



Choosing Green Mobility for Commuting: Who and Where? Exploring the Effect of Urbanisation on Commuting Mode Choice

Florian Fouquet, Emma Weiss-Blanchard

► To cite this version:

Florian Fouquet, Emma Weiss-Blanchard. Choosing Green Mobility for Commuting: Who and Where? Exploring the Effect of Urbanisation on Commuting Mode Choice. 2025. <hal-04927945>

HAL Id: hal-04927945

<https://hal.science/hal-04927945v1>

Preprint submitted on 4 Feb 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

Choosing green mobility for commuting: who and where?

Exploring the effect of urbanisation on commuting mode choice

Florian Fouquet^a

florian.fouquet@univ-lemans.fr

Emma Weiss-Blanchard^a

emma.weiss-blanchard@univ-lemans.fr, *Corresponding author*

Affiliation :

^a GAINS-TEPP, Le Mans Université, Avenue Olivier Messiaen 72085 Le Mans Cedex 9, France.

Abstract

Although central in individuals' daily life, commuting is a major environmental burden due to greenhouse gas pollution. In this context, green mobility might play a role towards a more sustainable commuting behaviour. The aim of this work is to explore the determinants of a green commuting mode choice, investigating both individual factors and contextual drivers. To this end, we estimate multinomial logit models using mobility data from the French population census. Our results show the role of socio-demographic characteristics in the choice of a green transportation mode, but also highlight the importance of local characteristics, especially transport infrastructures (public transport and bicycle paths). However, exploring the spatial heterogeneity between areas with different degrees of urbanisation, we show that this is true only in large cities, while the effect in less urbanised areas becomes insignificant.

Keywords: green mobility, sustainable mobility, commuting, individual behaviour, contextual effects, spatial heterogeneity

JEL Codes: P25, Q52, R41

1. Introduction

An important part of the fight against climate change is related to the reduction of greenhouse gas (GHG) emissions. Transportation contributes to between a quarter and a third of GHG emissions in the world (International Energy Agency, 2020; United Nations, 2019), among which individual mobility accounts for a large amount. Despite its strong negative environmental externalities, individual mobility is an essential part of our modern lives, as it allows access to different amenities and activities, such as employment, education, leisure or social events, etc. Therefore, sustainable mobility, or green mobility¹, is central in reducing GHG pollution. In order to promote sustainable mobility, work-related travels are of particular interest: in 2017 in France, 74% of the workers used their private car daily for commuting (Brutel and Pages, 2021). Although this share might have decreased since the Covid-19 pandemic with the expansion of teleworking (Kalter et al., 2021; Reiffer et al., 2023), many jobs cannot be done at home (Dingel and Neiman, 2020), leading to a still strong reliance on private transportation modes for commuting. It remains therefore crucial to explore the determinants of commuting mode choices in order to highlight the factors that could lead to behavioural changes towards green mobility.

This paper aims to explore the factors influencing the choice of a sustainable mobility for daily commuting. Especially, we want to distinguish between individual drivers and contextual effects in the probability of choosing a green mobility for commuting. Some studies have conducted cross-countries comparisons to explore the influence of contextual effects on the adoption of green mobility (see e.g. Buehler, 2011; Buehler and Pucher, 2012; Echeverría et al., 2022b; Panik et al., 2019). However, transportation policies (public transports, urban planning and management, etc.) are often implemented by local territorial authorities rather than nationwide. Using data from the French population census for year 2019 and information from various sources on the local context, we mobilise multinomial logit models to estimate the impact of individual and contextual variables, observed at the scale of the French NUTS3 areas², on commuting mode choices. In addition, we rely on spatial regimes models to account for spatial heterogeneity depending on the degree of urbanisation of areas.

Our results highlight the role of individual characteristics on the choice of a green transportation mode, but also the importance of local contextual factors. Consistent with previous literature, we show that women and older workers tend to be more prone to use sustainable mobilities, and evidence a clear effect of the educational level and job characteristics. We also show that commuting distance has a negative impact on the use of active transportation modes, but has limited effects on public transport use. As for contextual factors, we show that the presence of transport infrastructures and additional public expenditures increase the use of green mobility, but that this effect holds only in large urban areas, questioning the levers to promote it in other areas. Besides, public transport prices do not seem to be a lever either.

The remainder of the paper is organised as follows. Section 2 provides a review of previous evidence about drivers of commuting mode choices. Section 3 describes the data and variables. Section 4 explains

¹ We understand here by “green mobility” or “sustainable mobility” transportation modes that produce low(er) levels of GHG emissions, such as public transports or active mobilities (walk or bike).

² These statistical divisions, defined by Eurostat, correspond to French administrative division of the country in *départements*.

the empirical strategy and spatial regimes models. Section 5 presents and discusses the results. Section 6 concludes.

2. Literature review

Previous research explored some of the drivers of commuting mode choice. The first element to note is that some drivers are different for active mobility and public transports, especially due to differences in associated flexibility and well-being (Echeverría et al., 2022a). At the individual level, the use of a green mobility is related to a number of socio-demographic characteristics. Age has been shown to affect this choice, with younger people favouring green mobility (Adams, 2010; Buehler and Pucher, 2012; Kim and Ulfarsson, 2008). Older people, on the contrary, tend to be more reliant on private vehicles because of health problems and public transports less adapted to their needs (Wong et al., 2017, 2018). For middle aged people, the lower use of sustainable mobility can be related to the lack of flexibility of these commuting modes. Indeed, strong constraints, such as the presence of young children, can make public transport less suitable for this population (Thorhauge et al., 2020). Gender also has a significant influence on the choice of mobility. Men prefer car for commuting, while women have a marked preference for public transport and active mobility (Buehler, 2011; Echeverría et al., 2022b). This preference can be explained by the location of the job furthest away for men (Havet et al., 2021; McQuaid and Chen, 2012), which influences commuting mode choice. Also, disparities in housework responsibilities, especially in presence of children, can explain heterogeneous mobility choices across genders (Giménez-Nadal and Molina, 2016). More generally, household composition (marital status and presence of children) influences the choice of mobility (Buehler, 2011; Echeverría et al., 2022b; Kim and Ulfarsson, 2008; Panik et al., 2019). On the one hand, households with children often have significant time management and constraints, leading to heavy car use. On the other hand, the presence of children can encourage individuals to live closer to economic centres, in order to have access to most services in the same area, allowing a greater use of active mobility. However, previous evidence suggests that the first mechanism outweighs the second (Echeverría et al., 2022a). Then, occupation is an important factor in the choice of mobility (Adams, 2010). Furthermore, in different occupational categories, the characteristics of the job can influence mobility preferences. For example, people in managing occupations tend to make a lower use of active mobility (Adams, 2010). This trend can be explained by professional requirements that call for greater flexibility in working hours, implying greater use of the car. The educational level also plays a significant role in the commuting mode choice (Echeverría et al., 2022b). Individuals with higher levels of education tend to favour active transportation to go to work (Kruger et al., 2008; Panik et al., 2019), and green mobility in general (Plaut, 2005). This preference can be explained by a greater awareness of environmental issues, that increases with education (Ajibade and Boateng, 2021). However, a higher educational level can also be associated with a high level of income, which negatively influences the use of green mobility like active transportation (Kruger et al., 2008), nuancing the effect of education. Indeed, income is a determining factor, with people with higher incomes having a tendency to use cars more, as they are more likely to own one (Buehler, 2011), and to make a lower use of active mobility (Plaut, 2005).

Commuting mode choices are also influenced by characteristics of the areas where people live and work. In particular, access to transport infrastructures can play an important role (Echeverría et al., 2022b). In

urban areas, public transport options are often more developed, offering individuals a viable alternative to the car. In rural areas, on the contrary, public transport options are often limited, which can lead to greater dependence to private modes for daily travel. This same mechanism plays a key role when it comes to active mobility. For instance, Pucher and Buehler (2008) showed that access to extended bicycle roads is a key element in encouraging the use of cycling as a mode of transport: increasing the length of the bicycle network has a positive impact on the adoption of this form of mobility (Santos et al., 2013). Thus, since jobs are mainly located in city centres (Ottaviano and Thisse, 2004), people living in rural areas tend to have a greater commuting distance, which may also lead them to choose to use a private vehicle. In addition, the choice of mobility is also affected by their costs: the higher the cost of a transportation mode, the greater the disincentive to adopt it. This applies to both vehicle purchase and fuel costs, which can reduce car use for commuting (Belloc et al., 2024; Dargay and Hanly, 2007; Santos et al., 2013). Similarly, high prices for public transport can also discourage their use (Santos et al., 2013). Besides, mobility choices can be influenced by weather conditions (De Witte et al., 2013). For example, cycling may become less attractive in rainy regions (Kim and Ulfarsson, 2008), which may lead people to opt for other modes of transport. Similarly, topography can have an impact on the choice of mobility (Kim and Ulfarsson, 2008): the use of active mobility is harder in mountain regions.

3. Data and variables

3.1. Data

We use data from the *Professional mobilities* base of the French population census for year 2019, which include information about the main commuting mode of working individuals, as well as socio-demographic, economic and geographical variables for a large sample. This dataset includes precise information about family structure, job characteristics, along with the residential and workplace locations at the municipality level. Many studies about transportation choices rely on time-use surveys (see e.g. Adams, 2010; Echeverría et al., 2022b; Giménez-Nadal et al., 2024; Panik et al., 2019), as they include detailed information about activities performed during the day, allowing to determine a precise schedule of individuals, especially regarding commuting time. We rather choose to use census data for two main reasons. Firstly, the last time-use survey carried out in France was in 2009-2010, which makes it relatively out of date, given that mobility behaviours are likely to have changed considerably since then, due to increasing environmental awareness (see in particular Caferra et al., 2025, on how natural disasters increase environmental awareness, which in turn affects mobility choices). Secondly, census data cover the entire country and provide a large sample size (around 8 million individuals), allowing us to investigate the effects of a large set of variables, both at the individual and local levels.

We exclude from our sample individuals living and/or working in overseas territories and Corsica, individuals working abroad, as well as individuals over 65 years old. We also exclude individuals who report not using any transportation mode for commuting, because these people live and work in the same place. Our final sample consists of 7,330,225 working individuals³.

³ We also exclude from our sample the 3,026 individuals for which METRIC does not compute commuting distances. Most of them live on islands, making it impossible for METRIC to compute road distances.

Regarding contextual variables, we gather data from several sources in order to have information on transport infrastructure, local and geographical characteristics at the scale of the NUTS3 areas⁴. We use data from the *Enquête TCU* from Cerema, GART & UTP (2017) to compute the length of the public transport network, the average price of public transport and the presence of a self-service bicycle system. This database does not include information about Paris and its region, we thus retrieve its public transport network from *Île-de-France Mobilités*, which is the region's public transport management organisation. We use the *Géovélo* data available on the website of the French Ministry of transports for the length of the bicycle paths network. Finally, we use census data to compute the unemployment rate in each area and include public expenditures related to transport at the NUTS3 areas from the 2019 local authority accounts.

One limitation using these various sources is that all information is not available for year 2019. Therefore, we use information ranging from 2015 to 2021 depending on the source, especially for lengths of networks. This has to be kept in mind interpreting our results, as it might affect our estimations. However, historical data from the *Enquête TCU* show that public transport networks do not vary much over the years, which should prevent excessive bias.

3.2. Variables

3.2.1. Individual variables

Our data allow us to explore the effects of a large set of variables. As for demographic characteristics, we include gender, age, nationality, and household structure (living in a couple and having children). Given that the household structure is likely to have heterogeneous effects depending on gender (Giménez-Nadal and Molina, 2016; Havet et al., 2021), we interact gender with couple status and presence of children. We also include information about the educational attainment of individuals, as it has been shown to affect commuting mode choice towards green mobility (Echeverría et al., 2022b; Panik et al., 2019). Previous literature showed that income influences the choice of a green mobility (Buehler, 2011; Kruger et al., 2008). Unfortunately, our data do not include information about income. Instead, we include information about home ownership and job characteristics (part-time work, temporary contracts, occupation, employment sector), which should allow us to proxy, although not perfectly, income disparities. Finally, we include information about commuting possibilities, with the number of cars owned by the household and commuting distance. We calculate commuting distance using METRIC, the distance calculator built by Insee⁵. METRIC computes the shortest road distance between the municipality of residence and the municipality of work. For people who both live and work in the same municipality, METRIC computes the distance between a random point on the surface and the area where most of the population is concentrated (generally around the city hall). Although the distance calculated this way might suffer from a lack of precision, this allows us not to assume that people who live and work in the same municipality travel a null distance to go to work⁶. Nevertheless,

⁴ All data sources are summarised in Table A1 in Appendix A.

⁵ METRIC can be accessed upon request at <https://data.progedo.fr/studies/doi/10.13144/apf-0004>.

⁶ To check for the robustness of our choice, we also estimate the model using the Euclidean distance between centroids of the municipalities and affecting null values to people who both live and work in the same location. As shown in Table B2 in Appendix B, this does not substantially affect our results.

this bias is likely to lead to an underestimation of the actual commuting distances (especially in urban areas) and, to some extent, distort our understanding of the mechanics of mobility choices. However, this phenomenon will be partially taken into account in models of spatial regimes, given that most of the workers who live and work in the same municipality are located in urban areas.

Table 1 – Descriptive statistics – Individuals variables

	Whole sample Mean	Rural Mean	Suburban Mean	Small urban Mean	Large urban Mean	Paris Mean
<i>Commuting mode</i>						
Private vehicle	0.677	0.875	0.870	0.801	0.643	0.405
Active mobility	0.130	0.102	0.077	0.139	0.164	0.125
Public transport	0.193	0.023	0.053	0.060	0.193	0.470
Woman	0.489	0.478	0.494	0.490	0.492	0.493
Living with a partner	0.637	0.742	0.725	0.623	0.572	0.599
Having children	0.492	0.553	0.563	0.485	0.431	0.487
<i>Age</i>						
15-19 years old	0.016	0.019	0.016	0.020	0.016	0.011
20-29 years old	0.193	0.139	0.145	0.186	0.243	0.204
30-39 years old	0.254	0.242	0.241	0.236	0.261	0.273
40-49 years old	0.260	0.289	0.284	0.266	0.234	0.253
50-59 years old	0.235	0.271	0.273	0.251	0.206	0.213
60-64 years old	0.042	0.040	0.041	0.042	0.040	0.046
Foreigner	0.075	0.021	0.028	0.052	0.077	0.146
<i>Education</i>						
Lower than secondary	0.129	0.126	0.106	0.146	0.117	0.138
Secondary education	0.428	0.544	0.460	0.485	0.382	0.330
Short-cycle higher education	0.287	0.262	0.308	0.277	0.309	0.288
Long-cycle higher education	0.183	0.076	0.137	0.115	0.218	0.297
<i>Occupation</i>						
Farmers and craftspeople	0.072	0.118	0.077	0.070	0.054	0.050
Manager / professional	0.211	0.146	0.186	0.140	0.221	0.314
Associate professional	0.275	0.290	0.296	0.267	0.278	0.257
Employee	0.286	0.312	0.276	0.306	0.284	0.256
Blue-collar worker	0.199	0.292	0.188	0.238	0.168	0.126
<i>Employment sector</i>						
Agriculture	0.019	0.062	0.011	0.014	0.004	0.001
Industry	0.113	0.160	0.138	0.138	0.093	0.069
Construction	0.060	0.080	0.065	0.063	0.051	0.049
Services	0.494	0.390	0.453	0.445	0.512	0.609
Administration, health, education	0.315	0.308	0.333	0.340	0.340	0.273
Temporary employment	0.140	0.122	0.112	0.156	0.169	0.123
Working part-time	0.164	0.168	0.165	0.174	0.181	0.136
<i>Car ownership</i>						
No car	0.119	0.015	0.019	0.057	0.125	0.274
One car	0.402	0.263	0.286	0.409	0.497	0.451
Two cars	0.386	0.553	0.546	0.439	0.325	0.226
Three cars or more	0.092	0.169	0.149	0.096	0.053	0.048
Home owner	0.548	0.772	0.700	0.529	0.427	0.447
Commuting distance (in km)	19.98	24.99	22.47	21.24	17.96	16.17
Number of observations	7,330,225	1,686,158	490,664	1,257,731	1,989,307	1,906,365

Source: French population census, *Professional mobilities* data.

Descriptive statistics about the individual variables in our sample are reported in Table 1. Private vehicles are the main commuting mode in our sample (67.7%), far ahead of public transport (19.3%) and active mobility (13%). However, there are differences depending on the urbanisation of the place of residence. Active mobility represents between 10% and 15% in all regimes, except in suburban areas. Disparities in terms of public transport and car use are much stronger: around 88% of the individuals use their private vehicle for commuting in rural areas against 2% using public transport; these shares are respectively 64% and 19% in large urban areas. Suburban areas appear to have a distribution of commuting mode choices close to rural areas, while small cities show a slightly higher reliance on active mobility. Paris has a completely different distribution of transportation modes, with public transport

being the main mode (47.0%) and private vehicles the second (40.5%). The average commuting distance is also higher for workers living in rural municipalities, which is consistent with jobs being primarily located in cities (Ottaviano and Thisse, 2004). Maybe as a consequence, car ownership (and multiple cars) is more frequent in rural than in urban areas. Except for the Paris region, the vast majority of households possesses at least one car. As for demographics, the population appears to be slightly older in rural than in urban areas or in Paris. Workers are also more educated and occupy more often managing occupations in urban areas, and even more in Paris, consistent to previous evidence (Combes et al., 2012). Household structures are larger in rural and suburban areas, with individuals more often living with a partner and having children. More generally, we observe a strong opposition between rural and urban areas, and to an even greater extent with Paris, which reinforces the need to explore spatial heterogeneity.

3.2.2. *Contextual variables*

One of our aims is to explore how local characteristics can affect commuting mode choice. We include variables about transport infrastructures, namely the density of the public transport network (calculated as the length of the public transport network divided by the number of kilometers of road in each NUTS3 area) and the length of bicycle paths in each area, as well as public transport prices (average price of a single use ticket). We choose to include the unemployment rate to have information on the labour market dynamism of the areas. We include public expenditure on transport at the NUTS3 areas level. It has to be noted that in France, the management of public transports is a regional rather than a *département* responsibility. Therefore, our variable reflects political choices and investment decisions at the local level rather than mandatory public expenditures. We also include geographical information: areas sharing a border with another country might benefit from cross-border transport infrastructures that do not appear in our database; littoral and mountain variables are included to account for the difference of topography between areas. Descriptive statistics about the contextual variables in our sample are reported in Table 2.

Table 2 – Descriptive statistics – Contextual variables

	Mean	Min	Max
Length of public transport network (in km)	1,033.12	0	14,719.75
Density of public transport network	0.25	0	2.40
Average price of public transport network (in €)	1.20	0	1.90
Length of bicycle paths network (in km)	641.79	56.51	2980.29
Self-service bicycle system	55.3%		
Public expenditure on transport per capita (in €)	16.97	0	272.30
Unemployment rate	0.128	0.086	0.188
Border area	23.4%		
Littoral area	43.9%		
Mountain area	50.3%		
Number of observations	94		

Source: *Enquête TCU* (Cerema, GART & UTP, 2017), *Île-de-France Mobilités* data, *Géovélo* data, Local authorities accounts data, French population census, Massifs perimeters ANCT data.

The average length of the public transport network is around 1,033km, but this hides strong disparities between areas: some areas have extensive public transport infrastructures, while we have one area without any regular public transport lines. The average price of public transport tickets is moderate,

especially in comparison with other European countries. It also has to be noted that some areas provide free public transport services. All areas have bicycle paths, however, as for public transport, we observe strong spatial disparities. On average, public transport networks represent 25% of the length of NUTS3 areas road networks. However, this density varies considerably, with particularly high densities in the Paris region, which benefits from a high concentration of transport infrastructures on a relatively small surface. Only a small number of areas do not invest in transports, but the average transport expenditures per capita remains quite small, around 17€.

4. Empirical strategy

4.1. Modelling commuting mode choice

The aim of this work is to model commuting mode choice in order to explore the drivers of green mobility behaviour. Following Anas (1981) or Schwanen and Mokhtarian (2005), we use a multinomial response model, which can be written (using a latent variable) as:

$$y^{k*} = \beta_0^k + X\beta_1^k + u \quad (1)$$

$$\text{where } y = \begin{cases} k & \text{if } y^{k*} > y^{m*}, \forall k \neq m \\ m & \text{otherwise} \end{cases}$$

with k and m denoting alternative commuting mode choices. We consider three commuting modes in our analysis: (1) private vehicle, (2) public transport and (3) active mobilities (walking or biking). In such a model, coefficients are estimated as variations from a baseline category. We choose to consider the use of a private vehicle as the baseline category because it is both the main commuting mode in our sample and the least ecological. We report our results in terms of relative risks (RR): for instance, a RR of 1.2 associated to a given variable implies that individuals with this characteristic have a 20% higher probability to choose this alternative than individuals without that same characteristic.

Multinomial models are based on the independence of irrelevant alternatives (IIA) assumption. This assumption implies that the inclusion of an additional alternative does not modify the odd ratios between the other alternatives. In our case, this means for instance that individuals who choose to use their private vehicle over active mobilities in absence of public transport would not decide to walk/bike instead of driving if we add the possibility to take the bus. This assumption would be likely to be violated in the case of multi-modal commuting choice (i.e. a mix of different transportation modes). However, our data reports only the main commuting mode, and our three modalities are mutually exclusive and distinct. Moreover, as a robustness check, we estimate the models removing the different modes alternatively and obtain substantially similar results (see Table B1 in Appendix B), which supports the IIA assumption.

4.2. Spatial heterogeneity

How commuting behaviours are affected by both socio-demographic and local characteristics might vary depending on the localisation on the individuals, suggesting spatial heterogeneity has to be taken into account (Anselin, 1988; Le Gallo, 2004). In particular, it has been shown that mobility behaviours vary between rural and urban areas for both work-related trips (Giménez-Nadal et al., 2020) and non

work-related trips (Giménez-Nadal et al., 2024), especially due to differences in transport infrastructures (Echeverría et al., 2022b). Besides, employment tends to be mostly localised in cities (see Ottaviano and Thisse, 2004, for a review about the localisation of economic activities), implying longer commuting distances on average for individuals living in rural areas. In addition, Giménez-Nadal et al. (2020) highlight that spatial heterogeneity in commuting behaviours varies by gender and employment status.

We take spatial heterogeneity into account using spatial regimes models. This kind of model allows us to estimate heterogeneous coefficients for the variables depending on the type of localisation. We consider five spatial regimes, depending on the population density and urbanisation of the area, based on the municipal density grid of Insee⁷. The regimes are as follows: rural municipalities, suburban municipalities, small to mid-size urban municipalities, large urban municipalities, and the Paris region. Small to mid-size urban municipalities typically are secondary cities of the areas, while large urban municipalities are the economic centre. However, in some areas, the largest economic center is categorised as a mid-size urban city.

We consider a specific regime for the Paris region (i.e. the administrative region *Île-de-France*), because this area has a population density strongly higher than the rest of the country, concentrates 20% of the French labour force (see Combes et al., 2012, 2015, about the central role of Paris on the French labour market) and has a specific urban structure, which translates into strong differences in mobility behaviours (see Table 1). More generally, the spatial and urban structure of the *Île-de-France* region is very different from that of the rest of France. Of the eight départements in the region, the four central ones are composed exclusively of municipalities classified under the large urban spatial regime. In terms of population and transport networks, these areas have distinct characteristics compared with the rest of the country. Besides, its high density of transport network favours the creation of numerous employment sub-centres (Garcia-López et al., 2017a, 2017b), giving the *Île-de-France* region specific characteristics that differentiate it from other French regions. Although we could include the municipalities of the Paris region in the other regimes based on the density grid, we only include them in the Paris regime, so that the five regimes are mutually exclusive. Besides, by defining *Île-de-France* as a distinct spatial regime, this makes it possible to isolate its particularities without impacting other spatial regimes, even though results for this regime must be taken with caution.

Among the 34,767 municipalities in our sample, 29,934 (23.5% of the individuals) are in the rural regime, 1,751 (6.8% of the individuals) are in the suburban regime, 1,336 (17.2% of the individuals) are in the small urban regime, 459 (26.8% of the individuals) are in the large urban regime, and 1,287 (25.7% of the individuals) are in the Paris regime. Following Le Gallo (2004), our model can be written as:

$$y^{k*} = X\beta_R^k D_R + X\beta_C^k D_C + X\beta_{U2}^k D_{U2} + X\beta_{U1}^k D_{U1} + X\beta_P^k D_P + u \quad (2)$$

$$\text{where } y = \begin{cases} k & \text{if } y^{k*} > y^{m*}, \forall k \neq m \\ m & \text{otherwise} \end{cases}$$

where D_R , D_C , D_{U2} , D_{U1} and D_P are the dummy variables denoting the spatial regimes, respectively equal to 1 if the individual is living in a rural municipality, living in a suburban municipality, a small to

⁷ Grille communale de densité à 7 niveaux, Insee, Observatoire des territoires; <https://www.insee.fr/fr/information/6439600>

mid-size urban municipality, a large urban municipality, and the Paris region (0 otherwise). The results of the Chow test in Table 4 confirms that coefficients differ depending on the regime, hence the presence of spatial heterogeneity.

5. Results

5.1. Determinants of commuting mode choice

Table 3: Determinants of commuting mode choice - Multinomial logit models

	Specification 1				Specification 2			
	Active mobility		Public transport		Active mobility		Public transport	
	RR	SE	RR	SE	RR	SE	RR	SE
Individual variables								
Woman	0.853***	0.004	1.285***	0.005	0.865***	0.033	1.364***	0.028
Living with a partner	1.215***	0.005	1.305***	0.006	1.203***	0.022	1.172***	0.040
Having children	0.865***	0.004	1.033***	0.004	0.848***	0.011	0.912***	0.016
Woman x Living with a partner	1.501***	0.008	1.248***	0.007	1.485***	0.016	1.226***	0.031
Woman x Having children	1.113***	0.006	0.955***	0.005	1.118***	0.018	0.948***	0.013
<i>Age (ref: 20-29 years old)</i>								
15-19 years old	2.587***	0.025	2.861***	0.025	2.440***	0.046	2.785***	0.101
30-39 years old	0.870***	0.004	0.773***	0.003	0.888***	0.008	0.782***	0.005
40-49 years old	1.017***	0.004	0.799***	0.003	1.036***	0.014	0.810***	0.012
50-59 years old	1.214***	0.005	0.898***	0.003	1.223***	0.020	0.883***	0.016
60-64 years old	1.417***	0.009	0.987**	0.006	1.413***	0.031	0.903***	0.020
Foreigner	1.257***	0.006	2.213***	0.009	1.173***	0.054	1.679***	0.058
<i>Education (ref: Lower than secondary)</i>								
Secondary education	0.900***	0.003	0.883***	0.003	0.905***	0.006	0.915***	0.009
Short-cycle higher education	0.949***	0.004	1.166***	0.004	0.941***	0.012	1.122***	0.011
Long-cycle higher education	1.433***	0.006	1.792***	0.007	1.354***	0.044	1.484***	0.026
<i>Occupation (ref: Blue-collar worker)</i>								
Farmers and craftspeople	2.248***	0.010	0.553***	0.004	2.556***	0.130	0.503***	0.020
Manager / professional	1.628***	0.007	2.127***	0.009	1.525***	0.039	1.449***	0.069
Associate professional	1.240***	0.004	1.437***	0.006	1.218***	0.028	1.139***	0.030
Employee	1.833***	0.006	1.712***	0.006	1.821***	0.027	1.483***	0.035
<i>Employment sector (ref: Services)</i>								
Agriculture	1.396***	0.012	0.077***	0.002	1.591***	0.091	0.198***	0.018
Industry	0.707***	0.003	0.437***	0.002	0.727***	0.019	0.530***	0.026
Construction	0.350***	0.003	0.414***	0.003	0.362***	0.009	0.446***	0.024
Administration, health, education	1.308***	0.004	0.782***	0.002	1.370***	0.037	0.938	0.053
Temporary employment	1.108***	0.004	1.208***	0.004	1.118***	0.016	1.394***	0.017
Working part-time	1.097***	0.004	1.046***	0.003	1.105***	0.013	1.204***	0.016
<i>Car ownership (ref: One car)</i>								
No car	6.005***	0.025	11.16***	0.040	5.433***	0.219	7.854***	0.575
Two cars	0.389***	0.001	0.252***	0.001	0.405***	0.010	0.343***	0.010
Three cars or more	0.373***	0.002	0.245***	0.001	0.387***	0.009	0.328***	0.012
Home owner	0.781***	0.002	0.795***	0.002	0.797***	0.012	0.841***	0.023
Commuting distance (in km)	0.971***	0.000	1.002***	0.000	0.973***	0.004	1.003***	0.000
Constant	0.198***	0.001	0.192***	0.001	0.171***	0.036	0.001***	0.001
Contextual variables								
Density of public transport network (log)					0.976	0.039	2.020***	0.197
Average price of public transport ticket (in €)					1.004	0.086	1.302	0.281
Length of bicycle paths network (log)					1.021	0.034	1.773***	0.164
Self-service bicycle system					1.128**	0.056	0.913	0.082
Public expenditure on transport per capita					1.004***	0.000	1.002**	0.001
Unemployment rate					0.983**	0.007	1.061***	0.023
Border area					1.052	0.053	0.773**	0.087
Littoral area					0.883***	0.040	0.605***	0.084
Mountain area					1.020	0.035	1.028	0.106
Log-likelihood	-4,976,052.6				-4,664,900.6			
Pseudo-R ²	0.1987				0.2488			
Number of observations	7,330,225				7,330,225			

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Note: Specification 1 only includes individual variables. Specification 2 includes both individuals and contextual variables. Relative risks (RR) are reported rather than coefficients. Standard errors are clustered by NUTS3 areas.

Source: Authors' calculations based on French population census data, *Enquête TCU* (Cerema, GART & UTP, 2017), *Île-de-France Mobilités* data, *Géovélo* data, Local authorities accounts data, Massifs perimeters ANCT data.

Table 3 presents the results of the multinomial models. The first specification corresponds to a model based solely on individual variables, while the second includes both individual and contextual variables. As the effects of the individual variables differ very little between the two specifications, we focus on the second specification in the following.

Overall, the effects of individual variables on the use of green mobility are consistent with the literature. Being a woman is associated with a probability of using active modes of transport around 14% lower than being a man, and the probability of using public transport is about 36% higher. However, we observe an opposite effect when we interact the gender with the presence of children: mothers are more likely to walk to work, and less likely to take public transport. More generally, living with a partner increases the probability of using green mobility, probably as a result of sharing a car. In opposition, having children reduces slightly this probability, related to an increased need for flexibility. Young people aged 15-19 have a higher probability of using green mobility than 20-29 year olds, mainly because they cannot have a driving licence under 18. The probability of using active modes of transport increases with age, as does the probability of using public transport, although the latter remains negative relatively to car use. The probability of using green transport increases with the level of education, with a notable rise between short and long higher education. In addition, we observe results that go in the same direction with professional categories, in particular for managers who are approximatively 50% more likely to use sustainable mobility than a car. This suggests that the negative effect of income on usage of green mobilities (Kruger et al., 2008) is compensated by a greater environmental awareness among people with high levels of education (Ajibade and Boateng, 2021). Part-time workers or those on fixed-term contracts are more likely to use green transportation modes, which are on average less costly, than people in more stable professional situations. Foreigners are 68% more likely to use public transport, maybe due to an income effect and their greater concentration in urban areas, where transport infrastructures are more developed. Unsurprisingly, people who do not own a car are more likely to use green transport than those who do. On the contrary, owning several cars has a considerable negative effect on the probability of using green mobility. Homeowners have a lower probability to use green mobilities as they tend to live in rural areas, farther away from their work. Finally, the distance between the place of residence and the workplace has a negative effect on the use of active modes of transport, while the effect on public transport is almost null.

In terms of contextual variables, the density of the public transport network has a significant and positive effect on the probability of choosing public transport. A 1% increase in density doubles the probability of using public transport, all things equal elsewhere. In addition, the length of the cycle path network also has a positive and significant effect. These results suggest that a more committed transport policy on the part of local authorities tend to favour green mobility (regardless of which one) over car use. On the contrary, these two variables (density of public transport and length of cycle paths) do not have any significant effect on the probability of using active mobility. On the other hand, the presence of self-service bicycles has a positive and significant effect on active mobility, increasing the probability of their use by 12%. We do not find any effect of public transport prices on the use of green mobility. This may at first seem surprising, but this is in line with the results of Belloc et al. (2024), who showed that an increase in gasoline prices leads to a very moderate shift from private transportation to public transport, especially in rural areas. In addition, public transport prices are relatively low in France, leaving little room for using prices as a lever for changing behaviours. Moreover, this suggests that the

choice of these modes of transport are related to the availability and accessibility of public transport infrastructures, rather than on their prices. Finally, transport expenditures per capita in NUTS3 areas has a positive and significant effect on the probability of using green mobilities. An increase of 10 euros per capita in transport expenditures increases the probability of using active mobility by 4%, and that of using public transport by 2%. These results highlight the positive impact of voluntary investments made by NUTS3 areas, even when such expenditures are not mandatory. The effect is higher for active mobility, which could be explained by the fact that this expenditure includes initiatives that are less expensive and quicker to implement, such as subsidies for the purchase of electric bicycles. We observe a negative effect of the unemployment rate in the use of active mobility. This can be related to the fact that, in less dynamic areas, workers are tempted to accept jobs located farther from their home, limiting their use of active mobility. Finally, living in a littoral area reduces the probability of using green mobility, which might capture an unobserved income effect, as people living in these areas are on average richer⁸

5.2. Heterogeneity between rural, urban and Paris regimes

Table 4 reports the results of the spatial regimes model. Most effects of the individual variables are consistent with the previous models. Still, there are a few notable differences.

Although still negative, the gap between men and women in the use of active mobility in suburban areas is twice as in the other regimes (around -33% against -17%). Interestingly, we observe a positive effect of the interaction term between gender and the presence of children on the use of public transport in large urban areas, while it is negative elsewhere. Effects of the occupation on active mobility in rural areas are lower (and even negative for associate professionals), which is consistent with higher skilled jobs being concentrated in cities (Ottaviano and Thisse, 2004), making it harder to commute by walking or biking because of the distance. The effects reported for employment sectors support the importance of the localisation of jobs in commuting mode choice: in rural and suburban areas, there is a strong positive effect on active mobility for individuals working in the agricultural sectors, while the effects are strongly negative in urban areas. Perhaps surprisingly, the effect of distance is similar across all regimes, implying that the longer commuting distance observed in rural areas is not central in the mobility choice. The spatial regimes model reveals interesting patterns in the effects of transport infrastructures. Indeed, we show that greater lengths of the public transport and bicycle paths networks have a significant positive effect on the related commuting mode choice only in large urban municipalities (including the Paris region), and to a lesser extent in rural municipalities, although the effect is barely significant at the 10% level. This suggests that extending transportation networks have an effect mostly when there are already important infrastructures. The same kind of effect is observed regarding public expenditures, that appears to favour public transport use only in large cities. Besides, the cross effect of bicycle paths on the probability of using public transport is always positive and significant, which tend to confirm the interpretation of this variable as an indicator of more active transport local policies.

⁸ *Observatoire des territoires* data, Median income by NUTS3 area, accessed on 15 May 2024.

Table 4 - Determinants of commuting mode choice - Spatial regimes multinomial logit models

	Active mobility					Public transport				
	Rural RR	Suburban RR	Small urban RR	Large urban RR	Paris RR	Rural RR	Suburban RR	Small urban RR	Large urban RR	Paris RR
Individual variables										
Woman	0.833***	0.677***	0.828***	0.832***	1.061	1.051**	1.220***	1.206***	1.359***	1.539***
Living with a partner	1.019	1.072**	1.246***	1.363***	1.078***	0.937**	1.107**	1.341***	1.333***	1.040
Having children	0.868***	0.915***	0.854***	0.868***	0.937**	0.922***	1.001	0.949**	0.844***	0.962**
Woman x Living with a partner	1.623***	1.859***	1.479***	1.454***	1.559***	0.998	1.107***	1.125***	1.324***	1.315***
Woman x Having children	1.145***	1.125***	1.056***	1.095***	1.062	0.759***	0.807***	0.869***	1.065***	0.921***
<i>Age (ref: 20-29 years old)</i>										
15-19 years old	2.284***	2.953***	2.911***	2.416***	2.367***	4.182***	4.843***	3.693***	2.943***	2.353***
30-39 years old	0.965**	0.903***	0.915***	0.929***	0.855***	0.766***	0.730***	0.876***	0.853***	0.779***
40-49 years old	1.240***	1.150***	1.104***	1.035***	0.982	0.873***	0.794***	0.958*	0.907**	0.797***
50-59 years old	1.562***	1.369***	1.288***	1.173***	1.141**	0.946	0.853***	0.981	0.993	0.866***
60-64 years old	2.081***	1.767***	1.484***	1.255***	1.248***	0.860***	0.813***	0.936*	1.008	0.877***
Foreigner	1.623***	1.369***	1.093***	0.991	1.198**	1.694***	1.694***	1.648***	1.655***	1.475***
<i>Education (ref: Lower than secondary)</i>										
Secondary education	0.912***	0.843***	0.955***	0.895***	0.912***	0.835***	0.876***	0.883***	0.901***	0.954***
Short-cycle higher education	0.807***	0.706***	0.957***	1.012	0.962**	1.123***	1.059	1.056**	0.995	1.150***
Long-cycle higher education	1.091***	0.988	1.238***	1.432***	1.278***	1.627***	1.377***	1.425***	1.264***	1.429***
<i>Occupation (ref: Blue-collar worker)</i>										
Farmers and craftspeople	3.553***	2.783***	2.437***	2.181***	1.130**	0.402***	0.403***	0.485***	0.590***	0.392***
Manager / professional	1.149***	1.097***	1.424***	1.858***	1.345***	1.888***	1.548***	1.492***	1.315***	1.297***
Associate professional	0.874***	0.912***	1.168***	1.442***	1.239***	1.221***	1.166***	1.099***	1.099***	1.097**
Employee	1.797***	1.824***	1.716***	1.933***	2.005***	1.288***	1.449***	1.331***	1.549***	1.506***
<i>Employment sector (ref: Services)</i>										
Agriculture	2.515***	2.940***	0.855	0.399***	2.080***	0.197***	0.345***	0.256***	0.353***	0.404***
Industry	0.908***	0.945*	0.712***	0.614**	0.762***	0.460***	0.475***	0.520***	0.550***	0.609***
Construction	0.495***	0.477***	0.352***	0.279***	0.340***	0.300***	0.329***	0.353***	0.400***	0.534***
Administration, health, education	1.436***	1.620***	1.412***	1.316***	1.242***	1.002	0.974	1.088***	1.140***	0.795**
Temporary employment	1.176***	1.202***	1.060***	1.030*	1.286***	1.193***	1.413***	1.304***	1.377***	1.520***
Working part-time	1.027	1.103***	1.062***	1.173***	1.226***	1.026	1.169***	1.199***	1.335***	1.203***
<i>Car ownership (ref: One car)</i>										
No car	3.959***	5.047***	6.193***	6.555***	4.380***	4.883***	7.135***	10.19***	9.531***	5.856***
Two cars	0.519***	0.470***	0.430***	0.347***	0.453***	0.693***	0.494***	0.464***	0.319***	0.383***
Three cars or more	0.498***	0.436***	0.402***	0.369***	0.442***	0.574***	0.406***	0.413***	0.374***	0.396***
Home owner	0.678***	0.772***	0.823***	0.943***	0.894***	1.111***	1.107***	1.056**	0.873***	0.943**
Commuting distance (in km)	0.974***	0.991**	0.977***	0.992***	0.913***	1.004***	1.004***	1.004***	1.002***	1.002
Contextual variables										
Density of public transport network (log)	1.316**	1.020	0.823**	0.975	1.409***	1.646*	0.999	0.847	1.877***	1.716***
Average price of public transport ticket (in €)	0.997	1.015	1.075	0.979	-	0.854	0.875	0.914	1.109	-
Length of bicycle paths network (log)	0.986	0.971	1.008	1.093**	1.118	1.264**	1.470***	1.346***	1.566***	0.712*
Self-service bicycle system	1.013	1.080	0.959	1.171**	0.312	1.127	1.082	1.018	1.232*	108.1***
Public expenditure on transport per capita	0.999	0.999	0.999	1.000	1.003***	1.004	1.003	1.004	1.005**	1.003***
Unemployment rate	0.978***	0.962***	0.991	0.942***	1.010	0.981	0.973	1.002	0.955**	1.040***
Border area	1.126***	1.126*	1.134**	0.895	-	1.232**	0.853	1.107	0.800**	-
Littoral area	0.931*	0.996	0.831***	0.822**	-	0.682**	0.604***	0.572***	0.704***	-
Mountain area	1.009	1.004	0.959	1.115**	-	0.843	0.769**	0.750**	1.016	-
Constant	0.192***					0.010***				
Log-likelihood	-4,523,083.1									
Pseudo-R ²	0.2716									
Chow test for structural instability	1.5 x 10 ⁵ ***									
Number of observations	7,330,225									

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Note: Specification 1 only includes individual variables. Specification 2 includes both individuals and contextual variables. Relative risks (RR) are reported rather than coefficients. Standard errors are clustered by NUTS3 areas.

Source: Authors' calculations based on French population census data, *Enquête TCU* (Cerema, GART & UTP, 2017), *Île-de-France Mobilités* data, *Géovélo* data, Local authorities accounts data, Massifs perimeters ANCT data.

6. Conclusion

Although central in individuals' daily life, commuting generates important environmental externalities, due to greenhouse gas pollution. One solution may lie in the promotion of green mobility. However, commuting behaviours are complex and require in-depth studies of their determinants in order to understand how to induce these changes in mobility. The aim of this work was to explore the determinants of a green commuting mode choice, investigating both individual factors and contextual drivers. Indeed, commuting mode choices are influenced not only by characteristics of the individuals themselves, but also by their local environment and available transportation options. To this end, we estimated multinomial logit models using mobility data from the French population census and contextual data from various sources. We also used spatial regimes models in order to explore spatial heterogeneity depending on the degree of urbanisation of the place of residence.

Our results show the role of socio-demographic characteristics on the choice of a green transportation mode, but also the importance of local characteristics. Regarding individual factors, we confirm previous evidence that women and older workers are more prone to use sustainable mobilities. Our results also suggest that the negative effect of income observed in the literature (Kruger et al., 2008) is at least partly compensated by a greater environmental concern from more educated workers (Ajibade and Boateng, 2021), as we highlight a clear increase in the use of green mobility as both educational levels and occupational levels increase. As for contextual factors, we show that better transport infrastructures, namely public transport network, bicycle paths and self-service bicycles, increase probabilities of choosing green mobility for commuting. However, exploring heterogeneity between different urban structures, we show that this is true only in large cities, while the effect in less dense areas becomes insignificant. This may be related to longer distances to cover between the place of residence and the workplace, since jobs tend to be located primarily in cities, and an under-development of the infrastructures in those areas. We also highlight that public transport prices appear not to be a lever to promote green mobility, as they do not have any significant effects. From a public policy point of view, this claims for targeted policies towards specific socio-demographic groups of workers, as they appear to have various profiles, but also a need for differentiated actions depending on the urbanisation of the areas. In particular, policies aiming to extend transportation networks might be effective only in large areas, which underlines the need to think about other types of policies in other areas.

CRedit authorship contribution statement

Florian Fouquet: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

Emma Weiss-Blanchard: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing.

Acknowledgements

This work benefited from comments from Salima Bouayad Agha, and participants to the GAINS seminar and EDGE workshop. The authors would also like to thank Nicolas Pitout from Cerema for providing access to the *Enquête TCU* data, and Sofyane Hesni for his help using GIS softwares.

Emma Weiss-Blanchard reports benefiting from financial support from the chair *Neutralité Carbone 2040* of *Le Mans Métropole*. Naturally, the conclusions of this study are the sole responsibility of its authors.

Data availability statement

Programmes to permit replication can be provided, but we are not allowed to share some of the data used in this manuscript. Links to the databases in open access are reported in Appendix A. The *Enquête TCU* has been provided by Cerema. Access to population census data can be granted by the Adisp (French National Archive of Data from Official Statistics) upon request at <http://www.progedo-adisp.fr/rrp.php>.

References

- Adams, J., 2010. Prevalence and socio-demographic correlates of “active transport” in the UK: Analysis of the UK time use survey 2005. *Prev. Med.* 50(4), 199–203. <https://doi.org/10.1016/j.ypmed.2010.01.006>
- Ajibade, I., Boateng, G.O., 2021. Predicting why people engage in pro-sustainable behaviors in Portland Oregon: The role of environmental self-identity, personal norm, and socio-demographics. *J. Environ. Manag.* 289, 112538. <https://doi.org/10.1016/j.jenvman.2021.112538>
- Anas, A., 1981. The estimation of multinomial logit models of joint location and travel mode choice from aggregated data. *J. Reg. Sci.* 21(2), 223–242. <https://doi.org/10.1111/j.1467-9787.1981.tb00696.x>
- Anselin, L., 1988. Spatial heterogeneity. In *Spatial econometrics: Methods and models*. Springer, pp. 119–136.
- Belloc, I., Gimenez-Nadal, J.I., Molina, J.A., 2024. The gasoline price and the commuting behavior of us commuters: Exploring changes to green travel mode choices. *J. Transp. Geogr.* 121, 104006. <https://doi.org/10.1016/j.jtrangeo.2024.104006>
- Brutel, C., Pages, J., 2021. La voiture reste majoritaire pour les déplacements domicile-travail, même pour de courtes distances. *Insee Première*, 1835.
- Buehler, R., 2011. Determinants of transport mode choice: A comparison of Germany and the USA. *J. Transp. Geogr.* 19(4), 644–657. <https://doi.org/10.1016/j.jtrangeo.2010.07.005>
- Buehler, R., Pucher, J., 2012. Demand for public transport in Germany and the USA: An analysis of rider characteristics. *Transp. Rev.* 32(5), 541–567. <https://doi.org/10.1080/01441647.2012.707695>
- Caferra, R., Morone, A., Morone, P., 2025. After the storm: Environmental tragedy and sustainable mobility. *Ecol. Econ.* 227, 108409. <https://doi.org/10.1016/j.ecolecon.2024.108409>
- Cerema, GART & UTP, 2017. Enquête TCU - Années 2011 à 2017 [dataset] - Cerema, en partenariat avec la DGITM, le SDES, le Gart et l’UTP [Accessed on 30 April 2024].
- Combes, P.-P., Duranton, G., Gobillon, L., 2015. Salaires et salariés en Ile-de-France. *Rev. Econ.* 64(2), 317–350. <https://doi.org/10.3917/reco.pr.2.0039>
- Combes, P.-P., Duranton, G., Gobillon, L., Roux, S., 2012. Sorting and local wage and skill distributions in France. *Reg. Sci. Urban Econ.* 42(6), 913–930. <https://doi.org/10.1016/j.regsciurbeco.2012.11.003>
- Dargay, J., Hanly, M., 2007. Volatility of car ownership, commuting mode and time in the UK. *Transp. Res. A.* 41(10), 934–948. <https://doi.org/10.1016/j.tra.2007.05.003>
- De Witte, A., Hollevoet, J., Dobruszkes, F., Hubert, M., Macharis, C., 2013. Linking modal choice to motility: A comprehensive review. *Transp. Res. A.* 49, 329–341. <https://doi.org/10.1016/j.tra.2013.01.009>
- Dingel, J.I., & Neiman, B., 2020. How many jobs can be done at home? *J. Pub. Econ.* 189, 104235. <https://doi.org/10.1016/j.jpubeco.2020.104235>

- Echeverría, L., Giménez-Nadal, J.I., Molina, J.A., 2022a. Green mobility and well-being. *Ecol. Econ.* 195, 107368. <https://doi.org/10.1016/j.ecolecon.2022.107368>
- Echeverría, L., Giménez-Nadal, J.I., Molina, J.A., 2022b. Who uses green mobility? Exploring profiles in developed countries. *Transp. Res. A.* 163, 247–265. <https://doi.org/10.1016/j.tra.2022.07.008>
- García-López, M.-À., Hémet, C., Viladecans-Marsal, E., 2017a. How does transportation shape intrametropolitan growth? An answer from the Regional Express Rail. *J. Reg. Sci.* 57(5), 758–780. <https://doi.org/10.1111/jors.12338>
- García-López, M.-À., Hémet, C., Viladecans-Marsal, E., 2017b. Next train to the polycentric city: The effect of railroads on subcenter formation. *Reg. Sci. Urban Econ.* 67, 50–63. <https://doi.org/10.1016/j.regsciurbeco.2017.07.004>
- Giménez-Nadal, J.I., Molina, J.A., 2016. Commuting time and household responsibilities: Evidence using propensity score matching. *J. Reg. Sci.* 56(2), 332–359. <https://doi.org/10.1111/jors.12243>
- Giménez-Nadal, J.I., Molina, J.A., Velilla, J., 2020. Commuting and self-employment in Western Europe. *J. Transp. Geogr.* 88, 102856. <https://doi.org/10.1016/j.jtrangeo.2020.102856>
- Giménez-Nadal, J.I., Molina, J.A., Velilla, J., 2024. The daily mobility of older adults: Urban/rural differences in ten developed countries. *Ann. Reg. Sci.* 72(1), 141–161. <https://doi.org/10.1007/s00168-022-01192-0>
- Havet, N., Bayart, C., Bonnel, P., 2021. Why do gender differences in daily mobility behaviours persist among workers? *Transp. Res. A.* 145, 34–48. <https://doi.org/10.1016/j.tra.2020.12.016>
- International Energy Agency, 2020. Tracking transport 2020. IEA, Paris.
- Kalter, M.-J.O., Geurs, K.T., Wismans, L., 2021. Post COVID-19 teleworking and car use intentions. Evidence from large scale GPS-tracking and survey data in the Netherlands. *Transp. Res. Interdiscip. Perspect.* 12, 100498. <https://doi.org/10.1016/j.trip.2021.100498>
- Kim, S., Ulfarsson, G.F., 2008. Curbing automobile use for sustainable transportation: Analysis of mode choice on short home-based trips. *Transp.* 35, 723–737. <https://doi.org/10.1007/s11116-008-9177-5>
- Kruger, J., Ham, S.A., Berrigan, D., Ballard-Barbash, R., 2008. Prevalence of transportation and leisure walking among US adults. *Prev. Med.* 47(3), 329–334. <https://doi.org/10.1016/j.ypmed.2008.02.018>
- Le Gallo, J., 2004. Hétérogénéité spatiale, principes et méthodes. *Econ. Prev.* 162(1), 151–172. <https://doi.org/10.3917/ecop.162.0151>
- McQuaid, R.W., Chen, T., 2012. Commuting times - The role of gender, children and part-time work. *Res. Transp. Econ.* 34(1), 66–73. <https://doi.org/10.1016/j.retrec.2011.12.001>
- Ottaviano, G., Thisse, J.-F., 2004. Agglomeration and economic geography. In *Handbook of Regional and Urban Economics* Vol. 4. Elsevier, pp. 2563–2608,
- Panik, R.T., Morris, E.A., Voulgaris, C.T., 2019. Does walking and bicycling more mean exercising less? Evidence from the US and the Netherlands. *J. Transp. Heal.* 15, 100590. <https://doi.org/10.1016/j.jth.2019.100590>

- Plaut, P.O., 2005. Non-motorized commuting in the US. *Transp. Res. D.* 10(5), 347–356. <https://doi.org/10.1016/j.trd.2005.04.002>
- Pucher, J., Buehler, R., 2008. Making cycling irresistible: Lessons from the Netherlands, Denmark and Germany. *Transp. Rev.* 28(4), 495–528. <https://doi.org/10.1080/01441640701806612>
- Reiffer, A., Magdolen, M., Ecke, L., Vortisch, P., 2023. Effects of COVID-19 on telework and commuting behavior: Evidence from 3 years of panel data. *Transp. Res. Rec.* 2677(4), 478–493. <https://doi.org/10.1177/03611981221089938>
- Santos, G., Maoh, H., Potoglou, D., von Brunn, T., 2013. Factors influencing modal split of commuting journeys in medium-size European cities. *J. Transp. Geogr.* 30, 127–137. <https://doi.org/10.1016/j.jtrangeo.2013.04.005>
- Schwanen, T., Mokhtarian, P.L., 2005. What affects commute mode choice: Neighborhood physical structure or preferences toward neighborhoods? *J. Transp. Geogr.* 13(1), 83–99. <https://doi.org/10.1016/j.jtrangeo.2004.11.001>
- Thorhauge, M., Kassahun, H.T., Cherchi, E., Haustein, S., 2020. Mobility needs, activity patterns and activity flexibility: How subjective and objective constraints influence mode choice. *Transp. Res. A.* 139, 255–272. <https://doi.org/10.1016/j.tra.2020.06.016>
- United Nations, 2019. Emissions gap report 2019. United Nations Environment Programme (UNEP): Gigiri Nairobi, Kenya.
- Wong, R.C.P., Szeto, W.Y., Yang, L., Li, Y.C., Wong, S.-C., 2017. Elderly users' level of satisfaction with public transport services in a high-density and transit-oriented city. *J. Transp. Heal.* 7, 209–217. <https://doi.org/10.1016/j.jth.2017.10.004>
- Wong, R.C.P., Szeto, W.Y., Yang, L., Li, Y.C., Wong, S.-C., 2018. Public transport policy measures for improving elderly mobility. *Transp. Policy.* 63, 73–79. <https://doi.org/10.1016/j.tranpol.2017.12.015>

Appendix A : Data sources

Table A1 – Data sources

Variables	Data sources
All individual variables	French population census 2019, <i>Professional mobilities</i> database
Public transport network (except Île-de-France)	<i>Enquête TCU</i> - Years 2011 to 2017, Cerema, GART & UTP (2017)
Public transport network (Île-de-France)	<i>Tracés des lignes de transport en commun</i> (source GTFS), Île-de-France Mobilités, accessed on 6 May 2024 https://prim.iledefrance-mobilites.fr/jeux-de-donnees/traces-des-lignes-de-transport-en-commun-idfm
Public transport prices	<i>Enquête TCU</i> - Years 2011 to 2017, Cerema, GART & UTP (2017)
Bicycle paths network	<i>Géovélo</i> data, Year 2021, accessed on 2 April 2024 https://transport.data.gouv.fr/datasets/amenagements-cyclables-france-metropolitaine
Self-service bicycle system	<i>Enquête TCU</i> - Years 2011 to 2017, Cerema, GART & UTP (2017)
Public expenditure on transport	Local authorities accounts https://www.collectivites-locales.gouv.fr/finances-locales/finances-locales-departements
Unemployment rate	French population census 2019, Individual database
Mountain areas	Massifs perimeters, ANCT, accessed on 6 May 2024 https://www.data.gouv.fr/fr/datasets/les-perimetres-de-massifs/#/resources

Appendix B – Robustness checks

Table B1 - Determinants of commuting mode choice - Binary logit models

	Active mobility		Public transport	
	RR	SE	RR	SE
Individual variables				
Woman	0.882***	0.034	1.426***	0.044
Living with a partner	1.210***	0.029	1.172***	0.044
Having children	0.845***	0.010	0.919***	0.018
Woman x Living with a partner	1.488***	0.015	1.215***	0.034
Woman x Having children	1.139***	0.016	0.938***	0.014
<i>Age (ref: 20-29 years old)</i>				
15-19 years old	2.334***	0.041	2.757***	0.101
30-39 years old	0.903***	0.007	0.772***	0.006
40-49 years old	1.059***	0.012	0.790***	0.013
50-59 years old	1.248***	0.017	0.860***	0.016
60-64 years old	1.454***	0.026	0.869***	0.018
Foreigner	1.149***	0.039	1.737***	0.057
<i>Education (ref: Lower than secondary)</i>				
Secondary education	0.903***	0.006	0.905***	0.009
Short-cycle higher education	0.929***	0.012	1.118***	0.012
Long-cycle higher education	1.335***	0.045	1.478***	0.032
<i>Occupation (ref: Blue-collar worker)</i>				
Farmers and craftspeople	2.374***	0.109	0.420***	0.015
Manager / professional	1.465***	0.042	1.457***	0.079
Associate professional	1.188***	0.023	1.166***	0.030
Employee	1.811***	0.026	1.500***	0.035
<i>Employment sector (ref: Services)</i>				
Agriculture	1.698***	0.110	0.167***	0.015
Industry	0.754***	0.017	0.516***	0.022
Construction	0.365***	0.008	0.438***	0.026
Administration, health, education	1.446***	0.026	0.917*	0.044
Temporary employment	1.113***	0.014	1.413***	0.021
Working part-time	1.111***	0.012	1.233***	0.013
<i>Car ownership (ref: One car)</i>				
No car	5.535***	0.261	8.207***	0.650
Two cars	0.391***	0.010	0.342***	0.010
Three cars or more	0.375***	0.008	0.327***	0.012
Home owner	0.764***	0.009	0.854***	0.022
Commuting distance (in km)	0.979***	0.003	1.003***	0.000
Constant	0.149***	0.032	0.001***	0.001
Contextual variables				
Density of public transport network (log)	0.939	0.040	2.041***	0.201
Average price of public transport ticket (in €)	1.025	0.084	1.282	0.280
Length of bicycle paths network (log)	1.042	0.034	1.789***	0.169
Self-service bicycle system	1.103**	0.054	0.930	0.087
Public expenditure on transport per capita	1.004***	0.000	1.002***	0.001
Unemployment rate	0.980**	0.008	1.063***	0.024
Border area	1.061	0.055	0.767**	0.091
Littoral area	0.905**	0.042	0.602***	0.086
Mountain area	1.041	0.035	1.044	0.111
Log-likelihood	-2,148,458.2		-2,126,074.3	
Pseudo-R ²	0.1752		0.3717	
Number of observations	5,909,036		6,380,684	

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Note: Specification 1 only includes individual variables. Specification 2 includes both individuals and contextual variables. Relative risks (RR) are reported rather than coefficients. Standard errors are clustered by NUTS3 areas.

Source: Authors' calculations based on French population census data, *Enquête TCU* (Cerema, GART & UTP, 2017), *Île-de-France Mobilités* data, *Géovélo* data, Local authorities accounts data, Massifs perimeters ANCT data.

Table B2 - Determinants of commuting mode choice - Spatial regimes multinomial logit models – Alternative measure of distance

	Active mobility					Public transport				
	Rural RR	Suburban RR	Small urban RR	Large urban RR	Paris RR	Rural RR	Suburban RR	Small urban RR	Large urban RR	Paris RR
Individual variables										
Woman	0.835***	0.677***	0.825***	0.831***	1.064	1.052**	1.221***	1.209***	1.360***	1.538***
Living with a partner	1.023	1.074***	1.247***	1.365***	1.082***	0.934**	1.105**	1.337***	1.332***	1.041
Having children	0.869***	0.916***	0.855***	0.868***	0.935**	0.921***	1.000	0.948**	0.843***	0.961**
Woman x Living with a partner	1.608***	1.852***	1.476***	1.451***	1.556***	1.000	1.109**	1.128***	1.325***	1.314***
Woman x Having children	1.142***	1.123***	1.053***	1.093***	1.062	0.759***	0.808***	0.870***	1.065***	0.921**
<i>Age (ref: 20-29 years old)</i>										
15-19 years old	2.279***	2.950***	2.884***	2.421***	2.369***	4.175***	4.836***	3.687***	2.940***	2.353***
30-39 years old	0.964***	0.903***	0.911***	0.928***	0.854***	0.767***	0.731***	0.875***	0.852***	0.779***
40-49 years old	1.226***	1.148***	1.096***	1.034***	0.978	0.873***	0.793***	0.957**	0.907***	0.797***
50-59 years old	1.531***	1.364***	1.271***	1.171***	1.134**	0.945	0.853***	0.979	0.993	0.866***
60-64 years old	2.023***	1.757***	1.456***	1.251***	1.236***	0.859***	0.812***	0.934*	1.008	0.877***
Foreigner	1.592***	1.366***	1.086***	0.990	1.192**	1.697***	1.696***	1.647***	1.656***	1.475***
<i>Education (ref: Lower than secondary)</i>										
Secondary education	0.920***	0.846***	0.954***	0.895***	0.913***	0.836***	0.876***	0.883***	0.901***	0.954***
Short-cycle higher education	0.822***	0.711***	0.961**	1.014	0.965**	1.122***	1.058	1.056**	0.995	1.150***
Long-cycle higher education	1.110***	0.995	1.245***	1.436***	1.282***	1.622***	1.375***	1.423***	1.263***	1.429***
<i>Occupation (ref: Blue-collar worker)</i>										
Farmers and craftspeople	3.312***	2.738***	2.353***	2.172***	1.114**	0.402***	0.403***	0.484***	0.590***	0.392***
Manager / professional	1.160***	1.101***	1.428***	1.864***	1.345***	1.347***	1.542***	1.482***	1.312***	1.298***
Associate professional	0.881***	0.914***	1.168***	1.444***	1.238***	1.217***	1.164***	1.095***	1.098***	1.098***
Employee	1.777***	1.818***	1.700***	1.932***	1.996***	1.285***	1.447***	1.329***	1.548***	1.506***
<i>Employment sector (ref: Services)</i>										
Agriculture	2.382***	2.899***	0.854	0.404***	2.060***	0.199***	0.347***	0.256***	0.353***	0.406***
Industry	0.902***	0.945*	0.716***	0.618***	0.761***	0.461***	0.476***	0.521***	0.550***	0.609***
Construction	0.488***	0.477***	0.352***	0.279***	0.338***	0.300***	0.330***	0.353***	0.400***	0.534***
Administration, health, education	1.418***	1.614***	1.399***	1.315***	1.238***	1.006	0.975	1.091***	1.141***	0.794**
Temporary employment	1.176***	1.203***	1.060***	1.032*	1.283***	1.198***	1.415***	1.307***	1.377***	1.520***
Working part-time	1.012	1.099***	1.055***	1.172***	1.222***	1.026	1.169***	1.201***	1.335***	1.203***
<i>Car ownership (ref: One car)</i>										
No car	3.880***	5.020***	6.135***	6.538***	4.400***	4.905***	7.142***	10.18***	9.534***	5.854***
Two cars	0.527***	0.471***	0.434***	0.348***	0.452***	0.694***	0.494***	0.465***	0.319***	0.383***
Three cars or more	0.506***	0.438***	0.405***	0.370***	0.442***	0.574***	0.406***	0.413***	0.374***	0.397***
Home owner	0.689***	0.775***	0.829***	0.944***	0.901***	1.110***	1.107***	1.055**	0.873***	0.943**
Commuting distance (in km)	0.956***	0.985**	0.965***	0.988***	0.888***	1.006***	1.005***	1.005***	1.003***	1.002
Contextual variables										
Density of public transport network (log)	1.194*	1.004	0.786**	0.974	1.468***	1.704*	1.019	0.865	1.880***	1.710***
Average price of public transport ticket (in €)	0.996	1.008	1.085	0.977	-	0.857	0.877	0.914	1.111	-
Length of bicycle paths network (log)	0.997	0.977	1.013	1.099**	1.062	1.263**	1.468***	1.345***	1.564***	0.714*
Self-service bicycle system	1.011	1.079	0.962	1.174**	0.423	1.126	1.083	1.017	1.232*	105.6***
Public expenditure on transport per capita	0.999	0.999	0.999	1.000	1.003***	1.004	1.002	1.004	1.005**	1.003***
Unemployment rate	0.983**	0.964***	0.993	0.943***	1.004	0.980	0.973	1.001	0.955**	1.041***
Border area	1.123***	1.120*	1.135*	0.897	-	1.233**	0.854	1.109	0.800**	-
Littoral area	0.923**	0.989	0.826***	0.816**	-	0.679**	0.603***	0.572***	0.705***	-
Mountain area	0.990	1.004	0.951	1.109*	-	0.850	0.771**	0.753**	1.018	-
Constant	0.184***					0.010***				
Log-likelihood	-4,152,912.9									
Pseudo-R ²	0.2733									
Chow test for structural instability	1.5 x 10 ⁵ ***									

Number of observations	7,330,225
------------------------	-----------

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

Note: Specification 1 only includes individual variables. Specification 2 includes both individuals and contextual variables. Relative risks (RR) are reported rather than coefficients. Standard errors are clustered by NUTS3 areas.

Source: Authors' calculations based on French population census data, *Enquête TCU* (Cerema, GART & UTP, 2017), *Île-de-France Mobilités* data, *Géovélo* data, Local authorities accounts data, Massifs perimeters ANCT data.