



Research paper



Influence of neighborhood characteristics on e-commerce deliveries: The case of Belo Horizonte, Brazil

Luísa Tavares Muzzi de Sousa^{a,b}, Leise Kelli de Oliveira^{a,b,*}, Jorge Luiz dos Santos Junior^b, Bruno Vieira Bertoncini^c, Cassiano Augusto Isler^d, Ana Margarita Larranaga^e

^a Federal University of Pernambuco, Brazil

^b Federal University of Minas Gerais, Brazil

^c Federal University of Ceará, Brazil

^d São Paulo University, Brazil

^e Federal University of Rio Grande do Sul, Brazil

ARTICLE INFO

Keywords:

e-commerce deliveries

Neighborhood characteristics

Negative binomial regression

ABSTRACT

Business-to-consumer shoppers in e-commerce increased significantly in recent years, along with the number of urban freight trips derived from deliveries. Therefore, understanding the factors that influence e-commerce demand is essential to providing practical solutions to the problems that arise from deliveries. This study assesses the relationship between neighborhood characteristics and the number of urban e-commerce deliveries using negative binomial regression models applied to Belo Horizonte, Brazil data. The number of e-commerce deliveries between 2019 and 2021 was modeled considering the number of retail shops, sociodemographic data, and neighborhood area. The results show that income, number of retail shops, and neighborhood land area positively influence e-commerce deliveries, while household size negatively impacts the number of deliveries. The elasticity values and *t*-test indicate that the impact of different characteristics changed in 2020, remaining similar between 2019 and 2021. Income was the most impactful variable in the number of deliveries in 2020. The neighborhood characteristics bring knowledge for developing more effective business models for e-commerce delivery services.

1. Introduction

The global retail economy has increased significantly because of digital technology growth. The number of e-commerce shoppers increased by 7% in 2019, reaching 1.48 billion and generating 4870 billion USD in sales (UNCTAD, 2021). The restrictions related to the COVID-19 pandemic significantly contributed to such expansion. In 2020, the e-commerce demand increased by 22%, accounting for 65% of sales (UNCTAD, 2021). In 2021, online sales increased by almost 14% worldwide compared to the previous year (Statista, 2022a). More specifically, the e-commerce market in Brazil grew by 16%, 30%, and 27% in 2019, 2020, and 2021, respectively (E-bit and Nielsen, 2022).

E-commerce sales generate many deliveries to customers' residences or workplaces and increase the number of urban freight trips (Allen et al., 2018). As a result, negative externalities are observed, such as congestion, noise, visual and air pollution (Moroz and Polkowski, 2016), traffic accidents, and damage to the transport infrastructure (Park et al.,

2016). However, urban planning usually needs to address the issues related to urban freight transport (Allen et al., 2018) to increase livability and sustainability in urban environments (Taniguchi et al., 2014).

Understanding the factors that influence the e-commerce demand provides practical solutions to the problems that arise from deliveries, which rely upon the behavior of several stakeholders such as consumers, public agents, urban planners, and logistics operators (Tadić and Veljović, 2020). Thus, this study focuses on the following research question: which neighborhood characteristics influence the number of urban e-commerce deliveries?

According to Beckers et al. (2022), the most common variables to predict e-commerce household freight deliveries are age, car ownership, gender, income, product type, sustainability, urbanization rate, and accessibility. Furthermore, the preference for online shopping is related to the income and the number of inhabitants per household (e.g., Cheng et al., 2021; Saphores and Xu, 2021; Sener and Reeder, 2012; Zhou and

* Corresponding author. Federal University of Minas Gerais, Brazil.

E-mail address: leise@etg.ufmg.br (L.K. Oliveira).

<https://doi.org/10.1016/j.retrec.2023.101329>

Received 31 May 2022; Received in revised form 5 December 2022; Accepted 5 July 2023

Available online 17 July 2023

0739-8859/© 2023 Elsevier Ltd. All rights reserved.

Wang, 2014). Moreover, accessibility to physical retail stores is a variable that influences e-commerce shopping (e.g., Cheng et al., 2021; Hood et al., 2020; Kirby-Hawkins et al., 2019; Motte-Baumvol et al., 2017). However, the effects of neighborhood characteristics on e-commerce shopping and, consequently, on e-commerce deliveries are not well-defined. Thus, this paper aims to assess the relationship between neighborhood characteristics and e-commerce deliveries. We estimated negative binomial regression models with data regarding the e-commerce deliveries performed by a carrier in Belo Horizonte, Brazil, over 2019, 2020, and 2021, and the number of retail shops, sociodemographic data, and the neighborhoods' area.

The contributions of this paper are as follows: (i) the analyses are transferable to developing countries, where different urban and socioeconomic characteristics from developed countries are observed (Song, 2021), and spatial distribution of e-commerce deliveries may differ; (ii) differently from other studies that considered survey data, except by Cheng et al. (2021) and Kirby-Hawkins et al. (2019), it comprises e-commerce carrier data with national coverage and significant market share in the studied city that poses challenges to the analyses and interpretation; (iii) it includes spatial variables that remain unclear or underestimated (Song, 2021), while few studies have addressed them for similar purposes (e.g., Cheng et al., 2021; Kirby-Hawkins et al., 2019; Ren and Kwan, 2009; Song, 2021); and (iv) it considers that the importance of the attributes may vary over time as the spatial pattern of e-commerce deliveries between 2019 and 2021 are compared, in opposition to other research that usually considered cross-sectional data.

The outline of this paper is as follows. Section 2 presents a literature review addressing e-commerce deliveries and details the hypotheses of this study. Section 3 describes the studied area and the data and details the research method. Section 4 presents the results and addresses the importance of neighborhood characteristics to e-commerce deliveries by discussing policy implications in this context. Finally, Section 5 provides conclusions to the study and rows for future research.

2. Factors influencing e-commerce deliveries

The relationship between income, household size, accessibility to physical retail shops, and e-commerce deliveries has been identified in Table 1. Income is the most frequent factor linked to e-commerce deliveries. In most of the studies, it has a positive influence on e-commerce (Beckers et al., 2018; Cao et al., 2013; Cheng et al., 2021; Clarke et al., 2015; De Blasio, 2008; Farag et al., 2007, 2006a, 2006b, 2005, 2003; Hood et al., 2020; Lee et al., 2017, 2015; Motte-Baumvol et al., 2017; Ren and Kwan, 2009; Saphores and Xu, 2021; Sener and Reeder, 2012; Song, 2021; Zhou and Wang, 2014). However, Ren and Kwan (2009) did not find statistical significance between income and e-commerce behavior in the Columbus metropolitan area (US), possibly because of the dataset comprising upper- and middle-class, well-educated, and car owners white Americans.

Household size influences e-commerce. Studies performed in the US and Spain show that people who live alone are more likely to buy online (Pérez-Hernández and Sánchez-Mangas, 2011; Zhou and Wang, 2014). However, the effect of the number of household inhabitants and the number of children on e-commerce presented ambiguous results. Some studies found that the number of household inhabitants positively correlates with e-commerce (Cheng et al., 2021; Sener and Reeder, 2012), while others found the opposite (Pérez-Amaral et al., 2020; Zhou and Wang, 2014). A positive effect of the number of children on online shopping was identified by Jaller and Pahwa (2020), Saphores and Xu (2021), and Van Droogenbroeck and Van Hove (2017); but a negative effect was found by Pérez-Hernández and Sánchez-Mangas (2011).

The relationship between accessibility and e-commerce was also studied. Accessibility is usually measured by the number of physical stores accessible by car from the consumers' homes (Farag et al., 2006a). However, accessibility to shopping is not homogeneous over the territory (Cao et al., 2013; Motte-Baumvol et al., 2017) such that residents

with lower levels of accessibility to local shopping opportunities are more likely to buy online (Cao et al., 2013; Cheng et al., 2021; Clarke et al., 2015; Loo and Wang, 2018; Ren and Kwan, 2009). Moreover, urban residents buy online more often than suburban citizens due to faster Internet connection (Farag et al., 2003, 2005, 2007). Therefore, an urban lifestyle may promote e-commerce shopping (Farag et al., 2006a).

Few studies used operational data to assess the relationship between e-commerce and neighborhood characteristics (e.g., Cheng et al., 2021; Kirby-Hawkins et al., 2019; Opesade, 2020; Song, 2021), in opposition to the most recurrent use of self-declared data as indicated in Table 1. Kirby-Hawkins et al. (2019) explored the e-commerce geography based on online sales of a major UK grocery retailer by identifying the demographic characteristics of online consumers per geodemographic type at the county level. Opesade (2020) investigated the patterns of e-commerce in Nigeria using data from Google Trends and the socioeconomic factors that affect diffusion at the county level. The results are based on descriptive analysis and correlation tests and indicate different distributions across the cities.

Song (2021) identified the spatial distribution of e-shopping in China using online data from the Alibaba group at the county level. The author estimated a geographically weighted regression model and identified the relationship among sociodemographic variables, land use, personal characteristics, the physical retail economy, and geographical factors. Findings showed that gender and mobile penetration affect e-commerce purchases negatively, while the other attributes affect them positively. Cheng et al. (2019) investigated the impact of locational and household characteristics on e-commerce home delivery demand in Singapore using carrier data. The authors estimated a linear regression model to explore the relationship between locational and household characteristics and online shopping, considering urbanization level, accessibility, household characteristics, and household type. Results showed a positive effect of population density, household income, size and type, and vehicle ownership on the delivery demand for online shopping. On the opposite, the age of the residential buildings, accessibility to shopping malls, and public transportation have a negative effect on it.

Cheng et al. (2019) used operational data similar to this paper but considered different variables. Other studies used retail (Kirby-Hawkins et al., 2019; Song, 2021) and Google Trends data (Opesade, 2020) to assess the e-commerce pattern at the county level.

The myriad of methods is directly related to the goals of each study and the type of data available. For example, most of the analyses used logistics regression to assess the use of e-commerce (Clarke et al., 2015; De Blasio, 2008; Farag et al., 2006a; 2006b; Jaller and Pahwa, 2020; Lee et al., 2015; Loo and Wang, 2018; Motte-Baumvol et al., 2017; Pérez-Amaral et al., 2020; Ren and Kwan, 2009; Saphores and Xu, 2021; Van Droogenbroeck and Van Hove, 2017), notwithstanding the application of structural equation modeling (Cao et al., 2013; Farag et al., 2007; Zhou and Wang, 2014), analysis of variance (Brashear et al., 2009; Hashin et al., 2009) and chi-squared test (Farag et al., 2006a). Therefore, using traditional models to fit the data may help achieve the goals of a given study.

Most of the studies referring to the relationship between e-commerce and neighborhood characteristics using data from developed countries, such as Belgium (Van Droogenbroeck and Van Hove, 2017), France (Motte-Baumvol et al., 2017), Italy (De Blasio, 2008), Netherlands (Farag et al., 2003, 2005; 2006a; 2006b, 2007), Singapore (Cheng et al., 2021), Spain (Pérez-Amaral et al., 2020; Pérez-Hernández and Sánchez-Mangas, 2011), UK (Clarke et al., 2015), and US (Cao et al., 2013; Cheng et al., 2021; Farag et al., 2006a; Jaller and Pahwa, 2020; Lee et al., 2017, 2015; Ren and Kwan, 2009; Saphores and Xu, 2021; Sener and Reeder, 2012; Zhou and Wang, 2014). However, while e-commerce has grown in developing countries, studies using data from these locations are less frequent. Analyses have been carried out in Malaysia (Hashin et al., 2009), China (Loo and Wang, 2018; Song, 2021), Indonesia (Lubis, 2018), and Nigeria (Opesade, 2020). A comparison of e-shoppers profiles explored by Brashear et al. (2009)

Table 1
Summary of literature.

Reference	Variable			Place		Data		Method				
	Income	Household size	Accessibility to physical retail shops	Developed countries	Developing countries	Real data	Self-declared survey data	Logistic regression	ANOVA	Chi-square test	Structural equation modeling	Other
Cao et al. (2013)	•		•	•			•				•	
Cheng et al. (2021)	•	•	•	•		•						•
Clarke et al. (2015)	•		•	•			•	•				
De Blasio (2008)	•		•	•			•	•				
Farag et al. (2005)	•		•	•			•					•
Farag et al. (2006a)	•		•	•			•	•		•		
Farag et al. (2006b)	•		•	•			•	•				
Farag et al. (2007)	•		•	•			•				•	
Hashin et al. (2009)	•				•		•		•			
Hood et al. (2020)	•		•	•			•			•		
Jaller and Pahwa (2020)		•		•			•	•				
Lee et al. (2015)	•			•			•	•				
Lee et al. (2017)	•			•			•					•
Loo and Wang (2018)			•		•		•	•				
Lubis (2018)					•		•	•				
Motte-Baumvol et al. (2017)	•		•	•			•	•				
Opesade (2020)	•				•	•	•					•
Pérez-Amaral et al. (2020)	•	•		•			•	•				
Pérez-Hernández and Sánchez-Mangas (2011)		•		•			•					•
Ren and Kwan (2009)	•		•	•			•	•				
Sener and Reeder (2012)	•	•		•			•					•
Saphores and Xu (2021)	•	•		•			•	•				
Song (2021)	•				•	•	•					•
Van Droogenbroeck and Van Hove (2017)		•		•			•	•				
Zhou and Wang (2014)	•	•		•			•				•	

included data from the United States, England, New Zealand, China, Brazil, and Bulgaria.

Moreover, the literature needs to be more conclusive about the influence of household size on e-commerce and provide evidence about its effects in developing countries. Furthermore, the impact of accessibility to retail shops on e-commerce should be analyzed in different contexts, as local characteristics influence consumer behavior. Thus, these issues must be investigated to explain the effects of household, accessibility and income on e-commerce deliveries.

2.1. Research hypotheses

Based on the evidence found in the literature regarding the influence of neighborhood characteristics on e-commerce, the first hypothesis of this study is (H1): The average income of a neighborhood influences e-commerce deliveries in Belo Horizonte, Brazil.

The second hypothesis establishes the relationship between e-commerce and the accessibility to retail shops as follows (H2): The number of retail shops in a neighborhood influences e-commerce deliveries in Belo Horizonte, Brazil.

The third hypothesis refers to the relationship between household size and online shopping (H3): The average household size in Belo Horizonte influences e-commerce deliveries.

Finally, the influence of neighborhoods area on e-commerce is analyzed in the fourth hypothesis (H4): The neighborhood area of a Brazilian city influences e-commerce deliveries.

These hypotheses were designed based on the data available at the neighborhood level that represent its characteristics.

3. Method

3.1. Study area and data description

Belo Horizonte is the capital of the state of Minas Gerais, located in the Southeast region of Brazil. It was founded in 1889 as the first planned Brazilian city. The broad streets and wide squares intended to allow the movement of people and goods and the urban densification by high-rise buildings at the beginning of the 20th century symbolized progress and modernity (Fernandes, 2021). The area initially planned for the city shown in Fig. 1 was designed for 200,000 inhabitants; however, in 1940, 211,377 inhabitants lived in it (IBGE, 2022b). The town has nine administrative units and 477 neighborhoods (IBGE, 2010) across 331 km² (IBGE, 2022a). In 2019, the population was estimated at around 2.5 million as the 6th most populous Brazilian city.

Fig. 2(a) illustrates the population distribution over the territory: 37% of the neighborhoods concentrate 80% of the population, with 2.54 inhabitants/household on average. Fig. 2(b) illustrates the household size distribution, where 44% of neighborhoods have between 2.41 and 2.58 inhabitants per family. Still, the household size is smaller than the average in 54% of the most populated districts. Despite the heterogeneity of the population distribution, the size of households is homogeneous. Fig. 2(c) shows the spatial and frequency income distribution in Belo Horizonte. The income is higher in the central region than in its outskirts. The average monthly income is BRL 1555.92 or USD 311.18 (consider 1.00 USD = 5.00 BRL on April 27, 2022). However, the income variation is considerable because the standard deviation is BRL 1503.50 (US\$300.70). Therefore, 74% of the neighborhoods have an income lower than the average. Still, 6% of the districts have income over 4,000, while 19% of the most populated areas are above the average. Therefore, income is heterogeneous in Belo Horizonte and concentrates below BRL 2000. Fig. 2(d) shows the distribution of retail shops in 2019. At the time, there were 43,341 commercial establishments registered in the municipality. The downtown concentrated 11% of them, while 90% of the neighborhoods had less than 90 shops. Thus, the distribution of retail shops is also heterogeneous over the territory.

These data were included in our dataset, which comprises

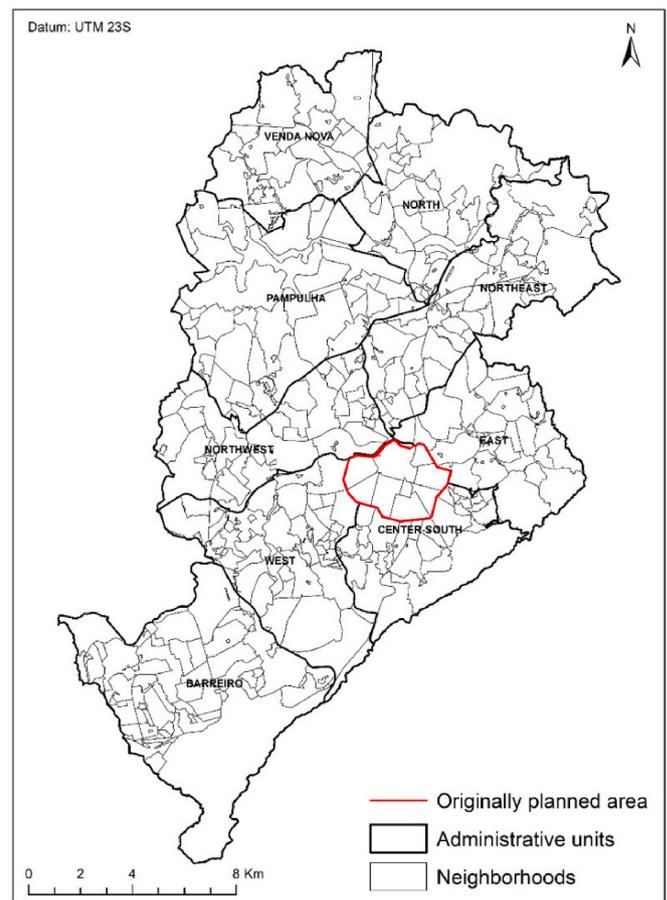


Fig. 1. Administrative regions emphasizing the planned area of Belo Horizonte.

information from different sources to represent neighborhoods and delivery characteristics. The characteristics of neighborhoods are described by: (i) the average income obtained from the 2010 census (IBGE, 2010); (ii) the number of retail shops per neighborhood (Belo Horizonte, 2022); (iii) the area of the neighborhood in square kilometers obtained from the municipality database (Belo Horizonte, 2022); (iv) the household size based on the population size obtained from the 2010 census and extrapolated to 2019, 2020, and 2021 according to the population growth index; and (v) the number of households obtained from the 2010 census (IBGE, 2010).

The e-commerce delivery data were obtained from a carrier of national coverage with a large market share in Belo Horizonte. The company performed 393,904 deliveries in 2019. It increased by 66% in 2020, reaching 652,660 deliveries. In 2021, 801,990 e-commerce deliveries were performed, 23% higher than in the previous year. In comparison, around 100 million e-commerce purchases in Brazil were made in the first semester of 2021 (E-Bit and Nielsen, 2022), whereas 62% occurred in the South-eastern region (Statista, 2022b), where Belo Horizonte is located. The e-commerce deliveries are home-based and spread over the territory in the studied case. Deliveries from 2019, 2020, and 2021 (before and during the COVID-19 pandemic) were considered in this study. The spatial pattern of total deliveries per year is shown in Fig. 3. In 2019, 30% of neighborhoods concentrated 80% of the e-commerce deliveries. In 2020 and 2021, 32% and 27% of the areas had 80% e-commerce deliveries, respectively. Still, 25% of the neighborhoods did not receive deliveries in 2019 (123 neighborhoods), 21% in 2020 (101 neighborhoods), and 22% in 2021 (106 neighborhoods). The neighborhoods with a low number of deliveries are in the suburban regions where 3% of the population lives.

Table 2 presents the descriptive statistics and the histograms of e-

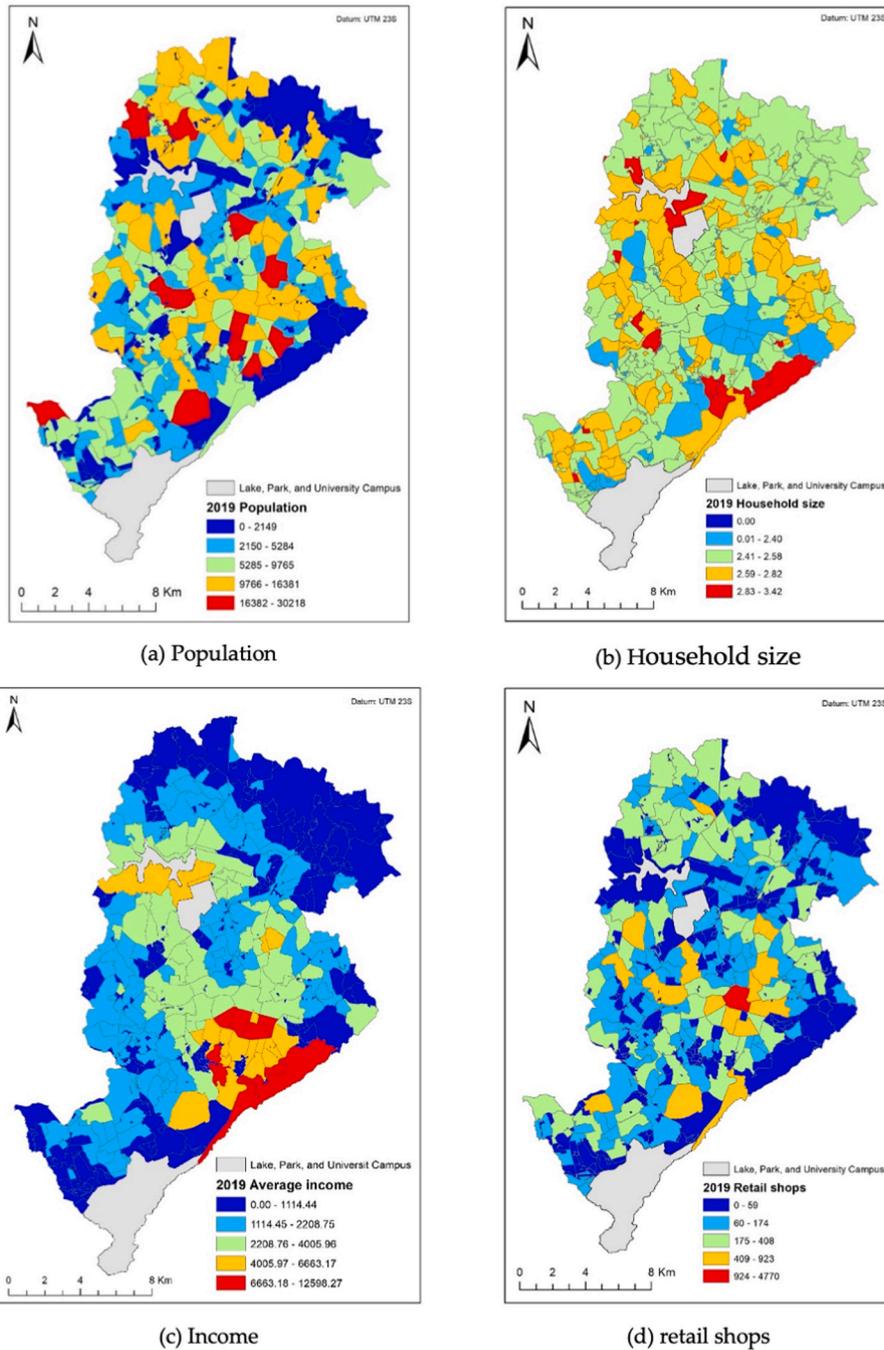


Fig. 2. Population (a), household size (b), Income (c), and retail shops (d) in Belo Horizonte, Brazil.

commerce data. Frequency represents the number of neighborhoods in Belo Horizonte. In 2019, 121 neighborhoods did not have e-commerce deliveries. Neighborhoods had 826 deliveries in 2019 on average; the histogram is skewed to the left, showing that a few neighborhoods demand a high delivery rate. In 2019, 75% of the neighborhoods had up to 1202 deliveries, while 211 had at least one delivery and less than 1000 deliveries. In 2020, 98 neighborhoods did not have e-commerce deliveries, and the remaining neighborhoods had 1089 deliveries on average. The histogram is also skewed to the left, and 75% of the neighborhoods had up to 1598 deliveries, while 203 had at least one delivery and less than 1000 deliveries. Finally, in 2021, 105 neighborhoods did not have e-commerce deliveries, while 171 neighborhoods had at least one delivery and less than 1000 deliveries. Most neighborhoods without deliveries are slums without zip codes for e-commerce

deliveries. The delivery rate in the neighborhoods where they occurred was: 0.21 delivery/inhabitant.year in 2019, 0.22 delivery/inhabitant.year in 2020, and 0.38 delivery/inhabitant.year in 2021.

Table 3 shows the descriptive statistics and the histograms of the characteristics of the neighborhoods: income; number of retail shops in 2019; household size; and neighborhood area. Income data from 2010 were extrapolated to 2019, 2020, and 2021. Using census data, the extrapolation was based on the ratio between the average income in the most recent year and the average income in 2010 for Belo Horizonte. In 2019, 231 neighborhoods had an average income lower than BRL 998 (the minimum wage in Brazil in 2019). On average, the neighborhood income was BRL 1555.9. In 2020, the minimum wage was BLR 1,039, and 195 neighborhoods had an average income lower than this value. In 2021, 204 neighborhoods had an average income lower than the

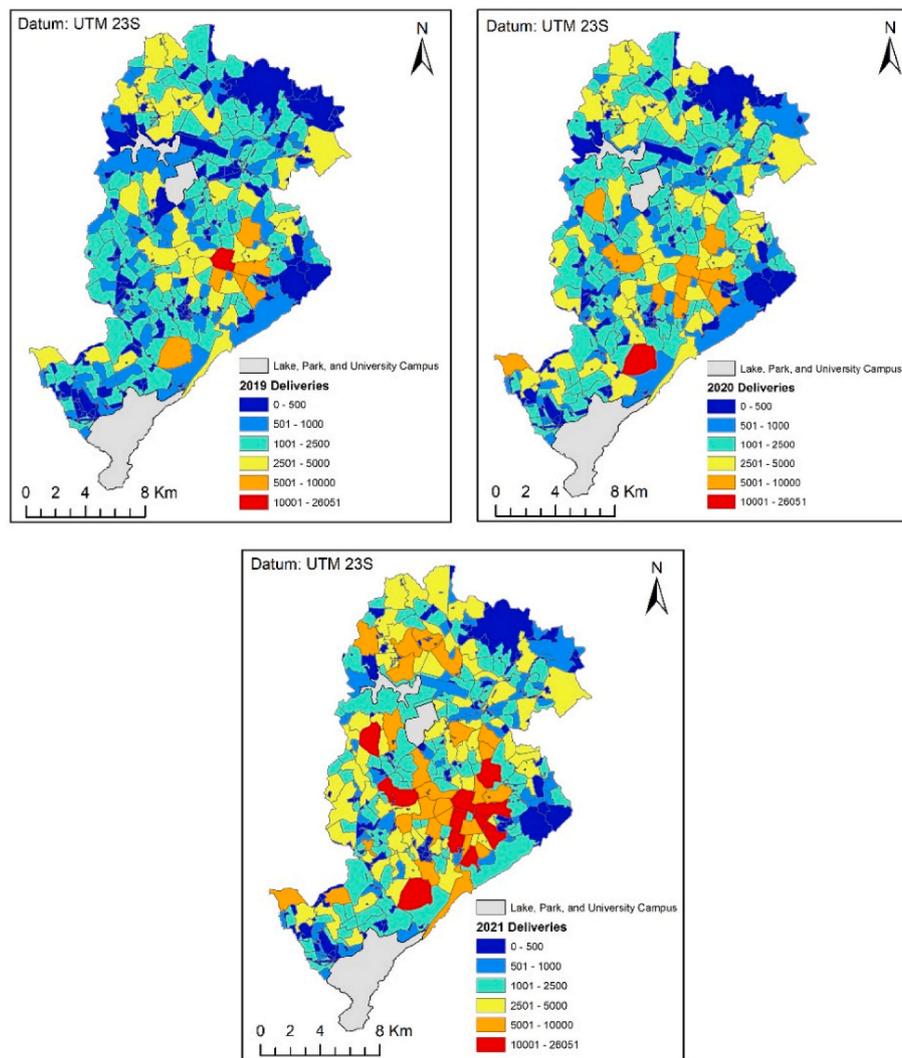


Fig. 3. Deliveries per neighborhood in 2019, 2020, and 2021.

Table 2
Descriptive statistics of e-commerce data.

Variable	Statistics	Value	Histogram
Number of deliveries in 2019	Minimum	0.0	
	1st quartile	0.0	
	Median	380.0	
	Mean	825.8	
	3rd quartile	1202.0	
	Maximum	11638.0	
	Number of deliveries in 2020	Minimum	
1st quartile		6.0	
Median		538.9	
Mean		1089.0	
3rd quartile		1598.0	
Maximum		10277.0	
Number of deliveries in 2021		Minimum	0.0
	1st quartile	3.0	
	Median	647.0	
	Mean	1669.0	
	3rd quartile	2132.0	
	Maximum	26051.0	

Table 3
Descriptive statistics of the characteristics of the neighborhood.

Variable	Statistics	Value	Histogram
Income 2019	Minimum	315.2	
	1st quartile	727.0	
	Median	1012.1	
	Mean	1555.9	
	3rd quartile	1620.2	
	Maximum	12598.3	
Retail shops 2019	Minimum	0.00	
	1st quartile	4.00	
	Median	33.00	
	Mean	90.86	
	3rd quartile	105.00	
	Maximum	4770.00	
Household size (average per neighborhood) 2019	Minimum	1.71	
	1st quartile	2.440	
	Median	2.540	
	Mean	2.544	
	3rd quartile	2.630	
	Maximum	3.420	
Neighborhood's area	Minimum	0.002	
	1st quartile	0.050	
	Median	0.310	
	Mean	0.677	
	3rd quartile	0.860	
	Maximum	17.360	

minimum wage (BLR 1100). The histogram is skewed to the left, where 75% of the neighborhoods have an average income lower than BLR 1620.20. Thus, at least 50% of the neighborhoods in Belo Horizonte have low incomes.

Regarding the number of retail shops, there were 43,341 stores in 2019, followed by 43,338 in 2020 and 52,187 in 2021. The average number of retail shops per neighborhood was similar over the years: 91 in 2019, 113 in 2020, and 139 in 2021. The downtown has 4770 shops, and 75% of the neighborhoods have up to 105 shops. We have applied the municipality population growth to all the neighborhoods regarding the household size. Thus, the frequency of household size distribution is the same in all the years, with 1598 houses/neighborhood and 2.54 inhabitants/house. On average, 0.54 deliveries/house were performed in 2019, followed by 0.70 in 2020 and 0.94 in 2021. Therefore, the histogram of the household size presents a normal distribution, as shown in Table 3.

Finally, the area of the neighborhoods varied between 0.002 km² and 17.360 km². The neighborhoods with smaller sizes are slums, and the largest have high incomes. The histogram is skewed to the right (Table 3), where 75% of the neighborhoods have up to 0.8 km².

3.2. Modeling approach

The methodological procedure includes two steps: (i) a comparison of the geographical distribution of the neighborhood characteristics and the e-commerce deliveries; and (ii) the analyses of the relationship between the number of e-commerce deliveries and the characteristics of the neighborhoods.

In the first step, we compared the distribution of deliveries in the different years using the chi-square test of independence followed by the adjusted residual analysis to explore association trends between neighborhoods. This analysis identifies whether e-commerce delivery patterns in other neighborhoods have changed between 2019 and 2021 (for example, changes in the destination of shipments during the pandemic because people who received their deliveries at work started receiving them at home) or remained in the same proportion.

The chi-square test examines the difference between expected and observed distributions. The expected distribution refers to the number of deliveries scheduled for each neighborhood if the annual growth in

deliveries had been the same (i.e., if the neighborhood and year were independent). The observed distribution refers to the number of deliveries observed in each neighborhood. The null hypothesis (H0) states that there is no significant difference between the expected and observed data. The alternative hypothesis (H1) states that there is a difference between them. The statistic for the chi-square test is computed as

$$\chi^2 = \sum_{i=1}^R \sum_{j=1}^C \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{1}$$

where O_{ij} is the observed cell count in the i th row (neighborhood) and the j th column (year) of the cross-tabulation table. The statistic χ^2 is compared with the critical value from the chi-square distribution table with degrees of freedom $df = (R - 1)(C - 1)$ and 95% confidence level, where R is the number of neighborhoods and C is the number of years.

The adjusted residual analysis was performed to provide information on the location of the differences, that is, which neighborhoods had observed values greater, lower, or equal to the expected value over the pairs of years compared (2019/2020, 2019/2021, and 2020/2021). The adjusted residuals (standardized residuals) are the difference between the observed and expected values by the square root of the expected value. We performed the adjusted residual analyses by applying the Bonferroni correction to reduce the likelihood of a statistically significant result (error Type I, for example) when performing multiple tests (MacDonald & Gardner, 2000).

In the second step, we estimated generalized linear models for count data (Poisson and negative binomial regressions) using e-commerce delivery information from 2019, 2020, and 2021 to assess the influence of neighborhood characteristics on the number of e-commerce deliveries. The number of e-commerce deliveries is a counting variable; thus, Poisson or negative binomial distribution represents its probability distribution more adequately.

The procedure started with the estimation of Poisson models, which canonic form is as follows:

$$Prob[Y = y_i | x_i] = \frac{\exp(-\lambda_i) \lambda_i^{y_i}}{\Gamma(1 + y_i)} \tag{2}$$

$$\lambda_i = \exp(\alpha + \mathbf{x}'_i \beta), y_i = 0, 1, \dots, i = N$$

where Y is a count data, x_i is a vector of covariates, and $i = 1, \dots, N$ represents the sample (Greene, 2011). However, the response variable presented overdispersion, i.e., the variance was larger than the observed average values, not fulfilling the assumptions for the Poisson distribution (Gelman and Hill, 2007; Washington et al., 2020).

Thus, we estimated negative binomial models (NBM) that relax the equidispersion restriction of the Poisson model (Greene, 2011). The functional form of NBM is

$$E[Y|x_i, \varepsilon_i] = \exp(\alpha + x_i'\beta + \varepsilon_i) = h_i\lambda_i \tag{3}$$

where $h_i = \exp(\varepsilon_i)$ is assumed as gamma distribution ($G(\theta, \theta)$), with mean value equals 1 and variance $1/\theta = k$ (Greene, 2011).

The overdispersion check was performed using the AER package (Kleiber and Zeileis, 2008), while the NBM was estimated using the MASS package (Venables and Ripley, 2002) in the R environment (R Core Team, 2020).

Models for 2019, 2020, and 2021 were estimated, and the parameters show the influence of each independent variable (income, retail shops, household size, and neighborhood area) on the number of e-commerce deliveries. The Variance Inflation Factor (VIF) was calculated to identify multicollinearity among the explanatory variables. The estimated parameters rely upon the units of measurement. The elasticities and pseudo-elasticities for the indicators were computed to compare the effect of the modeled variables (Washington et al., 2020). The elasticity represents the sensitivity in percentage change in the dependent variable resulting from a 1% change in an independent continuous variable. The pseudo-elasticity computed for indicators represents the incremental shift in frequency due to changes in the indicator variables. These measures were calculated for each individual and then averaged for the population using an enumeration sample.

4. Results and discussion

4.1. Comparison of the geographical distribution

The chi-squared test showed significant statistical differences between the spatial pattern comparing 2019/2020, 2019/2021, and 2020/2021 (confidence level 95%). The estimated χ^2 Statistic is 63,909.5, and the critical value from the chi-square distribution with the 784 degrees of freedom and 95% confidence level is 720. Therefore, the null hypothesis is rejected, and data suggest an association between deliveries in the neighborhood over the years.

The adjusted residuals showed that the number of deliveries in some neighborhoods differs from expected values comparing 2019, 2020, and 2021. The adjusted residual obtained by the Bonferroni correction to control for false positives (MacDonald and Gardner, 2000) considered the significance level of 5%, i.e., standardized residual ± 1.96 , which was adjusted to a significance level of 8,3% associated with the standardized residual cutoff of ± 2.64 . We computed the adjusted residual for every 477 neighborhoods. Table 4 shows the results of the neighborhood "Aeroporto" as an example. The adjusted residual for 2019 is -4.9 , significantly lower than the cutoff point (-2.64). Thus, the number of deliveries in 2019 (236) would be smaller than expected (312) if the annual growth in deliveries had been the same in all the neighborhoods. Similarly, the adjusted residual for 2021 (6.0) was

Table 4
Example of chi-square cross-tabulation table for the neighborhood "Aeroporto".

Neighborhood	Measures	Year			Total
		2019	2020	2021	
Aeroporto	Count	236	378	741	1355
	Expected Count	312	412	631	1355
	% Within Neighborhood	.2	.3	.5	1
	Adjusted Residual	-4.9	-2.0	6.0	-

significantly higher than the cutoff point, showing that the number of deliveries in 2021 (741) was considerably higher than expected (631) if the annual growth in deliveries had been the same in all the neighborhoods. However, in 2020, the difference between the number of observed (378) and expected (412) deliveries are not significant as the adjusted residual (-2.0) is lower than the cutoff.

Fig. 4 summarizes the results of the adjusted residual for 2019, 2020, and 2021. Neighborhoods marked in red (residual greater than 2.64) show that the number of deliveries would be significantly higher than expected if the annual growth in deliveries had been the same in all neighborhoods (i.e., if neighborhood and year were independent). Conversely, neighborhoods marked in blue (residual lower than 2.64) show that the number of deliveries would be significantly lower than expected if the annual growth in deliveries had been the same in all neighborhoods. On the other hand, those that did not show a significant difference in the number of observed and expected deliveries are highlighted in gray.

In 2019, the North and Northeast portions of Belo Horizonte had more neighborhoods with e-commerce deliveries than expected. These are low-income neighborhoods with large household sizes. In 2020, e-commerce deliveries also increased in neighborhoods located in the southern portion of Belo Horizonte. However, in 2021, neighborhoods with higher e-commerce deliveries than expected did not have fewer deliveries than expected in the previous years.

4.2. Model results

Table 5 shows the estimated parameters of the final models. No collinearity was identified in the models because the VIF values were lower than 5.00 (Hair et al., 2019). In all the models, the signal of the estimated coefficients for the variables has the same pattern, showing that the effect did not change over the years.

Income positively influences e-commerce deliveries (number of deliveries in 2019, 2020, 2021), with minor variations between the models. The t -test (95% confidence level) showed the difference between the impact of income in 2019 (the pre-pandemic period) and 2020. Supposedly, other factors emerged because of the pandemic, such as lockdown measures to reduce the virus spread and the closure of non-essential shops (Oliveira et al., 2022). In 2021, the impact returned to values similar to 2019.

The number of retail shops (retail shops) positively influences the e-commerce deliveries (number of deliveries in 2019, 2020, 2021), and the parameters vary from 0.00056 (2019 and 2021) to 0.00058 (2020). The impact of this variable differs over the years, considering the 95% confidence level for the t -test.

Household size negatively impacts e-commerce deliveries, and the estimated coefficients vary from -0.188 (2020) to -0.926 (2021). Finally, neighborhood area influences e-commerce deliveries positively, and the estimated coefficients vary from 0.148 (2021) to 0.155 (2020). As for income and retail shops, a significant difference was observed in household size and neighborhood area differs over the years.

Table 6 shows the elasticities and pseudo-elasticities values. The elasticity represents the percentage change in the number of e-commerce deliveries by a 1% change in income, retail shops, and neighborhood area. The pseudo-elasticity expresses the incremental shift in the number of e-commerce deliveries due to changes in Household size.

4.3. Discussion and policy implications

Overall, the positive relationship between income and e-commerce deliveries was also identified in the literature. Additionally, the number of retail shops positively influences e-commerce deliveries, differently from what was found by Cheng et al. (2021), who identified a negative influence of accessibility to shopping malls on delivery demand in Singapore. The economic development of Singapore compared to Brazil may explain the difference. Therefore, further studies must be

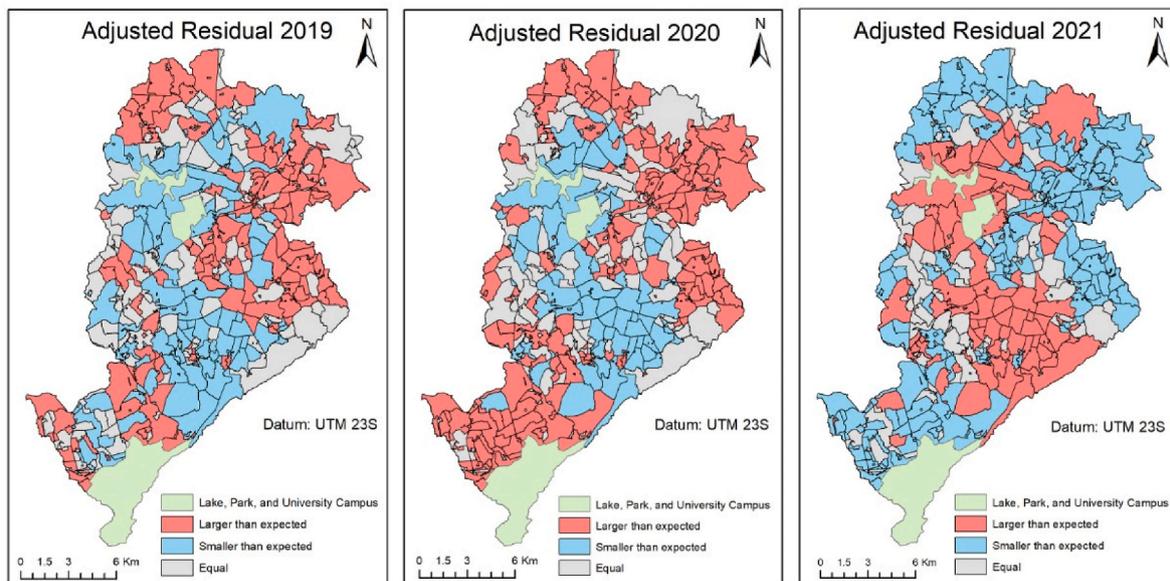


Fig. 4. Adjusted residual of e-commerce deliveries.

Table 5
Estimated coefficients of NBM.

Variable	2019			2020			2021		
	Estimate	z-value	VIF	Estimate	z-value	VIF	Estimate	z-value	VIF
Intercept	7.7233	352.52 ***	–	7.055	784.08 ***	–	8.950	680.10 ***	–
Income	0.00019	320.23 ***	1.06	0.00014	255.28 ***	1.07	0.00021	524.20 ***	1.07
Retail Shops	0.00056	323.73 ***	1.19	0.00058	361.14 ***	1.17	0.00056	657.7 ***	1.14
Household size	–0.645	–74.15 ***	1.20	–0.188	–72.93 ***	1.21	–0.926	–175.6 ***	1.15
Neighborhood Area	0.149	225.02 ***	1.06	0.155	292.52 ***	1.01	0.148	294.9 ***	1.06
Observations	477			477			477		
AIC	420,406			558,896			789,577		

Significance level: “***” 0.001.

Table 6
Elasticities of e-commerce deliveries.

Variable	Year		
	2019	2020	2021
Income	0.30	0.26	0.34
Retail Shops	0.05	0.06	0.05
Household size ^a	–0.91	–0.21	–1.52
Neighborhood Area	0.10	0.11	0.10

^a Pseudo-elasticity.

conducted for evidence of the impact of retail shops on e-commerce delivery patterns.

Household size negatively influences e-commerce delivery, i.e., the number of deliveries decreases as the size of the household increases, similar to the findings of Pérez-Amaral et al. (2020) and Zhou and Wang (2014). On the other hand, income positively impacts e-commerce deliveries, as found in the literature. Finally, the neighborhood area influences e-commerce deliveries positively as the neighborhoods with large areas concentrate the highest number of deliveries. This variable shows the importance of bringing spatial factors to econometric models as an alternative to spatial modeling.

The elasticity of the number of e-commerce deliveries concerning income indicates that a 1% change in income changes 0,3% the number of e-commerce deliveries. The elasticities relating to retail shops and neighborhood areas show that 1% increments in these variables result in approximately 0.05% and 0.1% increase in deliveries, respectively. Regarding household size, increments of one unit in household members

decrease between 0.21% and 1.52% in e-commerce deliveries. The elasticity of the number of e-commerce delivery values shows the importance of the explanatory variables per year (with different measurement scales). The most critical variable in 2019 and 2021 was the household size, followed by income. However, income was the most important variable affecting the number of deliveries in 2020. Income becomes more critical for deliveries between 2019 and 2020 because of the pandemic and its externalities (unemployment, lower income, and decreasing purchases overall). The number of retail shops (retail shops) reduced its impact on deliveries from 2019 to 2021. This result may be related to social isolation, lockdown measures, and changes in consumer behavior. The pandemic changed how people buy products. However, this causal relationship requires further investigation.

4.4. Practical implications

Findings showed that the geographical distribution of e-commerce deliveries is not homogenous in Belo Horizonte over the years. Thus, home delivery solutions should consider the neighborhoods’ characteristics. Identifying locations with increasing deliveries, regardless of their characteristics, is fundamental to proposing economically feasible solutions to e-commerce delivery. Additionally, e-commerce shopping can reduce the number of trips for shopping purposes, despite increasing home deliveries and traffic in urban regions. In general, e-commerce products are small, and the destination is dispersed in the territory. The lack of alternative systems for home deliveries contributes to congestion and accessibility problems, damages the transport infrastructure, and increases costs and delivery times for the consumer. These impacts

reduce the mobility of people and goods, especially in regions already affected by this problem. Thus, understanding the characteristics of the areas with the highest delivery rates collaborates to reduce the impacts of e-commerce delivery.

In this study, 341 neighborhoods have the number of e-commerce deliveries increased between 2019 and 2021 (Fig. 5). However, although most neighborhoods with e-commerce deliveries are the same, dispersion has been observed over the years. For example, between 2020 and 2021, 198 neighborhoods did not have deliveries that comprised low-income communities or slums with no zip codes.

On the other hand, everyone must have access to e-commerce deliveries, not just some neighborhoods. Thus, e-commerce deliveries should achieve low-income areas (Schaefer and Figliozzi, 2021). For these neighborhoods, delivery services such as lockers, pick-up points, or crowdshipping are alternatives to reduce the negative impacts of e-commerce deliveries. For example, Oliveira et al. (2017) suggested the location of lockers in high-density areas. Crowdshipping systems using public transportation services provide economic and environmental benefits for urban areas (Gatta et al., 2019). Marcucci et al. (2017)

identified that delivery timing and punctuality are well evaluated by people who receive goods via crowdshipping service. Therefore, the neighborhood characteristics bring knowledge for developing effective business models for e-commerce delivery services. Thus, future studies must analyze the relationship between e-commerce and low-income consumers.

5. Conclusion

This paper analyzed the relationship between neighborhood characteristics and urban e-commerce deliveries. We identified which neighborhood characteristics influence the number of e-commerce deliveries in Belo Horizonte based on deliveries performed in 2019, 2020, and 2021 by an e-commerce carrier. We identified the geographical distribution pattern of e-commerce deliveries between 2019 and 2021. Negative Binomial models showed that income has a negative influence on e-commerce deliveries (hypothesis H1), the number of retail shops if the neighborhood influences the number of e-commerce deliveries positively (hypothesis H2), and the household size of a community



Fig. 5. Delivery increase in the neighborhoods over the years.

impacts e-commerce delivery negatively (hypothesis H3). The neighborhood area influences e-commerce deliveries positively (hypothesis H4). The elasticity values indicate that household size is essential for e-commerce deliveries in 2019 and 2021, followed by income. However, in 2020, the effect of the different features changed when income became the most impactful variable in the number of deliveries.

Regarding the generalization of the results, e-commerce distribution is closely related to urban characteristics. Latin American cities are more dispersed because of the fast and unplanned growth, thus generating higher inequality over space. Moreover, low-income families live on the outskirts of the city with poor infrastructure. The characteristics of the developing countries collaborate to extend the conclusions presented in this paper to other locations. However, attention should be taken to the differences in income and access to technologies. Therefore, the analyses rely on the context, but studies in different regions of developing countries may be limited to data availability.

Opportunities for future research derive from this study. For example, the influence of individual income versus e-commerce deliveries could be further explored. Moreover, further analyses may include variables such as urbanization level instead of neighborhood area for specific locations and consumer characteristics such as car ownership, internet access, use, and public transportation access. These variables would impact the estimated effects but were not explored in this paper due to a lack of data at the neighborhood level.

The relationship between the rate of e-commerce deliveries and the accessibility to physical stores could also be studied, considering the positive relationship between the number of physical stores and e-commerce deliveries, in opposition to the findings in the literature. Therefore, further studies should investigate the relationship between proximity, availability, and access to retail shops and e-commerce deliveries.

Finally, it is argued that e-commerce deliveries increased because of the lockdown measures. However, only a few studies have addressed such analyses. Thus, investigating the causal relationship between e-commerce deliveries and lockdown measures to quantify the contribution of the COVID-19 pandemic to the growth of e-commerce deliveries would be a topic for future research.

CRediT authorship contribution statement

Lúisa Tavares Muzzi de Sousa: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Leise Kelli de Oliveira:** Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Jorge Luiz dos Santos Junior:** Data curation, Writing – original draft, Writing – review & editing. **Bruno Vieira Bertoncini:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Cassiano Augusto Isler:** Methodology, Writing – original draft, Writing – review & editing. **Ana Margarita Larranaga:** Methodology, Investigation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

Acknowledgements

The authors thank the transport company for data availability which allowed the development of this research. We also thank CNPq (grant

number 303171/2020-0 and 307085/2021-0) and CAPES for their financial support. Finally, the authors thank FAPEMIG and FACEPE for the scholarship to the first author during her master's and Ph.D.

References

- Allen, J., Pieczyk, M., Piotrowska, M., McLeod, F., Cherrett, T., Ghali, K., Nguyen, T., Bektas, T., Bates, O., Friday, A., Wise, S., & Austwick, M. (2018). Understanding the impact of e-commerce on last-mile light goods vehicle activity in urban areas: The case of London. *Transportation Research Part D: Transport and Environment*, 61, 325–338. <https://doi.org/10.1016/j.trd.2017.07.020>
- Beckers, J., Cardenas, I., & Sanchez-Diaz, I. (2022). Managing household freight: The impact of online shopping on residential freight trips. *Transport Policy*, 125, 299–311. <https://doi.org/10.1016/j.tranpol.2022.06.009>
- Beckers, J., Cárdenas, I., & Verhetsel, A. (2018). Identifying the geography of online shopping adoption in Belgium. *Journal of Retailing and Consumer Services*, 45, 33–41. <https://doi.org/10.1016/j.jretconser.2018.08.006>
- Belo Horizonte. (2022). BHMMap [WWW Document]. URL <http://bhmap.pbh.gov.br/v2/mapa/idebgeo>. (Accessed 14 May 2022).
- Brashear, T. G., Kashyap, V., Musante, M. D., & Donthu, N. (2009). A profile of the internet shopper: Evidence from six countries. *Journal of Marketing Theory and Practice*, 17, 267–282. <https://doi.org/10.2753/MTP1069-6679170305>
- Cao, X., Chen, Q., & Choo, S. (2013). Geographic distribution of E-shopping: Application of structural equation models in the twin cities of Minnesota. *Transportation Research Record*, 2383, 18–26. <https://doi.org/10.3141/2383-03>
- Cheng, Y., Huang, A., Qi, G., & Zhang, B. (2019). Mining customized bus demand spots based on smart card data: A case study of the Beijing public transit system. *IEEE Access*, 7, 181626–181647. <https://doi.org/10.1109/ACCESS.2019.2959907>
- Cheng, C., Sakai, T., Alho, A., Cheah, L., & Ben-Akiva, M. (2021). Exploring the relationship between locational and household characteristics and E-commerce home delivery demand. *Logistics*, 5, 29. <https://doi.org/10.3390/logistics5020029>
- Clarke, G., Thompson, C., & Birkin, M. (2015). The emerging geography of e-commerce in British retailing. *Regional Studies, Regional Science*, 2, 371–391. <https://doi.org/10.1080/21681376.2015.1054420>
- De Blasio, G. (2008). Urban–rural differences in internet usage, e-commerce, and e-banking: Evidence from Italy. *Growth and Change*, 39, 341–367. <https://doi.org/10.1111/j.1468-2257.2008.00422.x>
- E-Bit, Nielsen. (2022). Webshoppers [WWW Document]. URL <https://www.ebit.com.br/webshoppers>. (Accessed 5 January 2022).
- Farag, S., Dijst, M., & Lanzendorf, M. (2003). Exploring the use of E-shopping and its impact on personal travel behavior in The Netherlands. *Transportation Research Record*, 1858, 47–54. <https://doi.org/10.3141/1858-07>
- Farag, S., Krizek, K. J., & Dijst, M. (2006a). E-Shopping and its relationship with in-store shopping: Empirical evidence from The Netherlands and the USA. *Transport Reviews*, 26, 43–61. <https://doi.org/10.1080/01441640500158496>
- Farag, S., Schwanen, T., & Dijst, M. (2005). Empirical investigation of online searching and buying and their relationship to shopping trips. *Transportation Research Record*, 1926, 242–251. <https://doi.org/10.1177/0361198105192600128>
- Farag, S., Schwanen, T., Dijst, M., & Faber, J. (2007). Shopping online and/or in-store? A structural equation model of the relationships between e-shopping and in-store shopping. *Transportation Research Part A: Policy and Practice*, 41, 125–141. <https://doi.org/10.1016/j.tra.2006.02.003>
- Farag, S., Welttevreden, J., van Rietbergen, T., Dijst, M., & van Oort, F. (2006b). E-shopping in The Netherlands: Does geography matter? *Environment and Planning B: Planning and Design*, 33, 59–74. <https://doi.org/10.1068/b31083>
- Fernandes, P. C. A. (2021). The foundation of Belo Horizonte: Order, progress, and hygiene, but not for all. *Cadernos Metrópole*, 25, 1061–1084. <https://doi.org/10.1590/2236-9996.2021-5210.e>
- Gatta, V., Marcucci, E., Nigro, M., Patella, S. M., & Serafini, S. (2019). Public transport-based crowdshipping for sustainable city logistics: Assessing economic and environmental impacts. *Sustainability*, 11, 145. <https://doi.org/10.3390/su11010145>
- Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. Cambridge; New York: Cambridge University Press.
- Greene, W. (2011). *Econometric analysis*. Upper Saddle River: Pearson Educational.
- Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2019). *Multivariate data analysis*. Hampshire: Cengage.
- Hashin, A., Ghani, E. K., & Said, J. (2009). Does consumers' demographic profile influence online shopping?: An examination using Fishbein's Theory. *Canadian Social Science*, 5, 19–31. <https://doi.org/10.3968/j.css.1923669720090506.003>
- Hood, N., Urquhart, R., Newing, A., & Heppenstall, A. (2020). Sociodemographic and spatial disaggregation of e-commerce channel use in the grocery market in Great Britain. *Journal of Retailing and Consumer Services*, 55, Article 102076. <https://doi.org/10.1016/j.jretconser.2020.102076>
- IBGE. (2010). *Censo demográfico 2010. Brasília*.
- IBGE. (2022a). Belo Horizonte [WWW Document]. URL <https://cidades.ibge.gov.br/bras-il/mg/belo-horizonte/panorama>.
- IBGE. (2022b). *History of Belo Horizonte* [WWW Document]. IBGE Cidades. URL <https://cidades.ibge.gov.br/brasil/mg/belo-horizonte/historico>. (Accessed 15 November 2022).
- Jaller, M., & Pahwa, A. (2020). Evaluating the environmental impacts of online shopping: A behavioral and transportation approach. *Transportation Research Part D: Transport and Environment*, 80, Article 102223. <https://doi.org/10.1016/j.trd.2020.102223>

- Kirby-Hawkins, E., Birkin, M., & Clarke, G. (2019). An investigation into the geography of corporate e-commerce sales in the UK grocery market. *Environment and Planning B: Urban Analytics and City Science*, 46, 1148–1164. <https://doi.org/10.1177/2399808318755147>
- Kleiber, C., & Zeileis, A. (2008). *Applied econometrics with R*. New York: Springer-Verlag.
- Lee, R. J., Sener, I. N., & Handy, S. L. (2015). Picture of online shoppers: Specific focus on Davis, California. *Transportation Research Record*, 2496, 55–63. <https://doi.org/10.3141/2496-07>
- Lee, R. J., Sener, I. N., Mokhtarian, P. L., & Handy, S. L. (2017). Relationships between the online and in-store shopping frequency of Davis, California residents. *Transportation Research Part A: Policy and Practice*, 100, 40–52. <https://doi.org/10.1016/j.tra.2017.03.001>
- Loo, B. P. Y., & Wang, B. (2018). Factors associated with home-based e-working and e-shopping in Nanjing, China. *Transportation*, 45, 365–384. <https://doi.org/10.1007/s11116-017-9792-0>
- Lubis, A. N. (2018). Evaluating the customer preferences of online shopping: Demographic factors and online shop application issue. *Academy of Strategic Management Journal*, 17, 1–13.
- MacDonald, P. L., & Gardner, R. C. (2000). Type I error rate comparisons of post hoc procedures for $I \times J$ chi-square tables. *Educational and Psychological Measurement*, 60(5), 735–754. <https://doi.org/10.1177/00131640021970871>
- Marcucci, E., Le Pira, M., Carrocci, C. S., Gatta, V., & Peralice, E. (2017). Connected shared mobility for passengers and freight: Investigating the potential of crowdshipping in urban areas. In *2017 5th IEEE international conference on models and technologies for intelligent transportation systems (MT-ITS)*. Presented at the 2017 5th IEEE international conference on models and technologies for intelligent transportation systems (MT-ITS) (pp. 839–843). Naples, Italy: IEEE. <https://doi.org/10.1109/MTITS.2017.8005629>
- Moroz, M., & Polkowski, Z. (2016). The last mile issue and urban logistics: Choosing parcel machines in the context of the ecological attitudes of the Y generation consumers purchasing online. *Transportation Research Procedia*, 16, 378–393. <https://doi.org/10.1016/j.trpro.2016.11.036>
- Motte-Baumvol, B., Belton-Chevallier, L., Dablan, L., Morganti, E., & Belin-Munier, C. (2017). Spatial dimensions of E-shopping in France. *Asian Transport Studies*, 4, 585–600. <https://doi.org/10.11175/eastsats.4.585>
- Oliveira, L. K. de, Morganti, E., Dablan, L., & Oliveira, R. L. M. de (2017). Analysis of the potential demand of automated delivery stations for e-commerce deliveries in Belo Horizonte, Brazil. *Research in Transportation Economics*, 65, 34–43. <https://doi.org/10.1016/j.retrec.2017.09.003>
- Oliveira, L. K. de, Oliveira, I. K. de, Bertoncini, B. V., Sousa, L. S., Santos Junior, & dos, J. L. (2022). Determining the impacts of COVID-19 on urban deliveries in the metropolitan region of Belo Horizonte using spatial analysis, 03611981221078846 *Transportation Research Record*. <https://doi.org/10.1177/03611981221078846>
- Opesade, O. A. (2020). Discovering patterns in electronic commerce diffusion in Nigeria using google trends web data. *Journal of Information Science, Systems and Technology*, 4, 1–20.
- Park, H., Park, D., & Jeong, I.-J. (2016). An effects analysis of logistics collaboration in last-mile networks for CEP delivery services. *Transport Policy*, 50, 115–125. <https://doi.org/10.1016/j.tranpol.2016.05.009>
- Pérez-Amaral, T., Valarezo, A., López, R., Garín-Muñoz, T., & Herguera, I. (2020). E-commerce by individuals in Spain using panel data 2008–2016. *Telecommunications Policy*, 44, Article 101888. <https://doi.org/10.1016/j.telpol.2019.101888>
- Pérez-Hernández, J., & Sánchez-Mangas, R. (2011). To have or not to have Internet at home: Implications for online shopping. *Information Economics and Policy*, 23, 213–226. <https://doi.org/10.1016/j.infoecopol.2011.03.003>
- R Core Team. (2020). *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing.
- Ren, F., & Kwan, M.-P. (2009). The impact of geographic context on E-shopping behavior. *Environment and Planning B: Planning and Design*, 36, 262–278. <https://doi.org/10.1068/b34014t>
- Saphores, J.-D., & Xu, L. (2021). E-shopping changes and the state of E-grocery shopping in the US - evidence from national travel and time use surveys. *Research in Transportation Economics*, 87, Article 100864. <https://doi.org/10.1016/j.retrec.2020.100864>
- Schaefer, J. S., & Figliozzi, M. A. (2021). Spatial accessibility and equity analysis of Amazon parcel lockers facilities. *Journal of Transport Geography*, 97, Article 103212. <https://doi.org/10.1016/j.jtrangeo.2021.103212>
- Sener, I. N., & Reeder, P. R. (2012). An examination of behavioral linkages across ICT choice dimensions: Copula modeling of telecommuting and teleshopping choice behavior. *Environment & Planning A: Economy and Space*, 44, 1459–1478. <https://doi.org/10.1068/a44436>
- Song, Z. (2021). The geography of online shopping in China and its key drivers. *Environment and Planning B: Urban Analytics and City Science* 23998083211002188. <https://doi.org/10.1177/23998083211002189>
- Statista. (2022a). *Retail e-commerce sales worldwide from 2014 to 2025* [WWW Document]. URL <https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/>.
- Statista. (2022b). *Distribution of online orders in Brazil in 2021, by region* [WWW Document]. URL <https://www.statista.com/statistics/770077/e-commerce-brasil-buyers-region/>. (Accessed 20 May 2022).
- Tadić, S., & Veljović, M. (2020). Home delivery: A framework for structuring. *International Journal of Traffic and Transportation Engineering*, 11, 30–74. [https://doi.org/10.7708/ijtte.2021.11\(1\).03](https://doi.org/10.7708/ijtte.2021.11(1).03)
- Taniguchi, E., Thompson, R. G., & Yamada, T. (2014). Recent trends and innovations in modelling city logistics. *Procedia - Social and Behavioral Sciences*, 125, 4–14. <https://doi.org/10.1016/j.sbspro.2014.01.1451>
- UNCTAD. (2021). *Estimates of global e-commerce 2019 and preliminary assessment of covid-19 impact on online retail 2020* [WWW Document]. URL https://unctad.org/system/files/official-document/tn_unctad_ict4d18_en.pdf.
- Van Droogenbroeck, E., & Van Hove, L. (2017). Adoption of online grocery shopping: Personal or household characteristics? *Journal of Internet Commerce*, 16, 255–286. <https://doi.org/10.1080/15332861.2017.1317149>
- Venables, V. M., & Ripley, B. D. (2002). *Modern applied statistics with S*. New York: Springer.
- Washington, S. P., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and econometric methods for transportation data analysis*. New York: Chapman and Hall/CRC.
- Zhou, Y., & Wang, X. (Cara) (2014). Explore the relationship between online shopping and shopping trips: An analysis with the 2009 NHITS data. *Transportation Research Part A: Policy and Practice*, 70, 1–9. <https://doi.org/10.1016/j.tra.2014.09.014>