



Transportation network company wait times in Greater Seattle, and relationship to socioeconomic indicators

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ABSTRACT

Transportation network companies (TNC) which use smartphone apps to connect travelers to drivers for point to point, intra-city trips have expanded rapidly in recent years, yet the impacts of their services on urban transportation systems, for good or ill, are not fully understood. These services may increase access to transportation for some individuals, but it is unclear whether these benefits are equitably distributed across different neighborhoods. In this paper, we explore the spatial variability in wait times for a TNC vehicle throughout the Seattle, WA region, testing whether areas with lower average income or a greater percentage of minorities experience different waiting times than other areas. We collected approximately 1 million observations of estimated waiting times, quasi-randomly sampled over approximately two months in 2015. We analyzed spatial and temporal patterns using local regression, which suggested lower wait times in densely populated areas of the Seattle region, and the lowest wait times during midday hours. We developed a spatial error regression model to investigate relationships between wait times and socioeconomic indicators at the census block group (CBG) level. We find that conditional on other covariates, expected waiting times are longer in CBGs with higher average income, and shorter in CBGs with greater population density and employment density. After adjusting for differences in density and income, a higher percentage of minorities in a CBG is associated with longer waiting times late at night and shorter waiting times during the day, with an average effect of close to zero. Geographically weighted regression indicates that the strength, and in some cases the sign, of these relationships varies throughout the Seattle region. Overall, the results suggests that transportation network companies offer higher performance in dense urban areas, and that adequate access to TNC services is not necessarily restricted to areas that are “white and wealthy.”

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1. Background

Transportation network companies (TNCs, sometimes known as “ride-sourcing” platforms) are a relatively new urban transportation option that has seen rapid growth in recent years. Through smartphone applications, TNCs connect individuals willing to pay for a ride with independent drivers willing to provide a ride in their privately owned vehicles. The number of drivers in the U.S. using the largest TNC platform, Uber Technologies, Inc. (Uber), grew from close to zero in 2012 to >160,000 in 2014 (Hall and Krueger, 2015). In comparison, the Bureau of Labor Statistics estimates that the number of taxi drivers and chauffeurs will grow from 233,000 in 2012 to 269,200 employees in 2022 (Bureau of Labor Statistics, 2014).

The leading TNCs in U.S. markets are Uber and Lyft, which offer similar services providing smartphone users with an easy way to request

point to point rides on-demand. Rather than using a traditional taxi dispatch system in which a driver is identified and dispatched to a rider, the TNC technology platform links the rider with one of (usually) many drivers in the area who are connected to the application. Some TNCs claim to be technology companies, not transportation companies, because their primary product is a technological platform for connecting riders and drivers (Zilbermint, 2015), and the drivers are independent contractors rather than employees. This model has proven to be an efficient way to connect people in need of rides with people willing to drive them, as evidenced by rapid growth in popularity and use of the services.

The popularity of these companies is a result of improved performance, convenience, and cost over traditional taxi systems. Rayle et al. showed that wait times for TNCs in San Francisco are significantly lower than those for taxi services (Rayle et al., 2014). Moreover, TNC rides appear to regularly cost less than those in a taxi. In a study funded by Uber, the Botec Analysis Corporation found that the average price for an Uber trip in a low-income neighborhood in Los Angeles was \$7.26 compared to \$17.09 for an equivalent taxi trip (Smart et al., 2015).

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TNCs attract a younger demographic of riders than traditional taxis, as shown in the Rayle et al. (2014) survey. One of the sources of greater convenience with TNCs is that payment is done automatically in the mobile phone application; cash is not accepted. However, the requirement for owning a smartphone and a credit card could be a barrier to access for low-income individuals. According to the US Census Bureau, between 1995 and 2007, as household income falls, households are less likely to have access to a credit card (U.S. Census Bureau, 2012).

TNCs have faced strong resistance in many cities from traditional taxi operators, and public entities are grappling with whether and how to regulate these new competitors. One of the reasons for this is that current transportation regulatory language was not written with these types of services in mind, although regulations are being updated in many jurisdictions. The California Public Utilities Commission (CPUC) recently defined a TNC as “an organization...operating in California that provides prearranged transportation services for compensation using an online-enabled application (app) or platform to connect passengers with drivers using their personal vehicles” (California Public Utilities Commission, 2013). Rayle et al. provides a thorough summary of previous regulatory issues across the U.S. (Rayle et al., 2014).

Because of their recent introduction and rapid growth, the overall impact of TNCs on urban transportation systems is unclear. TNCs are often compared to taxi companies in that they provide point to point, intra-city trips. Like taxis, TNCs could increase or decrease overall vehicle miles travelled for different reasons (Anderson, 2014), and TNCs could impact ridership of transit systems in a variety of ways (Rayle et al., 2014). The inequitable distribution of services and access is a widely known issue in the taxi industry (Harris and Ahuja, 2009). This could also arise as an issue in TNC operations, and is of particular interest to us in this work. Understanding these potential impacts of TNCs will allow policymakers to design more effective regulation of the industry.

Shared-use transportation services, including TNCs, have been studied from the perspectives of system design, pricing, demand, and interactions with the rest of the transportation system, among others. However, to date there has been little research quantitatively evaluating the real-world performance of TNCs, particularly when compared with the large amount of work addressing more established shared-use services such as carsharing. Rayle et al. reviewed performance characteristics of ridesourcing in San Francisco, CA with a survey of 380 users in 2014 (Rayle et al., 2014). More recently, Uber funded a report by Smart et al. (2015), which compared wait times and trip costs between equidistant taxi and Uber trips in low-income neighborhoods in Los Angeles, CA. Other papers have looked at the most efficient way of policymaking to regulate TNCs without stifling technological innovations (Ranchordás, 2015).

Against this backdrop of regulatory activity and uncertain social costs and benefits of TNCs, it is timely to study whether TNCs are providing equitable access across the regions where they operate. Equity of access is an explicit or implicit priority of many taxi regulations, with jurisdictions requiring taxis to transport riders to and from locations without regard to neighborhood characteristics. At the federal level, the U.S. Department of Transportation has made equity of access an explicit priority with its Ladders to Opportunity program, which aims to ensure that our transportation system “will simultaneously expand economic opportunity and socioeconomic mobility” (U.S. Department of Transportation, 2016). A relevant question, therefore, is whether TNCs are providing a comparable level of access to travelers in neighborhoods with differing socioeconomic characteristics.

In this study, we use the estimated wait time for an UberX vehicle (UberX is the most popular service model Uber offers) as our measure of access, as it is one of the direct determinants of the overall travel time associated with a trip. Moreover, Rayle et al. (2014) showed that the expectation of short wait times was the second most popular reason for using a ride-sourcing service, behind ease of payment. Whereas Smart et al. (2015) were concerned with the differences between UberX and taxis at the same locations and times, we focus in this

work on how the waiting time for UberX varies with time, location, and neighborhood characteristics.

We collected approximately 1 million observations of waiting times for an UberX vehicle throughout Uber's Greater Seattle service area. We use local regression to identify various hot and cold spots of the city, and to explore how waiting times vary throughout the week. We tested for spatial correlations in the data, and developed spatial error and geographically weighted regression models to understand how waiting times are related to the density, average income, and percentage of minorities in the neighborhood where a ride is requested.

2. Data

We collected estimated wait times for an UberX vehicle through Uber's developer application programming interface (API) over two months in 2015. Uber has been operating in the Seattle region since 2013, and at the time of this study its service area extended beyond the city borders, covering many of the “East-side” communities located across Lake Washington from the city of Seattle proper.

Waiting times were observed at quasi-randomly selected locations throughout the Seattle service area. We used the Puget Sound Regional Council's (PSRC's) transportation analysis zones (TAZs) to grid the region, and then generated equally spaced cells within each TAZ. Over the course of 1 h, a random subset of the TAZs were chosen, and a request for the estimated wait time at a random grid point within each TAZ was made. One data point was requested approximately every 3 1/2 s, and data were collected over a period of nearly two months from May to July 2015. Public holidays falling on weekdays were removed from the data set. The final data set included slightly > 1 million data points.

We acquired socioeconomic data from the 2000–2013 American Community Survey 5-year estimates for King County, WA. We calculated the population density in individuals per square mile by census block group (CBG) using GIS software. Average income per CBG (in U.S. dollars) was calculated as a weighted average of the midpoints of census income brackets by using the number of households within each bracket for each CBG. We calculated the percentage of minorities by dividing the number of non-white individuals by the total population of each CBG. Employment density was calculated at the census block group level using Puget Sound Regional Council's (PSRC) 2013 employment data and is measured in jobs per square mile.

3. Methodology

We began our analysis with non-parametric, local regression (LOESS) models to understand the general spatial and temporal patterns in waiting times. We estimated LOESS curves to observe the variation in average wait times by hour of day and day of week. We also estimated two-dimensional LOESS surfaces in order to visualize wait times across space and used these to create smoothed heat maps of waiting times.

We next fitted an ordinary least squares (OLS) regression model of average estimated waiting time on population density, employment density, average income, and minority population fraction, at the CBG level. The residuals of this model were heteroskedastic and non-normally distributed, and the model produced negative fitted values for waiting time for some observations, which is nonsensical. Therefore, we used the natural logarithm of waiting time as our dependent variable in all subsequent models. We modeled the log waiting time in CBG i as:

$$\text{LogWaitTime}_i = \beta_0 + \beta_1 * [\text{Populationdensity}]_i + \beta_2 * [\text{Employmentdensity}]_i + \beta_3 * [\text{Averageincome}]_i + \beta_4 * [\text{Minoritypopulationfraction}]_i + \varepsilon_i$$

where the four explanatory variables are measured at the CBG level, and the β 's are semilog coefficients for each explanatory variable. In the case

of OLS, ε_i is assumed to be an independently and identically distributed error term.

The physical design of a TNC network leads us to suspect spatial and temporal correlation of model residuals, which would violate the assumptions of the OLS model. Fundamentally, the wait time for a TNC vehicle depends upon the distance from the passenger to the vehicle that will be dispatched, and the travel speed of that vehicle. The former will depend, inversely, on the density of vehicles available in the traveler's vicinity, and the latter will depend on local traffic conditions and the road network design. All of these factors are likely to be correlated in time and space. For example, if there is an unusually large number of drivers on a TNC's platform at 9:00, then there will probably also be an unusually large number of drivers on the platform at 9:01. And, if there is a large number of drivers around a particular location, then wait times for that location will be lower than average. Since the TNC vehicles are inherently mobile, this means that those drivers will also be able to respond to requests from other nearby locations, so the waiting times in those locations will tend to be lower than average too.

Since we are principally interested in the relationships between neighborhood characteristics and waiting times, we used the average waiting time for an UberX in a CBG as the dependent variable. We tested for spatial autocorrelation in our model residuals, and developed models that account for spatial correlation. To explore how the relationships may vary by time of day, we estimated a separate spatial regression model for each hour of the day.

We tested the residuals of an OLS model for spatial autocorrelation using the R Statistical Software package *spdep* (Bivand et al., 2015). We built a neighbors list for the CBGs in the Seattle area, identifying all pairs of CBGs with centroids within 5 miles of one another. We constructed a globally standardized spatial weights matrix for use in the spatial statistics tests and models, using the inverse of the distance between CBGs as the weight. A Moran index test for spatial dependence on the average waiting time by CBG indicated significant spatial dependence ($I = 0.61$, $p < 2.2 \times 10^{-16}$). A Moran index test on the residuals of the OLS model also indicated significant positive spatial autocorrelation in the model residuals ($I = 0.36$, $p < 2.2 \times 10^{-16}$), suggesting that we should account for spatial error correlation in our model.

We next applied Lagrange multiplier tests for spatial autocorrelation to the OLS model, to determine whether a spatial lag or a spatial error model was more appropriate. The extremely low p -values of the robust forms of these two tests (both $< 2.2 \times 10^{-16}$) indicated that either spatial model type would be appropriate. Bansal et al. (2015) suggest that a spatial error model is more appropriate in a case like this one, since it would account for correlation in unobserved factors that influence the dependent variable. In contrast, a spatial lag model would assume that the estimated wait times of adjacent CBGs directly influence the wait time of a given CBG. We find the assumption of correlation in unobserved factors to be more plausible, and thus conclude that the spatial error model is more appropriate in this case.

The specification of our spatial error model is similar to that used for OLS, above, except that in the spatial error model we assume that the vector of error terms, ε , incorporates a spatial effect:

$$\varepsilon = \lambda W\varepsilon + \zeta$$

where λ is the spatial coefficient, W is the spatial weights matrix, and ζ is a vector of uncorrelated error terms. We used the *spdep* package in R to estimate the spatial error models using maximum likelihood estimation. As noted above, we estimated a separate spatial error model for each hour of the day.

Finally, we conducted a geographically weighted regression to explore spatial heterogeneities in the associations between waiting times and the socioeconomic variables. The spatial error models

described above account for spatial correlations in residuals between nearby locations. By estimating a separate model for each hour of the day, we were able to explore the temporal variation in the correlations between waiting times and the socioeconomic variables of the CBGs. However, in all cases, the spatial error models estimate the average relationship between the outcome and predictor variables across the entire region. Yet it is plausible that the strength of the relationships between waiting time and socioeconomic characteristics may vary across different areas in the region. Geographically weighted regression allowed us to estimate locally weighted regression coefficients for each CBG in the data set, generating a different estimate of the coefficients for each CBG.

4. Results

4.1. Summary statistics

Table 1 summarizes the population and employment density, average income, and fraction of minorities in the census block groups (CBGs) studied. Fig. 1 shows how these variables are distributed throughout the Seattle region, and identifies several key parts of the city and region. Lake Washington (5) is the large feature in the center of the map, dividing the city of Seattle proper (1,2) from the “East side” communities including Bothell (3) and Bellevue (4). In Lake Washington is Mercer Island (6), a residential community connected to the west and east shores of the lake by Interstate 90 at its north end. Seattle-Tacoma International Airport (7) is directly south of downtown.

Table 2 presents a correlation matrix for these variables and expected waiting time for an UberX. In general, the correlations between the explanatory variables are weak to moderate. The strongest correlation (-0.51) was between the fraction of minorities and the average income of CBGs. As average income of a CBG increases, the average estimated wait time increases. As population and employment density increase, the average estimated wait time decreases. This indicates, unsurprisingly, that wait times for the nearest UberX vehicle were lower in denser areas of the city. Finally, there is only a weak correlation between the fraction of minorities in a CBG and the average waiting time for an UberX vehicle.

4.2. Locally weighted regression

The fitted locally weighted regression (LOESS) curves for average waiting time by day of week are shown in Fig. 2. These represent average times across the entire region. In general, the average wait times fall within a relatively small range of 5 to 7 min.. The hours of the week with the highest estimated wait times occurred in the early morning hours of weekdays. These wait times peak at a little over 7 min early on Tuesday mornings. Wednesdays, Thursdays, Fridays, and Saturdays show a second peak in the later afternoon. Minimum expected waiting times vary by day of week, with the shortest being Monday and Tuesday afternoons, and Thursday and Friday nights. Both Saturday and Sunday show much less variation in estimated wait time by hour than do weekdays.

Table 1
Summary statistics of census data.

Census variable	Mean	Minimum	Maximum	Standard deviation
Population density (individuals per sq. mi.)	8509.9	–	110,787.4	8691.8
Employment density (jobs per sq. mi.)	5415.5	41.5	204,779.9	17,459.7
Average income (USD)	85,047.8	–	165,036.0	27,774.8
Minority population fraction	0.3	–	0.9	0.2

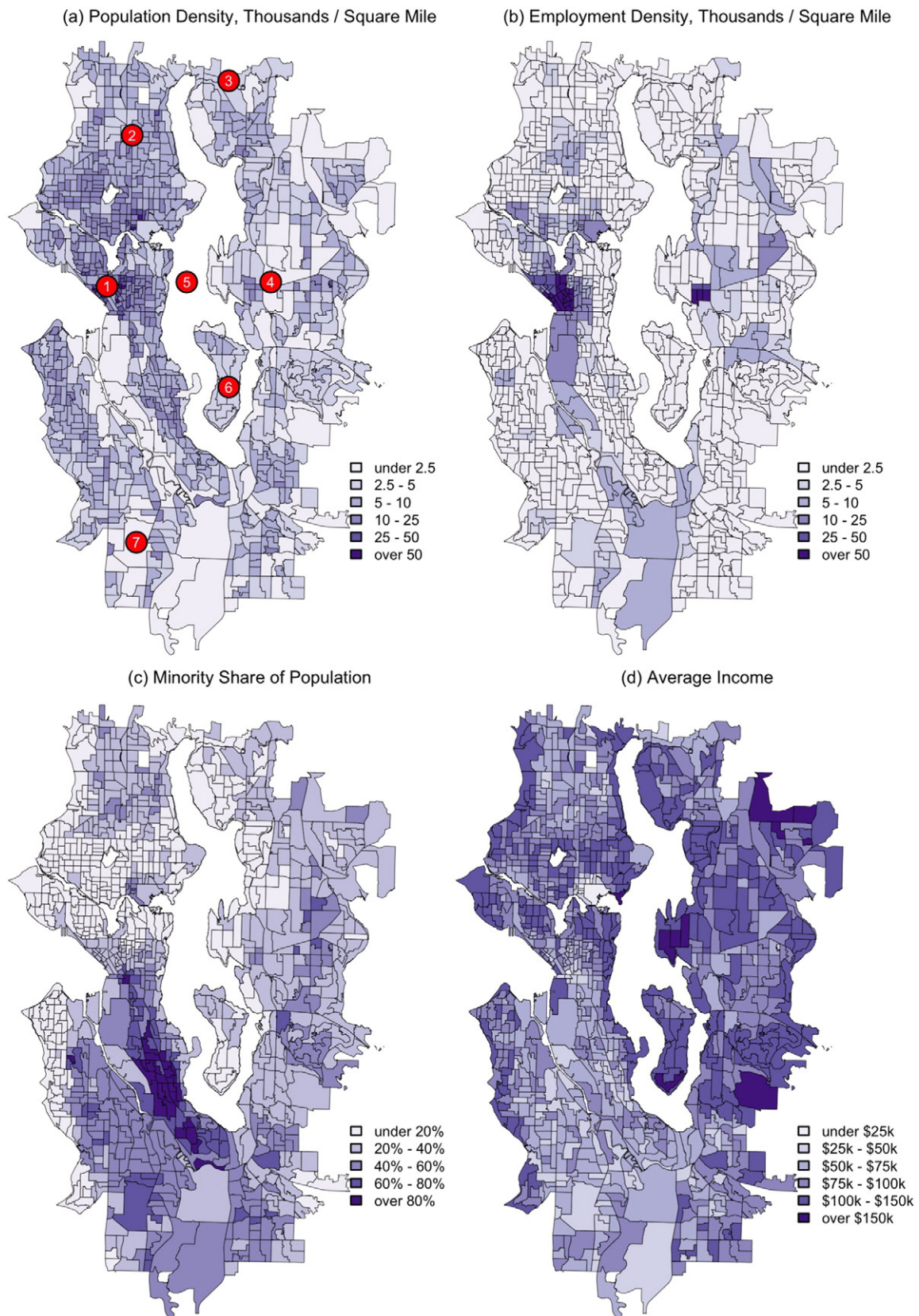


Fig. 1. Characteristics of census block groups in the Seattle region, and key landmarks: (1) Downtown Seattle (2) North Seattle (3) Bothell (4) Bellevue (5) Lake Washington (6) Mercer Island and (7) Seattle-Tacoma International Airport.

Heat maps showing the fitted values from the 2-dimensional LOESS model are presented in Fig. 3. These maps show how the predicted wait times vary across the region during different periods of the day. The

lowest average wait times, <4 min, were observed in downtown Seattle. This may reflect the high density of population, jobs, and retail which creates high demand for Uber rides. More residentially oriented areas

Table 2
Correlation matrix for explanatory variables.

	Wait time	Average income	Population density	Minority population fraction	Employment density
Wait time	1.00	0.23	−0.26	−0.05	−0.23
Average income		1.00	−0.24	−0.51	−0.16
Population density			1.00	−0.05	0.34
Minority population fraction				1.00	0.02
Employment density					1.00

of the region including east of Downtown Seattle and North Seattle also show relatively low wait times.

Most of the North Seattle region had average wait times of < 6 min. South and West Seattle show more variety than North Seattle. The area stretching south of Downtown Seattle appears to have low average wait times. The area around Seattle-Tacoma International Airport had average wait times under 6 min. At the time these data were collected, UberX drivers were allowed to drop off, but not pick up, passengers at the airport; the low wait times in this area may be the result of a surplus of drivers who recently dropped passengers off at the airport. The highest average wait times were found on Mercer Island, south of Bothell, and south of Bellevue. In some of these areas, average wait times exceeded 14 min. These poor wait times were a surprising result given the relative affluence of these areas; a potential explanation is the lower population densities found in these areas.

Consistent with the time-of-day curves in Fig. 2, the midday hours in Fig. 3 show the most coverage of low wait times across the region, while the nighttime hours showed the highest predicted wait times across the region. These differences are most noticeable in the areas to the east of Lake Washington, and to the south of downtown Seattle. Overall, the data appeared to be strongly spatially correlated. Together, Fig. 2 and Fig. 3 show more variability in waiting times based on location than by time of day.

4.3. Spatial error models

The estimated values and 95% confidence limits for the four coefficients are presented in Fig. 4 for each of the 24 spatial error models (one for each hour of the day). With a couple of exceptions (noted below), the relationships between the CBG characteristics and waiting

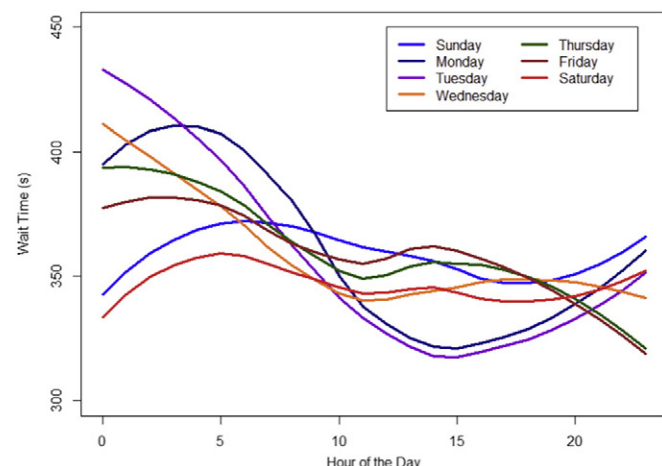


Fig. 2. LOESS curves for wait times, by hour of day and day of week.

times are statistically significant and directionally consistent throughout the day.

Higher population density is associated with significantly shorter waiting times throughout the day, after adjusting for differences in employment density, average income, and the fraction of minorities in a CBG. This effect is strongest between midnight and 2:00 AM, when an increase in population density of 1000 per square mile is associated with a 1.8% reduction in waiting time. It is weakest around 9:00 AM, when an increase in population density of 1000 per square mile is associated with just a 0.4% decrease in expected waiting time.

Higher employment density is also associated with shorter waiting times, after adjusting for the other covariates. This effect is strongest around 11:00 AM, when an increase of 1000 jobs per square mile is associated with a 0.3% decrease in expected waiting time. It is weakest around 5:00–7:00 PM, when it is not significantly different from zero at the 95% confidence level.

The relationship between the fraction of minorities in a CBG and expected waiting times varies between positive and negative throughout the day. After adjusting for differences in density and income, a CBG with 10% (i.e. 10 percentage points) more minorities can expect waiting times for an UberX to be approximately 2.5% longer at midnight, but 3.6% shorter at 9:00 AM, compared with a similar CBG with fewer minorities. For much of the day, the association between the fraction of minorities and waiting time is not statistically significant, and averaged over all 24 h, it is essentially zero.

Finally, the association between the average income of a CBG and expected waiting time is positive and significant throughout the day. The coefficient estimates do not show an obvious temporal pattern, and indicate that an increase in average income of \$10,000 in a CBG is associated with a 2.3% increase in the expected waiting time for an UberX vehicle, averaged over the course of the day.

4.4. Geographically weighted regression

The results of the geographically weighted regression are summarized in Fig. 5. In general, the results are consistent with the results of the spatial error model reported above, although Fig. 5 highlights that the magnitudes and, in some cases, the signs of the effects vary throughout the region.

Apart from a few isolated pockets, the relationship between income and waiting time is positive in most parts of the Seattle region, and the magnitude of the positive coefficients is generally larger than the magnitude of the negative coefficients. This is evident from the prevalence of purple-colored CBGs in Fig. 5(d), and suggests that after adjusting for the effects of density and minority fraction, waiting times for an UberX were generally longer in CBGs with higher average income levels. The relationship between income and waiting times is particularly strong (the darkest purple) in the Capitol Hill neighborhood east of downtown, and on the isolated and well-to-do Mercer Island in Lake Washington.

The relationship between minority fraction and waiting times is more variable. Much of the Seattle region shows negative relationships between minority fraction and waiting time, as indicated by the prevalence of gold-colored CBGs in Fig. 5(c). In addition, the magnitudes of negative relationships are generally larger than those of positive relationships. Nevertheless, a higher percentage of minorities is associated with longer waiting times in a few CBGs: the Capitol Hill neighborhood east of downtown; in a band running east-west across the city of Seattle, to the north of downtown and Lake Union; and in a number of CBGs to the south of Lake Washington. With the exception of the latter, most of these are areas with a lower-than-average percentages of minorities, compared with the region as a whole (Fig. 1(c)).

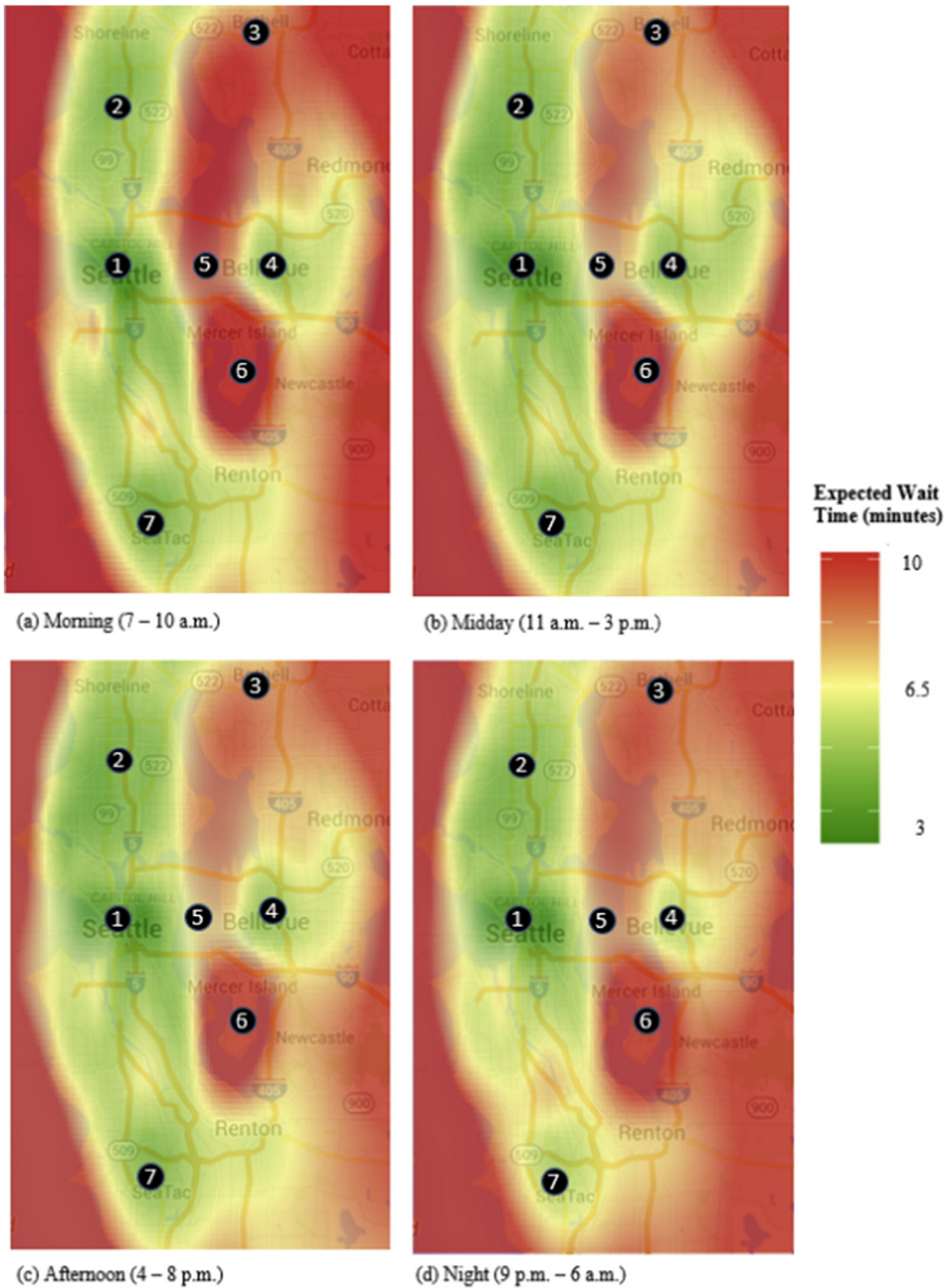


Fig. 3. Heat maps of predicted wait times across the region for (a) peak morning traffic hours, (b) midday hours, (c) peak afternoon traffic hours, and (d) nighttime and early morning hours. Key locations include (1) Downtown Seattle (2) North Seattle (3) Bothell (4) Bellevue (5) Lake Washington (6) Mercer Island and (7) Seattle-Tacoma International Airport. [Background maps: Google].

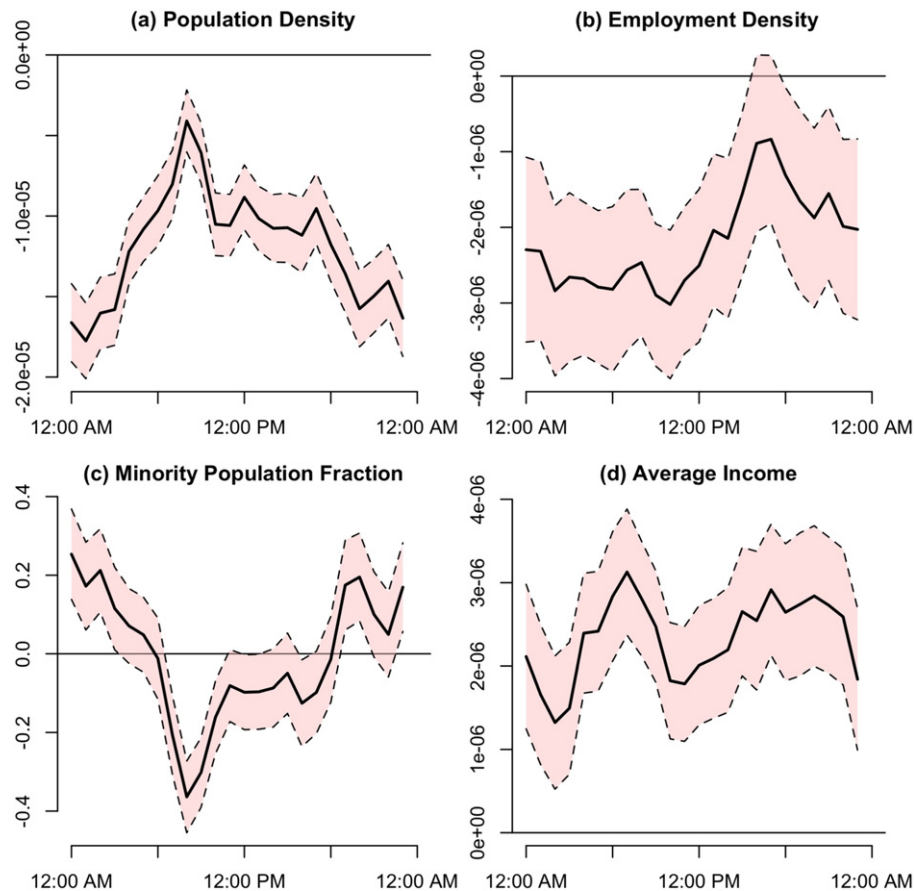


Fig. 4. Summary plots showing the coefficient estimates and 95% confidence limits for (a) population density, (b) employment density, (c) minority population fraction, and (d) average income, across the 24 models representing each hour of the day.

5. Conclusions

Using a large data set of estimated wait times for the nearest UberX vehicle across the Greater Seattle region, this study has revealed interesting and important patterns in the performance of a transportation network company. We have used non-parametric regression, spatial error models, and geographically weighted regression to observe patterns in the data as to characterize the relationships between wait time and several key socioeconomic indicators at the census block group (CBG) level. Statistically significant relationships were identified even when accounting for the spatial autocorrelation in model residuals.

Heat maps generated from locally weighted regression (LOESS) show concentrated areas of high and low expected wait times throughout the region. As expected, the Downtown Seattle core showed the densest concentration of low wait times. However, Downtown Bellevue, a large portion of North Seattle, and several pockets in South Seattle also showed lower wait times. These areas vary significantly in population density and average income, and the similarity in expected wait times is striking.

The regressions of waiting times on CBG characteristics yielded both some expected and some surprising results. The finding that higher population density and higher employment density are associated with shorter waiting times is to be expected, since greater density presumably means more frequent trip requests, which would attract more drivers to the area and reduce waiting times. Less intuitively, our results suggest that the effect of population density is weakest shortly after the morning rush hour, and that of employment density is weakest around the evening rush hour. A possible explanation for this is that the pool of available drivers in

high-density residential areas has been depleted following the morning rush, while it is depleted in high-density employment centers following the afternoon rush.

Perhaps the most interesting of our findings are the relationships between expected waiting time and the average income and fraction of minorities in a CBG. These results suggest that although lower income communities still face barriers to accessing TNCs (e.g. the need to have a smartphone and credit card), areas with lower average income nevertheless experience better service, as measured by expected waiting time for an UberX vehicle. This was the case even after adjusting for the effects of population and employment density. Moreover, although CBGs with more minorities can expect longer wait times at some times of day and shorter waits at others, on average there is essentially zero relationship between the waiting time for an UberX and the percentage of minorities in a CBG, after controlling for density and income.

The results of this analysis of wait times in the Seattle region suggest that transportation network companies offer higher performance in dense urban areas, and that adequate access to TNC services is not necessarily restricted to areas that are “white and wealthy.”

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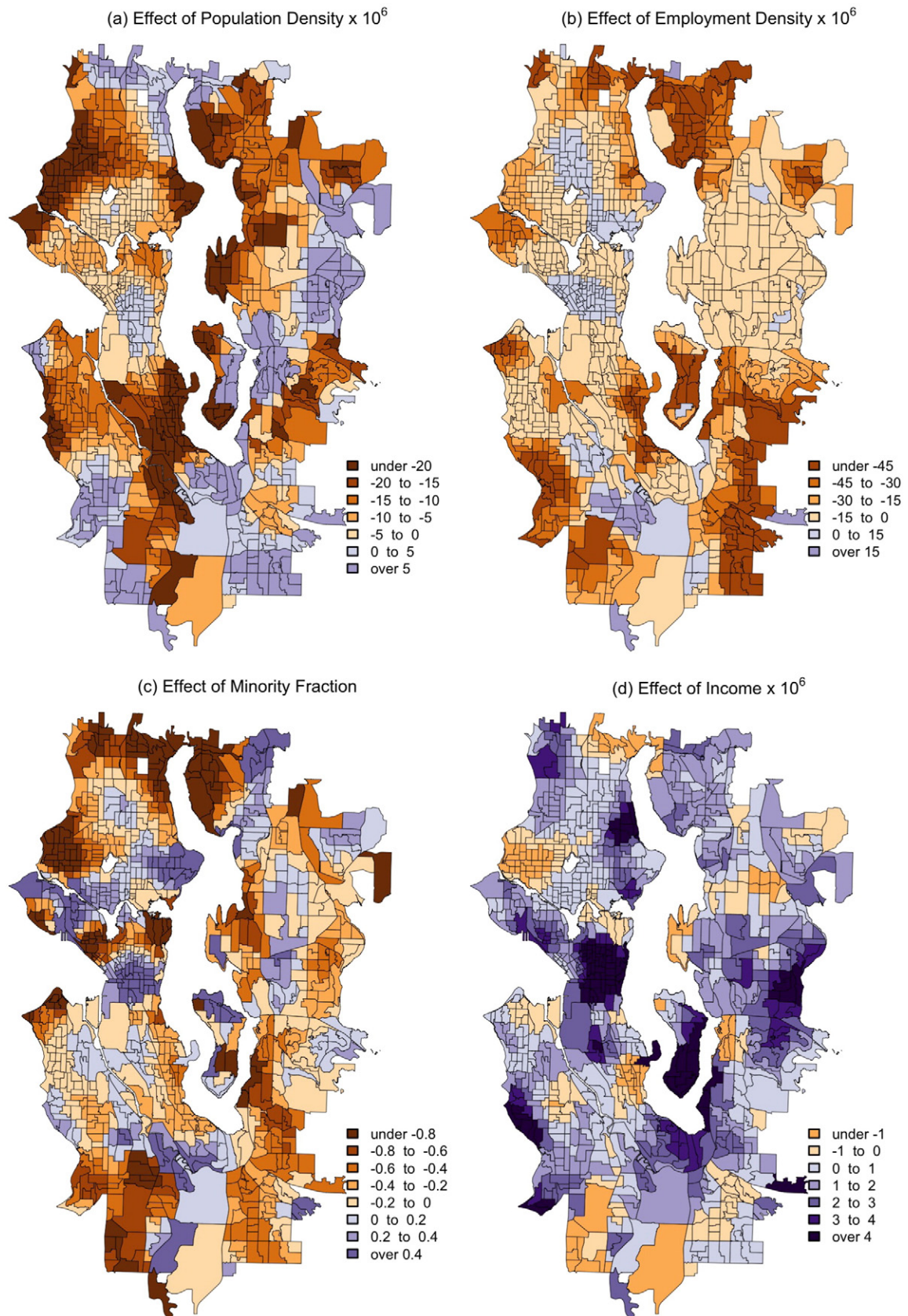


Fig. 5. Coefficients from geographically weighted regression, indicating local correlations between predictor variables and expected (log) waiting time. Purple indicates a positive association between (conditional) expected waiting time and the socioeconomic variable; gold indicates a negative association. The intensity of the color indicates the relative strength of the association. The effects of income and density have been multiplied by 10^6 .

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