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Modelling context-specific relationships between neighbourhood socioeconomic disadvantage and private car use

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Abstract

Car use generates negative externalities, which are responsible for many health, environmental and economic problems. To tackle this issue, more work is needed to identify better the correlates of car use, especially at the contextual level. In this study, a mobility-focused questionnaire involving 1,722 working French adults living in the Paris area (France) was used to explore gender-stratified relationships between residential socioeconomic deprivation and car use as the main transport mode against public transport, after controlling for potential confounders. While the vast majority of similar studies have assumed linear and global statistical relationships, the present work involved a random slope hierarchical generalised additive modelling framework, which revealed both non-linear and territorially-varying relationships. Among women, living in a more deprived neighbourhood was associated with an increase in the odds of reporting car use up to a certain threshold, after which the relationship plateaued, while among men, this relationship is linearly negative. In the most deprived department of the Paris region (Seine-Saint-Denis), living in a more deprived neighbourhood was associated with a lower odds of car use among men while a more complex nonlinear bell-shaped relationship was observed among women. The opposite was found in the wealthiest department (Yvelines), with a negative relationship among women and a U-shaped one among men. In Paris inner city, again a strong opposite trend was distinguished according to sex, with a negative relationship among women. These findings suggest that spatial contexts, characterised by complex interactions between socioeconomic factors, the built environment and the distance to Paris, play the role of moderators in the relationship between residential deprivation and car use. In conclusion, this study reinforces the idea that environment-transport relationships should be understood through local analyses (e.g. random slope multilevel or spatially-varying coefficients models) rather than global ones only, in order to guide specific public policies more effectively.

1. Introduction

Private car use is associated with significant environmental and health costs. As a completely inactive mode, car use has been associated with health-related issues, such as cardiovascular diseases (Warren et al., 2010) and obesity (Wen et al., 2010). It was also responsible for 49 road

deaths per mln. inhabitants in the European Union in 2018 (European Transport Safety Council, <https://etsc.eu/euroadsafetydata/>) and health issues due to air pollution (Krzyżanowski et al., 2005). Moreover, cars generated more than half of the French transport sector CO₂ emissions in 2017 (Citepa, 2019), thus contributing to global warming.

These effects have prompted the scientific community to explore the determinants of car use in order to identify potential levers for a shift toward alternative and healthier modes, including active mobility (walking and cycling) and public transport. Many studies have focused on the relationship between car use and built environment characteristics, highlighting negative relationships with public transport accessibility, residential density, activity space walkability and land use mix, and positive relationships with the presence of parking places at work/home (den Braver et al., 2020; Ewing & Cervero, 2010). Other studies have also revealed strong relationships between socioeconomic status and car use at the individual level, indicating that disadvantaged communities are less likely to have access to a car (Licaj et al., 2012; Rachele et al., 2015).

However, very little work has been done on the relationships between car use and residential neighbourhood deprivation, independently of individual and built environment factors. Moreover, these rare studies have reported inconsistent results, revealing the complexity of the process mechanism involved. In the European context, a first hypothesis assumes that the most deprived areas are those pushed further away from city centres and thus remote from the associated opportunities and services – while having fewer public transport facilities and other amenities favouring alternative modes to the car – generating more frequent private car use on average (Goodman, 2013; Xiao et al., 2018). In the economic literature, this hypothesis is consistent with a monocentric model in which deprived households have a lower valuation of accessibility and amenities of the Central Business District (CBD) than of dwelling size (Alonso, 1964; Brueckner et al., 1999; Mills, 1967; Muth, 1969; Wheaton, 1977) or with a Tiebout-like (1956) mechanism which leads the richest households to concentrate in the CBD and make housing unaffordable for poor households there. Car ownership is also shown to be related to household composition (number and age of children) and the bargaining power of spouse in couples (Picard et al., 2018) which also depend on household income.

A second hypothesis assumes an inverse relationship, based on the fact that the ownership and number of cars per household is lower on average in the most deprived neighbourhoods, implying a lower car use (Licaj et al., 2012). It is very likely that the remoteness of neighbourhoods from urban amenities interacts with this relationship between the residential socioeconomic context

and car use through mediation or moderation effects (Lucas et al., 2018). Therefore, this relationship cannot be correctly considered without integrating a territorial or spatial dimension, and thus an appropriate modelling framework.

Based on a mobility-focused questionnaire involving 2,002 working French adults living in the Paris area, we explored this research question through successive statistical models. This relationship between residential neighbourhood deprivation and car use was first modelled with an adjusted parametric logistic model, then with a generalised additive model to capture the non-linearity of the relationship. Because neighbourhood deprivation is spatially structured, this non-linearity amounts to spatial heterogeneity of relationships, which was emphasised through a random slope hierarchical (multilevel) generalised additive model. To the best of our knowledge, this is the first application of this method in the field of transport geography.

2. Data and methods

2.1. Research design and sampling

A specific questionnaire was designed within the VEDECOM Institute and the University of Paris-Saclay. Briefly, it was distributed by the BVA Survey Institute to a sample of 2,002 workers in the Paris region in September 2016. The sample was selected to be representative of the workers who travel within the Paris region, in terms of gender, age, socio-occupational category and department of residence. In order to correct possible bias, the respondents were given weights (using a calibration technique on margins) that indicated their representativeness in the population (see Bulteau et al. (2019) for more details). Among the 2,002 initial respondents, 108 were excluded from the analyses because of either missing data regarding residential addresses ($n = 13$), not having a driving license ($n = 75$), declaring main modes other than car or public transport ($n = 172$), or working outside the Paris region ($n = 20$), leading to a final sample of 1,722 participants.

2.2. Car use outcome estimation

Every participant was asked the following question: "What is your main transport mode, for commuting or non-commuting trips, among the following: (i) car as a driver; (ii) car as a passenger; (iii) public transport; (iv) motorised two-wheeler; (v) walking (> 10 minutes); (vi) cycling; (vii)

other”. Participants who chose the first option were summed ($n = 1,130$, i.e. 59.7%) against public transport users ($n = 592$, i.e. 29.6%), while those who chose the three other options were disregarded. This procedure allows to reduce travel heterogeneity, since car and public transport are typically used on comparable travels in terms of time and/or distance, and are therefore more substitutable than with walking or cycling for instance, which concern shorter trips. This position is based on consumer choice theory, assuming that agents make rational choices between different competing or substitutable alternatives to maximize their individual utility (Ben-Akiva & Lerman, 1985; Cervero, 2002; Domencich & McFadden, 1975). Usually, we consider that the modal choice can be reduced to a trade-off between the generalized cost of the transport mode and the accessibility zone defined in time and space (Cervero, 2002; Joly et al., 2006). This is why we focused only on these two modes, which can be considered as two competing modes in terms of travel times, costs, and accessibility zone. The resulting binary variable was used as the dependent variable in the subsequent regression models.

2.3. Neighbourhood deprivation quantification

Neighbourhood deprivation was captured through the French deprivation index, in order to ensure comparability with many other contextual studies. This index was calculated following the protocol described elsewhere (Rey et al., 2009). Theoretically, deprivation was initially defined by Townsend as a “state of observable and demonstrable disadvantage relative to the local community or the wider society to which an individual, family or group belongs” (Townsend, 1987). Empirically, it was quantified here as the first component of a principal component analysis including four socioeconomic variables (median household income, percentage of high school graduates in the population aged 15 years and older, percentage of blue-collar workers in the active population, and unemployment rate). The index was quantified at the IRIS Census unit scale (data from 2014). The IRIS areas (acronym for “Aggregated Units for Statistical Information”), representing the smallest unit for dissemination of French infra-municipal data, were provided by the French National Institute of Statistics and Economics, as well as all the population data. The index is mapped in Figure 1.

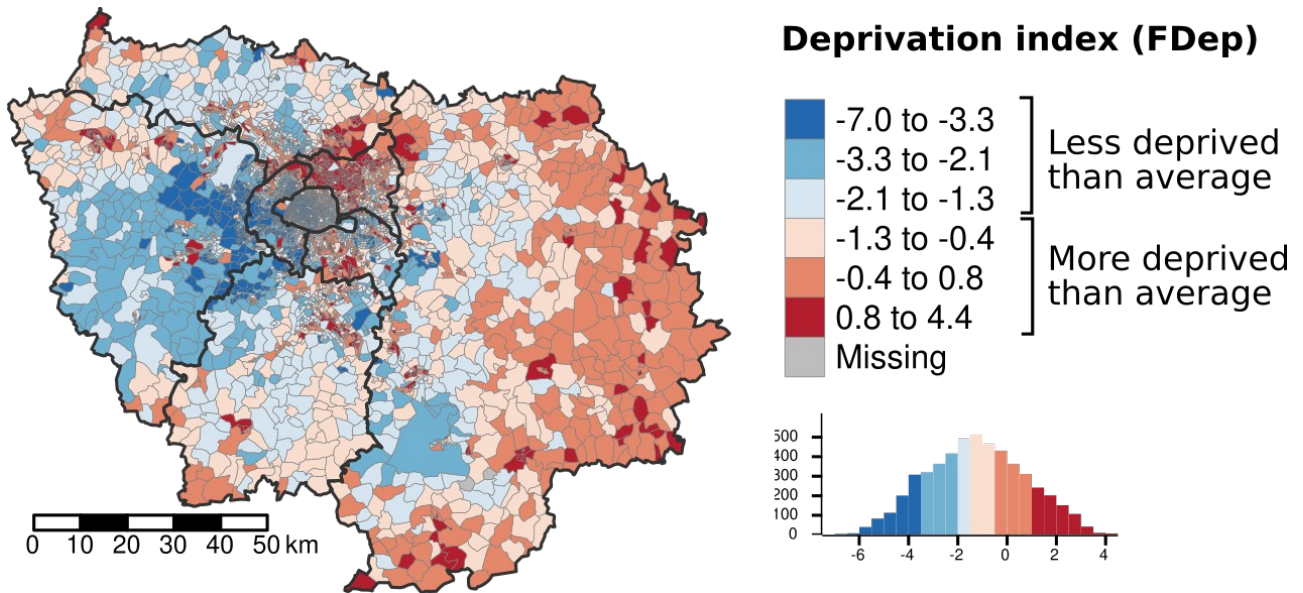


Figure 1. Map of the French deprivation index (year 2014) in the study area. This index is a latent variable built on four socioeconomic population variables.

2.4. Individual and contextual covariates

According to the literature, a number of covariates are likely to be confounders of the studied relationships and were controlled for in the models. At the individual level, demographic variables included age, gender and household size. In particular, sex-specific preferences in urban work trip duration and mode choice are supposed to differ, leading us to perform gender-stratified models. Socioeconomic status (SES) was captured through a latent variable derived from the first principal component of a multiple correspondence analysis (MCA), **allowing to overcome the multicollinearity issue**. The MCA integrated the three following variables: income, educational level and socioprofessional class, quantified as categorical variables in the survey. A low value in this latent variable indicates a greater socioeconomic disadvantage. Cost and travel time for each mode were added as alternative specific variables. At the contextual level, built environment covariates were added, as they are deemed to be related to both car ownership (Bhat & Guo, 2007) and travel behaviour (Ewing & Cervero, 2010). Built environment was captured through three variables: population density (inhabitants/km² at the IRIS scale), the distance from the residential address to the closest rail transport stations, including subway, tramway, RER (acronym for the regional express network) and suburban trains, and the distance from the residential address to the centre of Paris. This last distance is assumed to capture major geographical structures in this region characterized by a strong hub-and-spoke effect, such as density of public transport, destinations and amenities or job opportunities.

2.5. Modelling strategy

Our modelling strategy followed three steps. The first consisted of estimating a parametric binary logistic adjusted model to assess the global linear mean effect of neighbourhood deprivation on the likelihood of using a car as the main transport mode against using public transport. The binary logistic regression models the log odds of probability that Y equals 1 (i.e. car use in this case, noted π) as a function of a set of k explanatory variables X_k :

$$\text{logit}(\pi) = \log\left(\frac{1-\pi}{\pi}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$

where β_0 is an intercept term. Each regressor was regressed against all the others in order to estimate variance inflation factors (VIFs) to control for multicollinearity. All VIFs were lower than 2 and thus all regressors were kept. In a second step, we used a generalised additive model (GAM) to deal with potential non-linearity in the relationships. The GAM is a method enabling statistical relationships between explanatory variables and the response to be described by smooth curves, usually splines (Hastie & Tibshirani, 1999; S. Wood, 2017). This model is expressed as follows:

$$E(Y) = g^{-1}\left[\beta_0 + \sum_{j=1}^J f_j(x_j)\right]$$

where $E(Y)$ is the expected value of the response Y (with an appropriate distribution and link function g - in the present study, a logit link was selected since the response is binary), f_j is a smooth function of the covariate x_j , β_0 is an intercept term, and g^{-1} is the inverse link function (Pedersen et al., 2019). The smooth function f_j is represented by the sum of K simpler, fixed basis functions ($b_{j,k}$) multiplied by the corresponding coefficients ($\beta_{j,k}$), which need to be estimated:

$$f_j(x_j) = \sum_{k=1}^K \beta_{(j,k)} b_{(j,k)}(x_j)$$

A smoothing penalty is applied to basis function coefficients to avoid overfitting i.e. excess wiggleness (see Pedersen et al., 2019) for formal details). Here, thin plate regression splines were used as smooth functions, as recommended for non-cyclic data (Wood, 2003).

In a third step, we used a hierarchical generalised additive modelling (HGAM) framework to explore context-specific territorial and functional heterogeneity in the relationships between deprivation index and car use. This method combines hierarchical (or multilevel) models and generalised additive models into a single framework (Pedersen et al., 2019). Hierarchical or

multilevel models are an extension of linear models accounting for the hierarchical structure of the data (Goldstein, 1987), for instance individuals nested in neighbourhoods. Multilevel models specify models at individual and contextual levels in a single framework. In this way, they enable contextual effects accounting for individual ones to be considered, avoiding both ecological and atomistic fallacies (Owen et al., 2016). As such, multilevel models have been recommended as a relevant methodological framework for modelling mode choices, since individuals live, work and make choices in specific spatial contexts that cannot be ignored (Bhat, 2000). Moreover, random slope (i.e. mixed) multilevel models allow statistical relationships to vary by levels of the grouping variable, typically spatial contexts.

HGAMs combine GAM and multilevel models and allow varying non-linear relationships by levels of the grouping variable. **While these two methods have already been used separately in the transport geography literature (for GAM, see e.g. de Buen Kalman, 2021; Yang et al., 2020; for multilevel modelling, see e.g. Ding & Cao, 2019; Licaj et al., 2012; Schwanen et al., 2003, combination of the two methods in a single framework has never been applied in transport studies, to the best of our knowledge.** In this study, the grouping variable corresponds to the departments, a mesoscale French administrative division between municipalities and the region, similar to US counties. Eight departments compose the Paris region: Paris *intra muros*, surrounded by three small but dense departments (inner suburbs), and four others corresponding to the outer suburbs (Fig. 2). Pedersen et al. (2019) identified four possible HGAMs. The first two, referred to as GS (global smoother) and GI (global smoother with individual effects), are characterised by a global smooth function. The difference is that in the model GS, group-level smoothers have the same wiggleness, that is to say individual effects have a shared penalty. This model is a close analogue to a classic generalised multilevel model with random slopes. The model GI also has a global smoother, but with differing wiggleness in their group-level smoothers. The last two models, referred to as model S and model I, have no shared trend (i.e. no global smoother) but do have group-level trends. Model S constrains group-level smoothness by a shared penalty, while model I includes individual penalties i.e. different smoothness in group-level trends. Model I is the least constrained of the four in terms of penalties and can result in highly varying group-level relationships. In our analyses, we tested the four models using the restricted maximum likelihood estimation method. We selected the model that minimised the AIC, as recommended by Pedersen et al. (2019). Model I appeared to be the best one and was therefore selected as the final model.

Note that all models have been gender-stratified. All the statistical analyses were performed with R (R Development Core Team, 2018). The **mgcv** package (Wood, 2011) was used to compute HGAMs, following the codes of Pedersen et al. (2019).

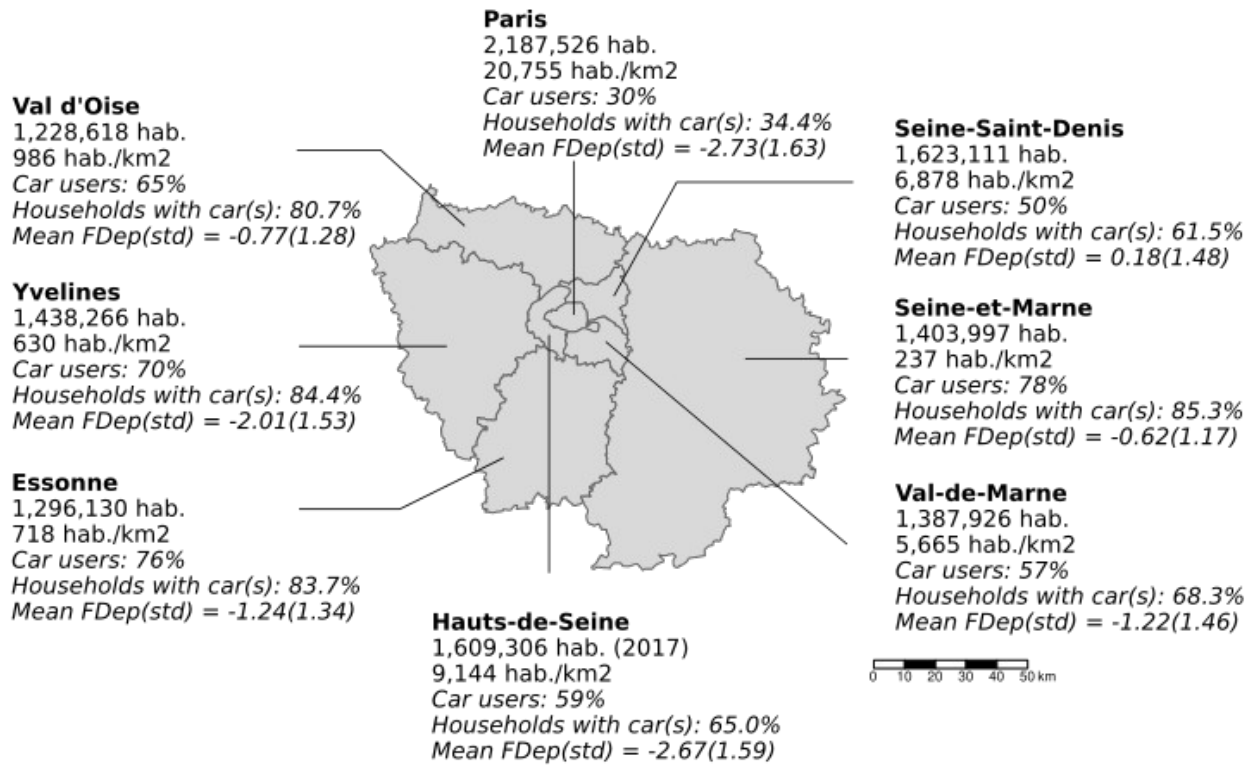


Figure 2. Location and demographic characteristics of the eight administrative departments of the Paris region. Percentages of car users were derived from our sample data, while statistics about households with at least one car were obtained from 2017 population census data (French National Institute for Statistics and Economic Studies, <https://www.insee.fr/fr/statistiques/2012694>).

3. Results

In this section, we present the sample descriptive statistics and the raw model outputs, while the next section is dedicated to the discussion and interpretation of these results.

The sample was composed of 1,722 workers (55.6% women) mainly aged between 25 and 49 years (Table 1). Among them, 1,170 (67.9%) reported using a car as their main transport mode for commuting and non-commuting trips. Descriptive statistics of those who reported car use and of the others highlighted some differences. Notably, women were over-represented in the car user

group (58.03% vs. 51.66% in the non-car user group). In addition, travel times were higher using public transport compared to car, meaning that the car was probably mostly used for short trips. In terms of individual socioeconomic status (SES), it is interesting to note that among car users, women are particularly socially disadvantaged compared to men and compared to women among public transport users. Regarding contextual variables, the car user group lived in less dense neighbourhoods, farther from the centre of Paris, with poorer public transport accessibility than the other group (lower density being associated with more parking opportunities).

Table 1. Descriptive statistics of the sample of 1,722 French adults working in the Paris region and participating in the study.

| Variable | Whole sample (%) | | | Among car users (%) | | | Among public transport users (%) | | |
|---|------------------|-------|-------|---------------------|-------|-------|----------------------------------|-------|-------|
| | Pool | Men | Women | Pool | Men | Women | Pool | Men | Women |
| Gender | | | | | | | | | |
| Men | 44.40 | | | 41.97 | | | 47.46 | | |
| Women | 55.60 | | | 58.03 | | | 52.54 | | |
| Age (years) | | | | | | | | | |
| 16-24 | 3.02 | 1.46 | 4.23 | 2.99 | 1.02 | 4.42 | 3.08 | 2.29 | 3.79 |
| 25-39 | 36.60 | 30.30 | 41.60 | 34.44 | 25.20 | 41.10 | 41.30 | 39.70 | 42.80 |
| 40-49 | 40.50 | 42.50 | 38.90 | 39.74 | 43.40 | 37.10 | 42.03 | 40.80 | 43.10 |
| 50-65 | 19.90 | 25.80 | 15.30 | 22.82 | 30.40 | 17.40 | 13.59 | 17.20 | 10.30 |
| Travel time for commuting using car (min) | | | | <i>Revealed</i> | | | <i>Stated</i> | | |
| < 15 | 17.90 | 14.70 | 20.40 | 20.70 | 15.90 | 24.20 | 12.10 | 12.60 | 11.70 |
| 16-30 | 30.70 | 31.50 | 30.10 | 36.20 | 37.30 | 35.50 | 19.90 | 20.60 | 17.60 |
| 31-45 | 21.10 | 22.40 | 20.10 | 22.60 | 24.20 | 21.40 | 18.10 | 19.10 | 17.20 |
| 46-60 | 14.40 | 14.70 | 14.10 | 13.70 | 14.30 | 13.20 | 15.90 | 15.60 | 16.20 |
| > 61 | 15.80 | 16.60 | 15.20 | 6.84 | 8.30 | 5.70 | 34.80 | 32.10 | 37.20 |
| Travel time for commuting using PT (min) | | | | <i>Stated</i> | | | <i>Revealed</i> | | |
| < 15 | 5.80 | 5.60 | 6.00 | 6.90 | 6.72 | 7.07 | 3.50 | 3.44 | 3.45 |
| 16-30 | 16.40 | 15.30 | 17.30 | 16.20 | 13.60 | 18.00 | 17.00 | 18.30 | 15.90 |
| 31-45 | 19.30 | 21.90 | 17.30 | 17.00 | 18.10 | 16.20 | 24.30 | 29.00 | 20.00 |
| 46-60 | 25.50 | 25.20 | 25.70 | 23.50 | 25.20 | 22.20 | 29.70 | 25.20 | 33.80 |
| > 61 | 32.90 | 32.00 | 33.60 | 36.40 | 36.20 | 36.50 | 25.50 | 24.00 | 26.90 |
| Monthly cost for commuting using car (€) | | | | <i>Revealed</i> | | | <i>Stated</i> | | |
| < 65 | 32.20 | 34.90 | 28.80 | 37.00 | 32.80 | 40.10 | 22.10 | 21.40 | 22.80 |
| 65-75 | 5.80 | 6.30 | 5.20 | 4.80 | 3.70 | 5.60 | 7.97 | 8.00 | 7.90 |
| 75-120 | 27.40 | 27.80 | 26.80 | 26.50 | 25.20 | 27.40 | 29.20 | 29.80 | 28.60 |
| > 120 | 34.60 | 31.10 | 39.20 | 31.70 | 38.30 | 27.00 | 40.80 | 40.80 | 40.70 |
| Monthly cost for commuting using PT (€) | | | | <i>Revealed</i> | | | <i>Stated</i> | | |
| < 65 | 26.80 | 25.10 | 28.10 | 33.40 | 31.60 | 34.80 | 12.70 | 13.0 | 12.40 |
| 65-75 | 44.40 | 45.30 | 43.60 | 34.40 | 36.00 | 33.10 | 65.60 | 62.60 | 68.30 |
| 75-120 | 21.00 | 20.00 | 21.80 | 23.60 | 21.80 | 24.90 | 15.60 | 16.80 | 14.50 |
| > 120 | 7.80 | 9.60 | 6.50 | 8.60 | 10.60 | 7.20 | 6.10 | 7.60 | 4.80 |

| Household size (no of people) | | | | | | | | | |
|--|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| 1 | 14.60 | 11.30 | 17.20 | 20.20 | 15.70 | 23.40 | 2.90 | 3.00 | 2.80 |
| 2 | 30.40 | 30.90 | 30.00 | 36.20 | 37.10 | 35.60 | 18.10 | 19.50 | 16.90 |
| 3 | 23.30 | 26.20 | 21.20 | 23.10 | 24.40 | 22.10 | 23.90 | 29.40 | 19.00 |
| 4 | 18.90 | 18.10 | 19.60 | 13.70 | 14.30 | 13.20 | 30.10 | 25.20 | 34.50 |
| 5 | 12.70 | 13.60 | 12.00 | 6.80 | 8.50 | 5.60 | 25.00 | 22.90 | 26.90 |
| Individual SES (latent variable) (mean - sd) - standardised variable | | | | | | | | | |
| 0 (1) | 0.09 (0.87) | -0.06 (0.74) | -0.03 (0.81) | 0.09 (0.88) | -0.11 (0.74) | 0.08 (0.80) | 0.11 (0.85) | 0.05 (0.75) | |
| Neighbourhood deprivation (FDep) (mean - sd) - standardised variable | | | | | | | | | |
| -1 (2) | -1.48 (1.72) | -1.38 (1.66) | -1.38 (1.61) | -1.49 (1.63) | -1.31 (1.59) | -1.52 (1.83) | -1.47 (1.87) | -1.56 (1.80) | |
| Population density (hab./km ²) (mean - sd) | | | | | | | | | |
| | 9,245 (10,045) | 9,538 (10,186) | 7,949 (8,947) | 7,063 (8,030) | 7,884 (8,918) | 6,467 (7,268) | 11,992 (11,435) | 12,638 (11,612) | 11,409 (11,261) |
| Distance to the nearest PT station (m) (mean - sd) | | | | | | | | | |
| | 1,212 (1,452) | 1,189 (1,380) | 1,315 (1,577) | 1,436 (1,626) | 1,355 (1,434) | 1,495 (1,749) | 885 (1,083) | 878 (1,219) | 893 (949) |
| Distance to the centre of Paris (m) (mean - sd) | | | | | | | | | |
| | 18,973 (14,766) | 18,297 (14,222) | 20,740 (15,333) | 21,752 (15,189) | 20,118 (14,387) | 22,934 (15,648) | 15,261 (13,247) | 14,885 (13,275) | 15,601 (13,267) |

In a first step, we performed three binary logistic models: a male model, a female model and a pool model (see estimated odds ratio in the Table 2). The three models exhibited an absence of a significant relationship between neighbourhood deprivation and the odds of reporting car use as the main transport mode, while adjusting for individual and other contextual covariates (Table 2). Among the covariates, travel time for commuting using public transport (>60 min) is positively associated with the odds of using car in the three models, while travel time for commuting using car (>30 min) exhibited negative associations. Monthly cost using public transport (65-75€) appeared statistically significant. Age (50-65 years versus 16-24 as the reference category) appeared positively associated with the odds of using car only among men. However, distance to the nearest public transport station is only negatively associated with the outcome among women. Gender differences are also noticed regarding residence department (please refer to Figure 2 for locating toponyms): living in the Seine-et-Marne, Yvelines, Seine-Saint-Denis and Val d'Oise departments compared to living in Paris is positively associated with the odds of using car only among women, while living in the Essonne department is significant in both sex. Other odds ratio are not statistically significant.

Table 2. Summary of the binary logistic regression outputs (n=1,722).

| Variable | Units | Pool model | | | Male model | | | Female model | | |
|--|--------|------------|-------------|---------|------------|--------------|---------|--------------|--------------|---------|
| | | Odds Ratio | CI.95 | p-value | Odds Ratio | CI.95 | p-value | Odds Ratio | CI.95 | p-value |
| <i>Interest variable</i> | | | | | | | | | | |
| FDep14 | | 0.96 | [0.88;1.06] | 0.44 | 0.92 | [0.80;1.05] | 0.221 | 1.04 | [0.90;1.19] | 0.625 |
| <i>Covariates</i> | | | | | | | | | | |
| Individual SES (latent variable) | | | | | | | | | | |
| | | 1.19 | [1.00;1.41] | 0.051 | 1.24 | [0.97;1.58] | 0.083 | 1.09 | [0.84;1.42] | 0.516 |
| Gender | female | Ref | | | / | / | / | / | / | / |
| | male | 0.84 | [0.65;1.09] | 0.195 | / | / | / | / | / | / |
| Age (years) | 16-24 | Ref | | | Ref | | | Ref | | |
| | 25-39 | 1.07 | [0.51;2.21] | 0.862 | 1.75 | [0.43;7.07] | 0.434 | 0.97 | [0.38;2.46] | 0.942 |
| | 40-49 | 1.3 | [0.62;2.70] | 0.483 | 2.85 | [0.71;11.45] | 0.14 | 0.97 | [0.38;2.48] | 0.945 |
| | 50-65 | 2.63* | [1.22;5.70] | <0.05 | 5.52* | [1.33;22.93] | <0.05 | 1.95 | [0.70;5.42] | 0.201 |
| Household size (number of people) | | | | | | | | | | |
| | 1 | Ref | | | Ref | | | Ref | | |
| | 2 | 0.76 | [0.52;1.12] | 0.162 | 0.9 | [0.51;1.58] | 0.708 | 0.61 | [0.35;1.07] | 0.087 |
| | 3 | 1.13 | [0.75;1.70] | 0.56 | 1.09 | [0.62;1.93] | 0.765 | 1.14 | [0.61;2.14] | 0.678 |
| | 4 | 0.85 | [0.57;1.27] | 0.421 | 1.15 | [0.64;2.07] | 0.638 | 0.58 | [0.32;1.05] | 0.07 |
| | 5 | 0.8 | [0.47;1.33] | 0.386 | 0.87 | [0.42;1.80] | 0.705 | 0.58 | [0.27;1.26] | 0.17 |
| Travel time for commuting using public transport (min) | | | | | | | | | | |
| | <15 | Ref | | | Ref | | | Ref | | |
| | 15-30 | 0.74 | [0.39;1.41] | 0.362 | 0.54 | [0.20;1.40] | 0.204 | 0.9 | [0.35;2.30] | 0.831 |
| | 30-45 | 0.86 | [0.44;1.66] | 0.652 | 0.63 | [0.24;1.67] | 0.355 | 1.05 | [0.40;2.77] | 0.921 |
| | 45-60 | 1.51 | [0.77;2.99] | 0.232 | 1.78 | [0.64;4.95] | 0.266 | 1.08 | [0.41;2.84] | 0.882 |
| | >60 | 4.79*** | [2.34;9.81] | <0.001 | 3.28* | [1.14;9.47] | <0.05 | 6.77*** | [2.38;19.28] | <0.001 |
| Travel time for commuting using private car (min) | | | | | | | | | | |
| | <15 | Ref | | | Ref | | | Ref | | |
| | 15-30 | 1.05 | [0.69;1.59] | 0.827 | 1.36 | [0.71;2.60] | 0.349 | 0.98 | [0.54;1.77] | 0.943 |
| | 30-45 | 0.45** | [0.27;0.73] | <0.01 | 0.6 | [0.29;1.26] | 0.179 | 0.41** | [0.20;0.80] | <0.01 |
| | 45-60 | 0.31*** | [0.18;0.52] | <0.001 | 0.37* | [0.17;0.84] | <0.05 | 0.25*** | [0.12;0.52] | <0.001 |
| | >60 | 0.03*** | [0.02;0.06] | <0.001 | 0.06*** | [0.02;0.13] | <0.01 | 0.02*** | [0.01;0.04] | <0.001 |
| Monthly transport cost using private car (€) | | | | | | | | | | |
| | <65 | Ref | | | Ref | | | Ref | | |
| | 65-75 | 0.68 | [0.39;1.18] | 0.173 | 0.54 | [0.23;1.29] | 0.165 | 0.78 | [0.36;1.67] | 0.519 |
| | 75-120 | 0.67* | [0.47;0.95] | <0.05 | 0.56* | [0.33;0.95] | <0.05 | 0.8 | [0.49;1.32] | 0.384 |
| | >120 | 0.68* | [0.48;0.98] | <0.05 | 0.7 | [0.42;1.19] | 0.187 | 0.67 | [0.40;1.13] | 0.13 |

Monthly transport cost using public transport (€)

| | Ref | | | Ref | | | Ref | | |
|-------------------------------------|--------|-------------|-------|---------|--------------|--------|---------|--------------|--------|
| <65 | Ref | | | Ref | | | Ref | | |
| 65-75 | 0.3*** | [0.21;0.42] | <0.01 | 0.37*** | [0.22;0.61] | <0.001 | 0.23*** | [0.14;0.39] | <0.001 |
| 75-120 | 0.73 | [0.48;1.11] | 0.145 | 0.65 | [0.35;1.19] | 0.163 | 0.89 | [0.48;1.66] | 0.709 |
| >120 | 0.92 | [0.52;1.63] | 0.779 | 1.09 | [0.49;2.41] | 0.836 | 0.62 | [0.26;1.47] | 0.273 |
| Population density | | | | | | | | | |
| | 1.00 | [1.00;1.00] | 0.319 | 1.00 | [1.00;1.00] | 0.313 | 1.00 | [1.00;1.00] | 0.789 |
| Residence department | | | | | | | | | |
| Paris | Ref | | | Ref | | | Ref | | |
| Seine-et-Marne | 2.85* | [1.08;7.50] | <0.05 | 2.06 | [0.53;8.00] | 0.297 | 4.97* | [1.12;22.00] | <0.05 |
| Yvelines | 2.92* | [1.23;6.93] | <0.05 | 2.09 | [0.64;6.87] | 0.224 | 4.98* | [1.28;19.38] | <0.05 |
| Essonne | 3.98** | [1.63;9.73] | <0.01 | 4.01* | [1.12;14.35] | <0.05 | 5.17* | [1.33;20.10] | <0.05 |
| Hauts-de-Seine | 1.89 | [0.96;3.71] | 0.065 | 1.53 | [0.63;3.72] | 0.349 | 3.02* | [1.02;8.93] | <0.05 |
| Seine-Saint-Denis | 1.78 | [0.77;4.11] | 0.174 | 0.81 | [0.26;2.57] | 0.726 | 4.73* | [1.27;17.58] | <0.05 |
| Val-de-Marne | 2.31* | [1.05;5.09] | <0.05 | 1.88 | [0.62;5.65] | 0.263 | 3.59* | [1.06;12.12] | <0.05 |
| Val d'Oise | 2.04 | [0.85;4.88] | 0.109 | 2.11 | [0.61;7.27] | 0.237 | 2.87 | [0.76;10.91] | 0.122 |
| Distance to the nearest PT stations | | | | | | | | | |
| | 1.00 | [1.00;1.00] | 0.067 | 1.00 | [1.00;1.00] | 0.566 | 1.00* | [1.00;1.00] | <0.05 |
| Distance to the centre of Paris | | | | | | | | | |
| | 1.00 | [1.00;1.00] | 0.191 | 1.00 | [1.00;1.00] | 0.705 | 1.00 | [1.00;1.00] | 0.152 |

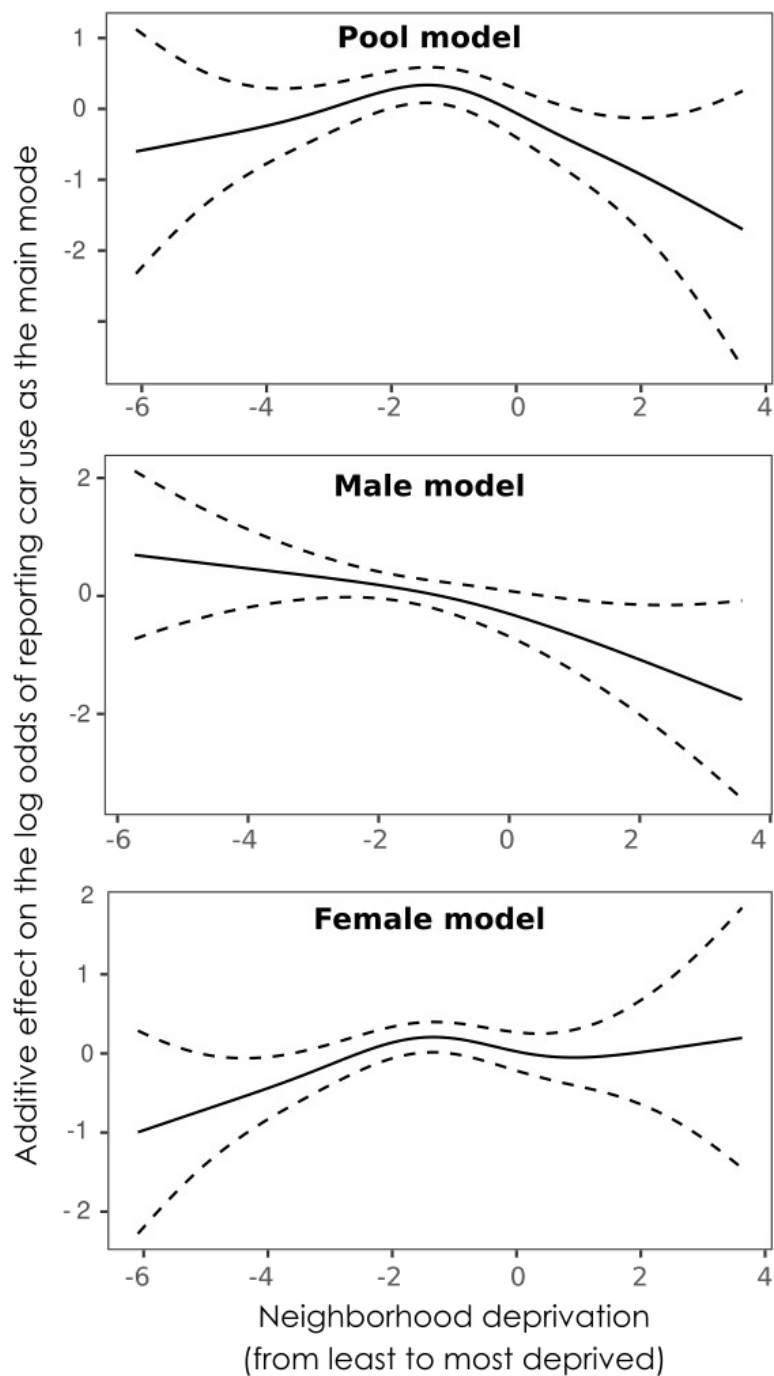


Figure 3. Non-linear relationship between residential neighbourhood deprivation and the odds of reporting a car as the main transport mode among a sample of 1,722 French working adults. The relationship was modelled using a generalised additive model (GAM) adjusted for gender, age, monthly transport budget, travel time for commuting, household size, population density and public transport accessibility.

In a second step, nonlinearity of relationships were explored through GAM, for now without any consideration of territorial nuances. The adjusted GAM indicated a strong non-linear, bell-shaped

relationship between neighbourhood deprivation and the outcome variable in the pool model (Fig. 3). This bell-shaped form means that among the least deprived neighbourhoods, living in a less deprived neighbourhood was associated with a higher odds of reporting car use than public transport. Beyond a certain threshold corresponding to moderately deprived neighbourhoods, the relationship was reversed. However, this scheme differed by gender. Among men, the relationship is essentially linear and decreasing, while among women, the relationship is increasing from less to moderately deprived neighbourhoods, and plateaued thereafter, in the most deprived neighbourhoods.

Finally, the results of hierarchical GAM exhibited relationships that differed both in shape and in intensity as a function of the broader context, i.e. department (Fig. 4), but in different ways according to gender. In Seine-Saint-Denis, the most deprived department of the Paris region, the relationship was strongly negative, whereas in the Yvelines, the wealthiest one after Paris, the relationship was strongly positive, but only in the most deprived neighbourhoods. In Seine-et-Marne and Val d'Oise, the relationships are negative but weak, while no major signals appeared in the remaining departments. This pool model failed to reveal some strong and interesting gender specificities. For instance, the absence of significant relationship in Paris in the pool model hid an opposite trend: among women, relationship was significantly positive - meaning that the most deprived the neighbourhood, the higher the odds is to report car using - but negative among men. Such an opposite trend was also observed, in a less measure, in the Val d'Oise department. In Seine-Saint-Denis, the relationship is strongly negative and linear among men, but bell-shaped among women (fig. 4).

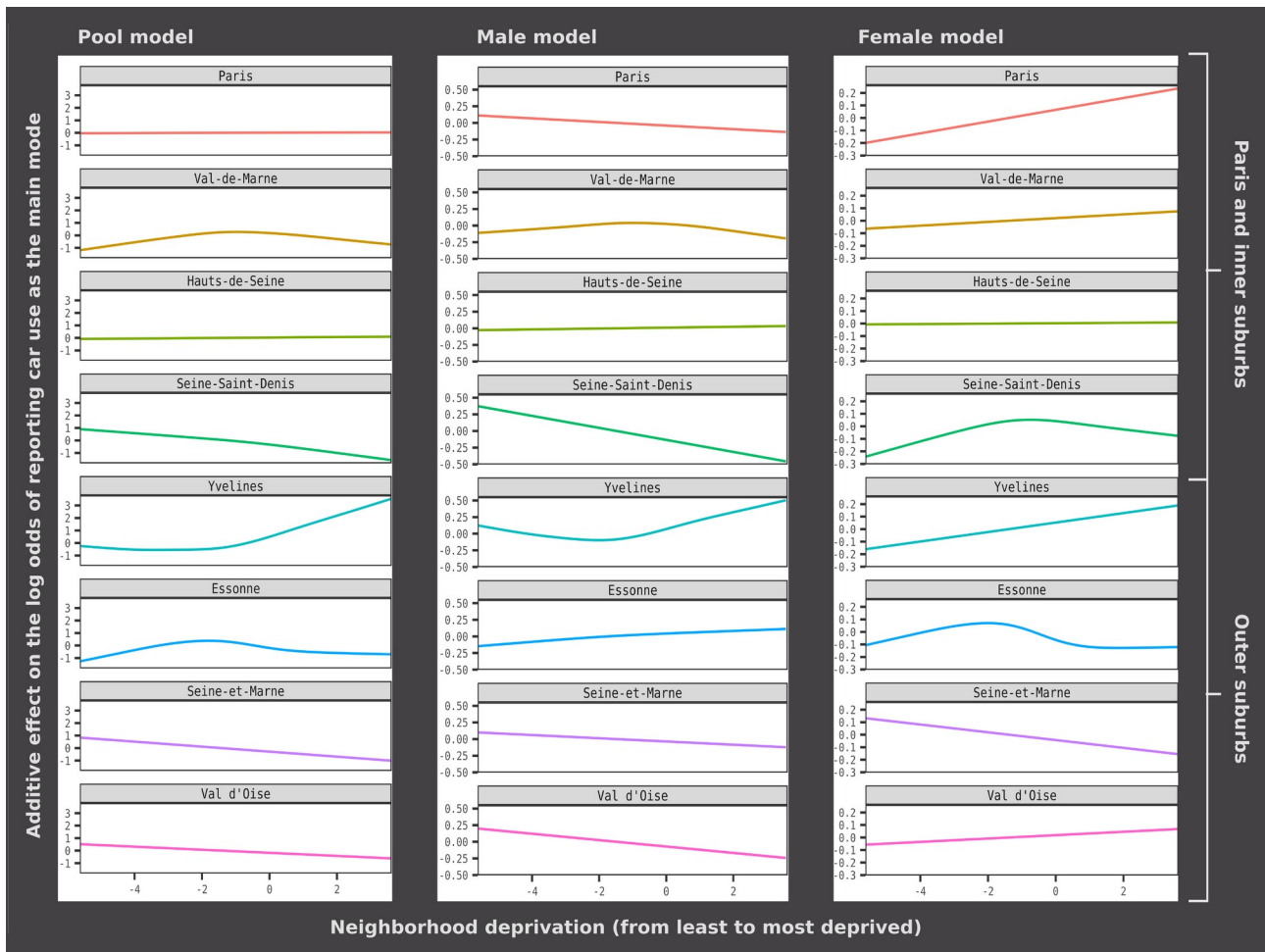


Figure 4. Non-linear relationship between residential neighbourhood deprivation and the odds of reporting a car as the main transport mode among a sample of 1,722 French working adults, according to department (i.e. the grouping variable). These relationships were modelled using a hierarchical generalised additive model (HGAM) adjusted for gender, age, monthly transport budget, travel time for commuting, household size, population density and public transport accessibility.

4. Discussion

This study focused on the relationship between car use and residential neighbourhood socioeconomic deprivation in the Paris region, a rather under-studied contextual dimension of car use determinants compared to built environment ones. We have highlighted some interesting complex mechanisms linking these two variables, while adjusting for a number of potential confounders. Our main finding is that this relationship is insignificant on average (i.e. over the whole study area), actually hiding a non-linear functional form revealed by the appropriate GAM

modelling framework. The sign of the relationship is reversed according to whether one lives in a deprived or an advantaged area. Since the deprivation in the Paris area is spatially patterned, this non-linearity implies a spatial heterogeneity of relationships, as highlighted in the hierarchical GAM outputs. Regarding the pool models (i.e. including both men and women), in the most deprived department (Seine-Saint-Denis), living in a more deprived neighbourhood is associated with a lower odds of reporting car use, while in the wealthiest department (Yvelines), living in a more deprived neighbourhood is associated with a higher odds of car use. This context-specific relationship contributes to a better understanding of inconsistent findings emerging from the literature, with some studies reporting negative relationships between neighbourhood socioeconomic deprivation and the odds of car or motorised transport use (e.g. Rachele et al. (2015) in Australia; Licaj et al. (2012) in France; Van Dyck et al. (2010) in Belgium) and others reporting positive relationships (e.g. Goodman (2013) in England; Xiao et al. (2018) in the US).

Specifically in the Paris region, this territorial heterogeneity of the relationship between neighbourhood deprivation and car use is generally consistent with the results derived from the main transport survey conducted in this region in 2009-2011 among 18,000 households (43,000 individuals). This survey, coordinated by the organization controlling the regional public transport network (Île-de-France Mobilités), provided descriptive statistics about travel modal shares (active modes, car and public transport) at an intradepartmental scale, within sectors each encompassing a few municipalities (Schmidt, 2013). For instance in the Seine-Saint-Denis department, the modal share of private car appeared lower in the western sectors (~21% in the municipalities of Saint-Denis and Aubervilliers) and higher in the southeastern part (e.g. ~40% at Le Raincy and ~50% at Noisy-le-Grand) (OMNIL, 2013a). Given that the geography of socioeconomic deprivation in this department follows a similar gradient, a negative relationship between deprivation and car use close to the one we highlighted might be extrapolated. Conversely, in the Yvelines department, the modal share of car reached 70% in the western most sectors, against only ~40% in the eastern sectors (OMNIL, 2013b). Yet, the Yvelines deprivation exhibits a west-east gradient, the least deprived areas being located eastward, implying a positive relationship between deprivation and car use.

Some hypotheses can be put forward to better understand these context-specific findings. Such territorially heterogeneous relationships necessarily reflect contextual effects, involving complex interacting mechanisms, at different geographical scales. Beyond the intrinsic characteristics of each spatial context, their spatial position in the broader urban system hierarchy plays a key role, as it relates to the built environment and in particular to the accessibility of alternative modes to

the car, i.e. to public transport density that in turn conditions car use (den Braver et al., 2020; Ewing & Cervero, 2010; Park et al., 2018). Living in a deprived neighbourhood in the immediate suburbs of Paris, or in remote peri-urban areas, obviously affects the odds of driving as it relates to accessibility and distances to opportunities. The opposite trends that were observed in the Seine-Saint-Denis and Yvelines departments, whether among men or women, could be explained by these considerations. These two departments are differently patterned and situated in the broader urban hierarchy. In Seine-Saint-Denis, some of the most deprived places are located just near Paris, and therefore may benefit from a well-developed public transport network. Obviously, some deprived neighbourhoods are isolated from car alternatives (in the northern part of the department), but one can hypothesise that in these very deprived places – actually the most deprived areas even at the country scale – people favour a cheaper mode of transport than the car (Calvier & Jacquesson, 2015). Hypotheses regarding the positive relationship between car use and deprivation in the Yvelines department might be different. In this outer belt and generally wealthier-than-average department, the most deprived neighbourhoods are those furthest from Paris (western part), beyond some exceptions. In these less dense remote areas, deprived at the department scale but within the average at the regional scale, it would be beneficial to use a car because of the greater distances and more car-oriented environments. Public transport supply in these outer suburbs is often partial with a weak territorial grid, since the network is radial, oriented toward Paris and not to other suburbs (Cornut & Madre, 2017). In other words, the built environment (in terms of drivability and public transport accessibility) and socioeconomic deprivation are likely to be correlated. In addition, the absence of relationship in the Hauts-de-Seine department could be explained by context-specific built environmental characteristics. In this department, car alternative modes are more used than in other inner suburbs, whatever the level of deprivation, because commuting travels are shorter. This is related to the higher job densities, notably due to the presence of La Défense, the largest business district of the Paris region (Calvier & Jacquesson, 2015). In any case the very specific context of Paris in its broader region must be considered. Within Paris, only 30% of the participants use their car, versus more than 60% in the whole sample, which is consistent with car ownership statistics provided by the population census data in this region (Calvier & Jacquesson, 2015). The density of public transport in Paris is considerable, favouring a higher use of car alternative modes, whatever the deprivation level (Feuillet et al., 2015). Paris also includes on average highly advantaged neighbourhoods, implying to keep a sense of proportion regarding its disadvantaged ones.

A second hypothesis for explaining context-specific relationships could relate to the role of the car as a symbol of individual's social status. It has been shown that possessing a car has symbolic values, as the car "projects how we like to see ourselves, and how we would like others to see us" (Moody & Zhao, 2019:335). One can assume that this 'car pride' could be higher in deprived neighbourhoods surrounded by well-to-do areas – as is the case in this Yvelines context. Yet, this 'car pride' is in turn associated with car ownership and use (Moody & Zhao, 2020). A third explanation could involve the current austerity context that has weakened the car ownership – financial circumstances relationship context, leading to a forced car ownership issue (Curl et al., 2018). These last authors have shown in their study that most households maintain or acquire a car despite financial distress, as the car can be viewed as a route out of poverty (Curl et al., 2018). In turn, this can lead to transport poverty, i.e. when car-related costs (car ownership and usage) exceed what disadvantages households can afford (Lucas et al., 2018).

Another major finding of our study is to have exhibited some strong gender-specific relationships. Such sex-specific preferences in travel behaviour have already been highlighted in many studies since the pioneering work of Rosenbloom (1978). In the Greater Paris Region, Picard et al. (2018) indicated for instance higher disutility of travel time (whether private car or public transport) for women than for men. In our study, we emphasised that the relationship between car use and neighbourhood deprivation among women was mostly positive, especially in Paris and Yvelines. Therefore the spatial context of residence affects differently the use of car according to gender. Even if this finding is difficult to interpret without further in-deep qualitative analyses on this subsample, one can assume that this could be due to the feelings of insecurity in public transport among women that is, in average, stronger than among men (Vanier & d'Arbois de Jubainville, 2017). This is confirmed by the results of a recent survey conducted in 2019 in the Greater Paris area among 50,000 adults having a transit pass, and focusing on the feeling of insecurity in public transport (Noble, 2020). According to this survey, 49.6% of men stated they never have been afraid in public transport, while only 32.6% of women. Therefore women's heightened concern for personal safety, as well as their lower perceptions of safety, affect their mobility choices and behaviours (Loukaitou-Sideris & Fink, 2009; Stark & Meschik, 2018; Valentine, 1989). In some contexts, private car use is considered as the only option for women to avoid negotiating their fears in public space (Dobbs, 2005; Hidayati et al., 2020; Masood, 2018). It could be assumed that this perceived insecurity would be higher in deprived neighbourhoods, as reported in similar geographical contexts (Gardner & Abraham, 2007; Loukaitou-Sideris, 2014; Yavuz & Welch, 2010), leading women to prefer the car alternative in these specific areas.

Whatever the true causal mechanisms generating such context-specific elasticities, this study reinforces the idea that relationships between the residential environment and transport choices are place-specific, as reported in other transport-related contextual studies (Chiou et al., 2015; Feuillet et al., 2015, 2016; Goodman et al., 2012; Salon, 2015). Places, as complex spatial systems, play the role of moderators in the more general causal pathways linking environmental characteristics to travel behaviours. This insight means that only looking at global (i.e. average) statistical relationships may disregard local ones and lead to biased or incomplete interpretations of the actual pathways. The implications for public policies are important, since the effectiveness of social or land use planning decisions on car use may vary according to local contexts. Therefore, such environment-transport relationships should be understood through local analyses (e.g. random slope multilevel or spatially-varying coefficients models) rather than global ones only. Such a context-specific strategy could help to balance the new challenges facing policy makers for tackling private car use in favour of public transport, in relation to the COVID-19 outbreak. Physical distancing recommended by most governments seriously challenges the very concept of mass public transportation (Tirachini & Cats, 2020) and some recent studies indeed demonstrated a significant decrease of the use public transport following the outbreak (Beck & Hensher, 2020; Zambrano-Monserrate et al., 2020). New solutions and measures will be needed in the post-epidemic transport world, that could involve locally tailored adaptations.

The limitations of this study relate to its cross-sectional design, impeding any causal inferences, as well as the non-consideration of activity spaces other than residential ones, which may potentially influence mode choices (Perchoux et al., 2014). Finally, our questionnaire and analyses combined both revealed and stated preferences regarding alternative specific variables (i.e. mode cost and travel time). This can cause a 'state dependence' effect, defined by Hensher (2008) as the influence of the actual (revealed) choice on the stated choices of the individual. This influence may be positive (e.g. due to habit persistence or inertia to explore another alternative) or negative, for instance as the result of latent frustration associated with the revealed choice (Bhat & Castelar, 2002). In order to assess this possible bias, all the models were estimated by replacing specific alternative variables by revealed cost and travel time for the used mode only. These models led to very similar results than the ones presented in this study (data not shown).

Conclusion

This study focused on the relationship between residential neighbourhood socioeconomic deprivation and the use of the private car among a gender-stratified sample of 1,722 French workers of the Paris area, after controlling for potential confounders (age, mode cost and travel time, household size, population density, distance to Paris and public transport accessibility). We hypothesized in Introduction that this relationship could be non-linear and territorially patterned, which might partly explain inconsistent findings found in the scientific literature. To this end, we used an original modelling technique combining generalized additive models with multilevel models. Results showed that among women, living in a more deprived neighbourhood was associated with an increase in the odds of reporting car use up to a certain threshold, after which the relationship plateaued. Among men, this relationship appeared linearly negative. Locally, in the Seine-Saint-Denis department, the most deprived of the Paris region, living in a more deprived neighbourhood was associated with a lower odds of car use among men while a more complex nonlinear bell-shaped relationship was observed among women. The opposite was found in the wealthier Yvelines department, with negative relationship among women and U-shaped one among men. In Paris inner city, again a strong opposite trend was distinguished according to sex, with negative relationship among women, that could be due to a greater feeling of unsafety in public transportation among women in deprived neighbourhoods. The same rationale could be applied in the Yvelines department. We explained these geographical nuances by the interaction between the deprivation and specific spatial position of the studied neighbourhoods in the broader urban system hierarchy (from inner suburbs to peri-urban areas). Overall, this study suggests that the relationship between neighbourhood deprivation and private car use cannot be seen in average over an entire study area, as it depends on spatially patterned moderating factors that shape spatial local contexts. The resulting territorially heterogeneous relationships might in turn explain the paradox stated in introduction, i.e. conflicting results according to study locations. Consequently, public policies aiming at reducing car use should be not only gender-specific, but also context-specific rather than global.

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