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Longitudinal macro-analysis of car-use changes resulting from a TOD-type project: The case of Metro do Porto (Portugal)

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ABSTRACT

Transit-oriented development has been widely studied in recent years as a means to reduce car trips and promote sustainable transport modes. However, longitudinal studies on the matter are still rare. This paper contributes to longitudinal research of Transit-Oriented Development (TOD) effects on travel behavior by analyzing the evolution of the number of car trips after the implementation of a light-rail metro system in the Porto region (Portugal). As Metro do Porto is a large infrastructure project (a metro network of 67 km), we relied on a macro-analysis performed at the civil parish level. Changes in the number of car trips are evaluated using a difference-in-differences model, extended to a spatial model to account for the metro's spillover effects. These effects became obvious as metro ridership is reported not only in the directly metro-served parishes but also in adjacent non-served parishes. The results highlight the importance of the metro system in reducing the number of car trips, and this effect is visible not only in metro-served parishes but also in the neighboring ones, which are not directly served by the new transport system. Furthermore, we compare the performance of parishes predominantly served with TOD stations to those with transit-adjacent (TAD) and park-and-ride (P&R) stations. We conclude that both station types can reduce the number of car trips, yet only TOD parishes generated significant spillover effects. The importance of other potentially influential factors like building density or socio-economic characteristics is also discussed.

1. Introduction

Rapid urbanization has always been a major concern for urban planners challenged by the need to accommodate population growth and address increasing travel demand while preserving the environment and quality of life. From a planning perspective, this challenge can be addressed through the concept of transit-oriented development (TOD), which aims to tackle traffic congestion and urban growth simultaneously by providing dense and mixed-used settlements around public transport nodes. Transit-oriented development was defined by Calthorpe (1993, 7) as a "mixed-use community within average 2000-foot [600 meters] walking distance of a transit stop and core commercial area. TODs mix residential, retail, office, open space, and public use in a walkable environment, making it convenient for residents and employees to travel by transit, bicycle, foot, or car." Since the 1990s, TOD has been gaining prominence, with TOD projects implemented worldwide (like the Grand Paris project and the Corridors of Freedom Initiative in Johannesburg launched in 2010 and 2014, respectively). This growth is also reflected in a substantial increase of TOD-related publications in scientific journals (Ibraeva et al., 2020).

Since TOD is supposed to foster a reduction in car trips and the transition to sustainable transport modes, its influence on travel behavior has been the focus of numerous studies. The findings vary due to different national contexts and methods used for assessment, yet, in general, TOD is associated with fewer car trips and greater public transport patronage than in comparable automobile-oriented neighborhoods (see Section 2). Despite recent notable progress in the analysis of TOD effects on travel behavior (Ibraeva et al., 2020), studies addressing this issue using a longitudinal research approach are rare. Nevertheless, longitudinal analysis can bring several advantages compared to the typically adopted cross-sectional research design. First of all, a longitudinal analysis of panel data allows exploring more informative data and more variability, while still accounting for heterogeneity (Baltagi, 2005). Second, incorporating the temporal

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dimension in the analysis permits detection of a transport evolution occurring over years, which is essential in the analysis of TOD influence on travel behavior: as a new public transport service is introduced, it takes some time for people to adjust their habits and mode choice to the new transport option. The same applies to slowly occurring changes in the built environment of station areas.

In this paper, we develop and apply a longitudinal research approach to analyze the impact of the Metro do Porto – a metro system launched in Portugal in the early 2000s – on the use of private cars for commute trips (work or study). Introduced in just nine years on a territory that had no rapid transit service until then, Metro do Porto can be considered as a natural experiment in the sense that we analyze actual post-intervention changes in mode choice as opposed to preliminary project feasibility studies or studies based on stated preferences. To evaluate metro effects on mode choice, we have used a difference-in-differences (DID) model. This is a type of model that, to the best of our knowledge, has never been used before in the context of TOD travel behavior, but is highly appropriate for before/after analyses. A DID model estimates the effect of a treatment (in this case, the effect of the introduction of the metro) by comparing the average differences in an outcome variable (car trips) between a treated group and a control group (metro-served and non-metro-served civil parishes, respectively). To address potential bias from spillover effects and spatial autocorrelation, we also used a spatial DID (SDID) model.

The Metro do Porto network has a total length of 67 km and comprises 82 stations, of which 14 are underground (https://www.metrodoporto.pt). In addition to serving dense urban areas (notably the central area of Porto), it also serves residential suburbs and rural outskirts. In several cases, the introduction of the metro was accompanied by the rehabilitation and/or renovation of adjacent areas to make them more attractive, safe, and vibrant (Pinho and Vilares, 2009). These interventions resonate with TOD principles, and this is why we classify Metro do Porto as a TOD-type project. Note, however, that Metro do Porto was not formally launched as a TOD project, and that, depending on the surrounding environment, station types vary. Some of them ideally comply with TOD characteristics, while others can be better classified as transit-adjacent (TAD); i.e., stations located in proximity to urban settlements but not properly articulated with them – or park & ride (P&R). In our analyses, we account for the difference between station types and compare their effects on mode choice.

In contrast to previous studies that have mostly concentrated on immediate station areas, this is a macro-analysis conducted at the level of the (civil) parish ("freguesia"), as one of our goals is to know whether the effect of a large TOD investment is visible not only in the proximity of stations but also on a wider scale. The main research question is: to what extent did the introduction of the metro affect the number of (private) car trips since, in the absence of the metro, the car was the most convenient and fast mode of transport in the Porto region? We believe that a ten-year interval is appropriate for the purpose, as this period may encompass not only changes in residents' preferences but also emerging transformations in the built environment (Crowley et al., 2009; Dong, 2016). Thus, we also evaluate the influence of the additional covariates typically present in TOD research such as land-use and socio-economic variables.

The remainder of the paper is structured as follows. The next section provides an overview of the existing literature on the effects of TOD on travel behavior, aiming to present existing research findings and some uncertainties (frequently associated with the lack of longitudinal research) that remain in this field. After that, we describe the case study, focusing on the socio-economic, urbanization, and travel mode trends observed in the Porto region. Special attention is given to the evolution of car use in metro-served and non-metro-served parishes. Our methodological approach is explained in the following section, where we provide a description of our DID model and its spatial extension. Subsequently, we present and discuss the modelling results we have obtained, and provide a performance analysis of TOD- and TAD-served parishes. Finally, in the last section, we summarize our study and identify some directions for future research.

2. Literature overview

This section is intended to provide an overview of the numerous studies addressing the influence of TOD on travel behavior. The resulting estimations of the TOD effects vary depending on the methodology applied, variables used, and national or urban context considered. Nevertheless, it is possible to generalize existing findings to some extent.

Considering transit-related variables, proximity to a transit station largely determines the attractiveness of transit use for residents (Cervero, 2007; Crowley et al., 2009; Lindsey et al., 2010; Zhang et al., 2017). Besides, a station's opening year is relevant, as older stations often perform better in terms of ridership than recently-opened stations (Loo et al., 2010; Pan et al., 2017). While this could partially be explained by time-invariant characteristics (like the location of older stations in city centers where car use is restricted), a temporal dimension is also involved. With time, people get used to transit service and start using it more frequently and/or station areas gradually attract new residents that are predisposed to transit and are willing to use it (the latter phenomenon is called self-selection in the literature). Finally, the number of bus stops in a station area is considered important in several studies (Chatman, 2013; Loo et al., 2010; Nasri and Zhang, 2014; Park et al., 2018).

The physical characteristics of TOD are typically measured by street, building, and/or intersection densities, complemented by specific indicators aimed to capture the walkability of a location like a walk score (Renne et al., 2016). The functional performance of a neighborhood is typically estimated through residential density (Cervero and Arrington, 2008; Chatman, 2013; Loo et al., 2010; Nasri and Zhang, 2014; Pan et al., 2017), retail density, and/or employment density, or through composite mixed-use indexes (Chatman, 2013; Loo et al., 2010; Nasri and Zhang, 2014; Pan et al., 2017; Singh et al., 2014). When considered separately, the influence of land-use variables on transit ridership tends to be moderate, but their cumulative effect can be significant, especially for walking trips to a station. It has been empirically demonstrated that residents in walkable neighborhoods with a dense street pattern commute 1.4% to 5.1% more by public transport than residents of otherwise similar but automobile-oriented neighborhoods (Cervero and Gorham, 1995). Kamruzzaman et al. (2014) estimated that the probability of transit trips in residential TOD neighborhoods is 1.4 times higher than in non-TOD neighborhoods.

It is necessary to highlight that all the aforementioned studies account for socio-economic characteristics. Among them, household income stands out as particularly significant (Cervero, 2007; Cervero and Day, 2008; Chatman, 2013; Nasri and Zhang, 2014; Park et al., 2018; Pongprasert and Kubota, 2018), with higher income levels being associated with higher car ownership rates and a higher number of car trips. Admitting the overall importance of income level for travel behavior, several concerns remain. First, income does not always define mode choice. As shown in Cervero and Gorham (1995), comparable socio-economic groups may have different behavior in TOD and non-TOD environments. Similarly, the majority (83%) of residents in the Subiaco TOD (Perth, Australia) reported a decrease in car use even though the area was characterized by income levels higher than the regional average (Griffiths and Curtis, 2017). Second, even if some groups are predisposed to use the car for their trips, it is still necessary to encourage other transit-favorable groups to maintain their preferences, and, for that, it is essential to provide developments with convenient access to transit service. Third, young adults nowadays seem to be less car-oriented (lower levels of car ownership, use, and, sometimes, tenure of a driving license) than equally aged adults in the past. While the underlying reasons for this phenomenon ('peak car') are still being debated (Goodwin and Van Dender, 2013; Klein and Smart, 2017; McDonald, 2015; Newman and Kenworthy, 2011), the trend is noticeable and may remain in the future.

While the majority of studies are cross-sectional, when evaluating the influence of TOD on travel behavior at one moment in time, some authors have highlighted the need for a longitudinal approach, since mode choice, as a habit, does not change easily or quickly. A longitudinal approach is also extremely advantageous to control for residential self-selection (Cao et al., 2009; Wang and Lin, 2019), which has gained major attention in recent years. The potential effect of TOD on travel behavior has been questioned because it is unclear whether frequently reported increases of transit ridership are indeed due to the TOD characteristics of a neighborhood or due to the positive attitude some people have towards transit that eventually makes them settle in (self-select) that type of neighborhood. Van de Coevering et al. (2016) analyzed data from an internet questionnaire conducted in 2005 and 2012 for three Dutch cities (Amersfoort, Veenendaal, and Zeewolde) using a cross-lagged panel model (CLPM), and concluded that, with time, people well served by transit start to use it more often, while car use is reinforced with time among people living farther away from a transit station. Attitudes concerning certain mode choices were not found to be significant predictors of location choice. Instead, they appeared as flexible and responding to changes in the environment: as people start to live close to a station, they become more favorable to transit. Similar findings were reported by Brown and Werner (2008), who included attitudes in their before/after analysis of changes in travel mode choices caused by the opening of an LRT station. Some residents had a positive attitude to transit even before the station's opening. However, though they could reach another station farther away, they were not using transit until a station was opened nearby (within a half-mile distance). This means that the influence of attitudes on mode choice may be limited if these attitudes are not sustained by the surrounding environment.

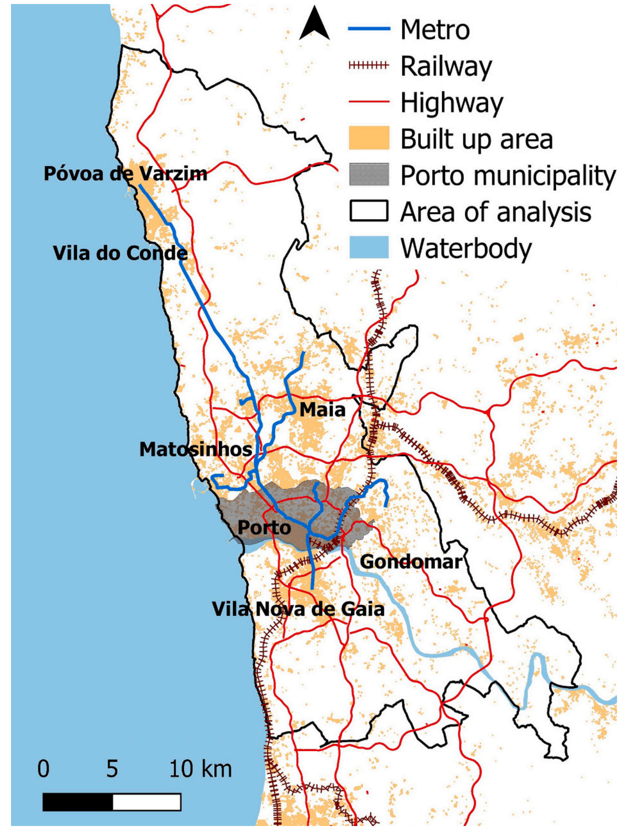

Fig. 1. Porto region.

3. Porto region evolution

Focusing essentially on temporal changes, we provide in this section an overview of the dominant urbanization, transport system, and travel mode trends in the Porto region in the years before the launch of Metro do Porto and after the first nine years of its operation. For this purpose and, more broadly, for the analyses conducted later in this paper, we designate the Porto region as a group of seven municipalities served by the metro system: Gondomar, Maia, Matosinhos, Porto, Póvoa de Varzim, Vila do Conde, and Vila Nova de Gaia (Fig. 1). Altogether, these municipalities comprise 120 civil parishes (the units of analysis). The Porto region is located in the northwest of Portugal, one of the two most important areas of economic activity and employment in the country (the other is Lisbon). It approximately coincides with the Porto Metropolitan Area (PMA) as delimited when Metro do Porto was launched (since then, PMA boundaries were enlarged on several occasions through the incorporation of new municipalities). According to the latest census (2011), the total population of the Porto region was 1.2 million, remaining practically unchanged in the previous ten years.

Unless otherwise stated, all the data used in the analyses come from population censuses conducted by Statistics Portugal (INE) and from the respective mobility information. The figures were elaborated based on publicly available information (CAOP - Carta Administrativa Oficial de Portugal and OpenStreetMap).

3.1. Urbanization and transport system trends (1950–2011)

The suburbanization process in the Porto region started in the 1950s with increasing motorization levels and dispersion of settlements, some already monofunctional (e.g., exclusively residential) (Breda Vázquez, 1992). This trend intensified over time: while in 1960 the number of residents in the five municipalities adjacent to Porto was 40% higher than in Porto municipality (around 422×10^3 in the periphery vs. 303×10^3 in Porto), in 1981 there were twice the number of residents in the periphery compared to Porto (641×10^3 in the periphery vs. 327×10^3 in Porto).

With the integration of Portugal in the European Union, which took place in 1986, a strong emphasis was put on the expansion of a road network that was still underdeveloped compared to other European countries like France (Padeiro, 2018). In the 1990s, major investments in the highway network were undertaken and, in 2009, this network became the 5th longest (in total length) of the European Union (PORDATA, 2021). As a consequence of these investments, Porto is now surrounded by three circle expressways (A20, N12, and A41, commonly known as Via de Cintura Interna, Estrada da Circunvalação, and Circular Regional Exterior do Porto, respectively), which intersect with six radial expressways (A28, A3, A4, A1, A43, and A29).

Between 2001 and 2011, employment in the region was mostly concentrated in the central areas of municipalities' main towns. Porto accumulated 8 out of the 10 most important (civil) parishes in terms of employment, with central business district (CBD) parishes offering 70% more employment than the regional average (Pinho, 2009). As Porto is mainly specialized in the tertiary sector (shops and offices), besides commuters, it also attracts numerous commerce and service consumers, together with a growing number of tourists. Matosinhos and Vila Nova de Gaia also provide significant employment opportunities, while the eastern municipality of Gondomar is largely residential, with population working mostly in the neighboring municipalities. The Metro do Porto project was launched in this setting, with the opening of the first of its six lines connecting Matosinhos to Porto's central area in 2002. Other lines followed shortly (Fig. 2, left), until in 2011 the municipality of Gondomar was finally connected to the metro system.

The implementation of the project significantly altered the preexistent railway network: about 50 km of the existing metro lines are former railway lines, abandoned or very little used. In other cases, railway segments were closed (connection Muro-Trofa) or started to coexist with the metro (connection São Bento-Campanhã).

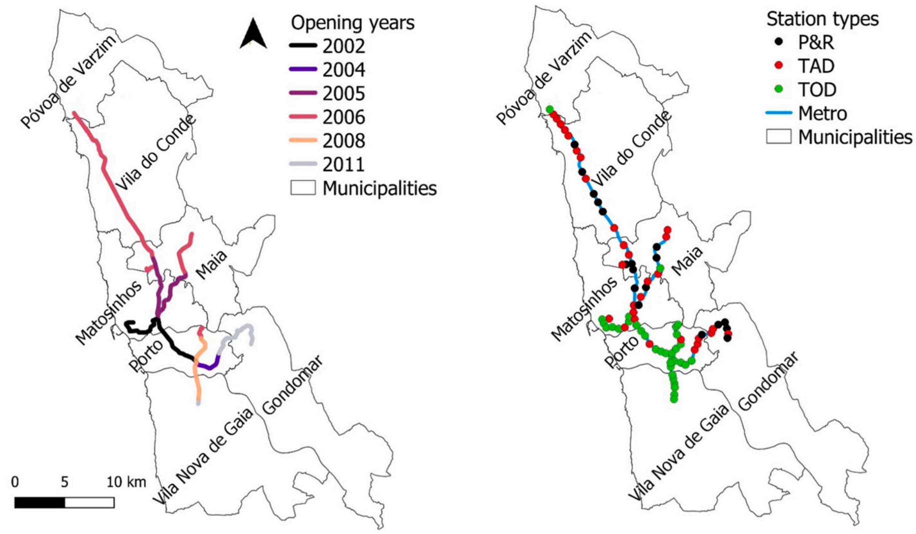

Fig. 2. Metro do Porto lines: opening years (left) and station types (right).

It is essential to highlight the heterogeneity of the metro-served parishes and, consequently, of the station environments. As shown in Fig. 2 (right) and exemplified in Fig. 3, some stations, located in dense and mixed-uses urban settings, are TOD, while others are transit-adjacent (TAD), simply placed in proximity to a settlement as an additional service, or park & ride (P&R).

It should be underlined that, while a TOD strategy was not openly assumed when Metro do Porto was launched, several measures have been taken in this sense during the project execution. Since, in many cases, the metro was provided to already dense urban areas (often historic), major interventions (like large construction projects) were not possible. In these conditions, efforts were concentrated on improving the overall pedestrian and biking environment, and on implementing traffic calming measures. For instance, the upper deck of Dom Luís I bridge, connecting central areas of Porto and Vila Nova de Gaia (north and south bank of the river respectively), was closed off to car traffic and assigned to metro, pedestrian, and bike use only. On Avenida da República, Vila Nova de Gaia's main avenue, the number of traffic lanes was substantially reduced, not only to accommodate metro lines (one each way) but also because sidewalks were substantially widened. Overall, Metro do Porto introduced 268×10^3 m^2 of sidewalks, 179×10^3 m^2 of green areas, and 3.6×10^3 m^2 of cycle lanes (Pinho and Vilares, 2009). In addition to the above measures, multimodality was promoted by the metro project, providing integrated ticketing for passengers of bus and metro and as well as a single ticket for metro trips and parking next to P&R stations.

3.2. Mode choice trends (1991–2011)

In 1991, the majority (54%) of the trips to work or study in the Porto region were made by walking or bus. Globally, only 15% of the trips were made by car. These trips were most common in the suburban residential areas around Porto (Maia, Ramalde, Paranhos) and in high-income neighborhoods near the ocean (Foz do Douro, Miramar). The share of car trips increased substantially until 2001, reaching about 33% (i.e., it more than doubled in ten years), and then increased again, to 43%, in 2011. Thus, even though the region showed an average decrease of 7% in the overall number of trips (probably due to the economic crisis that severely affected Portugal after 2008), the share of car trips still increased. Instead, the share of other transport modes has diminished steadily in the period 1991–2011 (Fig. 4).

The decline in bus patronage up until 2011 may be partially due to the Metro do Porto project. In fact, between 2001 and 2011 many bus routes were adjusted and linked to metro stations to facilitate intermodalism, and also several routes (with a length of 137 km in total) were eliminated thus affecting passenger flows. Although there are no data available about the mode choice changes in populations affected by the redesign of bus routes, we cannot exclude such changes and the impacts

Fig. 3. Different station environments within a 400-m buffer.

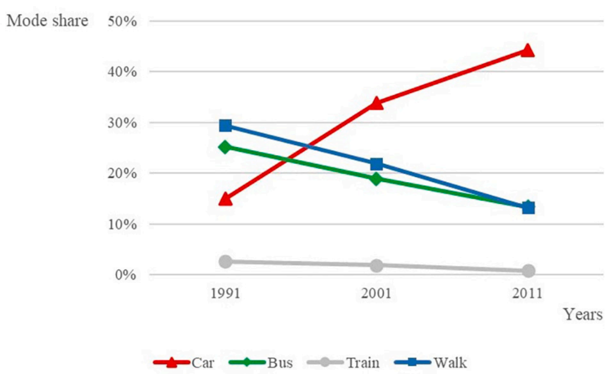

Fig. 4. Evolution of mode choice in the Porto region between 1991 and 2011.

they could have had on travel behavior. The reduction of bus ridership may appear to have been caused by passengers switching from buses to metro, yet this certainly was not the only reason. The share of bus trips was falling relatively uniformly in almost the entire Porto region, served or not by the metro. Besides, in 2011, the metro was even weaker in terms of ridership than bus service, so even if it did attract some passengers from other buses, this attraction was certainly modest.

Analyzing the mode choice trends at the parish level, it is evident that the increase in car trips was especially noticeable in the northern rural areas, where the respective share went from below 10% to above 40%. This increase [of car use in northern rural areas] may be partially due to a 9% increase in the average number of trips to other municipalities for work or study between 1991 and 2011. Nevertheless, most trips were short-distance, as the average trip time for the area increased from 15 to 17 min. The use of a car in these conditions might be explained by poor or absent public transport service. At the same time, it is evident how the central area and urban parishes, where car trips were frequent in 1991, gradually ceded the leadership in car trips to peripheral suburban parishes (Fig. 5).

Bus service used to be quite important particularly in the municipalities of Vila Nova de Gaia and Gondomar, with a 41–54% share of trips in some parishes in 1991; yet, even in those municipalities, the share went down to 23–28% in 2011 (still the largest share among the parishes in the region). This decline could be attributed to the introduction of the metro, but it appears that the preference for the metro over the bus was limited to the centers of Porto and Vila Nova de Gaia (Fig. 6).

Although the share of metro trips in the directly served parishes is noticeable, this does not necessarily signify a decrease of car trips in these parishes. Based on car-use data, it is possible to analyze whether metro-served and non-metro-served parishes in the Porto region reveal different dynamics after the implementation of the metro. For this purpose, a parish was considered to be metro-served if it was covered by a 400 m buffer from a station. As a result, 37 parishes out of 120 were classified as metro-served. The analysis showed that the increase in car trips in metro-served parishes was markedly smaller in the period 2001–2011 than in non-metro-served parishes, even though the metro-served parishes had higher car trip shares in 1991 and 2001 (Fig. 7). Between 1991 and 2001, both served and non-served parishes showed common trends. However, after the introduction of the metro, the trend for metro-served parishes declined, while for non-served parishes it remained quite stable. Thus, one can question whether the metro, though unable to decrease the share of car trips, still contributed to decreasing the growth rate of car usage, and, if so, to what extent.

4. Methodological approach

In this section, we focus on the methodological approach adopted in our study (Fig. 8). Once we decided to study the impact of Metro do Porto on travel mode choice, we looked for the data available. As stated before, the unit of analysis was the civil parish. After collecting the relevant data (population, land use, transport system, and mode choice), and performing a preliminary analysis to observe the mode choice trends for metro-served and non-metro-served parishes in the period 1991–2011, we decided to use a difference-in-differences model. This is a widely used approach to evaluate a treatment effect in a natural experiment setting (see, e.g., Abadie, 2005; Lechner, 2011; Strumpf et al., 2017; Vermeersch, 2007). It is especially appropriate when a treatment status is assigned externally, and only to a fraction of the units in a sample. The visualization of car-use trends in the Porto region revealed a classic setup for the application of such an approach. Therefore, it should perfectly suit our needs, as we later were able to confirm.

Below, we first present the DID model upon which we have based our study. Then, we explain the extension of this base model to the spatial

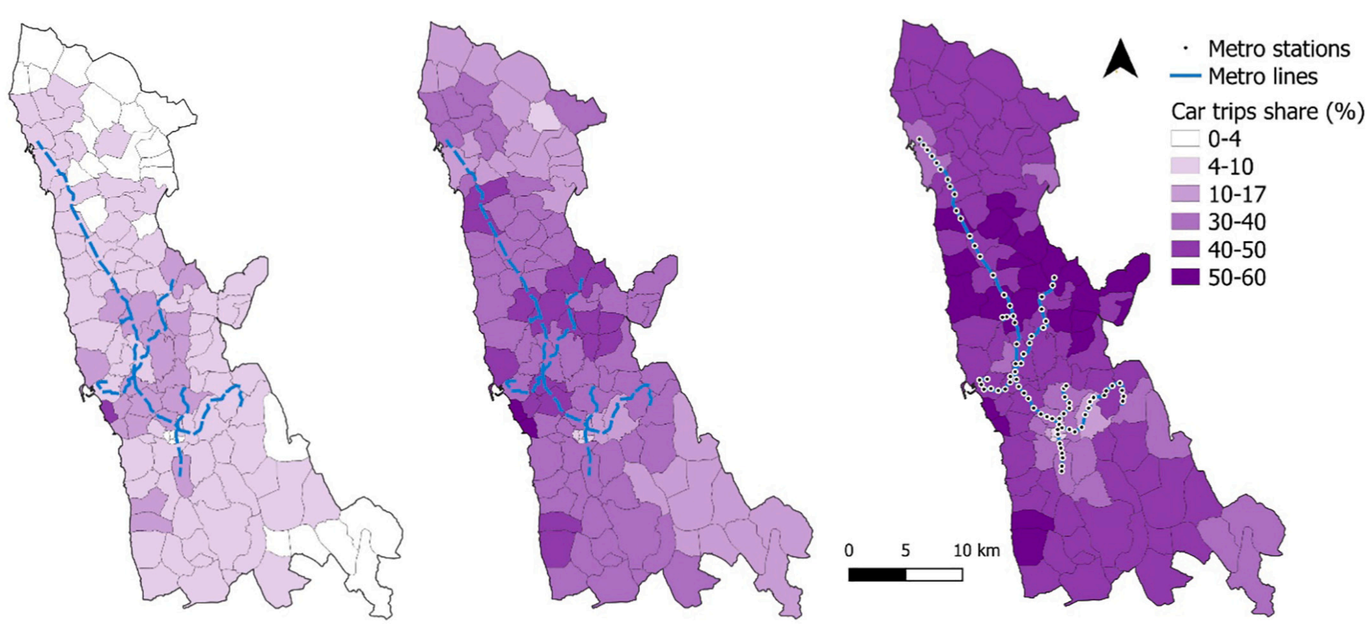

Fig. 5. Car trip shares in the Porto region in 1991 (left), 2001 (middle) and 2011 (right).

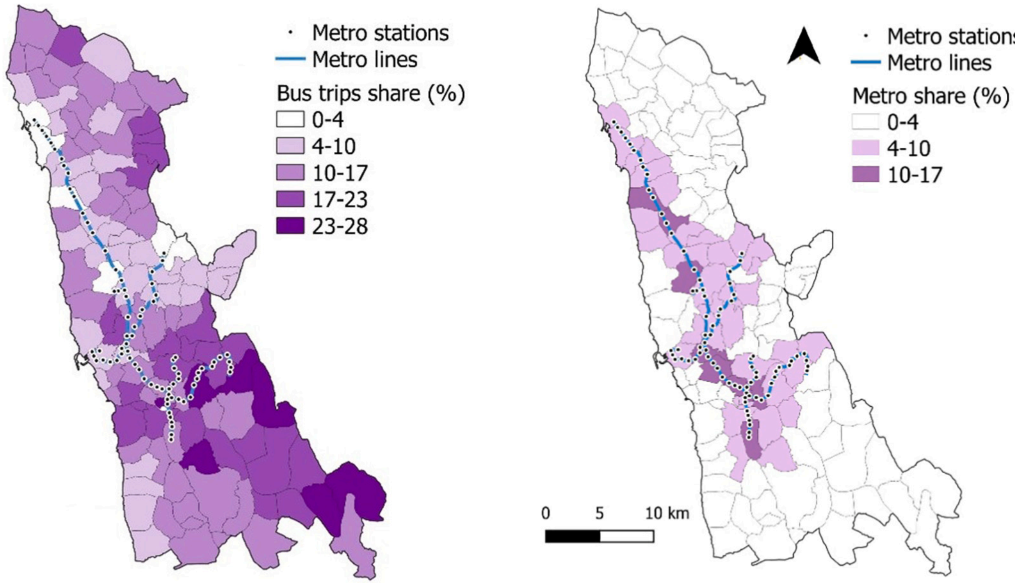

Fig. 6. Distribution of bus trips (left) and metro trips (right) in 2011.

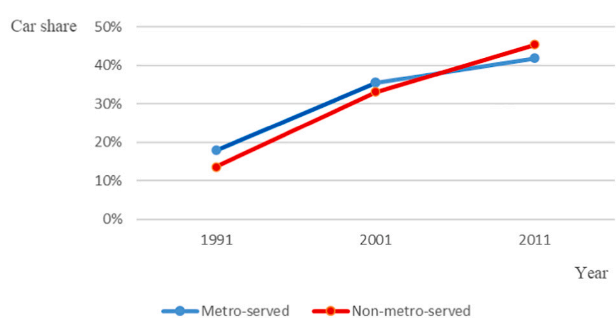

Fig. 7. Car trips share in the metro-served and non-metro-served parishes of the Porto region.

difference-in-differences (SDID) model that we have developed to account for heterogeneity and spatial correlation between the units of analysis. Finally, we describe all the variables included in the models.

4.1. Difference-in-differences model

We have applied the DID model to a period defined by two census years: 2001 and 2011. The number of parishes and their boundaries remained intact in the study period, allowing for a panel dataset. Since the metro was introduced in 2002 and the last stations were built in 2011, it is possible to perform a before-after analysis, considering metro implementation as a natural experiment. However, it should be emphasized that, since the metro was introduced gradually over the years, the estimates provided by the model mix long-, medium- and short-term effects. Since census data are available only once every ten years, this shortcoming is inevitable. Still, as the metro system was not fully completed until 2011, probably the influence of the metro, even in the older stations, did not manifest expressively. This was confirmed by a series of tests we have performed to check for the statistical significance of the impact of station age on the number of car trips.

In a DID model, the units of analysis are divided into a treatment group and a control group based on their exposure status. In our case, treated parishes were those served by the metro, while other parishes served as controls. The model assumes that, in the absence of treatment (metro), both groups would follow the same trend. This common trends assumption limits the application of a DID model to cases where both treated and control groups follow the same trend in the pre-intervention period. Therefore, it is strongly recommended to visualize data for more than two periods to check if the assumption holds (Ryan et al., 2019; Strumpf et al., 2017). The outcome of the model is the evaluation of the treatment effect based on the comparison between the observed values

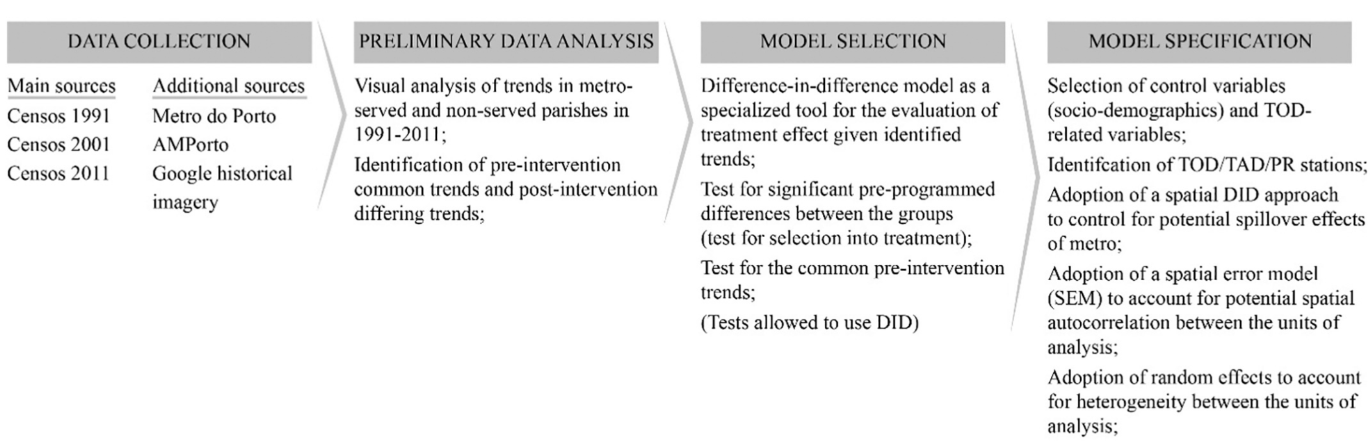

Fig. 8. Stages of the methodological approach.

and the hypothesized counterfactual values that treated units would show in the absence of treatment. The counterfactual values are estimated based on the trend of the control group (Fig. 9). For this reason, the treatment status of a unit should not affect the outcome in other units; in other words, the stable unit treatment value assumption (SUTVA) has to hold (Angrist et al., 1996; Delgado and Florax, 2015).

A DID model is mathematically formulated in the following way (Abadie, 2005):

$$Y_{ijt} = \beta_0 + \beta_1 E_j + \beta_2 T_t + \beta_3 E_j T_t + \sum_n \beta_{4n} X_{ijtn} + \varepsilon_{ijt} \tag{1}$$

where: Y_{ijt} is the dependent variable for unit i of group j in period t; $E_j = 1$ if j is the treated group, and $E_j = 0$ if j is the control group; T_t is a binary variable equal to 1 if t is the post-treatment period and equal to 0 if t is the pre-treatment period; E_jT_t is the interaction term between the group and time indicator (or the treatment variable); X_{ijt} are n covariates, i.e., other variables that also influence the dependent variable; β_0, β_0, …, β_{4n} are regression coefficients; and ε_{ijt} is the error term.

The coefficient β_1 of variable E_j yields the average difference between the treated group and the control group, and controls for unobserved group effects (Angrist and Pischke, 2008). Ideally, regressing the dependent variable on E_j would result in a non-significant p-value, as this would mean that there are no significant pre-programmed differences between the treated group and the control group, so the groups are similar. Therefore, chances of receiving a treatment are also similar for both groups and there is no selection into treatment. The coefficient β_2 of variable T_t reflects the average common changes in both groups between the pre- and post-treatment periods. The β_3 coefficient of the interaction term E_jT_t discloses the time difference between the two groups (difference in differences), i.e., the treatment effect.

For the sake of simplicity, we will write eq. (1) in matrix format (without subscripts) as follows:

$$\boldsymbol{Y} = \beta_0 + \beta_1 \boldsymbol{E} + \beta_2 \boldsymbol{T} + \beta_3 \boldsymbol{E} \circ \boldsymbol{T} + \boldsymbol{\beta_4} \circ \boldsymbol{X_4} + \varepsilon, \tag{2}$$

where ∘ denotes element-by-element multiplication or Hadamard product.

Despite DID models accounting for time-invariant characteristics of both groups, omitting time-varying variables can bias the results. In the context of our study, the economic stagnation faced by Portugal after 2001 was a potential threat. This threat was controlled by including the unemployment rates in the model as a covariate. Other socio-economic variables were included because they are important for mode choice, allowing control for potential changes in the composition of both groups over the years (Lechner, 2011; Ryan et al., 2015). To address other possible time-varying confounders, an analysis of Google satellite imagery was performed to check whether significant changes happened in the period 2001–2011 in terms of street density and highway/railway networks. Other than the metro, few transport infrastructure developments were implemented in the region between 2001 and 2011: the road and rail networks were already well-established, so confounding effects from them were unlikely to exist. The same applies to street density: though certain changes took place in parallel with the Metro do Porto project, their effect was not (statistically) significant at our level of analysis. Furthermore, the set of main travel destinations in the region remained almost intact: one new shopping mall was opened (Vila do Conde Fashion Outlet) and the Asprela Campus of the University of Porto, located in the north of the city, was substantially expanded; however, these changes were not found to be significant.

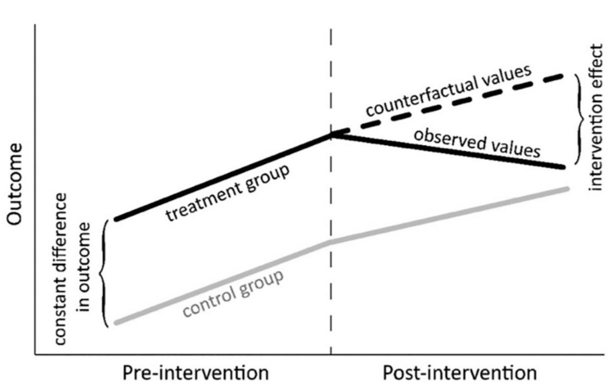

Fig. 9. Graphical representation of DID.

To test for selection into treatment (whether one group had greater chances to receive treatment than the other group), the number of car trips per 1000 inhabitants in 2001 (pre-treatment year) was regressed on the binary group variable E_j (treated vs non-treated parishes). The coefficient of the group variable was not significant, so even though there are preprogrammed differences between the treated and control parishes, they are still quite similar, which can be confirmed also in Fig. 7: in 1991, the difference in car modal share between the treated and control parishes was quite clear, but in 2001 both groups were very close to each other. Since the difference between the groups narrowed between 1991 and 2001, the significance of the interaction term was also checked for the pre-treatment period. The interaction term for that period was not found to be significant, meaning that groups did not follow divergent trends (Ryan et al., 2015).

4.2. Spatial difference-in-differences model

Despite the ease of estimation and interpretation of a DID model, problems may arise in the presence of spillover effects from the treatment, since such effects would violate the SUTVA assumption. In the case of Metro do Porto, some spillover effects were already visible in Fig. 6: metro trips are reported in several parishes that were not directly served by the metro. Since the metro attracted ridership from parishes adjacent to metro-served parishes, the adoption of a technique that would account for the spillover effects of the metro was necessary. Specifically, we selected the spatial DID (SDID) model proposed by Delgado and Florax (2015).

Extending the initial DID equation to SDID leads to the following equation:

$$\begin{aligned} \boldsymbol{Y} &= \beta_0 + \beta_1 \boldsymbol{E} + \beta_2 \boldsymbol{T} + \beta_3 (\boldsymbol{I} + \rho \boldsymbol{W}) \boldsymbol{E} \circ \boldsymbol{T} + \boldsymbol{\beta_4} \circ \boldsymbol{X_4} + \varepsilon \\ &= \beta_0 + \beta_1 \boldsymbol{E} + \beta_2 \boldsymbol{T} + \beta_3 \boldsymbol{E} \circ \boldsymbol{T} + \beta_3 \rho \boldsymbol{W} \boldsymbol{E} \circ \boldsymbol{T} + \boldsymbol{\beta_4} \circ \boldsymbol{X_4} + \varepsilon \end{aligned} \tag{3}$$

where: $\boldsymbol{I}$ is the identity matrix; ρ is the spatial autoregressive parameter, $\boldsymbol{W}$ is an $(NT \times NT)$ block-diagonal matrix combining spatial weight matrices ($\boldsymbol{W_N}$) of different time periods. In our case, the cross-sectional matrix remains the same for all time periods, so $\boldsymbol{W} = \boldsymbol{I_T} \otimes \boldsymbol{W_N}$ (where $\otimes$ denotes the Kronecker product) $\boldsymbol{W_N}$ is row-standardized, thus $\boldsymbol{WE} \circ \boldsymbol{T}$ "is the share of unit's i neighbors that are treated" (Bardaka et al., 2018; Bardaka et al., 2019; Delgado and Florax, 2015).

The average treatment effect (*ATE*) is the sum of the average direct treatment effect (*ADTE*) and the average indirect treatment effect (*AITE*):

$$ATE = \mathrm{E}[ATE(w) \,|\, \boldsymbol{WE}] = \beta_3 + \beta_3 \rho(\overline{w}) = \beta_3 (1 + \rho \overline{w}) \tag{4}$$

where $w \in \boldsymbol{WE}$, $0 < w \leq 1$, and $\overline{w}$ is the proportion of treated neighbors.

ADTE is represented by the aforementioned interaction term $\boldsymbol{E} \circ \boldsymbol{T}$, while the *AITE* for each unit is estimated based on the proportion of the treated units among the unit's neighbors. Since metro spillover effects on mode choice are consistently visible mostly in parishes directly adjacent to treated parishes, the spillover is estimated for the first-order neighbors (queen adjacency) of these parishes.

As nearby units of analysis frequently tend to be similar to each other in a number of ways, including travel behavior (positive Moran's I), we chose a spatial error model to control for spatially correlated errors (Bardaka et al., 2018, 2019; Croissant and Millo, 2019). Additionally, random effects estimation was preferred since it also addresses unobserved random heterogeneity between units (Bardaka et al., 2018, 2019; Croissant and Millo, 2019).

To confirm the model specification, conditional Lagrange multiplier tests that detect spatially-correlated errors even in the presence of random effects and vice versa were run, confirming the existence and significance of both spatially correlated errors and random effects (Baltagi et al., 2003). We used the Kapoor et al. (2007) model specification as it accounts for time-invariant and time-varying spillover effects (Baltagi et al., 2013), assuming the same spatial autocorrelation process in both individual effects and the remaining error components.

4.3. Model variables

The dependent variable in both models (DID and SDID) is the number of car trips per 1000 inhabitants: as the parishes differ in size, the total number of car trips had to be transformed to per capita values to allow for comparison. A summary of the independent variables is provided in Table 1. The principal data source of the variables was Statistics Portugal (INE).

Since metro stations also vary in their characteristics (Fig. 3), we account for this variability with binary variables TOD, TAD, and Park and Ride (P&R). The last class is set as reference (and not included in the model) and is used to compare the performance of TOD and TAD relative to P&R. The TOD, TAD and P&R variables were defined initially based on the street density inside the 400-m buffer from a station. Street density inside the buffer was then classified into three groups. After that, a station-level analysis was made, evaluating other TOD elements such as the location of a station in the surrounding built environment, high- or low-rise development, the existence of mixed uses and local businesses, and availability of parking. A parish was classified as TOD, TAD or P&R based on the predominant station type in each case: if the majority of stations was TOD, then the parish was considered TOD. In three cases without a predominant station type, a classification was assigned to a parish according to the type of the station that had the largest passenger volume in that parish in 2011. The resulting classification is illustrated in Fig. 10.

5. Study results and discussion

In this section, we present, analyze and discuss the results obtained through the estimation of the models using the *splm* package of the R software (Millo and Piras, 2012). It is divided into two subsections, dedicated, respectively, to the DID model and the SDID model. In the last part of the second subsection, we focus on the performance of parishes depending on the predominant type of metro service (TOD, TAD, and P&R) they offer.

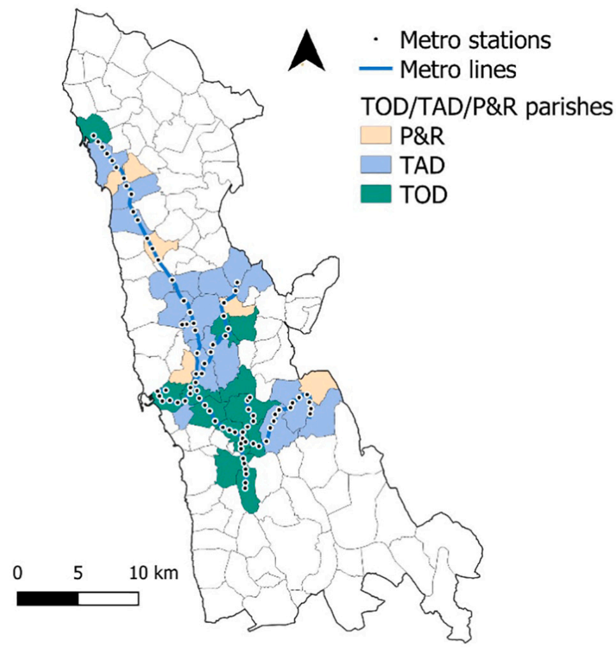

Fig. 10. Classification of the parishes of Porto region based on station types.

Table 2
DID model estimation results.

Variable	Estimate	Std.Error	*t*-Value	*p*-Value
(Intercept)	238.46067	41.78831	5.706	3.57e-08*
year	57.13790	9.24600	6.180	2.93e-09*
group	7.02750	5.67564	1.238	0.216920
triptime	−2.98380	0.39384	−7.576	8.85e-13*
landmix	−10.52828	25.75519	−0.409	0.683083
buidense	−0.05444	0.00645	−8.440	3.69e-15*
education	1140.74170	78.33885	14.562	< 2e-16*
unemployed	−0.32056	0.07443	−4.307	2.46e-05*
more65	−0.35508	0.09753	−3.641	0.000336*
less13	0.24968	0.15655	1.595	0.112118
metro	−19.91631	7.06818	−2.818	0.005261*
cbd_dist	−1.42877	0.32711	−4.368	1.90e-05*
*R*2	0.8275			
Adjusted *R*2	0.8192			
Residual std. error	24.5 (*df* = 228)			
F statistic	99.42* (*df* = 11,228)			

Note: * $p < 0.05$.

Table 1
Explanatory model variables.

Variable type	Variable designation	Variable description	Data source
DID	"group"	equal to 1 for metro-served parishes, and equal to 0 for non-metro-served parishes	our classification
	"metro"	equal to 1 if in 2011 a parish was served by metro, and equal to zero otherwise	Metro do Porto
	"year"	equal to 1 in the post-treatment period (i.e., after the implementation of metro), and equal to 0 in pre-treatment period	n/a
Land-use	"buidense"	building density	INE, Census
	"landmix"	proportion of buildings with multiple uses	INE, Census
Location	"cbd_dist"	straight line distance from a parish (centroid) to Porto CBD	n/a
	"triptime"	average trip time in one direction for the main daily trip reported by the citizens	INE, Census
Parish	"TAD"	equals to 1 if the majority of metro stations in a parish are of the TAD-type, and equal to zero otherwise	our classification
	"TOD"	binary variable, equals 1 if the majority of metro stations in a parish are of the TOD-type, and equal to zero otherwise	our classification
Socio-economic	"education"	the proportion of people with complete secondary education (a proxy for income)	INE, Census
	"less13"	the proportion of people aged less than 13 years old	INE, Census
	"more65"	the proportion of people aged more than 65 years old	INE, Census
	"unemployed"	the proportion of unemployed per 1000 active residents);	INE, Census

5.1. DID model

The results of the estimation of the DID model are presented in Table 2. The large value of the R-squared coefficient (0.81) and the preponderance of highly significant variables suggest that the model is quite strong in explaining the dependent variable. As can be seen for the "year" variable, the number of car trips increased over 10 years in both groups in a similar manner (as shown by the coefficient of the variable "group", the difference between treated and non-treated parishes is only 7 additional car trips per 1000 inhabitants on average).

The interpretation of the model is straightforward: the coefficients show the impact of a unit change in the different explanatory variables on the number of car trips per 1000 inhabitants between 2001 and 2011. The treatment effect of the metro was confirmed to be highly significant and associated with an average decrease of around 19.91 car trips per 1000 inhabitants in the metro-served parishes. Among other TOD-related variables, building density was the most significant ($t = -8.44$), confirming the importance of a dense built environment for the promotion of sustainable modes and providing support for densification as a means to decrease the attractiveness of car use. In contrast, mixed uses appear to not have been a factor contributing significantly to the decrease in car use. It should be noted however that the respective variable ("landmix") is not very precise: it is based on all mixed-uses buildings, yet we had no information on whether these uses are local shops or large shops and office centers.

Regarding socio-economic variables, as expected, higher unemployment rates and greater proportions of the elderly population decrease the number of car trips. The proportion of young residents, though positively associated with car use, was not found to be significant. The only socio-economic variable significantly associated with an increase in car trips is the level of education (used as a proxy for income level) with extremely high influence on the dependent variable: an extra percentage point of residents with secondary education leads to 1.14 additional daily car trips per person. It should be noted that the highest income neighborhood of Porto (Foz do Douro) is not served by the metro, so in this case the wealthiest residents likely use a car.

Somewhat surprisingly, the number of car trips decreases as the distance to the Porto CBD increases. Similarly, longer trip times are associated with lower car use. Perhaps this is the consequence of metro service being available in the distant northern parishes of Póvoa de Varzim and Vila do Conde, where people working in the central parishes of Porto, Matosinhos, or Vila Nova de Gaia (with plenty of employment opportunities) could have switched to the metro to avoid transport costs (including those corresponding to a loss of time caused by traffic congestion). Alternatively, in the distant parishes, that effect might also be explained by the use of buses/coaches or walking which, ceteris paribus, signifies longer trip times than travelling by car. Besides, residents in distant parishes might have less interaction with the Porto CBD, mostly working in local businesses, and thus are less dependent on the use of a car.

5.2. SDID model

The estimation of the SDID model with spatial errors, random effects, and spillover effects (Table 3) confirmed the presence of significant individual heterogeneity (ϕ parameter) and spatially correlated errors (ρ parameter).

The average treatment effect (ATE) of metro implementation in the presence of spillover effects can be estimated using Eq. (4) (Delgado and Florax, 2015):

$$ATE = \mathrm{E}[ATE(w)\,|\boldsymbol{WE}] = \beta_3(1+\rho\overline{w}) = -22.06 + (-25.03 \times 0.3) = -29.57 \tag{5}$$

Thus, after accounting for both direct and indirect effects, the average treatment effect of metro increased compared to the DID model, consisting of a reduction of almost 30 car trips per 1000 inhabitants. With respect to the other variables, the direction of the relationships between the dependent and explanatory variables remained stable, and the coefficients changed only slightly.

Overall, the results confirm the potential of the metro in limiting the number of car trips even when car trip rates were rapidly growing before the intervention. Considering the effect of the metro implementation, it is evident that, even on a macro level of analysis, the metro had a positive and significant effect on the evolution of the number of car trips. The same applies to the spillover effects of the metro, though the indirect effect is naturally less significant than the direct one.

Table 3
SDID model estimation results.

Variable	Estimate	Std.Error	*t*-Value	*p*-Value
(Intercept)	184.9039448	37.6552505	4.9104	9.087e-07*
year	52.6443263	9.1347194	5.7631	8.258e-09*
group	−4.0377630	5.5941124	−0.7218	0.4704248
triptime	−1.3135456	0.5908249	−2.2232	0.0261996*
landmix	−3.8481888	17.8659895	−0.2154	0.8294618
buidense	−0.0349263	0.0075189	−4.6451	3.399e-06*
education	991.8120649	72.9349486	13.5986	< 2.2e-16*
unemployed	−0.1491637	0.0614796	−2.4262	0.0152566*
more65	−0.3066042	0.0860939	−3.5613	0.0003691*
less13	0.1975709	0.1251760	1.5783	0.1144866
metro	−22.0680296	7.0946238	−3.1105	0.0018675*
cbd_dist	−0.4022318	0.6020271	−0.6681	0.5040511
spillover	−25.0335332	11.9811875	−2.0894	0.0366714*
ϕ	1.327998	0.383650	3.4615	0.0005372*
ρ	0.668218	0.063556	10.5138	< 2.2e-16*
Pseudo - $R2$	0.7686659			

Note: * $p < 0.05$.

5.2.1. Performance of TOD, TAD and P&R parishes

In order to analyze the performance of parishes considering the respective station environments, we estimated the SDID model with the inclusion of binary variables for TOD and TAD parishes (Table 4). The inspection of this table reveals that both TOD and TAD parishes performed significantly better than P&R parishes: as attested by the regression coefficients, in TOD parishes this effect was more intense (additional decrease of 26.6 trips per 1000 inhabitants) and more significant ($t = -3.6$), whereas in TAD parishes the additional decrease was just of 13.9 trips ($t = -2.2$). Moreover, TOD parishes were characterized by significant spillover effects ($t = -2.0$), as opposed to TAD parishes ($t = -0.9$). This is quite surprising, as it would be reasonable to expect that the spillover effect from TAD parishes would be noticeable

Table 4
SDID model estimation results distinguishing parish types.

Variable	Estimate	Std.Error	*t*-Value	*p*-Value
(Intercept)	190.5992642	37.3905375	5.0975	3.441e-07*
year	53.5398220	8.9134637	6.0066	1.894e-09*
group	−5.8713394	5.3248665	−1.1026	0.2701894
triptime	−1.3502034	0.5819435	−2.3202	0.0203321*
landmix	−1.4595306	19.0530566	−0.0766	0.9389390
buidense	−0.0323379	0.0074589	−4.3355	1.454e-05*
education	994.0264672	72.0859764	13.7895	< 2.2e-16*
unemployed	−0.1820588	0.0620645	−2.9334	0.0033529*
more65	−0.3249594	0.0856314	−3.7949	0.0001477*
less13	0.1963332	0.1250725	1.5698	0.1164720
TOD	−26.5969383	7.3403817	−3.6234	0.0002908*
TAD	−13.8937251	6.3511990	−2.1876	0.0287006*
TODspill	−32.9865845	16.1647787	−2.0406	0.0412861*
TADspill	−14.4419914	16.4029713	−0.8804	0.3786157
cbd_dist	−0.4844707	0.5817444	−0.8328	0.4049634
ϕ	1.270915	0.379173	3.3518	0.0008029*
ρ	0.654524	0.066432	9.8525	< 2.2e-16*
Pseudo - $R2$	0.7848339			

Note: *$p < 0.05$.

since it is generally easy to park a car and leave it for the day next to TAD stations. Hence, in principle, TAD parishes could be expected to attract residents of neighboring parishes. The strength of the spillover effects of TOD parishes is possibly due to the fact that they offer a more developed bus network with greater geographical coverage than TAD parishes, which facilitates the use of the metro by residents of neighboring parishes.

To sum up, and as could be expected, the influence of the metro on mode choice is stronger in the parishes where metro service is offered, and it propagates to the neighboring parishes. The magnitude of the spillover effects also depends on parish types, as parishes where TOD stations are dominant reveal greater catchment potential than TAD or P&R parishes. This finding provides important support for TOD policies: TOD projects are often compromised by substantial investment costs (Cervero and Murakami, 2009; Searle et al., 2014; Tan et al., 2014; Yang et al., 2016) that are not so easy to justify if potential benefits are confined to a relatively small station area. Instead, if TOD projects, complemented by a bus network, can produce advantageous spillover effects in nearby parishes, then they might gain more support from both local populations and authorities.

6. Conclusion

In this paper, we presented a study aimed to analyze the impact of Metro do Porto on the use of private cars for commute trips (work or study). The analysis extends over a ten-year period (2001−2011) and is essentially based on census data: 120 civil parishes ("freguesias") were selected as units of analysis to explore whether metro, as a large infrastructure project, produced effects noticeable on a macro scale. While the majority of studies about the effect of TOD on car use comes from the USA, our study diversifies the existing research by bringing evidence from a TOD-type project in southern Europe.

Given the natural experiment setting, a difference-in-differences model was selected as the most appropriate statistical approach. To our best knowledge, this is the first study where such approach was used to analyze the impact of TOD on travel behavior. Since metro usage was also reported in parishes not served by the metro directly, the basic DID model was extended to a spatial DID model permitting the capture of spillover effects from the metro. Our findings suggest that not only the direct metro effect is significant, but also the indirect metro spillover effect to neighboring units is clearly noticeable. Investigating the relative performance of TOD, TAD, and P&R parishes in explaining car use, we found that the influence of TOD parishes is significantly related to a lower number of car trips in the neighboring non-directly metro-served parishes. This finding may seem counter-intuitive at first, because TOD stations are generally less accessible to cars compared to P&R stations. Therefore, it could be expected that their influence would be limited to areas close to stations (up to 0.8–1.6 km from a station). The fact that TOD parishes attracted passengers from areas farther out might be due to the reconfiguration of bus routes that was made specifically to make access to the metro easier. TAD and P&R stations probably have fewer connecting services, and this limits their spillover effects. Also, the spillover of TOD might be greater due to the overall attractiveness of the consolidated urban fabric, which provides a safer and more pleasant environment compared to relatively isolated TAD/P&R stations.

Certain policy implications can be derived from our results. TOD effects may not be limited to immediate station areas; instead, TOD spillover effects can be significant. As such, TOD investment in a given area can be beneficial not only for that particular area, but also for adjacent larger areas. To further exploit TOD spillover potential, increases in allowable densities and mixed-use settlements should be promoted, together with regular and reliable bus service linking the metro stations and adjacent parishes. The combination of these factors can significantly reduce the number of car trips even in situations where motorization rates are increasing. In the case of Metro do Porto, the planned expansion of metro lines to the southern municipality of Vila Nova de Gaia provides rich opportunities to develop new stations according to TOD principles. This expansion will possibly be reinforced by a bus rapid transit (BRT) system. The knowledge we acquired through our study can support the planning of BRT station areas as well.

As made clear above, our study already provided interesting conclusions concerning the impact of Metro do Porto on travel behavior. But we see several opportunities for future research. The first involves the application of the same methodological approach (difference-in-differences) to similar projects in other European countries to understand whether the results we have obtained are also observed in other geographical contexts – particularly in France, Italy, and Spain, where numerous light-rail and fast-tram TOD-type projects were put in place in the last 25 years. Indeed, despite the growing interest that TOD is attracting in European countries, up to now the research efforts regarding its impacts on travel behavior are descriptive in nature (see, e.g., Bertolini et al., 2012; Knowles, 2012; Pojani and Stead, 2018; and Paulsson, 2020). Another enticing research direction to pursue is the development of a micro-analysis of the impact of Metro do Porto, conducted at the census tract level ("secção estatística") to complement the macro-analysis we have performed at the parish level. This micro-analysis could provide more precise insights into the gradient of spillover effects (for example, using distance-decay functions), as well as into the relative performance of different types of stations. The main problem here is that census tract limits often change considerably from census to census, whereas parish limits stay essentially the same (another problem is that parish data are generally free while census tract data are expensive). This complicates the application of a longitudinal research design. Additionally, since our analysis was limited to work and study trips, it could be further developed in the future by also addressing other travel purposes (but this is not possible using census data in Portugal at this point). Finally, because the data from the 2021 census will become available soon, a study on the impact of Metro do Porto covering the period 2001–2021 based on panel data from three census years could be an interesting avenue for future research. Since practically nothing happened in Portugal in the last decade with respect to infrastructure investment (due to the "sovereign debt" crisis that severely affected the country and the consequent bailout program), new data make it possible to study the long-term effects of the project, since these effects do not suffer from contamination of the effects of new lines or new line extensions.

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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