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Evaluating the environmental impacts of online shopping: A behavioral and transportation approach

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ABSTRACT

Various fields and commercial sectors have witnessed a transformation with the advent of the internet. In the last decade, the retail sector in particular has witnessed the massive growth of e-commerce. This has also significantly altered our shopping experiences, influencing a range of decisions, from where, how, and how much to shop. With the consistent growth of e-commerce transactions, more trucks than ever before are entering cities today, bringing with them the negative externalities of increased congestion and pollution. This study first unravels underlying shopping behaviors–both in-store and online–using the 2016 American Time Use Survey (ATUS) data. The authors also develop an econometric behavioral model to understand the factors that affect shopping decisions. At a macro level, the disaggregate individual shopping behaviors are studied by implementing the model to synthetic populations to estimate potential vehicle miles traveled and environmental emissions in two metropolitan areas, Dallas and San Francisco (SF). Finally, the study estimates the impacts of rush deliveries, basket size, and consolidation levels by developing a breakeven analysis between in-store and online shopping. These results confirm the importance of managing the urban freight system, including delivery services and operations, to foster a more sustainable urban environment.

1. Introduction

On August 11, 1994 the first internet-based retail transaction took place, and the internet has been continuously reshaping the way we shop ever since (Lewis, 1994). E-commerce, a term completely unknown a couple of decades ago, is gradually becoming a fundamental part of our daily lives. Today, almost a third of internet users in the US shop online at least once a week, while another third buys something online at least once a month (Walker Sands, 2017). In 2017, the retail sales from e-commerce in the US were $448.3 billion, accounting for 8.8% of the total retail sales, compared to 5.3% in 2012 (U.S. Census Bureau, 2018). Moreover, these sales have consistently experienced an annual growth of roughly 15% in the past five years. E-commerce is significantly affecting our shopping behaviors and the places we live. A UPS (2017) study found that unlike the traditional way of shopping, wherein a person would search and buy products in a store, today, 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. The underlying question is whether online shopping activity today is substituting, complementing, or modifying physical shopping activity (Mokhatarian, 2004). While there have been many studies suggesting a complementary effect between the two, there have been only a handful suggesting a substitution effect, and a few that have suggested an asymmetric effect of one on the other. For example, Farag et al. (2007) found that online

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searching had a positive effect on in-store shopping, and in turn, a positive effect on online purchasing. On the other hand, Weltevreden and Rietbergen (2007) found that the more often people buy online, the lower are their chances of making a shopping trip and purchasing in-store. In another study, Zhou and Wang (2014) found a negative effect of the propensity for buying in-store on the propensity for buying online, while they found a positive effect the other way, thus suggesting an asymmetric effect. A fuller understanding of the effect of online shopping on in-store shopping would be key to understanding the overall impact of e-commerce on society, and vehicle traffic. The 2016 ATUS data reveals that 14% of all the trips made during the day are shopping trips, and while it is likely that the number of shopping trips would decrease due to e-commerce, the total shopping travel (trips and tours from personal shopping and delivery trucks) might increase, as previously suggested by Mokhatarian (2004).

A number of authors have analyzed the impact of e-commerce on the environment (Brown and Guiffrida, 2014; Durand and Feliu, 2012; Siikavirta et al., 2003; Wiese et al., 2012; Wygonik and Goodchild, 2016). These studies suggest that since delivery trucks optimize their routes, e-commerce has the potential to decrease the negative impacts of shopping on the environment, and therefore is much more sustainable than shopping trips to stores using personal cars. For instance, Siikavirta et al. (2003) estimated a potential of 54% to 93% reduction in distances traveled, and an 18% to 84% reduction in greenhouse gas (GHG) emissions due to e-commerce. However, to the authors' knowledge, the literature has not considered the underlying shopping behaviors to analyze the environmental impacts of e-commerce, while only a few studies (Shang et al., 2017; Thirumalai and Sinha, 2005) have linked last-mile operations with customer behavior. Most of the literature assumes 100% penetration of e-commerce (with full substitution of shopping travel), an assumption that might exaggerate the potential of e-commerce to cut congestion and emissions.

This study is an effort to fill this gap by analyzing shopping behaviors across different demographic groups using the American Time Use Survey (ATUS) data (Hofferth et al., 2017) for 2016, thereby providing a more realistic view of e-commerce's impact. Specifically, this work: (1) estimates econometric models to understand the factors affecting shopping decisions, i.e. whether to shop in-store and/or online; (2) quantifies the impacts of changes of different variables in shopping behaviors; (3) estimates the complementary or substitution relationship between in-store and online shopping; (4) conducts a synthetic reconstruction of populations based on census tract demographic information to implement the models for two large metropolitan areas; (5) estimates the potential vehicle miles traveled and environmental emissions (greenhouse gases and criteria pollutants) for the simulated shopping choices; and (6) estimates the impact of rush deliveries, basket size and consolidation levels by developing a breakeven analysis to compare the sustainability of in-store versus online shopping. These results offer insights into the type of system-level strategies (e.g., demand consolidation, use of zero-emission vehicles, alternative delivery modes) needed to foster a sustainable urban system, as well as the impacts from service providers' operations and practices.

2. Literature review

2.1. Impacts of e-commerce on shopping behaviors

The internet is the cornerstone of e-commerce. In 2016, > 88% of the U.S population accessed the web (Internet Live Stats, 2016), resulting in a huge market for e-commerce. With 55% of US shopping conducted online (eMarketer, 2017), e-commerce is significantly reshaping individual lifestyles to such an extent that 79% of all purchases today are influenced by e-commerce (UPS, 2017). An essential question is the nature of online shopping in relation to in-store shopping; whether online shopping is substituting (i.e., online shopping purchases replace purchases made at physical stores), complementing (i.e., online shopping generates more physical shopping trips), or modifying (i.e., online shopping changes the mode, time and duration of physical shopping activity) in-store shopping. (Mokhatarian, 2004).

2.2. Complementary and substitution effects

A complementary effect occurs when part of an individual's overall shopping activity transpires online and part takes place in-store, while a substitution effect occurs when the online shopping activity replaces shopping trips to a store. The majority of the literature on shopping behavior has observed a complementary effect of online shopping on physical shopping trips. Rotem-Mindali and Salomon (2007) suggest that a substitution effect, if evident, is only minor in magnitude; only a handful of studies have found a significant substitution effect. In a Dutch study, Weltevreden and Rietbergen (2007) developed binary logit models for assessing the impact of online shopping on in-store shopping, specifically city center shopping. The authors specifically addressed the impacts of online shopping on the frequency of visits to the city center, and the amount of purchases made in city center stores, both of which reduced significantly for people who made online purchases. However, in another study in the Netherlands, Farag et al. (2007), using structural equation modeling, found a positive effect of online searching on both online and in-store shopping, thus suggesting a complementary effect. Following this approach, Zhou and Wang (2014) employed the National Household Travel Survey (NHTS) data to assess shopping behaviors. This is one of the few studies that used a travel survey to determine the relation between online and in-store shopping. While the authors found a complementary effect of online shopping on in-store shopping, they found a substitution effect the other way, thus suggesting an asymmetric effect. Ferrel (2004) and Lee et al. (2017) also found a complementary effect of online shopping on in-store shopping. Other than these two major effects, a third effect is the induced demand that can transpire either on one's own shopping trips, hence inducing demand under complementary; or online when one purchases products that would not have been bought otherwise, hence inducing demand under substitution (Lee et al., 2017). In general, all of these effects are modifying, in different ways and forms, the way we shop.

2.3. Translating the impacts of e-commerce on the environment

With e-commerce accounting for 8.8% (U.S. Census Bureau, 2018) of the total retail sales in the US in 2017, there is no doubt that physical in-store shopping still dominates the retail sector. However, the consistent growth of e-commerce sales in the last decade raises questions of whether e-commerce is having a positive or a negative impact on the environment. Literature pertaining to the environmental impacts of e-commerce is growing. For instance, a study in the capital city of Finland, Helsinki (Siikavirta et al., 2003), analyzed the GHG emissions from the food production and consumption system using e-grocery commerce as the case study. Simulating shopping-related travel, the authors found that e-grocery shopping performed significantly better environmentally than the scenario wherein everyone used their personal cars to shop at the physical grocery store, cutting the distances driven by 54– 93%, and emissions by 18–87%. Wygonik and Goodchild (2016) found similar results, suggesting the potential of e-commerce to reduce the negative externalities associated with transportation. Accounting for a market penetration of 50%, Durand and Feliu (2012) found a potential reduction of VMT by nearly 20% with e-grocery. The above 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. To further evaluate the impacts, this study analyzes, at the micro-level, shopping behaviors across different demographic groups using the 2016 ATUS data, and then expands these shopping behaviors to a macro-level, estimating the environmental impacts of changing shopping practices.

3. Data & descriptive statistics

3.1. The American time use survey

The authors used the 2016 American Time Use Survey (ATUS) data to analyze shopping behaviors. ATUS, a time use study funded by the US Bureau of Labor Statistics (BLS), logs the place and time of all daily activities for participating individuals, providing information on time spent on more than 400 detailed activities. Additionally, the data contains key demographic variables and weights assigned to each respondent (to account for under- or over-representation), which can help discern the underlying behaviors. For the purpose of this study, the authors considered an individual as the unit of analysis.

Although the ATUS contains shopping as an activity, it does not differentiate between in-store and online shopping. For instance, the "shopping" category in ATUS includes "grocery shopping," "purchasing gas," "purchasing food (not groceries)," "shopping except groceries, food and gas," "comparison shopping," "shopping, not elsewhere classified (N.E.C.)," "researching purchases, N.E.C.," and "consumer purchases, N.E.C." This paper first defines a shopping activity as all of the aforementioned activities except "purchasing gas," and "purchasing food (not groceries)" specifically when performed at any place other than "grocery store," "other store/mall," "post office," "restaurant or bar," and "other place." Table 1 shows the types of activities and the locations considered in the analyses. Since the purpose of this study is to understand in-store and online shopping behaviors, the authors define online shopping as all of the shopping activities performed at any place other than the aforementioned places. In-store shopping includes the same activities as shopping, performed at any of the aforementioned places.

Table 1
Shopping activities definition.

	Activity	Location
Shopping activity	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

Table 2
Descriptive statistics for the 2016 ATUS data.

		2016 ATUS Data (10493)	**No Shopping** (6227)	**In-Store** (4038)	**Online** (121)	**Both** (107)
Gender	Male	45%	47%	41%	35%	34%
	Female	55%	53%	59%	65%	66%
Age	Silent [71,91][a]	15%	15%	14%	9%	8%
	Baby Boomer [52,70][a]	31%	31%	31%	36%	37%
	Generation X [37,51][a]	27%	25%	29%	26%	35%
	Millennials [22,36][a]	21%	21%	21%	23%	17%
	Gen Z [4,21][a]	6%	7%	5%	6%	3%
Education level	No education	0%	0%	0%	0%	0%
	Primary	2%	2%	1%	1%	0%
	Secondary	38%	41%	34%	39%	30%
	Graduate	60%	57%	64%	60%	70%
Employment status	Employed	61%	59%	63%	68%	70%
	Unemployed	3%	3%	4%	1%	3%
	Not in labor force	36%	38%	34%	31%	27%
Family income	Poverty Level	23%	25%	20%	21%	20%
	Low	12%	12%	11%	9%	9%
	Lower Middle	13%	13%	13%	13%	11%
	Median	18%	17%	19%	24%	17%
	Middle Middle	12%	11%	13%	10%	14%
	Upper Middle	12%	11%	13%	10%	12%
	High	10%	10%	10%	13%	17%
Mobility related difficulty	Has no difficulty in mobility	96%	95%	98%	97%	99%
	Has difficulty in mobility	4%	5%	2%	3%	1%
Region	Northeast	16%	16%	17%	14%	18%
	Midwest	23%	24%	22%	20%	21%
	South	39%	39%	39%	44%	32%
	West	22%	22%	22%	22%	29%
MSA size	Pop > 1million	53%	52%	53%	56%	64%
Season	Winter	27%	27%	27%	21%	23%
	Spring	25%	25%	25%	21%	28%
	Summer	24%	25%	24%	21%	21%
	Fall	23%	23%	23%	37%	28%

[a] Age as of 2016.

The authors acknowledge the limitations of such a dataset for understanding shopping behavior, specifically for complementary and substitution effects, and induced demand, considering that the data only represents a single day activity diary. Nevertheless, this study is a step towards understanding the influence of e-commerce on shopping behaviors, and in so doing, estimating the subsequent impacts on the environment.

3.2. The 2016 ATUS data – Descriptive statistics

The 2016 ATUS data includes the time use log and demographics for 10,493 individuals summarized in Table 2. Additionally, the table contains the demographics of individuals for different shopping categories, as defined below. The U.S. sample consists of 45% males and 55% females, and is almost uniformly distributed between ages 15 and 85. Grouping the data across different age groups, such as the Silent generation (born from 1925 to 1945), Baby Boomers (born from 1946 to 1964), Generation X (born from 1965 to 1979), Millennials (born from 1980 to 1994), and Generation Z (born from 1995 to 2012), shows Generation Z as the group least represented, and Baby Boomers as the most represented group in the sample (see Table 2).

In terms of education levels, 60% of the sample have at least some graduate-level education, 38% have a secondary level education, and only 2% have just a primary level education. To analyze family income, the authors grouped the data into different income groups, such as "Poverty Level," "Low," "Lower Middle," "Median," "Middle Middle," "Upper Middle," and "High" (Amadeo, 2018).

For the purpose of the study, the authors constructed a binary variable "MSA > 1mill," indicating that an individual lives in an MSA with a population > 1 million. In the 2016 ATUS sample, 53% of individuals live in these locations. A household variable of "Family structure," encompassing the ratio of kids to adults in the household, was also constructed by the authors. Finally, to discern shopping behaviors, the authors split the ATUS data into four sub-datasets - "No Shopping," includes individuals who did not perform any shopping activity (6227 individuals). "In-Store" is all of the individuals who exclusively performed in-store shopping (4038 individuals). "Online" is those who shopped exclusively online (121 individuals), and "Both" includes individuals who shopped in-store as well as online (107 individuals). Table 2 shows the descriptive statistics for the entire dataset (unweighted values), as well as the sub-datasets. It highlights some salient differences, which are later tested as the authors model the shopping behaviors.

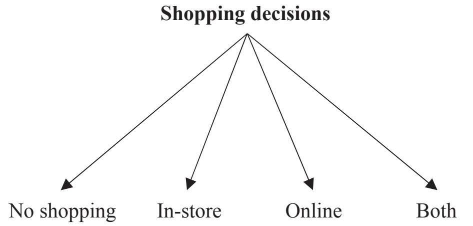

Fig. 1. Shopping decision as multinomial logit model.

4. Shopping behaviors

4.1. Modeling the shopping behaviors

The authors modeled the shopping behaviors as a Multinomial Logit (MNL) 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 Fig. 1). Table 3 shows the weighted MNL model, correcting for under/over representation, with the base choice being not shopping at all, i.e., No Shopping. The estimates represent the effect of the variables on the log of probability of choosing the alternative relative to the probability of the base alternative. Some statistically non-significant independent variables are in the

Table 3
Multinomial Logit (MNL) model.

Alternatives	**Frequency**	**Adjusted Mc Fadden R^2**	
No shopping	0.593	Equally likely based	0.459
Exclusively in-store	0.385	Market share based	0.010
Exclusively online	0.012	**Chi-square test w.r.t. market share model**	
Both	0.010	Chi square value	325.5 (p-value = 0)

	Estimate, t − values and Significance (respectively)								
Variable	**In − store** (4038)			**Online** (121)			**Both** (107)		
(intercept)	−0.94	(−9.29)	***	−4.93	(−9.52)	***	−6.35	(−9.49)	***
MSA > 1mill	0.07	(0.61)		−0.70	(−1.10)		−0.27	(−0.46)	
Female	0.04	(0.50)		1.09	(2.52)	*	1.40	(2.37)	*
Diff. in Mobility	−0.64	(−5.30)	***	−0.87†	(−1.33)		−2.20†	(−1.75)	.
Family Structure	−0.33	(−1.89)	.	−0.43	(−0.44)		2.54	(3.01)	**
Graduate	0.16	(2.66)	**	−0.39	(−1.33)		−0.31	(−0.96)	
Gen X	0.17	(3.06)	**	−0.06	(−0.21)		0.70	(2.23)	*
Baby Boomer	0.20	(3.25)	**	0.44	(1.57)		1.32	(4.04)	***
Silent	0.27	(3.58)	***	0.16	(0.43)		0.82‡	(1.92)	.
Low	−0.18	(−1.54)		0.65	(1.43)		0.92	(1.33)	
Lower Middle	0.01	(0.08)		0.23	(0.47)		1.05	(1.65)	.
Median	−0.07	(−0.78)		−0.35	(−0.68)		0.34	(0.51)	
Middle Middle	−0.03	(−0.31)		−1.13	(−1.37)		1.46	(2.58)	**
High	−0.20	(−1.80)	.	−0.37	(−0.66)		1.56	(2.69)	**
Northeast	0.24	(2.32)	*	0.46	(1.02)		−1.58	(−1.56)	
South	0.20	(2.62)	**	0.26	(0.74)		−0.24	(−0.62)	
West	0.10	(1.13)		−0.49	(−0.92)		0.46	(1.14)	
Fall	0.10	(2.06)	*	0.78	(3.93)	***	0.29	(1.31)	
MSA > 1mill * Female	0.01	(0.10)		−0.84	(−1.94)	.	0.84	(1.88)	.
MSA > 1mill * Fam. Str.	−0.11	(−0.64)		1.77	(2.09)	*	−1.46	(−1.76)	.
MSA > 1mill * Graduate	0.20	(2.31)	*	0.84	(2.05)	*	0.57	(1.34)	
MSA > 1mill * Northeast	−0.31	(−2.28)	*	−1.06‡	(−1.30)		1.66	(1.53)	
MSA > 1mill * South	−0.23	(−2.14)	*	0.69	(1.20)		0.13	(0.24)	
MSA > 1mill * West	0.02	(0.14)		1.57	(2.22)	*	−0.33	(−0.59)	
Female * Family Str.	0.69	(3.90)	***	−0.31	(−0.35)		−1.24	(−1.44)	
Female * Low	0.18	(1.24)		−1.67†	(−2.33)	*	−1.1‡	(−1.41)	
Female * Lower Middle	0.05	(0.38)		−0.58‡	(−0.91)		−2.07‡	(−2.50)	*
Female * Median	0.24	(2.03)	*	0.54	(0.89)		−0.44	(−0.59)	
Female * Middle Middle	0.18	(1.31)		1.04‡	(1.13)		−1.52‡	(−2.21)	*
Female * High	0.27	(1.81)	.	0.39	(0.54)		−2.04‡	(−2.73)	**

Significant levels: 0% '***' 0.1% '**' 1% '*' 5% '.' 10% ' ' 100%.
† Less than 5 observations.
‡ Less than 10 observations.

model because they are included as part of interaction terms.

It is important to note that although there may be shopping instances resulting from impulse buying behaviors, which could affect the understanding of shopping decisions, it is beyond the scope of this study to differentiate between impulse/non-impulse shopping decisions, particularly due to the lack of information in the ATUS to differentiate these behaviors. Additionally, the behavior model does not model shopping frequency, however the study accounts for shopping frequency later when estimating externalities.

In-store shopping behavior (exclusively)–For in-store shopping behavior, the MNL model indicates that in the high-income group, females have higher chances of shopping compared to males. Such an observation is consistent with previous studies, such as Srinivasan and Bhat (2005) and Farag et al. (2005). Further, as the number of kids in the household increases, the propensity for shopping in-store increases for females, while it decreases for males. Interestingly, the older the individual, the greater are their chances of shopping in-store. The reason for this could be the higher comfort an elderly person might derive from traditional in-store shopping owing to a lack of experience with online shopping. Consistent with previous literature work (Cao et al., 2012; Lee et al., 2017), the authors found education level to positively influence the likelihood of shopping in-store. Individuals with a graduate degree have a higher propensity for shopping in-store, which is further amplified for people with a graduate degree living in a populated (> 1 million) location. The results also show seasonal and regional variations in shopping behaviors. An increase in in-store shopping is seen in the Fall, owing to sales around the holidays. Northeasterners and Southerners living in a small city (not a largely populated MSA) are more likely to shop in-store compared to their fellow Americans. Finally, the model indicates that mobility issues hamper the chances of shopping in-store, which is understandable.

Online shopping behavior (exclusively)–As for the online shopping behavior, the authors found females have a higher propensity for shopping online compared to males, which is in contradiction to Farag et al. (2007), however this gap diminishes for those individuals living in largely populated (> 1million) locations. Much like in-store shopping behavior, for individuals living in a largely populated cities, education level positively affects one's chances of shopping online. Living in these locations also affects individuals with kids in the household, as their propensity to shop online increases with an increased number of kids in the household. Yet again, owing to the sales during the holiday season, the model indicates a hike in online shopping in the Fall. As far as regional variation is concerned, people in Western largely populated cities have a higher propensity for shopping online. Black (2007) discussed such differences in shopping

behaviors across the regions in the US. Whereby mobility issues will hinder one's chances of shopping in-store, online shopping is unaffected by mobility issues.

Both (in-store as well as online)–For the shopping behavior encompassing in-store and online together, one can understand the complementary effects, however, it is important to note that substitution and complementary effects must only be discussed for each shopping category separately (for example, grocery shopping or book shopping). Generalizing substitution or complementary effects over the entire shopping behavior leads to aggregation impacts. For instance, an individual substituting all of his/her shopping activities in all but one category will still exhibit a complementary effect on aggregate. Since the ATUS data does not categorize different shopping activities in detail, it limits our analyses to general substitution and complementary effects. Further, ATUS provides a one-day data window; it does not include what an individual does the next day or beyond. From the model, one can observe that females have a higher propensity for shopping through both channels, indicating stronger complementary behavior compared to males, and unlike the gender gap in exclusive online shopping, this gap increases in largely populated cities. However, this gap tends to lessen as males exhibit a stronger complementary behavior, engaging more in in-store as well as online shopping as their income increases. Individuals with kids have a higher propensity for engaging in complementary behavior. Such behavior, however, is observed more strongly in less populated cities than in large cities. Since mobility issues affect one's chances of shopping in-store, it also hampers one's ability to engage in complementary behavior, as the model suggests.

5. The environmental impacts of shopping

5.1. Scenario development

This work extends previous behavioral work to study the impacts of e-commerce freight transportation on the environment in terms of the negative externalities, particularly vehicle miles traveled and emissions. Without loss of generality, the authors conducted environmental analyses for two large metropolitan areas: Dallas and San Francisco (SF), which have significant differences in demographics and belong to different regions in the US. Using the 2010 Census Data, the authors generated a synthetic population, replicating the inhabitants for each census tract for the two cities. This process reconstructed each individual attribute, such as gender, age, income level etc., assuming a Categorical distribution (Bernoulli/Multinoulli distribution). For each individual, the authors then implemented the behavioral multinomial choice model described above. From the resulting probabilities and subsequently assuming a Multinoulli distribution for channel choice, the study determined who would shop in-store, online, or engage in both channels. After estimating the shopping behavior, the study evaluated the externalities generated by the population's shopping activity.

Online shopping-related travel considered commercial delivery tours to bring the goods to the individualś residences (Holguín-Veras et al., 2015; Jaller et al., 2018), while in-store shopping-related travel considered "shopping tours" (using personal vehicles) constructed using the shopping travel statistics in Fig. 2. This work considers a 'shopping tour' as any tour that includes at least one shopping activity regardless of tour origin or primary purpose. For shopping tours, the study first considered the distribution for number of shopping tours per person (Fig. 2a). Then for each shopping tour, the tour length was estimated by evaluating the number of stops in a tour (Fig. 2b), thereby evaluating the shopping tour length (Fig. 2c). Finally, the authors estimated the externalities from

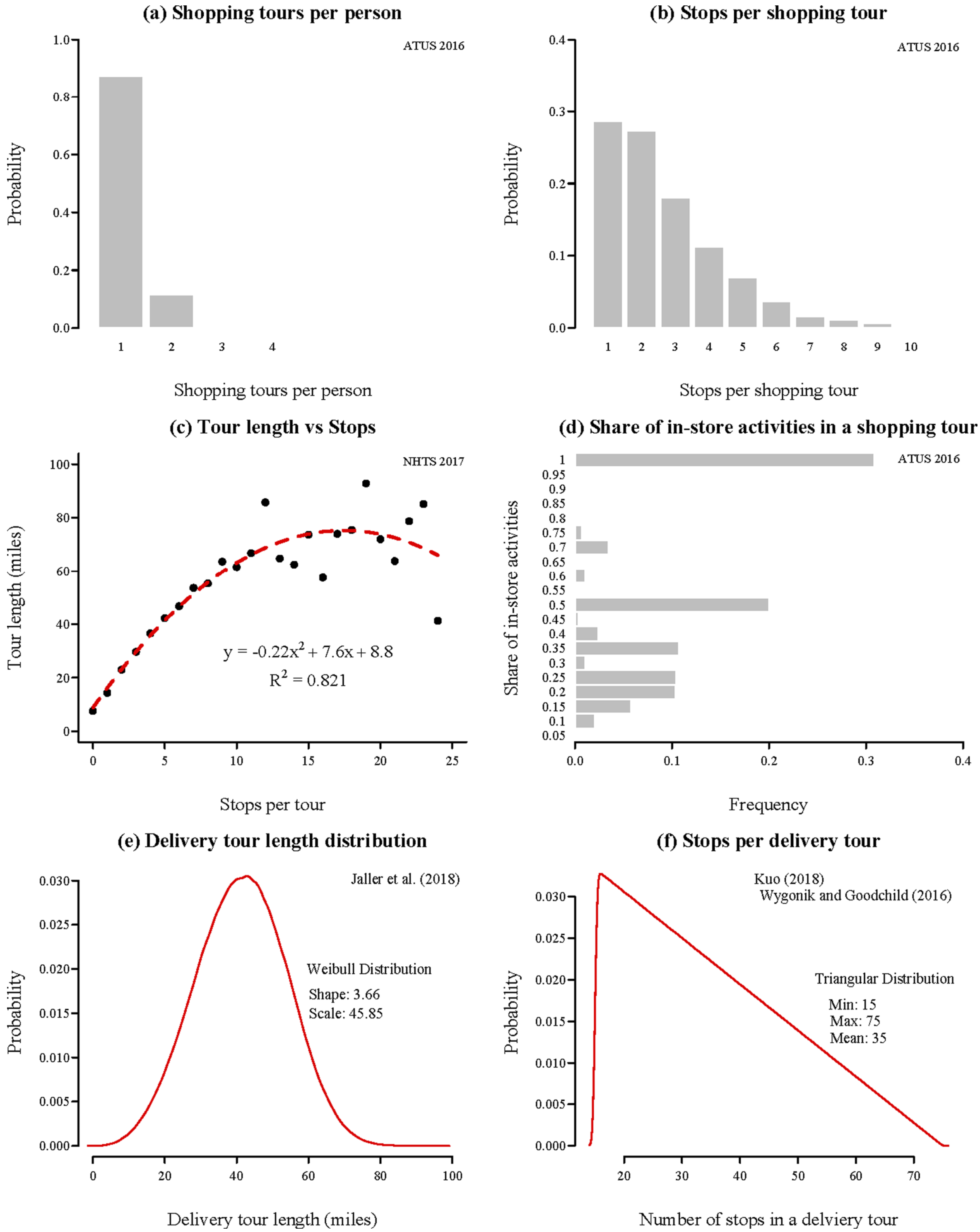

Fig. 2. Shopping travel statistics.

shopping-related travel by assuming one stop in the tour to be shopping related, thereby proportionally accounting for the externalities. Alternatively, and not shown here, the authors estimated the externalities as a fraction of the in-store shopping activity in the tour resulting from estimated distributions, such as the one in Fig. 2d, for different numbers of stops along the tour. The authors constructed Fig. 2a, b, and d using the data from ATUS, while Fig. 2c is based on the 2017 National Household Travel Survey (NHTS) (Bureau of Transportation Statistics, 2018).

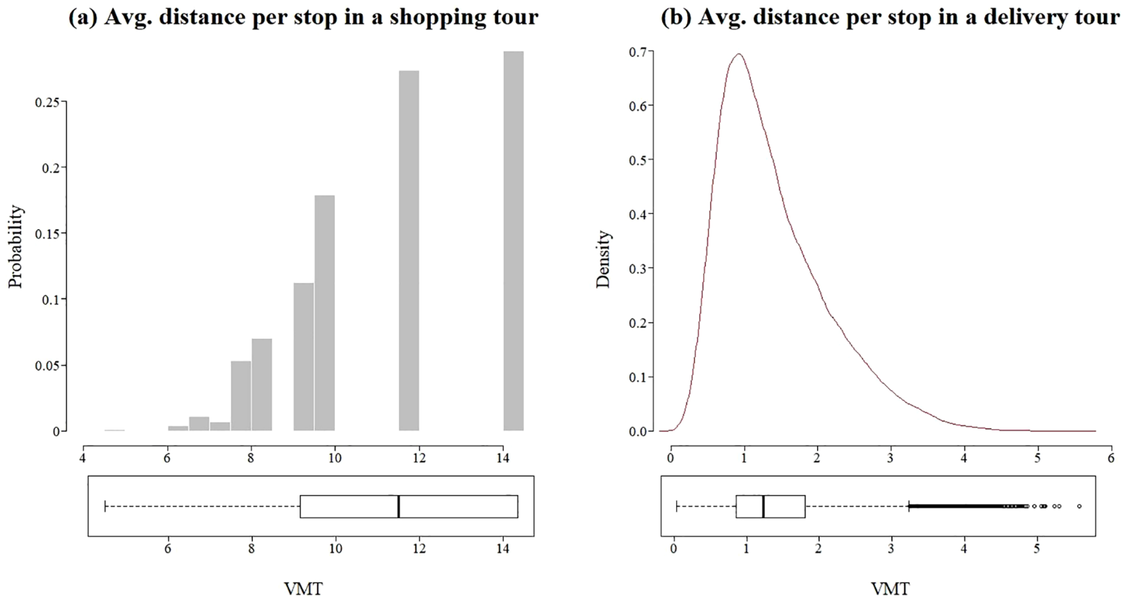

Fig. 3. Average distance per stop in a shopping and a delivery tour.

To construct delivery tours, the study used the commercial (parcel) delivery tour length distribution developed by Jaller et al. (2018) (Fig. 2e). To determine the number of deliveries in a tour, the authors assumed a triangular distribution (Fig. 2f), with a minimum of 15, and a maximum of 75 deliveries in a tour (Kuo, 2018); averaging at 35 deliveries, an industry standard (Wygonik and Goodchild, 2016). Employing the two procedures for constructing tours, Fig. 3 shows the VMT to be attributed towards shopping in a shopping and delivery tour, and the resulting variability. With an average of 11.25 miles generated from an in-store purchase, and 1.4 miles generated by an online purchase, the VMT reduction heavily weighs in favor of e-commerce by a ratio of 1:8, i.e., 8 online purchases generate, on average, the same VMT as a single in-store purchase.

Table 4 shows the emission rates, developed by the California Air Resource Board (2018), used in this study to estimate GHGs and criteria pollutants generated from shopping-related travel. Although speeds have a significant effect on emissions rates, and additional traffic would increase congestion and reduce speeds, the aggregate scope of this study limits the analyses to constant emission rates (Barth and Boriboonsomsin, 2009; Barth et al., 1999). Additionally, since this study is an effort to capture emissions at an aggregate level, emissions from specific vehicle dynamics such as cold starts and idling, as well as tire and brake wear and tear among other factors, are largely a part of the average emission rates, while some other vehicle dynamics such as cold starts have been omitted to simplify the analyses.

Thus, starting with population synthesis, then generating shopping behaviors and finally generating shopping travel, the study estimated the externalities from shopping. This entire process, simulated using the Monte Carlo technique, generated 100 replicates each for SF and Dallas. For each replicate, the process synthesized the population by generating individuals in accordance with the socio-economic parameters in every census tract. After generating individuals and their attributes, the process used the developed shopping behavior model (described above) to identify individuals who shop in-store, online and individuals who do not shop at all. The process then employed the travel statistics discussed above to simulate shopping-related travel. Using the emission rates from Table 4, the process finally concludes with the externalities from shopping.

To evaluate the impacts of e-commerce, the authors developed three retail channel scenarios: Omni-channel, replicating today's shopping behavior (in-store and/or online); Single Channel (SC)–in-store, with all people shopping exclusively in-store; and, Single Channel (SC)–online, where all those who shop, shop exclusively online. Fig. 4 illustrates the entire modeling framework. The authors

Table 4
Emission rates.

Parameter		Shopping tour	Delivery tour
Vehicle		Passenger cars	Light-Heavy Duty Trucks (GVWR 8501–14,000 lbs.)
Emission rates (g/mile)	CO	1.07	1.1
	NO_x	0.08	0.8
	CO_2	307.7	929.45
	PM 10	0.002	0.009
	PM 2.5	0.002	0.009
	SO_x	0.003	0.009
	N_2O	0.008	0.04

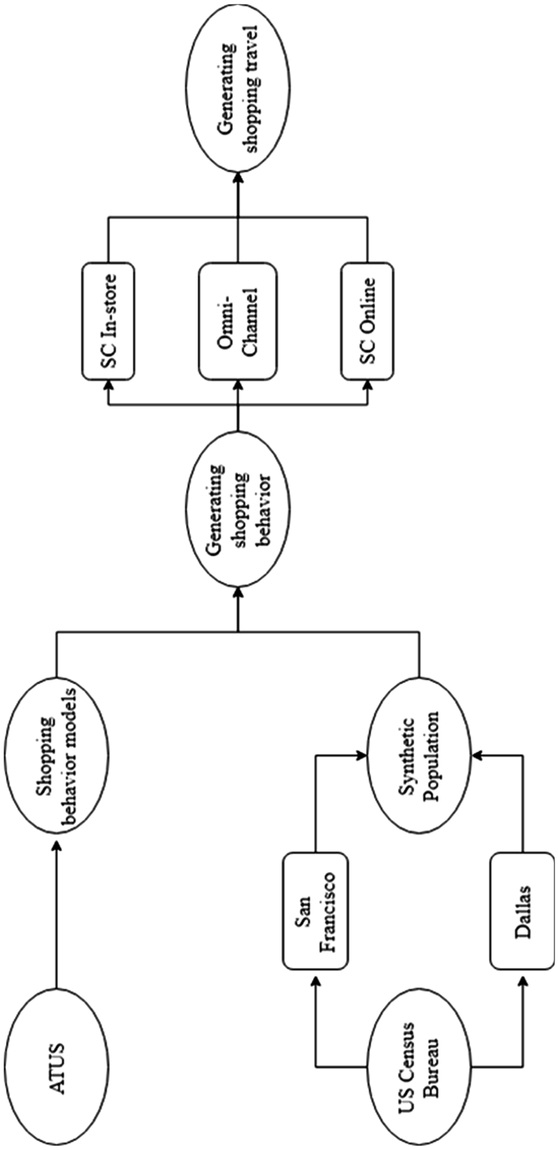

Fig. 4. Modeling framework.

then pair-wise compared the three scenarios using a breakeven analysis to determine the minimum number of stops in a delivery tour that breaks even the two scenarios. This work assumes temporal stability of parameters, and therefore does not include induced demand. Further, to build the latter two scenarios (SC in-store and SC online) the study assumes online activity to be equivalent to in-store activity in terms of basket size, i.e., an individual makes the same amount of purchases online as the individual would make in one visit to the store. However, the authors test the impacts of differences between online and in-store activity (in terms of basket size) in the breakeven analyses.

5.2. VMT and emission results

Based on the discussion above, Table 5, Figs. 5 and 6 show the results from the Monte Carlo simulation. While Table 5 tabulates the mean values of the negative externalities, Figs. 5 and 6 show a comparison for Omni-channel and SC online with SC in-store, respectively. An interesting feature of these results is that while the population of Dallas (county) is three times that of San Francisco (county), the externalities do not align similarly due to the demographic and regional differences between the two cities, thereby creating different shopping patterns. As observed from the shopping decision model, people in San Francisco are more likely to shop in stores compared to people in Dallas, thus shopping-related externalities produced in Dallas are 2.3 times greater than those produced in San Francisco, instead of 3 times greater.

Table 5
Mean value of negative externalities from shopping for Dallas and SF.

Variables		Dallas	SF	Ratio	% change w.r.t. SC in-store	
Population		2,513,054	847,192	2.97		
Area		957,812	382,286	2.51		
Census tracts		527	194	2.72	Dallas	SF
VMT	SC in-store	10,159,374	4,460,713	2.28		
	Omni channel	9,429,994	4,169,172	2.26	−7.179%	−6.536%
	SC online	1,260,982	553,570	2.28	−87.588%	−87.590%
CO (kg)	SC in-store	10,871	4,773	2.28		
	Omni channel	10,093	4,462	2.26	−7.151%	−6.510%
	SC online	1,387	609	2.28	−87.240%	−87.242%
NOx (kg)	SC in-store	813	357	2.28		
	Omni channel	829	363	2.28	1.977%	1.798%
	SC online	1,009	443	2.28	24.120%	24.099%
CO2 (Metric ton)	SC in-store	3,126	1,373	2.28		
	Omni channel	2,966	1,309	2.27	−5.124%	−4.665%
	SC online	1,172	515	2.28	−62.508%	−62.514%
PM 10 (kg)	SC in-store	20	9	2.28		
	Omni channel	20	9	2.27	−3.619%	−3.295%
	SC online	11	5	2.28	−44.146%	−44.155%
PM 2.5 (kg)	SC in-store	20	9	2.28		
	Omni channel	20	9	2.27	−3.619%	−3.295%
	SC online	11	5	2.28	−44.146%	−44.155%
SOx (kg)	SC in-store	30	13	2.28		
	Omni channel	29	13	2.27	−5.145%	−4.684%
	SC online	11	5	2.28	−62.764%	−62.770%
N2O (kg)	SC in-store	81	36	2.28		
	Omni channel	79	35	2.27	−3.110%	−2.832%
	SC online	50	22	2.28	−37.940%	−37.951%

From the results, it is obvious that certain parameters, such as VMT, significantly decrease (by around 7.2% and 87.6% for Omni-channel and SC online, respectively) as consolidated trucks replace passenger cars; however, since the trucks are relatively heavy emitters of NO_x (with emissions 10 times those of a passenger car), the concentration of NO_x could increase by as much as 24% due to e-commerce, unless tailpipe emissions or truck technologies improve. With the introduction of electric trucks (Bandeira et al., 2019), cargo bikes (Tipagornwong and Figliozzi, 2014), drones (Goodchild and Toy, 2018) and other zero tailpipe emission vehicles, some impacts of last-mile operations from online orders could be successfully brought down, though other impacts, such as curb-space access requirements, may remain, or grow more problematic (Allen et al., 2018). On the other hand, retail companies that provide attractive delivery options, such as 1-h, 2-h or same-day deliveries might nullify the consolidation benefits of online shopping. In the following section, we discuss the impacts of expedited or rush (e.g., fast deliveries, short lead times) deliveries on externalities from shopping.

5.3. Expedited deliveries and the impacts of consolidation level

With the e-commerce market becoming increasingly competitive, retail companies have started to provide additional services to retain and grow their market share. One of these additional services is related to delivery times (e.g., same day, two-hour, one-hour). Although very complex logistically, some e-retailers have successfully implemented such expedited deliveries for certain products and markets, with other companies poised to follow. However, these services lead to lower consolidation levels, and therefore increase freight's negative externalities. Fig. 7 shows that the negative externalities such as vehicle miles traveled (VMT) per delivery stop increase rapidly as the number of deliveries per tour reduce, consequently generating a large increase in total VMT for the same level of demand. However, Lin et al. (2018) test the feasibility of same-day deliveries under different delivery paradigms and suggest that a rise in demand volume could potentially bring down the externalities.

The authors conducted a breakeven analysis and compared the shopping channels in terms of the number of customers, c (without loss of generality, assuming one customer per stop) that need to be catered to in one single delivery tour. However, such a breakeven value would vary with the parameters (e.g., VMT, CO, NO_x) compared across the channels. Hence, for the purpose of the breakeven analyses, the authors define m_{PC} and m_{LHDT} as the parameters for passenger car and light heavy-duty truck, respectively. This work also tested the impact of differences between online and in-store activity (in terms of basket size) in the breakeven analyses. To generalize, the study assumes ρ online deliveries to be equivalent to one visit to a physical store, i.e., to say that the basket size of in-store shopping is ρ times the basket size of online shopping. The study also assumes that an online purchase, regardless of the basket size, only generates a single delivery (vendor does not send partial shipments). Additionally, X_{INS} is the number of people who shop exclusively in-store, X_{ONL} is the number of people who shop exclusively online, and X_{BOTH} is the number of people who shop online as well as in-store. The λs represent the corresponding average frequency of shopping. It is important to note that to simplify the breakeven analysis, the authors do not assume the triangular distribution for the number of stops in the tour, but instead assume a

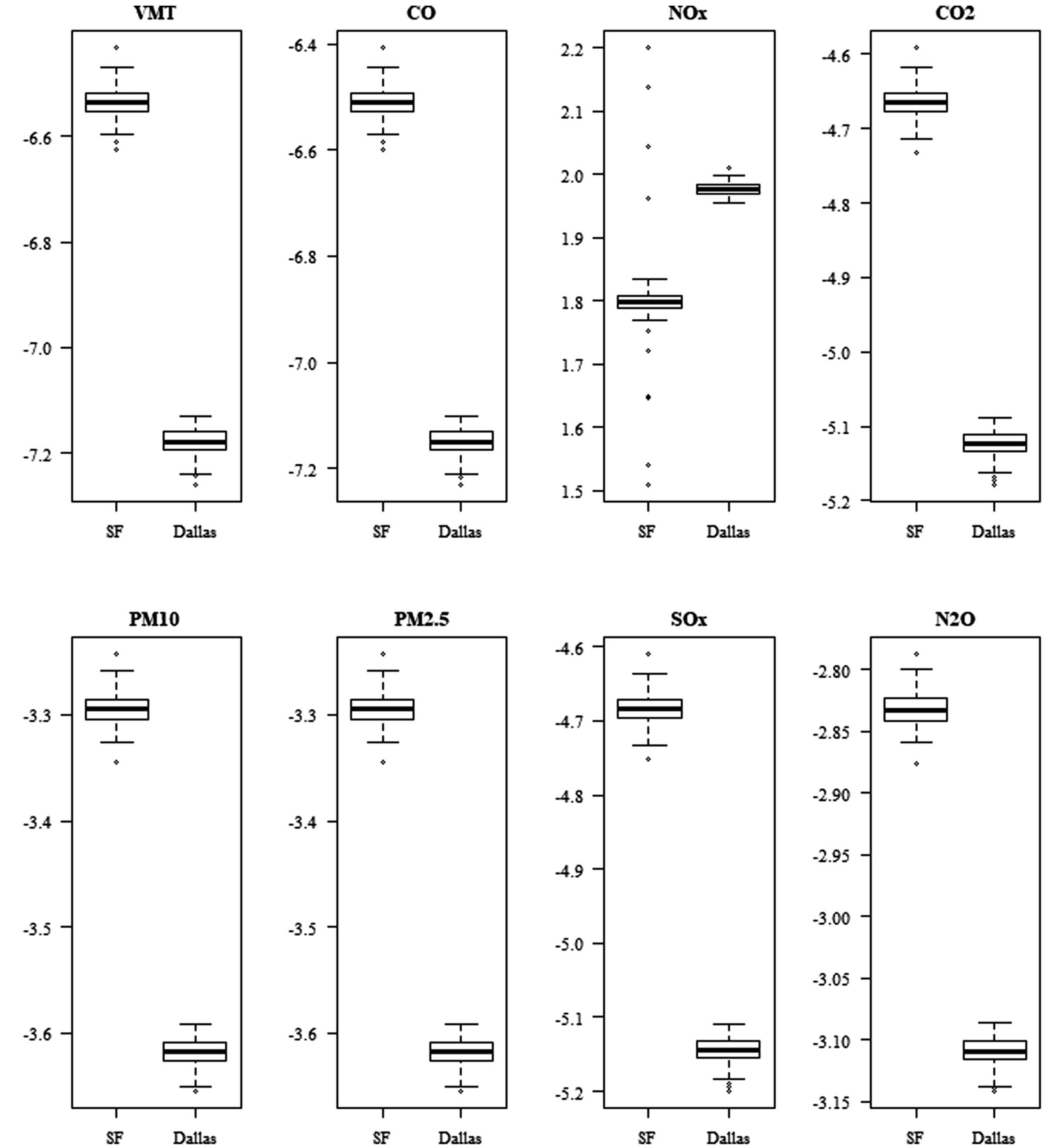

Fig. 5. Comparison of Omni-channel with SC In-store (% change).

single point value of the same. To perform the breakeven, the study first defines externalities under each scenario, as follows:

$$Z_{OmniChannel} = X_{INS}\lambda_{INS}m_{PC} + \frac{X_{ONL}\lambda_{ONL}m_{LHDT}}{c} + X_{BOTH}\left(\lambda_{INS}m_{PC} + \frac{\lambda_{ONL}m_{LHDT}}{c}\right) \tag{1}$$

$$Z_{SCInstore} = X_{INS}\lambda_{INS}m_{PC} + \frac{X_{ONL}\lambda_{ONL}m_{PC}}{\rho} + X_{BOTH}\left(\lambda_{INS} + \frac{\lambda_{ONL}}{\rho}\right)m_{PC} \tag{2}$$

$$Z_{SCOnline} = \frac{X_{INS}\lambda_{INS}\rho m_{LHDT}}{c} + \frac{X_{ONL}\lambda_{ONL}m_{LHDT}}{c} + \frac{X_{BOTH}(\lambda_{INS}\rho + \lambda_{ONL})m_{LHDT}}{c} \tag{3}$$

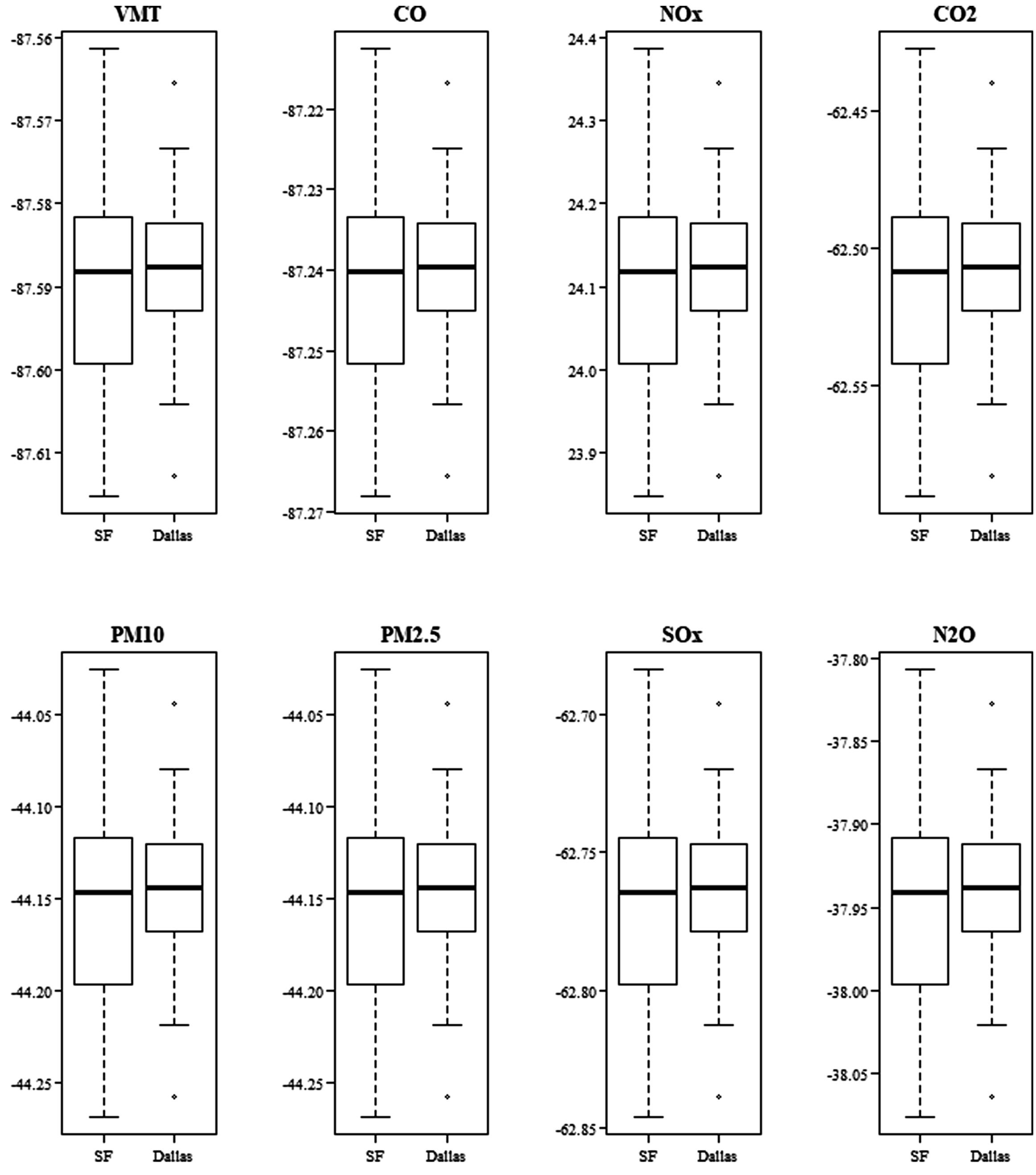

Fig. 6. Comparison of SC Online with SC In-store (% change).

For all possible pair-wise comparisons, the breakeven occurs at

$$m_{PC} = \frac{\rho m_{LHDT}}{c} \tag{4}$$

From the equation above, it is clear that the higher the basket size for in-store shopping relative to online shopping, the higher the consolidation level needs to be for externalities to break even. If the consolidation level is greater than the breakeven level of consolidation, then SC in-store renders the higher bound for externalities, while SC online exhibits the least externalities. If, however, the consolidation level is lower, then the bounds reverse, with SC in-store showing the least externalities and SC online producing the most. Table 6 shows the entire range of breakeven values under two different values of basket size, ratio $\rho = 1$ and $\rho = 2.5$. Note, the value of $\rho = 2.5$ results from assuming a basket size of 1.1 for online shopping (Gevaers et al., 2014) and 2.73 for in-store shopping (Nicasio, 2018).

The table shows that the consolidation level ranges from 4 to 92, which means that if there are fewer than 4 deliveries

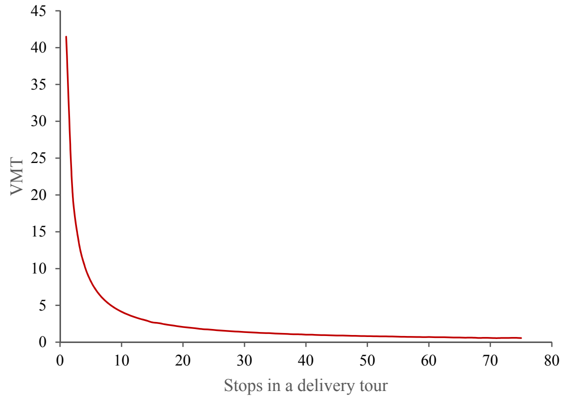

Fig. 7. VMT per delivery stop.

Table 6
Breakeven results for different basket size comparative assumptions.

Parameters	$\rho = 1$	$\rho = 2.5$
VMT	4	9
CO	4	9
NO_x	37	92
CO_2	11	28
PM 10	17	41
PM 2.5	17	41
SO_x	11	28
N_2O	18	46

consolidated in a delivery tour, all the parameters perform poorly for e-commerce compared to in-store shopping; however, if more than 92 deliveries are consolidated in a delivery tour, e-commerce performs better than in-store shopping in every aspect. From the above observations we can conclude that the responsibility for reduction of externalities from e-commerce starts with consumers, who must consolidate their online purchases into one basket, and ends with the vendors and last-mile carriers, who must consolidate as many customers as possible into a single delivery tour. These results are consistent with Loon et al. (2015) who also stress the importance of consolidation.

6. Limitations

Some of the main paper's limitations, as identified by the authors, include:

– To understand the different shopping behaviors, the study makes certain assumptions to differentiate in-store and online shopping activity. Results for studies employing ATUS to understand shopping behaviors are therefore sensitive to the assumptions made. As was done for the NHTS, if ATUS changes to explicitly categorize online shopping, better and more consistent results can be developed.
– To estimate the impacts from in-store shopping travel, the study assumes one stop in a shopping tour to be shopping-related and then proportionally allocates the externalities to shopping. These externalities can be estimated more accurately by accounting for the marginal impact of a shopping-related stop in the tour.
– The study uses EMission FACtors (EMFAC) emission rates developed by the California Air Resource Board (CARB). While these average emission rates would be fairly accurate for SF, the study assumes emission rates to be the same for Dallas as well. However, the different operating conditions in SF and Dallas can significantly impact the average emission rates at the two places.
– The study does not consider the impacts resulting from product searching-related travel, purchase returns, and delivery options (i.e. purchasing online and collecting at the store, or partial deliveries). While there are some general statistics about these factors, disaggregate data are not publicly available.

Notwithstanding these limitations, the study provides a realistic evaluation of the impacts of e-commerce, as summarized in the next section.

7. Conclusions

A host of studies in last-mile research discuss the potential of e-commerce in reducing negative externalities from shopping.

Assuming a large market penetration for e-commerce, these studies often over-estimate the potential for reductions in externalities. This study is an effort to fill this gap by modeling shopping behaviors as a multinomial logit model at the micro-level and across different demographic groups, using the 2016 ATUS data. The analysis then expands the shopping behaviors to a macro-level, estimating the broader impacts of shopping. Resulting estimates show that e-commerce has cut VMT by 7%, while consistent with previous literature, a potential reduction of 87% is possible if all individuals were to substitute towards online shopping. However, it is important to note that individuals using public transit, walking or biking to a store, can instead produce net gains in the externalities if they substitute towards online shopping. While this study assumes a 100% modal share of personal vehicles for shopping-related travel, the true modal shares are 79% in SF and 94% in Dallas, so a 7% reduction in VMT and a potential 87% reduction represent upper bound values for the same.

Additionally, the estimated externalities offer insights into the type of system-level strategies such as demand management using urban consolidation centers, alternate delivery locations (lockers/stores), and use of zero tailpipe emission vehicles, among others needed to foster a more sustainable urban system, as well as the impacts from the operations and practices of service providers (Jaller et al., 2019). However, it is important to note that these system-level strategies may not apply homogenously across the US. As observed from the results, while Dallas is three times larger than SF in terms of population size, the variation in demographics of the two cities also manifests in different shopping behaviors, resulting in Dallas externalities being just 2.3 times those of SF.

This study employs a breakeven analysis to investigate impacts from rush deliveries, customer basket size and vendor consolidation levels. With 90 deliveries per tour, significant reductions in externalities can be realized with e-commerce compared to passenger trips to store. However, those impacts are sensitive, both to how receivers consolidate their order requests, and how vendors consolidate their shipment activities. A well-consolidated online basket reduces frequent deliveries to the consumer, thereby reducing the externalities resulting from the online purchase. These consolidation benefits are wiped out by rush deliveries. Although the definition of 'rush' varies for different retailers, only very large companies have the network in place and the volume to offer 2-day shipping, or next-day shipping, with only a marginal impact to their current operations. To compete in these short delivery timeframes, many companies may have to use other delivery methods that generate considerable negative impacts. Nevertheless, the environmental efficiency of deliveries reduces exponentially with same-day deliveries, and worsens with such expedited services as two- and one-hour offerings available in some markets.

This clarifies how important consolidation is as a factor in how online shopping compares to in-store shopping in relation to the externalities produced, and the potential to lower those externalities. Thus, the responsibility for improving last-mile sustainability is shared, beginning with the online shopper in consolidating their purchases, with the vendors and last-mile carriers in consolidating as many customers as possible into a single delivery tour, and with planners, regulators, and civic society in demanding/implementing improved tailpipe emission truck technologies. The potential to reduce the externalities—particularly VMT and emissions—associated with shopping-related travel are therefore less a broad question of online vs. in-store shopping, and more dependent on the efficiencies in manner and practices involved in each.

While the analyses provided here do not consider all of the factors that will ultimately affect the full sustainability impacts of these delivery services, they highlight the need to manage the urban freight system in general, and delivery operations and services in particular, to foster a more sustainable urban environment. Moreover, further studies are needed to understand the role that different stakeholders–such as planners, regulators, the private sector, and the civic society—can play in minimizing the impacts of such consumer behaviors as online shopping, which are becoming the norm in everyday life.

CRediT authorship contribution statement

Miguel Jaller: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Anmol Pahwa:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization.

Declaration of Competing Interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2020.102223.

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