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# Spatiotemporal patterns of online food delivery services before the Covid-19 pandemic

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**Abstract:** Public health concerns of the Covid-19 pandemic and the popularity of on-demand mobility services have led to a recent and prominent increase in online food delivery (OFD) service adoption. While app-based services that offer restaurant customers the convenience of a freshly prepared meal delivered to any location have existed, their present and future impacts to urban transportation networks and landscapes have become ever more apparent since the pandemic's onset and subsequent restrictions on restaurant dining. By analyzing route-level data collected by a ridehailing driver assistant app between October 2015 and October 2019, this study informs a baseline understanding of where and when these on-demand food delivery services were used within the Phoenix metro area prior to the pandemic. This identification of the spatiotemporal patterns of OFD service is accompanied by the estimation of traditional and spatially lagged negative binomial models of delivery counts using a robust set of predictors of the built environment and socioeconomic context found at the trip destination. Study results indicate that on-demand food delivery services were popular during dinner hours corresponding with evening peak travel and in neighborhoods characterized by higher activity density, greater drinking establishment access, and increased shares of residents under 45 years old.

**Keywords:** Online food delivery services, online shopping, on-demand food delivery, spatial Durbin model, built environment

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## 1 Introduction

Initial public health concerns of disease transmission and government-mandated shelter-in-place orders at the Covid-19 pandemic onset continue to have ramifications for long-standing daily routines in travel and activity (Beck & Hensher, 2020). Social distancing practices resulted in fewer out-of-home activities and an increase in the frequency of goods such as meals being purchased online (De Vos, 2020), as evidenced



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by a remarkable growth in online food delivery (OFD) services such as DoorDash, GrubHub, Postmates, and Uber Eats since March 2020. In April 2020, combined OFD sales across these four major platforms exceeded $300 million, a 59 percent increase from the previous month's sales and 162-percent increase in sales compared to the previous year (Kaczmarski, 2023). During the height of the Covid-19 pandemic, the availability of OFD services in the United States was instrumental in lessening the financial consequences experienced by restaurants forced to suspend dine-in services during the Covid-19 outbreak (Meena & Kumar, 2022).

While this increased adoption in app-based meal delivery services was accelerated by the pandemic, advancements in information and communication technologies including emergent on-demand mobility services had introduced the potential for OFD services in day-to-day dining experiences (Shamshiripour et al., 2020). Akin to ridesourcing platforms which digitally connect passengers to private car owners for door-to-door mobility services, OFD service platforms connect customers to a pool of restaurants and couriers that enable customers to place online meal orders for delivery to their front door (Liu & Li, 2023). However, unlike popular ridesourcing services, on-demand food delivery services had relatively low market penetration rates prior to the Covid-19 pandemic, and thus empirical study into their transportation impacts has been limited (Kim & Wang, 2021). An absence in the literature supported by a study of travel behavior changes resulting from the Covid-19 pandemic, which noted that approximately three-out-of-five sampled Chicago metro region OFD service adopters had never ordered food online from a restaurant prior to March 2020 (Shamshiripour et al., 2020).

Given this limited focus on OFD services prior to the Covid-19 pandemic, present researchers are unable to offer much insight into the past spatiotemporal adoption patterns of this service platform and its transportation-related implications regarding changes in vehicle travel patterns, congestion, and emissions. This study aims to help establish this missing baseline knowledge by investigating the neighborhood-level predictors of OFD service adoption in a major American metro region in the years leading up to the Covid-19 pandemic's onset. Accordingly, as the most severe mobility restrictions related to the pandemic have subsided and individuals return to safer dine-in experiences, the results of this research can help to inform the continued study of OFD service adoption. Particularly, by understanding where and when the popularity of OFD services may be most likely to persist in the immediate future, transportation planners can identify systemwide mobility changes related to the location and timing of deliveries that may exacerbate congestion, emissions, and overall system inefficiencies within a region as OFD adoption shifts (Lezcano et al., 2023) and subsequently promote transportation and land-use solutions to address the spatiotemporal impacts of OFDs.

The remainder of this paper is organized as follows. The next section offers an overview of the limited studies to-date that have examined pre-pandemic OFD trends and predictors. The third section provides an overview of the data source, measures, and spatial econometric modeling framework used in this study. The fourth section details the results of the presented spatial Durbin modeling strategy, which is followed by a fifth section discussing the implications of these empirical findings and contributions of this study.

## 2 Literature review

This section synthesizes the findings from a limited set of academic studies which have investigated the spatiotemporal factors attributed to an on-demand delivery of prepared meals before the Covid-19 pandemic. In general, this evidence base demonstrated that OFD service adoption prior to the pandemic was relatively infrequent, with variation regarding the sociodemographic and economic attributes of service adopters.

By utilizing household travel survey data for the Seattle region, Dias et al. (2020) estimated a multivariate ordered probit model of the number of days in a week that 705 sampled households engaged in online meal deliveries. The authors found that less than five percent of respondents adopted OFD services multiple times per week and that residents with a higher annual household income and children were more likely to adopt prepared meal delivery services. Study results also noted a negative association between OFD service adoption frequency and vehicle availability, home ownership, full-time employment, and population density. Spurlock et al. (2020) surveyed a sample of 1,012 San Francisco Bay Area residents about shopping travel preferences, including prepared meal deliveries, similarly finding that higher-income households and those with children tended to purchase online prepared meals more often. In a third pre-pandemic study, Kim and Wang (2021) analyzed mobility survey data from 3,301 residents of New York City using a seemingly unrelated regression modeling approach to explore the person- and household-level attributes associated with separate questionnaire responses to online food, grocery, and retail delivery frequencies. In their analysis of food deliveries, the authors found individuals who identified as Black/African American or non-White, Hispanic were more likely to receive online deliveries than White residents and that younger adults and lower-income residents were less likely to adopt these app-based food services. Analyzing the spatial patterns and predictors of OFD service adoption in Shenzhen, China using a negative binomial modeling framework, Wang and He (2021) found that 100-meter grid cells characterized by a higher population density, land-use mix, and urbanized context were positively associated with OFD service adoption frequency in October 2019.

Ai et al. (2021) analyzed the location of 980 restaurants in Chicago listed on the Eat24 online food ordering platform to understand spatial variation in vehicle miles traveled per meal order across three generalized neighborhood types and six delivery strategies. The authors concluded that neighborhoods with clustered restaurant locations and more expansive service areas in which a driver chains multiple orders per delivery trip will improve travel efficiencies. After interviewing OFD service drivers in London, in which the average driver reported traveling approximately 25 miles per day to complete an average of 10 deliveries that each took roughly 25 minutes from pick-up to delivery, Allen et al. (2021) highlighted the need to improve delivery efficiencies and subsequently reduce vehicle emissions. Another Chicago-based study (Shamshiripour et al., 2020) that examined the myriad transportation impacts brought on by Covid-19 using results from a stated preference survey of 915 residents found a 150% increase in the proportion of habitual users of OFD services and that a considerable portion of respondents stated this notable increase in online meal deliveries during the pandemic will sustain in the future.

While important research gaps were addressed in these early studies of OFD service adoption, this study aims to explore two areas of further research need. First, the reviewed studies have primarily analyzed personal and household attributes associated with greater OFD service usage from small samples of survey respondents. To help expand this nascent evidence base and offer new knowledge into the spatial patterns of OFD service use, this study analyzes trip-level data from a third-party driver assistant app to identify the neighborhood-level associations in food delivery frequency in the Phoenix metro region. Second, of those limited studies to have examined the spatial context of pre-Covid-19 pandemic OFD vehicle patterns, none to the authors' best of knowledge have employed a spatial econometric modeling framework to help account for the spatial dependencies of neighborhood predictors and clustering of on-demand food delivery locales. To advance this identified shortcoming, this study employs a spatial Durbin modeling framework to control for any spatial dependence in the endogenous and exogenous relationships of neighboring geographic units.

In all, the findings from this study are intended to establish baseline information of the spatiotemporal trip patterns of OFD service adoption and insights into the socioeconomic context and built environment factors attributed to the adoption of these services prior to their escalated growth during the Covid-19 pandemic needed by transportation planners to understand where future OFD service usage is likely to be generated. By identifying specific areas where an increase in OFD service demand is likely to lead to more vehicle activity and thus increases in vehicle congestion and emissions, transportation planners can identify needed transportation-land use solutions to help improve systemwide efficiency and mobility, including the promotion of car-free modes for last-mile food deliveries and improvement of their requisite infrastructure or creation of designated, temporary parking spaces for OFD vehicles in high-demand areas.

## 3 Data and methods

### 3.1 Online food delivery service data

For this study, OFD service data were provided by a third-party ridehailing driver assistant app, SherpaShare, which aids drivers in the accounting of their vehicle mileage and escorting activities. The route-level traces of ridehailing trips in this data set were collected for each October between 2015 and 2019 for the Phoenix metro region, which hereafter refers to the Census-defined urbanized area of Phoenix and Mesa that is located within Maricopa County, Arizona. The month of October was selected due to data availability limitations, with the calendar month adequately exemplifying typical travel conditions in the region as there are no observed holidays, schools are in session, and weather conditions are generally mild. Per 2015-2019 American Community Survey estimates, this characterization of the Phoenix metro region houses over 3.92 million residents, with Phoenix accounting for over two-fifths of the region’s population (1.63 million residents) and the City of Mesa an additional 499,720 residents.

Aside from temporal information describing the date and time of the food delivery for this sample of 976 trips, geographic coordinates were supplied for each trip end as well as a self-reported note by the driver describing the platform being used for the delivery. Utilization of this latter data field and a column specifying whether the activity undertaken by the driver was personal or business-related enabled these food delivery service trips to be identified from the larger SherpaShare ridehailing data set comprised of 65,240 route-level traces. In the food delivery service data set, the most popular platform was Postmates (801 deliveries), which was acquired by Uber Eats (10 deliveries) in February 2019, followed by Grubhub (144 deliveries) and DoorDash (21 deliveries). While analyzing these data has the advantage of providing insights on delivery information across multiple platforms, it must be noted that they are biased by driver participation—food delivery service drivers may use a competing mileage accounting service or none at all—and the related overall market penetration of this particular app—the sample’s breadth of delivery trips was conducted by 19 drivers. Therefore, the final study sample only included those OFD service adopters who were assigned a ridehailing driver who also conducted prepared meal deliveries, which is likely to alter the spatial distribution of sampled OFD service trips to areas of higher ridehailing activity and attributes to an underreporting of overall OFD service adoption in the region. In reviewing the number of October food deliveries within this data set, an overall increase in adoption occurs from 2015 (11 deliveries) to 2018 (426 deliveries), with a marked drop-off in activity occurring during October 2019 (45 deliveries). Yet, despite these identified shortcomings, these data offer a unique ability to understand the spatiotemporal patterns of food delivery services before the onset of the Covid-19 pandemic and their dramatic rise in popularity.

### 3.2 Neighborhood data and measures

Information on the number of food delivery service trip ends as well as data on the socioeconomic context and built environment of the Phoenix metro region were aggregated to a system of 553 hexagons with an apothem of one mile that were continuously casted across the study area. Hexagonal sampling areas have been adopted in previous studies (Gehrke & Huff, 2022; Jiao et al 2021) to allow for a consistent spatial distribution of zones across study areas, with the desirable property that the centroids of all neighboring hexagons have identical Euclidean distances between them. Socioeconomic context metrics were calculated using population estimates provided by the 2015-2019 American Community Survey (ACS) and employment figures derived from the 2018 Longitudinal Employer-Household Dynamics (LEHD) data set. These data were provided at US Census geographies—ranging in size from blocks to tracts—that were summarized to the hexagon spatial unit using an area-based apportionment process to generate a robust set of area-wide characteristics based on person- and household-level attributes. Variables at the former level describe the share of residents in a hexagon classified by different Census-designated categories of sex, age, education, race/ethnicity as well as immigrant and work status. These metrics are complemented by household-level variables related to annual income, poverty status, housing tenure, vehicle ownership, and internet access as well as the share of residents employed in low- ($1,250 per month or less), medium- ($1,251 to $3,333 per month), or high-wage (more than $3,333 per month) occupations.

Built environment measures describing land development patterns, including population, employment, and activity (sum of population and employment) as well as jobs-population ratio, were constructed using the aforementioned ACS and LEHD data sources. The share of workers within a hexagon across different categories contains the same wage breaks as the socioeconomic context metric but instead describes the area's workforce and reflects the area's businesses. Meanwhile, spatial data on the location of bars and breweries was collected from the Arizona Department of Liquor Licenses and Controls, with license types of series three, six, and seven relating to these drinking establishments. Urban design and transportation system variables were constructed from OpenStreetMap (OSM) data. The three metrics of intersection density, connected node ratio, and beta index describe the connectivity of the hexagon's street network (Gehrke & Welch, 2017), while shares of primary, secondary, tertiary, and residential roads was calculated using OSM's highway tags and denotes an area's predominant road infrastructure. Finally, the percent of a hexagon's area that lies within a one-half-mile areal buffer of a Valley Metro light rail transit station was created as another independent variable to test in the statistical modeling process.

### 3.3 Modeling strategy

These described neighborhood-level measures of socioeconomic context and the built environment were next used in a two-phased modeling approach to understand their relationship with food delivery service destinations. An initial strategy was to investigate the significance of these various metrics by specifying an aspatial negative binomial (NB) model where the count of total deliveries in a hexagon was a function of the area's socioeconomic context and built environment. The second strategy extended these findings by estimating a spatial Durbin model (SDM) that accounted for clustering impacts of the dependent variable as well as those predictors significant in the NB model specification.

Informed by the reviewed literature (Wang & He, 2021), the aspatial NB model was chosen to provide a base-level assessment of how the socioeconomic context and built environment may impact the utilization of food delivery services, given the non-negative value associated with this count information and the likely overdispersion nature of the dependent variable. By relaxing the equidispersion assumption, indicating equality in the condition mean and variance functions, inherent to a Poisson count model represents an important advantage of an NB count model, which will default to the former model structure if overdispersion is not determined in the estimation process. The structure of the aspatial NB model is presented as:

$$\lambda_i = exp(\beta x_i + \varepsilon_i)$$

Where, $x_i$ is a set of various socioeconomic and built environment predictors operationalized at hexagon zone $i$ and $\varepsilon_i$ is a Gamma-distributed error term with a mean equal to one and a variance of $\alpha^2$. This error term permits the variance to differ from the conditional mean:

$$var[y_i] = E[y_i] + \alpha E[y_i]^2$$

Specification of the final aspatial NB model of food delivery service trip destination counts was determined using a multistep approach. First, the unadjusted correlation between each socioeconomic context and built environment variable and the count outcome was calculated, where independent variables with a coefficient estimate of an absolute value above 0.1 were retained. The correlation between the remaining independent variables was then assessed and, amongst those variables that were strongly correlated, the variable with a weaker association with the dependent variable was removed from further consideration. Next, using this subset of independent variables, the Lasso statistical modeling approach, which employs regularization penalties on model fit and minimizes empirical error to produce a sparse and potentially more interpretable final specification, was implemented (Tibshirani, 1996; Zhao & Yu, 2006). The resulting Lasso model specification had a handful of coefficient estimates that were non-significant, so a backwards elimination process was performed to iteratively remove those independent variables until a specification where all remaining predictors were marginally significant, and the log-likelihood of the reduced model reflected a significant improvement from the Lasso specification. In the final step, categorical variables were added to the model to aid the interpretation of the aspatial NB model's significant predictors.

However, despite the benefit of a parsimonious model building process being undertaken, when analyzing data aggregated to a larger geographic unit—here a two-mile hexagon, unobserved spatial correlations amongst the predictors and outcome variable that could bias the NB model estimates are likely to persist. To assess whether spatial autocorrelation exists, a commonly accepted approach is to estimate the global Moran's *I* statistic (Anselin, 1995; Moran, 1950):

$$I = \frac{\sum_i \sum_j w_{ij} z_i \times z_j / S_0}{\sum_i z_i^2 / n}$$

Where, $w_{ij}$ represents the elements of a spatial weight matrix, $S_0 = \sum_i \sum_j w_{ij}$ is the sum of the weights, and n is the number of hexagons (observations). This formulation shows Moran's *I* to be a cross-product statistic between a variable and its spatial lag (the average value of that variable in neighboring hexagons), with the statistic expressed in terms of deviations from the mean. For this study's data, a null hypothesis stating that spatial randomness is present in the outcome variable was tested. In evaluating the Moran's *I* statistic and the significance of its accompanying test ($I$=0.30, $p<0.001$), the null hypothesis may be rejected, with the spatial distribution of high and low dependent variable values determined to be more spatially clustered than would be expected in a spatially random distribution of trip ends. Accordingly, this unobserved correlation should be accounted for with a spatially lagged extension of the aspatial NB model specification. Further examination by performing a likelihood ratio test to compare the aspatial NB model and a paired specification with the addition of spatially-lagged terms for the dependent and independent variables supported the estimation of an SDM accounting for spatial clustering.

An SDM produces unbiased coefficient estimates by considering the spatial dependence that exists in the endogenous and exogenous relationships of the hexagons and their neighboring units (LeSage & Pace, 2009). This spatial dependence is inherent to data sets where uniformity lacks in the effects of space as a result of regional hierarchies related to traditional urban growth patterns (Anselin, 1988). In this study's data set, varied but internally consistent spatial patterns are hypothesized to exist in the built environment and socioeconomic contexts of hexagons located closer to the central downtown district in comparison to hexagons in inner-ring and further outlying suburban neighborhoods. Relatedly, residents of immediately neighboring hexagons in this greater urban-suburban structure are considered more likely to share similar preferences regarding lifestyles and activity engagement (i.e., OFD service adoption) than residents of more spatially distant hexagons. Guided by an assessment of the Moran's *I* statistic to determine the existence of spatial autocorrelation in the dependent and independent variables, the SDM adopted in this study takes the following general structure:

$$y = \rho W y + \alpha l_n + \beta x_i + W x_i \Theta + \varepsilon_i$$

Where, ρ is the spatial autocorrelation coefficient, $W$ is the spatial weight matrix, $x_i$ is the socioeconomic and built environment predictors of hexagon $i$, and $l_n$ represents an n×1 vector of ones. The coefficient estimates are denoted by $\alpha$, $\beta$, and Θ, with $\varepsilon_i$ as the error term. Aside from the spatial lag of the outcome variable ($Wy$), the SDM presents spatially lagged independent variables ($Wx_i$) with a queen-contiguous spatial weight matrix in which any immediately neighboring hexagon was given a value of one. The combined choice of a queen-contiguous spatial weight matrix and symmetric two-mile hexagon zonal system captures a first-order spatial lag similar to the adoption of a distance band of an approximate three-mile radius.

The process for constructing the final SDM of food delivery service trip ends began with a full specification of the aspatial NB model with spatially-lagged dependent and independent variables. However, a number of these parameters were found to be non-significant, so a subsequent backwards elimination process was iteratively conducted until a final SDM was produced where all spatially lagged predictors were found to be statistically significant.

# 4 Results

## 4.1 Spatiotemporal patterns of online food delivery locations

Figure 1 offers a map of the Phoenix metro region with the count of food delivery service trip ends in the sample aggregated to the zonal system of two-mile hexagons. In examining the spatial distribution of trips, clustering of high activity locations appears in downtown Phoenix and South Scottsdale, which each have hexagons where more than 50 deliveries were completed. Another hexagon reflecting this highest level of activity can be found in a portion of southern Phoenix adjacent to South Mountain Community College. Several hexagons clustered in the north half of Tempe, which is home to Arizona State University's main campus and the densest jurisdiction in the study area, also display a higher count of OFD locations. Conversely, zones in the Phoenix metro region's outer stretches, roughly defined as hexagons located beyond Arizona State Route 101's semi-beltway, had limited food delivery service activity. Those jurisdictions, which include portions of Avondale, Gilbert, Glendale, Mesa, and Peoria, have no hexagons with greater than six recorded deliveries over the study's timeframe.

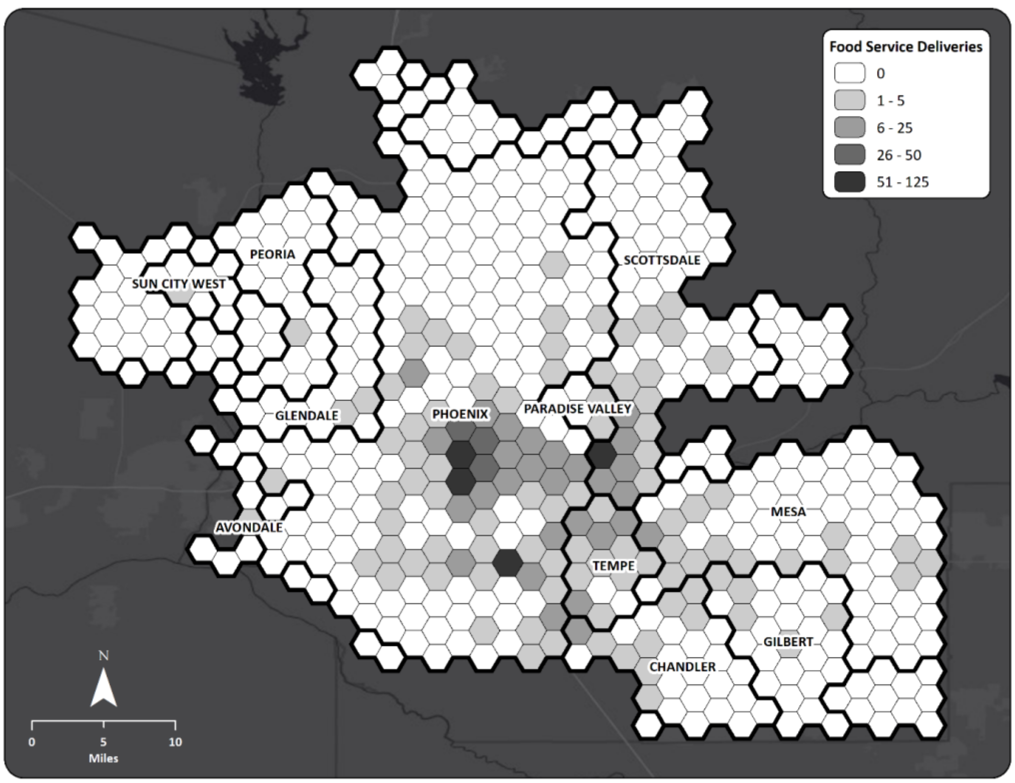


**Figure 1.** Spatial distribution of online food delivery service zones in Phoenix metro region

Distinguishing between zones with or without food deliveries and the neighborhood attributes of those hexagons, Table 1 provides a summary of the various socioeconomic context and built environment measures in the study area and the results of an unpaired t-test between the two groups of zones. Within the study sample, approximately one quarter (23.51%) of hexagons in the Phoenix metro region contained at least one food delivery location. In terms of socioeconomic context, the hexagons with delivery activity were more likely to have a higher share of male residents, young adults between 18 and 34 years of age, and a more racially and ethnically diverse composition of residents. However, non-delivery zones were more likely to have a higher percent of adults with an undergraduate college degree or some college education, more households with an annual income above $75,000, and fewer families living in poverty. As for home and vehicle ownership, hexagons with at least one reported food delivery service location were more likely to have a higher share of rental units and car-free or car-lite households. In terms of the built environment, hexagons with observed food delivery services tended to be denser (regarding both population and employment), characterized by a greater imbalance in jobs-to-residents, and have a more traditional gridiron street network design typically found within central business districts. Finally, active food delivery zones in the Phoenix metro region were more likely to be located in the walkshed of a light rail transit station.

**Table 1.** Descriptive statistics for neighborhood-level characteristics

| Variable | All Zones (n = 553) | | Delivery Zones (n = 130) | | Non-Delivery Zones (n = 423) | |
|---|---|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. | Mean | St. Dev. |
| *Socioeconomic Context* | | | | | | |
| Sex: Male* | 0.49 | 0.02 | 0.50 | 0.03 | 0.49 | 0.02 |
| Sex: Female* | 0.51 | 0.02 | 0.50 | 0.03 | 0.51 | 0.02 |
| Age: Less than 18 years old | 0.23 | 0.08 | 0.22 | 0.07 | 0.23 | 0.08 |
| Age: 18-34 years old* | 0.21 | 0.10 | 0.27 | 0.10 | 0.19 | 0.08 |
| Age: 35-44 years old* | 0.13 | 0.04 | 0.13 | 0.02 | 0.12 | 0.04 |
| Age: 45-64 years old* | 0.26 | 0.06 | 0.24 | 0.05 | 0.27 | 0.06 |
| Age: 65 years old or more* | 0.18 | 0.15 | 0.14 | 0.09 | 0.19 | 0.16 |
| Education: High school or less | 0.61 | 0.17 | 0.63 | 0.17 | 0.60 | 0.17 |
| Education: Bachelors or some college* | 0.24 | 0.10 | 0.23 | 0.10 | 0.25 | 0.10 |
| Education: Masters or PhD | 0.15 | 0.08 | 0.14 | 0.08 | 0.15 | 0.08 |
| Race/Ethnicity: Asian | 0.04 | 0.04 | 0.04 | 0.03 | 0.04 | 0.04 |
| Race/Ethnicity: American Indian/Native | 0.02 | 0.05 | 0.02 | 0.02 | 0.02 | 0.05 |
| Race/Ethnicity: Black/African American* | 0.05 | 0.04 | 0.07 | 0.05 | 0.04 | 0.04 |
| Race/Ethnicity: Hispanic/Latinx* | 0.17 | 0.15 | 0.22 | 0.16 | 0.15 | 0.14 |
| Race/Ethnicity: White, Non-Hispanic* | 0.63 | 0.24 | 0.52 | 0.23 | 0.66 | 0.23 |
| Immigrant Status: Population foreign-born* | 0.13 | 0.06 | 0.16 | 0.07 | 0.12 | 0.06 |
| Household Income: Less than $35,000* | 0.21 | 0.12 | 0.28 | 0.12 | 0.19 | 0.11 |
| Household Income: $35,000-$74,999* | 0.28 | 0.09 | 0.31 | 0.07 | 0.27 | 0.09 |
| Household Income: $75,000-$149,999* | 0.31 | 0.08 | 0.27 | 0.08 | 0.32 | 0.08 |
| Household Income: $150,000 or more* | 0.20 | 0.14 | 0.14 | 0.11 | 0.22 | 0.14 |
| Poverty Status: Families below poverty line* | 0.11 | 0.08 | 0.15 | 0.10 | 0.09 | 0.07 |
| Employment: Share of low-wage workers* | 0.19 | 0.04 | 0.20 | 0.03 | 0.19 | 0.04 |
| Employment: Share of mid-wage workers* | 0.31 | 0.10 | 0.35 | 0.09 | 0.29 | 0.10 |
| Employment: Share of high-wage workers* | 0.49 | 0.12 | 0.45 | 0.11 | 0.51 | 0.12 |
| Work Status: Adult unemployment* | 0.02 | 0.01 | 0.03 | 0.01 | 0.02 | 0.01 |
| Internet Access: Household subscriptions | 0.33 | 0.08 | 0.33 | 0.08 | 0.33 | 0.07 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Tenure: Homeowners* | 0.70 | 0.19 | 0.53 | 0.17 | 0.75 | 0.16 |
| Tenure: Renters* | 0.30 | 0.19 | 0.47 | 0.17 | 0.25 | 0.16 |
| Car Ownership: 0* | 0.02 | 0.02 | 0.04 | 0.03 | 0.01 | 0.02 |
| Car Ownership: 1* | 0.19 | 0.09 | 0.26 | 0.08 | 0.16 | 0.08 |
| Car Ownership: 2* | 0.45 | 0.07 | 0.42 | 0.07 | 0.45 | 0.07 |
| Car Ownership: 3 or more* | 0.35 | 0.10 | 0.28 | 0.08 | 0.37 | 0.10 |
| *Built Environment* | | | | | | |
| Persons per acre* | 4.29 | 3.51 | 6.72 | 3.19 | 3.54 | 3.25 |
| Jobs per acre* | 2.12 | 3.60 | 5.31 | 5.73 | 1.14 | 1.67 |
| Persons and jobs per acre* | 6.41 | 5.78 | 12.03 | 6.64 | 4.68 | 4.18 |
| Share of low-wage workplaces* | 0.23 | 0.11 | 0.19 | 0.08 | 0.24 | 0.12 |
| Share of mid-wage workplaces | 0.37 | 0.10 | 0.36 | 0.09 | 0.37 | 0.11 |
| Share of high-wage workplaces* | 0.40 | 0.16 | 0.45 | 0.14 | 0.39 | 0.16 |
| Bars and breweries* | 1.86 | 3.95 | 4.67 | 6.72 | 0.99 | 1.85 |
| Jobs-population ratio* | 0.65 | 1.96 | 1.05 | 1.48 | 0.52 | 2.07 |
| Intersections per acre* | 0.15 | 0.09 | 0.20 | 0.06 | 0.14 | 0.09 |
| Connected node ratio* | 0.78 | 0.15 | 0.82 | 0.06 | 0.76 | 0.16 |
| Beta index | 0.10 | 0.15 | 0.11 | 0.10 | 0.09 | 0.16 |
| Share of primary roads | 0.11 | 0.16 | 0.12 | 0.13 | 0.10 | 0.17 |
| Share of secondary roads* | 0.11 | 0.10 | 0.13 | 0.10 | 0.10 | 0.10 |
| Share of tertiary roads | 0.09 | 0.09 | 0.09 | 0.07 | 0.09 | 0.09 |
| Share of residential roads | 0.69 | 0.20 | 0.67 | 0.15 | 0.69 | 0.22 |
| Half-mile light rail transit shed* | 0.02 | 0.10 | 0.06 | 0.16 | 0.01 | 0.06 |

Note. * Significant (p>0.05) difference between variables when measured in a delivery or non-delivery zone.

To help understand the temporal conditions of food delivery service trips, Figure 2 offers an hour-by-hour breakdown of food deliveries in the study sample. Unsurprisingly, the hours of the day with the highest concentration of deliveries occur during customary lunch and dinner mealtimes, with notable peaks being evident on Fridays between 11am and noon, Tuesdays between 5pm and 6pm, and Sundays between 6pm and 7pm. Aggregating these data into conventional blocks of time that are of interest to transportation planners and engineers: 40.9% of these trips occur mid-day (9am-4pm), 31.6% occur in the evening peak period (4pm-7pm), and another 26.1% occur during the early night (7pm-12am), with the remaining 1.4% of sampled food delivery trips taking place between midnight and 9am.

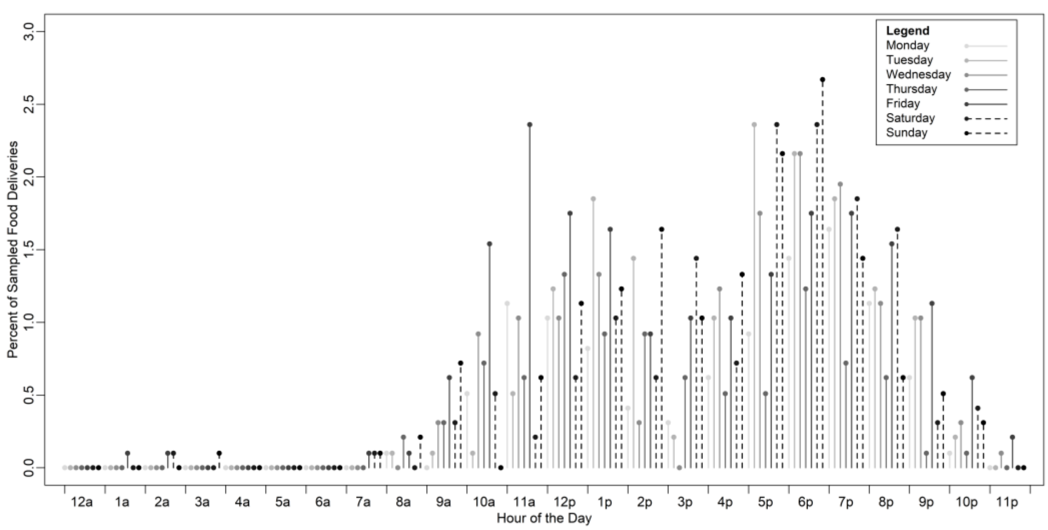


**Figure 2.** Time-of-day distribution of online food deliveries in Phoenix metro region across days of the week

While the transportation system impacts of having these zero-passenger trips occur during the early night and mid-day are noteworthy, the additional congestion and subsequent environmental impacts created by a substantial share of these car trips occurring during peak travel times warrants further investigation. Figure 3 illustrates the spatial distribution of food delivery service trips that terminate during the evening peak period, with delivery zones shaded based on the share of sampled trips that occurred in the hexagon during standard evening commute times. Looking first at the evening peak trip ends, a substantial cluster of deliveries can be observed in downtown Phoenix, which as the central business district of the city and region presumably already has significant volumes of automobile traffic on its streets as individuals depart their workplaces. South Scottsdale and Tempe, the former area of which is not served by the regional light rail system, can also be seen as having clusters of zero-passenger trips occurring during the evening peak. Turning to those hexagons with relatively few on-demand food delivery service trip ends but a higher share of them taking place during the evening peak (visually depicted in black), some evidence is found for the service popularity extending outward from the Phoenix region's center to more suburban neighborhoods whose residents appear to be adopting these services as a meal option during congested travel times.

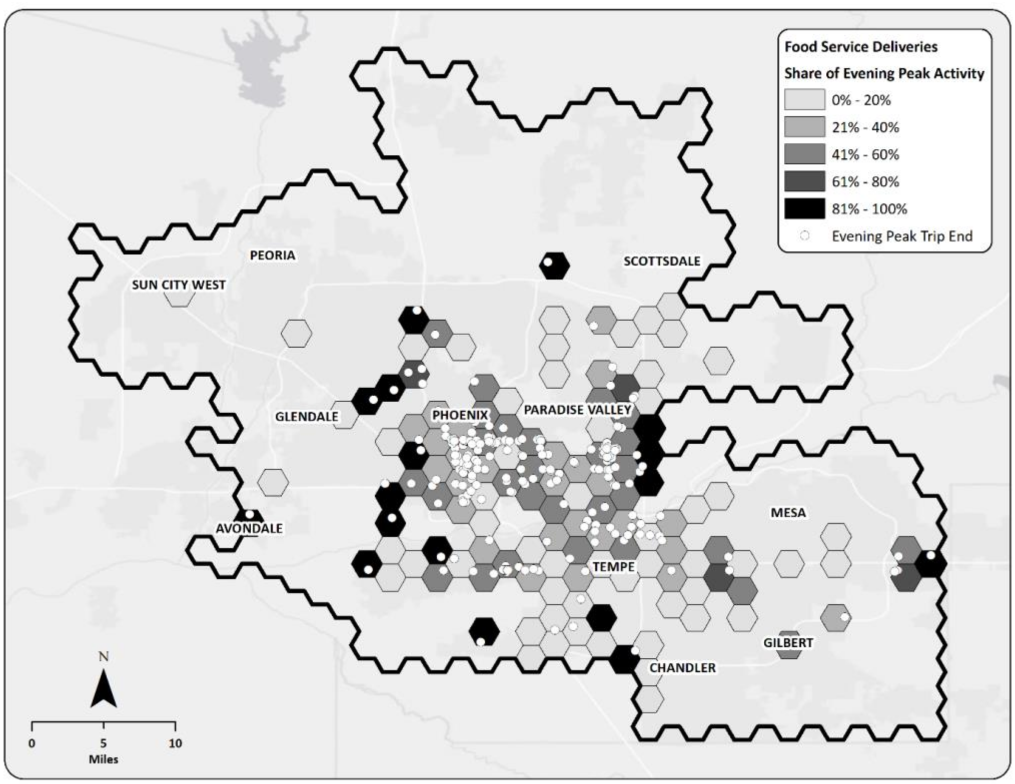


**Figure 3.** Spatial distribution of online food deliveries in Phoenix metro region during evening peak period

### 4.2 Spatial determinants of online food delivery locations

Analyzing the socioeconomic context and built environment of two-mile hexagons in the Phoenix metro region, Table 2 shows the estimation results for the aspatial NB model of food delivery service frequency. Extending the earlier descriptive findings of differences between hexagons with and without food delivery service activity, the NB model indicates that hexagons with a higher share of adults under 45 years of age and residents who identify as Black/African American were associated with an increased frequency of app-based food deliveries, which was observed elsewhere (Kim & Wang, 2021). Given the requirement of an internet-service plan to utilize these OFD services, the positive modeled association between household internet access at a neighborhood scale and the count of deliveries terminating in a hexagon is intuitive. Moreover, given the spatial pattern displayed in the above figures, which emphasized activity in denser communities, a negative association between the share of households in a hexagon with three or more vehicles and the count of food deliveries could be expected. These households, which have greater vehicle access, may be more likely to drive to a restaurant for an out-of-home meal rather than adopt an OFD service to eat at-home.

**Table 2.** Negative binomial (NB) model estimates of online food deliveries

| Variable | β | SE | p-value | dy/dx |
|---|---|---|---|---|
| Intercept | -6.56 | 1.74 | <0.001 | --- |
| *Socioeconomic Context* | | | | |
| Age: Less than 18 years old | 0.58 | 2.47 | 0.814 | 0.143 |
| Age: 18-44 years old | 3.78 | 1.17 | 0.001 | 0.926 |
| Race/Ethnicity: Black/African American | 16.18 | 2.52 | <0.001 | 3.966 |
| Internet Access: Household subscriptions | 8.87 | 2.76 | 0.001 | 2.174 |
| Car Ownership: 3 or more | -4.05 | 1.55 | 0.009 | -0.994 |
| *Built Environment* | | | | |
| Persons per acre | 0.24 | 0.03 | <0.001 | 0.059 |
| Jobs per acre | 0.13 | 0.03 | <0.001 | 0.032 |
| Bars and breweries | 0.12 | 0.02 | <0.001 | 0.030 |
| Half-mile light rail transit shed | -1.56 | 0.85 | 0.066 | -0.383 |
| Model summary | | | | |
| Log-likelihood | | | | -995.598 |
| Theta (SE) | | | | 0.474 (0.068) |

Regarding predictors describing a hexagon's land development pattern, an increase in either population or employment density was found to be linked to an increase in the number of deliveries made in a zone, which was reported in a previous study and possibly indicative of a higher proclivity for residents in urbanized areas who are more accustomed to online activity to demand more OFD services (Wang & He, 2021). Similarly, a significant association was found to exist between the number of bars and breweries within a hexagon and its number of food deliveries, with an increase in the count of drinking establishments in an area resulting in a higher frequency of OFD service adoption. This finding may be somewhat counterintuitive given residents of these areas may be more inclined to dine at nearby physical establishments such as breweries but may also relate to these zones having a greater share of younger and more technologically savvy residents who choose to live closer to clusters of bars and breweries. Finally, after controlling for the above determinants, areas with stronger access to light rail transit stations were predictive of a lower count of food delivery service trip ends; a finding that is likely associated with the improved access to out-of-home activity locations such as restaurants that are often characteristic of the rail transit station areas.

Extending the results of this aspatial NB model to account for the non-randomness of food delivery locations, an SDM with an identical base specification but the addition of spatially lagged variables for the hexagon-level frequency of deliveries and each of the predictors described above was estimated. The full SDM demonstrated a statistically significant improvement in fit over the aspatial model displayed in Table 2 (LRT statistic=38.52,p=<0.001), as did the reduced spatial model specification (LRT statistic=33.20,p=<0.001) that was ultimately selected as the final SDM (Table 3). The following discussion describes the marginal effects ($dy/dx$) for select significant predictor in the final SDM; interpreted as the expected change in the number of food delivery service trip ends per one-unit change in the independent variable, all else constant.

**Table 3.** Spatial Durbin model (SDM) model estimates of online food deliveries

| Variable | β | SE | p-value | dy/dx |
|---|---|---|---|---|
| Intercept | -5.21 | 1.74 | 0.003 | --- |
| Spatial lag: Online food deliveries | 0.06 | 0.02 | 0.003 | 0.013 |
| *Socioeconomic Context* | | | | |
| Age: Less than 18 years old | 3.13 | 2.42 | 0.197 | --- |
| Age: 18-44 years old | 2.41 | 1016 | 0.038 | 0.546 |
| Race/Ethnicity: Black/African American | 15.16 | 2.35 | <0.001 | 3.443 |
| Internet Access: Household subscriptions | 8.17 | 2.60 | 0.002 | 1.856 |
| Car Ownership: 3 or more | -0.98 | 1.73 | 0.571 | --- |
| Spatial lag: Car Ownership: 3 or more | -6.58 | 2.54 | 0.010 | -1.494 |
| *Built Environment* | | | | |
| Persons per acre | 0.22 | 0.03 | <0.001 | 0.050 |
| Jobs per acre | 0.06 | 0.03 | 0.037 | 0.013 |
| Spatial lag: Jobs per acre | 0.10 | 0.05 | 0.049 | 0.024 |
| Bars and breweries | 0.07 | 0.02 | <0.001 | 0.017 |
| Half-mile light rail transit shed | -1.68 | 0.79 | 0.034 | -0.382 |
| Spatial lag: Half-mile light rail transit shed | -2.59 | 1.20 | 0.032 | -0.588 |
| Model summary | | | | |
| Log-likelihood | | | | -962.395 |
| Theta (SE) | | | | 0.655 (0.107) |

In the SDM, as with the aspatial NB model estimates, the share of residents between 18 and 44 years of age, residents identifying as Black/African American, and households with an internet subscription located in a hexagon was positively associated with food delivery frequency. However, spillover effects did not exist for these socioeconomic context metrics, as their spatially lagged variables were not found to be statistically significant in the final SDM specification. However, the spatial lag variable for households with three or more vehicles was found to be significant, with a one percent increase in representation of three car households in a hexagon associated with a decrease of 1.49 food delivery service trips conducted. Interestingly, the non-lagged predictor for high car ownership households was no longer significant after accounting for this and other spatial lag variables, which may indicate a higher clustering of hexagons with households owning three or more vehicles who may be more likely to drive to a physical restaurant rather than order a prepared meal from an OFD service.

Regarding the built environment determinants of food delivery services, population and job density as well as the number of bars and breweries in a hexagon remained significant and positively associated with the modeled outcome in the final SDM specification. Looking closer at employment density, which had a significant spatial lag variable in the SDM, an increase of 100 jobs per acre in a hexagon was associated with a 1.30 increase in food delivery frequency; whereas, an increase of 100 jobs per acre in neighboring hexagons was linked to a 2.40 increase in the number of food delivery stops. Likewise, hexagons with a higher percent of their area inside a light rail transit station's walkshed were found to be significant in both the aspatial NB and SDM, with the spatially lagged transit shed variable also being significant in the SDM specification. The spatially lagged predictor also had a larger marginal effect, with a one percent increase in the share of neighboring zones found within a light rail station walkshed associated with a 5.88 decrease in the number of food deliveries completed in a given hexagon. At last, the spatial lag of the food delivery outcome was found to be a statistically significant predictor in which an increase of ten food deliveries in immediately surrounding hexagons was associated with a 1.30 increase in the count of delivery trips finished in a zone; indicating that presently popular food delivery services also had spatial spillover effects in the years prior to the Covid-19 pandemic's onset.

## 5 Conclusions

Notable contributions of this study relate to its investigation of a novel data set to shed light on the adoption of on-demand food delivery services, which garnered greater attention following the onset of the Covid-19 pandemic and have demonstrated year-to-year growth in sales over the past three years (Kaczmarski, 2023). This study differed from the handful of past studies of OFD services that have utilized self-reported survey data by analyzing spatial data observed by a third-party mileage tracking app. In doing so, this study offered new macro-scale insights into the effect of socioeconomic context and the built environment on the frequency of OFD service trips distributed across the Phoenix metro region. Findings from a traditional NB model were advanced by estimating an SDM that tested for the additional impact of spatially lagged zonal predictors and spatial effects related to OFD service adoption frequency.

Spatiotemporal patterns over the multiyear study timeframe revealed that on-demand food delivery services in the years prior to the pandemic were most popular in the region's inner core communities and during the latter parts of the day, with over three-out-of-ten deliveries occurring during evening peak travel periods. This study finding highlights a challenge for transportation planners associated with the increased popularity of a zero passenger, car-reliant meal service that coincides with the time and place in which many streets are already congested with commuters departing their central business district workplaces. In response, city officials should continue to support more efficient and sustainable mobility alternatives that alleviate car congestion but also give further consideration to curb management strategies that support both temporary parking for OFD service drivers and longer-term parking for patrons of restaurants who drive to the site and wish to dine-in. As the most severe mobility restrictions of the Covid-19 pandemic subside and travel behaviors return to pre-pandemic conditions, the spatiotemporal patterns revealed in this study also offer transportation planners evidence as to which neighborhoods may be most likely to continue sustained levels of on-demand food delivery service adoption and related traffic congestion and parking impacts. In these contexts, found in this study to be urban areas characterized by higher activity densities, transportation planners should seek to improve systemwide efficiencies via transport solutions such as the introduction of smaller, alternative last-mile delivery services (e.g., autonomous delivery vehicles), where viable, or land policies that promote residences in transit-oriented developments with an assortment of restaurants nearby.

In terms of social context, this study found that zones with higher shares of adults younger than 44 years old, residents who identify as Black/African American, and households with an Internet subscription were associated with higher adoption of on-demand food delivery services. While an early adoption of these services was also likely related to unobserved individual factors such as tech-savviness, these neighborhood factors suggest city officials should continue to seek actions that ensure local access to dining opportunities and food provisions within walking distances. Meanwhile, SDM estimates suggested the utilization of OFD services exhibited clustering effects and neighborhoods characterized by higher population, employment, and drinking establishment densities experienced higher frequencies in its adoption. Thus, neighborhoods with higher activity concentrations that are often more walkable and in proximity to restaurants exhibited higher OFD service adoption rates, carrying an undesirable potential for these vehicle-based services to counter the benefits of walkable environments. However, residing within a light rail transit walkshed was negatively associated with OFD service trip frequency, further emphasizing the aforementioned importance of increased high-quality non-auto accessibility to out-of-home activities.

While this research contributes to the study of on-demand food delivery services by helping to establish a baseline understanding of spatial factors associated with their adoption, there are limitations to be addressed by future research. Regarding the data set, its observed meal deliveries are likely to only reflect a marginal share of all trips made by on-demand food delivery services during the timeframe and their spatiotemporal patterns may exhibit a bias related to driver participation in the third-party mileage tracking app. Future research would benefit from constructing a larger study sample from a greater diversity in OFD drivers to account for possible variations in work schedules, service areas, and ultimately delivery locations and times. Moreover, analyzing neighborhood factors related to service adoption frequency are hindered in that any extraction of study findings to individual-level behaviors are subject to a contextual fallacy (Fowler et al., 2020) that can be resolved by ensuring future studies also account for individual- and household-level sociodemographic and economic attributes.

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## Author contribution

S. Gehrke: conceptualization, formal analysis, investigation, methodology, supervision, visualization, writing—original draft, writing—review and editing. M. Huff: data curation, formal analysis, software, visualization, writing—original draft. B. Russo: supervision, writing—review and editing. E. Smaglik: supervision, writing—review and editing.

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