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Estimating the Traffic Congestion Footprint of Retail E-Commerce

A Comparison Across Three U.S. Cities

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Summary

The last decade has seen pivotal changes in the "last mile" of logistics: online order volumes are growing, customers are expecting deliveries with quicker turnarounds, and new technologies such as drones and electric vehicles are reshaping suppliers' fulfillment strategies (World Economic Forum, 2020). The unintended consequences of this increased footprint of logistics on cities is only beginning to be understood. This study focuses on the effects of e-commerce logistics on urban mobility, seeking to quantify how shifting consumer shopping demands, and efforts by e-commerce suppliers and carriers to meet these demands, impact traffic congestion as experienced by city drivers. Because the impacts to traffic caused specifically by e-commerce operations is not directly observable, we estimate these effects using traffic simulation models. Our modeling framework also allows us to predict how these impacts might scale over time and what measures e-commerce firms can enact to limit negative externalities.

We find that the impact of last-mile e-commerce activities to traffic congestion depends heavily on changes to people's travel behavior as they purchase more goods online. If people make fewer daily shopping trips to brick-and-mortar stores, traffic congestion will improve. If people complement online shopping with in-store shopping, traffic congestion will degrade. To mitigate potential negative traffic impacts, we recommend carriers reform their delivery networks to limit the distances delivery vehicles must travel within cities. Introducing micro-fulfillment centers close to end customers, serving secure lockers where consumers can pick-up packages, transitioning to alternative delivery vehicles with smaller traffic footprints, and consolidating packages onto fewer delivery vehicles with larger cargo capacities can all help reduce the traffic congestion induced by last-mile operations.

Motivation / Introduction

U.S. consumer purchasing behavior is evolving, accelerated by lifestyle changes during the COVID-19 pandemic. Many city residents are increasingly ordering goods online via e-commerce platforms for shipment directly to their homes. In 2021 74% of people in the U.S. purchased goods online. This number is expected to rise to 80% by 2025 (Statista).

In response to these changes, e-commerce providers are reforming their supply chain networks to support faster, cheaper deliveries from warehouses and fulfillment centers directly to residents, the distance often designated the “last mile.” These network expansions create convenience for customers. However, routing additional delivery vehicles in urban areas exacerbates externalities such as greenhouse gas emissions and roadway safety concerns (McKinnon, 2010; Fernández Briseño et al., 2020).

A commonly voiced criticism is that e-commerce distribution in cities contributes significantly to traffic congestion, subsequently reducing mobility and accessibility for all transportation system users. This study aims to estimate the traffic congestion impacts of e-commerce activities in U.S. cities – whether positive or negative – and identify opportunities for e-commerce retailers and distributors to reduce their congestion footprints.

Precedent Studies

Few studies exist that attempt to measure the effects of e-commerce activities on traffic congestion. Below are listed three major precedent studies that helped inform our own work. Their overall findings differ widely, likely because of differences in the foundational assumptions they employ and the scopes of the congestion-impacting factors they consider.

Table 1. Previous studies describing the impacts of e-commerce distribution on urban traffic.

Authors	Year	Region of Study	Findings
Stinson et al.	2019	Chicago	E-commerce reduces total city vehicle VMT because residents likely make fewer in-store shopping trips.
World Economic Forum	2020	Chicago, Los Angeles, Singapore, Amsterdam, Paris, London	If left unchecked, increases in numbers of delivery vehicles on city streets could add 11 minutes to each driver's commute time by 2030.
Komanoff	2021	New York City	E-commerce delivery vehicles cost city drivers, truckers, and bus drivers traffic delays worth $400 million annually.

Our goal is to create a simple traffic modeling framework that can be generalized across major U.S. cities and used to compare results under different logistics operation scenarios. Additionally, because the ways e-commerce affects people's purchasing and travel behavior are only beginning to be understood, we consider a range of shopping behavior assumptions that help capture the uncertainties in our current understanding.

Research Questions

This study investigates how last-mile e-commerce distribution strategies affect roadway traffic in U.S. cities and what interventions suppliers, carriers, and consumers can enact to reduce any negative traffic externalities. Specifically, we explore the following questions:

I. How much traffic and congestion do urban delivery operations add to or subtract from U.S. city road networks? Do different cities experience these congestion externalities to different degrees?

II. How will traffic and congestion as experienced by city drivers evolve as e-commerce service continues to expand?

III. How can e-commerce providers reform their fulfillment strategies and how can consumers modify their purchasing behavior to improve mobility for all drivers?

Our study considers only a narrow definition of mobility: the time required for drivers of personal vehicles to reach their destinations using arterial-level (non-highway) city roads. We quantify our results in terms of automobile travel times and average roadway speeds. We challenge future authors, however, to consider both mobility and accessibility in broader contexts by exploring how e-commerce last-mile distribution impacts the abilities of transportation system users to reach destinations across travel modes, user income, age, ability, and other factors. The section Future Research identifies possible forms this research could take.

Methodology

Because the effects of last-mile logistics on city traffic cannot be directly observed or estimated, we tackle these three research questions by creating a city-level simulation framework that models roadway traffic during a typical weekday on an aggregated, macroscopic level. Though our modeling framework can be extended to any U.S. city, we specifically apply it to Seattle, WA; Chicago, IL; and New York, New York. Several simplifying assumptions make our approach possible.

- First, though we model a full 24-hour weekday, only results between 7am and 9pm are collected. The first seven hours of the day serve as a simulation warm-up period.
- We include vehicle trips that enter and exit each city, but only explicitly model traffic within city boundaries.
- We consider the traffic effects of last-mile e-commerce package distribution. We assume that first and middle-mile traffic exists fully outside city bounds or occurs overnight.
- We narrow our focus to business-to-consumer (B2C) retail e-commerce and delivery trips taken by suppliers and third-party carriers from distribution centers to end consumers. Food delivery and other storefront-based services fall outside our scope.

The following section describes the assumptions and variables that define the scenarios we tested.

Simulation Variables

Below we detail the variables we feed as input to our model. We organize them into three subsets: foundational assumptions, future cases, and alternative last-mile fulfillment strategies. A *modeling scenario* represents a unique combination of these variables. Testing multiple, varied scenarios allows us to capture not only current city-wide traffic levels, but how traffic might evolve over time under different carrier intervention strategies.

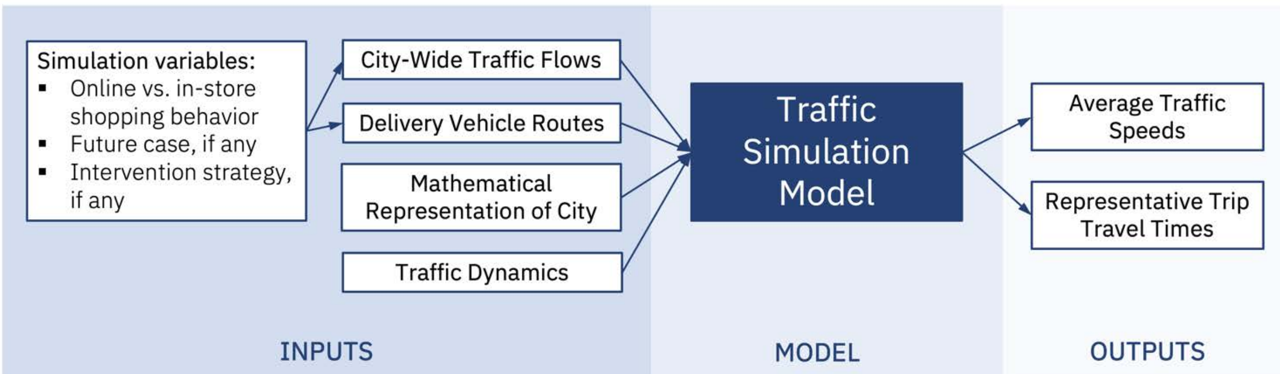

Figure 1. Traffic simulation model inputs and outputs.

Online Versus In-Store Shopping Consumer Behavior

Central to our investigation is a model of how increased demand for e-commerce package delivery influences the frequency with which people shop at brick-and-mortar stores. Greater demand for e-commerce services increases the required number of delivery vehicles required to serve customers. However, the direction and magnitude of this e-commerce versus in-store shopping relationship determines whether expanded e-commerce service leads to a net increase or decrease of vehicles on the road.

Understanding of this correlation within the academic community is still developing. Table 2 lists selected journal articles grouped by their findings. Some works suggest a substitutive relationship whereby households or individuals reduce the frequency, duration, or distance of in-person shopping trips as they increase the frequency or size of online orders. Other works report a complementary relationship whereby demand for in-person and online shopping increase jointly. Finally, some authors report mixed or inconclusive results.

Most authors conclude, however, that the nature of this relationship is heterogenous among households, impacted by sociodemographic characteristics such as age, income, and whether children live in the household.

Because of the inconclusiveness of this foundational assumption, we consider three possible relationships between online and in-store shopping demand in our simulation model. The major substitutive scenario assumes that in-person weekday shopping trip frequencies would increase 15% with no available e-commerce. Our minor substitutive scenario assumes only a 5% increase. Finally, the minor complementary scenario assumes that shopping trip frequencies would decrease by 5% with no e-commerce. Each scenario also assumes a further increase or decrease in in-store shopping trip frequency as the market penetration of e-commerce platforms continues to rise.

Table 2. Academic works describing the relationship between demand for e-commerce package delivery and in-store shopping trips.

Dominant Relationship	Example Academic Works
Largely Substitutive	Bjerkan et al. (2020), Xi et al. (2020)
Mixed Results	Zhai et al. (2017), Dias et al. (2020), Spurlock et al. (2020), Titiloye et al. (2022)
Largely Complementary	Ferrell (2004), Cao (2012), Cao et al. (2012), Lee et al. (2017)
No Relationship Found	NHTS (2018)

Future Case Variables

We include two variables that help us model predicted changes in personal vehicle usage and e-commerce delivery demand over time.

- *Traffic multiplier:* This value uniformly increases trip volumes across trip purpose, origin and destination, and departure time. Increasing the value of this variable allows us to model how traffic might evolve with increased urbanization and no corresponding changes to transportation systems or user travel behavior.
- *Delivery demand:* This variable modifies the average per capita demand rate for package delivery, modeling the growth of e-commerce over time along with the corresponding change in in-store shopping trips. Reducing this value to zero allows us to envision a case where all shopping is conducted in-person.

Intervention Strategies

Finally, we model four alternative fulfillment strategies that e-commerce suppliers and carriers might adopt to reduce their urban traffic footprints.

- *Micro-Fulfillment Centers (MFCs):* Small distribution centers are located within the densest city neighborhoods, reducing the distances to end consumers. We model this strategy by placing multiple low-capacity fulfillment centers in traffic regions with the highest population densities. Delivery vehicles stationed at these MFCs can subsequently reach end customers in less travel time.

- *Urban lockers:* Some customers elect to pick-up and return packages to secure locations within their neighborhoods. We model this strategy by assuming that proportions of customers pick up and return packages to locker locations near their residence or place of work. This consumer behavior reduces the number of carrier-provided delivery vehicles required to serve customers.
- *Alternative delivery vehicles:* Logistics carriers use multiple cargo bikes, e-scooters, “walkers", or other small-footprint modes to deliver packages from a given parked delivery van to customers in densely urban locations. To model this strategy, we assume the delivery vehicle does not contribute to traffic while it is parked. Alternative deliverers instead contribute to traffic during the delivery process at comparatively lower rates.
- *High-capacity delivery vans:* Carriers either use a fleet of vehicles with larger cargo holds or delivery drivers more efficiently load packages onto existing delivery vehicles. We assume that the overall size of the vehicle and its contribution to traffic, however, remains unchanged. We model this strategy by increasing the assumed number of packages a van can deliver on a single route by 75 percent. Increasing the capacities of delivery vans reduces the number of vehicles required to serve a given geographic area.

We selected these four potential intervention strategies because they have all been either tested or are currently used by e-commerce carriers in the U.S. or abroad. Additionally, we expected that these strategies would all reduce the traffic congestion of last-mile e-commerce by either reducing the numbers of delivery vehicles on the roads or the distances these vehicles must travel to serve end customers. See Appendix I: E-Commerce Fulfillment Strategy Modeling Assumptions for more information on how we mathematically incorporated these strategies into our model. For a more in-depth overview of potential interventions reported across stakeholders, see the report "The Future of the Last-Mile Ecosystem" by the World Economic Forum (2020).

Simulation Modeling Framework

Figure 1 illustrates the key information fed to and reported from our simulation model. Its inputs are threefold and will be detailed further in the subsequent sections:

I. *A simplified mathematical representation* of the city that reduces the size of the model and the computing time it requires to run.
II. *Traffic dynamics*, a set of rules governing how traffic moves throughout space.
III. *A matrix of traffic flows* dictating when, where, and how many vehicles move throughout the city and for what purposes.

The model outputs two forms of results:

- *The average speeds* in different areas of the city over time.
- *The average travel times* of representative trips within the model from and to different locations, at different times of day, and for different travel purposes.

The following sections describe each model input in more detail.

Mathematical Representation of Cities

Because modeling vehicular traffic across an entire city's street network would be computationally impractical, we reduce our model's representation of a city's road network into key components. First, we divide each city into traffic regions, each between 5 and 10 km^2 in area. Rather than track traffic flows on individual road segments, we monitor traffic accumulations as they move among traffic regions. We assume each traffic region has the same vehicle capacity as the totality of the road segments within it. When routing vehicles throughout the city, we consider representative paths both among traffic regions and to/from designated city entry/exit points (see Figure 2 for visualization). These simplifications allow us to reduce the size of our network from thousands of road lane-miles to a handful of regions through which vehicles are produced, attracted, and routed.

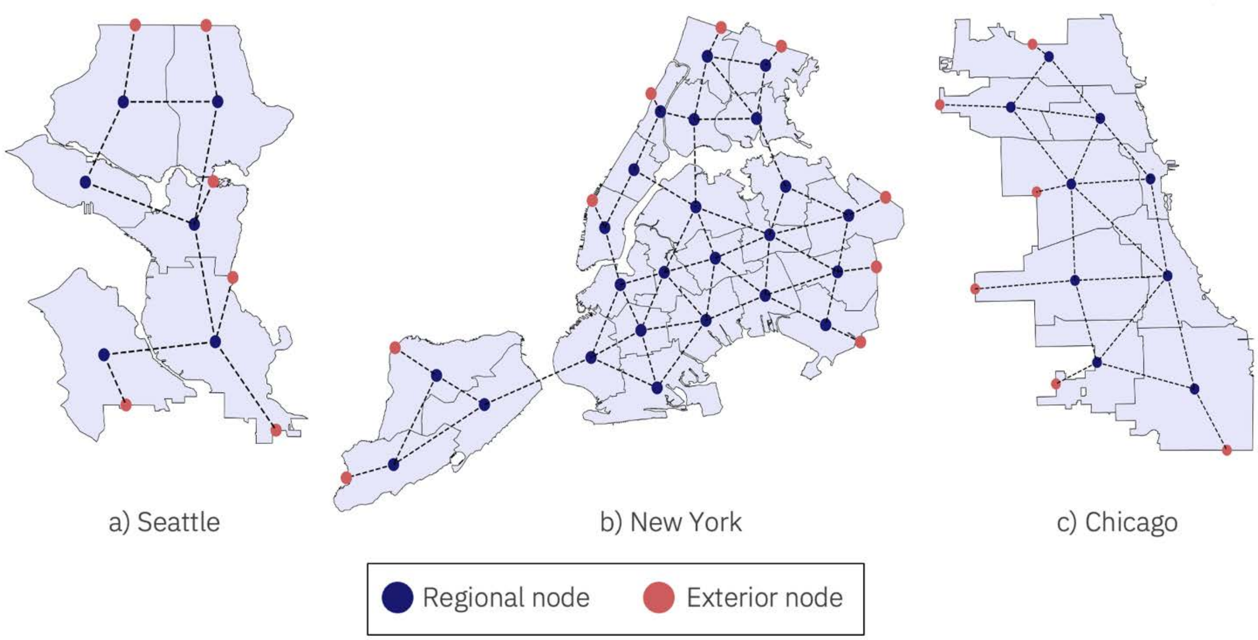

Figure 2. Network representations of each city (not to scale). Vehicles travel along black dotted lines to move between regions (consolidated into blue dots) and city entry/exit points (represented as red dots).

Traffic Dynamics

A second simplifying assumption further reduces the scale of our model. Rather than track the movements of individual vehicles, we group vehicles making the same trip into pods that move as single units.

To determine the travel speeds of vehicle pods throughout their journeys, we use macroscopic fundamental diagrams (MFDs), which describe the relationships among total traffic flow and density within each region. These MFDs dictate, for a given region, the average travel speed of vehicles within it given the total number of vehicles traveling on its roadways. When few vehicles are traveling within a region, they move at free-flow speeds. However, as more vehicles vie for space on the roadways, often during peak hours, streets become congested, and vehicles slow. An MFD describes the average speed of vehicle pods at every possible traffic state based on characteristics of the region's roadway network such as its total lane-miles, density of signalized intersections, and posted speed limit, among many other factors. For more information on MFDs, see Daganzo (2007) and Gerolimis and Daganzo (2008). Appendix II outlines how we estimate an MFD for each traffic region.

Given the average speed of each region at a given simulation instance, vehicle pods can determine their expected travel times from origin to destination. They select routes that minimize this expected travel times according to the principle of user equilibrium routing. See Sheffi (1985) for an overview of user equilibrium routing and other common vehicle routing approaches.

City-Wide Traffic Flows

To determine the effects of e-commerce distribution on city traffic, we require an understanding of current traffic volumes. For each city of study, we input to our model a matrix detailing the number of vehicles traveling between every two pairs of destinations, at what time, and for what purpose. We employ a modified four-stage travel demand model to estimate these quantities. In each step, we combine survey data, assumptions, and/or mathematical models to arrive at reasonable expected travel demands. See Table 4 for a list of the national, regional, and city travel surveys we consulted.

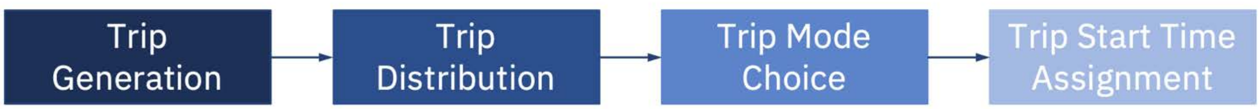

Figure 3. Modeling steps used to estimate trip volumes for each city of study.

The four steps we follow are outlined below.

1. ***Trip generation.*** We estimate the numbers of trips a given city region (or nearby region) is likely to produce or attract over the course of a weekday. We consider four main trip purposes: trips to and from work; trips to and from school; shopping and errands trips; and social and recreational trips. We employ recent travel survey data to estimate these totals whenever possible. Otherwise, we revert to trip totals derived from those reported by the 2017 National Household Travel Survey, listed in Table 3, and apply them to 2023 population estimates.

Table 3. Approximate per-capita daily trip totals used when more detailed survey data is unavailable.

Trip Purpose	Approx. Per-Capita Weekday Trip Count
Home to Work	0.4 – 0.5
Work to Home	0.5
Home to School	0.2 – 0.25
School to Home	0.25
Shopping and Errands	1.3 – 1.4
Social and Recreation	0.9
Total	***3.5 – 3.7***

2. ***Trip distribution.*** Next, we calculate the expected trip totals between every pair of origins and destinations. We use gravity models to estimate the decline in the numbers of people that will travel between pairs of locations as the distance between them grows. For more information on gravity models for travel demand estimation, see NCHRP Report 716 (2012). We run gravity models to determine origin-destination pairings for each trip purpose separately. Therefore, our model does not consider trip chaining. For more information on our trip generation and distribution methodologies, see Appendix III: City-Wide Travel Demand Estimation.
3. ***Trip mode choice.*** We only explicitly consider trips made by personal vehicles. Though other travel modes – mass transit, biking, and walking – may also experience and contribute to congestion, the per-capita traffic impact of automobiles is significantly higher. We use mode share percentages reported by city-wide travel surveys, assuming that only the longest trips are made by personal vehicles.
4. ***Trip start time assignment.*** Finally, we distribute trip start times throughout the day. This step helps us reflect that, for example, commuting trips are most likely to be made during peak hours and shopping trips are most likely to be made during afternoons and evenings. We consult the Chicago Metropolitan Agency for Planning (CMAP) 2010 report "Trips Underway by Time of Day by Travel Mode and Trip Purpose for Metropolitan Chicago" for this purpose. To estimate the times at which vehicles that start their journeys outside the city enter city bounds, we use assume an outside-city travel speed of 45 mph.

To ensure that our estimates of travel demand volumes and our descriptions of regional traffic dynamics are accurate, we compare the average regional speed measurements our models produce against both speed measurements reported by city transportation agencies and average travel times gleaned from Google Maps' Distance Matrix API.

Table 4. Travel surveys and reports used to estimate travel demand for cities of study.

City of Study	Resources Used to Estimate Travel Flows
Seattle, WA	2019 Puget Sound Regional Travel Study 2022 Seattle Commute Survey
New York, NY	2009 New York State National Household Travel Survey Add-On 2019 NYC Department of City Planning Commuting Report 2019 NYC Department of Transportation Mobility Report
Chicago, IL	2007 Chicago Metropolitan Agency for Planning (CMAP) Household Travel Inventory 2016 CMAP On To 2050 Snapshot Report
All Cities	2009 National Household Travel Survey 2017 National Household Travel Survey U.S. Census Bureau American Community Survey (2015-2019)

Delivery Vehicle Routes

Delivery vehicle traffic flows are the final input to our simulation model. To determine the locations of customers requiring delivery, we assume a geographically uniform base demand rate of 0.155 online orders per person per weekday, where one order corresponds to a single package. We increase this demand value in future-case scenarios to model the expected growth of retail e-commerce over time.

a) Amazon Prime Delivery Truck (credit: Todd Van Hoosear)

b) FedEx Express Cargo Van (credit: Thomas R Machnitzki)

c) USPS Postal Delivery Van (credit: Greg Goebel)

d) UPS Cargo Van (credit: Atomic Taco)

Figure 4: Delivery vans used by four major carriers with approximate cargo capacities similar to that of representative delivery vehicle considered in model. Images are selected from Wikimedia Commons under Creative Commons License. Images have been altered.

Though numerous e-commerce platforms operate in the U.S., we assume that packages are delivered by one of four carriers: Amazon, FedEx, UPS, or USPS. We consult Google Maps to find the locations of distribution centers, warehouses, and large post offices from which these carriers' delivery vehicles are likely to begin their routes. We solve a travel distance-minimizing mathematical optimization problem to find expected least-distance delivery routes that serve all required customers. To simplify our delivery model, we assume all packages are serviced by delivery vans with capacity of 200 packages. For information on the methodology by which delivery vehicle traffic was represented in the simulation models, see Appendix I: E-Commerce Fulfillment Strategy Modeling Assumptions.

Findings

We run simulation models to predict the impact to traffic congestion levels in each city under different assumptions of consumer purchasing behavior, values of e-commerce delivery demand, and congestion-reducing intervention strategies. Table 5 and Table 6 compare current-day operations against the imagined case where consumers purchase all goods in stores, none online. Table 5 provides the expected number of trips saved and Table 6 reports the expected total vehicle travel time saved due to the operation of e-commerce suppliers and carriers. Values in parentheses provide these city-wide quantities normalized by the population of each city 18 years and older.

Table 5. Predicted number of city-wide vehicle trips saved due to current e-commerce operations. Values in parentheses are normalized by the city's adult population.

City	Approx. Total Number of Avg. Weekday Vehicle Trips Saved		
	Major Substitutive	**Minor Substitutive**	**Minor Complementary**
Seattle, WA	63,800 (0.10)	17,000 (0.03)	-35,200 (-0.05)
New York, NY	446,100 (0.07)	90,700 (0.01)	-265,100 (-0.04)
Chicago, IL	273,600 (0.13)	64,200 (0.03)	-145,400 (-0.07)

Table 6. Predicted number of city-wide vehicle travel hours saved due to current e-commerce operations. Values in parentheses are normalized by the city's adult population.

City	Approx. Total Number of Avg. Weekday Vehicle Travel Hours Saved		
	Major Substitutive	**Minor Substitutive**	**Minor Complementary**
Seattle, WA	20,300 (0.03)	5,400 (0.01)	-11,400 (-0.02)
New York, NY	126,200 (0.02)	11,500 (0.00)	-108,200 (-0.02)
Chicago, IL	169,700 (0.08)	26,900 (0.01)	-87,800 (-0.04)

The results above show that the traffic impacts of current urban e-commerce operations depend heavily on our assumption of consumer purchasing patterns. Under the assumption that in-person shopping trips decreased by 15% due to the availability of e-commerce service (*major substitutive)*, both the number of vehicle trips and the total vehicle trip-hours each city experience on a given weekday are reduced. Assuming only a 5% decrease in in-store shopping trips (*minor substitutive)*, both citywide vehicle-trip and vehicle trip-hour counts decrease, but only slightly. When supposing that consumers have increased their frequency of trips to stores by 5% as e-commerce services expanded (*minor complementary)*, traffic levels degrade. Finally, we see that these effects when normalized by city population are less pronounced in New York, likely because a comparatively lower percentage of city residents use personal vehicles for daily trips.

As online order volumes continue to grow, we model how city traffic levels may be affected. Figure 5 illustrates how city-wide weekday vehicle travel times would respond as delivery demand rates climb.

We compare current estimated traffic levels corresponding to the current day scenario of a delivery rate of 0.155 packages per person against future cases in which this rate might increase. We find that results are again heavily dependent on the consumer purchasing behavior assumption we feed our model. This finding reiterates that though delivery vehicles contribute noticeably to traffic congestion, the daily travel behavior of the city's inhabitants have greater impact.

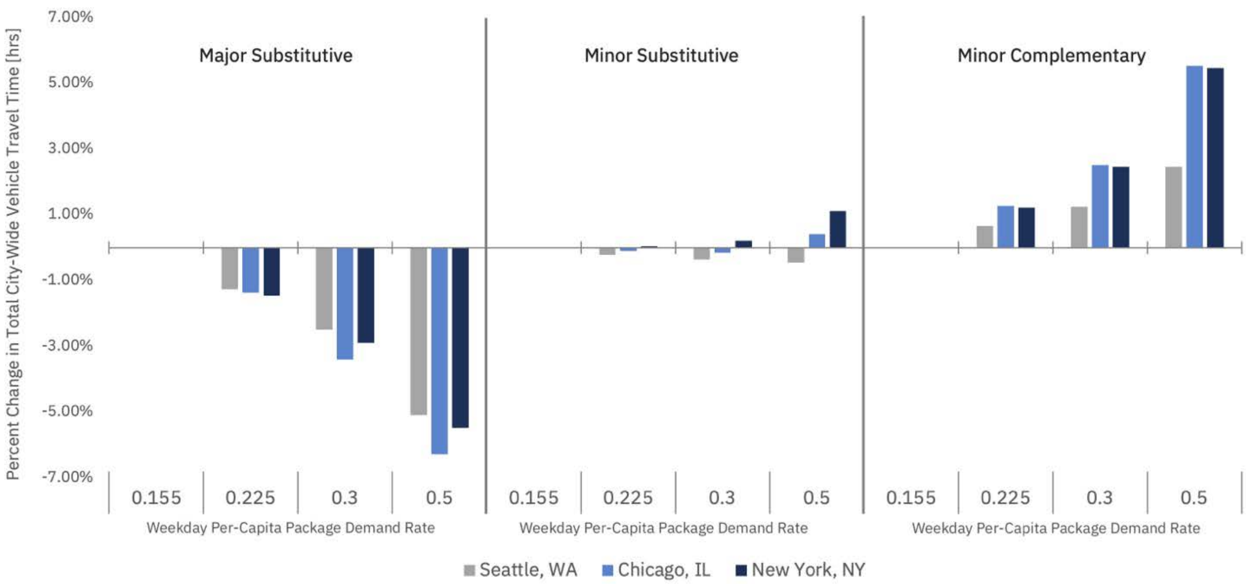

Figure 5. Expected impacts to total weekday city-wide vehicle travel times of increasing e-commerce delivery demand beyond the current assumed rate of 0.155 packages per capita per weekday. Results under different consumer purchasing behavior assumptions are reported separately. Note that positive percent change values correspond to an increase in city-wide travel times.

Finally, we model how e-commerce suppliers and carriers might reform their delivery networks to reduce their traffic footprints. We consider four strategies: micro-fulfillment centers located in dense urban neighborhoods; lockers to which carriers can deliver packages and via which customers can return orders; alternative delivery vehicles including cargo bikes and walkers; and high-capacity delivery vans able to distribute more parcels during a single route. Table 7 outlines the expected city-wide travel hours that might be saved on a typical weekday if these strategies are widely adopted.

Table 7. Total city-wide travel time expected to save under four tested intervention strategies with respect to current traffic levels on a typical weekday.

Intervention Strategy	Approx. Total Number of Avg. Weekday Travel Hours Saved With Respect to Current Operations		
	Major Substitutive	**Minor Substitutive**	**Minor Complementary**
Seattle, WA			
Micro-Fulfillment Centers	103	115	214
Urban Lockers	485	497	486
Alternative Delivery Vehicles	590	572	575
High-Capacity Delivery Vans	271	288	286
New York, NY			
Micro-Fulfillment Centers	353	507	484
Urban Lockers	338	362	345
Alternative Delivery Vehicles	1,794	1,902	1,908
High-Capacity Delivery Vans	751	758	752
Chicago, IL			
Micro-Fulfillment Centers	61	38	32
Urban Lockers	1,768	1,727	504
Alternative Delivery Vehicles	710	1,261	1,326
High-Capacity Delivery Vans	492	1,244	1,792

Time-savings estimates are approximate and highly dependent on model parameters. Still, we find that each strategy has the potential to reduce traffic levels. We encourage e-commerce providers to explore how these fulfillment schemes might reduce their own contributions to urban traffic.

Recommendations

Preserving the travel mobility of people within cities will require a concerted effort among all stakeholders: consumers, e-commerce service providers, and municipal governments. Though the scopes of the intervention strategies we tested in this study are limited in comparison, we can recommend several traffic mitigation strategies. Primarily, we encourage e-commerce suppliers and carriers to reform their delivery networks to reduce the distances large delivery vehicles travel on urban road networks. This can be accomplished by managing micro-fulfillment centers whereby high-volume goods are prepositioned close to customers; by delivering to lockers located in centralized locations easily accessible to consumers; by using cargo bikes, e-scooters, and "walkers" that impose smaller footprints on city roads; and by consolidating packages onto a smaller number of delivery vehicles with larger capacities.

Whenever possible, we also encourage consumers to combine in-store shopping trips with trips for other purposes; leverage mass transit, walk, or bike; and order multiple products per order that can be delivered in a single shipment.

Future Research

This research study is intended to provide a high-level understanding of the impacts of last-mile e-commerce fulfillment on traffic congestion in U.S. cities. We invite future authors to expand our analysis. Potential areas for development are outlined below.

- *Model additional cities.* Due to time and capacity restrictions, we limit our analysis to Seattle, Chicago, and New York City. These cities, however, all boast large populations who use sustainable transportation modes. We invite future authors to broaden the study to cities with populations that rely more heavily on personal vehicles.

- *Model additional travel modes.* We only explicitly model traffic caused by automobiles because personal vehicles contribute most heavily to traffic on a per-capita basis. A more robust traffic model might include the traffic impacts of bicycles, buses, and other common forms of transportation in urban areas.

- *Refine assumptions surrounding online order frequency.* The parcel delivery demand rates we assume are uniform across each city's population. This is a simplification. Future work could model demand rates as a function of household size, household income, age, and other sociodemographic factors.

- *Consider the broader effects of delivery traffic on mobility and accessibility.* Our study only quantifies the impacts of e-commerce fulfillment to vehicle travel times. The effects of e-commerce on urban mobility, however, are more extensive and nuanced. For example, delivery vehicles spend considerable time searching for parking while delivering (Muriel et al., 2021). Future authors could consider the impacts of e-commerce on parking availability. We also invite authors to consider how illegal delivery van parking contributes to traffic; the obstruction of bike lanes, bus lanes, and sidewalks; and the perceived safety of these transportation facilities.

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Appendix I: E-Commerce Fulfillment Strategy Modeling Assumptions

Below are listed the primary assumptions used to incorporate last-mile logistics fulfillment traffic into the simulation models. All listed assumptions lacking an explicit source were informed by conversations with industry experts.

Package Delivery Demand

We assume that every city resident orders 0.155 packages per weekday. This value was estimated based on results from the National Household Travel Survey (McGuckin and Fucci, 2017) adjusted for the increase in total e-commerce sector revenue between 2017 and 2023 as reported by Statista (2023). We assume the package ordering rate is uniform across geographic and sociodemographic variables.

Base Case

The "base case" scenario corresponds to current typical e-commerce parcel delivery strategies. This scenario is informed by the assumptions below:

- Orders are randomly assigned to a carrier according to the carrier's market share in the last-mile delivery sector, shown in Table 8. Market share values are reported by Calimlin (2022).

Table 8. Proportions of parcels served by primary last-mile logistics carriers.

Logistics Carrier	Percentage of Package Demand Delivered by Carrier
United States Postal Service (USPS)	32%
United Parcel Service (UPS)	24%
Amazon	22%
FedEx	19%

- We assume all routes are executed by delivery vans with capacity of 200 packages. We assume that all delivery vehicles are filled to capacity.
- Though delivery vans are larger than typical automobiles, they contribute equally to traffic congestion.
- Fulfillment center/ distribution center locations are sampled from Google Maps and Amazon-provided documentation. We assume fulfillment centers have a capacity of 70,000 packages or approximately 350 delivery vans.
- Delivery routes contain two components: a linehaul to reach the vehicle's assigned delivery area and back again, and a delivery time equal to 8-10 hours. During each simulation, we

randomly assign a delivery tour duration to each vehicle between 8 and 10 hours. These delivery times correspond to a rate of 20-25 packages per hour.

- Fulfillment centers are assigned to serve demand in specific traffic regions according to the solution of a carrier-specific optimization problem that minimizes the combined distances delivery vehicles must travel during their linehaul to serve all customer locations.

Urban Micro-Fulfillment Centers Model

The urban micro-fulfillment centers model is equivalent to the base case with the following modifications:

- MFCs are assumed to have capacity of 5,000 packages (Cuppett, 2022).
- Each carrier constructs and operates one MFC per every 3 square miles in study traffic regions where the population density exceeds 30,000 people per square mile in Chicago and NYC, and 15,000 in Seattle.
- Micro-fulfillment centers store up to one day's worth of inventory. Resupplying MFCs occurs overnight and adds negligibly to traffic.
- Because MFCs are located close to end customers, we assume delivery routes from MFCs require no linehaul component.

Package Locker Model

The package locker model is equivalent to the base case with the following modifications:

- Hub lockers are dispersed throughout each city of study such that every customer is within one mile of a locker location.
- 10% of customers regardless of carrier opt to receive their package at a locker location rather than use home or office delivery.
- 50% of customers regardless of carrier make package returns to a locker location rather than travel to a nearby retail store, post office, or UPS or FedEx store.
- Customers who elect to use lockers make such trips via travel modes consistent with shopping trip mode share in their city.
- Customers make trips to lockers at uniform times between 9am and 7pm.
- Lockers are filled/emptied overnight or at dispersed times during the day such that this action adds negligibly to traffic.

Alternative Delivery Vehicles Model

The alternative delivery vehicle model is equivalent to the base case with the following modifications:

- Delivery vans route from existing delivery station locations to each region between 10am and 12pm. Enough delivery vans are loaded to serve all customers. Each delivery van remains parked while walkers and bikers deliver packages, therefore contributing to vehicle traffic only during the line-haul. After enough time has passed for walkers/bikes to deliver all packages, the delivery van routes back to the delivery station.
- At any given time, 15 walkers or 10 bikes are delivering packages for each delivery van.
- Walkers deliver 2 packages in 10 minutes. Cargo bikers and e-scooters deliver 4 packages in 10 minutes.
- For the purposes of calculating contributions to vehicle traffic, each walker counts as zero vehicles. Each cargo bike and electric scooter counts as ½ vehicles.

High-Capacity Delivery Vehicles

The alternative delivery vehicle model is equivalent to the base case with the following modifications:

- Delivery vehicles are assumed to have capacity of 350 packages, a 75 percent increase over the base-case vehicle capacity of 200 packages.
- The delivery route time remains unchanged at 8-10 hours.

Appendix II: Regional Macroscopic Traffic Dynamics Estimation

Recognizing that creating detailed traffic simulation models at city scale would introduce insurmountable complexity and uncertainty, we choose to model average traffic behavior within clearly defined traffic regions. We concern ourselves with the movements of groups of vehicles within and among these regions. To estimate the possible traffic states within each region of study, we apply an aggregated modeling approach based on Macroscopic Fundamental Diagrams (MFDs). First introduced by Godfrey (1969), MFDs provide a way of describing average traffic states within geographic "reservoirs", each with approximately homogeneously distributed congestion that evolves slowly over time. MFDs provide us a means of estimating average vehicle speed within a given region based on the accumulation of vehicles within it. The shape of a well-defined MFD is based on myriad network factors including the geometry of the road network. For our cities of study, when possible, we estimate MFDs based on publicly available vehicle count and average speed measurements. When such information is unavailable, we estimate the shapes of MFDs based on those of other regions with similar characteristics.

Estimating Traffic Dynamics Using Average Speed and Vehicle Count Data

When possible, we estimate regional MFDs using vehicle volume and speed measurements provided by city agencies for street segments evenly distributed within regions' arterial road networks. Measurements are typically provided in 10 or 15-minute time intervals. Speed measurements are usually either estimated via GPS traces from vehicles such as buses or taxis, or loop detectors dispersed at fixed locations. Ideally, traffic volume and speed measurements are reported at corresponding roadway locations. In cases where speed and traffic sensor locations vary slightly, we pair volume and speed measurements using a procedure that ensures only measurements on the same roadway in the same travel direction are paired. Table 9 lists data sources we consulted.

Table 9. Traffic data sources consulted during study.

Data Set	Data Provider	Data Hosting Platform
Automated Traffic Volume Counts	New York City Department of Transportation (NYCDOT)	NYC Open Data
Real-Time Traffic Speed Data	NYCDOT Traffic Management Center (TMC)	BetaNYC
Chicago Traffic Tracker – Historical Congestion Estimates by Segments	City of Chicago	Chicago Data Portal
Hourly Traffic Data	Illinois Department of Transportation	Traffic Count Database System (TCDS)
2018 Traffic Flow Counts	Seattle Department of Transportation	Seattle GeoData

Once measurements have been cleaned and validated, we apply Equation 1 to collect the traffic accumulation n_i (veh/lane-mi) at each location and time (i, t) given its vehicle flow or production $p_{(i,t)}$ (veh/lane-hr) and average speed $v_{(i,t)}$ (mi/hr):

$$n_{(i,t)} = \frac{p_{(i,t)}}{v_{(i,t)}}. \tag{1}$$

We note that $v_{(i,t)}$ in Equation 1 denotes space-mean speeds. In situations where only time-mean speed values are available, we assume the measures are equivalent. For each defined region, we model its MFD as an exponential equation of form:

$$p = n \cdot v_{free} exp\left(-\frac{1}{2}\left(\frac{n}{n_{crit}}\right)^2\right) \tag{2}$$

We fit this equation to our observations $n_{(i,t)}, p_{(i,t)}$ to estimate parameters v_{free}, the region's free-flow average speed and n_{crit}, its critical accumumulation. To help find an adequate fit, we assume the jam density n_{jam} is 240 veh/lane-mi (150 veh/lane-km). In some cases, the fit of Equation 2 is poor and no discernable vehicle production-accumulation relationship is apparent. In these instances, we redraw region boundaries until a clearer fit can be approximated.

Finally, we multiply both sides of Equation 2 by d_{region} the total lane-miles of arterials in each region. We estimate this value using OpenStreetMap data accessed via the OSMnx Python package (Boeing, 2017). The result is a relationship describing production and attraction on a regional rather than per lane-mile basis.

We end this section by acknowledging that our approach for traffic dynamics is only approximate, both due to biases in the data we employ and the ability of MFDs to accurately describe traffic states in city regions as we define them. For more information on the estimation and veracity of MFDs, an active area of research, see Geroliminis and Daganzo (2008); Geroliminis and Sun (2011); and Leclercq et al. (2014).

Estimating Traffic Dynamics When No Data is Available

In cases where high-resolution traffic data is not available or accessible, we predict the shapes of regions' MFDs based on those of other regions with better-defined input data. We find that a region's average density of roadway intersections per mile (both signalized and unsignalized) provides an adequate predictor for its critical production p_{crit} (veh/lane-hr), the production value that corresponds to its critical accumulation n_{crit}. Regions with higher intersection density have lower critical production. We use this relationship as well as $n_{jam} = 240$ to provide a rough estimate for a given region's MFD.

Appendix III: City-Wide Travel Demand Estimation

When estimating travel demand within, from, and to our cities of study, we relied on published data sources whenever possible (see Table 4). In many cases, however, the detailed nature of our simulation models required that we make additional assumptions. Below we outline the methods we used and major assumptions we relied on to supplement travel demand information when necessary. We focus specifically on the trip generation and distribution phases of our four-step model.

Trip Generation: Production and Attraction

To estimate city-wide travel on a given weekday, we first aggregate the areas within and surrounding each city into discrete zones. Each zone serves as a point from which trips are *produced* and to which trips are *attracted*. The traffic regions we define all serve as zones. Additionally, in order to estimate the numbers of trips that enter and exit each city, we also consider zones beyond city boundaries. In Seattle we take all census tracts in Snohomish, King, and Pierce counties as zones. In Chicago we consider the townships that make up the CMAP region. The 26 counties outside New York City and within the New York Metro Region serve as zones in our New York City travel model (see report "The Ins and Outs of NYC Commuting" (2019)). For each city, our choice of zones is informed by the aggregation level at which published survey data is reported.

We assume all trips serve one of the following purposes: travel to and from work, travel to and from school; shopping and errands trips; and social and recreational trips. Whenever possible, we use published data to estimate both trip production and attraction for each city zone and trip purpose. When data is unavailable, we use the trip rates reported in Table 3 to estimate the trip generation within each city zone by travel purpose. These trip generation rates are reported on a per-capita basis and do not reflect the myriad other factors that might affect travel, which reflect the sociodemographic characteristics of the traveler and the distribution of land uses within the city zone.

Trip Distribution: Gravity Model Form and Parameters

Once we have estimates for the numbers of trips produced from and attracted to each zone, we approximate the numbers of trips travel from each origin to each destination for each travel purpose. This step is *trip distribution*. Numerous factors affect the likelihood of a given trip, generally related to the ease of travel between destinations, the presence of competing opportunities, and extenuating circumstances such as weather, for example. In the absence of trip distribution data, we posit that trip volumes are a product of three factors: the *emissivity* of the origin, the *attractiveness* of the destination, and the *ease of travel* between them. Gravity models, one of the most common trip distribution models, assume that trip volumes are directly proportional to the number of trips produced in the origin, directly proportional to the number of trips attracted by the destination, and inversely proportional to the cost of travel between these zones. We use Equation 3a to estimate the number of trips $T_{i,j}^{p}$ taken between a given origin region $i \in Z$ and destination $j \in Z$ for trip purpose p, where P_i^p denotes the trip production of the origin and A_j^p the attraction of the destination. Travel impedance function $F_{i,j}^{p}$ provides the travel impedance between these regions.

$$T_{i,j}^{p} = P_i^p \frac{A_j^p \cdot F_{i,j}^p}{\sum_{j' \neq j \in Z} A_{j'}^p \cdot F_{i,j'}^p} \tag{3a}$$

We use Equation 3a, a doubly-constrained gravity model, to estimate trip distribution in cases where both trip production and attraction are known. When only trip production is estimated, we use a singly-constrained gravity model, provided in Equation 3b.

$$T_{i,j}^{p} = P_i^p \frac{F_{i,j}^p}{\sum_{j' \neq j \in Z} F_{i,j'}^p} \tag{3b}$$

Both forms of the gravity model employ travel function $F_{i,j}^p$, reported in Equation 4. The subsequent travel impedance value is determined by the travel distance between the origin and destination zones $t_{i,j}$, as well as parameters a and b, which together represent the typical traveler's sensitivity to travel time. The parameter values we used for each city are reported in Table 10. We note that travelers in the New York region are especially sensitive to travel distance, more likely to travel to destinations within their own borough or neighborhood.

$$F_{i,j}^p = t_{i,j}^b \cdot exp\left(c \cdot t_{i,j}\right) \tag{4}$$

Table 10. Gravity model travel impedance function parameters.

City	Parameter	Value	
		Work Trips	Non-Work Trips
Seattle, WA	b	-0.503	-3.993
	c	-0.078	-0.019
New York, NY	b	-6.000	-8.000
	c	-0.01	-0.008
Chicago, IL	b	-0.503	-3.993
	c	-0.078	-0.019

We tuned the parameters in Table 10 by comparing the origin-destination trip volumes the subsequent models produced against known values provided in survey data. The forms of each trip distribution function as well as preliminary gravity model parameter values were informed by National Academies of Sciences, Engineering, and Medicine NCHRP Report 716 (2012).

By repeatedly solving Equation 3a or 3b, we create a *trip matrix*, which denotes the numbers of trips taken between each pair of zones for each travel purpose.