Research in Transportation Economics 103 (2024) 101382

Contents lists available at ScienceDirect

Research in Transportation Economics

journal homepage: www.elsevier.com/locate/retrec

Research paper

Ecommerce and environmental justice in metro Seattle

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ARTICLE INFO

JEL classification:
JEL
R490

Keywords:
Urban freight
Last-mile delivery
Equity
Environmental justice
Air pollution

ABSTRACT

Urban distribution centers (UDCs) are opening at unprecedented rates to meet rising home delivery demand. The trend has raised concerns over the equity and environmental justice implications of ecommerce's negative externalities. However, little research exists connecting UDC location to the concentration of urban freight-derived air pollution among marginalized populations. Using spatial data of Amazon UDCs in metropolitan Seattle, this study quantifies the socio-spatial distribution of home delivery-related commercial vehicle kilometers traveled (VKT), corresponding air pollution, and explanatory factors. Results reveal that racial and income factors are relevant to criteria air pollutant exposure caused by home deliveries, due to tracts with majority people of color being closer in proximity to UDCs and highways. Tracts with majority people of color face the highest median concentration of delivery vehicle activity and emissions despite ordering less packages than white populations. While both cargo van and heavy-duty truck emissions disproportionately affect people of color, the socio-spatial distribution of truck emissions shows higher sensitivity to fluctuations in utilization. Prioritizing environmental mitigation of freight activity further up the urban distribution chain in proximity to UDCs, therefore, would have an outsized impact in minimizing disparities in ecommerce's negative externalities.

1. Introduction

A visible consequence of the decades-long surge in home delivery demand has been the proliferation of urban distribution centers (UDCs). In 2018, warehouses and distribution centers surpassed office spaces as the dominant commercial and industrial land use in both number of buildings (1 million) and floorspace (roughly 1.7 billion square meters), following a nearly 100% growth trajectory since 2003 (U.S. Energy Information Administration, 2021). In 2020, real estate developers forecasted an additional 9.3 million square meters of warehousing space needed to meet home delivery demand by 2025 (Thomas, 2020).

For people living, working, and going to school near these facilities, there is concern about exposure to freight vehicle-related air pollution, noise, traffic, and collisions. Mounting pressure from environmental advocacy groups have pushed municipalities to adopt moratoriums on new warehousing developments (Victoria, 2022) and several major metropolitan and state authorities have introduced new regulations for mitigating UDC-derived emissions. In 2021, the South Coast Air Quality Management District, a state-led regulatory board managing air pollution in Los Angeles and surrounding counties, adopted the Warehouse Indirect Source Rule (ISR), which requires warehouse operators report truck traffic impacts and establishes a point-or-fee based system for large warehousing facilities to offset freight-generated emissions (South Coast, 2021). New York state has introduced similar legislation (NY State Assembly Bill A9799, 2022).

Despite growing political demands for an accounting of ecommerce's negative externalities, there is limited evidence to suggest how UDC-derived traffic distributes throughout the urban freight network. From an environmental justice (EJ) perspective, it is important to analyze the interplay between urban logistics land use and freight flows, given that marginalized (i.e., people of color and lower income) populations disproportionately live near UDCs (Waddell et al., 2021) and highway corridors that respectively generate and channel freight trips (Bullard et al., 2004; G. M. Rowangould, 2013). Therefore, this paper analyzes the socio-spatial distribution of pollutant emissions from delivery trips between UDCs and home consumers in Washington state's Seattle Metropolitan Statistical Area (MSA) and explanatory factors. This paper subsequently addresses two interrelated hypothesis.

- H1: Marginalized populations disproportionately reside near UDCs and associated activity.
- H2: Proximity to UDC activity influences unequal exposure to e-commerce related air pollution.

The theoretical background (Section 2) discusses how despite a

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https://doi.org/10.1016/j.retrec.2023.101382
Received 17 August 2022; Received in revised form 9 October 2023; Accepted 16 November 2023
Available online 2 December 2023

Acronyms and abbreviations

UDC	Urban distribution center
EJ	Environmental justice
MSA	Metropolitan Statistical Area
LMDS	Last-mile delivery station
SC	Sortation center
VKT	Vehicle kilometers traveled
TSP	Traveling salesperson problem
POC	Populations of color
highW	High income, white majority
highNW	High income, non-white majority
midW	Mid income, white majority
midNW	Mid income, non-white majority
lowW	Low income, white majority
lowNW	Low income non-white majority

growing body of research supporting H1 (although in different geographic contexts than Seattle and for different distribution chains than home delivery), research linking UDC localization, urban freight systems, and EJ is limited. The methodology (Section 3) uses a binary logit model to assign delivery trips across three distribution segments: line-haul for trucks, cargo vans, and an approximated traveling salesperson distance (cargo van only). In the results (Section 4), the study uses summary statistics, OLS regression, and nonparametric, one-way ANOVA to test the hypotheses. This study also tests operational sensitives between van- and truck-based emissions with implications for how improving vehicle load utilization could impact equity outcomes. Finally, the discussion (Section 5) explores land use and transportation policy priorities that could equitably mitigate home delivery-based vehicle kilometers traveled (VKT) and air pollution. The conclusion identifies research gaps and future directions (Section 6).

2. Theoretical background

2.1. Forming H1: warehouse geography and environmental justice

Research on logistics land use has conventionally focused on the spatial reordering of warehousing within metropolitan areas since the late 20th century. To limit supply chain uncertainties and leverage economies of scale, distribution centers expanded floorspace (Andreoli et al., 2010) and migrated from the urban core to the cheaper, better networked land in the suburban periphery (Bowen, 2008; McKinnon, 2009). Conversely, more recent work suggests demand for faster home deliveries pushed logistics providers to locate some ecommerce-related UDCs closer to urban consumers (Fried and Goodchild, 2023). Large bodies of research explore the geographic and economic nuances of warehouse localization (Aljohani & Thompson, 2016; Giuliano & Kang, 2018; Kang, 2020), including discussions on how local land use characteristics and regulations influence siting decisions (Cidell, 2011; Dablanc et al., 2014). However, discussions around warehouse geography rarely refer to EJ literature, which studies the disproportionate siting of environmentally hazardous land uses and its distinct socio-political history in the U.S.

U.S. cities in the early 20th century adopted comprehensive zoning ordinances to curb the looming shadows of ever-growing skyscrapers and increasingly noxious land uses (Shertzer et al., 2022). Zoning policies had (and continue to have) a major impact on the development of today's cities. Racial discrimination was often inherent in these early zoning policies. Policymakers, lenders and developers introduced mechanisms to protect homeowner property values from "black and ethnic encroachment," such as racial covenants and later "red-lining" (Aaronson et al., 2021; Sood et al., 2019). Zoning measures also had the effect of shielding white homeowners from environmentally hazardous land use siting (Shertzer et al., 2016; Taylor, 2014), which disproportionately localized industrial facilities near marginalized populations, improved firms' access to low-skilled labor markets, and offered "path of least resistance" development opportunities, i.e., opening facilities in politically marginalized communities where organizational opposition and social capital is institutionally dampened (Bullard & Wright, 1987; Cole & Foster, 2001).

EJ literature refers to this hypothesis as "disparate siting," where depressed land values draw in industrial firms, creating a concentration of environmentally hazardous land uses in proximity to marginalized populations (Maantay, 2001; Wilson et al., 2008). The counter hypothesis is "post-siting demographic shift," which suggests land values drop after industrial placement attracts low-income movers (Been & Gupta, 1997). In other words, did neighborhood marginalization precede industrial siting, or *vice-versa*?

Environmental and transport justice literature has not been without its empirical criticisms when testing these or similar hypotheses (Noonan, 2008), as biases emerge in the selection of spatial units (Baden et al., 2007), population segmentation (D. Rowangould et al., 2016), and equity indicators (Bills & Walker, 2017). However, when accounting for distance-based proximity, longitudinal studies seemingly provide robust evidence for the disparate siting hypothesis (Mohai & Saha, 2007, 2015; Pastor et al., 2001).

The findings implicate a long history of institutional decision making that placed polluting land uses in proximity to pre-established, marginalized populations or communities that were already demographically transitioning. While racially discriminatory practices are illegal today, path dependency entrenched many of these development patterns into the modern day. Twinam (2018) explores zoning impacts on contemporary land use in Seattle since the implementation of the city's first zoning ordinances in 1923–2015 and finds strong evidence for institutional hysteresis.

In that vein, Yuan (2018a, 2018b) observed disparate warehouse siting patterns in greater Los Angeles. The two studies found general warehouse localization and tracts with majority people of color (POC) significantly correlated. Additionally, the longitudinal effect was one-way, i.e., warehouses moved into neighborhoods with greater POC concentrations, not the other way around, confirming the disparate siting hypothesis. The author also observes new warehousing development undergoes limited or *ad hoc* environmental scrutiny by permitting municipalities, often economically opportunistic suburbs, due to the indirect nature of their environmental impact compared to more visibly noxious land uses (Yuan, 2019).

The author's conclusions provide an impetus for quantitatively analyzing the distributive impacts of ecommerce UDC localization. *Therefore, this study's first hypothesis (H1) posits that the closer in proximity one lives to systems further up the delivery chain the more likely they would belong to a marginalized population.*

2.2. Forming H2: urban freight and air pollution

However, confirming disparate UDC siting alone may not be enough to understand the socio-spatial dynamics of urban freight's negative externalities. Urban freight's "nuisances" are widely discussed (Browne et al., 2012), including evidence of its disparate impacts (Karner et al., 2009; Schneller et al., 2022; Schweitzer & Valenzuela, 2004). Logistics land uses, including UDCs, represent important nodes for freight trip generation (Holguín-Veras et al., 2021), serving as a vector for freight traffic-related externalities. For instance, Schweitzer (2006) analyzes hazmat transport spill data in metro Los Angeles and finds proximity to intermodal and transhipment depots increases incidence likelihood, which also clusters predominately in Hispanic neighborhoods. Moreover, considering diesel exhaust from commercial vehicles constitutes a major fraction of urban mobility-source air pollution (Kozawa et al., 2009; Minet et al., 2020), UDC localization would have important implications for traffic pollutant-related respiratory and heart disease morbidity and social costs (Boogaard et al., 2022).

Research on the pollution effects of urban freight has been widespread, though not without its limitations. Diesel exhaust as a result of freight movement is a primary factor in regional air quality (Steiner et al., 2016), contributing significantly to both to the population exposure to health-adverse Nitrogen Oxides (NOx) in the atmosphere, black carbon, and fine particulate matter (PM 2.5 mm and 10 mm). In the U.S., freight movements are responsible for half of NOx emissions from mobile sources and 27% of total NOx emissions, despite constituting roughly 10% of total surface VKT (FHWA, 2020). NOx and PM 2.5 particles are among the pollutants the World Health Organization (WHO) have linked to growing rates of respiratory disease, heart disease, and stroke. WHO estimates that 7 million deaths occur prematurely each year as a result of air pollution (WHO, 2021), and is projected to cost 1% of global GDP in medical bills, sick days, and reduced agricultural output by 2060 (OECD, 2016). Urban freight in particular is a cause for concern due to the emission rates of the top-selling vehicles used for home deliveries (AIR Index, 2019) and routes that circulate through communities and residential areas in the last-mile (Aljohani & Thompson, 2020).

Given the frequent use of highways by heavy duty vehicles, some studies have estimated traffic emissions along travel corridors (Minet et al., 2020). Others evaluate urban form, looking at distance traveled by freight vehicles as a function of proximity to urban centers or service-area distance (Allen et al., 2012; Wygonik & Goodchild, 2018). Jaller and Pahwa (2020) use an econometric approach to evaluate emission trade-offs between in-person and online shopping behaviors, concluding emissions are more sensitive to delivery's operational characteristics than consumer substitution of one shopping behavior over another.

Researchers have also studied transportation-related air pollution and how it relates to equity from the standpoint of general vehicle emissions and by vehicle category (The Union of Concerned Scientists, 2019). Racial and income disparities in NOx exposure due to diesel emissions from freight trips are significant, based on satellite measures of pollution (Demetillo et al., 2021). Building emissions inventories has also allowed for estimating the total amount of freight-derived NOx or PM 2.5, and identifies that Black and Hispanic communities experience disproportionate levels of these pollutants as a result (Lathwal et al., 2022). Diesel engine emission controls could reduce some of these disparities given the higher proportion of freight trips that pass through marginalized communities (Patterson & Harley, 2021).

However, these studies do not account for the location of warehouses from which these freight trips originate and how they might contribute to freight activity within and between neighborhoods. Research has focused on the impacts and distributions of diesel emissions across communities, but with a lesser emphasis on a) home delivery and ecommerce's specific contribution to emissions and b) how disparate warehouse siting may contribute to these inequities. Moreover, the impacts of upstream, "middle-mile" delivery flows near and between logistics facilities is under-researched compared to consumer-side, last-mile delivery (Tejada & Conway, 2022). *By way of proximity to logistics facilities and infrastructure, this study additionally tests whether marginalized populations are more subject to ecommerce-derived emissions (H2) than not marginalized populations.*

3. Methodology

To test these hypotheses, this study creates a survey-based delivery assignment model using binary logit regression and network analysis. Results are then analyzed to explore the relationships between freight activity, UDC proximity, network geometries, demand, income, and race. Additionally, the study quantifies and tests significance for how emissions distribute across income-race groupings using nonparametric, one-way ANOVA tests. Finally, the study tests the sensitivity of load factor assumptions, with implications for how fluctuating fleet quantities of cargo vans and trucks affect equity outcomes. Fig. 1 overviews the operational scope of the paper, which analyzes three delivery segments within Seattle MSA: truck-based line-haul between UDCs, van-based line-haul between UDCs and neighborhood centers (Census tracts), and van-based, intra-neighborhood traveling salesperson (TSP) circulation. Table 1 overviews the data and methodological approaches and assumptions described in this section.

3.1. Data sources and case study description

This study presents a case study exploring Amazon's logistical land use and operational configuration in metro Seattle. MWPVL International, a logistics consulting firm, provided proprietary data on Amazon UDCs (2021). MWPVL International collects monthly data on over 1199 active Amazon facilities in the U.S. (as of February 2022) since the construction of the first UDC in 1997. The dataset collects information on UDC location and some financial and operational characteristics, including estimates of average daily packages shipped. Although not the only ecommerce player, Amazon's position as the largest online retailer in Western markets presents a microcosm of logistical strategies that have transformed the last-mile delivery space (PYMNTS, 2022). Amazon's logistical land use and operations are representative of the whole U.S. ecommerce ecosystem.

This study evaluates currently operational UDCs in the U.S. Census Bureau-defined Seattle MSA, which comprises three counties (King, Peirce, and Snohomish) and several of the state's largest cities (e.g., Seattle, Tacoma, Bellevue, and Everett). Seattle MSA's population is roughly 3.8 million people, with roughly a fifth of the population living in Seattle.

Since this study is concerned with the UDC-to-consumer component of the ecommerce supply chain, the methodology selects UDCs that specifically serve a last-mile distribution function. These include *last-mile delivery stations (LMDS)*: medium-sized facilities that serve inbound trucks and outbound cargo vans adapted for dense urban street networks. LMDS have separate facilities for smaller parcels and heavier bulk items (e.g., furniture and large appliances); however, this study analyzes only small parcel facilities.

Further up the logistics chain are *sortation centers (SC)*: large-sized, cross-docking facilities that serve in-bound trucks on one side and outbound on the other, that usually sort parcels bound for LMDS. Therefore, this study analyzes the VKT and pollutant emissions of inbound and outbound flows for LMDS, assuming all LMDS receive their parcels from the regional SC. In the Seattle MSA, there are 10 LMDS constituting over 298,000 square meters in ground floorspace and shipping approximately 378,400 daily parcels. In three instances, two LMDS located near each other, i.e., shared a Census tract. Amazon occasionally co-locates multiple LMDS to manage spillover and peak holiday demands while still servicing the same delivery area. This study merges co-located facilities into a singular origin point with a combined package output. As a result, this study analyzes seven LMDS origin points (see Fig. 2 and Table 2). Meanwhile, there is one roughly 30,000 square meter SC, which this study assumes distributes the sum of daily parcels shipped by LMDS throughout the entire Seattle MSA.

Socio-demographic information at the Census-tract level was gathered from the U.S. Census Bureau 5-year American Community Survey (ACS) for 2019 (US Census Bureau, 2020). This study is concerned with environmental justice implications across income and race. Seattle MSA's mean household income is $90,074 (standard deviation = $37,185). Approximately, 70% of individuals in the Seattle MSA identified as white. While future studies can provide needed nuance to racial and ethnic classifications, for now this study defines "people of color" (POC) as non-white and non-Hispanic, as designated by the Census. To understand differences in the probabilities of receiving a package across different incomes and races, this study conducts a binary logit regression model using a household travel survey and synthesized population

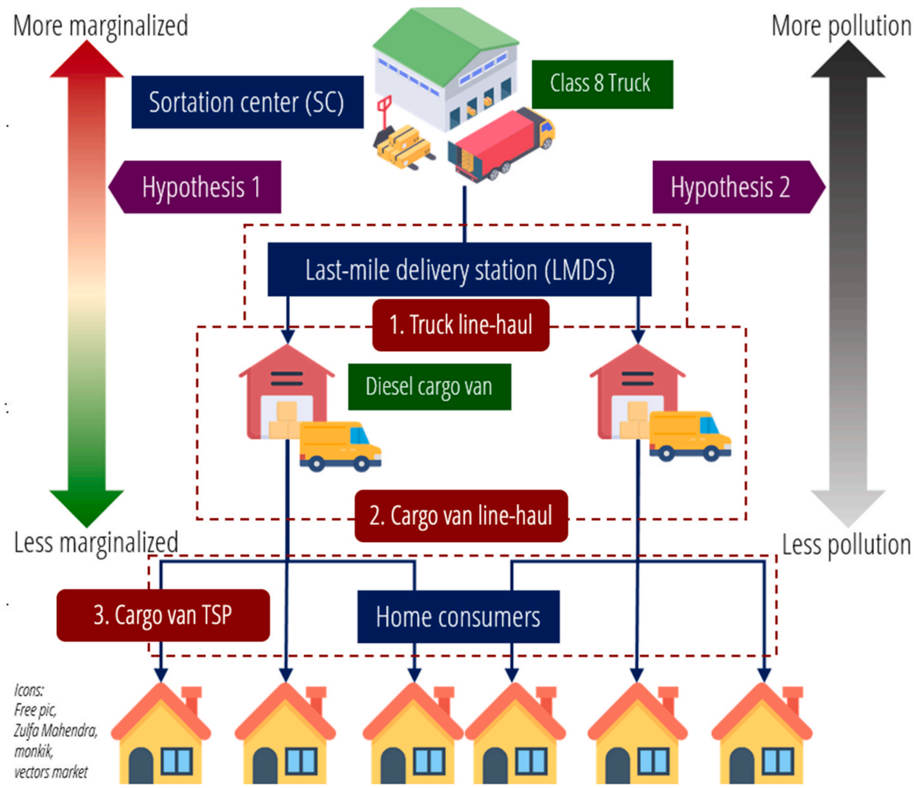

Fig. 1. Ecommerce last-mile supply chain, including hypothetical assumptions.

Table 1
Overview of delivery phases, data inputs, and method descriptions for hypothesis testing.

Delivery phase	Data inputs	Method desc. and assumptions	H1 testing	H2 testing
1. Truck line-haul	- MWPVL Amazon UDCs - OSM road network	Assign truck trips from SC to LMDS via network. Assumes fixed truck load factors.	- Summary statistics - OLS regression	- Kruskal–Wallis one-way ANOVA - Sensitivity analysis of truck and van load utilization
2. Cargo van line-haul	- MWPVL Amazon UDCs - OSM road network - PSRC travel survey data (2019) - U.S. Census Bureau 5-year ACS survey data (2019) (census tract)	Assign van trips from UDCs to closest tract centroid, using population- and logit-based weights. Assumes fixed package volumes and van load factors.		
3. Cargo van TSP	- U.S. Census Bureau 5-year ACS survey data (2019) (census tract) - Washington land use data	Estimate intra-neighborhood (tract) VKT using approximated TSP equation. Assumes fixed order volumes and van load factors.		
Emission calculations	- EPA MOVES	Convert outputted VKT to NOx and PM2.5 inventories for vans and trucks		

generated by the Puget Sound Regional Council (PSRC), the region's metropolitan planning organization. PSRC conducted the survey between April and July in 2017 and again in 2019.

3.2. Binary logit-based delivery assignment

The study utilizes PSRC survey data to construct a delivery assignment model that estimates probable demand for packages given tract-level demographic and geographic variables. PSRC's survey asks respondents the number of online-ordered packages received on a given weekday. Filtering the appropriate counties and missing responses, the survey found 1929 of 2532 respondents, roughly 76%, did not receive a package, with the remainder (603 respondents) receiving one or more. To build the initial model, this study controls for seven demographic variables (income, race, education level, household size, age, renter status, and children status), one transportation-related variable (number of daily trips), and one geographic dummy variable (did the respondent live in Seattle or a surrounding municipality) (see Table 3).

The selected variables are based on several past studies. Figliozzi and Unnikrishnan (2021) analyzed Portland, Oregon household travel survey data and found ecommerce subscriptions and delivery frequency across low-income, racial minority households as well as households with low education attainment, limited access to vehicles, smartphones, and internet subscriptions was lower. Spurlock et al. (2020) estimated shopping trip replacement with home delivery and found that high-income households with children are more likely to place orders online. Finally, Butrina (2018) used the same PSRC data (from 2015) and found income, household size and age (between 25 and 54 years-old) to be significant, positive predictors of receiving a package. In addition to applying the age groupings from Butrina (2018), this study creates three custom income groupings. PSRC categorizes respondent incomes into ten groupings at varying intervals ranging from "under $10,000" to "$250,000 or more." The model reclassifies income into *low* (<$50,000), *middle* (≥$50,000 and <$150,000) and *high* (≥$150,000), which most closely resembles one standard deviation below and above the mean household income in the Census data.

Table 4 presents the final, best-fitting model (Model 3) validated using a step-wise approach and interaction testing. Age, household size,

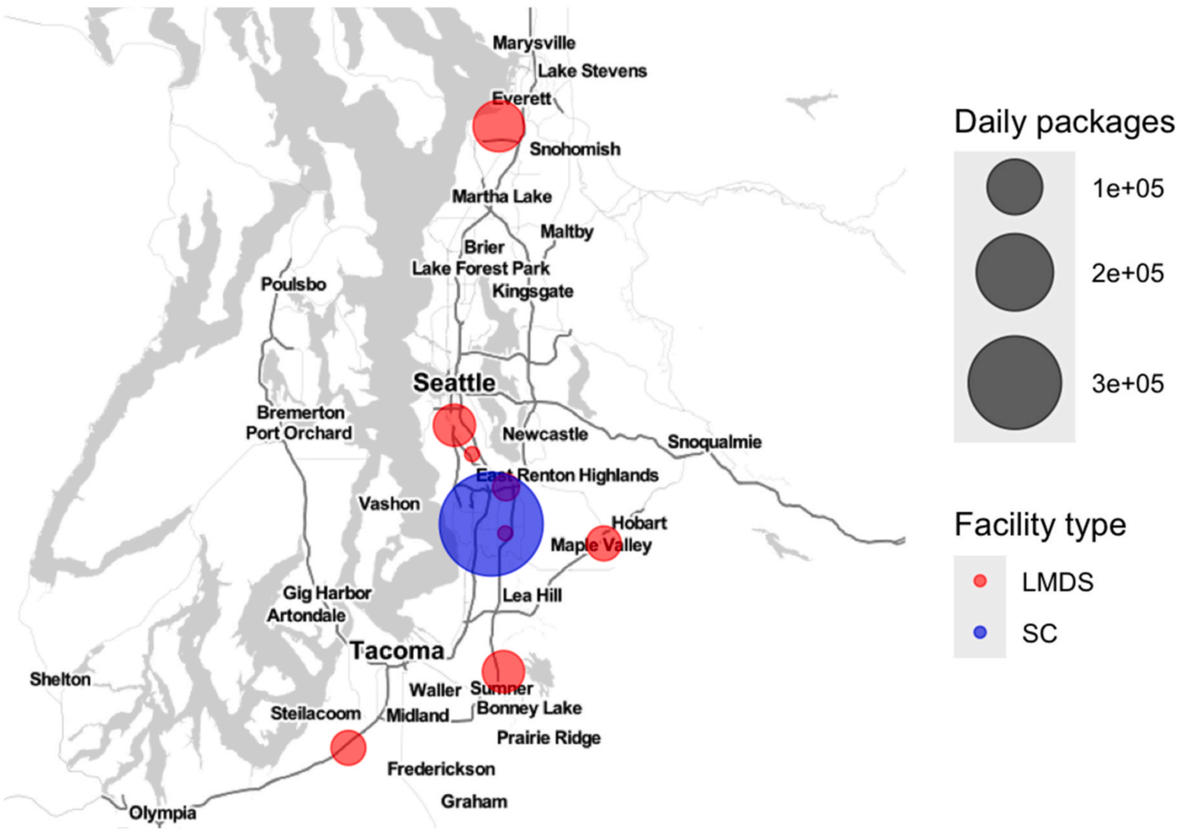

Fig. 2. Regional map of UDC facilities (map tiles by Stamen Design, data by OpenStreetMap).

Table 2
Characteristics of Seattle Metro UDCs (++ = co-located UDCs merged into one) (*Source:* MWPVL International).

UDC type	City	Ground floorspace (thou. sq. m)	Inbound daily packages (thou.)	Outbound daily packages (thou.)	Tot. daily packages (thou.)
LMDS	Tukwila	120.0	26.4	26.4	52.8
LMDS++	Seattle	526.2	59.4	59.4	118.8
LMDS	Renton	138.0	33.0	33.0	66.0
LMDS	Kent	692.0	26.4	26.4	52.8
LMDS++	Everett	510.2	85.8	85.8	171.6
LMDS	Maple Valley	150.0	44.0	44.0	88.0
LMDS++	Sumner	606.0	59.4	59.4	118.8
LMDS	Lakewood	470.0	44.0	44.0	88.0
SC	Kent	320.9	–	378.4	378.4

Table 3
Distribution of relevant demographic, transportation and geographic variables (N = 2532).

Variable	% Relative frequency (% non-response)	Variable	% Relative frequency (% non-response)
Age [25–54 years]	62.6 (0.0)	*Income*	(12.2)
Household with children	17 (0.0)	Low	25.4
Household size	(0.0)	Mid	45.2
1	38.3	High	17.3
2	41.5	Number of trips {mean}	{4.0}
3	10.7	*Education*	(0.0)
4	7.8	Graduate degree	35.5
5	1.1	Bachelor's degree or vocational training	47.3
6	0.4	Highschool or less	17.2
>7	<0.1	Renter	50.0 (2.9)
Race [white]	71.3 (0.0)	Lives in Seattle	56.6 (0.0)

race, income, and both transportation and geographic indicators prove positively significant. The authors omit the transportation variable due to lack of availability of this indicator at the tract-level. The inclusion of the interaction term between race and income shows high-level significance and a slight improvement of fit compared to the non-interaction model. The interaction effect is strong: identifying as mid-income white and high-income white influenced the likelihood of receiving a package 2.4 and 2.7-fold, respectively, compared to other groupings. That said, the final model only accounts for 5% of the variance in the binary data, suggesting a high degree of latency and standard error, which the inclusion of more variables can improve for future model iterations. For now, this study inputs the final model coefficients into the tract-based delivery assignment function, which includes terms for whether the tract's median age is between 25 and 54 years-old, median household size, whether the tract is located in Seattle's city limits, and the interaction of median income and the tract's majority race (white or non-white).

Package demand (v) in a tract (j) is a function of the output of the closest LMDS (i), tract population relative to the population of all tracts served by the same LMDS, and probability (*Equation 1)*. The closest LMDS is identified using the minimum Euclidean distance to the tract's centroid. *Equation 2* converts the logit coefficients to probabilities that an individual would receive a package on a given weekday.

Given the income-race interaction, this study creates six groupings that are analyzed for the remainder of the study: high income:non-white majority (*highNW*, n = 2), high:white (*highW*, n = 36), mid:non-white (*midNW*, n = 67), mid:white (*midW*, n = 538), low:non-white (*lowNW*,

Table 4
Binary logit model output (* = p < 0.1, ** = p < 0.05, *** = p < 0.01).

Daily package received (binary logit)	Model 1		Model 2 (w/o interaction)		Model 3 (w/interaction)	
	Coef.	*Std. e*	*Coef.*	*Std. e*	*Coef.*	*Std. e*
intercept	*−2.73****	*0.25*	*−2.58****	*0.20*	*−2.05****	*0.24*
age [25–54]	*0.28***	*0.12*	*0.25***	*0.11*	*0.27****	*0.11*
children [yes]	*−0.21*	*0.12*	-	-	-	-
hh size	*0.25****	*0.08*	*0.20****	*0.05*	*0.20****	*0.05*
race [white]	*0.27***	*0.12*	*0.31****	*0.12*	*−0.43**	*0.24*
income [mid]	*0.47****	*0.14*	*0.54****	*0.14*	*−0.19*	*0.25*
income [high]	*0.83****	*0.18*	*1.0****	*0.16*	*0.35*	*0.28*
num. trips	*0.05****	*0.02*	-	-	-	-
education [graduate degree]	*0.09*	*0.11*	-	-	-	-
education [HS or less]	*−0.06*	*0.16*	-	-	-	-
renter [yes]	*−0.12*	*0.11*	-	-	-	-
lives in Seattle [yes]	*0.21**	*0.11*	*0.22***	*0.11*	*0.20**	*0.11*
race [white]: income [mid]	-	-			*1.01****	*0.29*
race [white]: income [high]	-	-			*0.86****	*0.33*
	N	*2185*		*2224*		*2224*
	R^2 *Tjur*	*0.05*		*0.04*		*0.05*
	LL_0	*−1389.92*		*−1389.92*		*−1389.92*
	LL	*−1161.68*		*−1180.49*		*−1174*
	AIC	*2347.35*		*2374.97*		*2366.70*

n = 19), and low:white (*lowW,* n = 53).

Wealthier (to a larger extent) and whiter (to a lesser extent) tracts have higher predicted probabilities and, consequently, receive more packages (see Fig. 3). The predicted probability of receiving a package in a *highW* tract is 40%, which is approximately two-times higher than the probability in a *midNW, lowNW,* and *lowW* tract and 50% higher than *highNW* and *midW* tracts. The lowest probability tracts are *lowW* and *lowNW*. As a result, when inputting population and closest LMDS output, *highW* tracts receive the most packages on average, roughly 254% higher than *lowW* and 184% higher than *lowNW*.

Equation 1: Calculating package demand by tract j from closest LMDS

$$v_j = g_j * \frac{p_j * P(x)}{\sum_i p_j * P(x)}$$

Where:

v = package demand
p = population
g = fixed package output of the closest LMDS to tract j

Equation 2: General equation for converting binary logit coefficients (β) to probability of packages received, P(x), with interaction terms

$$P(x) = \frac{e^{\beta_0} + \beta_a * x_a * \beta_b * x_b + \beta_{a:b} * x_{a:b} \ldots \beta_n * x_n}{1 + e^{\beta_0} + \beta_a * x_a + \beta_b * x_b + \beta_{a:b} * x_{a:b} \ldots \beta_n * x_n}$$

3.3. Network analysis and TSP approximation

The next analysis phase calculates the delivery vehicles' VKT between origins and destinations (*line-haul*) and within destination tracts, using an approximated traveling salesperson problem (*TSP*) distance. To calculate line-haul distances, this analysis utilizes QGIS to conduct a network analysis using the free-to-use OpenStreetMap Route Service (ORS). The ORS tool finds the optimized path between origin and destinations using fastest travel-times. The underlying network uses OpenStreetMap data, an open spatial data platform. Total VKT is calculated in three segments, which constitute an approximated and optimal vehicle routing problem (Daganzo, 2005; Goodchild et al., 2018). First, is the two-way, line-haul distances between LMDS origins

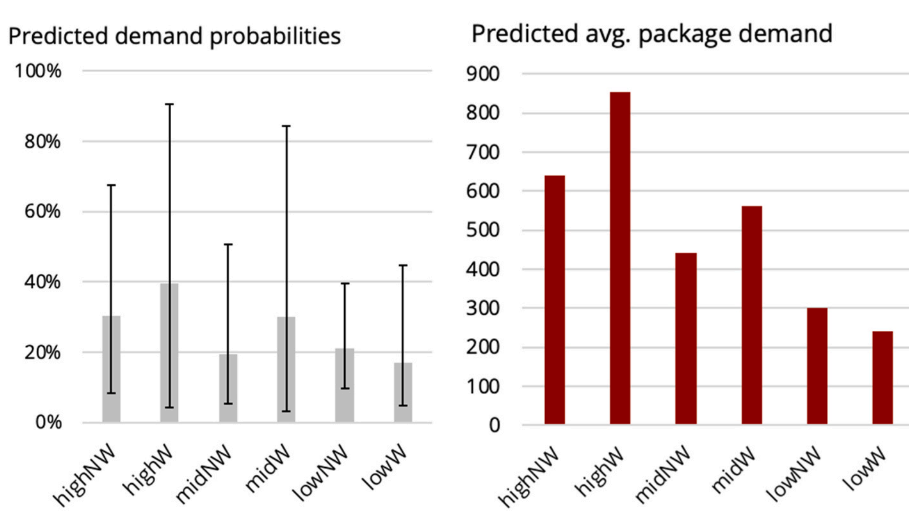

Fig. 3. Tract-level predicted probabilities (with 95% confidence interval) and average packages received (per weekday) by income-race group using Model 3 output and normalized by tract population.

and their closest tract centroid destinations, which are served by cargo vans. Second, is the two-way, line-haul distances between SC origins and their LMDS destinations, which are served by Class 8 trucks. The network analysis adds a constraint specific to heavy-duty vehicles, which are limited by what roads they can legally take. The length of the output line segments are summed by their containing tract along with the number of vehicles, which is the proportion of the total of throughput packages and the vehicle respective load factor (i.e., how many packages can fit in a vehicle) (see *Equation 3*).

This study assumes the standard use of a Class 2500 4-Cylinder Diesel Mercedes-Benz Sprinter Van. The cargo van payload capacity is estimated at 1900 kg and assuming an average 60% utilization gives 1140 kg of available payload (Vega, 2020). This study therefore estimates a cargo van capacity of 175 packages per cargo van delivery trip based on an average package weight of 6.5 kg, about 70% the maximum weight of a "Large standard-size" package (Amazon, n. d.). Using this estimate is consistent with key assumptions in the MWVPL dataset. For larger trucks with a payload capacity of 20,400 kg, this study assumes the same 6.5 kg package weight and 60% estimated utilization, giving an approximate 2000 packages per truck trip.

Equation 3: Calculating the line-haul VKT for cargo vans and trucks

$$Van\ line\ haul\ VKT_j = \sum_{i:(i,j)\in C} 2*c\left\lceil d_{(i,j)} / l_{van} \right\rceil, \forall j \in tracts$$

$$Truck\ line\ haul\ VKT_j = \sum_{i:(i,j)\in T} 2*t_{(i,j)}\left\lceil o_{(i,j)} / l_{truck} \right\rceil, \forall j \in tracts$$

Where.

$C_{(i,j)}$ = Set of cargo van connections from LMDS $i \in L$ *thru tract* $j \in T$.
$c_{(i,j)}$ = Route lengths (km) from LMDS $i \in L$ thru tract j.
$d_{(i,j)}$ = Demand of packages from LMDS i thru tract $j, (i,j) \in$ *tracts*.
l_{van} = Load factor, number of packages per cargo van (baseline = 175)
$T_{(i,j)}$ = Set of Class 8 truck connections from the SC to LMDS i thru tract j
$t_{(i,j)}$ = Route lengths (km) from the SC to LMDS i thru tract $j, (i,j) \in T$.
$o_{(i,j)}$ = Demand of outbound packages from the SC to LMDS i thru tract $j, (i,j) \in T$.
l_{truck} = Load factor, number of packages per truck (baseline = 2000)

The final analytical segment calculates an approximated TSP distance, or the VKT spent delivering packages within a tract. Daganzo (2005) presents an approximation of TSP assuming a square service area and, in this study's case, a Manhattan distance (see *Equation 4*). Given the size of Census tracts in the rural portions of the Seattle MSA, which is primarily undeveloped and National Forest land, the geometric tract area is subtracted by the area of non-urban and non-rural residential land use to remove areas where delivery vans cannot physically drive (data from Washington Geospatial Open Data Portal, 2022).

Equation 4: Approximated TSP calculation for cargo vans

$$\boldsymbol{Van\ TSP\ VKT_j} \cong \boldsymbol{k} * \sqrt{\boldsymbol{N_j} * \boldsymbol{A_j}}$$

Where:

N = Number of deliveries; v_j/packages per delivery (estimated as 1.44, according to MWPVL International).
A = Area of urban and rural residential land use
K = network constant; 0.92 for Manhattan distance.

3.4. Emission calculations

Emissions parameters are from the Bureau of Transportation Statistics (U.S. BTS, 2019), calculated using MOVES, the Environmental Protection Agency (EPA's) mobile source emissions modeling systems. MOVES provides estimates for total emissions across vehicle types in a particular area and time frame (Miller et al., 2003). The vehicles of choice for SC-to-LMDS and LMDS-to-tract segments are heavy duty tractor trailers (EPA Class HDV8) and heavy duty cargo vans (EPA Class HDV2b), respectively. Given that both Amazon's electric van and truck fleet have yet to see widespread implementation, this study assumes all trucks and cargo vans are diesel powered. This analysis selects two main criteria air pollutants, NOx and PM 2.5, with the following emissions coefficients in grams per kilometer: 2.846 NOx, 0.078 p.m. 2.5 for heavy duty tractor trailers, 1.309 NOx, 0.059 p.m. 2.5 for cargo vans. The final emission rates are calculated by multiplying the coefficients by the total cargo van TSP VKT, and the line-haul VKT for both cargo van and Class 8 trucks for inbound and outbound journeys.

4. Results

4.1. H1: do marginalized populations live closer to UDC activity?

To test the first hypothesis, this study examines observed UDC localization relative to income and race (see Fig. 4), using descriptive statistics and linear regression. Table 5 highlights the characteristics of tract centroids within three, Euclidean kilometers of at least one UDC (UDC+) versus those that are not (UDC-). The mean income for UDC+ is roughly 22% lower than UDC-, which is significant using a Welch's unequal variance *t*-test, rejecting the null hypothesis in favor of the alternative: there is a difference between the two means. Mean POC percentage is also significantly higher in UDC + over UDC-. The POC population in UDC+ is 8% higher than the Seattle MSA average. Results suggest there is a statistically significant difference in income and race between tracts that have a UDC than those that do not.

Moreover, delivery VKT exhibits a significant, moderately strong relationship with continuous distances from a UDC when controlling for tract area ($R^2 = 0.43$) (see Fig. 5). The closer a tract is to a UDC, the higher the delivery VKT passing through or terminating in that tract. Race and income also express non-linear correlations with UDC proximity and VKT. Both POC percentage and income have significant and moderate relationships with distance from UDCs, confirming higher POC percentages and lower incomes in more proximal tracts. POC percentage and income also correlate with delivery VKT density. However, the absolute correlation for POC percentage is over twice that of income, accounting for almost a third of the variance in VKT. In other words, race may have a stronger relational effect in terms of both UDC proximity and VKT exposure than socio-economic status alone.

The study further analyzes the relation between income, race, package demand, and the freight network's geometric properties (namely distance from UDC and highway density) by conducting an Ordinary Least Squares (OLS) linear regression analysis (see Table 6). Since the tracts' area largely determines the distance traveled between origin-destinations, the model tests the log-transformed total VKT density (per sq. km) and across all three delivery segments, i.e., van thru-traffic, TSP, and truck thru-traffic. Across all four models, POC concentration is significantly and positively correlated with VKT. However, income's negative relationship with VKT is only significant for trucks. Meanwhile, package demand is insignificant when accounting for total VKT. However, demand is significantly positive for all van-related VKT and negative for truck-related VKT. The finding suggests van traffic is likely to be higher in neighborhoods receiving more packages (understandably), but lower in neighborhoods experiencing higher truck traffic.

Finally, the geometric variables show significance across the aggregate VKT and all three delivery segments, except for UDC distance and TSP VKT (i.e., distance from UDC does not influence the distance traveled within a tract). Both higher highway densities are significantly and strongly associated with higher thru van and truck VKT. When controlling for demand and network geometry, the results suggest a strong link between VKT and race; whereas, income is only significant when accounting for trucks. In other words, results validate that race may

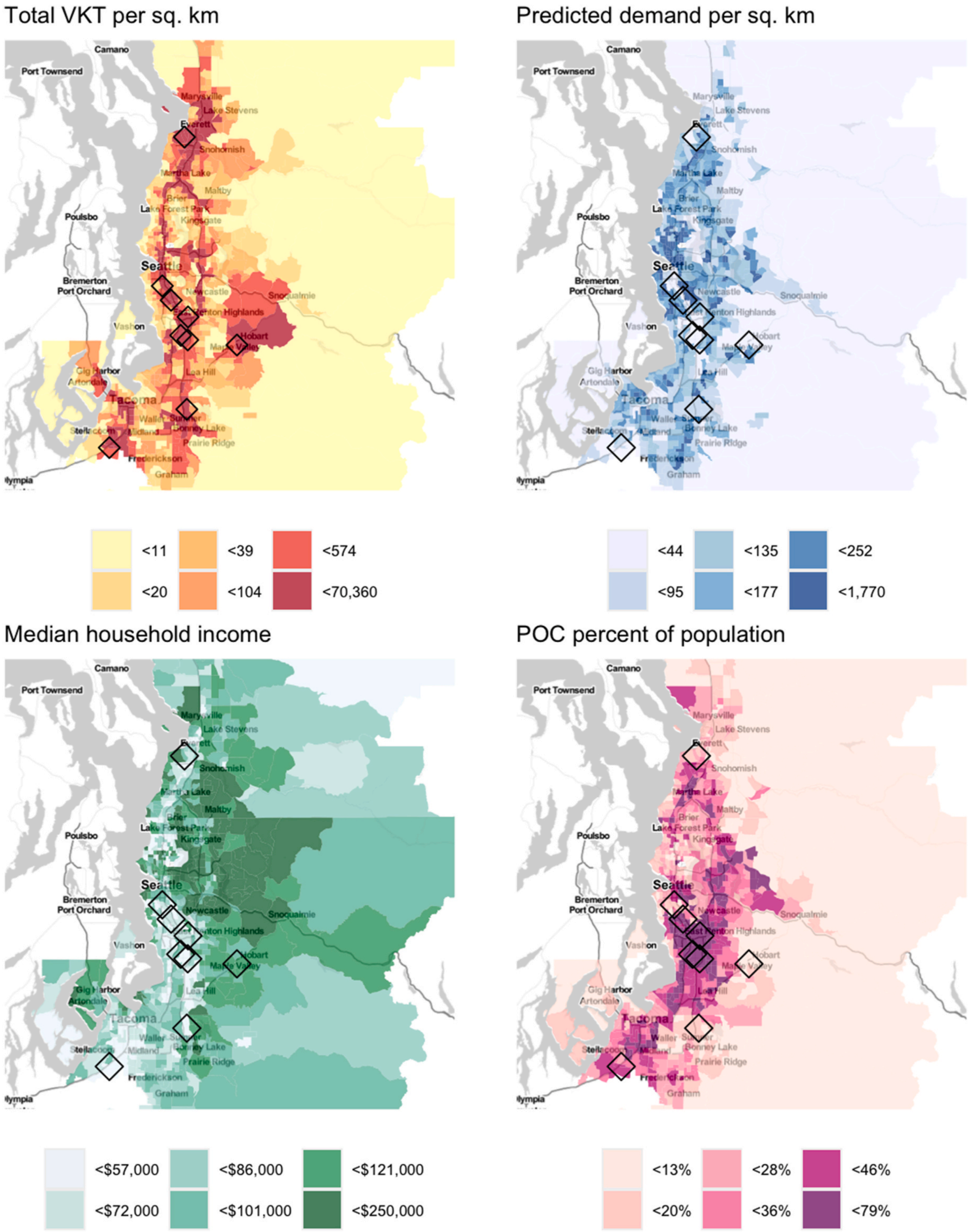

Fig. 4. Seattle MSA spatial visualizations: VKT density, demand density, median income, and POC percentage (diamonds = UDC locations).

have a stronger relational effect in terms of both UDC proximity and VKT exposure than income.

This observation is in-line with Yuan (2018a), who notes income's weaker overall effect as a predictor of warehouse location in comparison to majority-POC populations. Interestingly, there is also no significant correlation between delivery demand and total VKT, although package demand is positively correlated with income. This observation implies that warehouse proximity is a stronger determinant of delivery VKT in one's neighborhood rather than how many packages that neighborhood receives. This finding may appear obvious: the geometric nature of freight consolidation locally concentrates commercial vehicle activity near-regardless of *where* that demand is dispersing further afield. However, it does underline an inequity between what populations receive ecommerce's consumer benefit versus those who bear the cost. In accordance with H2, the differential distribution of the emission intensity across income-race groupings should, therefore, be detectable.

Table 5
Summary characteristics of a Census tract with at least one UDC (all types) compared to other Seattle metro tracts.

	N	Mean income (thou. $)	Mean % POC population	Mean total VKT (thou.) (sq. km)	Mean package demand	*Mean highway density (sq. km)*	*WELCH'S T-TEST (H0: +UDC income = -UDC income)*	*WELCH'S T-TEST, (H0: +UDC %POC = -UDC % POC)*
Tract w/ UDC (+)	*104*	*71.5*	*38.0*	*4.3*	*459.3*	*2.1*	*<0.001****	*<0.001****
Tract w/o UDC (−)	*609*	*91.3*	*29.0*	*1.4*	*540.8*	*0.9*		

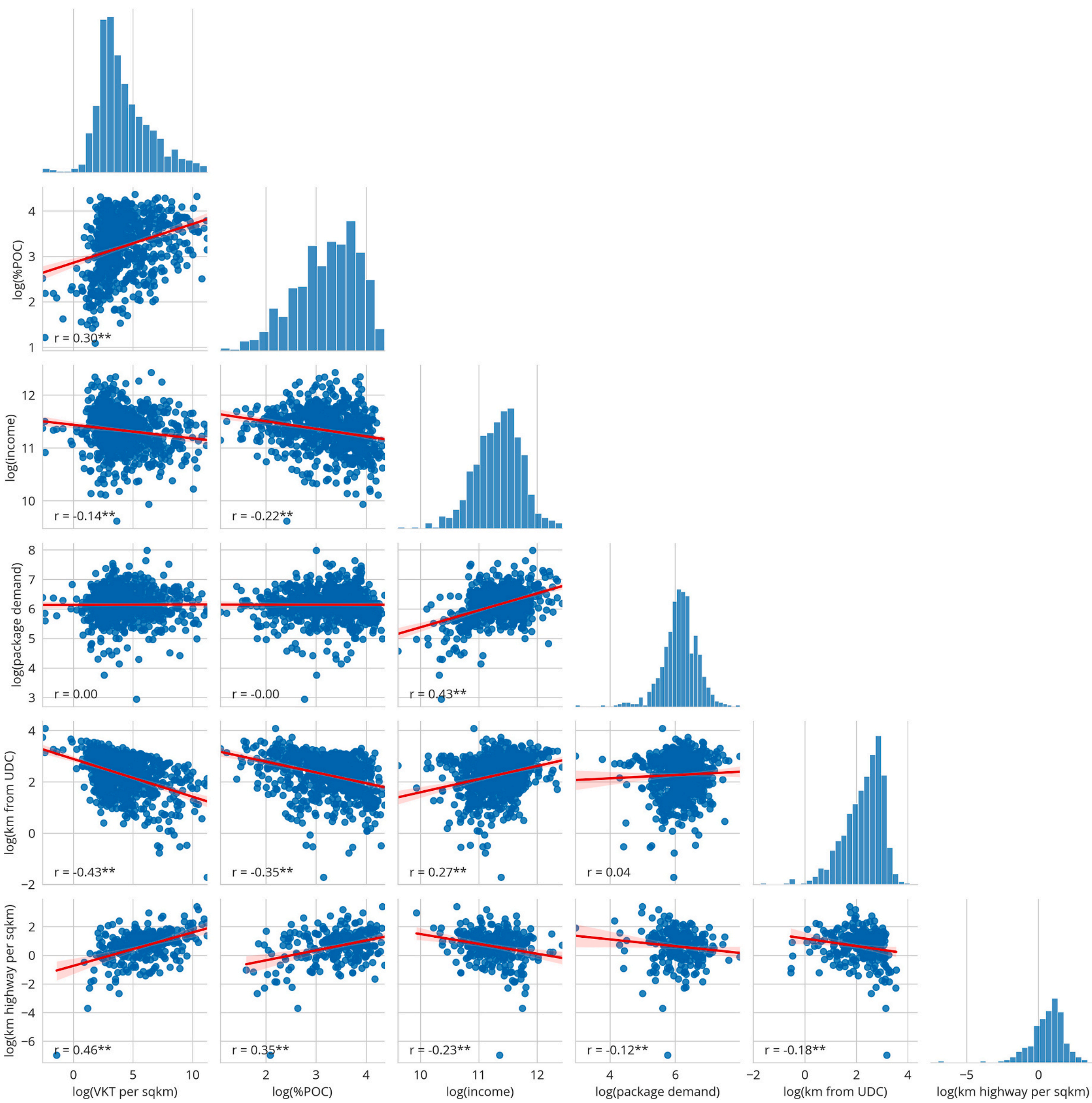

Fig. 5. *Pearson's correlation matrix between race, income, package demand and freight network geometry* (** = r significant at p < 0.05).

4.2. H2: does proximity to UDCs disproportionately influence air pollution exposure?

Most VKT derives from cargo vans, comprising roughly 98% of all kilometers traveled. The vast majority of van-based VKT is line-haul kilometers. Despite the emission coefficients for trucks being roughly 2.1-times higher for NOx and 1.3-times higher for PM 2.5, van-based emissions comprise 95% and 97% of the total, respectively.

Despite attracting the highest demand for packages, *highW* tracts exhibit the lowest levels of exposure to emission concentrations (see Fig. 6). On average, total NOx and PM 2.5 emissions for *highW* tracts (mean = 140.8 and 6.3 g/sqkm, respectively) is approximately 97% lower than *lowNW* tracts (mean = 4819.8 and 213.4 g/sqkm, respectively), the highest mean exposure tracts. Meanwhile, *midW* expresses the largest degree of variance from the mean. In fact, *midW* tracts constitute eight of the ten highest emission-concentrated tracts, with the remainder belonging to *lowNW*. Primarily, these tracts are located around highways that run through downtown Seattle where housing is more expensive. The tract (*midW*) with the highest emission concentration encompasses a predominately industrially-zoned district (with

Table 6
OLS Linear Regression output testing demand and geometric variables.

OLS Linear Regression	Log (Total VKT/sqkm)		Log (Cargo van (line-haul) VKT/sqkm)		Log (Cargo van (TSP) VKT/sqkm)		Log (Class 8 truck (line-haul) VKT/sqkm)	
	Coef.	*Std. e*	*Coef.*	*Std. e*	*Coef.*	*Std. e*	*Coef.*	*Std. e*
intercept	*3.75**	*1.98*	*2.83*	*2.39*	*−1.09*	*0.87*	*5.69****	*1.40*
Log(%POC)	*0.43****	*0.11*	*0.39****	*0.14*	*0.53****	*0.05*	*0.19***	*0.08*
Log(income)	*−0.01*	*0.19*	*−0.08*	*0.23*	*−0.02*	*0.08*	*−0.33***	*0.13*
Log(pkg demand)	*0.10*	*0.14*	*0.34***	*0.16*	*0.28****	*0.06*	*−0.29****	*0.10*
Log(highway length/sqkm)	*0.82****	*0.06*	*0.93****	*0.07*	*−0.16****	*0.02*	*0.56****	*0.04*
Log(km from UDC)	*−0.92****	*0.09*	*−1.00****	*0.11*	*−0.08*	*0.04*	*−0.28****	*0.07*
	N	*715*		*715*		*715*		*715*
	R^2 *adj*	*0.39*		*0.35*		*0.22*		*0.31*
	LL_0	*−1577.22*		*−1689.87*		*−898.34*		*−1288.6*
	LL	*−1398.50*		*−1535.62*		*−808.61*		*−1151.74*
	AIC	*2811.10*		*3085.24*		*631.22*		*2317.47*

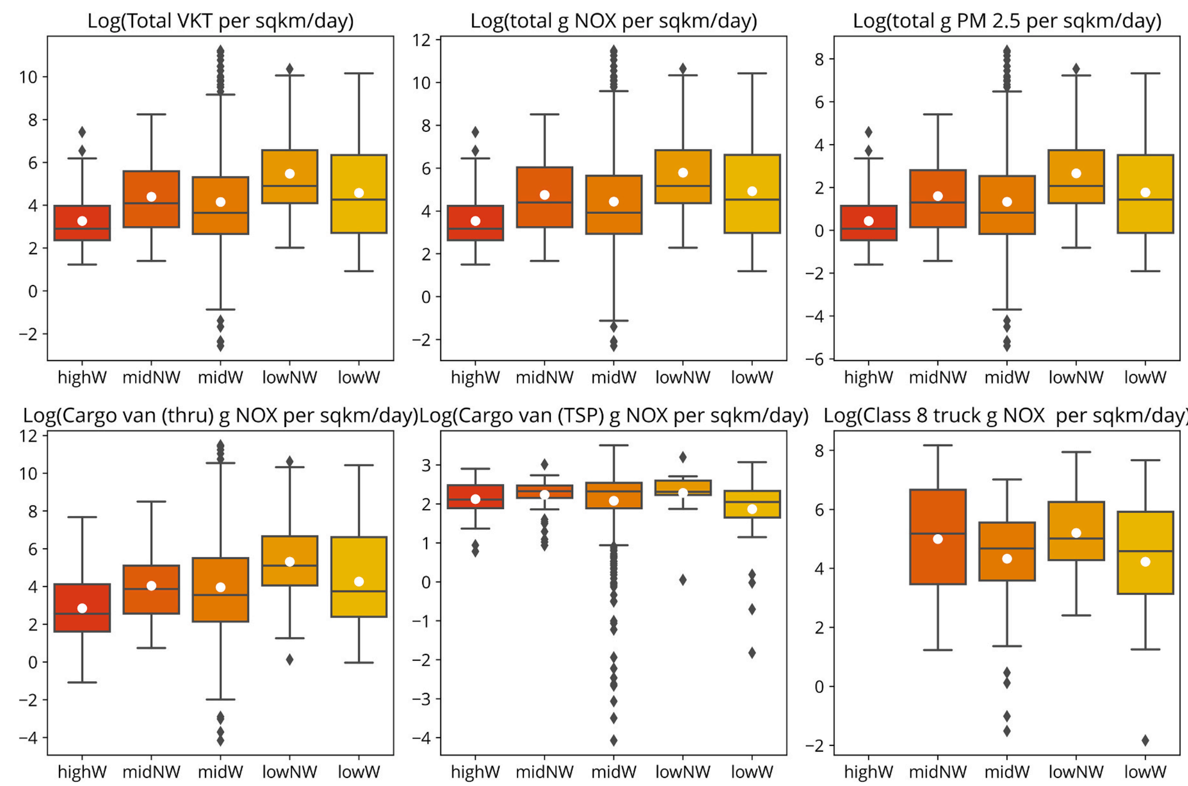

Fig. 6. *Boxplot of the log-transformed VKT, NOX and PM2.5 concentrations by income-race grouping (white dot = mean). NOTE:* Due to the low number of observations (n = 2), *highNW* is not included in the visualization. *"Line-haul" shortened to "thru" for easier visualization.*

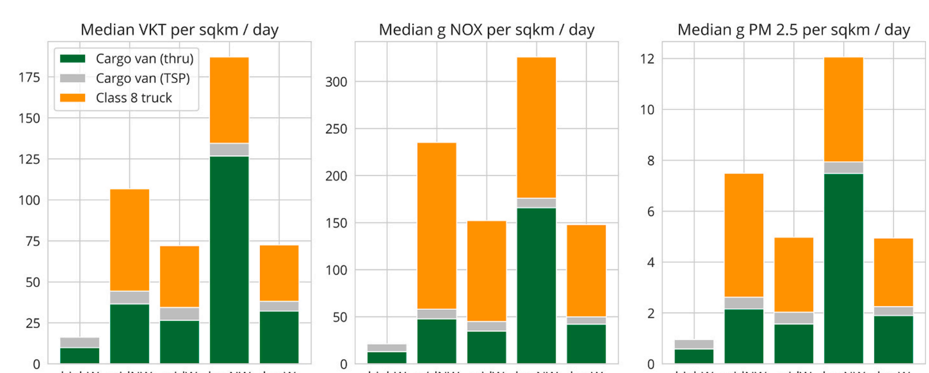

Fig. 7. Daily median VKT, NOX and PM 2.5 totals (top) and concentrations (bottom) by income-race grouping. NOTE: visualization excludes zero values.

some low-density housing) in Everett, including two co-located UDCs that service the northern MSA.

Due to these outliers, Fig. 7 visualizes the median emission concentrations between income-race groupings, and across all delivery segments. When assessing median emissions, racial discrepancies become more apparent. While cargo van TSP emissions remain relatively consistent across groupings, line-haul emissions disproportionately impact *lowNW* tracts. For instance, line-haul cargo van NOx emission concentration for *lowNW* tracts is roughly 246% higher than the second-highest grouping, *midNW*. However, between *midW, midNW,* and *lowW* the variation is more mild. Conversely, *midNW* is exposed to 18% more truck-related NOx emissions than *lowNW*. This observation is likely due to a higher portion of *midNW* tracts located near UDCs. Roughly, 33% of *midNW* tracts are within three km of a UDC, compared to 11% of *midW* tracts and 22% of *lowNW* tracts. Across the board, POC-majority tracts are generally more exposed to more emission concentrations than their white-majority counterparts.

To detect significant differences between the groupings, this study first conducts a rank-based, non-parametric analysis, Kruskal-Wallis H-test, between total VKT, PM2.5 and NOx concentrations, as well as for NOX concentrations across the three delivery segments. The results confirm a statistically significant difference in medians ($p < 0.05$), justifying *post hoc* analysis. Fig. 8 presents the results from a Dunn's test, which tests the null hypothesis that there are no significant differences between groupings. When evaluating aggregate VKT and emissions, all groupings are significant with *highW*, with *lowNW:midW* also showing significance ($p < 0.05$). Results confirm that *highW* tracts are disproportionately exposed to less overall emissions; however, this study cannot reject the null hypothesis across most income-race groupings when analyzing aggregate VKT and emission concentrations alone.

However, differences between the groupings emerge when analyzing NOx emissions across delivery segments. *LowNW* shows significant differences between all groupings when analyzing line-haul van emissions. Meanwhile, testing truck emissions confirm *midW* is significantly different across all groupings, as well as between *lowNW* and *midNW*. Results statistically validify that *lowNW* tracts are disproportionately exposed to higher cargo van emissions whereas *midNW* to higher truck emissions in comparison to white-majority tracts.

4.2.1. Sensitivity analysis of truck and cargo van utilization

Since this study makes static assumptions regarding the number vans and trucks needed to fulfill average daily delivery demand, a sensitivity analysis is conducted to identify the impacts of the model inputs on the findings. The number of vehicles needed to fulfill daily deliveries fluctuate based on several factors (e.g., holiday shopping demand or changing the volume of packages that can fit on a vehicle), thus affecting the distribution of emissions across the study's race-income groupings.

Therefore, the analysis looks at a variety of different combinations of load factors for both cargo vans and Class 8 trucks to account for varying package sizes, demand, weights, utilization, and etc. For cargo vans, load factors can range from 60 packages (34% of the baseline, 175) up to 350 (200%). Class 8 truck load factors range from 500 (25% of the baseline, 2000) up to 4000 (200%). The sensitivity analysis recalculates NOx density in each tract using varying load factor combinations. The analysis tests the output using Kruskal-Wallis-H tests to check for statistically significant differences in medians ($p < 0.05$) between income-race groupings.

Initial iterations of the sensitivity analysis revealed that every combination of load factor levels showed significant difference in exposure levels. This is consistent with expectations illustrated in Fig. 9: *highW* tracts have relatively low emission levels for cargo vans and zero truck emissions. Therefore, fleet volume fluctuation is comparatively less impactful for this group. The subsequent analysis excludes *highW* tracts, comparing only middle and low-income tracts against each other. Generally, the emission imbalance between income-race groupings remains across most load factor combinations. However, higher truck load factors paired with lower cargo van load factors show no significant differences between income-race groupings, resolving unequal emission

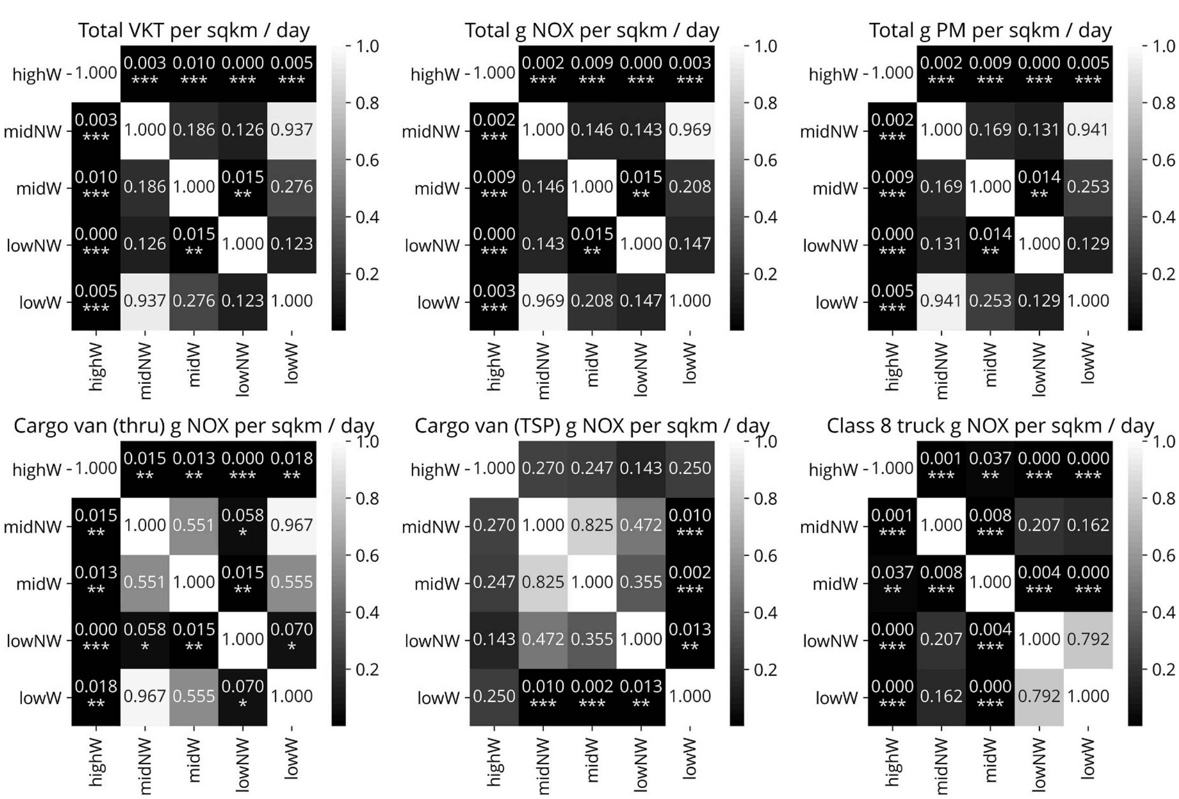

Fig. 8. Post-hoc Dunn test results of daily VKT, PM 2.5 and NOx emissions by income-race grouping; total sqkm/day (upper) and NOx emissions normalized by tract area (lower).

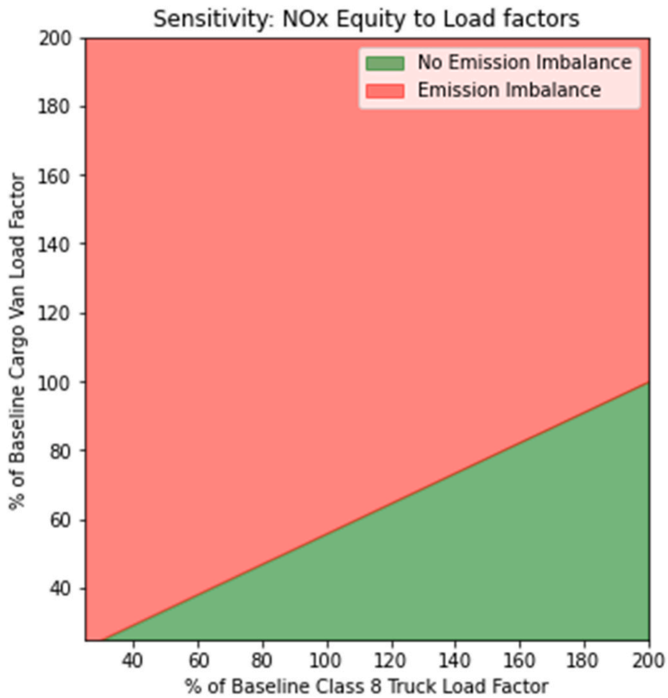

Fig. 9. Sensitivity analysis of NOx emissions per square km using Kruskal-Wallis tests by income-race grouping.

distribution. This combination is unlikely to occur naturally from daily fluctuations, since the circumstances that would lead to a higher load factor in trucks would likely affect vans in the same direction, not the opposite. Rather, the results demonstrate the disproportionate emission distribution of trucks versus van emissions.

The primary takeaways from this analysis are two-fold. First, the significance of this study's results are not highly sensitive to the assumptions the model makes regarding vehicle utilization, especially for cargo vans. That is, results are not sensitive to daily fluctuations in fleet volume and composition. Second, the number of trucks, in relation to cargo vans, affects observed discrepancies in emission exposure between race, low and middle income groupings. While introducing mechanisms that reduce environmental costs of cargo vans would have major benefits across race and middle/low-incomes, those that mitigate line-haul truck externalities would have an outsized impact for marginalized populations.

5. Discussion

5.1. Summary of results

This study explored ecommerce-related UDC localization and air pollution impacts through a lens of environmental justice. This study found a significant correlation between distance from UDCs, delivery VKT, and higher POC concentrations. When considering both trucks and vans, the relationship between delivery VKT and other network properties, including UDC proximity and highway density, appeared stronger than demand for packages.

When evaluating VKT and emissions across race and income, the discrepancy is more apparent. Both low-income and middle-income POC-majority populations were disproportionately exposed to ecommerce-related pollution. Some of this disparity can be attributed to Class 8 truck emissions, despite accounting for a much smaller fraction of overall emissions compared to cargo vans. Moreover, while the findings show that ecommerce activity negatively affected racially marginalized populations more than white populations, it did not permit the authors to conclude the relational effect between income and exposure to urban freight's negative, environmental externalities.

In fact, the findings are in-line with Yuan (2018a) and several other environmental justice researchers (e.g., Pastor et al., 2001) that find mixed relational effects between income, race and industrial siting. As stated by these authors, the racial make-up of a neighborhood can be a stronger determining factor for disparate industrial siting than its socio-economic status. In addition to a history of locked-in, racialized urban development practices (Pulido, 2017), there are likely reasons contextual to the warehousing sector and urban geography as well. For instance, low-income, POC-majority tracts in Seattle MSA have the highest population density across all groupings (3346 people per square-km), roughly 53% higher than middle-income POC-majority and 74% higher than middle-income, white-majorty tracts. High population densities could reflect spatial constraints that are unattractive to UDC operators' expansive floorspace needs, deterring urban siting in favor of larger, industrially zoned parcels in lower density suburbs where median incomes are higher.

5.2. Implications for land use and transportation policy

Research on equity in urban freight planning is nascent (Fried et al., 2023). Urban freight experts have proposed a plethora of solutions including off-hour delivery (Holguín-Veras et al., 2018), microhubs and cargo bikes (Katsela et al., 2022), parcel lockers (Urban Freight Lab, 2018), and dynamic curbside/loading zone management (Pérez et al., 2021), among other solutions. However, cities and companies have mostly implemented these solutions to reduce delivery times and/or VKT in dense urban centers, not in urban industrial zones or the suburban periphery where freight activity is more intensive and disproportionately impacting POC populations. In other words, mainstream "sustainable urban freight" strategies may benefit wealthier, more frequent online shoppers from white-majority neighborhoods rather than the populations disproportionately impacted by the delivery trips these shoppers induce.

Commercial vehicle electrification is also a crucial step to eliminating localized tailpipe pollution with major delivery companies focusing on electrifying cargo vans and some box trucks (Domonoske, 2021). While the market penetration of heavy-duty commercial vehicles is substantially lower compared to light-duty vehicles (IEA, 2021, p. 101), several states (including Washington) have adopted California's Advanced Clean Truck (ACT) policy, which sets sales mandates for commercial vehicles Class 2 through 8 (Bliss, 2022). Although important for air pollution reduction, electrification is not a panacea. Electrifying delivery trucks and vans would do little to mitigate other traffic-related externalities including crashes, congestion, infrastructure damage, and non-exhaust pollution.

Therefore, when considering urban freight strategies, additional emphasis should be placed on environmental mitigations further up the urban distribution chain. In addition to the vehicle-based air quality regulations around UDCs described in the introduction, consideration should be given to UDC's public health impacts. Given that municipal land use regulation (or lack thereof) is a strong determinant in a firm's decision to locate a UDC (Yuan, 2019), local governments should carefully assess industrial land use and permitting to better understand UDCs' localized health cost and economic benefit. Researchers have suggested several land use solutions that intend to steer UDC development to environmental and operationally efficient outcomes, such as logistics parks in the suburbs or multi-use, landscape-integrated logistics "hotels" in urban centers (Raimbault et al., 2018). Additional design implementations at the UDC can mitigate negative externalities for surrounding communities, such as nature-based buffers or "complete streets" road design that improve safe interactions between commercial vehicles and vulnerable road users (Conway et al., 2013; Pitera et al., 2017).

Logistics land use and transportation solutions such as these require a considerable degree of public support and cross-sector collaboration.

Larger, regional governmental bodies–such as state, counties, or MPOs–could provide guidance to environmentally conscientious UDC siting best practices and enable cross-regional coordination. Grassroots advocates and civil society also have a role in leading these discussions and ensuring urban freight and UDC siting remain pertinent to EJ discourse and political action (Schneller et al., 2022).

6. Conclusion

This paper is the first empirical effort to visualize and quantify socio-spatial inequities embedded in our urban freight system. Namely, the study tested two interrelated hypotheses. First, marginalized populations were more likely located near intensive freight infrastructure and activity, especially upstream in the home delivery chain. Second, this proximity consequently created higher exposures to freight-related criteria pollutant emissions. The results show marginalized populations disproportionately bear ecommerce's environmental costs unequally in metropolitan Seattle despite receiving less home deliveries. While the study analyzed Amazon UDC location data, the data present only a subset of broader warehousing activity with today's home delivery trends likely exacerbating long observed inequities in the urban freight system. This paper's theoretical review and methodological approach also helps highlight some gaps in warehouse geography research.

Most debates surrounding the impacts of warehousing's spatial reorganization add little to EJ considerations. Case studies suggest logistics decentralization or "sprawl" contributes to growing regional freight emissions (Dablanc & Rakotonarivo, 2010). Conversely, others argue logistics sprawl parallels decentralizing freight demand and spurs enhanced economies of scale at larger suburban warehouses, therefore, optimizing freight network efficiencies (Robichet & Nierat, 2021; Sakai et al., 2017). Arguably, compact city planning can reduce freight transport distances between distribution hubs and market terminals (Rivera-Gonzalez et al., 2023), especially where ecommerce is concerned given the recent trend that has placed some LMDS closer to consumers in denser urban areas (Fried et al., 2023). Condensing logistics facilities nearer to the urban core may trade-off some network efficiency improvements with exposing higher densities of people and sensitive land uses (e.g., schools and hospitals) to locally intensified freight activity. Given broad evidence to disparate siting, including in the warehousing sector (Yuan, 2018b), the rapid proliferation of ecommerce-UDCs presents fundamental EJ concerns. Recently, "proximity logistics" research offers some guidance to mitigating urban freight's negative externalities among communities living next to UDCs (Buldeo Rai et al., 2022). However, none of these studies frame UDC siting as a socio-political issue with equity and EJ implications (Fried et al., 2023).

Given this study's cross-sectional nature, it does not attempt to identify causal factors for disparate ecommerce pollution nor prescribe specific solutions that best mitigate urban freight's inequities. It also does not validate results against some geographic and social biases, such as by testing for the modifiable areal unit problem (MAUP) and/or utilizing different equity indicators besides the median-based tests employed in this study.

In addition to addressing these limitations, future studies could also introduce additional sensitivity parameters that allow the testing of variables beyond load factors, which was tested by this study. Doing so could allow researchers to audit sustainable urban freight strategies and evaluate what they entail for equity and EJ priorities. For example, using a routing API with historical traffic data can assess delivery time-window parameters to explore equity implications of off-hour deliveries. Finally, future studies should explore atmospheric models for air pollution dispersion, such as CMAQ or Polair3D (Minet et al., 2020). Following this approach would enable researchers to quantify the distribution of freight pollution-related morbidity and social costs in a dynamic urban environment.

CRediT authorship contribution statement

Travis Fried: Conceptualization, Data curation, Investigation, Methodology, Formal analysis, Visualization, Writing – original draft, preparation. **Rishi Verma:** Investigation, Methodology, Formal analysis, Visualization, Writing – original draft, preparation. **Anne Goodchild:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank Dr. Don MacKenzie, University of Washington, and Brice Nichols, Puget Sound Regional Council, for their guidance and feedback during the initial phases of this study.

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