Supplementary material
APPENDIX

Identifying the losers in the transport transition: evidence from Germany

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1 Definitions of transport poor

Table 1: Categories of Lucas et al. (2016).

Notion	Definition	References
Mobility poverty	A systemic lack of (usually motorised) transport that generates difficulties in moving, often (but not always) connected to a lack of services or infrastructures	Moore at al. (2013)
Accessibility poverty	The difficulty of reaching certain key activities – such as employment, education, healthcare services, shops and so on – at reasonable time, ease and cost	DfT (2014a), SEU(2003)
Transport affordability	The lack of individual/household resources to afford transportation options, typically with reference to the car (in developed countries) and/or public transport	Carruthers et al. (2005), Litman (2015), Serebrisky et al. (2009)
Exposure to transport externalities	The outcomes of disproportionate exposures to the negative effects of the transport system, such as road traffic casualties and chronic diseases and deaths from traffic related pollution. Often considered within the US literature from an environmental justice perspective	Barter (1999), Booth et al. (2000)

Note:This table is taken from Lucas et al. (2016) and correspond to Table 1. A lexicon of definitions for transport poverty.

Table 2: Categories of Berry et al. (2016).

Dimensions	Factor	Threshold (Exposed if)
Mobility practices	High fuel spending	$>$ 64€/active/month (2x median)
	Extra travel time	At least one person with $>$ 60 extra min/day when using public transport compared to using car
	Car use restriction	1
Conditions of mobility	Poor spatial matching	$>$ 382 km/active/month (median)
	No alternative	1
	Low vehicle performance or No vehicle	$>$ 10c€/km or 0 vehicle
Financial resources	Low income	$<$ 1580€/UC/month (median)

Note: This table is taken from Berry et al. (2016) and correspond to the first three columns of "Table 4. Results per factor and per indicator"

Table 3: Literature review.

Author & Year	Article name	Relevant definitions	Summary
Alonso-Epelde, García-Muros, and González-Eguino (2023)	Transport poverty indicators: A new framework based on the household budget survey.	Transport poverty indicators (10%, 2M & LIHC).	Calculation of the indicators to measure affordability of transport for the Spanish sample.
Banister (2018)	Inequality in Transport	Transport inequality indicators	State-of-the-art review of current trends in inequality in transport and their adverse consequences in the UK.
Berry et al. (2016)	Investigating fuel poverty in the transport sector: toward a composite indicator of vulnerability.	Fuel poverty in the transport sector	Classification of the French population in 2008 as fuel-poor, fuel-vulnerable & fuel-dependent. Proposition of a multidimensional definition of fuel-poor in the transport sector. Based on Sen (1992).
Boardman (1991)	Fuel Poverty: From Cold Homes to Affordable Warmth Hardcover.	Fuel poverty, 10% indicator.	First definition of the 10% indicator, a measure to quantify fuel poverty. A household is fuel poor if it spends more than 10% of income on energy services for the dwelling.
Boyd et al. (2023)	Fuel and transport poverty in Scotland : actions towards accurately identifying fuel and transport.	Fuel poverty & transport poverty	Study of a double vulnerability (fuel & transport) and review of the Scottish Fuel Poverty Act.
Charlier and Legendre (2018)	A Multidimensional Approach to Measuring Fuel Poverty	Fuel Poverty	Study of fuel poverty considering multiple dimensions, such as, monetary poverty, residential energy efficiency, and heating restriction.
Charlier, Legendre, and Ricci (2021)	Measuring fuel poverty in tropical territories: A latent class model.	Fuel poverty	Proposition of a scale of fuel-vulnerability based on latent class models for French tropical territories. Based on Sen (1992).
Day, Walker, and Simcock (2016)	Conceptualising energy use and energy poverty using a capabilities framework.	Energy poverty	Energy poverty study grounded in the Capability Approach of Sen (1992).
Lovelace and Philips (2014)	The 'oil vulnerability' of commuter patterns: A case study from Yorkshire and the Humber, UK.	Commuter oil vulnerability	Classification of commuters who spend more than 10% of income on travels.
Lowans et al. (2021)	What is the state of the art in energy and transport poverty metrics? A critical and comprehensive review.	Energy poverty & transport poverty	Complete review of the energy and transport poverty literature. In-depth definition of the concepts and literature gaps found.
Lucas (2012)	Transport and social exclusion: Where are we now?	Transport & mobility inequality/disadvantage	Study brings together research regarding transport disadvantage for the UK, as well as, their implications for social inclusion.
Lucas et al. (2016)	Transport poverty and its adverse social consequences.	Transport poverty	Definition of transport poverty as a multidimensional phenomenon considering four dimensions: mobility, accessibility, affordability and externalities.
Martiskainen et al. (2021)	New Dimensions of Vulnerability to Energy and Transport Poverty.	Energy poverty and transport poverty	Definition of the concepts and the overlap between the two. In line with the current context, the authors call for attention to both definitions for policy makers.
Mattioli (2017)	"Forced car ownership" in the UK and Germany: socio-spatial patterns and potential economic stress impacts.	Forced car ownership	Study of forced car ownership for the UK. The characteristics of and negative impacts for households in this case are detailed.
Mattioli, Lucas, and Marsden (2017)	Transport poverty and fuel poverty in the UK: From analogy to comparison.	Transport poverty and fuel poverty	Discussion of the main differences and similarities between the two concepts.
Mattioli, Wadud, and Lucas (2018)	Vulnerability to fuel price increases in the UK: A household level analysis.	Forced car ownership and fuel poverty (LIHC indicator)	Study of the vulnerability of households in light of rising fuel prices. Use of indicators of fuel poverty, such as, the LIHC.
Pereira and Karner (2020)	Transportation Equity.	Transportation equity	Highlight the importance of transportation for social life and how transportation can create equity issues. Proposition of a framework for transportation equity.
Verhorst, Fu, and Lierop (2023)	Definitions matter: investigating indicators for transport poverty using different measurement tools.	Transport poverty	Definition of transport poverty and highlight of the lack of a unified definition. Test of different definitions to identify if there is one that could unify the theory. Main conclusion is that depending on the context, a different definition could be used.

Source: Author's own elaboration.

2 Robustness: Purchase price and the LCOKm

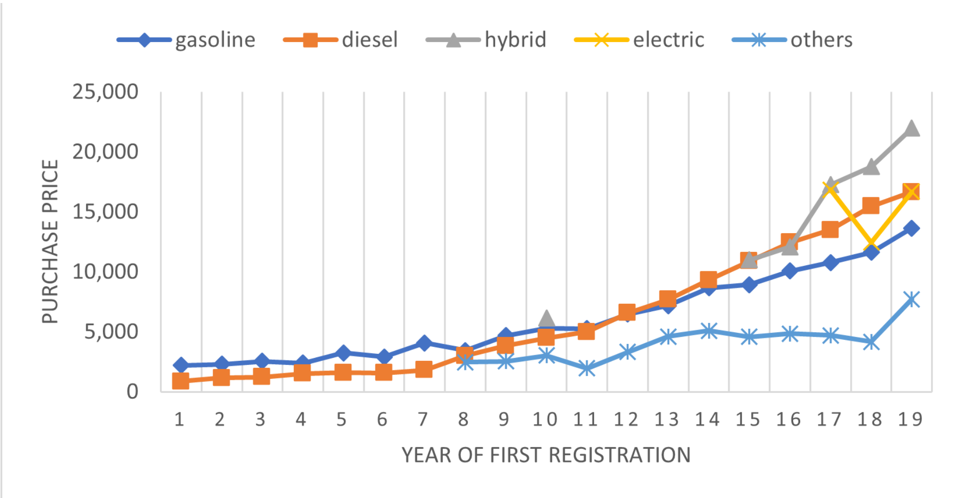
Using a 1.5 million dataset from leparking.fr, a search engine for used car sales, the prices of used cars in the sample are predicted using OLS. The dataset contains all ads on their website as of June 2021. Thus, variables include the sale/purchase price, make, model, year of registration, fuel type and location of the vehicle.

After matching the purchase price dataset from leparking.fr and the MOP dataset, 458 make-model combinations are obtained. For each combination, the purchase price is calculated following the equation below:

$$PurchasePrice = \alpha + \beta_1 make + \beta_2 model + \beta_3 age + \beta_4 fueltype + \epsilon \quad (1)$$

Figure 1 presents the estimated purchase price for a vehicle of a given age and fuel type on the MOP survey.

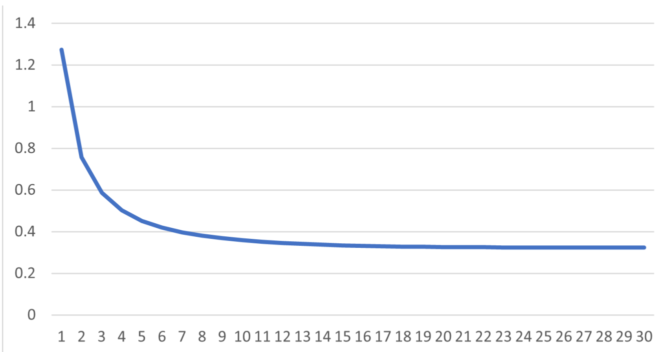
Fig. 1: Predicted car purchase price by type of fuel and age of car.



Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2019], leparking.fr [2021].

For robustness, the LCOKm is calculated using different lifetimes of the vehicle (Fig.2). However, the majority of the population keep their vehicle for ten years. Thus, the ten year lifespan is preferred.

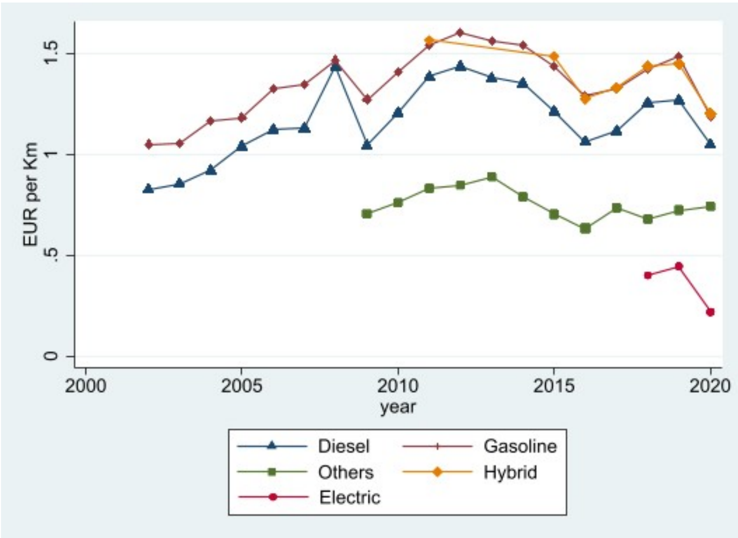
Fig. 2: Values of LCOKm by lifetime.



Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2019], leparking.fr [2021].

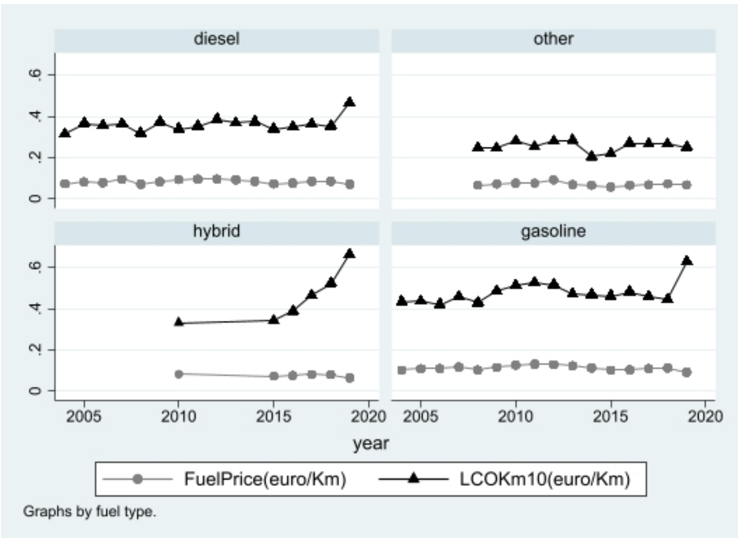
The sample includes 11 196 passenger cars. In terms of fuel, 66.68% use gasoline, 31.01% diesel, 0.88% hybrid and 1.43% other types of fuel. However, hybrid and electric have only appeared in the sample since 2015. Figure 3 presents the changes in fuel prices calculated using the current sample. Overtime, gasoline is more expensive than diesel. Only in 2008 there was an overlap in fuel prices of both gasoline and diesel.

Fig. 3: Sample fuel prices overtime.



Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2020].

Fig. 4: Comparison cost per kilometer by Fuel Type (Fuel vs. LCOKm).



Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2019], leparking.fr [2021].

3 Variables in detail

1. **Extra travel time**: Based on the work of Berry et al. (2016), extra travel time is calculated as the difference between the time a person would spend travelling a required distance by public transportation minus the time they would have spent travelling the same distance by car. The calculation of time spent by car is done by applying a speed rate based on urban/rural travel. In other words, for the households with at least one person using public transportation, the distance travelled by public transport is multiplied by a speed rate based on the location of public transportation taken[1].
   The formula then for calculating extra travel time is the following:
   $$Extra\,travel\,time = \sum_{i=1}^{n} TT_{pt} \; - \; TT_{car} \tag{2}$$
   where TT = travel time and pt = public transportation.
   $$TT_{car} = distance_{pt} \times speed\,rate \tag{3}$$
2. **Car use restriction**: There is no specific question asking MOP survey respondents whether or not they limit their car use based on cost. However, due to the level of detail of the survey, the distance travelled by car vs. the total distance travelled for the household are compared. This measure gives us the percentage of travelling done by other means of transportation. It simply states that there is a restriction but up until now, it cannot be attributed solely to monetary problems. The use of PCA explains whether or not restriction was based on preference for other means of transportation or on monetary constraints. The formula for calculating car use restriction is the following :
   $$Car\,use\,restriction = \sum_{i=1}^{n} \frac{Distance\,travelled - \; driven\,by\,private\,car}{Distance\,travelled} \tag{4}$$
3. **Poor spatial matching**: This variable is based on the definition of Berry et al. (2016). Itt represents the sum the total distance travelled by a household using all possible options of transportation. If the total of the household is above the mean of total distance travelled for the whole sample in a given year, they are classified as having poor spatial matching.
4. **No alternative other than car**: This variable is based on the definition of Berry et al. (2016). The MOP survey asks respondents to state why they chose to take each specific type of transportation. In the present paper, for those who state having no other option than car to go to their place of work or study, a binary variable is coded as 1 if there is at least one person in the household who has no option other than car and zero otherwise.
5. **No vehicle**: In order to identify households that do not even own a vehicle a binary variable is coded as 1 if the household has no vehicle and zero otherwise.
6. **Income**: Total disposable income of the household divided by the number of people in the household using the OECD-modified scale[2].
   The last three variables are inspired by the work of Lowans et al. (2021) who highlight the importance of measuring the degree of access to services and the work of Banister (2018) who based on trips' mode, distance travelled and time travelled create inequality measures:

7. **Monthly distance travelled for needs**[3]: It is calculated as the average distance travelled by all members of the household for necessary purposes : to go to work, to go to school, to drop of /pick someone up, to do groceries. It excludes hobbies and vacations.
8. **Monthly trips taken for needs**: Calculated as the average trips taken by all members of the household for necessary purposes.
9. **Monthly time travelled for needs**: Calculated as the average time travelled by all members of the household for necessary purposes.

One of the main contributions of the present paper is the development of the Levelized cost of driving one kilometer (LCOKm). The Corporate Finance Institute (2015) proposes a simple calculation of the levelized cost of electricity (LCOE). In general, the procedure is to discount the total costs and benefits of the project to calculate the average cost of one Kilowatt produced. The present paper takes into account the same general procedure and the result of the calculation is then the average cost of one kilometer driven (over the lifetime of the car) or levelized cost of driving one kilometer. The formula to calculate the levelized cost of one kilometer is the following:

$$LCOKm = \frac{\sum_{t=1}^{10}\left[\frac{PurchasePrice_t + OM_t + FuelExp_t}{(1+r)^t}\right]}{\sum_{t=1}^{10}\left[\frac{Km_t}{(1+r)^t}\right]} \tag{5}$$

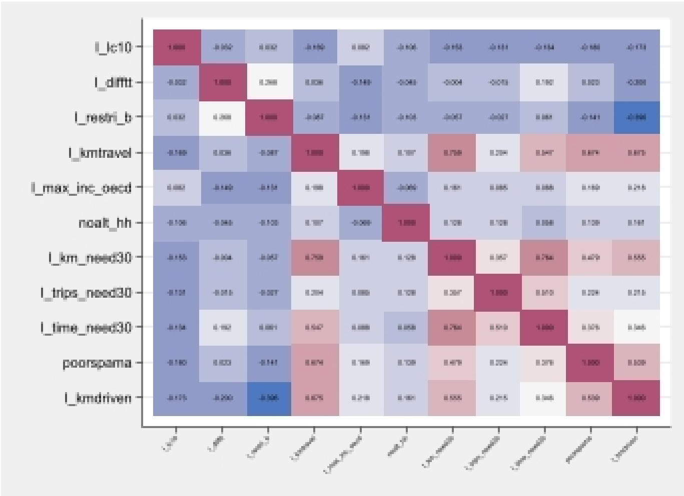
Where:

1. **Up front cost (PurchasePrice)**: The average value at the time of the survey for the totality of vehicles the household owns is calculated. Because the data is hard to obtain, it has not been previously used in indicators of this kind. As technology has advanced, authors may be inclined to use it for the purpose of advancing research. It is possible to obtain car prices using tools like web-scrapping. The data for this paper, however, was granted freely by leParking.fr. It included 1.5 million advertisements for used car sales in Germany found in their website in June 2021. Variables included in the sample provided include brand, model, year of registration, cylinder, sale price, fuel type and location. Prices are predicted based on an OLS regression accounting for make, year, model, age and type of fuel. See Appendix 2 for more details.
2. **Operation and maintenance (OM)** costs per year (insurance and repairs): Maintenance costs tend to be greater as the age of the car increases. In line with the work of Corporate Finance Institute (2015), an annual growth rate of two percent is chosen. The original OM used at year 1 is 700 euros. This number may represent a lower bound for a household with a well functioning car. Additional costs like parking could be included in this category. The difficulty here is finding a representative number as the costs are highly heterogeneous over time and depend on car characteristics, driving frequency, and even socio-economic characteristics of the driver/household.
3. **Fuel costs per year (FuelExp)**: Calculated from the sample for each type of fuel. Due to the level of detail of the survey, heterogeneous prices per region, year, and type of fuel are obtained. For electric vehicles, an equivalent is calculated for electricity expenditure based on kWh consumed (declared by the household) and electricity pricing per year. Prices include all taxes related to fuel and electricity consumption. See Fig. 3 for details.
4. **Kilometers driven per year (Km)**: Calculated from the sample for each car of the household.
5. **Lifespan of the project**: This variable is up for discussion. 86 percent of the sample has kept their car for a maximum of 10 years[4]. The mean is 5.33 years. As such, the calculation used here assumes an average lifespan of 10 years. However, for robustness, the LCOKm is recalculated using a lifespan of 5 and 20 years. See Appendix 2 for details.

6. **Discount rate (r)**: In line with the work of Corporate Finance Institute (2015), 8 percent is used for the calculations. Further testing could be done with different discount rates.

4 Robustness PCA: correlation

Fig. 5: Correlation Plot.



Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2019], leparking.fr [2021].

Table 4: Pair-wise correlation of variables used for PCA.

	I_lc10	I_difftt	I_restri	I_kmtravel	I_max_inc_oecd	noalt_hh	I_km_need30	I_trips_need30	I_time$_n eed$30	poorspama	I_kmdriven
I_lc10	1										
I_difftt	-0.0320*	1									
I_restri	0.0318*	0.2680*	1								
I_kmtravel	-0.1687*	0.0358*	-0.0875*	1							
I_max_inc_oecd	0.0821*	-0.1491*	-0.1307*	0.1979*	1						
noalt_hh	-0.1061*	-0.0453*	-0.1033*	0.1075*	-0.0690*	1					
I_km_need30	-0.1526*	-0.0044	-0.0568*	0.7592*	0.1606*	0.1277*	1				
I_trips_need30	-0.1309*	-0.0153	-0.0274*	0.2041*	0.0848*	0.1284*	0.3575*	1			
I_time_need30	-0.1336*	0.1922*	0.0606*	0.5466*	0.0882*	0.0580*	0.7645*	0.5096*	1		
poorspama	-0.1797*	0.0230*	-0.1411*	0.6738*	0.1694*	0.1385*	0.4788*	0.2241*	0.3761*	1	
I_kmdriven	-0.1725*	-0.1996*	-0.3960*	0.6746*	0.2178*	0.1606*	0.5550*	0.2149*	0.3456*	0.5388*	1

Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2019], leparking.fr [2021].
*Note: significance at the 1% level indicated by **

5 Robustness PCA: cronbach's alpha

Table 5: Cronbach's alpha.

Variable	N	Sign	Item-test correlation	Item-rest correlation	Average interitem correlation	**alpha**
I_lc10	11196	-	0.3737	0.2018	0.206	0.7218
I_difftt	14655	+	0.1076	-0.0768	0.244	0.7635
I_restri_b	14630	-	0.3017	0.1268	0.2197	0.7379
I_kmtravel	14655	+	0.7944	0.7114	0.1547	0.6466
I_max_inc_oecd	14343	+	0.3238	0.1505	0.216	0.7337
noalt_hh	14655	+	0.3231	0.1521	0.216	0.7337
I_km_need30	14655	+	0.7847	0.6993	0.1557	0.6483
I_trips_need30	14655	+	0.5113	0.3599	0.1916	0.7033
I_time_need30	14655	+	0.7042	0.594	0.1662	0.6659
poorspama	14655	+	0.7031	0.5932	0.1667	0.6667
I_kmdriven	14655	+	0.723	0.6187	0.1636	0.6617
Test scale					0.191	0.722

Source: Author's own elaboration.
Note: As highlighted by OECD (2008) "C-alpha is not a statistical test, but a coefficient of reliability based on the correlation between individual indicators. That is, if the correlation is high, then there is evidence that the individual indicators are measuring the same underlying construct. Therefore a high c-alpha, or equivalently a high "reliability", indicates that the individual indicators measure the latent phenomenon well. The sample is well above the requirement of 0.6 cronbach's alpha (here, the overall alpha = 0.722) (OECD, 2008).

6 Robustness PCA: KMO statistic

Table 6: Kaiser-Meyer-Olkin (KMO) Statistic.

Variable	KMO
I_lc10	0.8461
I_difftt	0.3607
I_restri_b	0.3865
I_kmtravel	0.7241
I_max_inc_oecd	0.7053
noalt_hh	0.6083
I_km_need30	0.7289
I_trips_need30	0.7011
I_time_need30	0.7074
poorspama	0.8456
I_kmdriven	0.7606
Overall	0.7223

Source: Author's own elaboration.
*Note: The KMO statistic measures sampling adequacy, the KMO statistic should be at leas 0.60, otherwise, PCA is not a feasible analysis (**oecd**). In this case, the sample is adequate to study using PCA (overall KMO = 0.72).*

7 Robustness PCA: alternative variables

The PCA is recalculated using different variables. Model 1 represents the model using a transformed income variable (using the OECD scale). While in Model 2, the variable used for income is a categorical variable from 1-10 indicating the bracket of income the household belongs to. Table **??** shows the results. As shown in the Table, both models are adequate enough to draw conclusions as the KMO statistic is larger than 0.6. The variance explained by each principal component is similar in both cases. For instance, for Model

Table 7: Alternative Income Variable for PCA.

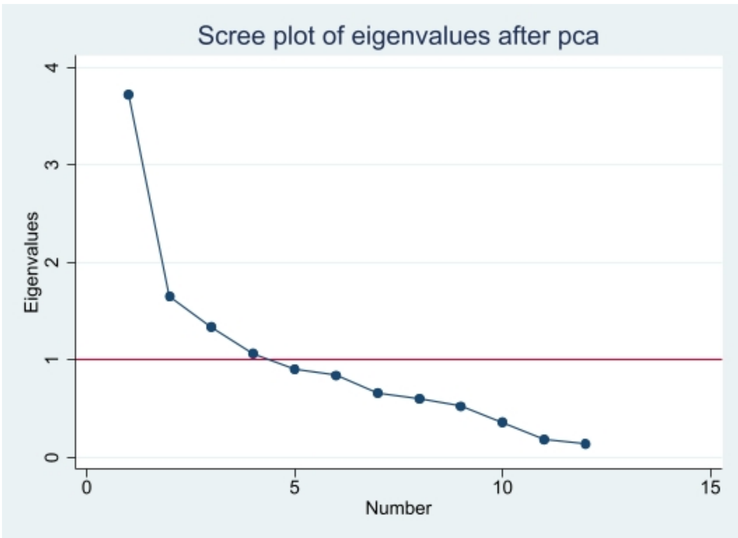
Model	KMO	PC1 (var.)	PC2 (var.)	PC3 (var.)	Total var. expl.	AIC	BIC
Model 1	0.7223	32.51	12.7	11.3	56.51	-121111	-120974.5
Model 2	0.7235	31.78	12.67	10.75	55.2	-57482	-57345

Source: Author's own elaboration.

1, PC1 explains 32.51% of the total variance, while for Model 2, PC1 explains 31.78% of the total variance. Lastly, the AIC and BIC criteria show the preferred model is Model 1. In addition, other variables were tested in the calculation of PCA, these included the time spent for needs, the efficiency of the car, the total cost of driving and the fuel expenditure. These variables were removed due to multicollinearity with the rest of the sample.

8 PCA: screeplot

Fig. 6: Screeplot principal components analysis.



Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2019], leparking.fr [2021].
Note:Selection of number of components to retain for PCA rotation. Threshold is having an eigenvalue greater than one, selected four components.

9 Normalization

Table 8: Summary statistics variables pre/post normalization

Variable	Obs	Mean	Std Dev	Min	Max
hh-hfs	11327	133.8526	99.2448	0	911.0233
hh-difftt	14786	74.17204	159.5242	-130.6	2353.6
restri	14786	357.1932	789.1816	0	17018.57
I-restri (perc)	14774	0.3440145	0.3695948	0	1
kmtravel	14786	1223.368	1193.903	0	17382.86
hh-careffi	11211	0.1017284	0.0280564	0.0279253	0.5096512
maxincome	14472	2917.548	1304.402	500	5500
oecd-scale	14786	1.487678	0.4883585	1	7.5
hh-carprice-mean	11319	7520.804	9445.159	0	273491.6
hh-carprice-sum	11327	9374.708	11544.17	0	273491.6
kmneed30	14786	377.5645	537.5985	0	11721.43
tripsneed30	14786	35.86085	20.53655	0	338.5714
timeneed30	14786	733.8576	636.8326	0	15861.43
poorspama	14786	0.4567158	0.4981398	0	1
hasnocar	14786	0.2339375	0.4233472	0	1
noalthh	14786	0.1646828	0.3709066	0	1
I-fs	11327	0.1469256	0.1089377	0	1
I-difftt	14786	0.0824298	0.0642155	0	1
I-restri-a	14786	0.0209884	0.0463718	0	1
I-restri-b	14774	0.3440145	0.3695948	0	1
I-kmtravel	14786	0.0703778	0.0686828	0	1
I-careffi	11211	0.1532056	0.0582415	0	1
I-maxinc	14472	0.4835096	0.2608805	0	1
I-incomecat	14472	0.5216203	0.2628273	0	1
I-oecdhhm	14786	0.0750273	0.0751321	0	1
I-carprices	11327	0.0342779	0.0422103	0	1
I-carpricem	11319	0.0274992	0.0345355	0	1
I-kmneed30	14786	0.0322115	0.0458646	0	1
I-tripsneed30	14786	0.1059181	0.0606565	0	1
I-timeneed30	14786	0.0462668	0.0401498	0	1

Source: Author's own elaboration.

Note: Variables pre and post normalization. Dummies are not normalized (poorspama, hasnocar, noalthh). I - indicates normalized

10 A note on variable normalization

In order to build indicators that are comparable, it is necessary that all variables have the same scale. As such, all variables that are not binary (no alternative other than car, No vehicle, Poor spatial matching) are normalized using the following formula:

$$I_q^t = \frac{x_q^t - min_{t \in T}(x_q^t)}{max_{t \in T}(x_q^t) - min_{t \in T}(x_q^t)} \tag{6}$$

Where x_q^t represents each variable at time t. This normalisation technique is chosen as it allows for comparison of indicators across time dimensions (OECD, 2008). The choice of this normalization technique allows us to compare the results obtained over time.

Appendix 9 present summary statistics of the variables used to build the indicators pre- and post-normalization.

11 Robustness LCM: choice of number of classes

The choice of the most appropriate model is done by taking into account the AIC and BIC criteria. Table 9 shows that the preferred model is the **four-class unconstrained** model which presents the lowest AIC and BIC.

Table 9: Comparison of models.

Model	N	LL(model)	df	AIC	BIC
two-c	13569	54635.71	19	-109233.4	-109090.6
two-u	14655	57395.77	10	-114771.5	-114695.6
three-u	14655	59538.91	14	-119049.8	-118943.5
four-u	14655	60573.57	18	-121111.1	-120974.5

Source: Author's own elaboration.
Note: c *means the model has been constrained by head of household characteristics.* u *means the model is unconstrained and the probability of belonging to a latent class is solely based on the principal components built in the previous sections. The preferred model is that with the lowest AIC and BIC and the highest LL.*

12 Robustness: Elasticities comparison of models

Table 10: Elasticity of driving demand, comparison of models.

	FE	RE	FE (VCE)	RE (VCE)
lnLCOKm	-0.146	-0.740***	-0.146	-0.740***
	(0.0996)	(0.0626)	(0.0996)	(0.0626)
lnIncome	0.102	0.0657**	0.102	0.0657**
	(0.0821)	(0.0310)	(0.0821)	(0.0310)
Class=2	0.838***	1.042***	0.838***	1.042***
	(0.0321)	(0.0243)	(0.0321)	(0.0243)
Class=3	0.553***	0.746***	0.553***	0.746***
	(0.0493)	(0.0316)	(0.0493)	(0.0316)
Class=4	-0.0483	-0.259***	-0.0483	-0.259***
	(0.127)	(0.0967)	(0.127)	(0.0967)
Fuel=gasoline	-0.0889	-0.213***	-0.0889	-0.213***
	(0.0633)	(0.0279)	(0.0633)	(0.0279)
Fuel=other	0.00226	-0.0757	0.00226	-0.0757
	(0.207)	(0.102)	(0.207)	(0.102)
Fuel=hybrid/EV	0.161	0.0217	0.161	0.0217
	(0.268)	(0.126)	(0.268)	(0.126)
No.Children	-0.0832	-0.0589**	-0.0832	-0.0589**
	(0.0594)	(0.0240)	(0.0594)	(0.0240)
HH Male	0.742	0.151***	0.742	0.151***
	(0.554)	(0.0274)	(0.554)	(0.0274)
HH Age	-0.0140	-0.00680***	-0.0140	-0.00680***
	(0.0120)	(0.00111)	(0.0120)	(0.00111)
HH in education	-0.190	-0.464***	-0.190	-0.464***
	(0.201)	(0.102)	(0.201)	(0.102)
HH driv. license	0.528**	0.709***	0.528**	0.709***
	(0.246)	(0.127)	(0.246)	(0.127)
Constant	4.943***	5.171***	4.943***	5.171***
	(0.984)	(0.286)	(0.984)	(0.286)
Other controls	Yes	Yes	Yes	Yes
Observations	10752	10752	10752	10752
R^2	0.126		0.126	

Source: Author's own calculations.
Note: Panel regression using fixed and random effects. Dependent variable is lnKmDriven*, controls include number of children and characteristics of head of household (HH). Other controls included highest degree achieved, employment status, year and household id fixed effects. Variable of interest is* lnLCOKm10*, the coefficient can be interpreted as an elasticity. A one percent increase in LCOKm leads to a -0.74% decrease in kilometers driven for a given household, all else equal. Columns (3) and (4) include VCE standard errors. The effect of belonging to an individual predicted class is also included in the regressions. Baseline class is Class1: Sufficient. Compared to class1, belonging to class2 leads to a 0.838 increase in kilometers driven, as shown in column (1). Compared to diesel cars, gasoline cars tend to be driven less. Standard errors in parentheses, as follows,* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

13 Application 2: Class Switches

The influence of the cost of transport and income on class change overtime is studied. The variation in class assignment of each household over the years is exploited to understand the effect of LCOKm on class change. Summary statistics and the transition probability of the sample are presented in Table 11.

Table 11: Transition Probability Matrix.

	Transport Poverty Class (TPC*)				
(TPC*)	1	2	3	4	Total
1	73.76	21.23	3.75	1.26	100.00
2	31.30	59.29	7.96	1.45	100.00
3	12.59	18.70	68.33	0.37	100.00
4	37.06	28.24	4.71	30.00	100.00
Total	48.87	34.25	15.00	1.87	100.00

Source: Author's own calculations.
Note: Classes do not have the same order as before, they have been ordered from worse to best (Transport-Poor [1], Car-Dependent [2], Sufficient [3], Independent [4]) for easier interpretation of Ordered Logit. 73% of those originally in Class 1 (row), remained in Class 1 (column).

An ordered-logit specification where the dependent variable quantifies the change in class from year-to-year is implemented. The variable shows that a household can either descend or ascend in the transport-poverty scale from one year to the next. Overall, 45% of households switch across classes over time, the remaining 55% stays in the same class. Table 12 presents the results.

Findings validate the idea that increases in transport pricing can worsen the transport poverty class assignment of the household, whereas, increases in income can improve class assignment. Table 13 presents average marginal changes of the probability of switching classes with respect to pricing and income, for each of the possible switches. Following an increase in LCOKm, a household has a higher probability of either switching to a lower class or remaining in its current class, and a lower probability to be in a higher class. The effect is the opposite for income. Higher income leads to higher probability of switching to a higher class and lower probability of either switching to a lower class or remaining in its current class.

Table 12: Probability of Changing Class (Ordered Logit)

	Change Class
LCOKm	-0.270***
	(0.0750)
LnIncome	0.246***
	(0.0363)
cut1	
Constant	-3.364***
	(0.327)
cut2	
Constant	-1.174***
	(0.296)
cut3	
Constant	0.605**
	(0.293)
cut4	
Constant	2.943***
	(0.296)
cut5	
Constant	4.581***
	(0.298)
cut6	
Constant	7.542***
	(0.348)
sigma2_u	
Constant	1.19e-33***
	(8.67e-35)
Observations	8812

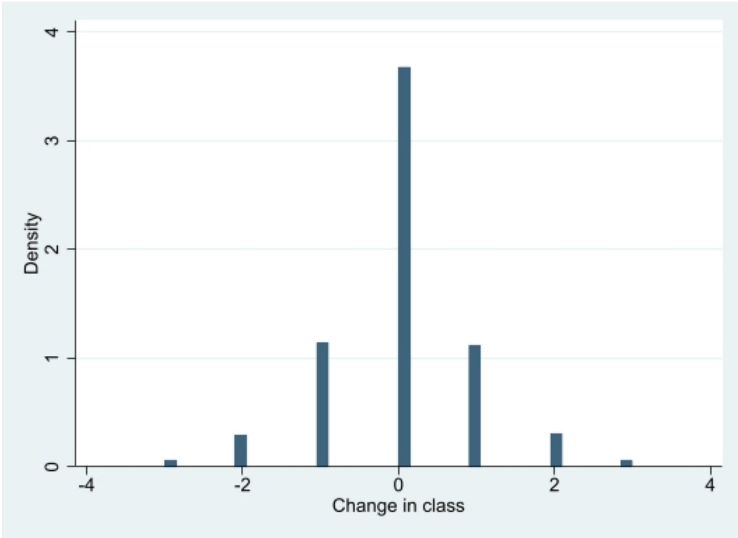
Source: Author's own elaboration.
Note: Model clustered at the household level to reduce the correlation over time as the same household is compared over a two year period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Average Marginal Effects

Change	LCOKm	LnIncome
-3	0.0015**	-0.0013***
	(0.0005)	(0.0003)
-2	0.0105***	-0.0096***
	(0.003)	(0.0015)
-1	0.0347***	-0.0317***
	(0.0096)	(0.0047)
0	0.0041**	-0.0037***
	(0.0014)	(0.0009)
1	-0.0351***	0.0321***
	(0.0098)	(0.0047)
2	-0.0147***	0.0134***
	(0.0041)	(0.002)
3	-0.0009**	0.0008***
	(0.0003)	(0.0002)

Source: Author's own elaboration.
Note: Average marginal changes (AME) in probability of changing transport poverty class following a shock in either LCOKm or LnIncome. Calculated using dydx option in Stata. Following an increase in LCOKm, the probability of switching towards a lower class increases. The effect is the opposite for income. There is a 3,4% probability of jumping to a lower class when there is an increase in LCOKm. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fig. 7: Distribution of Transport Poverty Class Change.



Source: Author's own elaboration. Data source: BMVBS (ed.): MOP data [2004-2019], leparking.fr [2021].

Table 14: Transport Poverty Class change.

Change	Freq.	Percent	Cum.
-3	106	0.90	0.90
-2	522	4.41	5.31
-1	2,033	17.19	22.51
0	6,525	55.18	77.69
1	1,986	16.80	94.49
2	548	4.63	99.12
3	104	0.88	100.00
Total	11,824	100.00	

Source: Author's own calculations.
Note: The table shows the distribution of change in class per year. For instance, a household can be classified as transport-poor in 2008, then, change to car-dependent in 2009. The variable change would reflect this change as "1".

14 Comparison of Transport poverty scale vs. Ten percent indicator

As discussed in Section 2, the ten percent indicator has widely been criticised in literature (Berry et al., 2016; Lucas et al., 2016). A household is considered transport or fuel poor if it spends more than 10% of its income on transport or fuel expenditures.

Table 15 illustrates the main reasons why the 10% percent indicator is not an acceptable measure of transport poverty. 675 households are classified as transport-poor using the 10% indicator. However, when comparing the results with that of the Transport Poverty Scale, there are 307 households in the wealthiest class (Class2: Sufficient) that have surpassed the 10% expenditure threshold in fuel expenditure. As pointed out by Berry et al. (2016), the 10% indicator can be biased by wealthy households who travel more than the average population. From Table 15, in every class of the Transport Poverty Scale there is a percentage of households who would be considered transport poor using the 10% indicator. Thus, the 10% indicator is not an efficient measure to identify those to target with efficient policies for the transition.

In addition, there is little overlap between those classified as transport-poor by the 10% indicator vs. the Transport Poverty Scale. There are 123 individuals classified as transport-poor by either measure. However, only 8 are classified using the 10% indicator, meaning that the 10% indicator can underestimate the toll of transport poverty on the most vulnerable population.

The transport poverty scale proposes a much more complete definition of what it is to be transport poor as it takes into account more dimensions than simply fuel expenditure, it considers the travel needs, travel preferences, alternatives, spatial matching, income and costs for all car related expenditures. Thus, the transport poverty scale represents an improvement in terms of methodology. The transport poverty scale allows to overcome the issues of the 10% indicator, such as, overstating the number of rich individuals who are considered transport poor and understating the number of poor individuals who are in fact transport poor.

Table 15: Comparison to ten percent indicator of fuel poverty.

Class vs. Ten Percent	No	Yes	Total
Class1 : Independent	4088	140	4228
Class2 : Sufficient	4017	307	4324
Class3 : Car-dependent	2058	220	2278
Class4 : Transport-Poor	115	8	123
Total	10278	675	10953

Source: Author's own elaboration.
Note: Comparison of results by class of latent class model vs. ten percent indicator of fuel poverty. For the ten percent indicator, a household is considered fuel poor if it spends more than 10% of its income on fuel expenditure.

15 Comparison of Transport poverty scale vs. multidimensional fuel-poverty indicator of Berry et al. (2016)

The most complete empirical work in fuel poverty is that of Berry et al. (2016) who classified their sample as fuel poor, vulnerable, and dependent based on a matrix of certain transport and socio-economic characteristics of the household[5]. As such, for the year 2008, in France, Berry et al. (2016) identify 7,8% of the population as fuel poor, 12% as fuel vulnerable and 7,5% as fuel dependent.

Following the methodology of Berry et al. (2016) and using the German sample discussed in Section 3, this paper classifies the households in the sample as fuel poor, vulnerable and dependent.

Table 16: TPS Classification

TPS	Freq.	Percent	Cum.
Independent	7005	47.8	47.8
Sufficient	5047	34.44	82.24
Dependent	2279	15.55	97.79
Transport Poor	324	2.21	100
Total	14655	100	

Source: Author's own elaboration.

Table 17: Berry et al. (2016) classification for the German sample

Class Berry	Freq.	Percent	Cum.
Poor	2246	16.52	16.52
Vulnerable	1093	8.04	24.55
Dependent	244	1.79	26.35
Other	10016	73.65	100
Total	13599	100	

Source: Author's own elaboration.

Table 18: Comparison of methods

TPS / Class Berry	Poor	Vulnerable	Dependent	Other	Total
Independent	1686	0	0	5260	6946
Sufficient	414	418	6	3695	4533
Dependent	36	675	238	938	1887
Transport Poor	110	0	0	123	233
Total	2246	1093	244	10016	13599

Source: Author's own elaboration.

As seen in Tables 17 and 16, when using the methodology of Berry et al. (2016), results differ from those of the Transport Poverty Scale. In particular, using the Transport Poverty Scale, 2.21% of the population is considered Transport-Poor, while using the classification of Berry et al. (2016) 16.52 of the population is considered Poor.

The results of the present paper may differ to those of Berry et al. (2016) due to the methodology used. For instance, the present work takes into account all household members with valid surveys and all vehicles of the sample, while the methodology of Berry et al. (2016) focuses on the household head. In addition, the present paper includes all vehicles of the household. By doing so, there is an additional 30% increase in fuel expenditures and kilometers driven. The indicators would be downward biased if these were excluded, thus the TPS presents an improvement in the calculations of transport poverty class assignment.

In addition, income, is presented here using the OECD scale, while in Berry et al. (2016), it is disposable income. Thus, in the current paper for each additional household member, a specific weight is assigned. The use of the OECD scale allows to control for the number of people in a household, their age and the relative position of the person in a household (i.e. if head of household, if another adult or if child). On top of these changes, the costs of driving the car are three times those of Berry et al. (2016), as all expenditures (purchase price, maintenance, operation, and fuel) are considered.

Most importantly, in the work of Berry et al. (2016), households are assigned to categories if they are under/over a certain threshold for each of the variables used. In this paper, and as highlighted in Sections 4.1 and 5.1, the decision threshold is based solely on the statistical properties of the sample. Thus, the methodology to obtain the TPS overcomes the issue of arbitrary thresholds identified in literature (Charlier, Legendre, and Ricci, 2021).