National Impacts of E-commerce Growth: Development of a Spatial Demand Based Tool

August 2022

A Research Report from the National Center for Sustainable Transportation

Miguel Jaller, University of California, Davis
Runhua (Ivan) Xiao, University of California, Davis
Sarah Dennis, University of California, Davis
Daniel Rivera-Royero, University of California, Davis
Anmol Pahwa, University of California, Davis

National Center for Sustainable Transportation

UC DAVIS Institute of Transportation Studies

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
NCST-UCD-RR-22-33	N/A	N/A

4. Title and Subtitle
National Impacts of E-commerce Growth: Development of a Spatial Demand Based Tool

5. Report Date
August 2022

6. Performing Organization Code
N/A

7. Author(s)
Miguel Jaller, Ph.D. https://orcid.org/0000-0003-4053-750X
Runhua (Ivan) Xiao, MSc. https://orcid.org/0000-0002-9676-8334
Sarah Dennis, MSc. https://orcid.org/0000-0002-2169-5046
Daniel Rivera-Royero, MSc. https://orcid.org/0000-0003-2137-5664
Anmol Pahwa, Ph.D. Candidate https://orcid.org/0000-0002-9431-3168

8. Performing Organization Report No.
UCD-ITS-RR-22-44

9. Performing Organization Name and Address
University of California, Davis
Institute of Transportation Studies
1605 Tilia Street, Suite 100
Davis, CA 95616

10. Work Unit No.
N/A

11. Contract or Grant No.
USDOT Grant 69A3551747114

12. Sponsoring Agency Name and Address
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology
1200 New Jersey Avenue, SE, Washington, DC 20590

13. Type of Report and Period Covered
Final Research Report (October 2020 – December 2021)

14. Sponsoring Agency Code
USDOT OST-R

15. Supplementary Notes
DOI: https://doi.org/10.7922/G25B00SM
Dataset DOI: https://doi.org/10.25338/B89H0F

16. Abstract
This project aims to study the impacts of e-commerce on shopping behaviors and related externalities. The objectives are divided into five major tasks in this project. Methods used include Weighted Multinomial Logit (WMNL) models, time series forecasting, and Monte Carlo (MC) simulations. The American Time Use Survey (ATUS) and the National Household Travel Survey (NHTS) databases are used for identifying the independent and dependent variables for behavioral modeling. At the same time, we collected all MSA population data from the U.S. Census Bureau and combined the shares of each variable from ATUS to generate a synthesized population, which serves as input into the MC simulation framework together with the behavioral model. This simulation framework includes the generation of shopping travel parameters and the calculation of negative externalities. We do this to estimate e-commerce demand and impacts every decade until 2050. The results and analyses provide information that supports the generation of shopping travel and the estimations of a series of negative externalities using MC simulation, which includes shopping travel parameters, last-mile delivery parameters, and emission rate per person. For different parameters, a unique probability distribution or a regression relation is obtained for different MSAs, and this distribution is fed into the subsequent MC simulation. Finally, we simulated shopping behaviors for synthesized populations (until 2050) and to estimate the expected negative externalities. The MC simulation generates aggregate average vehicle miles traveled (VMT) and emissions (negative externalities) for different shopping activities in the planning years and different MSAs.

17. Key Words	18. Distribution Statement
E-commerce; shopping behavior; externalities; forecast; Monte Carlo simulation	No restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	78	N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Disclaimer

Acknowledgments

This study was funded, partially or entirely, by a grant from the National Center for Sustainable Transportation (NCST), supported by the U.S. Department of Transportation (USDOT) through the University Transportation Centers program. The authors would like to thank the NCST and the USDOT for their support of university-based research in transportation, and especially for the funding provided in support of this project.

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Institute of Transportation Studies, University of California, Davis

TABLE OF CONTENTS

List of Tables

List of Figures

National Impacts of E-commerce Growth: Development of a Spatial Demand Based Tool

EXECUTIVE SUMMARY

Overall Objectives of Forecasting Tool

The intensity of last-mile delivery has been changing in the last decades because of the emergence of e-commerce, which has reshaped the way we shop. The growth of e-commerce prevails a potential of fewer in-store purchases, causing a cascading effect in today's retail market resulting in small and large stores closures throughout the U.S. These closures take away local availability, which can potentially accelerate online shopping. This project addresses the question of how the potential transportation related effects from these shifts will be, by analyzing societal aspects resulting from online shopping behaviors. The next important question is how much will e-commerce grow, where, and what would be the expected impacts to the transportation system? As supported by previous studies, there are geographical impacts on the likelihood of online shopping (e.g., urban vs. rural, west coast, large metropolitan statistical areas-MSA), we do not expect to have homogeneous impacts across the country. Therefore, the objectives of this project are to estimate location and temporal specific consumer shopping behavioral models; analyze trends in online shopping during the last decade through time series analyses; identify and synthesize population growth forecasts; and develop scenarios to quantify potential impacts on emissions and transport activity due assumptions on penetration levels, maturity, and different levels of technology used (e.g., electrification, rush deliveries, crowdshipping and automation/ efficiency improvements).

The objectives were divided into five major tasks. The tasks use different combinations of methods to enable the prediction of e-commerce shopping behavior for each MSA of interest at the individual level as well as the quantitative calculation of externalities. Methods used include Weighted Multinomial Logit (WMNL) models, time series forecasting, and Monte Carlo (MC) simulations. The American Time Use Survey (ATUS) and the National Household Travel Survey (NHTS) databases are used for identifying the independent and dependent variables for behavioral modeling. At the same time, we collected all MSA population data from the U.S. Census Bureau and combined the shares of each variable from ATUS to generate synthesized populations for each MSA, which serve as inputs into the MC simulation framework together with the behavioral models. This simulation framework includes the generation of shopping travel parameters and the calculation of negative externalities. We do this to estimate e-commerce demand and impacts every decade until 2050.

Empirical Results

We built and validated the WMNL behavioral models for different MSAs with specific sets of model coefficients that can be used to predict shopping behavior for a synthesized population. In the WMNL model, the dependent variable considers four categories, namely "No shopping", "In-store shopping", "Online shopping" and "Both shopping" during a regular day. The results of the WMNL models vary across MSAs, as reflected by the fact that different coefficients of variables are positive in some MSAs and negative in others. In general, however, female, high education, and low to moderate age group are the positive influences that make the respondents choose the online and/or both shopping. Four different population growth scenarios are specified with the combinations of high/moderate independent variable market share time series prediction and projected population. Moreover, the models are validated by the synthesized populations for the planning years, resulting in around 2% in the errors of dependent variable market share predictions (considering the historic ATUS data)

The results and analyses provide information that supports the generation of shopping travel and the estimations of a series of negative externalities using the MC simulation, which includes shopping travel parameters, last-mile delivery parameters, and emission rates per vehicle/person. For different parameters, a unique probability distribution or a regression relation is obtained for different MSAs, and this distribution is fed into the subsequent MC simulation.

Finally, we simulated shopping behaviors for synthesized populations (until 2050) and to estimate the expected negative externalities. The MC simulation generates aggregate average vehicle miles traveled (VMT) and emissions (negative externalities) for different shopping activities in the planning years and different MSAs. The six selected MSAs are New York City (NYC), Los Angeles (LA), Chicago, Washington D.C. (DC), San Francisco (SF) and Dallas. In all the tasks, the general findings include:

- Heterogeneous effects are shown in the MSA-wise WMNL models. The shopping choices: in-store shopping, online shopping, and both shopping have different influencing factors in different WMNL models. For in-store shopping behavior, age, gender, income, and mobility difficulties are all significant influencing factors, while different categories of independent variables have different positive and negative influences in different MSAs. For NYC, Chicago, and DC, female was a significant factor in making in-store shopping behavior more likely, while LA and Dallas showed a negative effect. In contrast, the odds ratio of in-store shopping for young adults with high income is less than 1, which means that these two factors may be positive influences on online shopping.
- For most MSAs, factors such as living in an MSA size greater than one million, middle to high income, retired/not in the workforce, and highly educated women are positive influencers of online shopping. However, there are differences, and for LA, Chicago, and Dallas, people living in areas with MSA size less than one million are more likely to choose online shopping.
- There is some correlation between the behavior of both shopping and online shopping, though small sample sizes hinder our judgment of the true trend. Therefore, it is not possible to compare the magnitude of the coefficients for online and both shopping.
- From the model validation results of the six MSAs, the distribution of DV market shares simulated using synthesized population differs from the actual data by less than 2%,

which is within an acceptable range. Therefore, it is confirmed that these WMNL models can be used for the subsequent MC simulations.

- Similarly, the number of stops per shopping tour (any travel tour with a shopping activity, regardless of main tour purpose) had a maximum probability of 1. Only minor differences were found in the parameter distributions of the individual MSAs, and the overall distribution trends were similar. Among the six MSAs, LA and Dallas have a higher shopping tour length and a higher proportion of private car trips. NYC, on the other hand, has the highest proportion of public transportation shopping trips among these MSAs.
- In the process of calculating the parameters for adjusting the coefficient to obtain the last-mile delivery, we found a high degree of overlap between the population activity shape-center and the transportation firm distribution shape-center for LA. This is certainly an important infrastructure support for the future development of e-commerce.
- The results of the delivery tour length distribution also tell us that the MSA with a higher overlap between LA, the shape center, has a shorter average delivery distance. Therefore, we believe that shortening the distance between population and transportation establishment centroids is one of the keys to reduce the average delivery distance, and ultimately the overall VMT.
- Comparing in-store shopping, the increase in daily VMT associated with online shopping is clearly greater. However, due to the base year (2020) condition, the market share of in-store shopping is still the largest in 2050. The calculation of various kinds of emissions shows that the emissions of NOx, PM10 and PM2.5 all decreased, except for CO2 and SO2 which increased slightly in the planning year.
- The MSAs of Chicago, SF, and Dallas are projected to have rapid population growth in 2050, but the change in shopping behavior varies across these MSAs. Despite the population growth, the change in shopping behavior in different regions shows that SF and NYC are more receptive to pure online shopping, while people in Dallas and LA are more inclined to in-store and both shopping behavior.
- The population growth in the planning years results for DC is essentially unchanged for the planning years, meaning that the total population of the region is not likely to grow in the future. As a result, there is shrinkage in shopping behavior in the simulation results. As a result, the total amount of pollutant emissions will decrease in the future.

Inevitably, the methods this project adopts has some limits throughout, which are based on certain assumptions that might bring some inaccuracy of the modeling, prediction, and simulation results. First, the process of variable selection is manual, which means that we must specify a unique WMNL model for each of the MSAs. Inherently, the specifications of WMNL models cannot be integrated into the spatial demand-based forecasting tool with automatic processes. To solve the problem, a diverse collection of supervised machine learning methods can be done to model and predict the shopping choices of individuals based on certain criteria. Moreover, the considerations about future shopping travel and last-mile delivery parameters assume that the internal population and logistics infrastructure maintain unchanged or slightly changed in the planning years. This may cause the problem that the forecasting tool does not consider the internal socio-demographic and infrastructure changes that may affect the overall shopping choices among the people, although the project has already considered the adoption trends and the changes of socio-demographic statistics at the macroscopic level of the MSAs. In the future, time series forecasts on a more detailed geographic areas of an MSA is preferable, such as ZIP codes and census tracts, which would enable us to understand the temporal and spatial changes in an MSA for the planning years and to integrate these into our forecasting tool when simulating the negative externalities. Also, we found that transportation mode has an impact on shopping behavior. In this project, we only study the aggregate data at the MSA level. Considering the future development of emerging technologies such as electrification and automated vehicles, the structure of transportation modes may see some big changes, not only about consumers' shopping travels, but also inseparable from the logistics and distribution industry. The emergence of new delivery technologies and methods, such as drones, self-driving trucks, and front-end warehouses, will significantly change the layout of the existing logistics industry infrastructure and indirectly affect people's shopping choices.

Last but not least, there is another important issue that can be important for future work, which is that the externality simulation results do not display a clear and significant trend of e-commerce growth. In the results, we find that the externalities generated by online and both shopping will increase in 2050, but the total market share will be less than 20% combined. This huge gap makes us think about finding the favorable factors that can really promote e-commerce development and refine the models in a subsequent tool development process.

Introduction

Last-mile distribution is one of the most costly and highest polluting segments of the supply chain in which companies deliver goods to the end consumers (e.g., business-to-business or business-to-consumer transactions). Last-mile deliveries are often inefficient due to failed delivery attempts, short time windows, inefficient routing, traffic congestion, and access to the curb, among other factors (1). The intensity of last-mile delivery has been changing in the last decades because of e-commerce, which has reshaped the way we shop. A study by UPS (2017) revealed that, in 2017, 36% of shopping activities (including search and purchase) are conducted via multiple channels, 43% solely online, and only 21% are done in-stores (2). In the same year, e-commerce retail sales in the US were $448.3 billion, accounting for 8.8% of the total retail sales, compared to 5.3% in 2012 (3). They are about 10-12% today, with annual growth of around 15% in the last five years, and significantly increasing during the COVID-19 pandemic in 2020. Moreover, around 33% of internet users in the U.S shop online at least once per week, another 33% buy online once per month, and e-commerce affects almost 80% of all shopping. Furthermore, a study suggests that the more often people buy online, the less likely their chances of making a trip to purchase in-store, increasing online shopping propensity (4). There is a potential of fewer in-store purchases, which is causing a cascading effect in today's retail market resulting in small and large stores closures throughout the U.S. These closures take away local availability, which can potentially accelerate online shopping. There were forecasts, before COVID-19, that between 20-25% of all shopping malls will close in the next 5 years (5).

Without analyzing societal aspects resulting from online shopping behaviors, or the potential effects on a segment of the economy (e.g., retail jobs), a key question is about the potential transportation related effects from these shifts. In general, there would be an increase in the number of commercial deliveries to urban areas, at increased numbers to what is today. Depending on the substitution level effect between deliveries and shopping trips, and vehicle technologies, the net outcome could be positive if the activities at the origin (e.g., facility location, efficiency), on-route (e.g., distribution vehicles, routes), and the destination (e.g., curbside access, parking, alternative delivery points) are optimized. Studies estimate that e-commerce could have the potential of large reductions in distance traveled (54% to 93%) as well as in GHG emissions (18% to 84%) at full substitution. However, (6) argues that assuming full substitution is overestimating such benefits, so (6) proposed a more realistic approach considering demographics and customer behavior variables to improve these estimations. The next important question is how much will e-commerce grow, where, and what would be the expected impacts to the transportation system? (6) showed evidence that there are geographical impacts on the likelihoods of online shopping (e.g., urban vs. rural, west coast, large Metropolitan Statistical Areas, MSAs), therefore we do not expect to have homogeneous impacts across the nation. However, forecast estimates that e-commerce will be over 35% of retail sales in the next decade, depending on changes in consumer behaviors, and changes in population numbers and concentrations, particularly in large growing areas (6). Nevertheless, the impacts of e-commerce are still far from being completely understood, and there are no tools available to estimate the impacts or forecast online shopping demand at the national, regional, and city levels. Therefore, concentrating in the US, the objectives of this project are to estimate the location and temporal specific consumer behavior purchasing models; analyze trends in online shopping during the last decade through time series analyses; identify and synthesize population growth forecasts; and develop scenarios to quantify potential impacts on emissions and transport activity due assumptions on penetration levels, maturity, and different levels of technology used (electrification, automation, shared mobility).

This report is organized as follows. The next section provides a review of the literature discussing key finding related online shopping and shopping behaviors; followed by a description of the methods used in the different tasks of the project. The third section discusses the data, and the fourth section describes and discusses the empirical results. The report ends with a conclusions section.

Literature Review

This section provides a comprehensive literature review focusing on e-commerce penetration forecasts, population growth, changes in shopping behaviors, and last-mile distribution. E-commerce sales have been increasing in the last few years, for instance, the retail e-commerce sales worldwide in 2020 (4280 US Billion Dollars) were more than two times higher than in 2014 (1336 US Billion Dollars), and it is expected to increase at a regular pace in the future based on Statista (7). In 2019, e-commerce sales amounted to about 10% of the total retail sales (3) and have continued to grow. A consequence of such changes in individual shopping behaviors is the considerable transformation of commodity flow and urban goods distribution. Based on (UPS, 2017), 36% of one's shopping activities (search and purchase) are conducted via multiple channels, another 43% are conducted solely online, and only 21% are conducted in stores (2). One interesting question is what is the role of e-commerce in the shopping behavior of consumers? In other words, is the role of e-commerce to substitute, complement or modify the in-person shopping behavior (8). In general, most of the papers in the literature found a complementary effect between online shopping and in-person shopping (9–11). For instance, (12) and (13) consider that there is a positive relationship between online shopping and in-person shopping. In other words, the more people buy online the more they buy in-person. However, (13) also considers that when people buy more in person, it is less likely to do it online, this means that an asymmetric relationship between both consumer behaviors. On the other hand, (4) and (14) consider that online shopping works as a substitute for in-person shopping. (11) considers that the low cost of acquiring information online can stimulate demand. This latter is an additional behavior effect to substitution and complementary behavior between in-person and online shopping. Note that in general e-commerce modifies society's shopping behavior.

Note that one of the main inputs for the projections of the penetration of e-commerce in time are the population projections and their profile. In the USA, there are several population projections but one of the most complete because of the level of details is given by (15). It provides a county-level population projection by age, sex, and race in five-year intervals for the period 2020-2100 for all U.S. counties. (15) uses autoregressive integrated moving average (ARIMA) models as inputs into Leslie matrix population projection models and controls the projection to the shared socioeconomic pathway. (16) explains how to project population based on sex and age by using the Hamilton-Perry method, which is a variant of the cohort-component projection technique. In general, US population projections are limited to the projection based on socio-demographic information such as age, sex, and/or race (17–19). Usually, such projections let aside variables like education, and income, among others (20).

For analysis related to freight traffic demand estimation, (21) used the U.S. National Household Travel Survey (NHTS) data to develop a binary choice model and a right-censored negative binomial model to predict the delivery frequency as a function of the characteristics of the individual, household, and the urbanization. (22) developed a household-level e-commerce model, which predicts the participation in e-commerce and the ratio of delivery to on-site shopping by also using household and accessibilities characteristics as the independent variables. Then, (23) estimates parcel delivery truck tours for POLARIS by using the model in (22). (6) used data from the 2016 American Time Use Survey (ATUS) to predict the shopping behavior of the individual (no shopping, in-store, online, or both channels shopping). (24) also estimated a probability model by using data collected from a survey carried out in Rome by using the same choices as (6).

Shopping behaviors may depend on socio-economic factors, for instance, (6,12,25) coincide that the high-income female population has a higher probability of shopping in person. While (6) considers that the more children in the house and the older the individual, is more likely to do in-person shopping. Additionally, the higher the education the greater the chances of shopping in person according to (6,11,26). Especially if the individual lives in a highly populated region. Additionally, (6) found that the likelihood of in-person shopping has a spatial and temporal pattern. For instance, fall has a higher chance of in-person shopping, while some small cities in the north- and south-eastern are more likely to shop in-store than the rest of the US. On the other hand, females have a higher propensity of shopping online, but if such female individual lives in a highly populated city such probability decreases. As well as in in-store shopping, the more the children and the higher the education, the greater the chances of shopping online. Additionally, based on (6), fall season has the highest chance of online shopping, and people living in western highly populated cities have a higher propensity of shopping online.

The e-commerce supply chain has characteristics with the potential of impacting the environment, however, some studies have analyzed these externalities from freight movement in the context of online shopping (6,27–30). Note that e-commerce delivery trucks use optimal routes, therefore it is expected a reduction of the negative impacts of shopping on the environment, because this delivery strategy may be more sustainable than private car travels (6). For instance (28,30,31) found a potential reduction of the negative externalities associated with transportation. (28) found a reduction of vehicle miles traveled (VMT) by 54-93% and emission by 18-87%, when comparing the e-grocery versus private car trips through simulation. At the same pace, (31) identified a reduction of VMT by nearly 20% by considering a market penetration of 50%. (6) found that VMT decreases by around 7.2% when the population uses both shopping channels (in-person and online) and 87.6 % for online shopping if the online platform becomes the dominant choice. However, as trucks are relatively heavy emitters of NOx, NOx emissions increase around 24% due to e-commerce. These studies suggest that with a sizeable market share, sustainable last-mile operations, and consumers substituting towards online shopping, e-commerce can manifest significant reductions in the negative externalities of freight transportation. Sizeable market share is indeed an essential requirement for e-commerce to function sustainably. Notice that the 2016 ATUS data shows only 4% of daily shopping activities to be conducted online, the above studies assumed some level of market penetration for e-commerce, thereby exaggerating benefits from e-commerce.

Based on the Pew Research Center (2018) report, internet is reaching saturation levels, however, e-commerce is far from being saturated (32). This presents a huge scope for e-retailers to further expand. On this, e-retailers make lucrative offers to their consumers to achieve larger market shares, such as free shipping, same-day, and 1-hr/2-hr expedited (rush) deliveries. Note that the positive effects expected because of trucks route optimization can be diminished by such strategies, because such strategies may cause negative externalities in society. For instance, to provide an acceptable level of service due to rush deliveries, e-retailers ship packages at lower consolidation levels leading to higher frequencies of shorter tours, by increasing distances driven, costs, and, emissions (33–36). In other words, the economic and environmental benefits from shopping online are banished because with reduced capacities, and shorter time delivery windows, the transport of goods out of these facilities uses smaller vehicles with reduced loads (37). For instance, (30) confirmed the strong correlation between time-window length and emissions, while (6) quantified a 180% increment in emissions from shorter time windows.

Another strategy used by e-retailers to pursue larger market shares is to offer free returns, (38) argues that return rates range between 25% and 45%, and are exceptionally high in the apparel industry. Usually, the tendency among online shoppers to return products is led by low satisfaction because of the lack of information about the product. For instance, 40% of online shoppers order multiple sizes of the same product and then return all but one (39). The consequences of free return seem similar to the rush deliveries, e.g., high VMT, costs, and emissions. However, not providing free returns puts retailers at the risk of losing their consumers, and such additional operational costs are inevitable to maintain an acceptable satisfaction level of consumers. Hence, in general, such strategies make last-mile more demanding in economic and environmental sustainability terms and have a negative consequence on the efficacy of last-mile distribution. Note that the studies highlight the importance of stakeholders, and consolidation of demand and deliveries is required to foster sustainability in the urban freight system.

The papers related to e-commerce demand models mainly focuses on the characteristic of the individual, and the delivery options are not fully considered. However, such analysis has been carried out by (40–44), (40,42,43,45,46) estimate a discrete choice model that considers delivery preferences in the US by focusing on different products. (44) develops an ordered logit model that considers market and household-level variables, as well as the delivery fee. (45) and (46) developed OLS regression models to predict an average order size considering delivery fee.

Overall, the sustainability of e-shopping and shopping behaviors have received increased attention in the last few years, yet there is a lack of forward looking research into what will be the level of shopping and their impacts in the future.

Methods

The tasks of this project employ different combinations of methods to enable the prediction of e-commerce shopping behaviors for each MSA of interest at the individual level as well as the quantitative calculation of externalities. Methods used include Weighted Multinomial Logit (WMNL) models, time series forecasting, and Monte Carlo (MC) simulations, which are utilized throughout Task 1 to Task 5. Figure 1 shows the general methodology through which those methods are used to perform the MC simulation for each MSA in our project as the main goal.

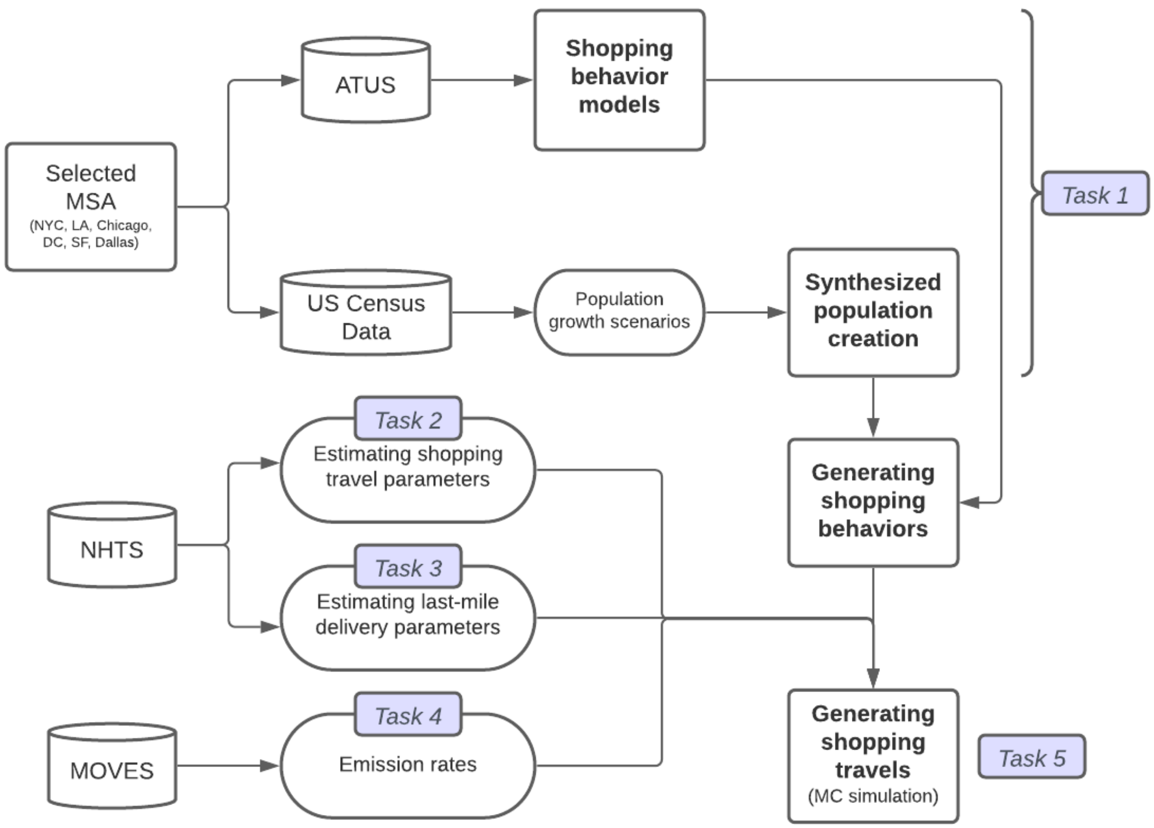

Figure 1. General methodology.

In the flow, the ATUS database is employed as the data source for identifying the independent and dependent variables for behavior modeling. At the same time, we collect all MSA population data from the U.S. Census Bureau and combine the shares of each variable from ATUS to generate the synthesized population, which will be input into the MC simulation framework together with the behavior model. This simulation framework includes the generation of shopping travel parameters and the calculation of externalities.

Task 1: Shopping Behavior Modeling

The general goal of the task is to build and validate behavior models for different geographic areas, which are the six specified MSAs in our project, with specific sets of model coefficients that can be used to predict shopping behavior for a synthesized population.

In this project, the classification of shopping behaviors is consistent with Jaller & Pahwa (2020), which represents the dependent variable with totally four categories, namely “No shopping”, “In-store shopping”, “Online shopping” and “Both shopping” (6). The definitions include: “No Shopping” means individuals who did not perform any shopping activity in a given day; “In-Store” is all of the individuals who exclusively performed in-store shopping; “Online” is those who shopped exclusively online, and “Both” includes individuals who shopped in-store as well as online. Descriptive statistics of these four shopping behaviors using ATUS data are described in the next section, and the process of identifying them is as follows: 1) collecting the "activity" and "location" variables from the activity logs in the ATUS data; 2) identifying the single activity of shopping behavior of individuals based on the combination of activities and locations in Table 1; and Table 3 count the number of shopping activities and classify them into the four aforementioned categories of shopping behavior. For example, if an individual has zero counts of shopping activities within a single day, then “no shopping” behavior will be labeled to the individual. Likewise, if an individual has both counts of in-store and online shopping activities, then “Both” will be labeled. The team selected the ATUS data as was the only available dataset that contains information about potential shopping channel, and trip composition across the US. Other data sources such as the NHTS are used for model trip distances and travel behaviors.

Table 1. Shopping activities classification using activity and location data from ATUS.

Shopping activity for a single activity record	Activity	Location
Shopping activity (including in-store and online)	Grocery shopping Purchasing food (not groceries) Shopping except groceries, food, and gas Comparison shopping Shopping, N.E.C. Researching purchases, N.E.C. Consumer purchases, N.E.C.	Anywhere Except purchasing food (not groceries) at any place other than grocery store, other store/mall, post office, restaurant or bar, and other place
In-store shopping	Grocery shopping Purchasing food (not groceries) Shopping except groceries, food, and gas Comparison shopping Shopping, N.E.C. Researching purchases, N.E.C. Consumer purchases, N.E.C.	Grocery store Other store/mall Post office Restaurant or bar Other place
Online shopping	Grocery shopping Shopping except groceries, food, and gas Comparison shopping Shopping, N.E.C. Researching purchases, N.E.C. Consumer purchases, N.E.C.	Anywhere other than: Grocery store Other store/mall Post office Restaurant or bar Other place

WMNL model

With the classification of shopping behaviors done, the dependent variable of the shopping behavior modeling is determined. We model the shopping behaviors as a WMNL model with the alternatives being: to not shop at all (No Shopping); to shop exclusively in-store (In-store); to shop exclusively online (Online), and to shop in-store as well as online (Both) (see choices in Figure 2). To correct for over-representation in the WMNL model, we use the "WT20" variable reporting the ATUS respondent probability weights as the weight terms in the model.

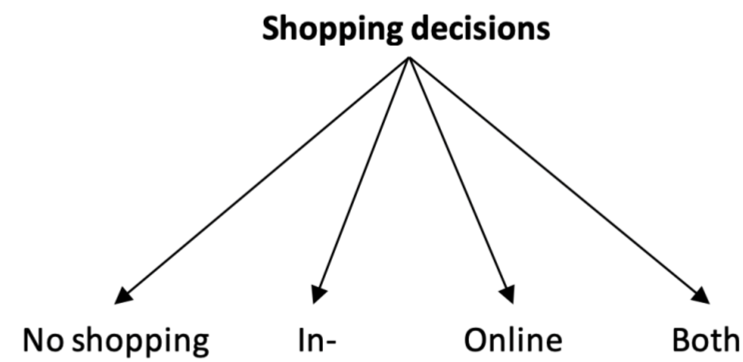

Figure 2. Shopping decision as multinomial logit model.

The WMNL, as a form of the generalized linear model, nominates one of the response categories of the response variable as a reference level and calculates log-odds for all other categories relative to the reference level. In the WMNL model, we assume that the log-odds of each response follow a linear model, which is shown in Equation (1):

$$\eta_{ij} = \log\left(\frac{\pi_{ij}}{\pi_{iJ}}\right) = \alpha_j + (w_i \cdot x_i)\beta_j \tag{1}$$

where $\frac{\pi_{ij}}{\pi_{iJ}}$ is the odds ratio (OR) that an observation i falls in category j as opposed to the reference level J, α_j is a constant term, and β_j is a vector of regression coefficients, for $j = 1,2, \ldots, J-1$. w_i is the weight term for observation i . The probabilities of the WMNL model can be written as

$$p_{ij} = \frac{\exp(\eta_{ij})}{\sum_{k=1}^{J} \exp(\eta_{ik})} \tag{2}$$

Note that Equation (2) will automatically yield probabilities that add up to one for each observation.

Generating synthetic populations

The generation of synthesized populations covers the year 2020, 2030, 2040 and 2050. The synthesized population process has two main uses, one is to validate the validity of each specified WMNL model, and the other is to be used for subsequent MC simulation and the calculation of externalities. For example, for a given MSA, we use the specified 2020 WMNL model to predict the shopping behavior of the synthesized 2020 population. If the predicted dependent variable market share is similar to the existing data, we consider the validation of the model to be successful. For the MC simulation, we are interested in the overall distribution of the shopping behavior of the synthesized population in future years. The market share of shopping behaviors and resulting externalities change due to different population growth scenarios.

We attribute the future population growth to two developments, one is the future change in the socioeconomic conditions of the region, reflected in the change in the market shares of the different independent variables, and the other is the future growth of the total population of the region. We delineate two growth patterns, a moderate pattern, which implies little change in future socioeconomic conditions from the present and no significant growth in total population, and a high growth pattern, which implies a significant growth in both socioeconomic conditions and total population projection. After permutation, Table 2 shows the four population growth scenarios that we have delineated.

Table 2. Population growth scenarios specification.

Scenario No.	IV Market Share Time Series Prediction	Total Population Projection
1	Moderate	Moderate
2	Moderate	High growth
3	High growth	Moderate
4	High growth	High growth

Note: IV = independent variables specified in WMNL models

Specifically, the formulation of the scenario contains two parts, one is the time series prediction of the share of the independent variable of the WMNL model, and the other is the projection of the total population. For IV market share prediction, we use an ARIMA time series model. Market shares within each variable group for the years 2003-2020 are used as inputs to the model. We select the parameters that make the best prediction accuracy of the model through an automatic parametric process and output the IV market shares for the years 2030, 2040, and 2050. For the total population projections, we refer to the Shared Socioeconomic Pathways (SSP) population projections for different MSAs and selected the population projections for 2020, 2030, 2040, and 2050 for use in this project (47).

Finally, with the specification of WMNL models and the creation of synthesized populations for 2020, 2030, 2040 and 2050, we can validate the WMNL models for each of the MSA and to provide inputs for the following MC simulation for externalities related to shopping behaviors.

Task 2: Shopping Travel Parameters

This project extends the previous work of (6) to study the impacts of e-commerce freight transportation on the environment of the six MSAs in terms of the negative externalities, particularly vehicle miles traveled (VMT) and emissions (6). The goal of Task 2 was to obtain travel parameters related to in-store shopping behavior from NHTS data. The shopping travel parameters include shopping tours per person (p_1), stops per shopping tour (p_2), shopping tour length associated with stops (p_3), the share of in-store shopping activities in a shopping tour (p_4), and major shopping travel mode (p_5).

For an individual, the emissions (EM) related to in-store shopping travel in a single MC simulation is calculated as

$$EM_{in-store} = \sum_{p_1} \big(p_3 p_4 ER(p_5)\big) \tag{3}$$

$$p_3 = D(p_2) \tag{4}$$

Where p_1 is the number of shopping tours of an individual; p_2 is the stops per shopping tour; p_3 is the tour length in miles; p_4 is the share of in-store activities in a tour, and p_5 is the mode of shopping travel with the longest share of tour length. ER is a function that calculates the average emission rate for a specific travel mode. D is the polynomial regression relationship between p_2 and p_3 with an optimal coefficient of determination.

Task 3: Last-Mile Delivery Parameters

Different from in-store shopping travels, online shopping-related travel for an individual is considered as part of commercial delivery tours to bring the goods to the individuals' residences (48). Thus, we can decompose the externalities generated by everyone's online shopping activity from a complete commercial delivery tour for a specific MSA. Consistent with (6), the parameters used for delivery tours are: 1) delivery tour length (p_6), and 2) stops per tour (p_7).

For an online shopping activity of an individual, the emission (EM) related to online shopping truck travel in a single MC simulation is calculated as

$$EM_{online} = \frac{p_6}{p_7} ER(trucks) \tag{5}$$

Where p_6 is the delivery tour length in miles, which follows a Weibull distribution, and p_7 is the stops per delivery tour that follows a triangular distribution (6). $ER(trucks)$ is the average emission rate for commercial trucks.

Task 4: Emission Rates

We use emission rates developed by the California Air Resource Board (2018), used in this study to estimate greenhouse gases (GHG) and criteria pollutants generated from shopping-related travel. Additionally, we compiled the emission rates from EPA's Motor Vehicle Emission Simulator (MOVES) model for different MSAs and planning years.

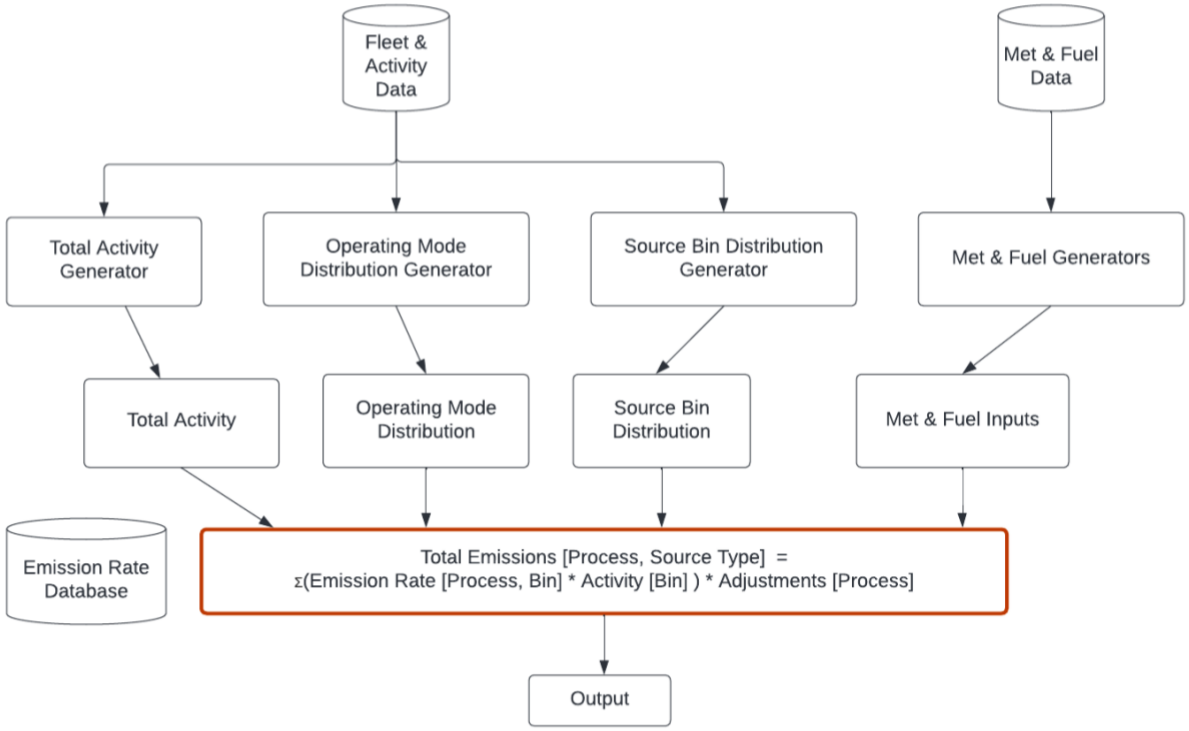

Figure 3. Emission estimation process in MOVES (49).

MOVES is a state-of-the-science emission modeling system that estimates emissions for mobile sources at the national, county, and project level for criteria air pollutants, greenhouse gases, and air toxics (50). Figure 3 shows the process for estimating emission rates. We select five types of pollutants in this project, namely CO_2, NOx, SO_2, PM10 and PM2.5. Emission rates for all the measured pollutants emitted (unit: grams) are averaged within each vehicle type by distance in miles.

Task 5: Generating Shopping Travels and Deliveries: Monte Carlo Simulation

Starting with the generated synthesized population, the estimated shopping behaviors and finally the generated shopping travel in Task 1, we estimate the externalities from shopping behaviors. This entire MC simulation process generates replicates under specific population growth scenario for the six MSA. For each replicate, the process synthesizes the population by generating individuals in accordance with the socio-economic parameters in every MSA. After generating individuals and their attributes, the process uses the developed shopping behavior model from Task 1 to identify individuals who shop in-store, online, both and individuals who do not shop at all. The process then employs the travel statistics from Task 2 and Task 3 to simulate shopping-related travels. Using the emission rates from Task 4, the goal of this task is to finally conclude with the externalities from shopping for different MSA and planning years.

Data

This project makes use of three primary datasets: American Time Use Survey (ATUS), National Household Travel Survey (NHTS), and population projections. The use of this data, and several modeling efforts then produced two primary data outcomes from this study. These data are produced for six MSAs, including, New York City, Los Angeles, Chicago, Washington DC, San Francisco, and Dallas.

Population Projections

As previously described, Hauer generates georeferenced population projections for US counties according to sex, race, and age (15). These population projections cover 2020 through 2100, although this study uses population projections through 2050. Population projections are produced with respect to different Shared Socioeconomic Pathways (SSPs) (51). The SSPs define different social scenarios representing plausible evolutions of society and ecosystems (51). This study focused on population projections derived from SSP2, representing intermediate challenges (termed the “middle-of-the-road” outlook) (51).

American Time Use Survey (ATUS)

The project uses the 2004-2020 ATUS data to analyze shopping behaviors. ATUS is a time use study funded by the US Bureau of Labor Statistics (BLS), and logs the location and time of all daily activities for participating individuals in a survey day, providing information on time spent on detailed activities. ATUS data also contains key demographic variables and weights assigned to each respondent (to account for under- or over-representation), which can help discern the underlying behaviors. While there are many other commercial surveys that provide similar data, ATUS provides a large dataset that has been sampled in various U.S. cities for many years, and using ATUS data ensures scale, consistency, and validity of data acquisition.

The use of ATUS data is mainly focused on Task 1, where we specify shopping behavior models and extract dependent variable (DV) and independent variables (IV), the IV market shares for different MSAs. Table 3 shows the variables that comprise the WMNL models and their descriptive statistics in Task 3.

National Household Travel Survey (NHTS)

Conducted by the Federal Highway Administration (FHWA), the NHTS is the authoritative source on the travel behavior of the American public. It is the only source of national data that allows one to analyze trends in personal and household travel. It includes daily non-commercial travel by all modes, including characteristics of the people traveling, their household, and their vehicles (52). The project uses the 2009 and 2017 NHTS data, which are based on trip-based surveys, to extract shopping travel parameters and last-mile delivery parameters for different MSAs. Compared to the ATUS data, NHTS has the advantage of providing trip length in miles and transportation mode shares within a survey day. The previous study has also shown that the measurements of travel behaviors of a trip-based survey and a time use survey provide similar results in a satisfactory way (53). Therefore, the use of NHTS data is mainly focused on

Task 2 and Task 3. In this work, a shopping tour is considered any tour that involves any shopping activity, regardless of main trip/tour purpose. Extracting shopping tours from NHTS requires identifying trip chains; we developed scripts to convert the raw trip-based data to tour-based data.

Table 4 shows the numbers of trips and tours for each MSA. We can see that the MSA that generates the most shopping tours is Dallas and the least is Chicago, a difference of almost eight times. At the same time, it can be found that the proportion of shopping tours to the total number of trips in LA is the highest, with its average number of trips being the lowest one.

Table 3. Variables and descriptive statistics of ATUS data.

Variables		**Observation Counts**					
		NYC	LA	Chicago	DC	SF	Dallas
MSA Size	under 1M*	1128	417	252	126	848	38
	over 1M	9162	7875	5205	5118	3668	1075
Income	Poverty Level*	1890	1893	920	528	578	189
	Low	914	924	486	367	336	121
	Lower Middle	1131	1070	689	530	427	147
	Median	1522	1379	916	846	672	193
	Middle Middle	1214	923	657	731	635	140
	Upper Middle	1370	890	632	968	669	144
	High	1462	872	611	1046	902	148
Sex	Male*	4574	3760	2456	2266	2105	501
	Female	5716	4532	3001	2978	2411	612
Age	>71*	1331	928	657	536	457	126
	52-71	2914	2159	1486	1460	1225	303
	37-51	3231	2423	1653	1771	1442	322
	22-36	2105	1956	1277	1133	1035	279
	4-21	709	826	384	344	357	83
Education	No education*	18	50	7	7	13	2
	Primary	249	527	100	62	106	39
	Secondary	3604	2913	1803	1444	1053	354
	Graduate	6419	4802	3547	3731	3344	718
Employment	Employed*	6317	4840	3435	3585	2919	722
	Unemployed	546	504	299	209	252	42
	Not in labor force	3427	2948	1723	1450	1345	349
Diff. in Mobility	No difficulty*	6935	5562	3746	3709	2878	834
	Difficulty	250	215	105	104	78	26
Family Structure (mean values)		0.41	0.46	0.44	0.43	0.41	0.45
Total observations (unweighted)		68138	55188	36047	35049	29755	7507

Note: the descriptive counts of observations are unweighted from the ATUS data; * means that the category of the variable is the reference level in the ongoing WMNL models.

Table 4. Number of trips and tours with shopping activities from 2009 and 2017 NHTS data

MSA (CBSA code)	Number of trips	Number of tours	Avg trips per tour
NYC (35620)	81121	28740	2.823
LA (31100)	37923	14091	2.691
Chicago (16980)	14031	5024	2.793
DC (47900)	24619	8668	2.840
SF (41860)	35976	12437	2.893
Dallas (19100)	114866	40177	2.859
Total	308536	109137	2.827

Note: the statistics are from the NHTS day trip diary data files.

Empirical Results

The presentation of the results is divided into five sections, each of which corresponds to the tasks. In this project, a total of six MSAs were selected for the study: New York City (NYC), Los Angeles (LA), Chicago (CHI), Washington D.C. (DC), San Francisco (SF) and Dallas (DAL). We will present and describe the results of the entire simulation process in the order of the six MSAs above.

Task 1: Shopping Behavior Modeling Results

WMNL model specifications

Starting with the classification of defining the dependent variable that is used in the WMNL models, six WMNL model specifications are performed for each of the six MSAs. In the process, the datasets for the MSAs are weighted using the "WT20" variable, which is the weights representing sample distribution in the selected areas. We process the weighting using the same variable and standardization scale, so that the significances of coefficient estimates can be examined.

Table 5, Table 6 and Table 7 show the WMNL model results including the estimates of coefficients for the six MSAs. First, the three categories of dependent variables: in-store shopping, online shopping, and both shopping have different influencing factors in different MSA models. For in-store shopping behavior, age, gender, income, and mobility difficulties are all significant influencing factors, while different IV categories have different positive and negative influences in different MSAs. For NYC, Chicago, and DC, female was a significant factor in making in-store shopping behavior more likely, while LA and Dallas showed a negative effect. In contrast, the odds ratio of in-store shopping for young adults with high income is less than 1, which means we found that these two factors may be positive influences on online shopping. Moreover, for most MSAs, factors such as living in an MSA size greater than one million, middle to high income, retired/not in the workforce, and highly educated women are positive influencers of online shopping.

However, there are differences, and we find that for LA, Chicago, and Dallas, people living in areas with MSA size less than one million are more likely to choose online shopping. This may be due to the different distribution of business districts and shopping centers in these MSAs, as residents of distant suburbs in these three MSAs are more likely to choose online shopping due to the presence of long travel distances and/or congestion issues. This may also be due to the different distribution of commercial areas and shopping centers in these MSAs. Additionally, we note that there is some correlation between the behavior of both shopping and online shopping, while fewer observations hinder our judgment of the true trend. Therefore, it is not possible to compare the magnitude of the coefficients for online and both shopping.

Table 5. Weighted Multinomial Logit (WMNL) Model Results for NYC and LA

		NYC			**LA**	
Alternatives		**Weighted Count**	**Freq.**		**Weighted Count**	**Freq.**
No shopping		6990	0.672		4479	0.624
In-store		3188	0.307		2476	0.349
Online		135	0.013		150	0.0212
Both		87	0.00837		45	0.00636
Adj. McFadden R2						
Equally likely based			0.485			0.374
Market share based			0.022			0.011
Chi-square test w.r.t. market share model						
Chi^2 value			127.3***			88.3*
Variable		**Estimate, significance, and t-value (respectively)**			**Estimate, significance, and t-value (respectively)**	
		Ref: No shopping			Ref: No shopping	
	In-store	Online	Both	In-store	Online	Both
(intercept)	-15.239***	-37.084***	-47.087***	77.948***	-43.305***	-34.189***
	(-0.27)	(-0.48)	(-0.35)	(-0.13)	(-0.23)	(-0.06)
MSA Size: > 1 million	0.167	32.244***	24.993***	-0.13	-1.696***	12.882***
(Ref: < 1 million)	(-0.20)	(-0.48)	(-0.35)	(-0.12)	(-0.28)	(-0.06)
Income: Low	-0.188			-0.308**		
(Ref: Poverty level)	(-0.34)			(-0.13)		
Income: Lower Middle	0.598**			-0.670***		
	(-0.30)			(-0.11)		
Income: Median	-0.149	-0.126		-0.857***	32.536***	
	(-0.30)	(-0.99)		(-0.10)	(-0.18)	
Income: Middle Middle	0.109			-0.778***		18.000***
	(-0.30)			(-0.10)		(-0.17)
Income: Upper Middle	0.143		24.748***	-0.516***	32.088***	
	(-0.28)		(-0.56)	(-0.10)	(-0.20)	
Income: High	0.368	-0.16	24.099***	-0.484***	31.433***	16.957***
	(-0.27)	(-1.02)	(-0.57)	(-0.10)	(-0.22)	(-0.18)
Age: 52-71	0.126	-1.555		0.683***	0.452	10.845***
(Ref: > 71)	(-0.24)	(-0.96)		(-0.10)	(-0.31)	(-0.06)
Age: 37-51	0.844***	-0.123	-0.01	0.272**	2.076***	
	(-0.27)	(-0.96)	(-1.46)	(-0.12)	(-0.35)	
Age: 22-36	0.222		0.251	0.467***	0.974***	
	(-0.28)		(-1.30)	(-0.10)	(-0.37)	
Age: 4-22	0.078			-0.706***		
	(-0.36)			(-0.15)		
Sex: Female	14.647***	4.352***	-17.674***	-0.253***	3.192***	-1.499***
(Ref: Male)	(-0.16)	(-0.55)	(-0.22)	(-0.09)	(-0.22)	(-0.17)

Variable	Estimate, significance, and t-value (respectively) Ref: No shopping			Estimate, significance, and t-value (respectively) Ref: No shopping		
	In-store	Online	Both	In-store	Online	Both
Education: Primary	-42.484***	-41.133***		-78.276***		
(Ref: No education)	(-0.25)	(-0.41)		(-0.16)		
Education: Secondary	13.476***	2.796***		-78.058***	8.792***	
	(-0.21)	(-0.71)		(-0.09)	(-0.22)	
Education: Graduate	13.770***	1.254*	-5.177***	-78.148***	8.847***	-8.753***
	(-0.18)	(-0.66)	(-0.35)	(-0.08)	(-0.19)	(-0.06)
Employment: Unemployed	-0.628			-0.223*		
(Ref: Employed)	(-0.49)			(-0.13)		
Employment: Not in Labor Force	0.413	-0.211	-26.005***	0.328***	-38.219***	
	(-0.26)	(-1.29)	(-0.22)	(-0.10)	(-0.17)	
Difficulty in Mobility	-1.415**	0.616		-0.487***		
(Ref: No difficulty)	(-0.61)	(-1.10)		(-0.17)		
Family Structure	-0.514***	0.286	0.913	-0.279***	-1.036***	-11.897***
	(-0.17)	(-0.48)	(-0.82)	(-0.06)	(-0.25)	(0.00)
Female * Unemployed	0.13			1.060***		
(Ref: Male * Employed)	(-0.64)			(-0.18)		
Female * Not in Labor Force	-0.548*	-0.539	50.752***	-0.057	41.145***	
(Ref: Male * Employed)	(-0.32)	(-1.43)	(-0.22)	(-0.12)	(-0.17)	
Female * Primary	42.527***			-0.042		
(Ref: Male * No Education)	(-0.25)			(-0.21)		
Female * Secondary	-13.805***			-0.299***	-4.782***	
(Ref: Male * No Education)	(-0.22)			(-0.10)	(-0.27)	
Female * Graduate	-14.076***	2.412***	6.208***	0.088	-4.307***	1.996***
(Ref: Male * No Education)	(-0.17)	(-0.54)	(-0.22)	(-0.09)	(-0.20)	(-0.17)

Note: Ref = reference category of the corresponding variable.

Table 6. Weighted Multinomial Logit (WMNL) Model Results for Chicago and DC

		Chicago			DC	
Alternatives		**Weighted Count**	**Freq.**		**Weighted Count**	**Freq.**
No shopping		2996	0.651		3861	0.685
In-store		1497	0.325		1600	0.284
Online		63	0.013		106	0.0188
Both		45	0.00972		73	0.013
Adj. McFadden R2						
Equally likely based			0.241			0.378
Market share based			0.009			0.014
Chi-square test w.r.t. market share model						
Chi^2 value			69.4*			104.6**
Variable	**Estimate, significance, and t-value (respectively)** Ref: No shopping			**Estimate, significance, and t-value (respectively)** Ref: No shopping		
	In-store	Online	Both	In-store	Online	Both
(intercept)	5.707***	-30.424***	-30.578***	908.388***	10.224	85.774***
	(-0.09)	(-0.06)	(-0.06)	(-0.15)	(-24.02)	(-0.15)
MSA Size: > 1 million	5.707***	-30.424***	-30.578***	-0.948***		
(Ref: < 1 million)	(-0.09)	(-0.06)	(-0.06)	(-0.13)		
Income: Low	1.034***			0.164		
(Ref: Poverty level)	(-0.21)			(-0.22)		
Income: Lower Middle	0.924***			-0.863***		
	(-0.21)			(-0.19)		
Income: Median	0.586***	15.095***	33.742***	-0.859***		
	(-0.18)	(-0.06)	(-0.06)	(-0.16)		
Income: Middle Middle	-0.019			-0.642***		
	(-0.21)			(-0.16)		
Income: Upper Middle	0.381**			0.012		
	(-0.19)			(-0.16)		
Income: High	0.668***			-0.954***		93.748***
	(-0.20)			(-0.15)		(-0.38)
Age: 52-71	-0.124	28.139***	35.611***	0.473***		
(Ref: > 71)	(-0.13)	(-0.09)	(-0.17)	(-0.14)		
Age: 37-51	0.209	45.835***		0.816***		1.834***
	(-0.15)	(-0.10)		(-0.16)		(-0.56)
Age: 22-36	0.069		35.411***	-0.01		
	(-0.14)		(-0.18)	(-0.16)		
Age: 4-22	0.283*			-0.745***		
	(-0.17)			(-0.21)		
Sex: Female	10.819***	20.521***		67.208***	446.156***	55.083***
(Ref: Male)	(-0.07)	(-0.10)		(-0.06)	(-24.02)	(-0.26)
Education: Primary	31.214***					
(Ref: No education)	(0.00)					
Education: Secondary	-12.934***	-31.511***		908.323***	-309.911***	-407.935***
	(-0.07)	(0.00)		(-0.10)	(-11.32)	(-0.13)

Variable	Estimate, significance, and t-value (respectively) Ref: No shopping			Estimate, significance, and t-value (respectively) Ref: No shopping		
	In-store	Online	Both	In-store	Online	Both
Education: Graduate	-12.574***	-16.407***	-9.511***	308.235***	-243.092***	-8.762***
	(-0.07)	(-0.06)	(-0.06)	(-0.09)	(-12.70)	(-0.14)
Employment: Unemployed	0.29			0.248		
(Ref: Employed)	(-0.29)			(-0.20)		
Employment: Not in Labor Force	0.067	32.885***	-0.004	0.784***	453.762***	-136.680***
	(-0.11)	(-0.09)	(-0.38)	(-0.14)	(-10.49)	(-0.19)
Difficulty in Mobility	0.328*					
(Ref: No difficulty)	(-0.20)					
Family Structure	-0.214***	0.528	-12.909***	0.171***	3.725***	-1.252**
	(-0.08)	(-0.47)	(0.00)	(-0.06)	(-0.36)	(-0.52)
Female * Unemployed	0.076			0.156		
(Ref: Male * Employed)	(-0.38)			(-0.31)		
Female * Not in Labor Force	-1.390***			-1.216***	-819.422***	231.428***
(Ref: Male * Employed)	(-0.17)			(-0.17)	(-10.49)	(-0.19)
Female * Primary	-9.641***			67.272***	526.572***	437.982***
(Ref: Male * No Education)	(-0.11)			(-0.11)	(-11.32)	(-0.13)
Female * Secondary	-10.754***	-4.287***		67.928***	206.388***	-55.967***
	(-0.07)	(-0.10)		(-0.07)	(-12.70)	(-0.24)

Note: Ref = reference category of the corresponding variable.

Table 7. Weighted Multinomial Logit (WMNL) Model Results for SF and Dallas

	SF			Dallas		
Alternatives		**Weighted Count**	**Freq.**		**Weighted Count**	**Freq.**
No shopping		2549	0.644		2586	0.673
In-store		1377	0.348		1130	0.294
Online		19	0.00469		39	0.0101
Both		16	0.004		86	0.0223
Adj. McFadden R2						
Equally likely based			0.238			0.374
Market share based			0.007			0.012
Chi-square test w.r.t. market share model						
Chi^2 value			64.3*			177.1**
Variable	**Estimate, significance, and t-value (respectively)** Ref: No shopping			**Estimate, significance, and t-value (respectively)** Ref: No shopping		
	In-store	Online	Both	In-store	Online	Both
(intercept)	51.937***	-210.377***	-139.535***	2.328***	11.669	83.826***
	(-0.17)	(0.00)	(-26.00)	(-0.23)	(-47.72)	(-0.07)
MSA Size: > 1 million	-0.157			1.566***	-162.144***	3.662***
(Ref: < 1 million)	(-0.10)			(-0.23)	(-47.66)	(-0.07)
Income: Low	2.861***			1.693***		
(Ref: Poverty level)	(-0.28)			(-0.20)		
Income: Lower Middle	0.863***			1.306***		30.510***
	(-0.23)			(-0.19)		(-0.28)
Income: Median	2.221***			0.311*		
	(-0.20)			(-0.16)		
Income: Middle Middle	-0.740***	55.241***		1.223***		
	(-0.23)	(0.00)		(-0.18)		
Income: Upper Middle	0.997***		75.090***	0.979***	46.479***	
	(-0.18)		(-0.06)	(-0.18)	(-1.11)	
Income: High	0.416**			-0.00001		
	(-0.18)			(-0.19)		
Age: 52-71	-0.614***			0.257*		
(Ref: > 71)	(-0.17)			(-0.15)		
Age: 37-51	-0.048			-0.456**		
	(-0.18)			(-0.19)		
Age: 22-36	0.693***	108.032***	21.114***	-0.22	-2.407	-210.769***
	(-0.16)	(0.00)	(-0.06)	(-0.18)	(-46.30)	(-0.22)
Age: 4-22	0.490**			-2.969***		
	(-0.20)			(-0.31)		
Sex: Female				-4.501***	60.612	-44.295***
(Ref: Male)				(-0.09)	(-41.95)	(-0.12)
Education: Primary	159.693***			14.545***		
(Ref: No education)	(0.00)			(-0.11)		

Variable	Estimate, significance, and t-value (respectively) Ref: No shopping			Estimate, significance, and t-value (respectively) Ref: No shopping		
	In-store	Online	Both	In-store	Online	Both
Education: Secondary	-54.683***			-6.564***		-18.621***
	(-0.14)			(-0.15)		(-0.13)
Education: Graduate	-53.073***			-5.653***	-119.958***	76.494***
	(-0.10)			(-0.13)	(-1.11)	(-0.15)
Employment: Unemployed	-1.069***					
(Ref: Employed)	(-0.24)					
Employment: Not in	-0.350**			0.644***		
Labor Force	(-0.17)			(-0.18)		
Difficulty in Mobility	0.479			-1.736***		
(Ref: No difficulty)	(-0.37)			(-0.32)		
Family Structure	-0.383***	133.103***	116.169**	0.637***	99.537	66.011***
	(-0.11)	(-0.00)	(-51.88)	(-0.09)	(-90.17)	(-0.22)
Female * Unemployed	2.633***			-116.340***		
(Ref: Male * Employed)	(-0.36)			(-0.16)		
Female * Not in Labor Force	0.011			-0.776***		
(Ref: Male * Employed)	(-0.19)			(-0.20)		
Female * Primary	196.950***			6.450***		92.694***
(Ref: Male * No Education)	(-0.14)			(-0.14)		(-0.13)
Female * Secondary	195.999***				21.325***	
(Ref: Male * No Education)	(-0.09)				(-1.11)	

Note: Ref = reference category of the corresponding variable.

Synthesized population results

Based on the WMNL model, we validate the model for different panning years (2020-2050) based on four population growth scenarios with different time-series predictions of IV variable shares and population projection. The idea of model validation is to compare the DV variable shares from the actual data with the DV market shares predicted by the synthesized population for 2020 using the WMNL model. If the results for the year 2020 are similar, then the model could be used for subsequent behavioral predictions and MC simulations.

Table 8. DV variable shares using actual data and synthesized populations

Year / Data Type	DV Variable Shares of WMNL Models (Averaged over Four Population Growth Scenarios)			
	No Shopping	In-store	Online	Both
NYC				
2020 Actual	*68.60%*	*29.60%*	*1.26%*	*0.57%*
2020 Synthesized	66.29%	27.08%	4.43%	2.20%
2030 Synthesized	65.03%	28.04%	4.10%	2.82%
2040 Synthesized	64.36%	28.41%	4.12%	3.11%
2050 Synthesized	63.76%	28.74%	4.23%	3.27%
LA				
2020 Actual	*62.40%*	*34.90%*	*2.12%*	*0.64%*
2020 Synthesized	62.93%	34.88%	1.95%	0.24%
2030 Synthesized	62.47%	33.01%	2.26%	0.74%
2040 Synthesized	61.25%	31.04%	3.45%	1.99%
2050 Synthesized	60.14%	28.60%	5.09%	5.61%
Chicago				
2020 Actual	*65.10%*	*32.50%*	*1.30%*	*0.97%*
2020 Synthesized	64.39%	32.71%	1.60%	1.30%
2030 Synthesized	63.57%	29.65%	2.68%	2.48%
2040 Synthesized	60.82%	28.00%	4.31%	5.11%
2050 Synthesized	60.38%	26.08%	5.36%	7.34%
DC				
2020 Actual	*68.50%*	*28.40%*	*1.88%*	*1.30%*
2020 Synthesized	69.47%	28.86%	0.54%	1.12%
2030 Synthesized	66.51%	27.15%	1.00%	3.25%
2040 Synthesized	65.21%	26.40%	1.26%	4.16%
2050 Synthesized	63.42%	26.21%	1.45%	6.75%
SF				
2020 Actual	64.40%	34.80%	0.47%	0.40%
2020 Synthesized	65.29%	33.84%	0.69%	0.18%
2030 Synthesized	64.88%	33.35%	2.35%	2.15%
2040 Synthesized	64.13%	30.31%	2.84%	5.68%
2050 Synthesized	62.15%	30.24%	5.52%	9.50%
Dallas				
2020 Actual	*67.30%*	*29.40%*	*1.01%*	*2.23%*
2020 Synthesized	62.41%	28.92%	5.94%	2.74%
2030 Synthesized	59.95%	27.67%	7.67%	4.71%
2040 Synthesized	59.66%	25.70%	8.21%	6.42%
2050 Synthesized	60.93%	23.62%	8.82%	6.63%

Note: DV = dependent variable; Italic rows mean that the data is from 2020 ATUS actual data with weighted samples.

Table 8 shows the comparison of DV variable shares using actual data and synthesized population across the six WMNL models. From the model validation results of the six MSAs, the distribution of DV variable shares simulated using synthesized population differs from the actual data by less than 2%, which is within an acceptable range. Therefore, it is confirmed that these WMNL models can be used for the subsequent MC simulations. In addition to this, Table 8 provides time series forecasts of DV market shares for 2030-2050. Despite the validation of the models, the future share of online shopping and both shopping for each MSA is still not high, with the highest being Dallas with 15.45%.

Task 2: Shopping Travel Parameters

In Task 2, we use NHTS data to first identify trip chains with shopping trips in the trip-based data, which are considered shopping tours. For each MSA, we use the identified shopping tours for the extraction of shopping travel parameters. Figure 4-Figure 8 show the distribution of different shopping travel parameters in different MSAs.

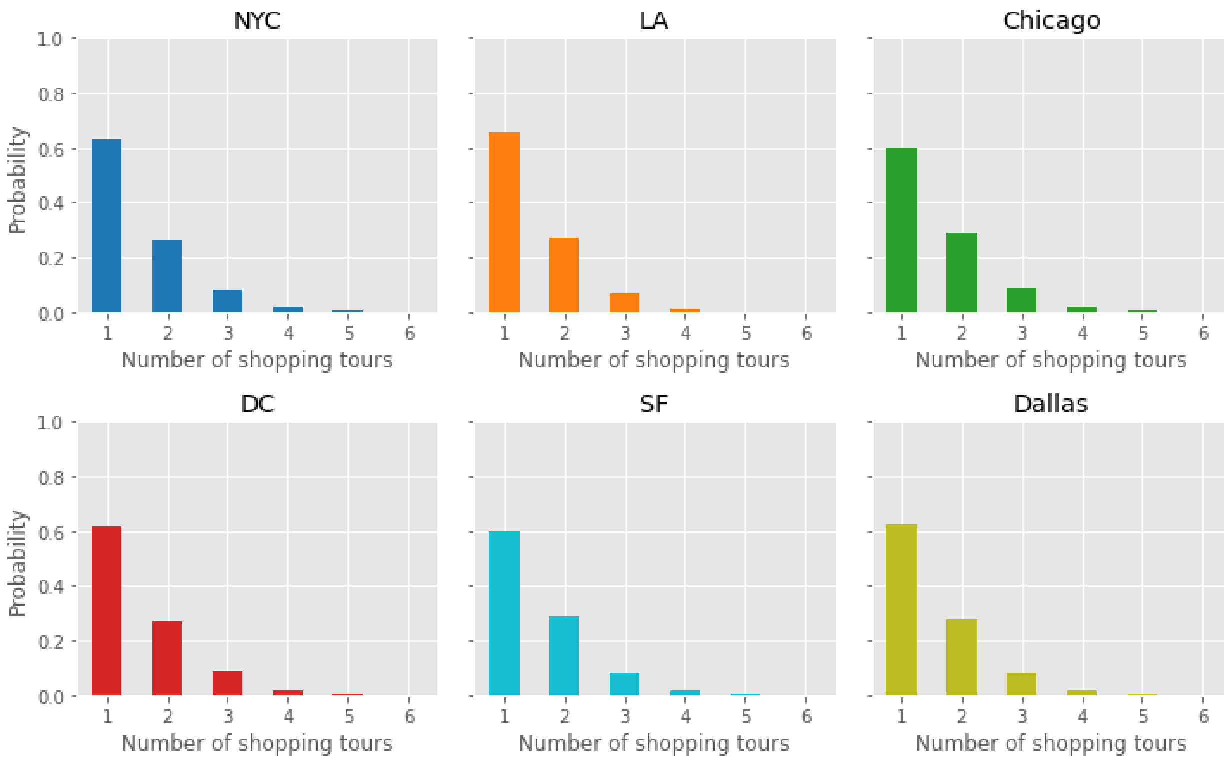

Figure 4. Shopping tours per person

Figure 4 shows the identified shopping tours per person in the six MSAs. The horizontal axes are number of shopping tours per person, and the vertical axes are the discrete probabilities. We can see that the probability of making one shopping tour in those who shop in-store in a survey day is approximately 60%. For the six MSAs, no obvious difference in the probabilities of this parameter can be found among them. When it comes to making two shopping tours, the probabilities sharply decrease to around 25%. There are over 85% of people in the six MSAs who make less than three shopping tours in a survey day. It should be noted that the maximum number of shopping tours per person for NYC, Chicago and DC is eight, whereas this maximum number of tours for other MSA in the South and West regions is seven.

It is also important to analyze the number of stops of a shopping tour as well as the tour length in miles, because those two parameters can provide the information necessary to estimate VMT related to shopping activities. Figure 5 shows the discreet probabilities of the number of stops per shopping tour, and Figure 6 shows the relations between tour length in miles and the number of stops per tour. The differences across MSAs are more obvious for these two parameters. The maximum numbers of stops for Dallas, NYC and DC exceed 15, while this number in Chicago is only 12. Meanwhile, the regressed tour length at 10 stops for Dallas is about 120 miles, while the estimated tour length for DC and SF is only around 60 miles. This may reflect that the MC simulation for Dallas might return higher estimates for VMT results.

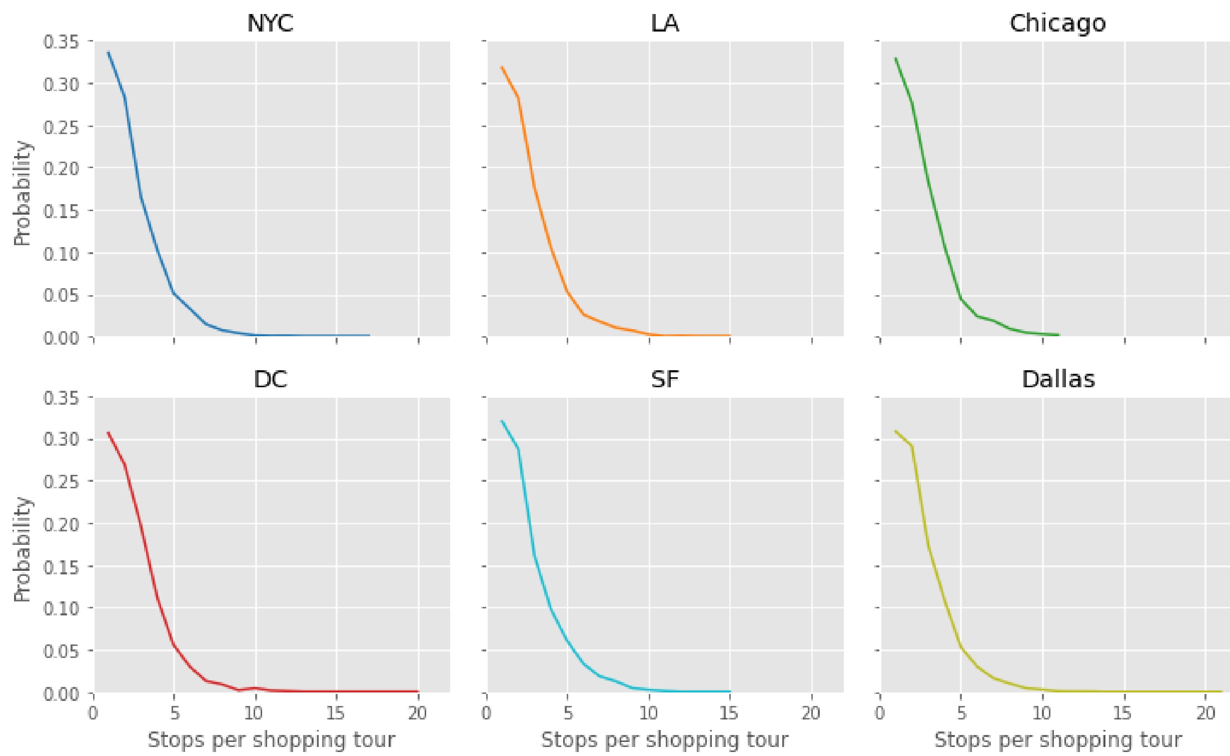

Figure 5. Stops per shopping tour

Figure 7 shows the shares of in-store shopping activities in a shopping tour and their corresponding probabilities. It can be noted that approximately 50% of shopping tours are purely for in-store shopping, with 100% of in-store shopping activity shares. No obvious difference in the pattern is observed across the six MSAs. Figure 8 shows the aggregated probabilities of travel mode shares of in-store shopping tours for the six MSAs. It can be found that private car travel is the most dominant mode among the six MSAs, with the highest share of over 90% in LA and Dallas. In NYC, low-emission travel modes such as transit and active transportation are the second most popular mode of travel among shopping tours, with a combined share of over 20%, the highest among all MSAs.

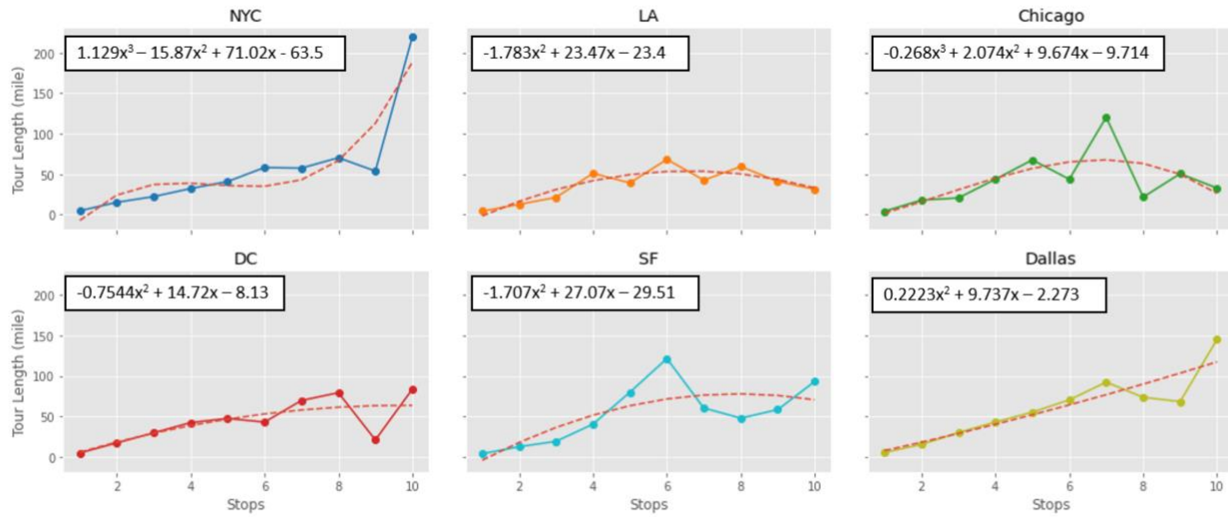

Figure 6. Tour length vs. stops.

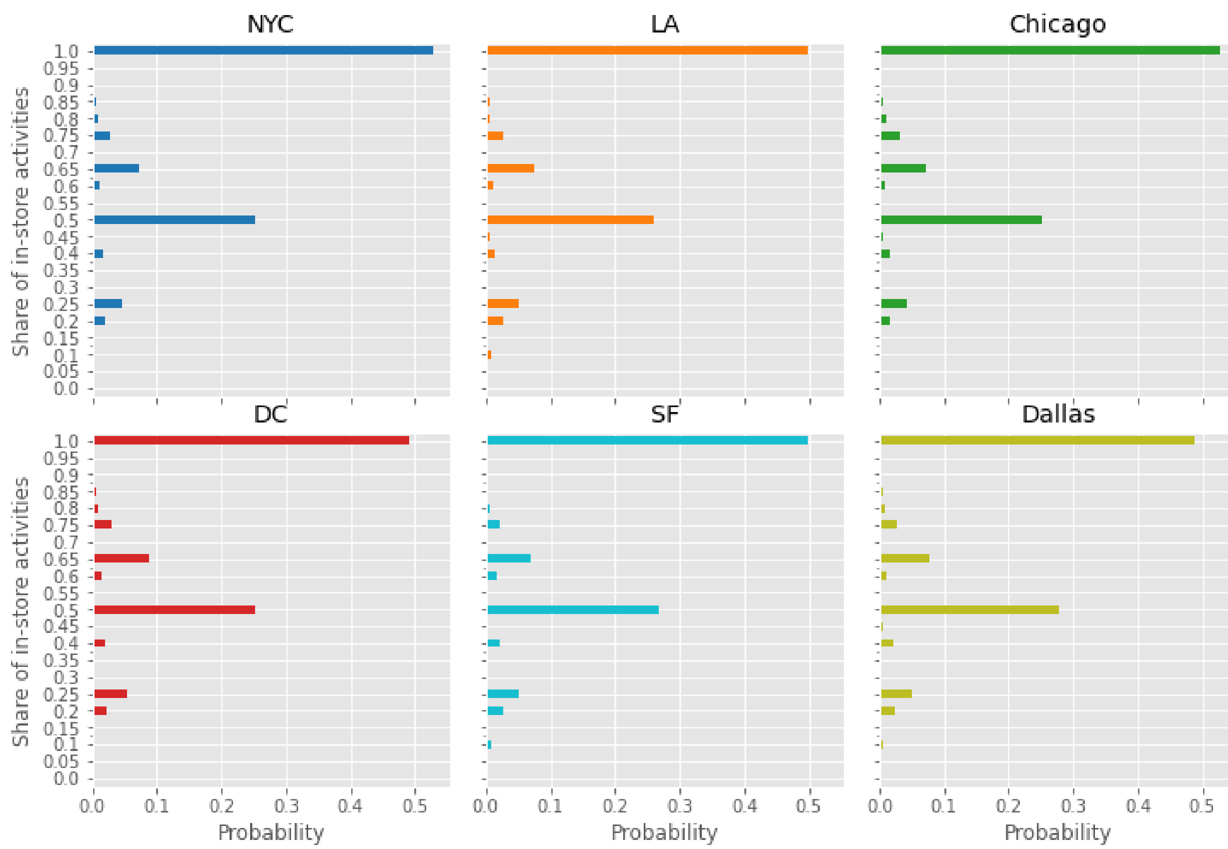

Figure 7. Shares of in-store activities in a shopping tour.

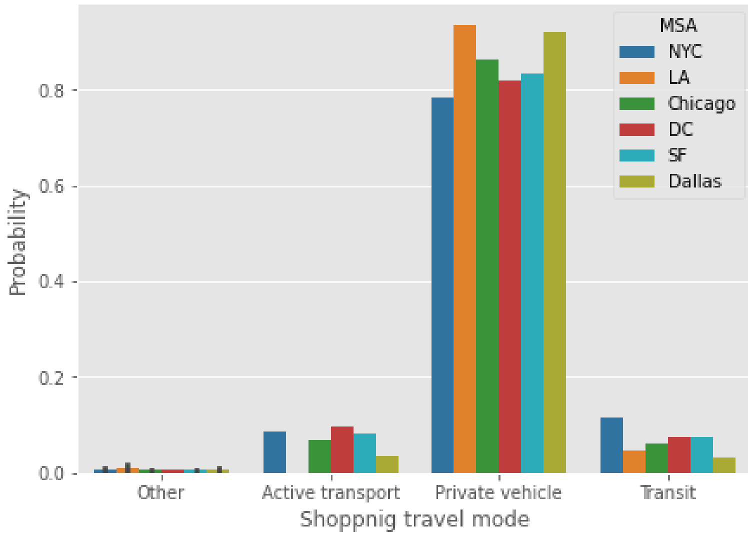

Figure 8. Shopping travel mode shares.

Task 3: Last-mile Delivery Parameters

In Task 3, prior to obtaining the parameters for last-mile deliveries in the six MSA, we created a set of adjustment factors to modify the original standard distributions of Jaller & Pahwa (2020) so that the distributions (respectively Weibull and triangular distribution, (6)) we use in the MC simulation can reflect more of the actual demographic and goods movement conditions of the current MSA. In this project, we create the adjustment factors by comparing the differences in distance between the population centroid and the transportation/warehousing industry centroid in each of the MSAs. It is important to mention that no other delivery data was available to the team, and the distributions used are assumed based on a review of the literature and approximations. This continues to be a limitation in last mile delivery studies.

To do this, first, census ZIP level data and ZIP business pattern (ZBP) data are collected using API from the U.S. Census Bureau. To compare the centroids, we collect two variables as weights in the centroid calculation: the number of establishments (ESTAB) and population (POP) at ZIP level. The differences in centroid distances are then normalized by element-wise comparison, which means the minimum adjustments factor is 1. Table 9 shows the differences in distances between transportation and warehousing establishments and population centroids.

The adjustment factors enable the modification of the standard Weibull distribution and triangular distribution for delivery tour length and stops per delivery tour, respectively. Figure 9 and Figure 10 show the estimation results of the modified probability density distributions for delivery tour length as well as stops per delivery tour.

Table 9. Differences in transport & warehousing establishments and population centroids

MSA name	Centroid distance (mile)	Adjustment factor
NYC	2.33834	2.25
LA	1.04157	1.00
Chicago	2.84697	2.73
DC	2.37408	2.28
SF	2.73104	2.62
Dallas	3.13123	3.01

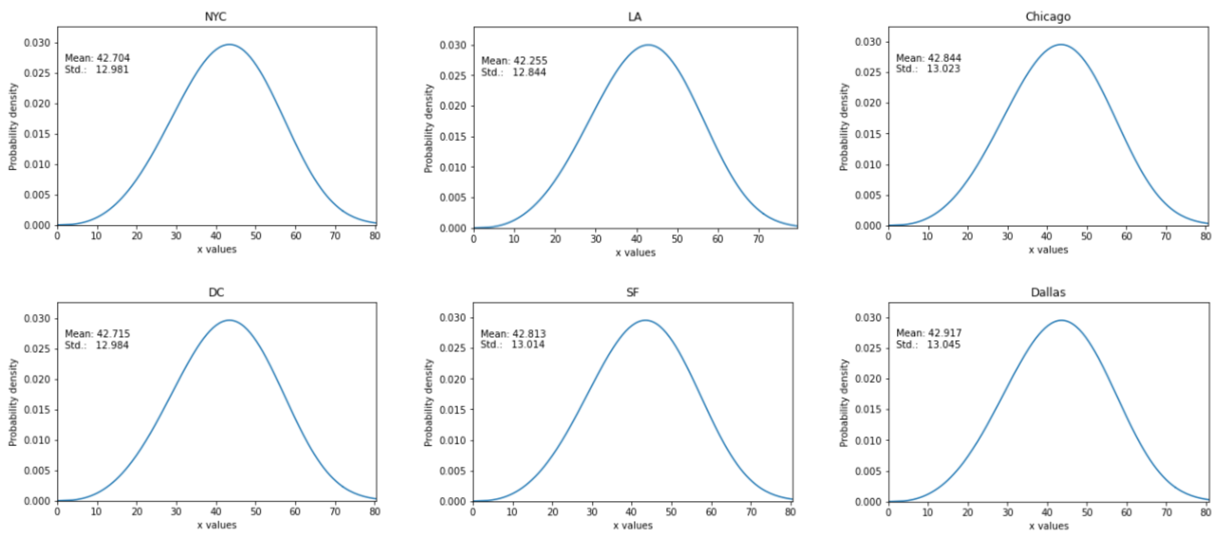

Figure 9. Distributions of delivery tour length in miles

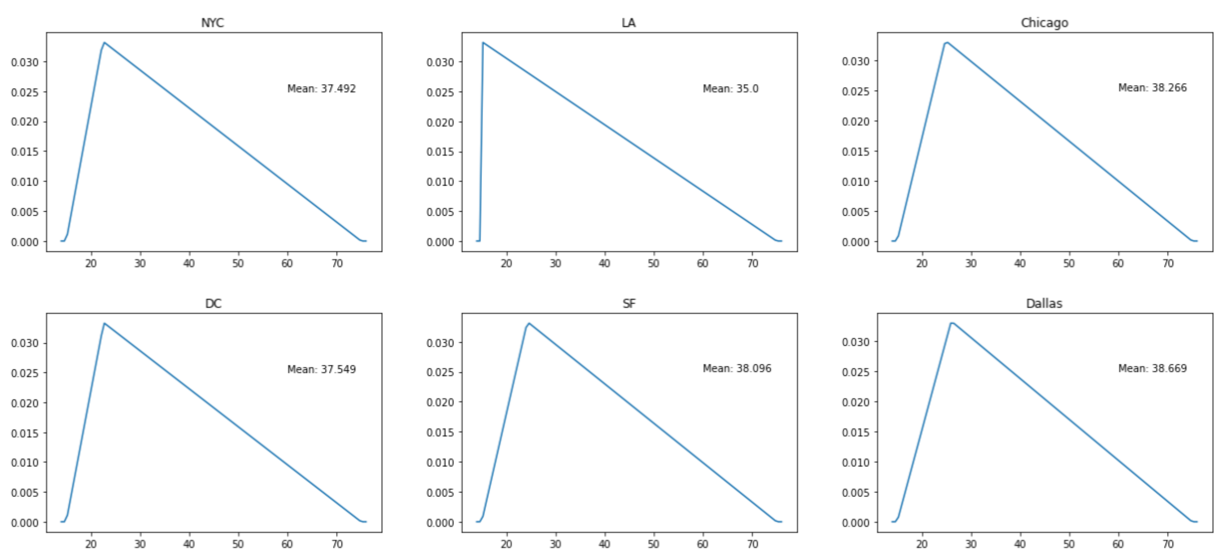

Figure 10. Distributions of stops per delivery tour

Task 4: Emission Rates Results

Task 4 mainly applies the MOVES model to obtain the average emission rates by different vehicle types in the six MSAs. We select five types of pollutants in this project, namely CO_2, NOx, SO_2, PM10 and PM2.5. Emission rates for all the measured pollutants emitted (unit: g) are averaged within each vehicle type by cumulative distance in miles (see Table 10). The average occupancies of vehicle types are pre-specified in the previous study, with many of these trends influenced by federal legislation (54).

Task 5: Monte Carlo Simulation Results

The simulation process is finalized by utilizing the results from Task 1 to 4, where the outputs of this part are the aggregate average VMT and emissions (negative externalities) for different shopping activities in the planning years and different MSAs. The aggregate simulation results mainly come from calculations of VMT and emissions of the datasets of synthesized populations for different planning years and population growth scenarios. While the datasets have huge sample sizes which are more than 20 million per dataset, we use python script to efficiently perform the disaggregate level calculations. For dataset size and memory limit reasons, we primarily display the mean value results of the MC simulation, including average VMT and generated emissions related to shopping over different population growth scenarios.

Results of negative externalities: baseline scenario

Table 11 shows the aggregate average daily VMT and emissions over four different population growth scenarios for different types of pollutants across the four planning years. After averaging the four scenarios, we found that the population growth patterns, consumer behavior distribution and even VMT show different growth patterns across MSAs.

To begin with, for NYC, the predictive simulations show an average population growth of 14% by 2050, with daily in-store, online and both shopping behaviors generating an increase in VMT of 76%, 140% and 291% respectively. Compared to in-store shopping, the increase in daily VMT associated with online shopping is clearly greater. However, due to the base year condition, the market share of in-store shopping is still the largest in 2050. The calculation of various pollutant emissions shows that the emissions of NOx, PM10 and PM2.5 all decreased, except for CO2 and SO2 which increased slightly in the planning year. At the same time LA shows a similar pattern of population growth, but the difference is that VMT from pure online shopping shrinks by 44% in 2050, while VMT from both shopping increases by more than 25 times. This means that the shift in shopping behavior in LA tends to be a hybrid one, so we can see that the daily CO2 generated by pure in-store shopping does not increase in 2050.

Table 10. Emission rate results for planning years (unit: g/person-mile)

Vehicle type	Year	Avg. Occ	Average Emission Rates (g/mile/person)									
			CO_2	NOx	SO_2	PM10	PM2.5	CO_2	NOx	SO_2	PM10	PM2.5
			NYC					**LA**				
Private vehicle	2020	2	205.7631	0.207	0.0012	0.0089	0.0081	204.1941	0.2065	0.0009	0.0083	0.0076
	2030	2	162.3793	0.0614	0.0009	0.003	0.0027	160.9791	0.06	0.0007	0.0024	0.0022
	2040	2	147.6326	0.0316	0.0009	0.0019	0.0017	146.3007	0.0303	0.0006	0.0014	0.0012
	2050	2	144.1467	0.0284	0.0008	0.0019	0.0017	142.8525	0.0272	0.0006	0.0014	0.0012
Truck	2020	2	583.0674	1.0954	0.0029	0.0248	0.0226	578.6906	1.0403	0.0022	0.0237	0.0217
	2030	2	512.662	0.5547	0.0021	0.0096	0.0089	508.9881	0.5097	0.0017	0.0093	0.0084
	2040	2	450.5761	0.4548	0.0022	0.0052	0.0047	447.0569	0.437	0.0017	0.0047	0.0043
	2050	2	444.2736	0.4443	0.0021	0.0049	0.0044	440.8345	0.427	0.0017	0.0045	0.004
Transit	2020	15	107.0327	0.1596	0.0005	0.0026	0.0023	106.7346	0.1536	0.0004	0.0025	0.0022
	2030	15	100.0639	0.1045	0.0005	0.0012	0.0011	99.8009	0.1001	0.0004	0.0011	0.001
	2040	15	94.0876	0.086	0.0005	0.0008	0.0007	93.8444	0.0823	0.0003	0.0007	0.0006
	2050	15	91.6075	0.0848	0.0005	0.0008	0.0007	91.3685	0.0811	0.0003	0.0007	0.0006
Other	2020	10	166.5278	0.3959	0.0008	0.0107	0.0097	166.185	0.3851	0.0006	0.0105	0.0096
	2030	10	156.0988	0.1957	0.0008	0.003	0.0027	155.8116	0.1884	0.0006	0.0028	0.0025
	2040	10	148.1812	0.1505	0.0008	0.0012	0.0011	147.9218	0.1445	0.0005	0.0011	0.001
	2050	10	144.7262	0.149	0.0008	0.0012	0.0011	144.4717	0.1431	0.0005	0.0011	0.0009
			Chicago					**DC**				
Private vehicle	2020	2	206.5658	0.2129	0.0012	0.0088	0.008	223.561	0.2312	0.0013	0.0098	0.009
	2030	2	162.9379	0.0623	0.0009	0.0029	0.0026	175.6546	0.0663	0.001	0.0028	0.0025
	2040	2	148.1175	0.0315	0.0009	0.0019	0.0017	159.4891	0.0335	0.0009	0.0016	0.0014
	2050	2	144.6227	0.0282	0.0008	0.0018	0.0016	155.739	0.0301	0.0009	0.0016	0.0014
Truck	2020	2	584.5567	1.0861	0.0029	0.0248	0.0226	1274.01	6.7859	0.0049	0.1527	0.1407
	2030	2	513.5317	0.5518	0.0021	0.0096	0.0089	1067.558	4.2516	0.0044	0.0511	0.0469
	2040	2	451.715	0.453	0.0022	0.0052	0.0047	958.6244	3.415	0.004	0.0272	0.0249
	2050	2	445.3926	0.4425	0.0021	0.0049	0.0044	937.7341	3.2772	0.0039	0.0226	0.0207
Transit	2020	15	107.4276	0.1597	0.0005	0.0026	0.0023	114.6169	0.1826	0.0006	0.003	0.0027
	2030	15	100.4272	0.1047	0.0005	0.0012	0.0011	106.7878	0.1268	0.0005	0.0014	0.0013
	2040	15	94.431	0.0863	0.0005	0.0008	0.0007	100.3262	0.1078	0.0005	0.0009	0.0008
	2050	15	91.9442	0.0851	0.0005	0.0008	0.0007	97.7109	0.1065	0.0005	0.0008	0.0008

Vehicle type	Year	Avg. Occ	Average Emission Rates (g/mile/person)									
			CO_2	NOx	SO_2	PM10	PM2.5	CO_2	NOx	SO_2	PM10	PM2.5
Other	2020	10	166.9177	0.3952	0.0008	0.0107	0.0098	177.834	0.4405	0.0009	0.0125	0.0114
	2030	10	156.4761	0.1958	0.0008	0.003	0.0027	166.0348	0.2405	0.0009	0.0034	0.0031
	2040	10	148.548	0.1508	0.0008	0.0012	0.0011	157.3732	0.1952	0.0008	0.0013	0.0012
	2050	10	145.0886	0.1493	0.0008	0.0012	0.001	153.7162	0.1936	0.0008	0.0013	0.0012
			SF					**Dallas**				
Private vehicle	2020	2	204.1941	0.2065	0.0009	0.0083	0.0076	208.712	0.2139	0.0012	0.0083	0.0076
	2030	2	160.9791	0.06	0.0007	0.0024	0.0022	164.4302	0.0612	0.001	0.0025	0.0022
	2040	2	146.3007	0.0303	0.0006	0.0014	0.0012	149.3962	0.0298	0.0009	0.0014	0.0013
	2050	2	142.8525	0.0272	0.0006	0.0014	0.0012	145.8806	0.0266	0.0008	0.0014	0.0012
Truck	2020	2	578.6906	1.0403	0.0022	0.0237	0.0217	578.0075	1.0098	0.0029	0.0237	0.0216
	2030	2	508.9881	0.5097	0.0017	0.0093	0.0084	508.3044	0.5103	0.0025	0.0092	0.0086
	2040	2	447.0569	0.437	0.0017	0.0047	0.0043	446.3543	0.4175	0.0021	0.0047	0.0043
	2050	2	440.8345	0.427	0.0017	0.0045	0.004	440.1056	0.4078	0.0021	0.0045	0.004
Transit	2020	15	106.7346	0.1536	0.0004	0.0025	0.0022	106.467	0.1514	0.0005	0.0025	0.0022
	2030	15	99.8009	0.1001	0.0004	0.0011	0.001	99.5369	0.0983	0.0005	0.0012	0.001
	2040	15	93.8444	0.0823	0.0003	0.0007	0.0006	93.5875	0.0806	0.0005	0.0007	0.0006
	2050	15	91.3685	0.0811	0.0003	0.0007	0.0006	91.1157	0.0794	0.0005	0.0007	0.0006
Other	2020	10	166.185	0.3851	0.0006	0.0105	0.0096	165.4183	0.376	0.0008	0.0105	0.0096
	2030	10	155.8116	0.1884	0.0006	0.0028	0.0025	155.064	0.1836	0.0008	0.0028	0.0026
	2040	10	147.9218	0.1445	0.0005	0.0011	0.001	147.1941	0.1401	0.0008	0.0011	0.001
	2050	10	144.4717	0.1431	0.0005	0.0011	0.0009	143.7554	0.1386	0.0007	0.0011	0.001

Note: Avg. Occ = average occupancy of the vehicle type

Moreover, the MSAs of Chicago, SF, and Dallas are projected to have rapid population growth of close to 40% in 2050, but the change in shopping behavior varies across these MSAs. In Chicago, total daily VMT generated by pure in-store and both increases by more than 80% in 2050, while VMT generated by online shopping increases by only 16%. Dallas is somewhat similar to Chicago, but VMT from online shopping declines by 48% in 2050. Despite the population growth, the change in shopping behavior in different regions shows that SF and NYC are more receptive to pure online shopping, while people in Dallas and LA are more inclined to in-store and both shopping behavior.

Additionally, the population growth in the planning years results for the DC MSA is essentially unchanged for the planning years, meaning that the total population of the region is not likely to grow in the future. As a result, we can see some shrinkage in shopping behavior in the simulation results. As a result, the total amount of pollutant emissions will decrease in the future.

Task 5 includes a map visualization of the negative externalities of each shopping channel. However, it is important to know that the prerequisite for map visualization is to have enough disaggregate level data, which also depends on the geographic scope we need, such as MSA, county, city, ZIP code, census tract, or even block. The implementation of disaggregate level analysis requires reliable and available data sources, but in our implementation process from Task 1 to Task 5, we mainly use two major sources of survey data, ATUS and NHTS, which do not provide the address information of the respondent, including the ZIP code and neighborhood. Therefore, we can only set the disaggregate level to the size of MSA in the simulation process.

Ideally, the disaggregate level should be as small as possible, or at least at the ZIP code level to ensure that the result is based on small geographical units. But the reality is that ATUS and NHTS do not contain smaller geographic information than MSA, and there is no other valid public data that can support the incorporation of more disaggregated data in the simulation process and less so for forecasting. Therefore, we need to find a proxy to disaggregate the negative externality estimation results at the MSA level to achieve the objective of disaggregate map visualization. This proxy should reflect the proportion of socio-demographic indicators between the various geographic units (e.g., ZIP codes) within each MSA, and this proximity is time-varying, i.e., it needs to be supported by time series or longitudinal data. One alternative to overcome the limitation of forecasted demographic data is the Statistics of Income (SOI) data provided by the Internal Revenue Service (IRS). SOI is a dataset published annually that provides aggregated information for all ZIP codes (55). The dataset shows selected income and tax items classified by State, ZIP Code, and size of adjusted gross income. Data are based on individual income tax returns filed with the IRS and are available for Tax Years 2004 through 2019. The data include variables for all income groups such as:

- Number of returns (N1), which approximates the number of households (55);
- Number of personal exemptions (N2), which approximates the population (55);
- Total adjusted gross income (AGI) (A00100); and
- Total wages and salaries (A00200).

Table 11. Aggregate average daily VMT and emissions for different shopping activities.

a) NYC

Variables		2020	2030	2040	2050
Projected Population (1,000)		20845.873	21924.853	22886.236	23738.456
VMT (1,000 mi)	In-store	74794.972	94984.929	114525.319	131687.421
	Online	305.819	408.883	562.263	734.855
	Both	577.580	1050.373	1614.059	2258.745
CO2 (kg)	In-store	13143003.072	13366768.184	14712653.506	16534353.700
	Online	178313.305	209618.526	253342.105	326476.551
	Both	111042.517	161572.992	227381.452	310559.576
NOx (kg)	In-store	13919.268	5967.672	4174.670	4485.065
	Online	334.995	226.807	255.717	326.496
	Both	127.606	84.704	82.122	108.307
SO2 (kg)	In-store	75.375	73.400	88.588	91.630
	Online	0.887	0.859	1.237	1.543
	Both	0.627	0.860	1.341	1.693
PM10 (kg)	In-store	554.260	239.976	182.999	210.494
	Online	7.584	3.925	2.924	3.601
	Both	4.682	2.908	2.810	3.903
PM25 (kg)	In-store	503.815	216.199	163.568	188.140
	Online	6.912	3.639	2.643	3.233
	Both	4.257	2.629	2.514	3.490

b) LA

Variables		2020	2030	2040	2050
Projected Population (1,000)		13913.468	14871.820	15588.934	16020.883
VMT (1,000 mi)	In-store	80796.136	83177.695	88353.832	87017.622
	Online	328.585	201.470	195.101	145.979
	Both	9018.266	8891.037	9077.739	8512.178
CO2 (kg)	In-store	16072982.887	13135967.970	12709371.610	12221976.610
	Online	190149.313	102545.992	87221.183	64352.632
	Both	1927847.909	1524704.870	1415428.744	1296100.836
NOx (kg)	In-store	16740.727	5339.054	3065.791	2767.060
	Online	341.827	102.689	85.259	62.333
	Both	2162.656	726.444	458.005	403.003
SO2 (kg)	In-store	70.384	56.871	51.608	50.825
	Online	0.723	0.342	0.332	0.248
	Both	8.324	6.426	5.708	5.345
PM10 (kg)	In-store	651.738	194.973	120.319	118.489
	Online	7.787	1.874	0.917	0.657
	Both	78.252	23.237	13.569	12.640
PM25 (kg)	In-store	596.413	178.595	103.216	101.496
	Online	7.130	1.692	0.839	0.584
	Both	71.614	21.243	11.737	10.875

c) Chicago

Variables		2020	2030	2040	2050
Projected Population (1,000)		6565.386	7439.866	8292.704	9123.342
VMT (1,000 mi)	In-store	8807.170	9662.929	11970.771	16005.850
	Online	544.789	557.965	592.159	633.089
	Both	4247.440	4561.196	5717.154	7826.091
CO2 (kg)	In-store	1640618.910	1432089.631	1615523.961	2108833.434
	Online	318460.134	286532.968	267486.900	281973.005
	Both	837949.709	747530.882	842234.592	1178861.355
NOx (kg)	In-store	1736.600	599.519	406.337	495.795
	Online	591.695	307.885	268.248	280.142
	Both	1073.952	429.006	334.202	382.571
SO2 (kg)	In-store	9.449	7.872	9.750	11.656
	Online	1.580	1.172	1.303	1.329
	Both	4.931	4.469	5.335	6.072
PM10 (kg)	In-store	69.118	25.164	20.338	25.816
	Online	13.511	5.356	3.079	3.102
	Both	38.256	15.090	10.801	13.984
PM25 (kg)	In-store	62.806	22.576	18.188	22.926
	Online	12.312	4.966	2.783	2.786
	Both	33.090	12.902	8.833	12.242

d) DC

Variables		2020	2030	2040	2050
Projected Population (1,000)		9697.991	9776.689	9718.978	9560.611
VMT (1,000 mi)	In-store	8807.170	9662.929	11970.771	16005.850
	Online	544.789	557.965	592.159	633.089
	Both	4247.440	4561.196	5717.154	7826.091
CO2 (kg)	In-store	1640618.910	1432089.631	1615523.961	2108833.434
	Online	318460.134	286532.968	267486.900	281973.005
	Both	837949.709	747530.882	842234.592	1178861.355
NOx (kg)	In-store	1736.600	599.519	406.337	495.795
	Online	591.695	307.885	268.248	280.142
	Both	1073.952	429.006	334.202	382.571
SO2 (kg)	In-store	9.449	7.872	9.750	11.656
	Online	1.580	1.172	1.303	1.329
	Both	4.931	4.469	5.335	6.072
PM10 (kg)	In-store	69.118	25.164	20.338	25.816
	Online	13.511	5.356	3.079	3.102
	Both	38.256	15.090	10.801	13.984
PM25 (kg)	In-store	62.806	22.576	18.188	22.926
	Online	12.312	4.966	2.783	2.786
	Both	33.090	12.902	8.833	12.242

e) SF

Variables		2020	2030	2040	2050
Projected Population (1,000)		5034.292	5738.684	6413.736	7059.992
VMT (1,000 mi)	In-store	36589.160	45414.819	61782.265	71460.062
	Online	212.521	428.687	804.032	1205.661
	Both	363.895	555.015	611.660	569.514
CO2 (kg)	In-store	6583541.306	6502479.078	8054971.468	9101985.718
	Online	1458.861	2385.543	3590.610	5581.519
	Both	71652.373	88064.107	88227.805	80108.281
NOx (kg)	In-store	6867.530	2698.789	2033.257	2157.440
	Online	2.623	2.389	3.510	5.406
	Both	81.716	43.794	30.641	27.109
SO2 (kg)	In-store	28.774	28.123	32.572	37.705
	Online	0.006	0.008	0.014	0.022
	Both	0.308	0.369	0.354	0.329
PM10 (kg)	In-store	264.091	95.848	75.959	87.929
	Online	0.060	0.044	0.038	0.057
	Both	2.883	1.342	0.845	0.780
PM25 (kg)	In-store	241.570	87.801	65.145	75.336
	Online	0.055	0.039	0.035	0.051
	Both	2.637	1.227	0.732	0.672

f) Dallas

Variables		2020	2030	2040	2050
Projected Population (1,000)		7888.023	9415.943	10973.075	12511.466
VMT (1,000 mi)	In-store	81831.631	91624.233	108562.329	118204.992
	Online	186.272	118.759	123.235	97.295
	Both	8760.317	11022.878	12202.316	12567.070
CO2 (kg)	In-store	16129989.616	14378065.202	15453313.821	16387060.636
	Online	107666.424	60365.878	55006.396	42820.264
	Both	1816716.571	1804992.058	1820920.702	1831073.296
NOx (kg)	In-store	16856.879	5699.271	3428.493	3382.629
	Online	188.097	60.603	51.451	39.677
	Both	1972.931	784.231	495.367	464.663
SO2 (kg)	In-store	92.290	86.943	92.772	89.736
	Online	0.540	0.297	0.259	0.204
	Both	10.317	10.784	10.771	9.941
PM10 (kg)	In-store	641.017	218.293	143.871	156.217
	Online	4.415	1.093	0.579	0.438
	Both	72.173	27.770	17.089	17.548
PM25 (kg)	In-store	586.707	192.119	133.400	133.985
	Online	4.023	1.021	0.530	0.389
	Both	66.039	24.562	15.829	15.089

Due to the inconsistency of the data format from year to year, we only select the data from 2011 to 2019 for time series forecasting in a similar way to the IV forecasting in Task 1. Using N2 (which approximates the population of ZIP code) for time series forecasting, we can then obtain the distribution of this proximity in each MSA from 2020 to 2050 and thus disaggregate the estimation results of negative externalities. The results of the map visualization for the VMT related to shopping activities for the planning years across the six MSAs are shown in the Appendix, see Figure 11 below for an example. The VMT disaggregation results are shown across the three shopping channels (in-store, online and both).

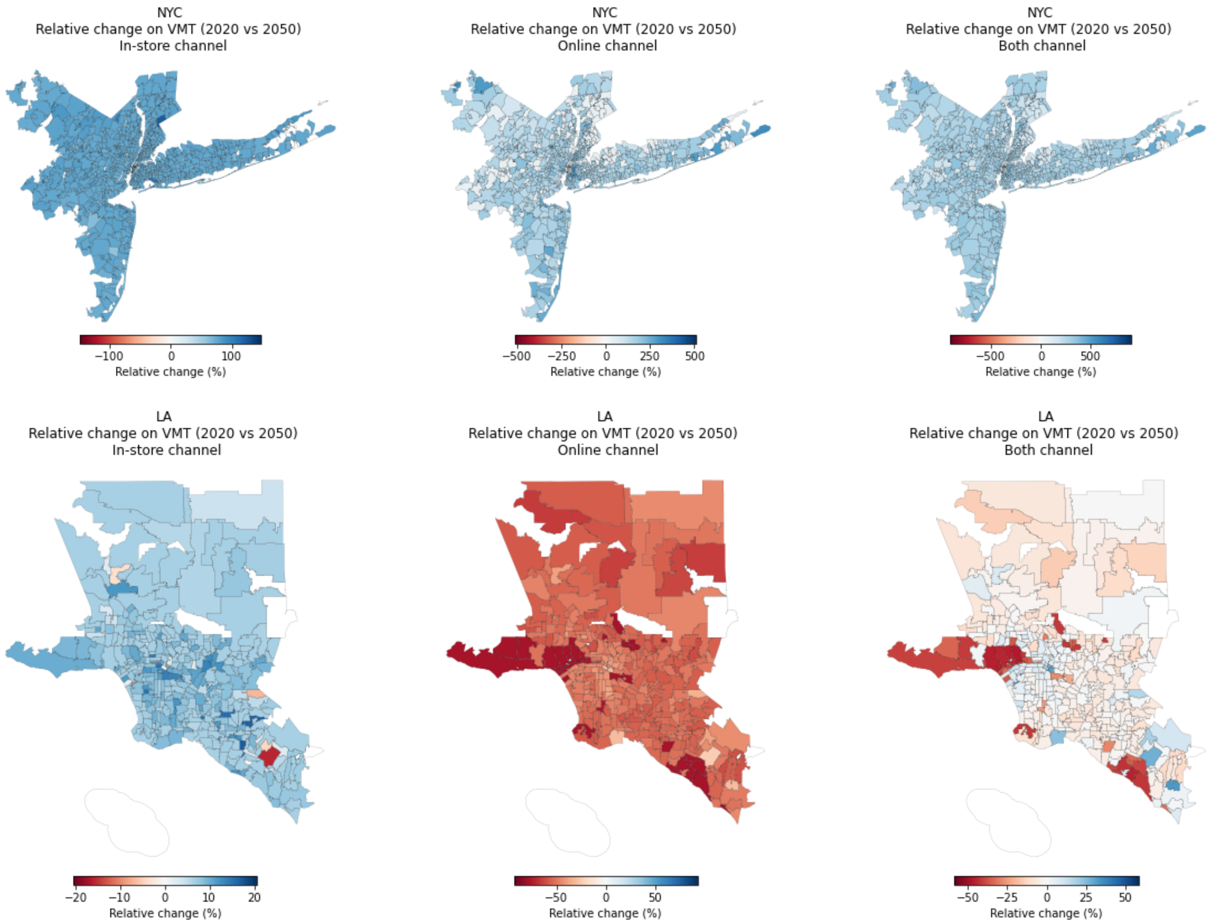

Figure 11. Relative change in VMT between 2020 and 2050 for NY (top) and LA (bottom)

There are two major findings through the map visualization:

- Externalities generated by In-store shopping activity remain the highest in 2050 for all MSAs, but the share is crowded out by the growth of online shopping. Compared to online shopping channel, its externalities are more evenly distributed across each region of the MSA. In contrast, externalities from online channel are more concentrated in specific areas of the MSA and increase each year as the year progresses (most MSAs); and
- The growth pattern of online shopping is shown differently in MSAs with different traffic trip structures. In MSAs with more balanced trip structures and higher public transportation use, such as NYC, DC, and Chicago, the share of online shopping activity rises more in 2050. In contrast, we see significant decline in VMT from online shopping

channel in MSAs where passenger cars dominate the transportation mode share, such as LA and Dallas.

It is also worth mentioning that the overall trend of negative externalities associated with shopping activities is decreasing due to the reduction of emission rates in the planning years, as shown by the results of the MC simulation of total pollutants such as CO2 from the unpresented.

Results of negative externalities: development scenarios

On top of the MC simulation that assumes no significant change on the transportation mode shares and technology adoptions, this project also developed scenarios to quantify potential impacts on emissions and shopping-related transportation activity due assumptions on penetration levels, maturity, and different levels of technology used, including electrification, rush deliveries, crowdshipping and automation/slash efficiency improvements. In this section, only two MSAs are selected to display comparative results, namely NYC and LA.

1) Electrification

As electrification being a trend for the future, electric vehicles start entering the commercial fleet space with benefits of reducing most of the negative externalities related to last-mile deliveries. A previous study shows that electric vans are able to reduce CO_2 emissions, even after accounting for the emissions related to electricity production (56). Also, an electrification trend for private vehicles is also clear in the future, bringing the benefit that private EVs with uncontrolled charging would reduce GHG emissions by 46% compared to gasoline vehicles (57). Based on this, we simulated the development of the electrification scenario. In this scenario, we set the electrification percentages of private vehicles and trucks to 25% and 30% in 2030, 50% and 75% in 2040 and 75% and 100% in 2050, respectively.

Table 12 shows the comparative results of negative externalities related to shopping activities for the baseline and the electrification scenarios. The comparison between the electrification scenario and the baseline scenario shows a significant reduction in emissions other than PM2.5 because of the spread of electric vehicles in the planning years. The results of the two MSAs also show that a 25% and 30% penetration of electric private vehicles and electric trucks, respectively, can already be effective in reducing most of the emissions associated with shopping activities.

Table 12. Comparative results of negative externalities for the electrification scenario.

a) NYC

Variables		**Baseline Scenario**				**Electrification Scenario**			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO_2 (kg)	In-store	13143003.1	13366768.2	14712653.5	16534353.7	13174642.7	20.84	10.05	2.57
	Online	178313.31	209618.53	253342.10	326476.55	178525.36	0.92	0.20	0.00
	Both	111042.52	161572.99	227381.45	310559.58	114381.79	1.13	0.00	0.00
NO_x (kg)	In-store	13919.27	5967.67	4174.67	4485.07	13921.63	0.02	0.01	0.00
	Online	334.99	226.81	255.72	326.50	335.39	0.00	0.00	0.00
	Both	127.61	84.70	82.12	108.31	131.78	0.00	0.00	0.00
SO_2 (kg)	In-store	75.37	73.40	88.59	91.63	75.59	0.00	0.00	0.00
	Online	0.89	0.86	1.24	1.54	0.89	0.00	0.00	0.00
	Both	0.63	0.86	1.34	1.69	0.64	0.00	0.00	0.00
PM10 (kg)	In-store	554.26	239.98	183.00	210.49	555.49	0.00	0.00	0.00
	Online	7.58	3.93	2.92	3.60	7.59	0.00	0.00	0.00
	Both	4.68	2.91	2.81	3.90	4.77	0.00	0.00	0.00
PM25 (kg)	In-store	503.81	216.20	163.57	188.14	504.94	217.44	164.50	188.14
	Online	6.91	3.64	2.64	3.23	6.92	3.64	2.64	3.23
	Both	4.26	2.63	2.51	3.49	4.33	2.68	2.51	3.36

b) LA

Variables		Baseline Scenario				Electrification Scenario			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		13913.47	14871.82	15588.93	16020.88	13913.47	14871.82	15588.93	16020.88
CO2	In-store	16072982.9	13135968.0	12709371.6	12221976.6	81518.45	83275.70	87738.50	86847.10
(kg)	Online	190149.3	102546.0	87221.2	64352.6	328.38	201.49	194.98	145.87
	Both	1927847.9	1524704.9	1415428.7	1296100.8	9070.68	8765.60	9080.46	8572.81
NOx	In-store	16740.73	5339.05	3065.79	2767.06	16222375.1	8.8	4.6	1.3
(kg)	Online	341.83	102.69	85.26	62.33	190032.7	0.0	0.0	0.0
	Both	2162.66	726.44	458.01	403.00	1939011.2	0.8	0.7	1.3
SO2	In-store	70.38	56.87	51.61	50.83	16880.33	0.01	0.00	0.00
(kg)	Online	0.72	0.34	0.33	0.25	341.62	0.00	0.00	0.00
	Both	8.32	6.43	5.71	5.35	2172.06	0.00	0.00	0.00
PM10	In-store	651.74	194.97	120.32	118.49	71.05	0.00	0.00	0.00
(kg)	Online	7.79	1.87	0.92	0.66	0.72	0.00	0.00	0.00
	Both	78.25	23.24	13.57	12.64	8.37	0.00	0.00	0.00
PM25	In-store	596.41	178.59	103.22	101.50	657.61	0.00	0.00	0.00
(kg)	Online	7.13	1.69	0.84	0.58	7.78	0.00	0.00	0.00
	Both	71.61	21.24	11.74	10.88	78.67	0.00	0.00	0.00

2) Rush deliveries

As the e-commerce market becomes more competitive, retail companies have begun to offer additional services to maintain and grow their market share. One of these additional services concerns delivery times (e.g., same day, two-hour, one-hour). Despite the logistical challenges, some e-retailers have successfully implemented such rush deliveries for specific products and markets, with others poised to follow, which leads to larger negative externalities (6). Hence, we simulated the rush deliveries scenario where two conditions are defined: 1) high-rush and 2) mid-rush. In the high-rush and mid-rush (low and medium consolidation) conditions, we set up 75% and 50% of reduction rate respectively, in the stops per delivery tour, which is equivalent to increasing the marginal delivery distance for every last-mile delivery.

Table 13 shows the comparative results of negative externalities for the scenario of rush deliveries, including high-rush and mid-rush conditions. The simulation results of Rush delivery show that the states of high-rush and mid-rush increase the VMT and corresponding emissions associated with online shopping by nearly 300% and 200%, respectively. Therefore, enhancing the consolidation of logistics facilities and reducing the length of a single delivery tour can help reduce the negative externalities associated with e-commerce.

3) Crowdshipping

Crowdshipping is a collaborative strategy that assigns delivery tasks to a large number of actors who act as ordinary couriers, with the goal of lowering delivery costs and promoting sustainability (58). By shifting some last-mile delivery demands from trucks to private vehicles and even to biking, the negative externalities are expected to reduce to a lower level. We establish the crowdshipping scenario to simulate the change in externalities, including three adoption conditions: low, medium, and high. In each of the three conditions, we assume that 10%, 50% and 75% of the delivery demands are carried by private vehicles, respectively.

Table 14 shows the comparative results of negative externalities for the crowdshipping scenario, including low, medium, and high adoption conditions. The results of crowdshipping simulations show that in NYC, the CO2 emissions associated with online shopping activities are reduced by about 7%, 34% and 51% in the three conditions of low, medium, and high adoptions, respectively. Emissions of CO2 associated with online shopping have declined at a similar rate in LA. This shows that crowdshipping does help to reduce last-mile delivery-related emissions, thus reducing negative environmental externalities. Also, we conducted simulations with the combination of crowdshipping and electrification. However, the difference is that in reality, NYC and LA will have different adoption rates for future crowdshipping due to the difference in travel mode structure. In contrast, LA, where private vehicle ownership is higher, is well positioned to achieve a higher level of adoption rates for crowdshipping.

Considering the combination of electrification and crowdshipping, Table 15 shows the results of simulated negative externalities for this combined scenario. In combination with the electrification scenario, the CO2 emissions associated with online shopping activities can be eliminated by 2040 in the three conditions of low, medium, and high adoptions.

Table 13. Comparative results of negative externalities for the scenario of rush deliveries.

a-1) NYC, high-rush

Variables		Baseline Scenario				Rush Deliveries Scenario (High-Rush)			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO_2 (kg)	In-store	13143003.1	13366768.2	14712653.5	16534353.7	13324895.2	13473671.1	14792238.6	16550147.5
	Online	178313.31	209618.53	253342.10	326476.55	713433.1	837151.3	1013756.9	1305754.8
	Both	111042.52	161572.99	227381.45	310559.58	152243.8	222992.8	302468.7	420080.7
NO_x (kg)	In-store	13919.27	5967.67	4174.67	4485.07	14085.05	6009.54	4209.74	4484.69
	Online	334.99	226.81	255.72	326.50	1340.32	905.80	1023.26	1305.83
	Both	127.61	84.70	82.12	108.31	201.31	146.96	158.49	216.31
SO_2 (kg)	In-store	75.37	73.40	88.59	91.63	76.46	73.99	89.05	91.72
	Online	0.89	0.86	1.24	1.54	3.55	3.43	4.95	6.17
	Both	0.63	0.86	1.34	1.69	0.84	1.12	1.71	2.21
PM_{10} (kg)	In-store	554.26	239.98	183.00	210.49	562.41	241.79	183.91	210.72
	Online	7.58	3.93	2.92	3.60	30.34	15.68	11.70	14.40
	Both	4.68	2.91	2.81	3.90	6.45	4.06	3.67	5.11
PM_{25} (kg)	In-store	503.81	216.20	163.57	188.14	511.24	217.84	164.38	188.34
	Online	6.91	3.64	2.64	3.23	27.65	14.53	10.57	12.93
	Both	4.26	2.63	2.51	3.49	5.87	3.70	3.30	4.57

a-2) NYC, mid-rush

Variables		Baseline Scenario				Rush Deliveries Scenario (Mid-Rush)			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO2 (kg)	In-store	13143003.1	13366768.2	14712653.5	16534353.7	13207863.2	13525007.6	14746685.9	16597626.3
	Online	178313.31	209618.53	253342.10	326476.55	356853.4	419169.3	506787.3	652867.4
	Both	111042.52	161572.99	227381.45	310559.58	130326.3	177760.2	265719.7	343108.5
NOx (kg)	In-store	13919.27	5967.67	4174.67	4485.07	13957.89	6019.71	4223.73	4503.30
	Online	334.99	226.81	255.72	326.50	670.42	453.54	511.54	652.91
	Both	127.61	84.70	82.12	108.31	157.59	103.69	113.59	145.43
SO2 (kg)	In-store	75.37	73.40	88.59	91.63	75.77	74.28	88.75	91.98
	Online	0.89	0.86	1.24	1.54	1.77	1.72	2.47	3.09
	Both	0.63	0.86	1.34	1.69	0.73	0.92	1.54	1.84
PM10 (kg)	In-store	554.26	239.98	183.00	210.49	556.64	242.81	183.18	211.29
	Online	7.58	3.93	2.92	3.60	15.18	7.85	5.85	7.20
	Both	4.68	2.91	2.81	3.90	5.50	3.22	3.25	4.24
PM25 (kg)	In-store	503.81	216.20	163.57	188.14	505.98	218.75	163.72	188.85
	Online	6.91	3.64	2.64	3.23	13.83	7.28	5.29	6.47
	Both	4.26	2.63	2.51	3.49	5.00	2.92	2.91	3.79

b-1) LA, high-rush

Variables		Baseline Scenario				Rush Deliveries Scenario (High-Rush)			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		13913.468	14871.820	15588.934	16020.883	13913.468	14871.820	15588.934	16020.883
CO_2 (kg)	In-store	16072982.9	13135968.0	12709371.6	12221976.6	16141091.0	13136480.1	12680932.0	12239036.1
	Online	190149.3	102546.0	87221.2	64352.6	760022.7	409915.1	348663.9	257611.6
	Both	1927847.9	1524704.9	1415428.7	1296100.8	2555765.5	2041311.7	1898212.9	1753829.1
NO_x (kg)	In-store	16740.73	5339.05	3065.79	2767.06	16816.79	5332.20	3049.75	2775.18
	Online	341.83	102.69	85.26	62.33	1366.28	410.49	340.82	249.53
	Both	2162.66	726.44	458.01	403.00	3276.94	1246.16	927.92	834.14
SO_2 (kg)	In-store	70.38	56.87	51.61	50.83	70.67	56.88	51.50	50.89
	Online	0.72	0.34	0.33	0.25	2.89	1.37	1.33	0.99
	Both	8.32	6.43	5.71	5.35	10.72	8.14	7.54	7.12
PM10 (kg)	In-store	651.74	194.97	120.32	118.49	654.23	195.04	120.08	118.64
	Online	7.79	1.87	0.92	0.66	31.13	7.49	3.67	2.63
	Both	78.25	23.24	13.57	12.64	103.91	32.71	18.63	17.30
PM25 (kg)	In-store	596.41	178.59	103.22	101.50	598.69	178.65	103.01	101.63
	Online	7.13	1.69	0.84	0.58	28.50	6.76	3.35	2.34
	Both	71.61	21.24	11.74	10.88	95.11	29.80	16.37	15.02

b-2) LA, mid-rush

Variables		Baseline Scenario				Rush Deliveries Scenario (Mid-Rush)			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		13913.468	14871.820	15588.934	16020.883	13913.468	14871.820	15588.934	16020.883
CO2 (kg)	In-store	16072982.9	13135968.0	12709371.6	12221976.6	16198853.5	13188779.4	12597863.6	12247935.0
	Online	190149.3	102546.0	87221.2	64352.6	379978.4	205064.0	174482.9	128707.6
	Both	1927847.9	1524704.9	1415428.7	1296100.8	2127131.5	1682387.9	1577157.5	1448203.5
NOx (kg)	In-store	16740.73	5339.05	3065.79	2767.06	16873.54	5357.56	3042.91	2769.71
	Online	341.83	102.69	85.26	62.33	683.08	205.35	170.56	124.67
	Both	2162.66	726.44	458.01	403.00	2525.67	891.28	615.52	546.30
SO2 (kg)	In-store	70.38	56.87	51.61	50.83	70.93	57.10	51.15	50.94
	Online	0.72	0.34	0.33	0.25	1.44	0.68	0.66	0.50
	Both	8.32	6.43	5.71	5.35	9.08	6.94	6.32	5.93
PM10 (kg)	In-store	651.74	194.97	120.32	118.49	656.78	195.81	119.25	118.75
	Online	7.79	1.87	0.92	0.66	15.56	3.75	1.83	1.31
	Both	78.25	23.24	13.57	12.64	86.50	26.18	15.26	14.19
PM25 (kg)	In-store	596.41	178.59	103.22	101.50	601.02	179.36	102.30	101.72
	Online	7.13	1.69	0.84	0.58	14.25	3.38	1.68	1.17
	Both	71.61	21.24	11.74	10.88	79.16	23.90	13.28	12.25

Table 14. Comparative results of negative externalities for the crowdshipping scenario.

a) NYC

Variables		Baseline Scenario				Crowdshipping (Low Adoption)			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO2 (kg)	In-store	13143003.1	13366768.2	14712653.5	16534353.7	13245522.3	13521823.6	14693397.3	16568021.7
	Online	178313.3	209618.5	253342.1	326476.6	168887.6	197277.7	239073.9	307760.8
	Both	111042.5	161573.0	227381.5	310559.6	110738.2	162904.2	222922.7	310393.9
Nox (kg)	In-store	13919.27	5967.67	4174.67	4485.07	14022.42	6010.07	4209.07	4505.79
	Online	334.99	226.81	255.72	326.50	310.03	207.28	232.62	296.50
	Both	127.61	84.70	82.12	108.31	127.01	86.84	81.41	109.12
SO2 (kg)	In-store	75.37	73.40	88.59	91.63	76.00	74.27	88.43	91.82
	Online	0.89	0.86	1.24	1.54	0.85	0.82	1.18	1.47
	Both	0.63	0.86	1.34	1.69	0.63	0.87	1.31	1.69
PM10 (kg)	In-store	554.26	239.98	183.00	210.49	559.57	242.87	182.52	210.85
	Online	7.58	3.93	2.92	3.60	7.19	3.69	2.77	3.42
	Both	4.68	2.91	2.81	3.90	4.69	2.93	2.75	3.90
PM25 (kg)	In-store	503.81	216.20	163.57	188.14	508.67	218.80	163.14	188.46
	Online	6.91	3.64	2.64	3.23	6.55	3.42	2.51	3.07
	Both	4.26	2.63	2.51	3.49	4.26	2.65	2.46	3.49
		Crowdshipping (Medium Adoption)				Crowdshipping (High Adoption)			
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO2 (kg)	In-store	13277267.6	13455494.6	14797146.6	16675841.9	13207536.5	13451577.2	14826623.8	16484833.3
	Online	130793.9	148501.0	181434.5	233173.6	106965.6	118108.0	145523.5	186544.5
	Both	113012.1	167131.8	224079.1	314210.3	115884.5	166162.5	237508.5	319216.2
Nox (kg)	In-store	14024.86	5990.21	4219.61	4515.62	13953.50	5964.33	4210.13	4487.76
	Online	209.46	129.90	139.62	177.03	146.52	81.55	81.55	102.35
	Both	131.77	87.79	85.89	116.23	137.28	89.63	89.70	117.52
SO2 (kg)	In-store	76.21	73.89	89.07	92.41	75.78	73.89	89.27	91.35
	Online	0.69	0.67	0.95	1.16	0.59	0.58	0.81	0.97
	Both	0.64	0.89	1.31	1.71	0.65	0.88	1.39	1.73
PM10 (kg)	In-store	560.53	241.55	183.92	212.34	556.71	241.67	184.40	209.77
	Online	5.59	2.77	2.17	2.72	4.59	2.20	1.79	2.28
	Both	4.77	3.02	2.75	3.92	4.87	2.99	2.93	3.99
PM25 (kg)	In-store	509.54	217.61	164.39	189.80	506.05	217.72	164.82	187.49
	Online	5.09	2.55	1.95	2.44	4.18	2.00	1.61	2.05
	Both	4.33	2.73	2.46	3.51	4.43	2.71	2.62	3.57

b) LA

Variables		Baseline Scenario				Crowdshipping (Low Adoption)			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		13913.47	14871.82	15588.93	16020.88	13913.47	14871.82	15588.93	16020.88
CO2 (kg)	In-store	16072982.9	13135968.0	12709371.6	12221976.6	16224476.0	13192704.5	12657690.6	12236551.5
	Online	190149.3	102546.0	87221.2	64352.6	179906.5	96528.4	82230.1	60600.7
	Both	1927847.9	1524704.9	1415428.7	1296100.8	1914966.0	1504376.9	1425469.1	1300178.1
Nox (kg)	In-store	16740.73	5339.05	3065.79	2767.06	16901.53	5359.01	3056.93	2772.86
	Online	341.83	102.69	85.26	62.33	316.45	93.98	77.47	56.54
	Both	2162.66	726.44	458.01	403.00	2155.50	718.66	465.34	407.79
SO2 (kg)	In-store	70.38	56.87	51.61	50.83	71.04	57.12	51.39	50.88
	Online	0.72	0.34	0.33	0.25	0.69	0.33	0.31	0.23
	Both	8.32	6.43	5.71	5.35	8.26	6.33	5.75	5.36
PM10 (kg)	In-store	651.74	194.97	120.32	118.49	657.75	195.85	119.82	118.62
	Online	7.79	1.87	0.92	0.66	7.37	1.75	0.86	0.62
	Both	78.25	23.24	13.57	12.64	77.73	22.96	13.67	12.68
PM25 (kg)	In-store	596.41	178.59	103.22	101.50	601.90	179.40	102.79	101.61
	Online	7.13	1.69	0.84	0.58	6.74	1.58	0.79	0.55
	Both	71.61	21.24	11.74	10.88	71.13	20.99	11.82	10.91
		Crowdshipping (Medium Adoption)				Crowdshipping (High Adoption)			
Population (1,000)		13913.47	14871.82	15588.93	16020.88	13913.47	14871.82	15588.93	16020.88
CO2 (kg)	In-store	16105432.0	13140441.6	12617456.8	12263185.5	16268456.5	13194625.4	12669329.9	12208943.1
	Online	139210.6	72721.8	62426.3	45847.6	113897.3	57673.7	50055.1	36747.3
	Both	1961925.5	1543411.2	1447201.8	1309960.8	1968748.3	1551319.9	1445074.3	1334107.8
Nox (kg)	In-store	16774.48	5330.80	3044.86	2777.50	16939.12	5364.06	3063.88	2753.42
	Online	215.41	59.33	46.50	33.66	152.56	37.58	27.14	19.53
	Both	2220.92	746.49	485.50	420.40	2240.28	759.51	492.91	438.75
SO2 (kg)	In-store	70.53	56.90	51.23	51.00	71.25	57.12	51.44	50.78
	Online	0.56	0.26	0.24	0.18	0.47	0.22	0.20	0.15
	Both	8.46	6.48	5.83	5.40	8.48	6.50	5.82	5.49
PM10 (kg)	In-store	653.08	195.08	119.45	118.89	659.75	195.91	119.92	118.39
	Online	5.69	1.26	0.64	0.46	4.64	0.95	0.50	0.37
	Both	79.63	23.60	13.89	12.80	79.92	23.77	13.89	13.02
PM25 (kg)	In-store	597.64	178.70	102.47	101.84	603.75	179.45	102.88	101.42
	Online	5.21	1.14	0.57	0.41	4.25	0.86	0.44	0.32
	Both	72.87	21.57	12.03	11.02	73.15	21.73	12.03	11.22

4) Automation/slash efficiency improvements

Automation encompasses several alternatives which rescind the need for human drivers: drone or unmanned aerial vehicles (UAVs), autonomous mobile robots (AMRs), and autonomous vans and trucks (59). The automation in trucks enables improved efficiency in time at levels impossible for a human being who needs to make several stops during the trip. In the automation scenario, we simulate the delivery tours by adding 20-30% of stops in a fixed length delivery tour, which refers to the situation that more packages can be delivered in a single tour.

Table 16 shows the comparative results of negative externalities related to shopping activities for the baseline and the automation scenarios. The simulation results for the automation scenario show that there is a reduction of about 25% in the various negative externalities (including VMT) related to online shipping as slash efficiency increases in the planning years. This illustrates that alternatives for automation have the potential to reduce operational costs, and emissions due to better efficiency in driving. Also, this advantage will be even more pronounced when truck fleets are electrified in the future.

Conclusions

This project consolidates the methodology of e-commerce shopping behavior modeling and predictions of related negative externalities. Five main tasks are completed with coherent and systematic utilizations of ATUS and NHTS datasets, including 1) shopping behavior modeling, 2) estimates of shopping travel parameters, 3) estimates of last-mile delivery parameters, 4) estimates of emission rates, and 5) MC simulation. Most importantly, this project develops a tool to simulate and visualize the results of negative externalities related to shopping activities across the six selected MSAs, which are NYC, LA, Chicago, DC, SF and Dallas.

In Task 1, we mainly build and validate the WMNL behavior models for different MSAs with specific sets of model coefficients that can be used to predict shopping behavior for a synthesized population. In the WMNL mode, the dependent variable with totally four categories, namely “No shopping”, “In-store shopping”, “Online shopping” and “Both shopping”. The results of the WMNL models vary across MSAs, as reflected by the fact that different coefficients of variables are positive in some MSAs and negative in others. In general, however, female, high education, low to moderate age group, and not in labor market are the positive influences that make the respondents choose the online and/or both shopping. Four different population growth scenarios are specified with the combinations of high/moderate IV market share time series prediction and projected population. Also, the models are validated by the synthesized populations for the planning years, resulting in around 2% in the errors of dependent variable market share predictions.

Table 15. Comparative results of negative externalities for the crowdshipping and electrification scenarios.

a) NYC

Variables		Electrification-Only Scenario				Crowdshipping & Electrification (Low Adoption)			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO2 (kg)	In-store	13174642.7	20.8	10.1	2.6	13129427.0	24.6	17.5	0.3
	Online	178525.4	0.9	0.2	0.0	169007.7	1.0	0.7	0.0
	Both	114381.8	1.1	0.0	0.0	117395.6	0.2	0.5	0.0
Nox (kg)	In-store	13921.63	0.02	0.01	0.00	13887.10	0.02	0.01	0.00
	Online	335.39	0.00	0.00	0.00	310.24	0.00	0.00	0.00
	Both	131.78	0.00	0.00	0.00	134.30	0.00	0.00	0.00
SO2 (kg)	In-store	75.59	0.00	0.00	0.00	75.33	0.00	0.00	0.00
	Online	0.89	0.00	0.00	0.00	0.85	0.00	0.00	0.00
	Both	0.64	0.00	0.00	0.00	0.66	0.00	0.00	0.00
PM10 (kg)	In-store	555.49	0.00	0.00	0.00	553.96	0.00	0.00	0.00
	Online	7.59	0.00	0.00	0.00	7.19	0.00	0.00	0.00
	Both	4.77	0.00	0.00	0.00	4.94	0.00	0.00	0.00
PM25 (kg)	In-store	504.94	217.44	164.50	188.14	503.56	218.87	164.11	187.73
	Online	6.92	3.64	2.64	3.23	6.56	3.42	2.51	3.07
	Both	4.33	2.68	2.51	3.36	4.49	2.65	2.49	3.54
		Crowdshipping & Electrification (Medium Adoption)				**Crowdshipping & Electrification (High Adoption)**			
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO2 (kg)	In-store	13327250.7	14.0	9.4	5.0	13222533.2	18.8	11.7	8.5
	Online	130801.4	2.0	0.1	0.0	107017.4	0.3	0.0	0.0
	Both	112848.9	1.5	0.1	0.0	121657.5	0.4	0.1	0.0
Nox (kg)	In-store	14075.63	0.01	0.01	0.00	13962.65	0.02	0.01	0.01
	Online	209.49	0.00	0.00	0.00	146.73	0.00	0.00	0.00
	Both	130.66	0.00	0.00	0.00	140.82	0.00	0.00	0.00
SO2 (kg)	In-store	76.49	0.00	0.00	0.00	75.89	0.00	0.00	0.00
	Online	0.69	0.00	0.00	0.00	0.59	0.00	0.00	0.00
	Both	0.64	0.00	0.00	0.00	0.69	0.00	0.00	0.00
PM10 (kg)	In-store	562.42	0.00	0.00	0.00	557.79	0.00	0.00	0.00
	Online	5.59	0.00	0.00	0.00	4.60	0.00	0.00	0.00
	Both	4.77	0.00	0.00	0.00	5.16	0.00	0.00	0.00
PM25 (kg)	In-store	511.26	219.43	163.17	188.05	507.05	218.75	164.39	187.71
	Online	5.10	2.55	1.95	2.44	4.19	2.00	1.61	2.04
	Both	4.34	2.77	2.44	3.46	4.69	2.73	2.57	3.69

b) LA

Variables		Electrification-Only Scenario 2020	2030	2040	2050	Crowdshipping & Electrification (Low Adoption) 2020	2030	2040	2050
Population (1,000)		13913.47	14871.82	15588.93	16020.88	13913.47	14871.82	15588.93	16020.88
CO2 (kg)	In-store	16222375.1	8.8	4.6	1.3	16165744.2	13.0	8.3	0.4
	Online	190032.7	0.0	0.0	0.0	179889.2	0.1	0.0	0.0
	Both	1939011.2	0.8	0.7	1.3	1931931.9	4.6	0.1	0.0
Nox (kg)	In-store	16880.33	0.01	0.00	0.00	16830.95	0.01	0.01	0.00
	Online	341.62	0.00	0.00	0.00	316.43	0.00	0.00	0.00
	Both	2172.06	0.00	0.00	0.00	2172.08	0.00	0.00	0.00
SO2 (kg)	In-store	71.05	0.00	0.00	0.00	70.80	0.00	0.00	0.00
	Online	0.72	0.00	0.00	0.00	0.69	0.00	0.00	0.00
	Both	8.37	0.00	0.00	0.00	8.34	0.00	0.00	0.00
PM10 (kg)	In-store	657.61	0.00	0.00	0.00	655.43	0.00	0.00	0.00
	Online	7.78	0.00	0.00	0.00	7.36	0.00	0.00	0.00
	Both	78.67	0.00	0.00	0.00	78.45	0.00	0.00	0.00
PM25 (kg)	In-store	601.79	179.00	102.48	101.33	599.80	179.44	102.43	101.50
	Online	7.13	1.69	0.84	0.58	6.74	1.58	0.79	0.55
	Both	72.00	21.01	11.73	10.95	71.80	21.09	11.74	11.00
		Crowdshipping & Electrification (Medium Adoption)				**Crowdshipping & Electrification (High Adoption)**			
Population (1,000)		13913.47	14871.82	15588.93	16020.88	13913.47	14871.82	15588.93	16020.88
CO2 (kg)	In-store	16192127.5	321.7	8.4	2.2	16193614.2	25.0	10.5	2.8
	Online	139278.9	0.0	0.1	0.0	113860.6	0.1	0.0	0.0
	Both	1944113.6	0.8	0.6	0.0	1979029.5	1.1	0.1	0.0
Nox (kg)	In-store	16845.73	0.32	0.01	0.00	16850.88	0.02	0.01	0.00
	Online	215.58	0.00	0.00	0.00	152.49	0.00	0.00	0.00
	Both	2203.64	0.00	0.00	0.00	2250.96	0.00	0.00	0.00
SO2 (kg)	In-store	70.92	0.00	0.00	0.00	70.92	0.00	0.00	0.00
	Online	0.56	0.00	0.00	0.00	0.47	0.00	0.00	0.00
	Both	8.38	0.00	0.00	0.00	8.52	0.00	0.00	0.00
PM10 (kg)	In-store	656.32	0.00	0.00	0.00	656.34	0.00	0.00	0.00
	Online	5.69	0.00	0.00	0.00	4.64	0.00	0.00	0.00
	Both	78.91	0.00	0.00	0.00	80.36	0.00	0.00	0.00
PM25 (kg)	In-store	600.61	178.51	102.24	101.27	600.63	178.74	102.72	101.44
	Online	5.21	1.14	0.57	0.41	4.25	0.86	0.44	0.32
	Both	72.22	21.53	11.93	11.12	73.54	21.82	12.05	11.11

Table 16. Comparative results of negative externalities for the automation scenario.

a) NYC

Variables		Baseline Scenario 2020	Baseline Scenario 2030	Baseline Scenario 2040	Baseline Scenario 2050	Automation Scenario 2020	Automation Scenario 2030	Automation Scenario 2040	Automation Scenario 2050
Population (1,000)		20845.87	21924.85	22886.24	23738.46	20845.87	21924.85	22886.24	23738.46
CO2 (kg)	In-store	13143003.1	13366768.2	14712653.5	16534353.7	13173152.7	13427860.9	14772030.9	16526793.8
	Online	178313.31	209618.53	253342.10	326476.55	142841.2	167572.8	202597.0	261112.1
	Both	111042.52	161572.99	227381.45	310559.58	114246.6	163087.4	227451.0	299383.0
Nox (kg)	In-store	13919.27	5967.67	4174.67	4485.07	13911.46	5982.69	4210.87	4456.33
	Online	334.99	226.81	255.72	326.50	268.35	181.31	204.50	261.13
	Both	127.61	84.70	82.12	108.31	128.61	82.90	78.59	102.38
SO2 (kg)	In-store	75.37	73.40	88.59	91.63	75.59	73.74	88.93	91.59
	Online	0.89	0.86	1.24	1.54	0.71	0.69	0.99	1.23
	Both	0.63	0.86	1.34	1.69	0.65	0.87	1.35	1.64
PM10 (kg)	In-store	554.26	239.98	183.00	210.49	555.32	241.12	183.62	210.56
	Online	7.58	3.93	2.92	3.60	6.08	3.14	2.34	2.88
	Both	4.68	2.91	2.81	3.90	4.81	2.94	2.81	3.76
PM25 (kg)	In-store	503.81	216.20	163.57	188.14	504.79	217.23	164.12	188.20
	Online	6.91	3.64	2.64	3.23	5.54	2.91	2.11	2.59
	Both	4.26	2.63	2.51	3.49	4.37	2.66	2.52	3.36

b) LA

Variables		Baseline Scenario				Automation Scenario			
		2020	2030	2040	2050	2020	2030	2040	2050
Population (1,000)		13913.47	14871.82	15588.93	16020.88	13913.47	14871.82	15588.93	16020.88
CO2 (kg)	In-store	16072982.9	13135968.0	12709371.6	12221976.6	16125695.4	13148125.0	12613166.0	12212018.4
	Online	190149.3	102546.0	87221.2	64352.6	152034.2	82052.1	69757.6	51474.1
	Both	1927847.9	1524704.9	1415428.7	1296100.8	1883472.0	1480643.4	1381227.9	1255903.6
Nox (kg)	In-store	16740.73	5339.05	3065.79	2767.06	16794.41	5333.98	3051.22	2763.87
	Online	341.83	102.69	85.26	62.33	273.31	82.17	68.19	49.86
	Both	2162.66	726.44	458.01	403.00	2083.97	683.05	428.37	370.88
SO2 (kg)	In-store	70.38	56.87	51.61	50.83	70.62	56.93	51.21	50.78
	Online	0.72	0.34	0.33	0.25	0.58	0.27	0.27	0.20
	Both	8.32	6.43	5.71	5.35	8.15	6.27	5.57	5.19
PM10 (kg)	In-store	651.74	194.97	120.32	118.49	654.01	195.23	119.38	118.40
	Online	7.79	1.87	0.92	0.66	6.23	1.50	0.73	0.53
	Both	78.25	23.24	13.57	12.64	76.42	22.47	13.21	12.24
PM25 (kg)	In-store	596.41	178.59	103.22	101.50	598.49	178.83	102.42	101.42
	Online	7.13	1.69	0.84	0.58	5.70	1.35	0.67	0.47
	Both	71.61	21.24	11.74	10.88	69.93	20.55	11.40	10.52

In Task 1, several findings are extracted to help provide insights of the shipping behavior modeling and support the ongoing analysis in the project. This task is not only regarding the factors influencing the shopping behaviors in different MSAs and groups of individuals, but also consolidates the feasibility of the ongoing analysis of MSA-wise shopping travel and last-mile delivery parameters in order to build the spatial demand-based e-commerce forecasting tool. These findings include:

1. Heterogeneous effects are shown in the MSA-wise WMNL models. The shopping choices: in-store shopping, online shopping, and both shopping have different influencing factors in different WMNL models. For in-store shopping behavior, age, gender, income, and mobility difficulties are all significant influencing factors, while different categories of independent variables have different positive and negative influences in different MSAs. For NYC, Chicago, and DC, female was a significant factor in making in-store shopping behavior more likely, while LA and Dallas showed a negative effect. In contrast, the odds ratio of in-store shopping for young adults with high income is less than 1, which means that these two factors may be positive influences on online shopping.
2. For most MSAs, factors such as living in an MSA size greater than one million, middle to high income, retired/not in the workforce, and highly educated women are positive influencers of online shopping. However, there are differences, and for LA, Chicago, and Dallas, people living in areas with MSA size less than one million are more likely to choose online shopping.
3. There is some correlation between the behavior of both shopping and online shopping, while fewer observations hinder our judgment of the true trend. Therefore, it is not possible to compare the magnitude of the coefficients for online and both shopping.
4. From the model validation results of the six MSAs in Table 5, Table 6 and Table 7, the distribution of DV market shares simulated using synthesized population differs from the actual data by less than 2%, which is within an acceptable range. Therefore, it is confirmed that these WMNL models can be used for the subsequent MC simulations.
5. In addition to this, Table 8 provides time series forecasts of DV market shares for 2030-2050. Despite the validation of the models, the future share of online shopping and both shopping for each MSA is still not high, with the highest being Dallas with 15.45%.

Tasks 2, 3 and 4 provide information that supports the generation of shopping travels and the calculation of a series of negative externalities in Task 5 using Monte Carlo simulation, which is shopping travel parameters, last-mile delivery parameters and emission rate per person, respectively. For different parameters, a unique probability distribution or a regression relation is obtained for different MSAs, and this distribution is fed into the subsequent MC simulation.

The logic from Task 2 to 4 is coherent and conjunct, with all tasks providing information to generate and simulate shopping travels and last-mile deliveries. There are also some major findings from these tasks, which includes:

1. Only minor differences were found in the parameter distributions of the individual MSAs, and the overall distribution trends were similar. Among the six MSAs, LA and Dallas have a higher shopping tour length and a higher proportion of private car trips. NYC, on the other hand, has the highest proportion of public transportation shopping trips among these MSAs.
2. In the process of calculating the parameters for adjusting the silver to obtain the last-mile delivery, we found a high degree of overlap between the population activity shape-center and the transportation firm distribution shape-center for LA. This is certainly an important infrastructure support for the future development of e-commerce.
3. The results of the delivery tour length distribution also tell us that the MSA with a higher overlap between LA, the shape center, has a shorter average delivery distance. Therefore, we believe that shortening the distance between population and transportation establishment centroids is one of the keys to reduce the average delivery distance.

Finally, Task 5 is performed as to serve the goal of the project: to simulate shopping behaviors for synthesized population and to calculate related negative externalities. The MC simulation process is finalized by utilizing the results from Task 1 to 4, where the outputs of this part are the aggregate average VMT and emissions (negative externalities) for different shopping activities in the planning years and different MSA. This aggregate simulation results mainly come from calculations of VMT and emissions of the datasets of synthesized populations for different planning years and population growth scenarios. Major findings include:

1. Compared to in-store shopping, the increase in daily VMT associated with online shopping is clearly greater. However, due to the base year condition, the market share of in-store shopping is still the largest in 2050. The calculation of various pollutant emissions shows that the emissions of NOx, PM10 and PM2.5 all decreased, except for CO2 and SO2 which increased slightly in the planning year. At the same time, LA shows a similar pattern of population growth, but the difference is that VMT from pure online shopping shrinks in 2050, while VMT from both shopping explodes. Hence, the shift in shopping behavior in LA tends to be a hybrid one, so we can see that the daily CO2 generated by pure in-store shopping does not increase in 2050.
2. The MSAs of Chicago, SF, and Dallas are projected to have rapid population growth in 2050, but the change in shopping behavior varies across these MSAs. Despite the population growth, the change in shopping behavior in different regions shows that SF and NYC are more receptive to pure online shopping, while people in Dallas and LA are more inclined to in-store and both shopping behavior.
3. The population growth in the planning years results for DC is essentially unchanged for the planning years, meaning that the total population of the region is not likely to grow in the future. As a result, there is shrinkage in shopping behavior in the simulation results. As a result, the total amount of pollutant emissions will decrease in the future.

Inevitably, the methods this project adopts has some limits throughout the five tasks, which are based on certain assumptions that slightly go inconsistent against the real world and thus might bring some inaccuracy of the modeling, prediction, and simulation results. First, in the Task 1, the process of variable selection is manual, which means that we must specify a unique WMNL model for each of the MSAs. Inherently, the specifications of WMNL models cannot be integrated into the spatial demand-based forecasting tool with automatic processes. To solve the problem, a diverse collection of supervised machine learning methods can be done to model and predict the shopping choices of individuals based on certain criteria. Moreover, for the shopping travel and last-mile delivery parameters we assume that the internal population and logistics infrastructure maintain unchanged or slightly changed in the planning years. This may cause the problem that the forecasting tool do not consider the internal socio-demographic and infrastructure changes that may affect the overall shopping choices among the people, although the project has already considered the adoption trends and the changes of socio-demographic statistics at the macroscopic level of the MSAs. In the future, time series forecasts on a more detailed geographic areas of an MSA are preferrable, such as ZIP codes and census tracts, which enables us to understand the temporal and spatial changes in an MSA for the planning years and to integrate these into our forecasting tool when simulating the negative externalities. Also, we found that transportation mode has an impact on shopping behavior. In this project, we only study the aggregate data at MSA level. Considering the future development of emerging technologies such as electrification and automated vehicles, the structure of transportation modes may see some big changes, not only about consumers' shopping travels, but also inseparable from the logistics and distribution industry. The emergence of new delivery technologies and methods, such as drones, self-driving trucks, and front-end warehouses, will significantly change the layout of the existing logistics industry infrastructure and indirectly affect people's shopping choices. we hope that this project will also work on this in the future.

Finally, there is another important issue that we can work on in the future, which is that the externality simulation results do not display a clear and significant trend of e-commerce growth. In the results, we find that the externalities generated by online and both shopping will increase in 2050, but the total market share will be less than 20% combined. This huge gap makes us think about finding the favorable factors that can really promote e-commerce development and refine the model in the subsequent tool development process.

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Data Summary

Products of Research

This study makes use of three primary datasets: American Time Use Survey (ATUS), National Household Travel Survey (NHTS), and population projections. The use of this data, and several modeling efforts then produced two primary data outcomes from this study. These data are produced for six MSAs, including, New York City, Los Angeles, Chicago, Washington DC, San Francisco, and Dallas. First, this study produces data describing emission rates for different vehicle types according to year, pollutant, and MSA, as outlined in Table 10. This is then used to help produce the final data outcome, which is the average daily VMT and emissions quantities for each shopping channel (see Table 11 and Figure 11).

Data Format and Content

Emissions Rates and Quantities. The emissions rates and quantities generated for 2020, 2030, 2040, and 2050 and for the six MSAs and for CO_2, NO_x, SO_2, PM10, and PM2.5. The quantities are also segmented by shopping channel. These data are stored in .csv format.

Average Daily VMT. The average daily VMT are also generated for the six MSAs and segmented by pollutant, year, and shopping channel. These data are stored in .csv format.

NHTS. The NHTS data used for this study was from 2009 and 2017 and included the person-level data (as opposed to household, vehicle, or trip-level data which are also available). The NHTS variables used for this study include TDCASEID, HHC_BSA and TRIPPURP. These files are provided in .csv format.

ATUS. The ATUS data used for this study is from 2004-2020 and has person-level observations. The ATUS variables used for this study include MSA size, socioeconomic and demographic characteristics (income, age, sex, education, employment), family structure, and disability status. The shopping (dependent) variables were derived using activity and location variables (using methods from(6), and described in Table 1). These files are provided in several formats, although the .csv format was used in this study. In the shopping behavior modeling, the respondents are weighted by the 2020 sample weight column (WT20) which is also provided in the ATUS dataset.

Population Projections. The population projection data are produced in five-year increments from 2020 through 2100. These files are provided in .csv format. This study uses the data from 2020 through 2050. The projections are provided as totals, or segmented by age category (in four-year increments), race/ethnicity and sex. The population projections used in this study were for those counties that make up the New York City, Los Angeles, Washington DC, Chicago, San Francisco, and Dallas MSAs.

Data Access and Sharing

All data sources used for this study (ATUS, NHTS, and population projections) are available for free online. ATUS data requires the user to create an account to extract selected data, NHTS data is available for direct download, and the population projections are publicly available at the following DOI: https://doi.org/10.25338/B89H0F. The data generated in this study are stored in .CSV, .XLSX and .SHP formats.

Reuse and Redistribution

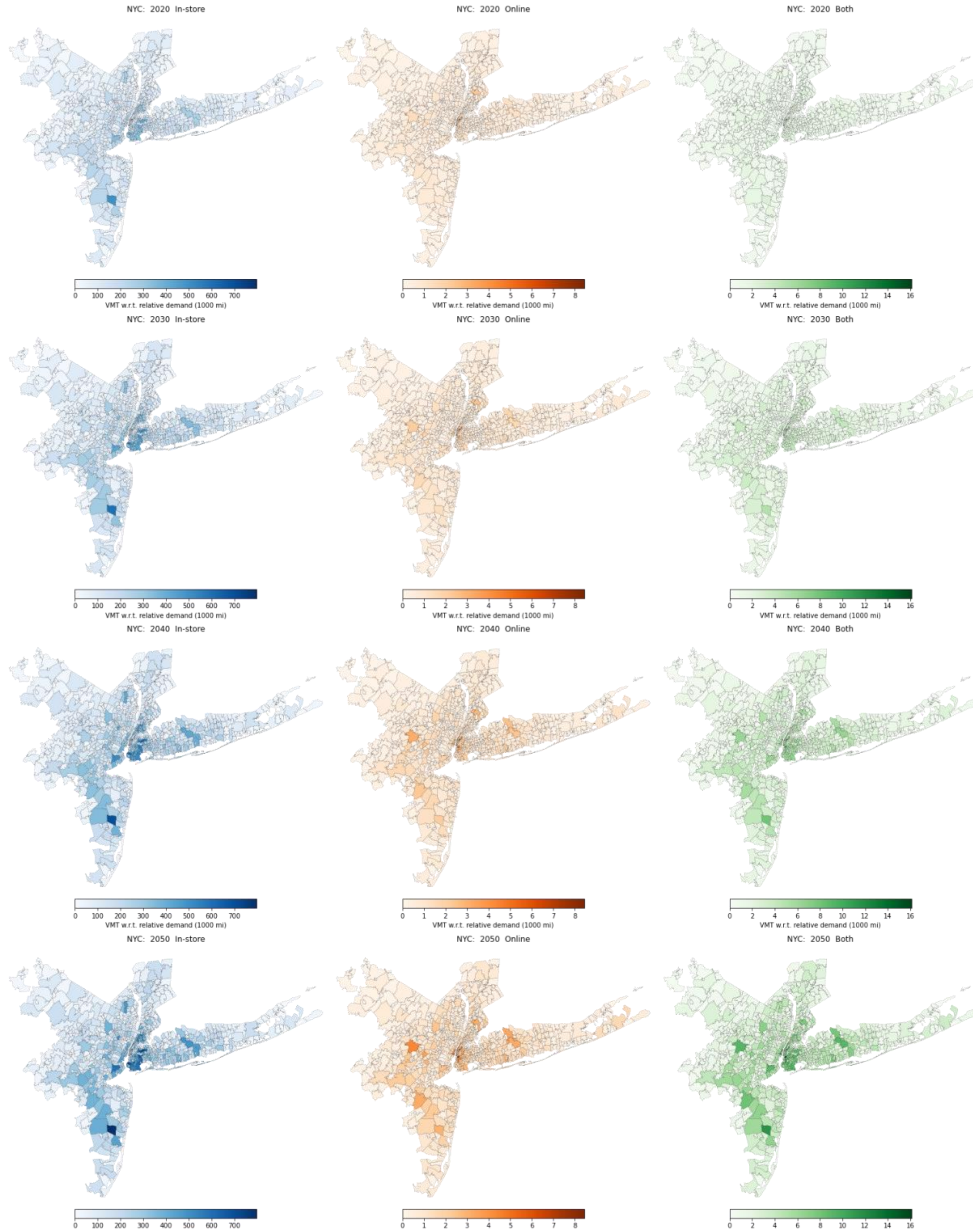
Dr. Miguel Jaller and the other co-authors of the work (identified in this Final Report) hold the intellectual property rights to the data generated by the research. Services providers hold the right to the bikeshare data, and the online portal comments data.

Data will not be able to be transferred to other data archives besides the ones approved by the PI and Co-PIs. The data can be used by anyone with proper referencing to the authors.

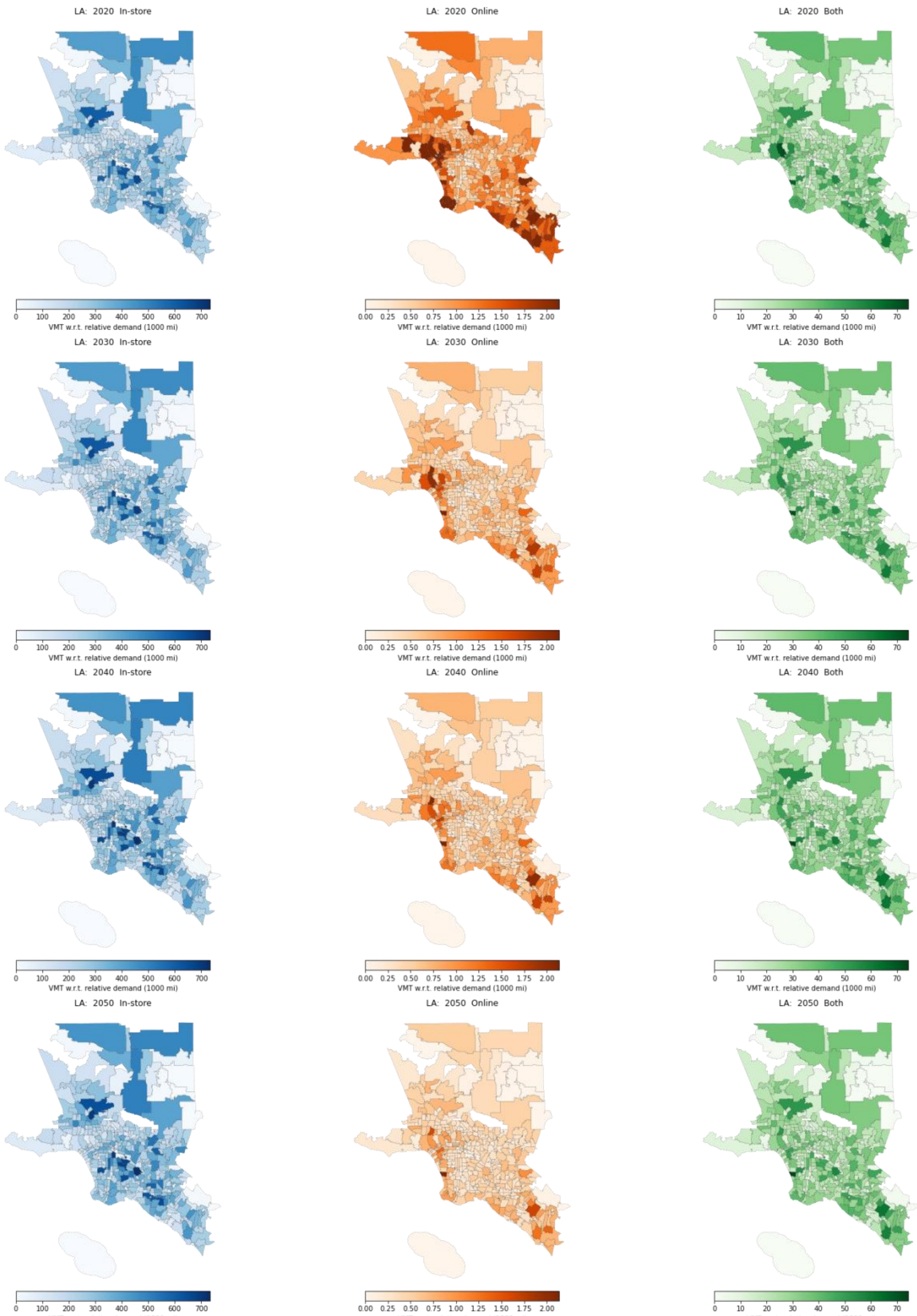
Appendix

Figure A-1. Relative VMT of different shopping channels

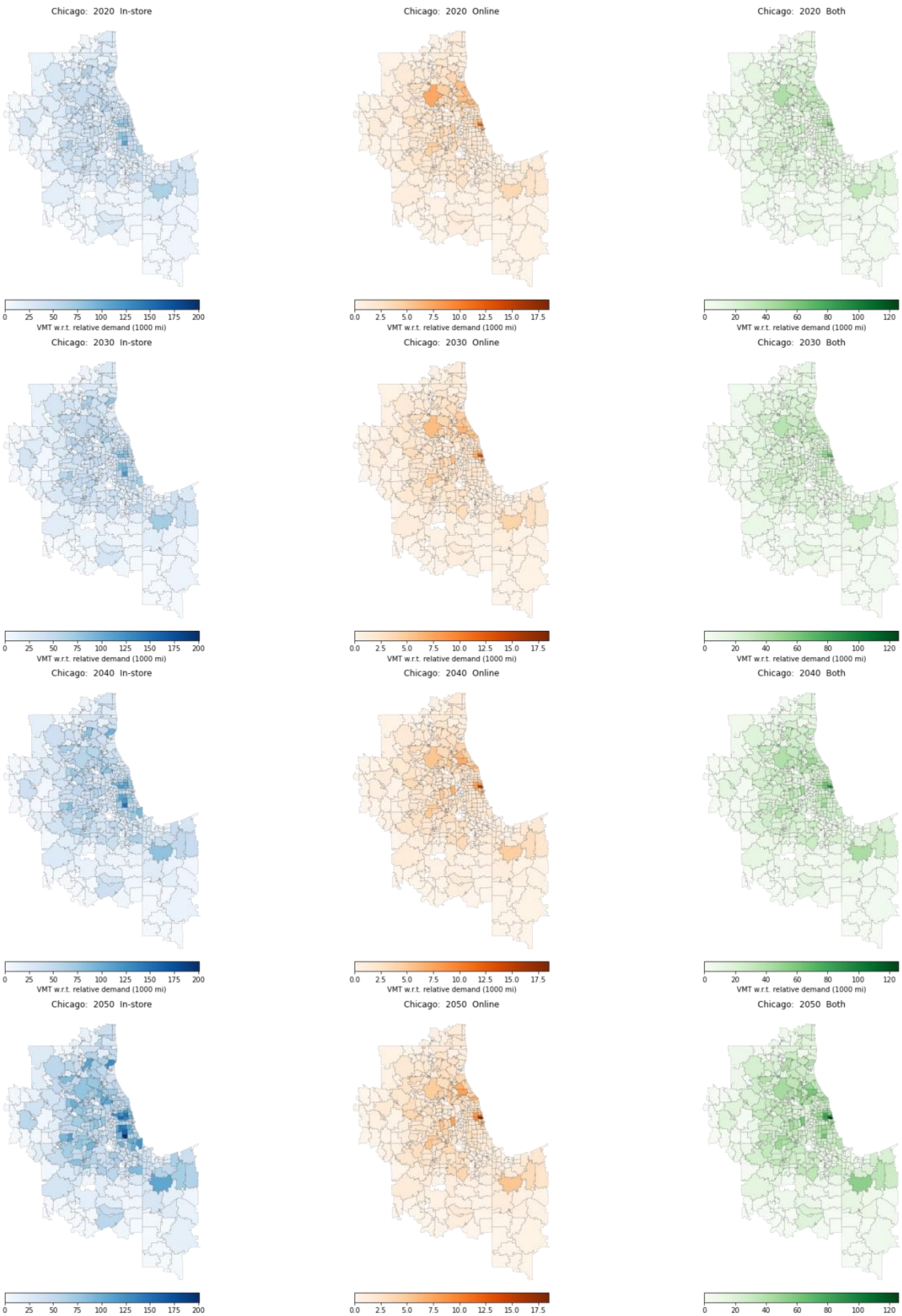
a) NYC



b) LA

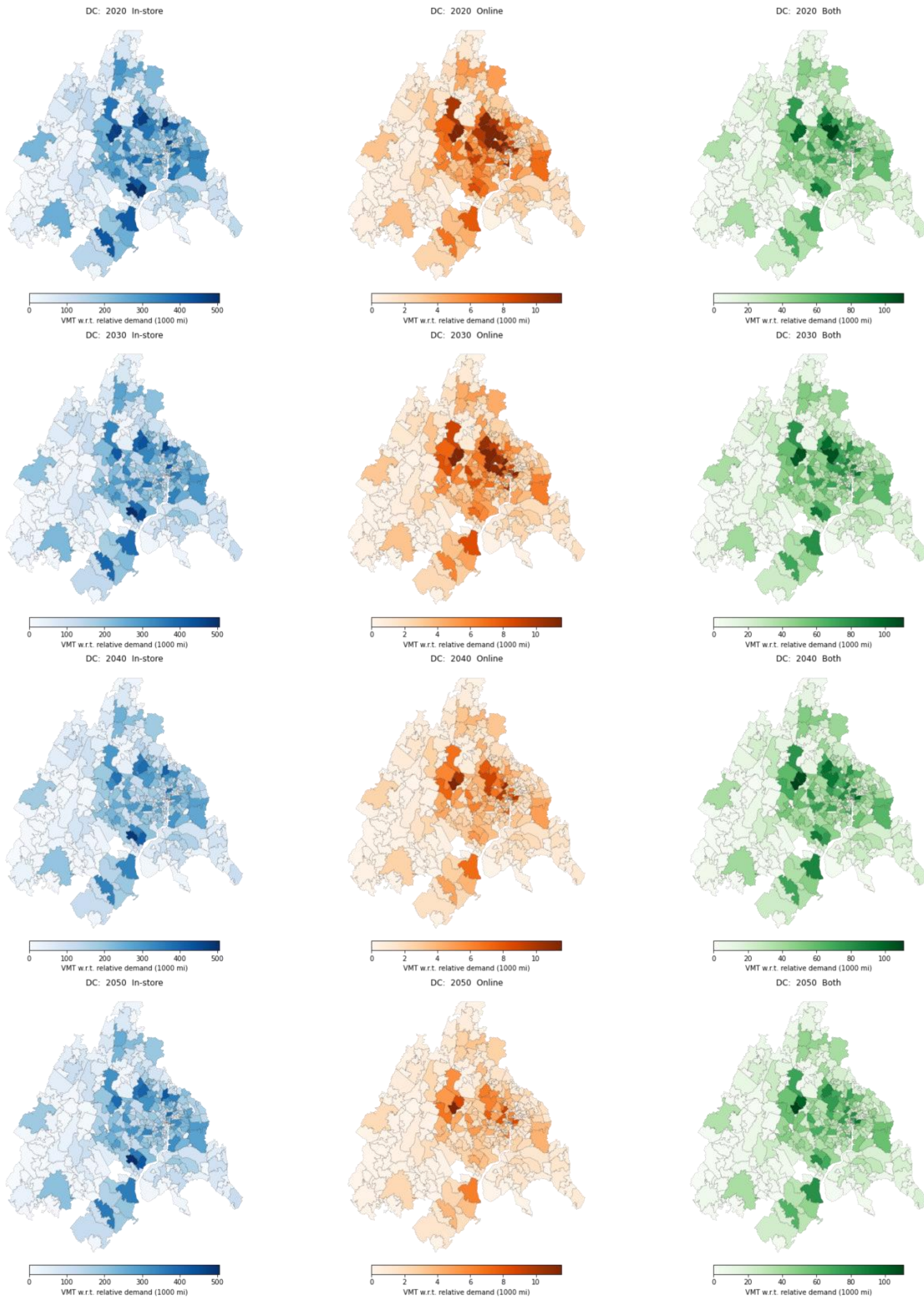

LA: 2020 In-store
LA: 2020 Online
LA: 2020 Both
0 100 200 300 400 500 600 700
VMT w.r.t. relative demand (1000 mi)
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
VMT w.r.t. relative demand (1000 mi)
0 10 20 30 40 50 60 70
VMT w.r.t. relative demand (1000 mi)
LA: 2030 In-store
LA: 2030 Online
LA: 2030 Both
0 100 200 300 400 500 600 700
VMT w.r.t. relative demand (1000 mi)
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
VMT w.r.t. relative demand (1000 mi)
0 10 20 30 40 50 60 70
VMT w.r.t. relative demand (1000 mi)
LA: 2040 In-store
LA: 2040 Online
LA: 2040 Both
0 100 200 300 400 500 600 700
VMT w.r.t. relative demand (1000 mi)
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
VMT w.r.t. relative demand (1000 mi)
0 10 20 30 40 50 60 70
VMT w.r.t. relative demand (1000 mi)
LA: 2050 In-store
LA: 2050 Online
LA: 2050 Both
0 100 200 300 400 500 600 700
VMT w.r.t. relative demand (1000 mi)
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
VMT w.r.t. relative demand (1000 mi)
0 10 20 30 40 50 60 70
VMT w.r.t. relative demand (1000 mi)

c) Chicago

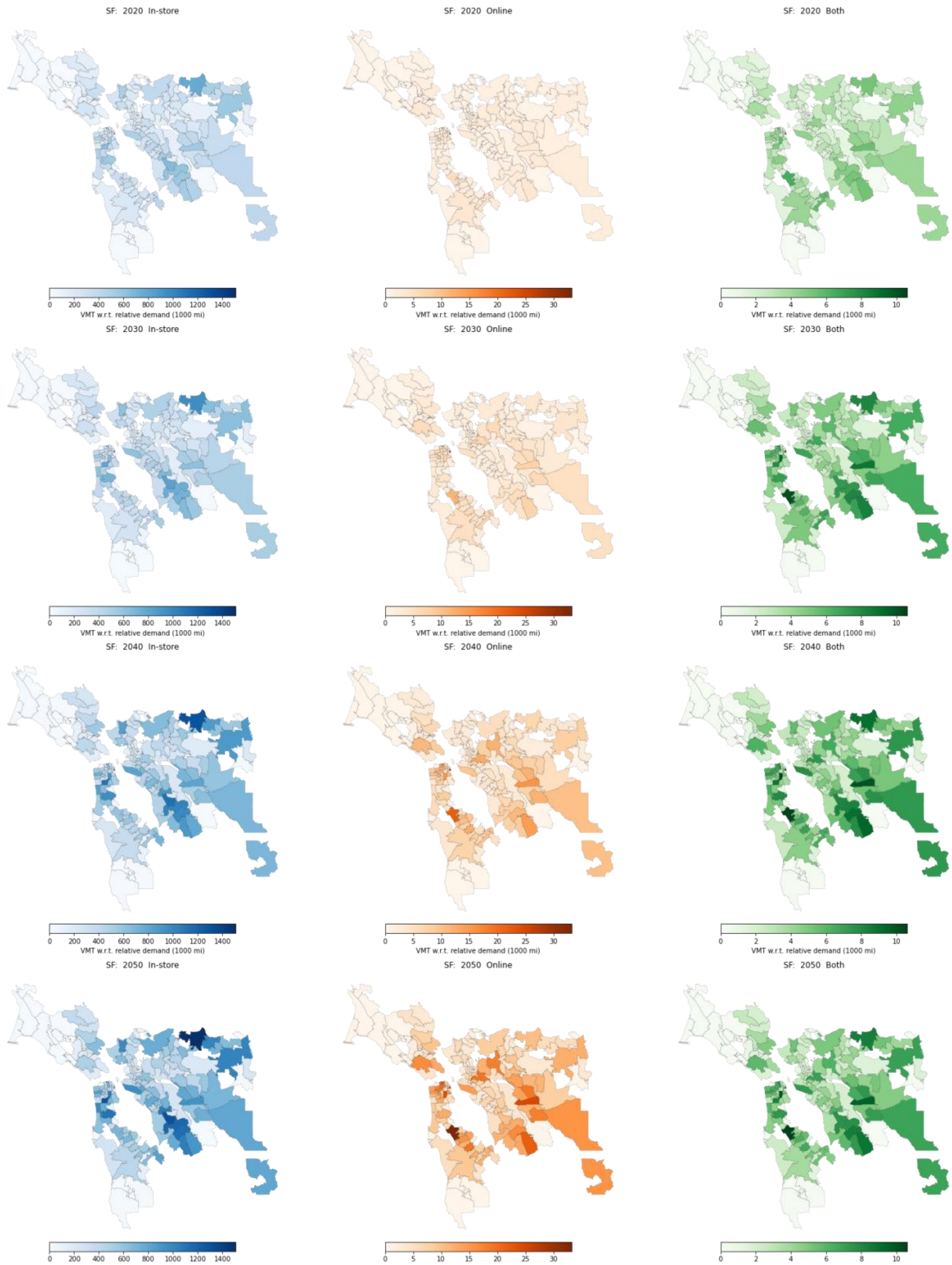


Chicago: 2020 In-store
Chicago: 2020 Online
Chicago: 2020 Both
Chicago: 2030 In-store
Chicago: 2030 Online
Chicago: 2030 Both
Chicago: 2040 In-store
Chicago: 2040 Online
Chicago: 2040 Both
Chicago: 2050 In-store
Chicago: 2050 Online
Chicago: 2050 Both
0 25 50 75 100 125 150 175 200
0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5
0 20 40 60 80 100 120
VMT w.r.t. relative demand (1000 mi)

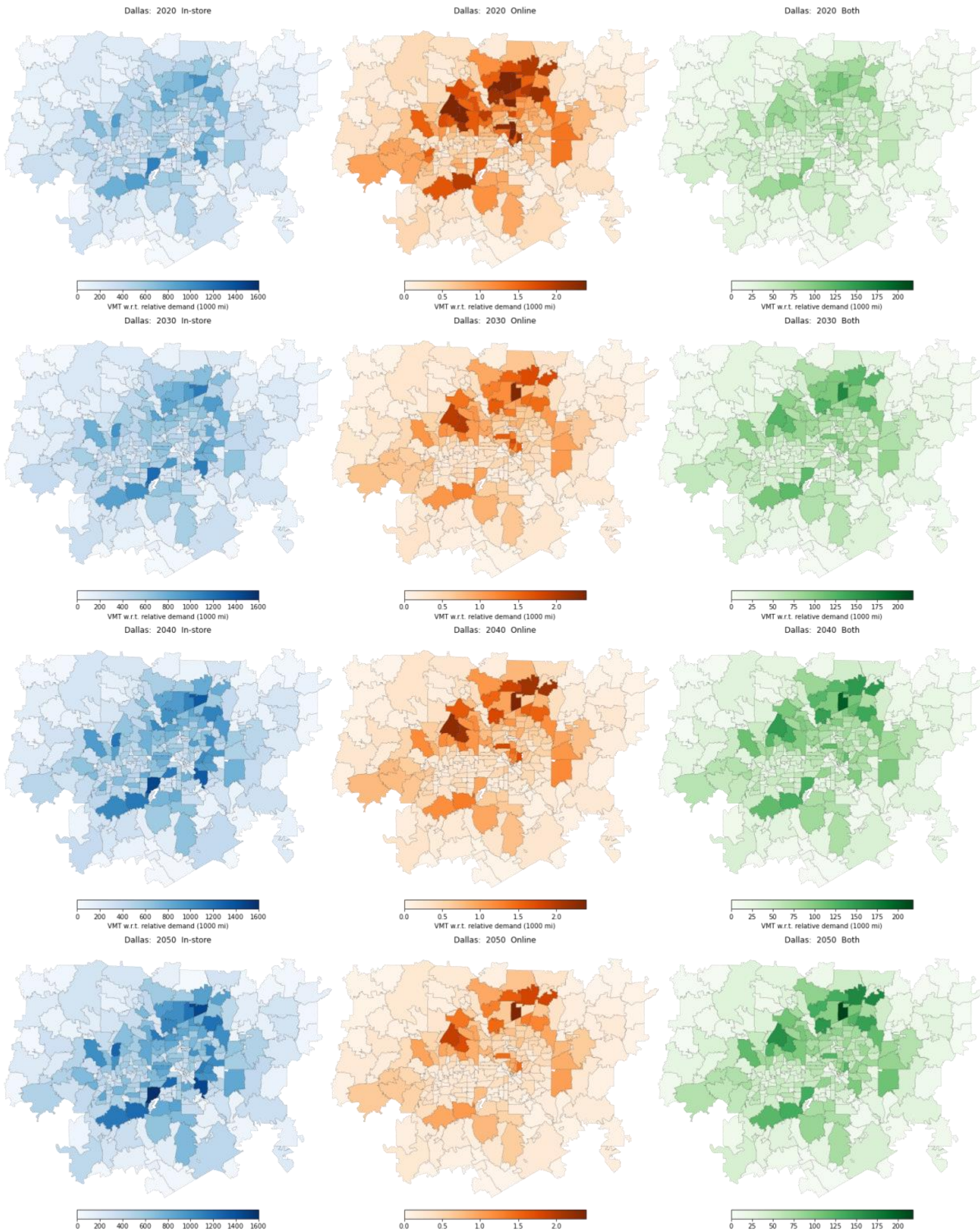
d) DC


DC: 2020 In-store
DC: 2020 Online
DC: 2020 Both
DC: 2030 In-store
DC: 2030 Online
DC: 2030 Both
DC: 2040 In-store
DC: 2040 Online
DC: 2040 Both
DC: 2050 In-store
DC: 2050 Online
DC: 2050 Both
0 100 200 300 400 500
0 2 4 6 8 10
0 20 40 60 80 100
VMT w.r.t. relative demand (1000 mi)

e) SF


SF: 2020 In-store
SF: 2020 Online
SF: 2020 Both
0 200 400 600 800 1000 1200 1400
VMT w.r.t. relative demand (1000 mi)
0 5 10 15 20 25 30
VMT w.r.t. relative demand (1000 mi)
0 2 4 6 8 10
VMT w.r.t. relative demand (1000 mi)
SF: 2030 In-store
SF: 2030 Online
SF: 2030 Both
0 200 400 600 800 1000 1200 1400
VMT w.r.t. relative demand (1000 mi)
0 5 10 15 20 25 30
VMT w.r.t. relative demand (1000 mi)
0 2 4 6 8 10
VMT w.r.t. relative demand (1000 mi)
SF: 2040 In-store
SF: 2040 Online
SF: 2040 Both
0 200 400 600 800 1000 1200 1400
VMT w.r.t. relative demand (1000 mi)
0 5 10 15 20 25 30
VMT w.r.t. relative demand (1000 mi)
0 2 4 6 8 10
VMT w.r.t. relative demand (1000 mi)
SF: 2050 In-store
SF: 2050 Online
SF: 2050 Both
0 200 400 600 800 1000 1200 1400
VMT w.r.t. relative demand (1000 mi)
0 5 10 15 20 25 30
VMT w.r.t. relative demand (1000 mi)
0 2 4 6 8 10
VMT w.r.t. relative demand (1000 mi)

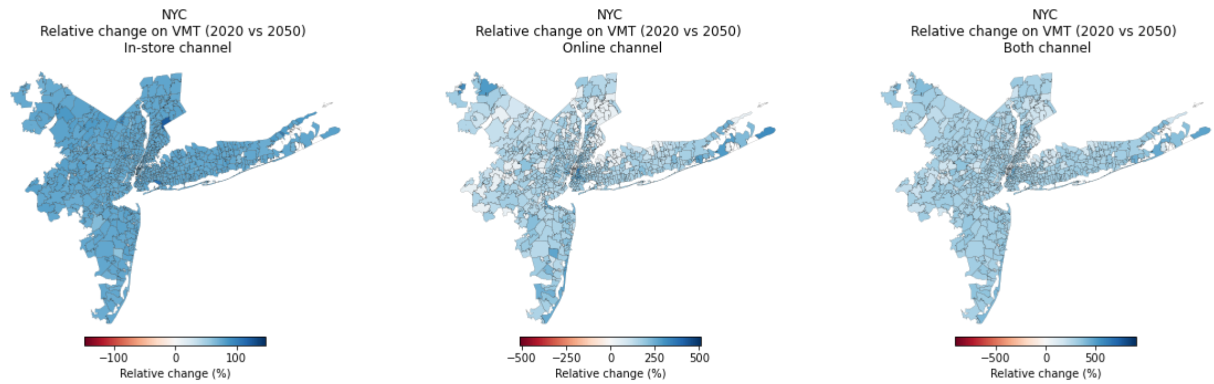
f) Dallas



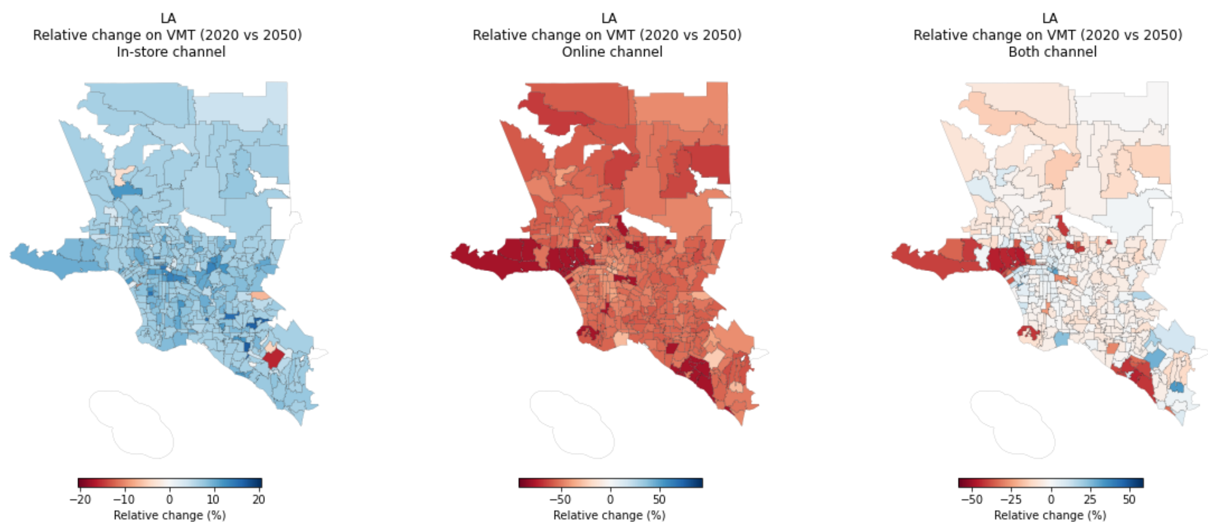
Dallas: 2020 In-store
Dallas: 2020 Online
Dallas: 2020 Both
0 200 400 600 800 1000 1200 1400 1600
VMT w.r.t. relative demand (1000 mi)
0.0 0.5 1.0 1.5 2.0
VMT w.r.t. relative demand (1000 mi)
0 25 50 75 100 125 150 175 200
VMT w.r.t. relative demand (1000 mi)
Dallas: 2030 In-store
Dallas: 2030 Online
Dallas: 2030 Both
0 200 400 600 800 1000 1200 1400 1600
VMT w.r.t. relative demand (1000 mi)
0.0 0.5 1.0 1.5 2.0
VMT w.r.t. relative demand (1000 mi)
0 25 50 75 100 125 150 175 200
VMT w.r.t. relative demand (1000 mi)
Dallas: 2040 In-store
Dallas: 2040 Online
Dallas: 2040 Both
0 200 400 600 800 1000 1200 1400 1600
VMT w.r.t. relative demand (1000 mi)
0.0 0.5 1.0 1.5 2.0
VMT w.r.t. relative demand (1000 mi)
0 25 50 75 100 125 150 175 200
VMT w.r.t. relative demand (1000 mi)
Dallas: 2050 In-store
Dallas: 2050 Online
Dallas: 2050 Both
0 200 400 600 800 1000 1200 1400 1600
VMT w.r.t. relative demand (1000 mi)
0.0 0.5 1.0 1.5 2.0
VMT w.r.t. relative demand (1000 mi)
0 25 50 75 100 125 150 175 200
VMT w.r.t. relative demand (1000 mi)

Figure A-2. Relative changes in percentages of VMT for 2020 vs 2050

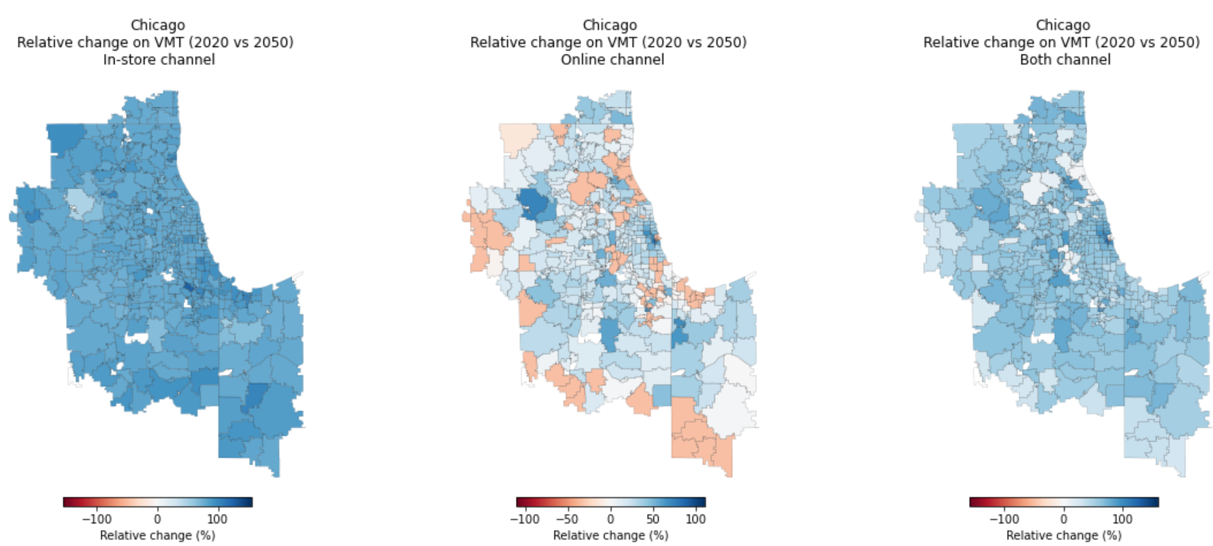
a) NYC



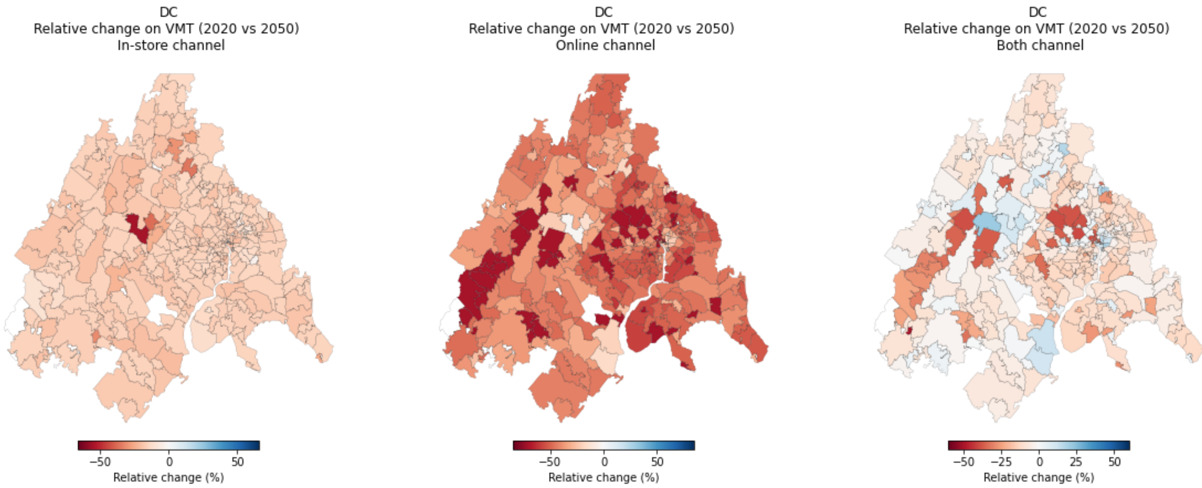
b) LA



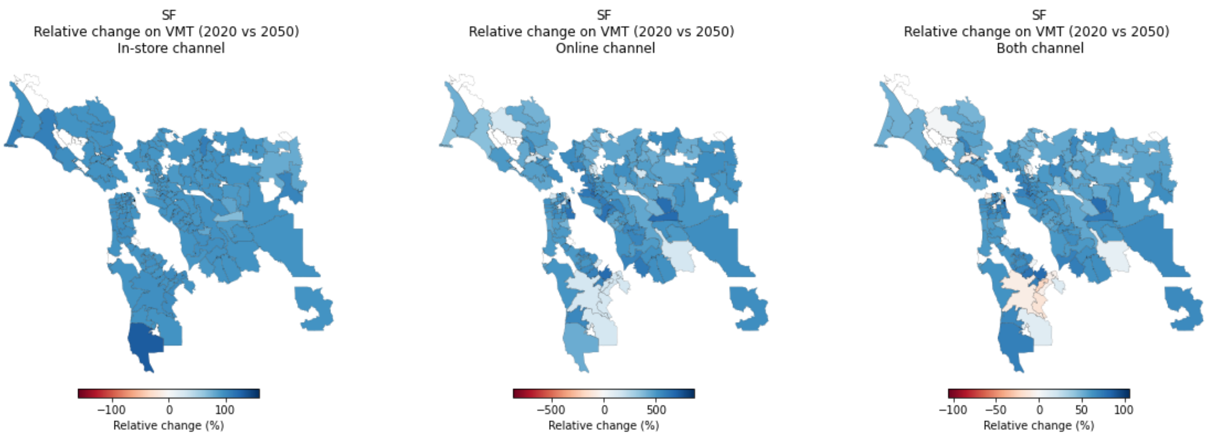
c) Chicago



d) DC



e) SF



f) Dallas