Model estimation results indicated the important (and varying across NDCM channels) effects of a range of variables, including individual and household demographics, employment status and job characteristics, residential location BE factors, and COVID-related perspectives. The results also showed clear evidence of complementary and substitution effects at play, even after controlling for spurious associations due to unobserved correlations; the delivery channel complements eating out, but substitutes takeout. Similarly, eat-out has a substitution effect on eat-in takeout.

A number of implications may be drawn from our study findings for multiple sectors, which we organize below and discuss in turn for each of the transportation, public health, and food services sectors. We conclude the paper with general travel demand modeling considerations.

6.1. Implications for the Transportation Sector

Work place locations of individuals are seeing a sea-shift from pre-COVID times, due to the forced remote and virtual work environments during the "shutdown" period of the pandemic. While how WPL choices may evolve over a longer time period is still an open area of research (and debate), our study unequivocally points to the importance of WPL choices of individuals on activity-travel patterns in a post-COVID era. While work arrangements were always an important determinant of overall spatial and temporal activity-travel patterns, work hybridization along with the increased introduction to, and comfort with, eat-in NDCM options, is likely to expand the range of activity-travel options of individuals. The innovation of the current study is in its rigorous investigation of the interplay of dining options within this expanded activity-travel landscape. According to our results, the most amount of total NDMC-related travel (in terms of trips) will be generated by individuals working always from the work place. On the other end, individuals working always from home (and particularly those residing in urban areas) are the most likely consumers of the two eat-in NDCM channels. Interestingly, both these types of workers, according to our results, will increase total NDCM-related travel compared to those who are not employed.

Additional research on the length of the generated trips and the spatial-temporal patterns of NDCM-related trips, both by personal vehicle and delivery vehicles, is needed to obtain a full picture of impact on vehicle miles of travel. Besides, this impact depends on the mode used for food pick-up and delivery. For traditional car deliveries, the surge in delivery orders placed by teleworkers at the end of work hours may cause congestion in residential locations that are not designed to handle such traffic volumes. In addition to delivering by car, food delivery companies in dense cities are allowing bikes, e-bikes, or other forms of micro-mobility for food delivery (DoorDash, 2022; Uber, 2022). While these delivery modes may aid in relieving vehicular congestion, they can cause a rapid spike in the bicyclist volume on bicycle lanes, which affects the level of service on such lanes, creating a separate set of safety challenges.

6.2. Implications for the Health Sector

Table 5 shows that young adults are particularly likely to be associated with high NDCM consumption. Further, NDCMs, especially eat-in takeouts and deliveries, often used by young adults, are typically associated with high calorie, low nutrition fast food options. To address this issue, policy efforts that highlight the strong connection between healthy eating and healthy living among this younger adult group are warranted. Further, given that old habits get wired in our neural pathways and are difficult to shed, 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.

Our ATE results also suggest that non-white individuals and low-income individuals consume takeout food more often than white consumers. This may reflect the time poverty experienced by minority and low-income individuals (Bruns and Pilkauskas, 2019; Miller, 2006). And time poverty is one of the main barriers to preparing home-cooked meals (Lavelle et al., 2016; Smith et al., 2013). Besides, the combination of the costs of fresh foods and vegetables at grocery stores, relative to easy-to-grab inexpensive food, further can lead to takeouts from fast foods.

Time poverty also affects those employed and who work long hours. Our results indicate that the time pressures experienced by employed individuals go beyond commute time. Even those working full time from home tend to have fewer DCM instances, and have a high count of eat-in takeout and eat-in delivery. This indicates that the increase in DCMs during the COVID-19 lockdown period, as suggested by studies such as Sarda et al., 2022, may have been short-lived and is fading as we move out of the strict lockdown period of the pandemic. Overall, we conclude that time-poor employed individuals prefer meals that are time efficient and convenient regardless of workplace location; interventions need to focus on providing these individuals with healthy NDCM options and perhaps batch cooking training to reduce the time and effort to prepare DCMs.

6.3. Implications for the Food Service Sector

Restaurants can use the results of this study to tailor their marketing and services toward specific segments of the population. Older consumers use food takeout and delivery services much less than younger individuals. A primary limiting factor for older individuals is the technological challenges associated with online ordering. In particular, the gerontology and psychology literature has established that aging is generally associated with a decline in cognitive ability (such as memory, attention, and verbal and visual/spatial information retention; see Deary et al., 2009 and Boot et al., 2013). This suggests the need for careful human-machine interface (HMI) design in ordering apps that reduce clutter and use simple displays with large screens and buttons.

Restaurants also need to develop strategies for detecting and addressing racial bias in their services. Non-white consumers patronize restaurants about an estimated 24% less frequently compared to their white counterparts. Restauranteurs need to ensure that their policies do not include any implicit discrimination against specific groups. For example, Jones (2020) provides an example of how athletic wear-related dress code policies tend to discriminate against Black customers. Another intervention includes holding anti-bias workshops, similar to the one

implemented by Starbucks in response to a racial discrimination incident (Dahlstrom, 2018), to train restaurant employees to avoid making racially biased decisions.

The frequency of NDCM consumption is additionally influenced by the presence of children in a household. Households with children eat-out less frequently compared to households without children. Thus, restaurants can encourage dine-ins by organizing family-friendly events or providing some form of childcare services or play areas. Also, to assuage any parental concerns about adverse health issues, restaurants would benefit from including healthier food options, both on-premise and through their delivery channels (individuals with children constitute a significant portion of the delivery demand segment). Finally, in a changing WPL landscape, restaurants need to adapt their business models and consider investing in the off-premise eat-in NDCM channels.

6.4. General Travel Demand Modeling Considerations

Finally, from a travel demand modeling perspective, our results underscore the importance of considering each of the NDCM channels as unique and separate from each other, especially in a landscape where emerging technology is reshaping activity-travel patterns, and, in turn, activity-travel behavior is shaping technology use. The factors affecting the count of NDCM consumption vary by channel type. At the same time, our study also reveals the complex interplay among the many channels, through unobserved error correlations as well as endogenous effects. To our knowledge, this is the first study of dining choices that considers all possible channels together using a uniform temporal scale of analysis (monthly dining consumption counts for each of the channels). The results point toward the need for future activity-travel surveys to include detailed questions about eat-in takeout and eat-in deliveries, along with out-of-home travel for eat-out. Then, the models of the type developed in this paper may be embedded within larger agent-based activity-travel systems by modeling additional location and mode dimensions in downstream models for each forecasted NDCM activity occasion, which we believe is an important direction for future research. This downstream follow-through would be similar to Suel and Polak's (2017) study that accommodates multi-channel grocery shopping, but is conditional on participation (that is, Suel and Polak assume activity generation is known from an earlier step, which is exactly the output from our model).

Of course, the current paper only considers dining choices. At a broader level, dining choices may be made jointly with other activity-travel choices, calling for the expansion of the set of dependent outcomes to include other grocery shopping and non-grocery shopping channels too. But, overall, our study provides valuable insights into the factors impacting the number of NDCM instances by each of the three channel types that can assist travel demand analysts in an environment where the use of all the three channel types is becoming increasingly prevalent.

ACKNOWLEDGEMENTS

This research was based on data collected for the study of work place location choices as part of Texas Department of Transportation (TxDOT) project number 0-7054: Integration of Stated

Preference and Revealed Preference Methods in Regional Travel Survey Programs. The authors are grateful to Lisa Macias for her help in formatting this document.

REFERENCES

Ahuja, K., Chandra, V., Lord, V., and Peens, C. (2021). Ordering in: The rapid evolution of food delivery. *McKinsey & Company*. https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/ordering-in-the-rapid-evolution-of-food-delivery

Ali, S., Khalid, N., Javed, H. M. U., and Islam, D. M. Z. (2020). Consumer adoption of online food delivery ordering (OFDO) services in Pakistan: The impact of the COVID-19 pandemic situation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 10.

Appelhans, B. M., Waring, M. E., Schneider, K. L., and Pagoto, S. L. (2014). Food preparation supplies predict children's family meal and home-prepared dinner consumption in low-income households. *Appetite*, *76*, 1–8.

Asmussen, K. E., Mondal, A., Bhat, C. R., and Pendyala, R. M. (2022). On modeling future workplace location decisions: An analysis of Texas employees. Technical paper, Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin. https://www.caee.utexas.edu/prof/bhat/ABSTRACTS/WPLSP.pdf

Bärebring, L., Palmqvist, M., Winkvist, A., and Augustin, H. (2020). Gender differences in perceived food healthiness and food avoidance in a Swedish population-based survey: A cross sectional study. *Nutrition Journal*, *19*, 140.

Bernardo, C., Paleti, R., Hoklas, M., and Bhat, C.R. (2015). An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. *Transportation Research Part A*, *76*, 71–91.

Bhat, C. R. (2015). A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B*, *79*, 50–77.

Bhat, C. R. (2018). New matrix-based methods for the analytic evaluation of the multivariate cumulative normal distribution function. *Transportation Research Part B*, *109*, 238–256.

Bhat, C. R., and Gossen, R. (2004). A mixed multinomial logit model analysis of weekend recreational episode type choice. *Transportation Research Part B*, *38*(9), 767–787.

Billingsley, B. L. (2016). Racialized and classed contexts: Shifting audiences and changes in emotional labor among restaurant servers. *Sociological Inquiry*, *86*(4), 641–657.

Boot, W. R., Simons, D. J., Stothart, C., and Stutts, C. (2013). The pervasive problem with placebos in psychology: Why active control groups are not sufficient to rule out placebo effects. *Perspectives on Psychological Science*, *8*(4), 445–454.

Bouarar, A. C., Mouloudj, S., and Mouloudj, K. (2021). Extending the theory of planned behavior to explain intention to use online food delivery services in the context of COVID-19 pandemic. In C. Cobanoglu, and V. Della Corte (Eds.), *Advances in Global Services and Retail Management* (pp. 1–16). USF M3 Publishing. https://www.doi.org/10.5038/9781955833035.

Bowen, S., Elliott, S., and Brenton, J. (2014). The joy of cooking? *Contexts*, *13*(3), 20–25.

Brewster, Z. W., and Heffner, A. V. (2021). Expressions of anti-black biases, job satisfaction, and turnover intentions in the full-service restaurant industry. *Journal of Hospitality and Tourism Research*, doi:10.1177/10963480211020098.

Bruns, A., and Pilkauskas, N. (2019). Multiple job holding and mental health among low-income mothers. *Women's Health Issues*, *29*(3), 205–212.

Bureau of Labor Statistics (2020). *Consumer Expenditures Report 2019*. https://www.bls.gov/opub/reports/consumer-expenditures/2019/home.htm

Business Research Company (2021). *Online Food Delivery Services Global Market Report 2021: COVID-19 Growth and Change to 2030*. https://www.researchandmarkets.com/reports/5315009/online-food-delivery-services-global-market

Castro, M., Paleti, R., and Bhat, C. R. (2012). A latent variable representation of count data models to accommodate spatial and temporal dependence: Application to predicting crash frequency at intersections. *Transportation Research Part B*, *46*(1), 253–272.

Chapman, J., Fox, E. H., Bachman, W., and Frank, L. D. (2021). *Smart Location Database: Version 3.0 Technical Documentation and User Guide*. Prepared for the U.S. Environment Protection Agency. https://www.epa.gov/sites/default/files/2021-06/documents/epa_sld_3.0_technicaldocumentationuserguide_may2021.pdf

Chiu, C., Wang, E. T., Fang, Y., and Huang, H. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: The roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal*, *24*(1), 85–114.

Clifford Astbury, C., Foley, L., Penney, T. L., and Adams, J. (2020). How does time use differ between individuals who do more versus less foodwork? A compositional data analysis of time use in the United Kingdom time use survey 2014–2015. *Nutrients*, *12*(8), 2280.

Cho, M., Bonn, M. A., and Li, J. J. (2019). Differences in perceptions about food delivery apps between single-person and multi-person households. *International Journal of Hospitality Management*, *77*, 108–116.

Collison, J. (2020). The impact of online food delivery services on restaurant sales. *Honors Thesis*, Department of Economics, Stanford University.

Dahlstrom, L. (2018). Beyond May 29: Lessons from Starbucks anti-bias training—And what's next. *Starbucks Stories & News*. https://stories.starbucks.com/stories/2018/beyond-may-29-lessons-from-starbucks-anti-bias-training-and-whats-next/

Deary, I. J., Corley, J., Gow, A. J., Harris, S. E., Houlihan, L. M., Marioni, R. E., Penke, L., Rafnsson, S. B., and Starr, J. M. (2009). Age-associated cognitive decline. *British Medical Bulletin*, *92*(1), 135–152.

Devine, C. M., Jastran, M., Jabs, J., Wethington, E., Farell, T. J., and Bisogni, C. A. (2006). "A lot of sacrifices:" Work–family spillover and the food choice coping strategies of low-wage employed parents. *Social Science and Medicine*, *63*(10), 2591–2603.

Dias, F. F., Lavieri, P. S., Sharda, S., Khoeini, S., Bhat, C. R., Pendyala, R. M., Pinjari, A. R., Ramadurai, G., and Srinivasan, K. K. (2020). A comparison of online and in-person activity engagement: The case of shopping and eating meals. *Transportation Research Part C*, *114*, 643–656.

Djupegot, I. L., Nenseth, C. B., Bere, E., Bjørnarå, H. B. T., Helland, S. H., Øverby, N. C., Torstveit, M. K., and Stea, T. H. (2017). The association between time scarcity, sociodemographic correlates and consumption of ultra-processed foods among parents in Norway: A cross-sectional study. *BMC Public Health*, *17*(1), 1–8.

DoorDash (2022). Become a driver & deliver with DoorDash. *DoorDash*. https://www.doordash.com/dasher/signup/. Accessed May 21, 2022.

Duque, M., Pink, S., Sumartojo, S., and Vaughan, L. (2019). Homeliness in health care: The role of everyday designing. *Home Cultures*, *16*(3), 213–232.

Faverio, M. (2022). Share of those 65 and older who are tech users has grown in the past decade. *Pew Research Center*. https://www.pewresearch.org/fact-tank/2022/01/13/share-of-those-65-and-older-who-are-tech-users-has-grown-in-the-past-decade/

Fulkerson, J. A., Farbakhsh, K., Lytle, L., Hearst, M. O., Dengel, D. R., Pasch, K. E., and Kubik, M. Y. (2011). Away-from-home family dinner sources and associations with weight status, body composition, and related biomarkers of chronic disease among adolescents and their parents. *Journal of the American Dietetic Association*, *111*(12), 1892–1897.

Giambattista, M. (2020). Survey: The first thing people are going to do after quarantine. *The Customer*. https://thecustomer.net/first-activities-after-quarantine/

Giurge, L. M., Whillans, A. V., and West, C. (2020). Why time poverty matters for individuals, organisations and nations. *Nature Human Behaviour*, *4*(10), 993–1003.

Goffe, L., Rushton, S., White, M., Adamson, A., and Adams, J. (2017). Relationship between mean daily energy intake and frequency of consumption of out-of-home meals in the UK National Diet and Nutrition Survey. *International Journal of Behavioral Nutrition and Physical Activity*, *14*(1), 1–11.

Gunden, N., Morosan, C., and DeFranco, A. (2020). Consumers' intentions to use online food delivery systems in the USA. *International Journal of Contemporary Hospitality Management*, *32*(3), 1325–1345.

Heckman, J. J., and Vytlacil, E. J. (2000). The relationship between treatment parameters within a latent variable framework. *Economics Letters*, *66*(1), 33–39.

Holm, L. (2013). Sociology of food and consumption. In *The Handbook of Food Research*, translated by W. Mintz Sidney, pp. 324–337, Bloomsbury Academic, London.

Hong, C., Choi, H. H., Choi, E.-K. C., and Joung, H.-W. D. (2021). Factors affecting customer intention to use online food delivery services before and during the COVID-19 pandemic. *Journal of Hospitality and Tourism Management*, *48*, 509–518.

Jones, C. (2018). Restaurant food choices by moms: An exploratory study. *Journal of Foodservice Business Research*, *21*(4), 377–393.

Jones, S. (2020). How to make sure your restaurant is welcoming to everyone. *Food & Wine*, F&W Pro. https://www.foodandwine.com/fwpro/how-to-make-sure-your-restaurant-is-welcoming-to-everyone

Josiam, B. M., and Henry, W. (2014). Eatertainment: Utilitarian and hedonic motivations for patronizing fun experience restaurants. *Procedia-Social and Behavioral Sciences*, *144*, 187–202.

Jung, J. M., Sydnor, S., Lee, S. K., and Almanza, B. (2015). A conflict of choice: How consumers choose where to go for dinner. *International Journal of Hospitality Management*, *45*, 88–98.

Kang, J.-W., and Namkung, Y. (2019). The information quality and source credibility matter in customers' evaluation toward food O2O commerce. *International Journal of Hospitality Management*, *78*, 189–198.

Kelso, A. (2022). Restaurant industry sales expected to hit $898 billion this year, up from $864 billion in 2019. *Forbes*, Food & Drink. https://www.forbes.com/sites/aliciakelso/2022/02/01/restaurant-industry-sales-expected-to-hit-898-billion-this-yearup-from-864-billion-in-2019/

Kertasunjaya, T. K., Mediasari, T. D., and Manaf, P. A. (2020). The relation between hedonic and utilitarian values on satisfaction and behavior intention among casual-dining restaurants customers. *Open Journal of Business and Management*, *8*(6), 2480–2492.

Kim, K. J., and Kim, D.-Y. (2021). I want to eat out, but something holding me back: Mom's cooking stress and family dining out constraints. *International Journal of Hospitality Management*, *99*, 103069.

Kim, W., and Wang, X. C. (2021). To be online or in-store: Analysis of retail, grocery, and food shopping in New York city. *Transportation Research Part C*, *126*, 103052.

Krause, C. G., Beer-Borst, S., Sommerhalder, K., Hayoz, S., and Abel, T. (2018). A short food literacy questionnaire (SFLQ) for adults: Findings from a Swiss validation study. *Appetite*, *120*, 275–280.

Lavelle, F., McGowan, L., Spence, M., Caraher, M., Raats, M. M., Hollywood, L., McDowell, D., McCloat, A., Mooney, E., and Dean, M. (2016). Barriers and facilitators to cooking from 'scratch'using basic or raw ingredients: A qualitative interview study. *Appetite*, *107*, 383–391.

Lavieri, P. S., Dai, Q., and Bhat, C. R. (2018). Using virtual accessibility and physical accessibility as joint predictors of activity-travel behavior. *Transportation Research Part A*, *118*, 527–544.

Lee, J., He, S. Y., and Sohn, D. W. (2017). Potential of converting short car trips to active trips: The role of the built environment in tour-based travel. *Journal of Transport and Health*, *7*, 134–148.

Li, W., Youssef, G., Procter-Gray, E., Olendzki, B., Cornish, T., Hayes, R., Churchill, L., Kane, K., Brown, K., and Magee, M. F. (2017). Racial differences in eating patterns and food purchasing behaviors among urban older women. *The Journal of Nutrition, Health and Aging*, *21*(10), 1190–1199.

Luong, G., and Charles, S. T. (2014). Age differences in affective and cardiovascular responses to a negative social interaction: The role of goals, appraisals, and emotion regulation. *Developmental Psychology*, *50*(7), 1919–1930.

Ma, J., Webb, T., and Schwartz, Z. (2021). A blended model of restaurant deliveries, dine-in demand and capacity constraints. *International Journal of Hospitality Management*, *96*, 102981.

Maddala, G. S. (1986). *Limited-Dependent and Qualitative Variables in Econometrics*. Econometric Society Monographs No. 3, Cambridge University Press, Cambridge.

Malon, A., Deschamps, V., Salanave, B., Vernay, M., Szego, E., Estaquio, C., Kesse-Guyot, E., Hercberg, S., and Castetbon, K. (2010). Compliance with French nutrition and health program recommendations is strongly associated with socioeconomic characteristics in the general adult population. *Journal of the American Dietetic Association*, *110*(6), 848–856.

Mehrolia, S., Alagarsamy, S., and Solaikutty, V. M. (2021). Customers response to online food delivery services during COVID-19 outbreak using binary logistic regression. *International Journal of Consumer Studies*, *45*(3), 396–408.

Miller, H. J. (2006). Social exclusion in space and time. In *Moving through Nets: The Social and Physical Aspects of Travel* (Axhausen, K.W., Ed.) Elsevier, Amsterdam, The Netherlands, pp. 353–380.

Mills, S., Adams, J., Wrieden, W., White, M., and Brown, H. (2018). Sociodemographic characteristics and frequency of consuming home-cooked meals and meals from out-of-home sources: Cross-sectional analysis of a population-based cohort study. *Public Health Nutrition*, *21*(12), 2255–2266.

Namin, A., Ratchford, B. T., Saint Clair, J. K., Bui, M. M., and Hamilton, M. L. (2020). Dine-in or take-out: Modeling millennials' cooking motivation and choice. *Journal of Retailing and Consumer Services*, *53*, 101981.

Neubauer, A. B., Smyth, J. M., and Sliwinski, M. J. (2019). Age differences in proactive coping with minor hassles in daily life. *The Journals of Gerontology: Series B*, *74*(1), 7–16.

Nogueira, L. M., Thai, C. L., Nelson, W., and Oh, A. (2016). Nutrition label numeracy: Disparities and association with health behaviors. *American Journal of Health Behavior*, *40*(4), 427–436.

Oblander, E. S., and McCarthy, D. M. (2022). Persistence of consumer lifestyle choices: evidence from restaurant delivery during COVID-19. *Columbia Business School Research Paper Forthcoming*. https://dx.doi.org/10.2139/ssrn.3836262

Okumus, B. (2021). A qualitative investigation of Millennials' healthy eating behavior, food choices, and restaurant selection. *Food, Culture and Society*, *24*(4), 509–524.

Oostenbach, L. H., Lamb, K. E., Crawford, D., and Thornton, L. (2022). Influence of work hours and commute time on food practices: A longitudinal analysis of the Household, Income and Labour Dynamics in Australia Survey. *BMJ Open*, *12*(5), e056212.

Paenchan, T., and Kookkaew, P. (2022). Technology acceptance affecting purchase decisions for food delivery by mobile phone application of consumers in Phra Nakhon Si Ayutthaya, Thailand. *PSAKU International Journal of Interdisciplinary Research*, *11*(1), 16–24.

Petersen, S., Zoffmann, V., Kjærgaard, J., Graff Steensballe, L., and Greisen, G. (2014). Disappointment and adherence among parents of newborns allocated to the control group: A qualitative study of a randomized clinical trial. *Trials*, *15*(1), 1–11.

Pop, L.-M., Iorga, M., Șipoș, L.-R., and Iurcov, R. (2021). Gender differences in healthy lifestyle, body consciousness, and the use of social networks among medical students. *Medicina*, *57*(7), 648.

Ramsey, K., and Bell, A. (2014). *Smart Location Database*. Version 2.0 User Guide. Available at: https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf.

Ray, A., and Bala, P. K. (2021). User generated content for exploring factors affecting intention to use travel and food delivery services. *International Journal of Hospitality Management*, *92*, 102730.

Renner, B., Cook, J., and Rogers, S. (2021). Surprise ingredients in the post-pandemic food story: Consumers cooking up concern for restaurants' return. *Deloitte*. https://www2.deloitte.com/us/en/pages/consumer-business/articles/food-service-restaurant-business-trends-post-covid.html

Robson, S. M., Crosby, L. E., and Stark, L. J. (2016). Eating dinner away from home: Perspectives of middle-to high-income parents. *Appetite*, *96*, 147–153.

Roh, M., and Park, K. (2019). Adoption of O2O food delivery services in South Korea: The moderating role of moral obligation in meal preparation. *International Journal of Information Management*, *47*, 262–273.

Rosenfeld, D. L., and Tomiyama, A. J. (2020). Taste and health concerns trump anticipated stigma as barriers to vegetarianism. *Appetite*, *144*, 104469.

Sarda, B., Delamaire, C., Serry, A.-J., and Ducrot, P. (2022). Changes in home cooking and culinary practices among the French population during the COVID-19 lockdown. *Appetite*, *168*, 105743.

Shi, L., and Xu, Z. (2021). Dine in or take out? Trends on restaurant service demand amid the COVID-19 pandemic. Available at SSRN: https://ssrn.com/abstract=3934589.

Smith, S. S. (2010). Race and trust. *Annual Review of Sociology*, *36*(1), 453–475. https://doi.org/10.1146/annurev.soc.012809.102526

Smith, L. P., Ng, S. W., and Popkin, B. M. (2013). Trends in US home food preparation and consumption: Analysis of national nutrition surveys and time use studies from 1965–1966 to 2007–2008. *Nutrition Journal*, *12*(1), 1–10.

Soh, J. (2019). US trends in food away from home. In *Financial Decision-Making in The Foodservice Industry* (Sharma, A., Ed.), Apple Academic Press, New York, pp. 41–62.

Solon, G., Haider, S. J., and Wooldridge, J. M. (2015). What are we weighting for? *Journal of Human Resources*, *50*(2), 301–316.

Sonneveld, A. (2019). Determinants of people's preference to consume food out of home. *MSc Thesis*, Department of Social Sciences, Wageningen University.

Spurlock, C. A., Todd-Blick, A., Wong-Parodi, G., and Walker, V. (2020). Children, income, and the impact of home delivery on household shopping trips. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*(10), 335–350.

Statista. (2020). *Average annual food away from home expenditures of United States households from 2010 to 2020 (in U.S. dollars)*. https://www.statista.com/statistics/237215/average-away-from-home-food-expenditures-of-united-states-households/

Stewart, H., and Yen, S. T. (2004). Changing household characteristics and the away-from-home food market: A censored equation system approach. *Food Policy*, *29*(6), 643–658.

Suel, E., and Polak, J. W. (2017). Development of joint models for channel, store, and travel mode choice: Grocery shopping in London. *Transportation Research Part A*, *99*, 147–162.

Sulek, J. M., and Hensley, R. L. (2004). The relative importance of food, atmosphere, and fairness of wait: The case of a full-service restaurant. *Cornell Hotel and Restaurant Administration Quarterly*, *45*(3), 235–247.

Terenzio, O. (2020). Eating out after COVID-19: OpenTable diners weigh in. *OpenTable Blog*. https://blog.opentable.com/diner-survey-covid-19/

Texas Demographic Center (2022). 2020 Census. Available at: https://demographics.texas.gov/. Accessed March 12, 2022.

Tumin, R., and Anderson, S. E. (2017). Television, home-cooked meals, and family meal frequency: Associations with adult obesity. *Journal of the Academy of Nutrition and Dietetics*, *117*(6), 937–945.

Ubeja, S. K., Hyde, A. M., and Mittal, R. (2021). Factors influencing selection of restaurants: An empirical study. In *Interdisciplinary Research in Technology and Management* (pp. 134–140). CRC Press.

Uber (2022). Become a delivery driver using Uber Eats. *Uber*. https://www.uber.com/us/en/deliver/. Accessed May 21, 2022.

Umberson, D. (1992). Gender, marital status and the social control of health behavior. *Social Science and Medicine*, *34*(8), 907–917.

Unnikrishnan, A., and Figliozzi, M. (2021). Exploratory analysis of factors affecting levels of home deliveries before, during, and post-COVID-19. *Transportation Research Interdisciplinary Perspectives*, *10*, 100402.

U.S. Department of Agriculture (2021). *Budget share for total food dropped by 10 percent in 2020, a new historical low*. Economic Research Service, USDA. http://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=76967

U.S. Department of Agriculture (2022). *Food Expenditure Series*. Economic Research Service, USDA. https://www.ers.usda.gov/data-products/food-expenditure-series/food-expenditure-series/#Current%20Food%20Expenditure%20Series

Venn, D., Banwell, C., and Dixon, J. (2017). Australia's evolving food practices: A risky mix of continuity and change. *Public Health Nutrition*, *20*(14), 2549–2558.

Wang, Z., and He, S. Y. (2021). Impacts of food accessibility and built environment on on-demand food delivery usage. *Transportation Research Part D*, *100*, 103017.

Warde, A., Cheng, S.-L., Olsen, W., and Southerton, D. (2007). Changes in the practice of eating: A comparative analysis of time-use. *Acta Sociologica*, *50*(4), 363–385.

Warde, A., Paddock, J., and Whillans, J. (2020). *The Social Significance of Dining Out: A Study of Continuity and Change*. Manchester University Press.

Wellard-Cole, L., Davies, A., and Allman-Farinelli, M. (2022). Contribution of foods prepared away from home to intakes of energy and nutrients of public health concern in adults: A systematic review. *Critical Reviews in Food Science and Nutrition*, *62*(20), 5511–5522.

Weltevreden, J. W., and van Rietbergen, T. (2009). The implications of e-shopping for in-store shopping at various shopping locations in the Netherlands. *Environment and Planning B: Planning and Design*, *36*(2), 279–299.

Wilkes, R., and Wu, C. (2018). Trust and minority groups. *The Oxford Handbook of Social and Political Trust*, 231.

Wooldridge, J. M., 1995. Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics*, *68*, 115–132.

Xiao, Y., Becerik-Gerber, B., Lucas, G., and Roll, S. C. (2021). Impacts of working from home during COVID-19 pandemic on physical and mental well-being of office workstation users. *Journal of Occupational and Environmental Medicine*, *63*(3), 181–190.

Yang, Y., Liu, H., and Chen, X. (2020). COVID-19 and restaurant demand: Early effects of the pandemic and stay-at-home orders. *International Journal of Contemporary Hospitality Management*, *32*(12), 3809–3834.

Yeo, V. C. S., Goh, S.-K., and Rezaei, S. (2017). Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. *Journal of Retailing and Consumer Services*, *35*, 150–162.

Zang, J., Luo, B., Wang, Y., Zhu, Z., Wang, Z., He, X., Wang, W., Guo, Y., Chen, X., Wang, C., Guo, C., Zou, S., Jia, X., and Wu, F. (2018). Eating out-of-home in adult residents in Shanghai and the nutritional differences among dining places. *Nutrients*, *10*(7), 951.

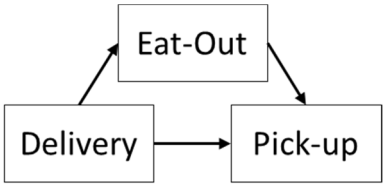
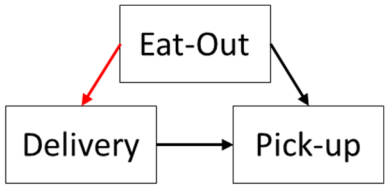
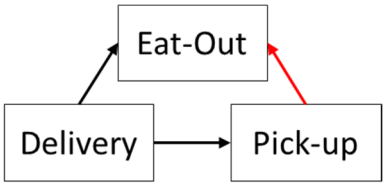
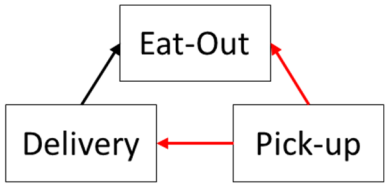
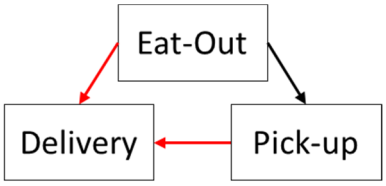
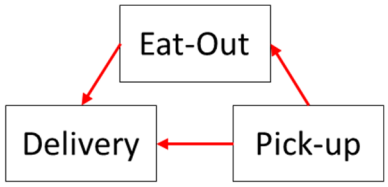
No.	Structure relationships	No.	Structure relationships
1		2	
3		4	
5		6	

Figure 1. Possible causal structures for endogenous variable effects

Table 1. Descriptive statistics for individual/household-level and employment status/job variables

Variable	Sample		Texas %
	Count	%	
Individual-Level Demographics			
Gender			
Male	466	42.7	49.7
Female	626	57.3	50.3
Age			
18 to 29	64	5.9	29.9
30 to 49	353	32.3	36.3
50 to 64	408	37.4	15.8
65 or more	267	24.4	18.0
Race			
White	944	86.4	68.6
Not White	148	13.6	31.4
Education level			
No degree	11	1.0	15.7
High school	87	8.0	46.2
Technical degree	104	9.5	7.4
Undergraduate	377	34.5	19.9
Graduate	513	47.0	10.8
Household Characteristics			
Annual income			
Under $24,999	38	3.4	12.3
$25,000-$49,999	81	7.4	8.9
$50,000-$74,999	148	13.6	17.6
$75,000-$99,999	176	16.1	12.5
$100,000-$149,999	313	28.7	15.6
$150,000-$249,999	231	21.2	7.0
$250,000 or more	105	9.6	6.0
Motorized vehicle ownership level			
0	18	1.6	5.2
1	244	22.4	32.3
2	501	45.9	40.1
3 or more	329	30.1	22.4
Household structure			
Living alone	175	16.0	25.1
Joint family (three adults or more with or without children)	80	7.3	--
Presence of children	413	37.8	32.7
Employment Status/Job Characteristics			
Employment status			
Not employed	229	21.0	24.0
Part-time employee	50	4.6	14.9
Full-time employee	813	74.4	61.1
Self-employment			
Self-employed	104	9.5	6.7
Variable	**Mean**	**SD**	**Texas**
Commute duration			
Commute (minutes)	22.8	14.3	26.6
Number of work days per month			
Number of days	21.5	9.2	22.0
Workplace location			
Percentage of work days from a third workplace location in the past month	53.2	26.6	--
Percentage of work days from a home in the past month	44.8	38.3	--

Table 2. Distribution of NDCM consumption count by channel

NDCM count per month	Eat-out		Eat-in			
			Takeout		Delivery	
	# obs.	%	# obs.	%	# obs.	%
0	283	25.92	730	66.85	623	57.05
1	140	12.82	103	9.43	122	11.17
2	160	14.65	104	9.52	138	12.64
3	79	7.23	29	2.66	64	5.86
4	117	10.71	35	3.21	58	5.31
5	97	8.88	28	2.56	45	4.12
6	39	3.57	63	5.77	42	3.85
7	12	1.11	0	0.00	0	0.00
8	41	3.75	0	0.00	0	0.00
9	5	0.46	0	0.00	0	0.00
10	119	10.90	0	0.00	0	0.00
Min	0		0		0	
1st Q	0		0		0	
Median	2		0		0	
Mean	3.23		0.97		1.19	
3rd Q	5		1		2	
Max	10		6		6	

Table 3. Estimation results

Variables	Eat-out		Eat-in Takeout		Eat-in Delivery	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Exogenous Variables						
Individual Demographics						
Gendered-Lifestyle						
Single female (no children)	-0.115	-1.09	--	--	--	--
Age (base: 18 to 29 years old)						
30 to 49 years old	-0.160	-1.18	--	--	--	--
49 to 64 years old	-0.160	-1.18	-0.420	-4.81	--	--
65 and older	-0.160	-1.18	-0.678	-5.74	-0.139	-1.63
Race (base: White)						
Not White	-0.189	-1.82	--	--	-0.241	-2.41
Educational level (base: below graduate degree)						
Graduate	-0.237	-4.00	-0.226	-2.74	--	--
Household Characteristics						
Income (base: <$100,000)						
≥$100,000	0.127	1.92	0.257	2.96	--	--
Car ownership (base: zero or one vehicle)						
Two vehicles	--	--	--	--	0.264	3.31
Three or more vehicles	0.338	4.46	--	--	0.264	3.31
Household structure (base: not living with children or family)						
Joint family	-0.332	-2.69	--	--	--	--
Presence of children	-0.383	-5.05	-0.116	-1.23	0.175	2.24
Employment Status/Job Characteristics						
Number of workdays per month						
Number of workdays	0.025	6.44	--	--	--	--
Employment status (base: not employed)						
Part-time	--	--	0.406	1.92	0.330	2.25
Full-time	--	--	0.222	1.61	--	--
Current workplace locations (base: work from the office)						
Fraction of work days from home in the past month	-0.585	-6.12	0.297	2.37	0.309	3.13
Residential Location BE Factors						
Community region type (base: rural)						
Suburban	--	--	0.690	5.59	0.137	1.47
Urban	--	--	0.727	5.18	0.335	3.13
Land-use mix						
Land-use Diversity Index	--	--	--	--	-0.446	-2.22
Restaurant density						
Number of restaurants per 100 square acres > 20	0.254	2.57	--	--	--	--
COVID-19 Perspectives						
COVID-19 was/still is a threat to my loved ones	-0.205	-3.04	--	--	--	--
My personal well-being was or still is at risk during the pandemic	--	--	0.234	2.68	0.180	2.56

Table 3. Estimation results (contd.)

Variables	Eat-out		Eat-in Takeout		Eat-in Delivery	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
COVID-19 Perspectives						
Someone I live with or frequently visit immunocompromised	-0.261	-3.67	--	--	--	--
Thresholds						
1	-0.382	-2.26	0.585	2.85	0.457	2.85
2	-0.034	-0.21	0.879	4.16	0.763	4.76
3	0.326	2.06	1.252	5.63	1.179	7.26
4	0.506	3.23	1.384	6.13	1.434	8.74
5	0.790	5.10	1.569	6.78	1.746	10.53
6	1.065	6.94	1.757	7.47	2.121	12.19
7	1.196	7.80	--	--	--	--
8	1.240	8.05	--	--	--	--
9	1.411	9.12	--	--	--	--
10	1.434	9.32	--	--	--	--
Endogenous Variables						
Monthly count of Eat-in Delivery is 1 or 2	0.648	4.96	--	--	--	--
Monthly count of Eat-in Delivery is 3 or 4	0.956	5.19	--	--	--	--
Monthly count of Eat-in Delivery is 5 or 6	1.331	5.49	--	--	--	--
Monthly count of Eat-in Delivery	--	--	-1.879	-2.60	--	--
Monthly count of Eat-out is between 1 or 4	--	--	-0.292	-1.95	--	--
Monthly count of Eat-out is between 5 or 8	--	--	-0.443	-1.87	--	--
Monthly count of Eat-out is 9 or 10	--	--	-0.788	-2.37	--	--
Correlation Terms						
Eat-out	1.000	--	--	--	--	--
Eat-in Takeout	-0.051	-0.19	1.000	--	--	--
Eat-in Delivery	-0.535	-2.25	0.411	1.28	1.000	--

Table 4. Goodness-of-fit statistics

Metric				Proposed Joint model	Independent model
Disaggregate fit measures					
Log likelihood at convergence				-4892.16	-4914.55
Number of non-constant parameters				44	34
Log likelihood at constants-only				-5119.30	-5119.30
Adjusted rho-squared value				0.0358	0.0334
Average probability of correct prediction				0.0357	0.0355
Likelihood ratio test: Joint vs Independent model				LR = 44.78> $\chi^2_{(10,0.05)}$ =32.67	
Aggregate fit measures					
Combination counts			**Observed count**	**Predicted count**	**Predicted count**
Eat-out	**Eat-in Takeout**	**Eat-in Delivery**			
0	0	0	105	108	119
0	0	1-2	33	38	43
0	0	>2	45	33	31
0	1-2	0	22	32	28
0	1-2	1-2	12	14	13
0	1-2	>2	13	12	11
0	>2	0	36	25	19
0	>2	1-2	9	12	10
0	>2	>2	8	10	9
1-3	0	0	147	150	153
1-3	0	1-2	58	57	58
1-3	0	>2	32	48	43
1-3	1-2	0	38	37	38
1-3	1-2	1-2	34	20	18
1-3	1-2	>2	17	15	16
1-3	>2	0	24	25	26
1-3	>2	1-2	9	15	14
1-3	>2	>2	20	11	13
>3	0	0	193	186	167
>3	0	1-2	68	63	67
>3	0	>2	49	51	51
>3	1-2	0	29	38	43
>3	1-2	1-2	27	22	21
>3	1-2	>2	15	16	19
>3	>2	0	29	25	30
>3	>2	1-2	10	17	16
>3	>2	>2	10	12	16
Weighted Absolute Percentage Error (WAPE)				**13.19%**	**16.62%**

Table 5. Average Treatment Effect (ATE) for all endogenous variables

Variable	Base Level	Treatment Level	Base level expected count				Treatment level expected count				ATE (% shift)			
			NDCM			DCM	NDCM			DCM	NDCM			DCM
			Eat-out	Eat-in Takeout	Eat-in Delivery		Eat-out	Eat-in Takeout	Eat-in Delivery		Eat-out	Eat-in Takeout	Eat-in Delivery	
Exogenous Variables														
Individual Demographics														
Single Female (no children)	No	Yes	3.72	1.00	1.09	16.20	3.35	1.04	1.09	16.52	-9.79	3.43	0.00	2.03
Age	Less than 30 years	More than 65 years	3.75	1.31	1.23	15.72	3.58	0.52	1.04	16.86	-4.32	-59.94	-15.47	7.22
Race	White	Non-White	3.34	0.93	1.23	16.50	2.55	1.11	0.91	17.43	-23.73	19.11	-25.71	5.64
Education level	Below graduate degree	Graduate degree	3.58	1.07	1.18	16.17	2.85	0.84	1.18	17.12	-20.22	-21.17	0.00	5.87
Household Characteristics														
Income	Less than $100,000	More than $100,000	3.00	0.78	1.18	17.03	3.39	1.07	1.18	16.35	12.85	37.38	0.00	-3.98
Vehicle ownership	Zero vehicles	Three or more vehicles	2.71	1.09	0.92	17.29	4.05	0.86	1.27	15.83	49.43	-21.30	38.40	-8.44
Joint family	No	Yes	3.34	0.95	1.18	16.53	2.38	1.04	1.18	17.39	-28.57	9.78	0.00	5.21
Presence of children	No	Yes	3.72	1.00	1.09	16.20	2.75	0.87	1.34	17.05	-26.05	-13.26	22.90	5.26
Employment Status/Job Characteristics														
Employment status and workplace location	Unemployed	Full-time-22ers with no work from home	2.29	0.72	1.04	17.95	3.96	0.84	1.04	16.16	73.26	16.46	0.00	-9.99
	Unemployed	Full-time-22ers with 33% workdays from home	2.29	0.72	1.04	17.95	3.45	0.97	1.18	16.40	50.90	34.58	13.38	-8.64
	Unemployed	Full-time-22ers with 66% workdays from home	2.29	0.72	1.04	17.95	2.97	1.11	1.33	16.59	30.02	53.79	27.71	-7.59

Table 5. Average Treatment Effect (ATE) for all endogenous variables (contd.)

Variable	Base Level	Treatment Level	Base level expected count				Treatment level expected count				ATE (% shift)			
			NDCM			DCM	NDCM			DCM	NDCM			DCM
			Eat-out	Eat-in Takeout	Eat-in Delivery		Eat-out	Eat-in Takeout	Eat-in Delivery		Eat-out	Eat-in Takeout	Eat-in Delivery	
Employment Status/Job Characteristics														
	Unemployed	Full-time-22ers with 100% workdays from home	2.29	0.72	1.04	17.95	2.52	1.26	1.49	16.73	10.20	74.78	43.53	-6.83
Residential Location BE Factors														
Community region type	Rural	Urban	3.07	0.40	0.97	17.56	3.45	1.02	1.44	16.09	12.29	154.12	48.75	-8.35
Land-use diversity index	0.42 (10th percentile)	0.79 (90th percentile)	3.34	0.91	1.31	16.44	3.15	1.00	1.08	16.77	-5.57	9.46	-17.76	2.03
Number of restaurants per 100 square acres > 20	No	Yes	3.15	0.97	1.18	16.70	3.95	0.89	1.18	15.97	25.53	-7.40	0.00	-4.38
COVID-19 Perspectives														
COVID-19 was/still is a threat to my loved ones	No	Yes	3.44	0.93	1.18	16.44	2.83	0.99	1.18	17.00	-17.89	6.17	0.00	3.39
My personal well-being was or still is at risk during the pandemic	No	Yes	3.13	0.84	1.05	16.98	3.33	1.05	1.30	16.31	6.43	25.28	24.06	-3.92
Someone I live with or frequently visit immuno-compromised	No	Yes	3.48	0.93	1.18	16.40	2.70	1.00	1.18	17.11	-22.38	7.90	0.00	4.30
Endogenous Variables														
Delivery	0	6	2.38	1.36	0.00	18.26	6.38	0.27	6.00	9.35	168.07	-80.15	NA	-48.79
Eat-out	0	10	0.00	1.06	1.19	19.75	10.00	0.35	1.19	10.46	NA	-66.98	0.00	-47.06