Car-fuel poverty in France: determinants and implication for energy policies

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ABSTRACT

In the face of inflation following the Ukranian crisis, the French government implemented a generalized gasoline subsidy. In contrast, the reduction of fossil-fuel consumption is crucial to mitigate the current energy and climate crises. Moreover, fossil-fuel consumption for transport increases with income, so a thorough investigatation of the nature of vulnerability to rising prices is needed to formulate targeted policies. Herein we first develop three alternative metrics of car-fuel poverty. We use multivariate statistical analysis methods to identify car-fuel poor household profiles. We then use the most recent French household travel survey to understand the socio-economic determinants of such vulnerability. Firstly, we find that aside from income, household composition, place of residence, access to public transport and household ownership significantly affect the risk of car-fuel poverty. Then, using our findings, we study the impact of the French subsidies installed in 2022 and compare it with a subsidy targeting only vulnerable households, finding that the measure has been inefficient and a targeted alternative would generate savings and fully compensate the most vulnerable. Our ongoing research complements the findings herein by studying the determinants of the demand for cars in the second-hand market, being able to get a full-picture of the car-poverty trap.

1. Introduction

The issue of car-fuel poverty is a key concern today for two reasons. Firstly, the energy crisis caused by the post-Covid demand increase and the Ukranian conflict has caused fuel prices to boom, reaching up to €2 per liter in France. This crisis has exacerbated the vulnerability of some households to the rising prices of fossil fuels. In response to the crisis, the French government has implemented an emergency diesel and gasoline subsidy, which has proven to be both very expensive and poorly targeted. The policy as functioned in three phases: a five-month subsidy of c€18/l, a two-and-a-half-month subsidy of c€30/l and a one-and-a-half-month subsidy of 10c€/l for all fossil fuels. For this policy, the government budgeted €7.6 billions in 2022. The second reason is the need to reduce the use of cars and to substitute the remaining fossil-fuel vehicles with electric vehicles in order to limit greenhouse gas emissions, since cars alone account for 16% of French national emissions. However, environmental policies aimed at reducing the consumption of fossil fuels risk (i) reinforcing existing inequalities and (ii) creating new ones Belaïd (2022a). Thus, issues of social and environmental justice are at the heart of current events in France. These questions have also been addressed in the economic literature through the issue of energy poverty since the 1970s. Since then, European countries with the UK as a pioneer, have established institutions to measure and monitor energy poverty, with a particular focus on the use of domestic fuels. Despite progress, the role of transport and mobility remains marginal in this literature. Indeed, the issue of poverty in transport has mainly been studied through the lens of inequalities in access to mobility and the resulting social exclusion (Lucas, Mattioli, Verlinghieri and Guzman (2016); Lucas (2012)).

In this paper, we focus on the issue of car poverty and particularly on the consumption of fossil fuels, leaving aside the issue of access to cars. First, we seek to define relevant indicators of energy poverty linked to car usage based on the literature on fuel and transport poverty. This allows us to identify three indicators of car-fuel poverty. Firstly, the Low-Income High Cost (LIHC), an indicator that identifies very mobile households whose residual income after fuel costs falls below a poverty threshold. Secondly, the 2M ("twice the median"), which identifies households spending a disproportionate share of their income on car fuels. Finally, the M/2 ("half the median"), a measure that identifies households spending very little compared to the French median. These are households that either do not have a car or restrict their fuel consumption for affordability reasons.

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We then apply these three measures to a representative sample of the French population using the most recent National Household Travel Survey (Enquête Mobilité des Personnes 2018-2019), which provides information on household socio-economic characteristics, equipment, and travels. We find that 3.2% of households are energy poor in terms of LIHC, 20% are 2M, and 31% are M/2. We then use statistical clustering methods to study the variability within these three categories. These methods allow us to identify eight typical profiles of households in situations of car-fuel poverty based on the metrics used (LIHC, 2M and M/2). The plurality of these profiles demonstrates the importance of choosing a relevant indicator before making policy recommendations.

In a second step, we restrict our sample to households owning at least one car. We then focus on the critical factors affecting the probability of falling into one of the three categories of car-fuel poverty (LIHC, 2M, and M/2) using binary logistic regression models. The results show that the most significant factors impacting the probabilities are (i) the number of cars, specific socio-professional category of the household head, renting a home in isolated rural areas with poor access to public transport for LIHC, (ii) being multimotorised, specific socio-professional categories, renting a home in either commuting or isolated rural areas with little or poor access to public transports for 2M, and (iii) owning only one car, living in urban centers with access to public transport, specific socio-professional categories and belonging to the poorest incomes deciles for M/2.

Our results have implications for public policies. Given the observation that the car-fuel subsidy implemented in 2022 by the French government was inefficient because it was too costly and not targeted enough, we propose alternatives to compensate the most vulnerable households and then suggest policy measures to tackle car-fuel poverty for the 6 identified car-fuel poor profiles.

The rest of this paper is as follows. In section 2, we review the literature on energy and transport poverty in order to identify the definitions, measures, and potential determinants of car-fuel poverty. In section 3, we describe the methods and data used in this study. We then present and discuss the statistical results in part 4. Finally, in part 5, we discuss the implications in terms of public policies.

2. Background and Literature Review

2.1. Fuel poverty

The issue of car-fuel poverty is a relatively unexplored dimension of the broader concept of energy poverty. Energy poverty can be defined as the 'inability to obtain sufficient energy for essential services such as cooking, heating, cooling and household lighting' (Belaïd (2018)). It is a generic concept that encompasses at least two aspects: affordability and access. The question of accessing modern energy sources is mostly relevant in developing economies (Belaïd (2022b)). On the other hand, the main focus of this paper is on fuel poverty, which is defined as the inability to afford adequate energy services. In developed economies, concerns about fuel poverty arose following the oil crises of the 1970s. Since then, defining and measuring fuel poverty has been at the heart of a rich and growing literature (Moore (2012); Belaïd (2018); Romero, Linares and López (2018)). The first measure that both infused UK policies and the academic literature was that of Brenda Boardman (Boardman (1991)). Using a 1988 consumer expenditure survey, she derives a burden indicator defined as the ratio of fuel expenditures over income. Under this definition of fuel poverty, households with ratios above twice the median (2M) were considered to spend a disproportionate amount of income on energy.

$$\text{Ratio} = \frac{\text{Fuel expenditures}}{\text{Income}} \tag{1}$$

Depending on the study, fuel expenditures can be actual household expenditures or required fuel expenditures. One of the advantages of using required fuel costs is that it takes under-consumption behaviors into account. Similarly, income can be gross or equivalised income, full income or income net of housing costs, etc. These methodological choices may be driven by data availability and have significant impacts on the composition of fuel poor households (Moore (2012)).

The ratio indicator became the UK official measure of energy poverty from 2001 to 2013 and is still used at the European level by the Energy poverty observatory (EPOV)[1], either in absolute terms (the 10% indicator) or in relative

[1]Thema, J., and Vondung, F. (2020), EPOV Indicator Dashboard: Methodology Guidebook. Wuppertal Institut für Klima, Umwelt, Energie GmbH

terms (the 2M indicator). Other expenditure based indicators are used at the EU level, such as the “half the median” (M/2) indicator that captures fuel under-consumption relative to the national median.

Over the years, Boardman’s 10% indicator has faced criticism. Hills (2012) and Romero et al. (2018) argue that the indicator is too sensitive to price increase, that the 10% threshold is arbitrary and that the indicator does not exclude rich households. In fact, spending more than 10% or income on fuels does not necessarily make a household at risk of falling into poverty. Hills (2012) states that the ‘definition can encompass households that clearly are not poor’, which has been confirmed in recent studies (for e.g. Legendre and Ricci (2015)). Hills’ report suggest two alternative indicators: the “after fuel cost” poverty indicator, which targets households that have residual income after fuel costs below the official poverty line (60% of national median income) and the Low-Income High Costs (LIHC) indicators, a dual indicator that identify households that are above a fuel cost threshold and below an income threshold. Under Hills’ LIHC metric, fuel poor households have (1) "required fuel costs that were above the median level" and (2) "were they to spend that amount, they would be left with a residual income below the official poverty line".[2] With the LIHC indicator comes the measure of the depth of fuel poverty through the ‘energy poverty gap’, i.e. the additional income required to get out of poverty.

Other indicators exist; for example Moore (2012) suggests using a budget standard approach, with fuel poor households having fuel costs above income net of housing and minimum living costs. Yet, the UK chose the LIHC to replace the 10% indicator in their revised energy poverty strategy. In the academic world, the LIHC indicator has been widely used, criticized and improved over the years. For e.g., Romero et al. (2018) considers the poverty threshold as 60% of median income net of average fuel costs. Legendre and Ricci (2015) use actual energy expenditures rather than modeled energy requirements. Belaïd (2018) changes units of energy costs from € to €/m^2 to better account for low income households living in small dwellings. Finally, Belaïd (2022a) considers the Low-Income Low Energy Efficiency (LILEE) indicator as an alternative to the LIHC. This indicator was introduced in the UK with the need to build an absolute measure to track progress and policy efficiency. It is meant to capture all low income households living in inefficient homes. The main measures of fuel poverty are summarized in Table 1.

Study	Energy poverty metrics	Determinants
Boardman (1991)	Ratio $= \frac{\text{Required Fuel expenditures}}{\text{Income}} > 10\%$ which corresponds to twice the median (2M) in the sample	Not studied
Hills (2012)	Low Income High Costs (LIHC) if 1. "required fuel costs that were above the median level" 2. "were they to spend that amount, they would be left with a residual income below the official poverty line" Residual income is considered after housing costs.	Not studied
Moore (2012)	Budget standard approach, Minimum Income Standard (MIS) fuel poor if fuel costs > Net household income – housing costs – minimum living costs	Not studied

[2] In his policy paper, he also makes several recommendations, among which he suggests to use income after housing costs normalised by consumption units in line with OECD recommendations `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Equivalised_disposable_income`

Romero et al. (2018)	• 10% indicator • Moore (2012)'s indicator: fuel costs > household income - housing costs - minimum living costs • Operational adaptation of Hills (2012)'s LIHC with : household income - household expenditure on energy < 60% [median household income - mean expenditure on energy]	Binary Logit Regression results: the most vulnerable to energy poverty are low-income households, with children, household heads with job instability
Belaïd (2018)	Hills (2012)'s LIHC with energy expenditures in €/m^2	Multiple Correspondence Analysis (MCA) and Ascending Hierarchical Classification (AHC) to identify 4 fuel poor profiles. "(i) foreign family, employed, in shared building group, (ii) single person, retired, in small size flat group, (iii) family in individual house with gas and individual central heating system group and (iv) owner of high size rural house group". Also use logit regression to identify critical factors impacting the odds of being fuel poor.
Belaïd (2022b)	same as Belaïd (2018)	Clustering and regression methods similar to Belaïd (2018). Fuel poor household types in Jordan and Egypt are: (i) older households with higher incomes relative to the rest of the fuel-poor households, homeowners living in rural areas (ii) married homemakers, living in apartments (iii) lower incomes relative to other fuel poors, homeowners living in appartments
Belaïd and Flambard (2023)	Extension of LIHC: defines three categories of fuel poor to disentangle the effects of housing and fuel consumption: 1. low income, high housing costs and high fuel costs 2. low income, high housing costs and low fuel costs 3. low income low housing costs and high fuel costs	Trivariate probit regression to investigate critical factors of fuel poverty in Egypt: fuel poor households have large families, live in detached houses and have a low educated household's head.

Belaïd (2022a)	Low-Income Low Energy Efficiency (LILEE) 1. "have an FPEER[3] equal or lower than D" 2. "were they to spend that amount, they would be left with a residual income below the national standard poverty line." Income threshold set at 60% national median equivalized residual income after all housing-related expenditures per consumption unit and energy bill	Not studied
Legendre and Ricci (2015)	• 10% indicator • After fuel cost: Income - housing costs - fuel costs < 60% median. Focus on *vulnerable* households that are not below the poverty line before fuel costs. • Hills (2012)'s LIHC	C log-log and mixed effect logit model to investigate wich factors influence the odds of being fuel vulnerable using the French 2006 National Housing Survey: the probability of being vulnerable is higher for retired households, living alone, renting their home, with poor roof insulation, using an individual boiler for heating and cooking with gas.
EU Energy Poverty Observatory (EPOV)[4]	Expenditure-based indicators • M/2: Low absolute energy expenditure. Energy expenditures below half the national median. • 2M: Share of energy expenditure over income above twice the national median	Not studied
French National observatory on Energy Poverty (ONPE)[5]	• 10% indicator restricted to the poorest 30% (TEE indicator)[6] • Hills (2012)'s LIHC • LIHC adaptation with energy expenses in relation to the size of the dwelling (m^2). • Qualitative declarative metrics of discomfort and cold	No studied

Table 1: Fuel poverty metrics and determinants

The choice of the fuel poverty indicator has significant effects on the extent of fuel poverty. Legendre and Ricci (2015) apply three indicators to french survey data (the 10% indicator, the after fuel cost indicator and the LIHC indicator) and find that 17% spend more than 10% of income on energy, 21% are under the poverty line after housing

[3] Fuel Poverty Energy Efficiency Rating

[4] https://energy-poverty.ec.europa.eu/system/files/2021-09/epov_methodology_guidebook_1.pdf

[5] https://www.ecologie.gouv.fr/sites/default/files/thema_essentiel_25_precarite_energetique_2021_mars2023.pdf

[6] Taux d'Effort Energétique in French

and fuel expenditures and 9.2% are fuel poor in terms of the LIHC indicator. Progress is still needed to find a consensual definition and measure of fuel poverty at the EU level (Belaïd (2022a)). Academics advocate taking into account the plurality of difficult situations related to energy poverty. In particular, there is a need for a clear lexicon, distinguishing between the notions of poverty, which is an immediate situation that generates a vicious circle of deterioration in living conditions - and the notion of vulnerability[7], which corresponds to people who are not poor but may become so once the energy bills have been paid (Legendre and Ricci (2015).

In France, the question of fuel poverty was introduced at the Grenelle roundtable in 2007, which led to law 2010-788 on national commitment to the environment. The French energy poverty strategy was inspired by the 10% indicator. In 2011, the National Fuel Poverty Observatory (ONPE) was created to monitor and measure fuel poverty. Since 2016, it has used several indicators to define fuel poverty : the 10% indicator restricted to the first three income deciles, versions of the LIHC indicator and a declared qualitative indicator of discomfort and cold in the home. To combat immediate fuel poverty, France has set up the annual energy voucher scheme, dedicated to the payment of housing energy bills. This device was generalized in 2018 to the entire national territory. Moreover, in order to reduce energy bills and accelerate the energy transition, the government has implemented aid for housing renovation, with mixed results.

2.2. Transport poverty

Contrary to energy poverty, there is not a consensual definition of transport poverty. In a joint review of the energy and transport poverty literature, Lowans, Furszyfer Del Rio, Sovacool, Rooney and Foley (2021) suggest to define transport poverty as the *"inability to adequately meet commuting and mobility needs in a household"*. In an earlier review, Lucas et al. (2016) try to establish a shared lexicon of transport poverty. According to them, individuals are transport poor if, *"in order to satisfy their daily basic activity needs, at least one of the following conditions apply : (i) There is no transport option available that is suited to the individual's physical condition and capabilities. (ii) The existing transport options do not reach destinations where the individual can fulfil his/her daily activity needs, in order to maintain a reasonable quality of life. (iii) The necessary weekly amount spent on transport leaves the household with a residual income below the official poverty line. (iv) The individual needs to spend an excessive amount of time travelling, leading to time poverty or social isolation. (v) The prevailing travel conditions are dangerous, unsafe or unhealthy for the individual."*. Several aspects emerge from this definition ; they are not mutually exclusive but imply different policy responses (Lucas et al. (2016)). We summarize them in Table 2 below.

Affordability	refers to the lack of financial resources to afford available transport options.
Mobility poverty	refers to the lack of adequate (often motorised) transport options that lead to difficulties in moving.
Accessibility poverty	happens when households experience difficulties reaching essential activities and services (for e.g. employment, healthcare, school or food shops) "*at a reasonable time, ease, and cost.*" Lowans et al. (2021)
Exposure	Unequal exposure to transport externalities, such as pollution.

Table 2: Transport poverty aspects, based on Lucas et al. (2016)'s framework

As with energy poverty, the UK has been a leader in both policy and research on the issue of transport poverty. A first wave of research occured after the 2003 Social Exclusion Unit report that established a link between social exclusion and transport disadvantage. The focus of this research has been on measuring inequalities in *mobility* (number of trips, distance travelled) and in *accessibility* of essential activities (employment, healthcare, school, food shops, etc) for different social groups (Lucas (2012)). Households in a situation of intense mobility poverty are usually very disadvantaged in terms of income and location, and do not own a car. Relatively less academic attention has been given to car-owers with difficulties affording their necessary travels in car-dependent societies (Mattioli (2017b)). The concept of *Forced Car Ownership* (FCO) emerged in Australian research to define households that have low income while being highly motorised. In the EU, it was used by Mattioli (2017b) to characterise a household that "*(i) owns at least one car and (ii) reports difficulties to afford at least one of five items (rent, mortgage, household maintenance, energy bills, and food)"* . Other notions refers to transport affordability in the transport poverty literature. For example,

[7] `https://onpe.org/sites/default/files/pdf/documents/rapports_onpe/livrable_4.1_4.2_onpe-mobilite-3-agir_vet-v20150618.pdf`

Nicolas, Vanco and Verry (2012) study household vulnerability to fuel price increase ; Mattioli, Wadud and Lucas (2018) investigates several measures of Car-Related Economic Stress (CRES).

Another strand of the literature has focused on transport *vulnerability*. The difficulty lies in the fact that this term moves away from the definition of vulnerability given in the literature on fuel poverty (households that are not poor but become poor after fuel costs). Instead, transport poverty research choose to use a concept imported from the climate science literature and used in IPCC[8] reports (Adger (2006). This definition of vulnerability covers three aspects (Mattioli et al. (2018); Mattioli, Philips, Anable and Chatterton (2019)): (i) exposure to fuel costs (ii) sensitivity (often measured by income) and (iii) resilience or adaptive capacity, measuring the ability to shift to other transport options, should car-fuel prices increase.

In this study, we build upon two strands of literature investigating the concepts of transport affordability and vulnerability. Table 3 presents the main measures of affordability and vulnerability. Affordability metrics are often adaptated from the fuel poverty literature and use household survey data while vulnerability measures are usually composite indicators accounting for the three aspects defined earlier and are often used in socio-spatial studies. For example, Sustran (2012) report maps the risk of transport poverty using three criteria: (i) low income, (ii) areas where people live more than one mile away from a bus station and (iii) reaching essential services takes more than 1 hour by public transport or walking. Mattioli et al. (2019) defines a composite indicator of exposure (define as the ratio of motor fuel expenditure over income), sensitivity (income) and adaptive capacity (sum of estimated travel time to reach 8 key services).

In terms of affordability indicators, the RAC foundation uses the controversial 10% indicator, which results in a very large number of UK households defined as fuel poor (21 million). Nicolas et al. (2012) derives the burden of daily mobility as the ratio of daily mobility expenditures over equivalised income. They define a threshold of "vulnerability"[9] that corresponds to the share of income spent on daily mobility of the highest 20%. Mattioli et al. (2018) modifies the LIHC indicator with a combination of the "After Fuel Costs" and 2M indicators; households in Car-Related Economic Stress have (1) equivalised income after housing and running motor vehicle costs below 60% of the median and (2) ratio of car spending over income is above twice the median (2M). In line with the energy poverty literature, they define the transport energy poverty gap as the mean difference between the cost ratio of CRES households and the cost ratio threshold. Berry, Jouffe, Coulombel and Guivarch (2016) adapts three fuel poverty measures to transport: the 2M indicator, defined as fuel spending over income, the LIHC indicator with (1) fuel costs per active persons instead of fuel costs, (2) residual equivalised income for the income threshold, and a composite indicator combining mobility practices, conditions of mobility and financial resources.

Study	Transport Poverty Metrics	Determinants
RAC foundation (2012)[10]	10% indicator: transport poor households spend more than 10% of income on running motor vehicles	Not studied
Mattioli (2017b)	Forced-Car Ownership if households 1. own at least one car 2. find difficulties to afford other essential needs such as rent, mortgage, domestic energy and food.	Binary logit regression to identify factors increasing probability of FCO in Germany and the UK. Factors include having children (in the UK, not Germany), low working activity, being tenants, living in semi-detached houses (UK) or small blocks of appartments (Germany), adults in the middle age groups, with low-to-middle incomes.

[8] Intergovernmental Panel on Climate Change
[9] Here, the term vulnerability denotes affordability issues
[10] https://www.racfoundation.org/media-centre/transport-poverty

Mattioli et al. (2018)	Combination of 2M Ratio and LIHC indicators Households experiencing CRES[11]: 1. equivalised income after housing and running motor vehicle costs is below 60% of the median 2. percentage of income spent on running motor vehicle > twice the median (2M) Also measure the **transport-energy poverty gap** : the mean difference (in percentage points) between the cost burden ratio of LIHC households and the cost threshold	Binary Logit regressions results: determinants include having children, unemployed household members and living in rural areas or Northern Ireland.
Nicolas et al. (2012)	Burden of daily mobility as a ratio of daily mobility expenditures over equivalized income. The 20% households spending the highest share of income on daily mobility spend more than 18% of income	Studies the distribution of Vulnerable households in the population: they have low income (25% lower than local average) and are very mobile (75% more km driven than local average). Factors of vulnerability include household size, living in peri-urban areas, Socio-Professional Categories (farmers, workers, independent), having several active people and being multimotorised
Berry et al. (2016)	• 2M indicator: fuel spending over income > twice median, with restriction to income poor households. • LIHC if 1. Fuel spending per (active) person is higher than the median 2. If its residual income per consumption unit is lower than the poverty line (60% median equivalised income) • Composite indicator combining – Mobility practices (high fuel spending, extra travel time & car use restriction) – Conditions of mobility (poor spatial matching, no alternative & low vehicle performance or no vehicle) – Financial resources (income)	Not studied

[11] Car-Related Economic Stress

Sustran (2012)[12]	**Composite risk of transport poverty index** : 1. Areas of low income, where running a car would put high stress on households' budgets. 2. Areas where people live more than one mile from nearest bus station 3. Number of essential services that would take more than 1 hour to access by walking, cycling and public transport	Not studied
Mattioli et al. (2019)	**Composite indicator of vulnerability** : 1. Exposure (ratio between estimated mean expenditure on motor fuel and median income) 2. Sensitivity (median income of area) 3. Adaptive capacity (sum of estimated travel time to eight key services by walking or public transport	Not studied

Table 3: Transport poverty metrics

As in the fuel poverty literature, different measures lead to significant differences in the extent of transport poverty. Mattioli et al. (2018) finds that 9% of the British population is at risk of Car Related Economic Stress (CRES). On the other hand, Sustran (2012) finds 1.5 million british households at risk of transport poverty. Berry et al. (2016) finds that 10.5% of French households are car-fuel poor in terms of the ratio indicator, but only 2% when she restricts to poor households. She also finds that 3.3% of French households are car-fuel poor in terms of the LIHC. Finally, using her composite indicator, she finds that 12% are fuel vulnerable, 7.5% are fuel dependent and 7.8% are fuel poor.

2.3. Determinants of fuel and transport poverty

A strand of the fuel poverty literature investigates factors affecting the probability of being fuel poor under different indicators (Belaïd (2018); Legendre and Ricci (2015); Romero et al. (2018); Belaïd (2022b); Belaïd and Flambard (2023). Key factors include household size and composition, employment status, floor area, dwelling and tenure type, insulation type, household head's age, energy used for heating and cooking and location (urban or rural). Having poor roof insulation, having an individual boiler and cooking with gas instead of electricity is increasing the chances of being fuel poor (Legendre and Ricci (2015)). On the other hand, the impact of socio-economic factors on the likelihood of experiencing fuel poverty varies between studies. While Legendre and Ricci (2015) finds that fuel poor households are retired households living alone and renting their house, Romero et al. (2018) and Belaïd (2018) find that the probability of fuel poverty is higher for low-income households with children, with household heads having either low education or experiencing job instability. In terms of methodologies, Belaïd (2018); Romero et al. (2018); Belaïd (2022b) use binary logit models, Belaïd and Flambard (2023) use a trivariate probit regression model, Legendre and Ricci (2015) uses a C log log regression model and a mixed logit model. Belaïd (2022b, 2018) also uses a two step clustering procedure combining Multiple Correspondance Analysis (MCA) and Ascendant Hierarchical Clustering to identify different profiles of fuel poor households in France, Egypt and Jordan.

In the transport poverty literature, only a few papers investigate factors contributing to the risk of fuel poverty, and to our knowledge, only two papers use logistic regression to do so (Mattioli (2017b); Mattioli et al. (2018)). Mattioli (2017b) finds that having children, low working activity, being a middle age tenant with low-to-middle income affects significantly the odds of being FCO. Mattioli et al. (2018) shows that determinants of CRES include having children, unemployed household members and living in rural areas or Northern Ireland.

[12] https://www.sustrans.org.uk/media/3706/transport-poverty-england-2012.pdf

In France, Nicolas et al. (2012) studies the distribution of vulnerable households in the French population and finds that vulnerable households have low income (25% lower than local average) and are very mobile (75% more km driven than local average). Factors of vulnerability include household size, living in peri-urban areas, socio-professional categories (farmers, workers, independent), having several active people and being multimotorised.

In this paper, we make several contributions to the energy and transport poverty literatures. First, we bridge the gap between the two literatures by adapting energy affordability indicators - which are extensibly used and accepted - to transport. We choose three indicators that we detail in section 3: an adaptation of Hills (2012)'s LIHC, the 2M indicator and the M/2 indicator. Because of the limitations in our data, we use average income of each income deciles in both the LIHC and 2M indicators. Despite the suggestions of Hills (2012), we do not consider income after housing costs because like Berry et al. (2016), we do not observe housing costs. We also choose not to normalise income with household consumption units since, differently from domestic consumption, travels might be motivated by individual needs. Second, we analyse both the extent and the diversity of car-fuel poor household profiles in France, following the clustering method of Belaïd (2018, 2022b), which has not been done in transport poverty research so far. Then, using binary logistic models, we investigate factors influencing the odds of being car-fuel poor under our definitions. Finally, we use our findings on car-fuel poverty profiles and key influencing factors to investigate alternative policy responses to the government's 2022 fossil fuel subsidy.

3. Data and Methodology

Following the fuel and transport poverty literatures, as well as the EU Energy Poverty Observatory directives, we choose to focus on three measures of car-fuel poverty.

- **Low-Income High Costs (LIHC)**: following Berry et al. (2016) and Mattioli et al. (2018), LIHC households are those who are both above a cost threshold and below a poverty line :
  1. [Household car-fuel expenditures] > [Median of car fuel expenditures]
  2. [Mean income of household net of car-fuel expenditures] < [60% median income net of car-fuel expenditures][13]
- **Twice the median indicator (2M)**: We refer to households that have car-fuel expenditures over average income above twice the median as **2M**.
- **Under-consumption: half the median (M/2)**: We refer to households that have car-fuel expenditures below half the median as **M/2**.

In contrast to the literature on fuel poverty, we use absolute fuel expenditures and not expenditures per consumption unit or m^2. Our choice is motivated by the fact that automobiles are more individualised goods than housing. It is more difficult to define car-consumption units, as was done by Berry et al. (2016). Her work focuses on constrained travelled (such as home work travels) for which she has information for every member of the household, which we do not in our dataset. Because of data availability, income are average income per income deciles and we do not include housing costs in residual income.

3.1. Data

To study the extent of car-fuel poverty in France and investigate key factors affecting the probability of being car-fuel poor, we use the 2018-2019 French National Household Travel Survey, which we refer to as EMP (Enquête Mobilité des Personnes). It was conducted face to face by INSEE[14] interviewers between May 2018 and April 2019, in 6-month waves of 2 months each, targeting 20,000 households in metropolitan France. The success rate of the survey is 75.6% which represents 13,825 households who made 45,169 daily trips in the 6 weeks prior to the survey. These households belong to dwellings drawn in the annual census surveys. The interview begins with the equipment census, hence the number of cars, vans, light-duty-vehicles, motorcycles, bicycles, that the household owns. For each car, we have information on age, fuel type and fuel consumption (l/100km). Then, one individual is drawn from the household and is surveyed on his or her local and long-distance travels. Information such as distance travelled is often poorly estimated by individuals. Therefore, data is consolidated using additional databases (for e.g., Répertoire

[13] 60% of national median income is set as the French poverty line. Following (Romero et al. (2018)), 60% of the median of sample car fuel expenditures are deducted from this poverty line

[14] Institut National de la Statistique et des Etudes Economiques

Statistique des Véhicules Routiers, built from registration data, to estimate annual kilometers driven). Because travels of one household's individual might not be representative of the entire household, we used the consolidated annual distances travelled of each car own by each household to compute their fuel expenditures. The database also contains socio-economic information such as income deciles, household size and composition, socio-professional categories of household heads, tenure type and information on the municipality of residence (density, employment, access to train stations, etc).

In the survey, we do not observe fuel expenditures but kilometers driven. To compute fuel expenditures, we use 2019 fuel prices from `http://data.gouv.fr`. The main drawback of our data is that we only observe households' income deciles and not their actual income. We thus use other available INSEE databases to get the mean income for each income decile[15].

3.2. Methodology

3.2.1. Multiple Correspondence Analysis and Hierarchical Ascendant Clustering

We identify different fuel poor household profiles using a two steps clustering procedure in line with the methodology used by Belaïd (2018, 2022b). First we use Multiple Correspondence Analysis (MCA), which is a data analysis method extending the principal component analysis to categorical variables. The main idea behind MCA is to represent the categorical variables in a multidimensional space by creating a set of synthetic variables called "principal components". Principal components are a set of continuous variables that combines our initial categorical variables. The MCA results are presented as a set of coordinates in the multidimensional space, where each point represents a category or a combination of categories. The proximity of the points in the space indicates the degree of association between the corresponding categories. The closer the points, the stronger the association. MCA can be used as a first step to data clustering, as it allows to identify factors that contributes the most to data variability; the weight of each category is shown by the absolute value of coordinates in the dimensions that explains the most data variability. For this step, we begin with a large number of variables, including income deciles, household size and composition, number of cars, gender, age and socio-professional categories of household heads, tenure type, location of residence and distance to the closest train station. The second step is Hierarchical Ascendant Clustering. It considers each observation (household) as a cluster and then combines them in larger clusters until all observations are merged into one single cluster. Formally, considering K variables, Q clusters of individuals and I_q individuals in each cluster, the total inertia (multidimensional variance) is:

$$\underbrace{\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}(x_{iqk}-\bar{x}_k)^2}_{\text{total inertia}} = \underbrace{\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}(x_{iqk}-\bar{x}_{qk})^2}_{\text{within inertia}} + \underbrace{\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}(\bar{x}_{qk}-\bar{x}_k)^2}_{\text{between inertia}} \tag{2}$$

With x_{iqk} the value of factor k for observation i in cluster q, $\bar{x}_{qk}$ the mean value of k in cluster q and $\bar{x}_k$ the mean of factor k accross all clusters. As in Belaïd (2018, 2022b), we use Ward's method (Jr. (1963)) to aggregate individuals into clusters. First, each observation is a cluster and total inertia is equal to between inertia. At each step of the algorithm, Ward's method merges two clusters minimizing the increase of within cluster inertia. The clustering results are presented in a dendrogram. Then, we need to choose the number of clusters. It can be done according to the dendrogram tree shape[16]. To determine the optimal number of clusters, we find the lowest number of cluster q for which the loss of between-cluster inertia is low. The idea is to get the smallest number of clusters with low variability within the cluster and large variability between clusters. Once we have determined the number of clusters, we can describe the main characteristics of households belonging to these clusters. This allows us to draw different household profiles according to our car-fuel poverty indicators.

3.2.2. Econometric model

We then investigate factors affecting the odds of being LIHC, 2M and M/2. Following the energy and transport poverty literature (Belaïd (2018); Legendre and Ricci (2015); Belaïd (2022b); Romero et al. (2018); Mattioli (2017b); Mattioli et al. (2018)) we develop three binary logistic regression models, one for each of our outcome variable ; these

[15] `https://www.insee.fr/fr/statistiques/5371205?sommaire=5371304#consulter`

[16] See the description of the algorithm in R by F.Husson `http://factominer.free.fr/more/HCPC_husson_josse.pdf`

models can be written as:

$$log(\frac{p}{1-p}) = \beta_0 + x_i'\beta_i \tag{3}$$

With p the probability of the outcome, hence being either LIHC, 2M or M/2. β_0 is the intercept and β_i are coefficients for predictors x_i. Each dependent variable is binary and can be written Y_n, with

$$Y_n = \begin{cases} 1 & \text{if observation n is LIHC, 2M or M/2 respectively} \\ 0 & \text{otherwise} \end{cases}$$

In line with the energy and transport literature, we consider the following factors for our regressions: income decile (when not used to derive the indicator), household composition (number of adults, number of children), motorization (number of cars), socio-professional categories, tenure type, location of residence and distance to nearest train station. In comparison with the energy literature, we drop variables specific to the domestic sector and add variables specific to mobility such as distance to train station as a proxy for access to public transportation. For the logistic regressions, we restrict the number of variables according to the dependent variable (LIHC, 2M or M/2). Details on the explanatory variables can be found in the appendix.

4. Results

4.1. Extent of car-fuel poverty and fuel poor household profiles

Applying our indicators to the French National Household Travel Survey (EMP 2019), we find that 3.2% households are car-fuel poor in terms of the LIHC indicator, 20% have high exposure, spending a disproportionate share of income on car-fuels (2M) and 31% are under-consuming (M/2) car-fuels in metropolitan France (including people with no car-fuel expenditures). Our results show that while all LIHC households are in the 2M category, only 18% of households of the 2M group are LIHC.

The two step clustering method helps us identify eight main car-fuel poor household types. Detailed statistics on the composition of clusters as well as the biplots and dendrograms for each poverty indicator can be found in the appendix. For the LIHC indicator, we have three clusters. Cluster 1 represents about half of LIHC households. Households falling into this group are single individuals, most are under 55 with an over-representation of women under 25, without children, belonging to the poorest 20% and renting a home in a rather dense location (urban or commuting area). Despite good access to public transport, the vast majority owns a car. These individuals are mostly employees, workers, unemployed or inactive. In cluster 2 (27% of LIHC), we have large families (two adults with an over-representation of two or more children) belonging the 30% poorest households. Typical household heads of cluster 2 are men, working as independent, farmers and employees or workers. They are homeowners living in isolated rural and commuting areas with poor access to public transport. They own two cars. Cluster 3 (23% of LIHC) contains retirees over 60, living alone in isolated rural or commuting areas, owning one car and belonging to the poorest 20%.

For 2M households, we obtain three clusters. Cluster 1 (32% of 2M) contains low-income single adult households (40% poorest) with either one child or no children and one car. There is a majority of employees and workers and an over-representation of inactive but also intermediaries and independents. They rent their home. There is a slight over-representation of commuting or isolated rural areas with poor access to public transport. Households in cluster 2 (48% of 2M households) are multimotorised large families belonging to the fifth income decile or above, with 22% belonging to D7. There is a large majority of homeowners living mostly in commuting areas. Household heads are men between 30 and 60 years old, with an over-representation of intermediaries, independents, farmers, employees and workers. This is in line with the literature (Hills (2012); Legendre and Ricci (2015)) that shows that the 2M (or 10%) indicator does not exclude rich households that can cope with an increase in fuel prices, and is - therefore - not the most relevant measure of fuel poverty. Cluster 3 (20% of 2M households) contains households below D6. They are two adults households with retired men over 60 as household heads. They live mostly in commuting areas with an over-representation in isolated rural areas and poor access to public transport. They have either one or two cars.

Finally, M/2 households can be partitioned into two clusters. Cluster 1 (55% of M/2 households) is composed of single individuals, mostly women, retired, over 70 years old. They belong to the poorest four income deciles in majority, own either one or no cars and live in dense urban areas with good access to public transport. Cluster 2 (45% of M/2 households) contrains a majority of single parent households with either one child or no children. They have low-income (30% poorest). The large majority does not have a car and are tenants living in urban areas with good access to public transport. They are less than 60 years old and are mostly employees and workers.

Therefore, we see that different definitions of car-fuel poverty leads to differences in the extent and composition of car-fuel poor, which is in line with Legendre and Ricci (2015). In section 5, we describe specific policies for each cluster.

4.2. Regression Results

Now that we have identified different fuel poor profiles, we are interested in the factors affecting significantly the probability of being fuel poor under each of our three criteria. We apply three binary logistic model to the most recent National Household Travel Survey (EMP 2018-2019). We restrict the sample to households owning at least one car. In table 4, we present logistic regression results for the three models. We display both regression coefficients, which are in the log-odds scale and do not bring much information appart from their signs, as well as odds-ratio, which yield the probability of being LIHC, 2M or M/2 over the probability of not belonging to these categories. We compare the odds of a social-group to a reference category: no children for the number of children, one adult for the number of adults, one car for motorization, retirees for socio-professional categories, owners for tenure type, urban center for municipality type, below 2km for distance to train station and the poorest income decile (D1) for income decile membership.

	LIHC	Odds Ratio	2M	Odds Ratio	M/2	Odds Ratio
1 child	−0.52**	0.60**	−0.09	0.91	−0.09	0.91
	(0.16)	(0.16)	(0.07)	(0.07)	(0.10)	(0.10)
2 children	−0.57**	0.57**	−0.12	0.89	−0.03	0.97
	(0.18)	(0.18)	(0.07)	(0.07)	(0.11)	(0.11)
3+ children	−0.33	0.72	0.02	1.02	−0.01	0.99
	(0.23)	(0.23)	(0.09)	(0.09)	(0.13)	(0.13)
2 adults	−1.74***	0.18***				
	(0.14)	(0.14)				
3+ adults	−2.02**	0.13**				
	(0.73)	(0.73)				
2 cars	0.53***	1.71***	0.59***	1.80***	−2.08***	0.12***
	(0.14)	(0.14)	(0.06)	(0.06)	(0.09)	(0.09)
3+ cars	0.68**	1.97**	1.33***	3.77***	−3.22***	0.04***
	(0.23)	(0.23)	(0.08)	(0.08)	(0.32)	(0.32)
Farmer	1.71***	5.50***	1.30***	3.67***	−0.95***	0.39***
	(0.26)	(0.26)	(0.16)	(0.16)	(0.28)	(0.28)
Independent	0.99***	2.69***	0.98***	2.67***	−0.90***	0.41***
	(0.22)	(0.22)	(0.10)	(0.10)	(0.15)	(0.15)
Executives and higher intellectual prof.	−0.68*	0.51*	−0.18	0.84	−0.80***	0.45***
	(0.31)	(0.31)	(0.10)	(0.10)	(0.12)	(0.12)
Employees and workers	0.79***	2.20***	0.97***	2.65***	−1.02***	0.36***
	(0.14)	(0.14)	(0.07)	(0.07)	(0.08)	(0.08)
Unemployed and other inactive	1.32***	3.74***	1.15***	3.15***	−0.26	0.77
	(0.21)	(0.21)	(0.14)	(0.14)	(0.14)	(0.14)
Tenant	0.94***	2.55***	0.65***	1.91***	−0.01	0.99
	(0.12)	(0.12)	(0.06)	(0.06)	(0.07)	(0.07)
Commuting area	0.19	1.21	0.45***	1.57***	−0.40***	0.67***
	(0.13)	(0.13)	(0.06)	(0.06)	(0.07)	(0.07)
Isolated rural	0.72***	2.05***	0.72***	2.06***	−0.51***	0.60***
	(0.18)	(0.18)	(0.09)	(0.09)	(0.13)	(0.13)
2-5km	0.33*	1.39*	0.22**	1.24**	−0.27***	0.77***
	(0.14)	(0.14)	(0.07)	(0.07)	(0.07)	(0.07)
5-10km	0.30	1.35	0.39***	1.48***	−0.27**	0.76**
	(0.17)	(0.17)	(0.08)	(0.08)	(0.10)	(0.10)
> 10km	0.73***	2.08***	0.71***	2.03***	−0.33***	0.72***

	LIHC	Odds Ratio	2M	Odds Ratio	M/2	Odds Ratio
	(0.16)	(0.16)	(0.07)	(0.07)	(0.09)	(0.09)
D2					−0.17	0.84
					(0.12)	(0.12)
D3					−0.26*	0.77*
					(0.12)	(0.12)
D4					−0.37**	0.69**
					(0.12)	(0.12)
D5					−0.65***	0.52***
					(0.12)	(0.12)
D6					−0.61***	0.54***
					(0.13)	(0.13)
D7					−0.95***	0.39***
					(0.14)	(0.14)
D8					−0.91***	0.40***
					(0.14)	(0.14)
D9					−1.28***	0.28***
					(0.16)	(0.16)
D10					−1.23***	0.29***
					(0.17)	(0.17)
AIC	3205.05	3205.05	11281.44	11281.44	8128.19	8128.19
BIC	3366.81	3366.81	11428.50	11428.50	8341.42	8341.42
Log Likelihood	−1580.53	−1580.53	−5620.72	−5620.72	−4035.10	−4035.10
Deviance	3161.05	3161.05	11241.44	11241.44	8070.19	8070.19
Num. obs.	11530	11530	11530	11530	11530	11530
McFadden Pseudo R-squared	0.15		0.11		0.24	
Nagelkerke	0.18		0.17		0.33	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4: Regression results.

4.3. Robustness of the three models

Logistic regression results in Table 4 shows that most of our independent variables are significant at the 5% or 1% level. Our predictors present a low correlation, with Variance Inflation Factors less than 2. To avoid collineary with income deciles, we exclude the number of adults from the predictors for the M/2 and 2M model[17]. Since we used income deciles in the LIHC and 2M calculations, we remove it from the predictors for these outcome variables, to avoid endogeneity issues.

To assess the predictive capacity of the three models, we use two pseudo R-squared indices:

- McFadden Pseudo R-squared is $R^2 = 1 - \frac{\text{Log-likelihood full model}}{\text{Log-likelihood null model}}$
- Nagelkerke's R-squared is similar to McFadden's but is adjusted for the sample size N. $R^2 = \frac{1-(\text{Log-likelihood null model}/\text{Log-likelihood full model}/)^{2/N}}{1-(\text{Log-likelihood null model})^{2/N}}$

Our McFadden pseudo R-squared is above 0.2 for the M/2 model (0.24) which suggests a good predictive capacity. It is close but less than 0.2 for the LIHC and 2M models (respectively 0.15 and 0.11), which is caused by the fact that we omit key variables such as income decile in the predictors because it would raise endogeneity issues. Low pseudo R-squared are common in this type of models, as in Mattioli et al. (2018) that also lack key information on households[18]

[17]The number of adults is correlated with income deciles because we choose to use income deciles instead of equivalised income deciles, hence we do not account for the number of consumption units in the households.

[18]for example they lack socio-professional categories and their urban-rural categorisation could be improved : "the urban-rural variable used here is a rather broad-brush categorisation (Pateman, 2011), which may mask considerable variation within each area."

and obtain a McFadden R-squared of 0.062. The same analysis applies to Nagelkerke's pseudo R-squared, which is considered a more complete measure of predictive capacity than McFadden's.

In terms of goodness of fit, the Hosmer and Lemeshow test (Hosmer Jr, Lemeshow and Sturdivant (2013)) compares the observed and predicted probabilies of the outcome variable for different (here, 10) groups in the sample. It tests if there is a significant difference between them. A non significant test validates the model. For our three models, the Hosmer and Lemeshow tests results in non-significant differences, which suggest a good fit of the models. Detailed tables are available in the appendix.

4.4. How the predictors affect the odds of being car-fuel poor

Having children has a significant and negative impact at the 5% level for LIHC households but not for 2M and M/2 households. In fact, Table 4 shows that the odds of being LIHC are 1.7 to 1.8 times greater for households that do not have children, compared to households with at least one child. This is not consistent with Mattioli et al. (2018) that find a positive relationship between the number of children and the probability to be in Car Related Economic Stress (CRES). Our results also show that single adult households have higher chances to be car-fuel poor; the odds of being car-fuel poor under the LIHC for a household with one adult are 6 times the odds of being vulnerable when there are respectively 2 and 3 and more adults in the household. In the energy poverty literature, there is no consensual effect of family size and composition. Belaïd (2018), finds that larger families have more chances to be fuel-poor while Legendre and Ricci (2015) find that single person households have higher risks of being vulnerable.

Increasing the number of cars in the household affects positively the risk of being LIHC and 2M and decreases the risk of underconsuming. In fact, households with two cars have 1.71 times (respectively 1.8 times) the odds of being LIHC (respectively 2M) than households owning only one car. On the other hand, households owning one car have 8.3 times the odds of underconsuming compared to households with two cars. We cannot compare with Mattioli et al. (2018) since they do not use the number of cars as a predictor.

We find that households with farmers, independent, employees and workers, unemployed and other inactive heads tend to be more car-fuel poor in terms of LIHC and 2M indicators compared to retirees, which is our reference category. In facts, the odds of being vulnerable of farmers, independents, employees and workers, unemployed and other inactive are respectively 5.5, 2.7, 2.2 and 3.8 times the odds of retirees for LIHC households (respectively 3.7, 2.7, 2.7 and 3.2 for 2M). In comparison, Mattioli et al. (2018) do not have detailed information on household socio-professional categories but find that having unemployed members in the households increases the probability of being vulnerable, which is consistent with our findings. Our results are also consistent with Romero et al. (2018); Belaïd (2018, 2022b) that find that having household heads with low education or job instability increases the probability of fuel poverty. Finally, the odds of restricting car-fuel consumption are higher for retirees than for most of the other categories. Executives, independents and farmers have the lowest chances to underconsume, when compared to retirees.

We find that renters have higher chances than owners to be LIHC and 2M while tenure type is not significant for M/2 households. This is in line with the energy poverty literature (Belaïd (2018); Legendre and Ricci (2015)) that find that private home renters are about twice as likely to experience fuel poverty than owners.

Our results show that the odds of being vulnerable for households living in isolated rural areas are 2 times those of households living in dense urban areas. Living in commuting areas have no significant impact on the probability to be LIHC but significantly increases the probability to be 2M and decreases the probability to be M/2 at the 1% level.

Results suggest that accessibility to public transport has a significant impact on our three outcome variables. We find that living above 2km away from a train station increases the probability to be 2M and decreases the probability to under-consume. The odds of being LIHC when living between 2 and 5km away (respectively 10km away) from a station are 1.4 (respectively 2.1) times the odds of a household living close to a station (below 2km). Distance to train station has a negative effect on under-consumption, increasing in absolute with distance.

Finally, income deciles affect significantly the probability of under-consuming from D3 (at the 10% level) to D10 (at the 1% level). The odds of restricting its consumption while being poor (D1) are 1.3 times the odds of underconsuming when belonging to D3 and 3.3 times the odds of rich households (D10).

5. Policy Implications

5.1. Impact of the 2022 energy crisis

Understanding what it means to be car-fuel poor and which factors are responsible for vulnerability has several implications for energy and climate policies. When assessing whether or not a measure is fair, choosing the relevant indicator is crucial. To demonstrate the inadequacies of the current methods used in France for examining matters of fairness, we use travel data from EMP to derive the average impact of 2022 energy inflation on different income groups[19]. Figure 1 presents the share of income spent on the increase in gasoline prices, assuming that fuel demand is inelastic. Looking at blue bars, we could argue that inflation hits more the middle class than the poor. Yet, this does not account for restriction behaviours or for the fact that cars are luxury goods that the poorest cannot afford. If we average accross households owning at leat one car, results appear more regressive (orange bars). Moreover, spending a high share of income on fuel expenditures does not have to be an issue in itself. It does not mean that households are left in a critical state, for example below a poverty line. This illustrates that using the "ratio" of expenditures over income is not always relevant to assess fairness issues and motivates the need for adequate indicators.

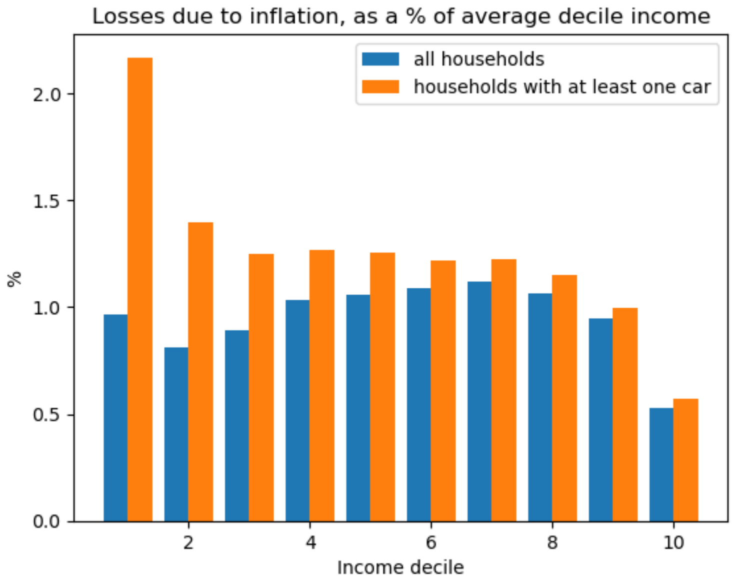

Figure 1: Assuming inelastic demand, average loss due to energy prices in 2022, as a % of income, for different income groups.

5.2. The 2022 French fossil fuel subsidy

In light of drastic increase of energy prices, the government implemented a subsidy on diesel and gasoline prices in April 2022. It has functioned in three different "phases": first, from April 1^{st} to August 31^{st} 2022, the amount was €18 cents per liter of gasoline. It reached €30 cents per liter from September 1^{st} until November 15^{th}, and it has decreased to €10 cents per liter from November 15th to December 31^{st} . This measure was meant to protect the most vulnerable. Yet, it is regressive, as it gives an equal subsidy to everyone for car-fuel consumption which, in average, increases with income. In Figure 2, considering the 9-month policy, we compute the average gain from the rebate per household belonging to each equivalized income decile. We find that the richest decile gains in average 2.5 more than the poorest decile if all households are considered, and 1.6 times if we only account for households that own at least one car. This result is in line with the work of the French economic analysis board[20] that investigates the effects of the first phase of the rebate (c€18/l for 4 months) using transaction data from Crédit Mutuel and find that the measure benefited the richest (10th decile) twice as much as the poorest (1st decile).

Using travel data from the most recent National Household Travel Survey (EMP 2018-2019), we estimate the total cost of the subsidy for private cars over the 9-month period. We do not account for other vehicles since we do not observe their kilometers driven. We find that the rebate cost €3.9 billions[21]. We consider two alternative subsidies:

[19]To do so, we use fuel prices from 2019 and 2022 from http://data.gouv.fr

[20]Conseil d'Analyse Economique

[21]The government announced a budget of €7.6 billion for the policy but here we only consider private cars. Our results for private cars' fuel consumption are in line with national accounts for individual cars.

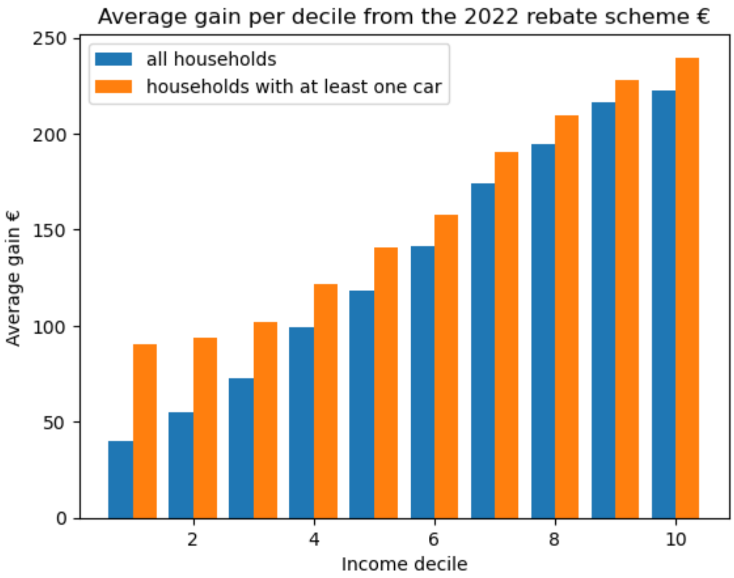

Figure 2: Average gain in euros from the 9-month rebate, own calculations, using distance travelled from EMP

1. A policy where the 2022 three-phases scheme is considered but targetting only car-fuel poor households (LIHC or 2M)
2. We investigate the costs of fully compensating LIHC or 2M from the 2022 price increase (against 2019 prices).

Policy	Costs
Government 2022 scheme	€3.9 billions
Target LIHC with 2022 measure	M€234
Target 2M with 2022 measure	€1.6 billions
Fully compensate LIHC	M€592
Fully compensate 2M	€4.2 billions

Table 5: Alternative policies and costs

We find that, if the government had chosen to target only the most vulnerable (LIHC) with their 2022 subsidy, they could have saved about €3.7 billion. If instead they had compensated completely the LIHC, they could have saved €3.3 billions. On the other hand, if the rebate had been targeted towards 2M households, it would have cost the state €1.6 billions. We also find that fully compensating the 2M households would have lead to additional expenses compared to the 2022 scheme. It seems difficult to fully compensate 2M household whenever fuel prices increase. Therefore, distinguishing among the 2M households between non-poor households that can cope with an increase in fuel prices and households that cannot is key. This is how clustering analysis can help. Considering the eight fuel-poor profiles identified in section 4, we suggest specific policies in Table 6.

Car-fuel poor profile description	policy suggested
LIHC-Cluster 1: single women without children, 20% poorest, tenants, urban but owning one car, employee, worker or inactive	Compensate via car-fuel subsidy. Free public transport or subsidy (additional to current feebate) to purchase light electric vehicles allowing to keep driving in urban low emission zones

LIHC-Cluster 2: Large families among the 30% poorest, with two cars, independent, farmers, employees and workers, isolated rural and commuting areas, poor access to public transport	Compensate via car-fuel subsidy. Additional subsidy to help shift to electric vehicles.
LIHC-Cluster 3: Retirees with low pensions living alone in isolated rural areas without public transport	Compensate via car-fuel subsidy. Additional subsidy to help shift to electric vehicles. Local transport planing to help the most vulnerable to achieve mobility needs (public transport, on-demand transport, car-sharing platform)
2M-Cluster 1: Low-income single adults with one or no children, employees, workers, inactive, intermediaries and independents, renting in commuting or isolated rural areas with poor access to public transport	Similar to LIHC-Cluster 2
2M-Cluster 2: large multimotorized family above the fifth income decile living in peri-urban and isolated rural areas with poor access to public transport, household head is among intermediaries, independent, farmers, employees or workers	Targeted subsidy for car dependent households to shift to more efficient low carbon modes (for. e.g. electric vehicles)
2M-Cluster 3: Two adult households, retirees over 60, among poor and lower middle class households with one or two cars living in commuting areas	similar to LIHC-Cluster 3
M/2-Cluster 1: single retired women over 70 among the 40% poorest living in urban areas with good public transport access	Free public transportation
M/2-Cluster 2: single adult households with one child or no children, with low income (30% poorest), no cars, tenants, living in urban areas with good access to public transport	Free public transportation

Table 6: Alternative policies for the 8 car-fuel poor profiles

Since January 2023, the policy has evolved and is now a 100€ voucher for the poorest 10 million active persons that use their cars to commute. To benefit from the policy, households need to register on a government website and certify that (1) they belong to the 5 poorest decile and (2) they use their car to commute. To this date, only 40% of eligible individuals have benefited from the policy[22]. Although this measure better is better targeted, our study showed that inactive people have high risks of being vulnerable as well. Figure 3 also shows that the 100€ voucher in 2023 has a rather low amount compared to what car-fuel poor households could have lost, if we assume that their fuel consumption did not change between 2019 and 2022.

6. Conclusion and discussion

In this paper, we bridge the gap between the transport poverty and energy poverty literature by adapting energy affordability indicators - which are extensibly used and accepted - to transport. We choose to focus on three affordability

[22] https://www.journaldunet.com/patrimoine/guide-des-finances-personnelles/1517121-indemnite-carburant-2023-6-travail

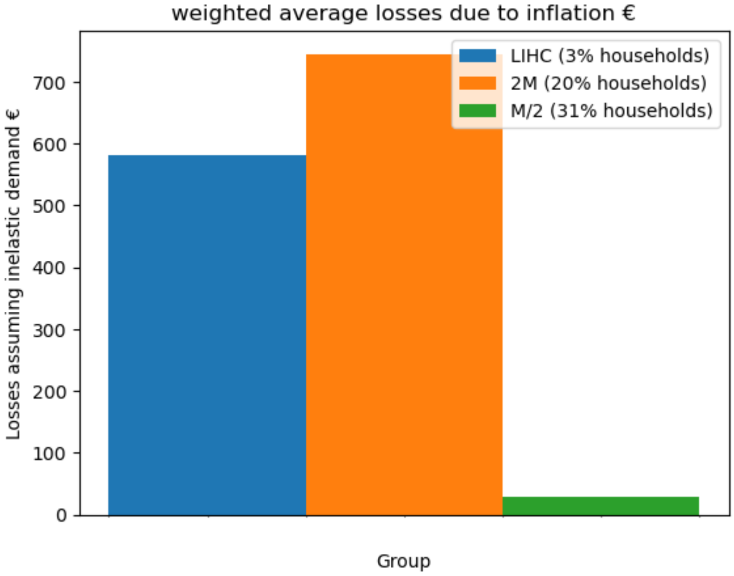

Figure 3: 2022 Losses due to car-fuel inflation in case of inelastic car-fuel demand for the three categories of car-fuel poor households, own calculations with EMP 2018-2019

indicators: (i) Hills (2012)'s Low-Income High Cost metric, which a measure of car-fuel poverty (ii) an indicator that identifies households that spend a disproportionate share of their income on car fuels (2M) and (iii) a measure of under-consumption (M/2), identifying both households that are restricting their fuel consumption for affordability reasons and households that benefit from good access to public transportation.

We study the extent of transport poverty in the french population and identify eight car-fuel poor household profiles that can help design targeted policies. We find that overall, only a small part of the french population is at risk of poverty when fuel prices increase (3.2%) while a larger part is very fuel dependent but not necessarily poor (20%). Then, we investigate key socio-economic factors that increase the risk of falling into car-fuel poverty. Our findings suggest that households at risk of poverty are single person households, households with low-income, households with farmers, employees, workers, unemployed or other inactive heads, renting their homes and living in isolated rural or commuting areas with very low access to public transport.

Finally, we use our results to suggest alternative policies to the French fossil fuel subsidy implemented by the government in April 2022. We show that targeted policies could have lead to major savings while compensating completely the most vulnerable. We use the 6 car-fuel poor profiles to suggest more specific policies.

Our study has focused on affordability indicators. Yet, transport poverty cannot be reduced to affordability issues. To better account for the multidimensional aspects of transport poverty, some papers develop composite indicators (Berry et al. (2016); Mattioli (2017a)). A new strand of the literature also investigates energy and transport poverty jointly, to account for the double vulnerability that certain household face (Lowans et al. (2021); Simcock, Jenkins, Lacey-Barnacle, Martiskainen, Mattioli and Hopkins (2021). This could be a topic for future research.

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