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Mobility impacts of a new metro system with transit-oriented development features

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ABSTRACT

Few studies have analyzed the mobility impacts of TOD using a longitudinal research approach, and even fewer incorporated origin–destination (OD) information in the analysis. In this paper, we examine the impacts of a metro system with TOD features on the share of car and bus trips using Metro do Porto as a case study. The application of an autoregressive beta regression modeling approach to parish and OD data from two mobility surveys (2000 and 2017) allowed to detect changes in travel behavior accounting for pre-metro mode shares. Metro implementation was associated with strong reductions of the share of car trips in OD pairs with metro at both trip ends, especially when stations were TOD. Metro influence on the share of bus trips varied from neutral to positive, suggesting that bus and metro complement each other rather than compete for passengers.

1. Introduction

In the last 25 years, Transit-Oriented Development (TOD) has been an increasingly prominent research theme both in urban planning and transport planning (Ibraeva et al., 2020). This concept, introduced by Calthorpe (1993), calls for mixed-use high-density urban developments around transit stations, as well as for parking limitations, traffic calming measures, and pedestrian/cycling-friendly local streets in nearby areas, in order to discourage the use of private cars, diminish their environmental impacts and promote sustainable mobility. Numerous projects inspired by the TOD concept have been emerging recently all over the world – e.g., FasTrack in Denver, U.S. (Ratner and Goetz, 2013), Stedenbaan in The Netherlands (Spaans and Stead, 2016), and Corridors of Freedom in Johannesburg, South Africa (Harrison et al., 2019). The attention that researchers are devoting to TOD is, in this case, undoubtedly aligned with the interest that TOD is attracting from both planning authorities and real estate development companies.

Amongst the frequently examined research topics, TOD impacts on travel mode choices certainly, and naturally, is one of the most relevant. A vast body of knowledge concerning the effects of TOD projects particularly on car use is now available. Most of this knowledge has been assembled based on cross-sectional studies, i.e., TOD impacts were evaluated as a function of socio-economic, land-use, and transport service characteristics of different areas of the region/city under analysis in a given time period. In

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Table 1
Selected articles on TOD, major transit investments, and mode choice.

Reference	Case study	Methodology	Data source	Timeframe	OD data
Gomez-ibanez (1985)	San Diego (USA), Calgary and Edmonton (Canada)	Descriptive statistics	Transit agency data/ household travel survey	3, 8 and 12 years (respectively)	No
Cervero (1995)	Stockholm, Sweden	Historic overview/ descriptive statistics	Official data (Census)	One workday	No
Cervero and Gorham (1995)	San Francisco, Los Angeles, USA	Descriptive statistics/ Multiple linear regression (OLS)	Official data (Census)	One workday	No
Cervero and Radisch (1996)	San Francisco, USA	Comparative analysis/ discrete choice modeling (binomial logit)	Field/mail survey	One workday	Yes
Handy et al. (2005)	San Francisco Bay Area, USA	Discrete choice modeling (ordered probit)	Field/mail survey	Retrospective quasi-longitudinal	No
Cervero (2007)	San Francisco, USA	Discrete choice modeling (nested logit)	Household travel survey	One workday	Yes
Brown and Werner (2008)	Salt Lake City, USA	General linear model	Field/mail survey	Two years	No
Cervero and Day (2008)	Shanghai, China	Multiple linear regression (OLS)/ discrete choice modeling (binomial logit)	Field/mail survey	Before/after household's relocation	No
Crowley et al. (2009)	Toronto, Canada	Descriptive statistics	Household travel survey	1986–2001	No
Loo et al. (2010)	New York City, USA, Hong Kong, China	Multiple linear regression (OLS)	Smart card data	One workday	No
Yáñez et al. (2010)	Santiago (Chile)	Descriptive statistics	Field/mail survey	2 years	No
Sung and Oh (2011)	Seoul, South Korea	Multiple linear regression (OLS)	Smart card data/ official data	Weekday/weekend; peak hour/non-peak hours;	No
Choi et al. (2012)	Seoul, South Korea	General linear model	Smart card data/ official data;	One workday; peak/non-peak hours;	Yes
Chatman (2013)	New Jersey, USA	Multiple linear regression (OLS)/ discrete choice modeling (logit regression)	Field/mail survey	One week	No
Forsey et al. (2013)	York (Canada)	Generalized Extreme Value modeling	Household travel survey	5 years	No
Wang et al. (2013)	Beijing, Changzhou, Guangzhou, Jinan, Kunming (China)	Discrete choice modeling (binary logit)	Field/mail survey	unspecified (quasi-longitudinal)	No
Nasri and Zhang (2014)	Washington, D.C., Baltimore, USA	Comparative analysis/ multilevel mixed-effect Regression	Household travel survey	One workday	No
Cao (2015)	Twin Cities, USA	Multiple linear regression (two-way ANOVA)	Field/mail survey	One week	No
Van de Coevering et al. (2016)	Amersfoort, Veenendaal, Zeewolde, the Netherlands	Cross lagged panel structural equation model	Field/mail survey	Seven years	No
Ewing et al. (2017)	Denver, Los Angeles, San Francisco, Seattle, Washington, D.C., USA	Descriptive statistics - comparative analysis	Field/mail survey	Five workdays	No
Pan et al. (2017)	Shanghai, China	Multiple linear regression (OLS)	Smart card data /official data	One workday	Yes
Tian et al. (2017)	Seattle, USA	Descriptive statistics	Field/mail survey	Two workdays	No
Park et al. (2018)	Atlanta, Boston, Denver, Miami, Minneapolis-St. Paul, Portland, Salt Lake City, Seattle, USA	Discrete choice modeling/negative binomial model	Household travel survey	One workday	Yes
Nasri and Zhang (2019)	Washington, D.C., Baltimore, USA	Multinomial logit (MNL)	Household travel survey	One workday	Yes
Guan and Wang (2020)	Beijing, China	Structural equation modeling (SEM)	Household travel survey	Two days	Yes
Khabazi and Nilsson (2021)	Charlotte, USA	Descriptive statistics, multiple linear regression (OLS)	Household travel survey	2002–2014	Yes
Joseph et al. (2022)	Dar es Salaam (Tanzania)	Descriptive statistics	Field/mail survey	2 years	No

contrast, longitudinal research studies, wherein the evolution of such characteristics over time is taken into account, are quite rare, and even less frequent are studies that focus on the trips made between its different areas (including areas where transit stations are located). In fact, to the best of our knowledge, there are no studies that have analyzed whether and to what extent the implementation of a TOD project impacted on the shares of different modes at the OD-pair level. This is precisely one of the main directions we pursue in this paper, focusing on the Porto region, in northwest Portugal.

In the 1990 s, this region, and especially Porto's city center as well as several radial expressways, were suffering from severe traffic congestion and pollution problems for which the essential cause was largely consensual: the lack of a rapid transit solution in a densely populated area with around 1.2 million inhabitants. Metro do Porto (MdP), a light-rail system consisting of 67 km of double-track lines and 82 stations (15 underground), was then launched to provide the foremost response to those problems. The construction works began in 1999, the first stations opened in 2002, and the last ones (to date) in 2011.

With the research presented in this paper and considering the case of MdP as a reference, we primarily pursue three goals:

— First of all, we aim to assess whether, and to which extent, metro implementation can be effective in decreasing the share of car trips. More specifically, our main goal is to analyze the impact of metro on the share of car trips performed in the study area focusing both on the trips generated in its (civil) parishes ("freguesias") and on their distribution across parish OD pairs.
— Second, we aim to evaluate the effects of metro implementation on bus ridership, as there are always concerns about whether people switch to rapid transit from car (desired outcome) or from other transit modes (Senior, 2009; Lee and Senior, 2013; Wu and Hong, 2017; Liu and Li, 2020).
— Last but not least, we aim to find whether and how much the impact of metro implemetation on mode choice varies depending on stations being of the TOD type (i.e., the design of station areas meets TOD principles) or not. Indeed, frequently, the introduction of a metro system (like in Porto) is accompanied by numerous interventions in some station areas (including traffic calming, sidewalk extension, cycle lanes, etc.), transforming them into TOD stations. In other words, we seek to evaluate the effect of TOD stations on mode choice as compared to other stations.

To achieve these goals we relied on autoregressive beta regression models and on two detailed mobility surveys carried out by INE – Statistics Portugal (https://www.ine.pt) in 2000 and 2017; i.e., shortly before MdP started operations, and six years after the opening of the last stations, hence time enough for MdP to have fostered the changes in mobility patterns expected from its implementation.

An important trait of our analyses is their quasi-experimental nature. In fact, the road network and transit services of the Porto region went through major changes between 1985 and 2000, but after that and up to now (May 2022) practically all major infrastructure investments in the Porto region have been dedicated to the implementation of the metro system. Besides, changes to the main trip generators across the region were rather minor in this period. This is an ideal setting for applying a longitudinal research approach.

The remainder of the paper is organized into six sections. The next one focuses on related literature and highlights the innovations we propose. Then, we provide essential information about the Porto region, its transport network and MdP. Afterwards, a brief description of the data sources is given. In the following two sections, we present the formulation of the autoregressive beta regression models, explain the choice of the explanatory variables, and examine the results of their estimation. To conclude the paper, we summarize its main contributions and point out some promising research directions to explore in the future.

2. Related literature

Mode choice is arguably one of the most studied subjects in Transport Planning. In this section, we refer and briefly discuss works that analyze mode choice in the context of TOD or major transit investments, particularly when they rely on a longitudinal research approach or use OD pair data. Table 1 summarizes the main features of the articles selected.

Ever since TOD was conceptualized, the characteristics of the built environment in station areas (like street density, building density, and mixed-use) have been taken into account in the analysis of mode choice. In the early works of Cervero (1995), Cervero and Gorham (1995), and Cervero and Radisch (1996), the travel behavior of residents in pedestrian-friendly station areas with dense street networks was compared to the travel behavior of residents in automobile-oriented neighborhoods with curvilinear street networks and poor pedestrian environment. These initial works revealed that people with similar socio-economic characteristics living in locations with similar transit supply showed different travel preferences depending on the type of their neighborhood: those living in TODs were more likely to use transit compared to those living in automobile-oriented neighborhoods. These findings motivated a plethora of research on this topic, introducing new relevant factors such as parking availability (Chatman, 2013; Ewing et al., 2017; Tian et al., 2017), destination accessibility (Ewing et al., 2017; Park et al., 2018; Sung and Oh, 2011), intersection density (Sung and Oh, 2011), connections to buses (Chatman, 2013; Loo et al. 2010; Nasri and Zhang, 2014; Park et al. 2018; Sung and Oh, 2011), station characteristics like the opening year (Loo et al., 2010; Pan et al., 2017), or the possibility of transferring to another line (Pan et al., 2017). In most studies, even after controlling for socio-economic and built environment characteristics, station proximity was generally reported as a significant predictor of mode choice (Cervero and Day, 2008; Crowley et al., 2009; Nasri and Zhang, 2014, etc.).

Significant research efforts have been in particular dedicated to disclosing the importance of self-selection, i.e., the contribution of an individual's attitude towards a particular travel mode in his/her residential location choice, revealed, for example, when a person normally traveling by transit chooses to reside in an area with rich transit supply. Attitudes have proven to be important and statistically significant (Handy et al., 2005; Cervero, 2007; Cao, 2015), yet this does not dismiss the importance of the built environment. The relationships between attitudes, built environment, and mode choice tend to be rather complex, and travel preferences are only one amongst many factors affecting residential location decisions (Guan and Wang, 2020). This can be confirmed by the behavior of dissonant residents, i.e., people that have pro-automobile attitudes but live in a TOD and vice versa (Cao, 2015). In this case, as shown by Brown and Werner (2008), attitudes matter if they are supported by the built environment, as pro-transit residents switched to transit only after a station was opened in the proximity. Similarly, Van de Coevering et al. (2016) demonstrated that people who have settled next to transit tend with time to use it more often, while De Vos et al. (2021) showed that recent movers to dense urban neighborhoods not only increase their transit use but also gradually develop favorable attitudes towards it. This phenomena of attitudinal changes in response to the surrounding environment (like when residents living near transit stations develop favorable attitudes to public transport over time) is commonly referred to as “reverse causality” (Van Wee et al., 2019).

In addition to the bidirectional influence of attitudes on residential location choices, there is evidence that travel destinations may also impact such choices. In particular, Cervero (2007) found out that people working within a mile (1.6 km) of a station tend to reside near transit. However, this does not necessarily mean that these residents would use transit. Indeed, as shown by Khabazi and Nilsson (2021), the introduction of a transit service may shorten travel times for high-income groups living in station proximity as it prioritizes connections between dense urban neighborhoods and the CBD, where high-wage residents are typically employed, yet these groups are frequently reported to use cars rather than transit (Cervero and Gorham, 1995; Cervero and Radisch, 1996; Laham and Noland, 2017).

In this context, it is important to analyze TOD impacts on mode choice from the perspective of OD pairs (considering both commute and leisure trips) thus accounting not only for residential location characteristics but also for the characteristics of frequent travel destinations (Wang, 2015). As noted by Guan and Wang (2020), land use characteristics at the workplace affect the residential location choice and indirectly affect mode choice. Furthermore, Choi et al. (2012) analyzed the influence of the built environment within a 500-meter station buffer on station-to-station ridership for all trips on a weekday. The relationship between transit ridership and built environment varied depending on the trip end and departure time. For the morning peak hours, their results suggest that residential density at the origin and employment density at the destination increase transit ridership, yet the importance of residential density for metro ridership declines during midday and evening peak-hour periods. On the other hand, the number of feeder bus lines and a pedestrian-friendly environment were positively related to transit ridership in all time periods.

Similarly, Nasri and Zhang (2019) found out that transit ridership was affected not only by trip travel time, traveler’s age and car ownership, but also by built environment characteristics at both the origin and the destination: TOD at both trip ends increased the probability of transit use or walk/cycle, even more so if TOD was at the destination, which could probably be explained by parking being typically limited at TOD sites. Overall, it was confirmed that high building densities and high street connectivity at both ends favored sustainable modes. However, the effect of land-use mix on transit was not significant.

Another type of related literature that will be mentioned here consists of before/after studies focusing on investments in transit infrastructure and services. Many such studies exist, but few address mode choice impacts and major city-wide transit investments. One of the first such studies is due to Gomez-Ibanez (1985), who presents a descriptive analysis of the evolution of ridership for new light-rail transit (LRT) systems in three different cities (San Diego, Calgary and Edmonton), highlighting rather diverse results. In the first case, the area served by the system registered a 22% increase in transit ridership (bus and LRT combined), while in the rest of the

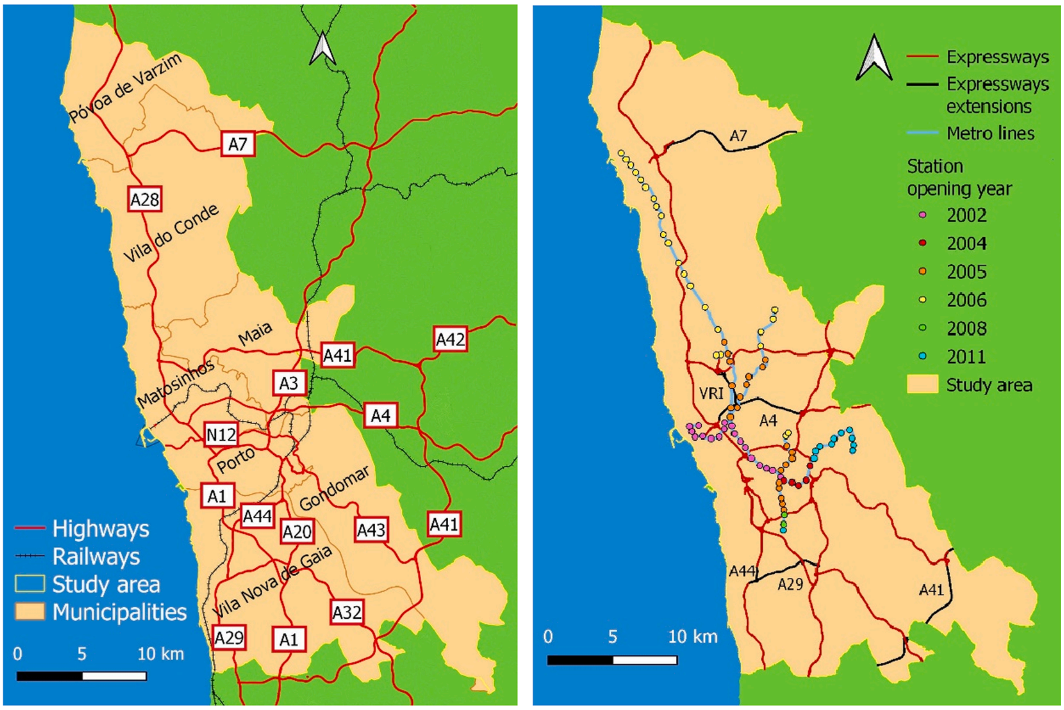

Fig. 1. Municipalities and road network of the Porto Region (left) and MdP opening years and expressway extensions (2000–2017, right).

metropolitan area this percentage fell by 18% during the study period. In the second case, in the five years preceding the introduction of the system, transit ridership per capita increased by 10%, but dropped by 6% three years after the intervention. In the third case, after three years of LRT operation, transit ridership levels grew by 9%. Unfortunately, a descriptive analysis does not allow to control for potential confounders, and, as the author recognizes, these figures could be partially explained by fare policy or other factors. A similar study was performed by Yáñez et al. (2010) concerning the Transantiago BRT system (Santiago do Chile). The panel data collected revealed that the implementation of the system led to transport mode changes for half of the respondents. The greatest mode share increase (from 6.1% to 20.4%) was observed in the combined use of bus and metro, while the share of bus-only fell sharply (from 37.9 to 20.6%) and car use slightly increased. Likewise, Wang et al. (2013) found that among BRT users in five different Chinese cities approximately 68–89% were former subway or bus passengers and only 3–8% diverted from cars, but additional factors affected the switch to BRT, such as travel time savings, trip cost and distance (the probability to shift to BRT increased for trips exceeding 5 km). Very recently, in a study of a new BRT system in Dar es Salaam (Tanzania), it was also found that car use did not change (Joseph et al., 2022). Contrary to these findings, Forsey et al. (2013) reported that car use decreased following the implementation of a BRT system in York (Ontario, Canada), in this case using a Generalized Extreme Value (GEV) model considering several explanatory factors (traveler's gender and age, travel time, vehicles per household). Unfortunately, none of these studies accounted for the possible influence of the station environment on mode choice.

The research we describe in this paper, though certainly inspired by some of the cited works, is nevertheless quite different from them. The fact that we had access to travel survey data for two years (2000 and 2017) with a considerable time interval in-between during which a new metro system was implemented allowed us to perform a quasi-experimental study of the evolution of mode choice over that period, within which the impacts of metro on car and bus use were evaluated and compared. Moreover, our paper offers what we believe to be the first attempt to combine a longitudinal research approach with OD data for analyzing the mode choice changes induced by the implementation of a metro system. The fact that this system involves stations with TOD features allows us to understand how this type of urban development can contribute to increase public transport ridership.

3. Porto region

The region under study consists of the seven municipalities served by Metro do Porto – Gondomar, Maia, Matosinhos, Porto, Póvoa de Varzim, Vila do Conde and Vila Nova de Gaia (Fig. 1, left). Though this region does not correspond to any administrative division, it approximately coincides with the Porto Metropolitan Area as defined when MdP was launched. The seven municipalities comprise 120 parishes, the smallest administrative units for which data are reported in the mobility surveys carried out by INE in 2000 and 2017.

The land use patterns of the study area (Fig. 2) are extremely heterogeneous. The continuous and well-connected urban fabric of the metropolitan core (municipality of Porto together with the central areas of Matosinhos and Vila Nova de Gaia) neighbors suburban settlements (e.g., Leça da Palmeira, Maia and Pedras Rubras), large shopping malls and industrial sites in the north of Porto, and low- and middle-rise developments and light manufacturing activities in the south. In the northernmost municipalities, the towns of Póvoa de Varzim and Vila do Conde (important seaside resorts where population increases considerably in Summer) are surrounded by mostly flat agricultural areas characterized by scattered settlements and low-rise buildings.

Most employment in the metropolitan core is offered in the service sector, so the area attracts not only the working population, but also large numbers of consumers. The role of a regional leader in the tertiary sector results in an inevitable drawback: heavy traffic flows, which the city of Porto started to experience particularly in the 1990s, following substantial investments in the regional road

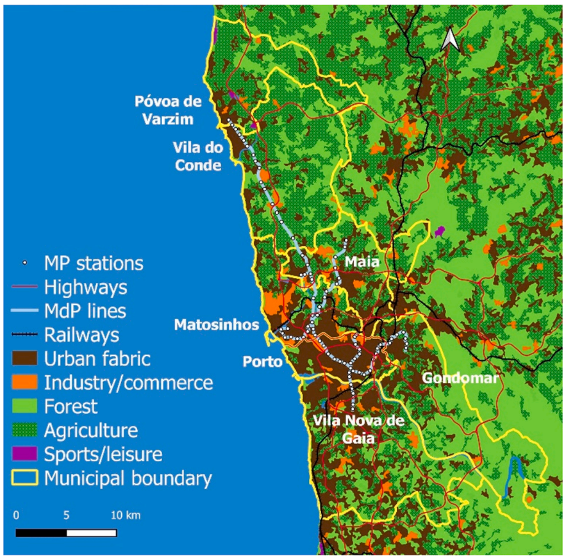

Fig. 2. Land-use patters in the Porto Region (source: Corine Land Cover, 2018).

network and a strong increase of motorization rates. Indeed, since the early 2000s, the city of Porto is served by seven radial expressways (A28, A3, A4, A1, A43, A29 and A44) that intersect three circle expressways (A20, N12, and A41) (Fig. 1, left). As the great majority of streets in the metropolitan core is quite narrow (Fig. 3), flows coming from the expressways could not be distributed around easily in the morning, and the opposite happened in the evening. More recently, between 2000 and 2017, several extensions were made to the expressway network (Fig. 1, right), though only a relatively small part of them occured within the limits of the study area (31 km out of 87 km).

Traffic pressure in the metropolitan core before 2000 was further aggravated by the fact that train connections between this area and surrounding municipalities were quite poor: some lines were offering unreliable service and others had even been abandoned. Public transport supply within the region was essentially secured by a dense and extensive bus network. However, in the absence of dedicated lanes, bus service was also compromised by traffic congestion. Besides, routes were operated by a variety of companies (over 30) with timetables and ticketing systems poorly integrated, making bus use complex and often inconvenient.

In these circumstances, MdP surged as a project that could reduce road traffic in the region by taking advantage of existing railway infrastructure. Approximately 50 km of railway lines (at the time abandoned or underused) were repurposed for metro use, and this allowed to implement the metro system in just nine years. The implementation of the metro system certainly had implications on the bus service: several routes, especially in residential areas of Vila Nova de Gaia, were reconfigured to provide feeder service to metro stations.

The mode split changes following this intervention (between 2000 and 2017) appear however as rather modest (Fig. 4). Car use remained the main transport mode, yet the greatest increases in car mode shares were recorded in parishes not served by metro, while these shares in the metro-served parishes and their neighbors were quite similar. Bus mode shares, quite similar across the region in 2000, observed an even decline throughout the region. Metro shares were meaningful only in the metro-served parishes (about 4%).

As the territory served by MdP is quite diverse with respect to land use and built environment, this has important implications in terms of station typology. In central urban areas of the metropolitan core, metro implementation was often accompanied by significant investments in surrounding spaces, including traffic calming measures, sidewalk extensions, and urban design improvements like planting trees or better lighting. The introduction of metro in already dense and mixed-use urban areas, coupled with measures aimed to promote and favor metro use and access, transformed several station areas into TODs (Fig. 5, left), while most stations in suburban and rural environments can be better classified as transit-adjacent development (TAD) (Fig. 5, center) or park-and-ride (P&R) (Fig. 5, right). Naturally, in these different environments, frequencies also vary: whereas on the central station where all lines intersect (Trindade) trains leave on average every two minutes (on workdays), frequencies in areas distant from the metropolitan core are considerably lower, with some stations of the Porto-Póvoa de Varzim line having only two trains per hour.

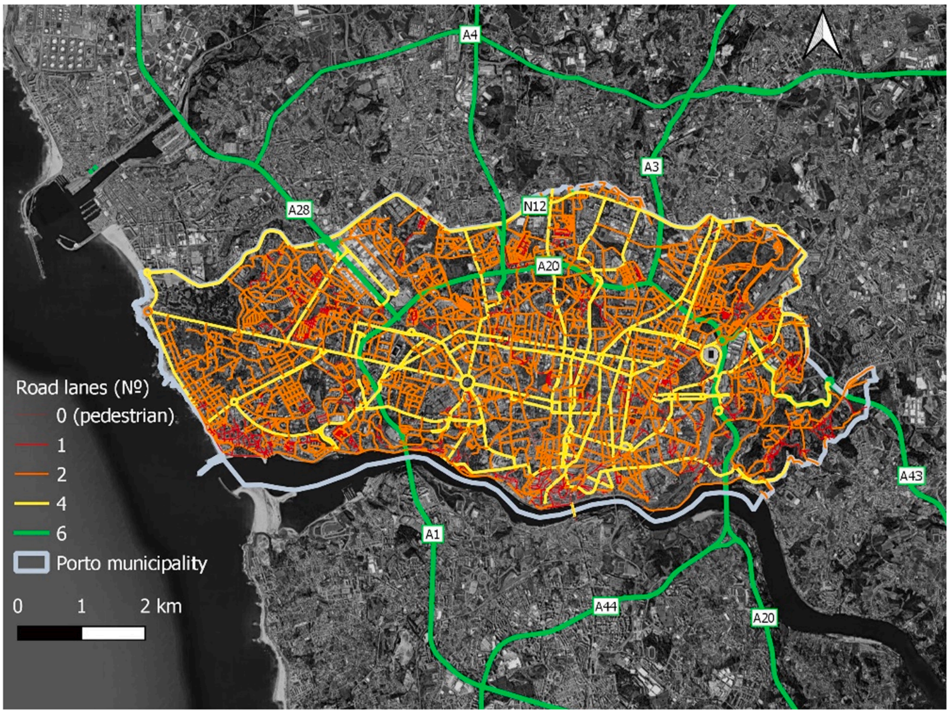

Fig. 3. Expressway and street network of Porto.

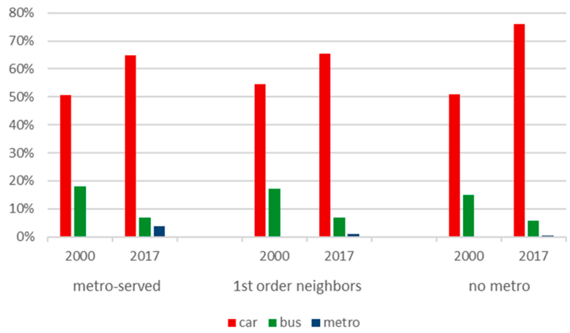

Fig. 4. Evolution of mode split in Porto region (source: mobility surveys 2000–2017).

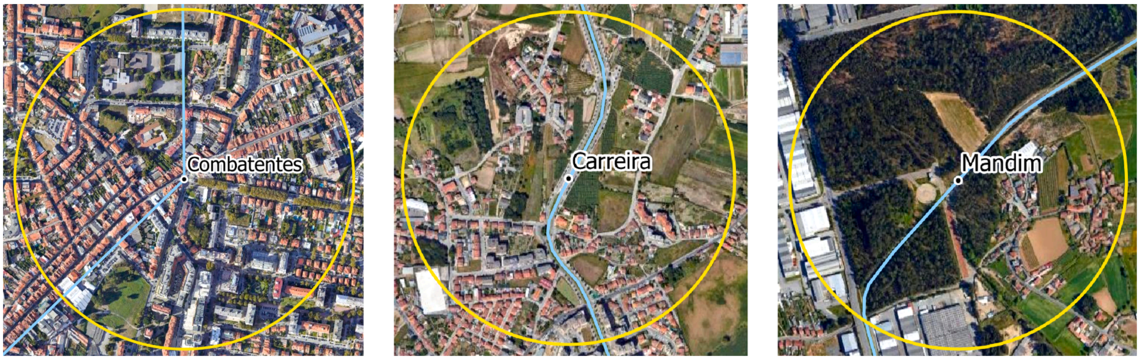

Fig. 5. MdP station environments within a 400-meter buffer (TOD, TAD, and P&R stations).

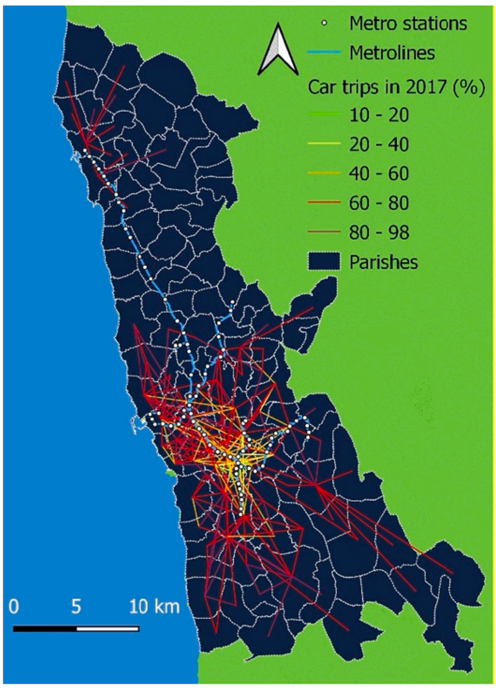

Fig. 6. Share of car trips on selected OD pairs (2017).

4. Data sources

For our analyses of Metro do Porto effects, the primary data sources were the mobility surveys performed by INE in 2000 and 2017. Data were collected for 119 parishes, after one rural parish was omitted due to missing data in the 2017 survey. The respondents in both years were asked to describe all their trips (i.e., commute, leisure, personal and shopping trips) on the day preceding the survey. Both surveys targeted the same objective: characterize the trips made by all residents, gathering essential information about trip origins, destinations, and travel modes at the parish level.

The current infrastructure network was identified using Open Street Map data, and historical satellite imagery from Google Earth was used to reconstruct the expressway network in 2000.

The remaining data we used come from:

— Population censuses of 2001 and 2011 (final results from the census of 2021 will only be published in the end of 2022), where socio-economic and some land-use information is available.
— Autoridade de Supervisão de Seguros e Fundos de Pensões, concerning the type and number of vehicles in different municipalities.
— Metro do Porto, concerning metro service levels.

Based on the data collected, we formed two panel datasets: one with parish data and the other one with OD-pair data. To perform the analysis of mode choice evolution on different OD pairs while ensuring representativeness of results, we selected pairs for which at least 20 trips were reported each way in the 2017 survey. The ensuing sample consists of a total of 222 bidirectional links covering the whole study region (Fig. 6) except northern rural areas, where the number of respondents was too small to enable meaningful conclusions about local travel behavior.

5. Regression modeling

In this section, the modeling approach we have developed to analyze the impact of MdP on travel mode choice in the Porto region is described. Overall, we considered six different models (Fig. 7). Three of them are parish models and the other three are OD-pair models (i.e., their units of analysis are the parishes and the OD pairs, respectively). In both cases, two of the models concern car mode shares (the first one was extended to capture TOD station effects) and the third concerns bus mode shares. In the first subsection we focus on model formulation and justify the choice of a beta regression approach, and in the second we describe the variables included in the models.

5.1. Model formulation

Since we aimed to compare the effect of metro on two major modes (car and bus), the dependent variables of the models were, respectively, the share of car trips and the share of bus trips. We relied on autoregressive models, thus controlling for the pre-existing shares of each mode in 2000. This approach allows separating the effect of metro from the pre-existing bus/car ridership levels.

Given that the dependent variables are expressed as proportions (of car/bus use) and hence their values are limited to the [0, 1] interval, we decided to use beta regression for the estimation of the models. This type of regression analysis is specifically indicated for models where the dependent variable is a proportion (Kieschnick and McCullough, 2003), as it accommodates different density distributions of the dependent variable, non-constant variances, and skewness (Ferrari and Cribari-Neto, 2004). Therefore, this approach can be applied to modeling car and bus mode shares (though their distributions vary), which facilitates the comparison between the models.

The specific beta regression model we chose can be formulated as follows:

$$g(\mu) = \beta_0 + \beta_1 Y_{-1} + \sum_n \beta_{2n} X_n \tag{1}$$

where: μ is the mean of the dependent variable Y (in our case, in 2017); Y_{-1} is the one-period lagged dependent variable (in 2000); X_{tn} are n covariates, i.e., other variables that also influence the dependent variable; $\beta_0, \beta_1, \cdots, \beta_{2n}$ are regression coefficients; and g is a strictly monotonic and twice differentiable link function that maps 0, 1 into $\mathbb{R}$. The link function we used was the logit function, i.e., $g(\mu) = \ln[\mu/(1-\mu)] = \ln(\text{odds}\mu)$.

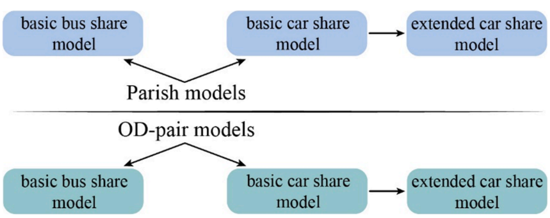

Fig. 7. Components of the modeling approach.

Beta regression models operate in the open (0, 1) interval, for this reason, scarcely occurring upper and lower bound values of 1 and 0 (representing 100% and 0% respectively) in our datasets were set to very close values of 0.001 and 0.998.

5.2. Model variables

The full list of variables included in the models is shown in Table 2, distinguishing between the dependent and autoregressive variables, the covariates of the parish models and the covariates of the OD-pair models.

In all models, the dependent variable is car or bus share in 2017. To account for potential interchange and competition between these modes during the study period, the models take into account the change in the other mode between 2000 and 2017; i.e., models explaining car share in 2017 have change in bus share among the covariates, and vice versa.

Besides analyzing changes in the share of car and bus trips in metro-served parishes, we have also considered the potential spillover effect of metro in the first-order neighbors of those parishes.

For evaluating the effect of TOD stations, several metro stations were classified as TOD. As some TOD criteria are difficult to quantify (like the neighbohood's orientation towards transit station or the perceived security level), a qualitative approach was deemed more appropriate. The classification of stations was therefore made based on the overall station's insertion in the surrounding built environment, its location related to the rest of the settlement, street density in the station area, and presence of high-rise buildings and service/commerce in the station area.

Since the area of analysis is highly heterogeneous in terms of the built environment, a variable reflecting common local amenities was added to all models. These amenities correspond to services that are present in all populated areas regardless of whether an area is a city center, a business district, or else, such as ATMs, post boxes/post offices, bakeries, laundries, haidressers, etc. As these are essentially local, hardly any resident would make a separate car or bus trip to get to these services, hence little correlation with mode choice is expected. At the same time they reflect rather well the built environment, being correlated with population density, building density and density of multi-use buildings (correlation coefficients of 0.53, 0.72 and 0.86, respectively). As a proxy variable for the built environment characteristics, it allows to incorporate them into the models at the same time reducing the risk of potential endogeneity between mode choice and the built environment. As parishes vary in size, in the parish-level models density of local amenities is used. In OD-pair models this covariate is represented by the multiplication of the number of local amenities at both trip ends.

To control for socio-economic characteristics, census data for 2011 (mid-term point of the study period) was explored. Among census variables, the percentage of active population and unemployment rate turned out to be significant for an initial model

Table 2
Regression model variables.

Variable type	Variable designation	Variable description
Dependent and autoregressive	Car_share17	Share of car trips of a parish or OD pair in 2017 (dependent variables)
	Bus_share_17	Share of bus trips of a parish or OD pair in 2017 (dependent variables)
	Car_share_00	Share of car trips of a parish or OD pair in 2000 (explanatory variables)
	Bus_share_00	Share of bus trips of a parish or OD pair in 2000 (explanatory variables)
Covariates – parish models	Metro	Equal to 1 or 0 depending on whether a parish is served by metro or not
	Metro_neighbor	Equal to 1 or 0 depending on whether a parish is a first-order neighbor of a parish served by metro or not
	High_freq	Equal to 1 or 0 depending on whether a parish is served by metro with a frequency higher than 15 min or not
	High_freq_neighbor	Equal to 1 or 0 depending on whether a parish is a first-order neighbor of a parish served by metro with a frequency higher than 15 min or not
	Low_freq	Equal to 1 or 0 depending on whether a parish is served by metro with a frequency lower than 15 min or not
	Δmotor_rate	Change in the motorization rate of a parish between 2000 and 2017
	N_hwys	Equal to 1 or 0 depending on whether a parish got new access (entry) to the expressway network between 2000 and 2017 or not
	Diff_carsh	Change in parish car share between 2000 and 2017
	Diff_bush	Change in parish bus share between 2000 and 2017
	Pc_popat	Percentage of active age population
	Unemployment	Unemployment rate
	Dens_amenties	Density of local amenities
Covariates – OD-pair models	Metro_1_end	Equal to 1 or 0 depending on whether one (and only one) of the parishes of an OD pair is served by metro or not
	Metro_2_ends	Equal to 1 or 0 depending on whether both parishes of an OD pair are served by metro or not
	TOD_2_ends	Equal to 1 or 0 depending on whether both parishes of an OD pair have TOD stations or not
	Wmotor_rate	Average motorization rate for the parishes of an OD pair weighted by the number of active residents in those parishes
	N_hwys	Equal to 1 or 0 depending on whether among top-3 alternative routes (according to Google maps) between two parishes at least one alternative involves use of a new expressway or not
	Diff_trtime	Difference in average trip time between a route involving new expressway segment and a route that existed in 2000
	Diff_carsh	Change in car share between 2000 and 2017 for a given OD pair
	Diff_bush	Change in bus share between 2000 and 2017 for a given OD pair
	Lcl_amenties	Multiplication of the number of local amenities at both trip ends

(including only autoregressive and infrastructure-related variables) and were added to the parish models.

Acknowledging that the share of car trips is largely dependent on car ownership, which in turn is strongly correlated with income levels (as we confirmed), our models account for the evolution of motorization rates in the Porto region.

Finally, as expressway extensions might have affected the shares of car/bus trips, variables controlling for changes in the expressway network were included in all models: a binary variable identifying parishes/OD pairs served by new highways and a continuous variable reflecting difference in trip time between two trip ends after the new expressways were introduced.

Given the heated debate that self selection motivated in recent years, a small note is needed regarding this issue. As metro did not exist in 2000 and the configuration of its network was decided very shortly before, it could not affect the residential location choice at that moment. Rather, self-selection could appear as a by-product of metro implementation: with time, people probably developed positive attitudes towards the new service. In this case, self-selection, being caused by metro, could be considered as part of the metro effect. Nevertheless, by considering mode shares in 2000 and 2017, our models should allow to indirectly reflect potential self-selection. It is reasonable to expect that, over a 17-year period, some residents might have relocated choosing a new residential area based on their attachment to metro. Unfortunately, with the data available (mobility survey), it is not possible to measure the scope of these possible residential relocation effects during the study period. However, if residents relocated following their preferences to areas where they could take advantage of the recently introduced metro service, then the significance of the autoregressive coefficient should be low as shares in 2017 would tend to be quite different from shares in the pre-metro period. If, instead, shares reported in 2017 were largely similar to those in 2000, this indicates that potential new residents ended up reproducing travel patterns that existed before metro, and in this case it is unlikely that metro availability affected significantly their residential location choices.

6. Estimation results

We present and discuss below in separate subsections the estimation results obtained for the parish and OD-pair models. The models were estimated using the “betareg” package for R (Cribari-Neto and Zeileis, 2009) and the marginal effects were obtained using the “mfx” package (Fernihough and Henningsen, 2019).

6.1. Parish models

The estimation results for the global effect of metro on the share of car trips and bus trips are shown in Tables 3 and 4, respectively. Defined for beta regression models as the square of the sample correlation coefficient between the linear predictor and the link-transformed response (Ferrari and Cribari-Neto, 2004), the pseudo R^2 values for the models range between 0.40 and 0.46. Given a specific set of explanatory variables, these values are satisfactory and rather common in the context of mode choice modeling: for example, averaging regression results from the articles cited in Section 2 (“Related Literature”) gives a mean R^2 value of 0.42 for a total of 43 models with an average of 10 explanatory variables.

For both models, the lagged dependent variable was found significant and positively associated with the respective values in 2017, meaning that shares of car and bus trips in 2017 were strongly related to the shares of both modes in 2000. As such, even in the event of a shock (the new metro), the inertia to continue using the same travel mode was strong, confirming that residents’ habits to patronize a particular mode do not change easily.

The implementation of metro led to a decrease in the share of car trips, not only in the directly served parishes but also in their respective neighboring parishes, where the effect appears to be even stronger and more significant. Indeed, by transforming the log-odds estimates of model coefficients to mode share estimates (marginal effects), it can be concluded that the share of car trips decreased on average 6.5 percentage points (p.p.) in metro-served parishes and 11 p.p. in adjacent parishes.

The increase in the motorization rate in the period 2000–2017 was, as expected, positively related to the share of car trips, being every increase of 100 cars per 1,000 residents associated with a 1.8 p.p. increase in car mode share. However, this effect is among the least significant in the model. Quite unexpectedly, new accesses to the expressway network were associated with a 7 p.p. decrease in

Table 3
Estimation results for the car parish model.

Variable	Coefficient	Marginal effect	Std. Error	*z*-value	*p*-value	
intercept	−0.5583	n/a	0.929	−0.601	0.5478	
car_share_00	2.8346	0.6135	0.7652	3.704	0.0002	*
metro	−0.2977	−0.0656	0.1384	−2.150	0.0315	*
metro_nb	−0.4997	−0.1108	0.1253	−3.987	6.68e-05	*
n_hwys	−0.3116	−0.0701	0.1499	−2.078	0.0377	*
Δmotor_rate	0.869	0.1881	0.5012	1.734	0.0829	.
diff_bush	−1.6494	−0.357	0.9914	−1.664	0.0961	.
pc_popat	2.0513	0.444	1.8943	1.083	0.2789	
unemployment	−0.0289	−0.006	0.016	−1.827	0.0676	.
dens_amenties	−0.0023	−0.0005	0.0014	−1.631	0.1029	
Pseudo *R2*	0.459					
AIC	−170.77					
Log-likelihood	96.38 ($df = 11$)					
Note: * $p < 0.05$,. $p < 0.01$						

Table 4
Estimation results for the bus parish model.

Variable	Coefficient	Marginal effect	Std. Error	z-value	p-value	
intercept	−3.5916	n/a	1.3268	−2.707	0.0067	*
bus_share_00	9.0433	0.4163	1.5588	5.801	6.58e-09	*
metro	0.3967	0.0196	0.2086	1.901	0.0573	.
metro_nb	0.5104	0.0253	0.2029	2.516	0.0119	*
n_hwys	0.0665	0.0031	0.2029	0.328	0.7433	
Δmotor_rate	−2.1698	−0.0999	0.7086	−3.062	0.0022	*
diff_carsh	0.1459	0.0067	0.6562	0.222	0.824	
pc_popat	−1.0236	−0.0471	2.5205	−0.406	0.6846	
unemployment	0.0139	0.0006	0.0241	0.581	0.5613	
dens_amenties	0.0022	0.0001	0.0015	1.532	0.1256	
Pseudo $R2$	0.393					
AIC	−474.8					
Log-likelihood	248.4 ($df = 11$)					

the car mode share.

Contrary to the effect on car mode share, the implementation of metro was associated with an increase of 1.9 p.p. and 2.5 p.p. in bus ridership for directly metro-served parishes and metro-neighboring parishes, respectively, yet this effect in the directly-served parishes is less significant. Nevertheless, even if there was a decline in bus ridership during 2000–2017, according to our results it should not be attributed to metro. Rather, it could be caused by car ownership growth, as an increase of 100 cars per 1,000 residents was associated with a 1 p.p. decrease in bus share in 2017.

Both car and bus share models reveal weak (if any) significance of the variable reflecting changes in the share of the other mode between 2000 and 2017. In the car share model, an increase in bus share was associated with a decrease in the share of car trips in 2017, suggesting that some interchange between these modes might exist, although this is not confirmed in the bus share model.

Further exploring the change in car mode share, we assessed the impact of metro service frequency considering parishes without metro as reference. As expected, compared to non-served parishes, both the direct and the spillover effects of high-frequency metro on the share of car trips were strong and significant (Table 5), being linked with a decrease of 9 p.p. in both metro-served and neighboring parishes. However, the effect of low-frequency metro was not significant, highlighting the importance of service frequency for car trips reduction. This is further confirmed by comparing the significance of the motorization rate in the basic model and the extended model: it appears significant in the first case, yet is insignificant in the latter once service frequency is accounted for, suggesting that having a car does not imply its use in cases when frequent transit service is available in proximity.

6.2. OD-pair models

In Tables 6 and 7, we show the estimation results for the OD-pair models, which analyze car and bus trips for OD pairs distinguishing pairs with metro at both trip ends and pairs with metro at only one end. The pseudo R^2 values obtained for these models range between 0.34 (bus share model) and 0.40 (car share model). The already reported strong significance of pre-existing shares of car/bus trips in explaining their subsequent shares was also observed for OD pairs.

The effect of metro on the car mode share was strong for OD pairs with metro at both trip ends, being expressed by an average decrease of 9 p.p. in the share of car trips. Considering that the analysis focused on the OD pairs with the highest number of daily trips, the effect of metro appears as rather solid. For OD pairs that only have metro at one end, the effect was not significant. In contrast to the estimation results obtained for the parish models, these results clearly indicate that the mere presence of a metro station in a parish is not enough to bring on a decrease in the share of car trips. At the same time, our models revealed an increase in the share of car trips for

Table 5
Estimation results for the extended car parish model.

Variable	Coefficient	Marginal effect	Std. Error	z-value	p-value	
intercept	0.0857	n/a	0.9422	0.091	0.9275	
car_share_00	2.6238	0.5676	0.8008	3.277	0.001	*
high_freq	−0.4027	−0.0906	0.1704	−2.362	0.0181	*
high_freq_nb	−0.4016	−0.0901	0.1506	−2.667	0.0076	*
low_freq	0.0781	0.0167	0.1748	0.447	0.6547	
Δmotor_rate	0.275	0.0595	0.5837	0.471	0.6375	
n_hwys	−0.189	−0.0419	0.1569	−1.204	0.2286	
diff_bush	−1.6101	−0.3483	1.0089	−1.596	0.1105	
pc_popat	0.8199	0.1773	1.9054	0.430	0.6669	
unemployment	−0.0282	−0.006	0.0162	−1.739	0.082	.
dens_amenties	−0.0022	−0.0005	0.0014	−1.548	0.1215	
Pseudo $R2$	0.428					
AIC	−163.95					
Log-likelihood	93.98 ($df = 12$)					

Table 6
Estimation results for the car OD-pair model.

Variable	Coefficient	Marginal effect	Std. Error	*z*-value	*p*-value	
intercept	−0.745	n/a	0.5569	−1.409	0.159	
car_share_00	4.471	1.015	0.5018	8.910	< 0.0001	*
metro_1_end	−0.0653	−0.0139	0.1228	−0.501	0.6164	
metro_2_ends	−0.3899	−0.0905	0.1434	−2.719	0.0066	*
wmotor_rate	−0.317	−0.0719	0.9176	−0.346	0.7297	
n_hwys	0.5564	0.1174	0.1774	3.135	0.0017	*
diff_trtime	0.1656	0.0376	0.1098	1.508	0.1315	
diff_bush	−2.798	−0.635	0.4197	−6.665	< 0.0001	*
lcl_amenties	−0.00002	−0.000004	0.000005	−3.22	0.0013	*
Pseudo $R2$	0.402					
AIC	−198.63					
Log-likelihood	109.3 ($df = 10$)					

Table 7
Estimation results for the bus OD pair model.

Variable	Coefficient	Marginal effect	Std. Error	*z*-value	*p*-value	
intercept	−0.6122	n/a	0.6889	−0.889	0.3742	
bus_share_00	3.85	0.3556	0.7495	5.137	< 0.0001	*
metro_1_end	0.44	0.0415	0.1461	3.011	0.0026	*
metro_2_ends	0.04	0.0037	0.1751	0.228	0.8193	
wmotor_rate	−3.09	−0.2853	1.108	−2.787	0.0053	*
n_hwys	−0.125	−0.011	0.1979	−0.632	0.5275	
diff_trtime	−0.1802	−0.0002	0.1161	−1.552	0.1206	
diff_carsh	−1.618	−0.1494	0.3298	−4.907	< 0.0001	*
lcl_amenties	−0.00002	−0.000001	0.000006	−2.270	0.0232	*
Pseudo $R2$	0.341					
AIC	−577.56					
Log-likelihood	299 ($df = 10$)					

OD pairs served by expressway extensions. The presence of a new expressway route (binary variable) was associated with an additional 12 p.p. increase in the share of car trips compared to OD pairs that did not benefit from expressway extensions. At the same time, diffference in travel times via expressway was not significant, probably because changes were small (4 min at most). As travel time savings for selected OD pairs are very limited, the effect from highway extension variable reflects the importance of having an alternative route. Surprisingly, the motorization rate of the parishes of an OD pair was not found to be significant in the car share model. According to these results, car ownership *per se* does not define the mode choice of a given OD pair; instead, changes in the network characteristics (like metro implementation or expressway extensions) appear as much more important.

Focusing now on the bus mode shares, OD pairs with metro at only one end were associated with a very significant increase of 4 p.p. in bus ridership. This probably happens because of the reconfiguration of the bus network, which improved the access to metro stations through feeder buses. At the same time, the share of bus trips did not appear to be affected in OD pairs with metro at both trip ends. Therefore, similarly to the parish model, it seems clear that metro and buses complement each other rather than compete. Furthermore, change in the motorization rate had a significant negative influence on the bus mode share, indicating that every additional 100 cars per 1,000 residents were associated with an average decrease of 2.8 p.p. in bus ridership, so it is reasonable to suggest that people who used to travel by bus on certain OD pairs bought a car and switched to driving.

Both models highlight the importance of changes in an alternative mode: changes in bus share (from 2000 to 2017) are inversely related to the share of car in 2017 and changes in car share similarly affect the share of bus trips in 2017. While these systemic interrelations are not surprising, in the parish-level models they were almost non-existent, probably because at a parish-level all trips are considered, including short/local trips by other modes (walking, cycling), while main OD pairs are likely to correspond to major commute trips frequently done by car or bus, so in this case the interdependencies between these modes might be stronger.

Moreover, both models suggest a negative influence of dense and diversified land use (multiplication of local amenities at both trip ends) on the share of car as well as bus trips. Although significant, this effect in both cases is very weak, and probably this happens because other modes like walking or cycling are often preferred to car or bus within dense areas.

Results for the extension of the car share model for OD pairs capturing the potential influence of TOD stations at both trip ends are presented in Table 8. Metro at both ends continues to be significant although at a lower confidence level (0.10), and the coefficient changed slightly, this time suggesting a 6 p.p. expected decrease in car mode share compared to OD pairs not served by metro. The change in the coefficient might be explained by the moderate correlation of 0.25 between the "Metro_2_ends" variable and the "TOD_2_ends" variable. The latter was found to be significant and even stronger in terms of the effect on the share of car trips than the "Metro_2_ends" variable, indicating a 7.4 p.p. decrease of that share for OD pairs with TOD stations. The value and significance of the coefficients of variables reflecting changes in the expressway network remained practically unchanged.

Table 8
Estimation results for the extended car OD-pair model.

Variable	Coefficient	Marginal effect	Std. Error	*z*-value	*p*-value	
intercept	−0.2223	n/a	0.584	−0.381	0.7034	
car_share_00	4.374	0.9923	0.4955	8.828	< 0.0001	*
metro_1_end	0.0299	0.0067	0.1258	0.238	0.812	
metro_2_ends	−0.2744	−0.0633	0.1484	−1.849	0.0645	.
wmotor_rate	−0.9478	−0.215	0.9325	−1.016	0.3094	
TOD_2ends	−0.3318	−0.0734	0.1238	−2.679	0.0074	*
n_hwys	0.5166	0.1096	0.1756	2.941	0.0032	*
diff_trtime	0.1655	0.0375	0.1081	1.530	0.1259	
diff_bush	−0.0279	−0.6342	0.4144	−6.747	< 0.0001	*
lcl_amenties	−0.00002	−0.000003	0.000005	−2.857	0.0043	*
Pseudo $R2$	0.421					
AIC	−204.18					
Log-likelihood	112.9 ($df = 11$)					

7. Conclusion

The movement towards a more sustainable mobility requires a substantial reduction of car use, and TOD is a successful urban planning concept aiming to achieve such reduction by promoting the use of environmentally-friendly transport modes.

The impacts of TOD on travel behavior have been widely examined and discussed in the literature. Several studies have dealt with this subject using a longitudinal research approach while other studies focused on destination characteristics using cross-sectional analysis. However, to the best of our knowledge, these two components (temporal dimension and destination characteristics) have not been analyzed together. The study described in this paper was aimed to fill this research gap by investigating the impacts of metro (MdP) implementation on travel behavior after 17 years of operation including both trip end characteristics in the analysis.

Two distinct issues were addressed in our research: the mode shares reported by different parishes and the mode shares observed for different origin–destination (OD) pairs. Since, in the absence of metro, residents of the study region largely relied on cars or buses in their daily routine, the effects of metro on the shares of these modes were analyzed and compared. This research design allows for a more comprehensive hence more complete analysis of the intervention effects.

Several conclusions can be drawn from our findings. To begin with, lagged variables were strong predictors of future mode choice, so even if a new metro service is opened, people do not change their habitual modes quickly. This goes in line with findings reported by Cervero and Day (2008) and Van de Coevering et al. (2016). Apparently pre-existing habits can be highly important in the mode choice analysis, so a longitudinal research approach becomes especially valuable: by accounting for pre-existing mode choices, metro/TOD effects visible in the analysis are separated from pre-existing travel behavior and not confounded with it.

Despite the force of a habit being rather strong in mode choice decisions, infrastructure changes can still affect it. What is more, the impact varies for different modes. According to our results, the impact of metro and TOD turned out to be strongly negative for car use, clearly suggesting that many of those who adhere to a new metro service are former car drivers. At the same time, with respect to bus patronage, metro's influence varied from neutral to positive, meaning that metro did not discourage bus use and even promoted it. As metro and buses rather complement each other than compete for the users, it appears that investment in a particular sustainable transport mode (metro in this case) can promote the use of other environmentally-friendly alternatives (e.g., buses). However, it should be highlighted that this finding contrasts with some previous works where subways negatively affected bus patronage (Senior, 2009; Lee and Senior, 2013; Wu and Hong, 2017; Liu and Li, 2020).

The reduction in car use associated with metro implementation can be further reinforced by a supportive station environment. Namely, TOD at both trip ends can have a substantial impact on the share of car trips for an OD pair: in the case of Porto, the reduction in the share of car trips for OD pairs between parishes served with TOD stations was greater compared to pairs simply connected by metro at both trip ends. In general, the analysis of OD pairs has proven to be extremely important in providing additional insights on factors influencing mode choice since characteristics at both trip ends are highly relevant, which confirms previously reported findings (Choi et al., 2012; Nasri and Zhang, 2019). Mode shares for an OD pair can be quite different from those reported at the parish level. For example, our sample included two parishes connected directly (without transfers) by high-frequency metro, one in the central area of Vila Nova de Gaia and the other hosting the main campus of the University of Porto (Asprela), whose average share of metro trips was only 2%, yet metro share for the OD pair reached 65%. One can argue that this figure might be explained by the fact that many transit users on the link connecting to the university campus are students and, being young people with limited budgentary resources, they probably do not have access to car. However, our results suggest that the significance of the motorization rate in explaining mode choice disappears once service levels are accounted for, and this is true both for parish models and OD pair models.

Some shortcomings of our approach should be pointed out. Due to data limitations, we were not able to perform a more detailed analysis, based for instance on residential blocks. Also, the dataset did not contain socio-economic data associated with the OD matrices, but their inclusion in the model could certainly improve the results, controlling for travellers' characteristics.

Several opportunities for future research derive from this study. As characteristics at both trip ends are relevant, future studies could analyze in more detail (and at a micro scale) the influence of socio-economic and built environment changes over the years on the changes in travel behavior. Besides, differentiating between trip purposes could provide additional insights since mode choice can also be affected by these types of factors. More precise results could be provided from studies that explicitly address self-selection and account for personal travel preferences in residential location choices. Expanding the analysis by adding more time periods could also help to understand the rate at which different people switch to a new service and why some switch faster than others. Eventually, these inputs would provide solid support for TOD planning and implementation.

CRediT authorship contribution statement

Anna Ibraeva: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Gonçalo Homem de Almeida Correia:** Conceptualization, Formal analysis, Writing – review & editing. **Cecília Silva:** Conceptualization, Writing – review & editing. **António Pais Antunes:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision.

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.2022.103357.

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