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# Car choice determinants in Italy and Norway: A comparison based on revealed and stated choices

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ABSTRACT

Norway is the leading country in electric car adoption in the world, while in Italy electric cars are only recently gaining acceptance. We compared car choices in the two countries highlighting commonalities and differences in the choice determinants, distinguishing between the small and the large car segment. We analyzed actual choices made in the real-world conditions and stated choices under hypothetical scenarios. The comparison between the preference structures of the two countries shows important differences when the revealed preference dataset is analyzed, while the differences are much reduced with the stated preference dataset. All in all, we feel that the two countries present only differences associated with longer car driving habits of the Norwegian drivers, the higher percentage of large cars in Norway, and the more developed public charging infrastructure. Since the supply of cars is quite similar, such a consideration leads us to believe that the huge discrepancy in electric car uptake is mainly due to the different car policies adopted in the two countries. The evolution of the policy setting and of the technology will determine whether Italy will follow the Norwegian model of gradual BEV uptake.

## 1. Introduction

Norwegian and Italian car drivers made very different car choices. Norway is the leading country in electric vehicle (EV[1]) adoption in the world, with EVs reaching a share of 86.2% of the total annual sales in 2021 (Fig. 1), most of which battery electric vehicles (BEVs). Italian car drivers have long preferred fossil fuel-based engine technologies (petrol, diesel, liquefied propane gas (LPG) and compressed natural gas (CNG)). Only recently, they started buying newer powertrains. In 2021, in Italy hybrid electric vehicles (HEVs) made up 29% of the total annual sales, plug-in hybrid electric vehicles (PHEVs) 4.7%, and BEVs 4.6% (UNRAE - Unione Nazionale Rappresentanti Autoveicoli Esteri, 2022).

The aim of this paper is to compare car drivers' choices in the two countries – one leading the world in EV adoption and the other trailing behind most European countries – in search of commonalities and differences in the choice determinants.

There is a long-standing tradition of studying consumers' preferences regarding car choice in both countries. In Italy, several researchers have carried out empirical car choice research. Rusich and Danielis (2015) published one of the first contribution in Italy estimating the total cost of ownership, social lifecycle cost and energy consumption of various automotive technologies. More recently, Danielis, Giansoldati, and Rotaris (2018) and Scorrano, Danielis, and Giansoldati (2020) updated and extended the analysis focusing exclusively on the total cost of ownership. Their main conclusion was that in Italy BEV competitiveness, both regarding private passenger cars and vans (Scorrano, Danielis, & Giansoldati, 2021), is highly dependent on public subsidies, and that the annual distance travelled, the percentage of urban trips, and the availability of a private parking space are crucial determinants for some segments of the population. Several studies have used stated preference (SP) experiments to explore Italian drivers' preference structure and to simulate BEV uptake (Scorrano & Danielis, 2022; Danielis, Rotaris, Giansoldati, & Scorrano, 2020; Giansoldati, Danielis, Rotaris, & Scorrano, 2018; Valeri & Cherchi, 2016; Valeri & Danielis, 2015). Rotaris, Giansoldati and Scorrano (2021) analyzed the role of knowledge and environmental awareness comparing car stated choices in two countries,

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[1] We use the term EV (electric vehicle) to include battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV). Although the acronyms contain the term vehicle, in this paper we mainly considered passenger cars.

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Italy and Slovenia, both characterized by a slow BEV uptake. A weakness of the Italian SP studies so far carried out is that the surveys took place in the very early stages of BEV uptake when respondents had little knowledge and experience of BEVs. In fact, Valeri and Danielis (2015) and Valeri and Cherchi (2016) used data collected in 2013–2014, Giansoldati et al. (2018) in 2017, Danielis et al. (2020) and Rotaris et al. (2021) in 2018.

The Norwegian situation is, of course, very different. BEV penetration started at a rapid pace a decade ago and it had been subject to many and highly data-intensive studies on many aspects of BEVs uptake. Figenbaum & Kolbenstvedt (2016) studied the everyday experience of using EVs. Many studies investigated the impact of the generous EV incentivizing policies (Bjerkan, Nørbech, & Nordtømme, 2016; ; Mersky, Sprei, Samaras, & Qian, 2016; Figenbaum, Assum and Kolbenstvedt, 2015). Hardman et al. (2018) analyzed consumer preferences for charging infrastructure, and Figenbaum (2020) explored the usage pattern of fast chargers. Very recently, Fridstrøm & Østli (2022) evaluated the willingness to pay for BEV driving range.

For the purpose of this study, we refer in particular to two studies based on car ownership data presented by Østli, Fridstrøm, Johansen, and Tseng (2017) and Fevang et al. (2021). The former developed a nested logit model of automobile choice, based on complete vehicle sales data for Norway for the period ranging from January 1996 until July 2011. Every single car sale is regarded as a discrete choice and every model variant available in the market in that year is included in the buyers' choice set. As acknowledged by the authors, such an approach has pros and cons. The main advantage is its high level of disaggregation and reliance exclusively on objective vehicle registration data. The disadvantage is that it disregards the human and social aspects of car choice, such as the individuals' income, education, family structure, residence pattern, employment, travel needs, peer pressure, ethical motivations, environmental concern, knowledge, interest for technology, and so on. The very recent contribution by Fevang et al. (2021) combined demographic information on car owners to detailed data on the characteristics of the cars owned, covering the entire population of private car owners in Norway. They found that some socioeconomic characteristics are strong predictors of the car portfolio. Specifically, BEV ownership resulted being positively correlated with wealth, income and education. They also found that BEV incentivizing policies (e.g., toll road exemptions, bus lane access) have increased BEV uptake. Their unit of analysis is the household and they estimated the marginal effects depending on fleet composition of the household (no cars, 1 internal combustion engine vehicle (ICEV), 2 + ICEVs, 1 BEV, 2 + BEVs, etc.).

To the best of our knowledge, only two studies have investigated car choice in Norway on the basis of SP experiments. A pioneering study was performed by Ramjerdi and Rand (2000), well-before the advent of EVs. More recently, Noel et al. (2019) conducted a choice experiment in five Nordic countries (Denmark, Finland, Iceland, Norway and Sweden) focusing on EVs and vehicle-to-grid technology. The respondents were asked to choose between two versions of EVs (some including vehicle-to-grid capability) and their preferred gasoline vehicle. Using a mixed logit model, they derived the willingness to pay for driving range, acceleration, recharging time, fuel source, and vehicle-to-grid capability.

This paper adds to the not abundant literature comparing consumers' car choice in different countries. We are aware of the following studies. Tanaka, Ida, Murakami, and Friedman (2014) compared the consumers' willingness to pay (WTP) for BEVs and PHEVs in Japan and four US states, two countries with similar wealth but different culture when EV uptake was at the early stages. Helveston et al. (2015) compared U.S. and China; in this case two countries different both in wealth and in culture. The already quoted Noel et al. (2019) compared stated car driver choices in five very similar Nordic countries: Denmark, Finland, Iceland, Norway and Sweden. Rotaris et al. (2021) compared preferences and attitudes in Italy and Slovenia, again similar in terms of wealth and both at the early stages of EV uptake. This paper adds to this comparative literature a case study concerning two European countries with similar car cultures, differences in wealth and at very different stages of EV penetration and development of fast charging network. How do these differences impact car choices?

In a recent paper, Scorrano, Mathisen, and Giansoldati (2019) compared the car market in Italy and Norway from the point of view of the total cost of ownership (TCO). They found very different situations: in Norway BEVs have the lowest average annualized TCO/km, while in Italy they have the highest TCO/km. Among other factors, such a result is due to the fact that in Norway the government encourages the purchase of BEVs by imposing much lower taxes than the ones imposed on

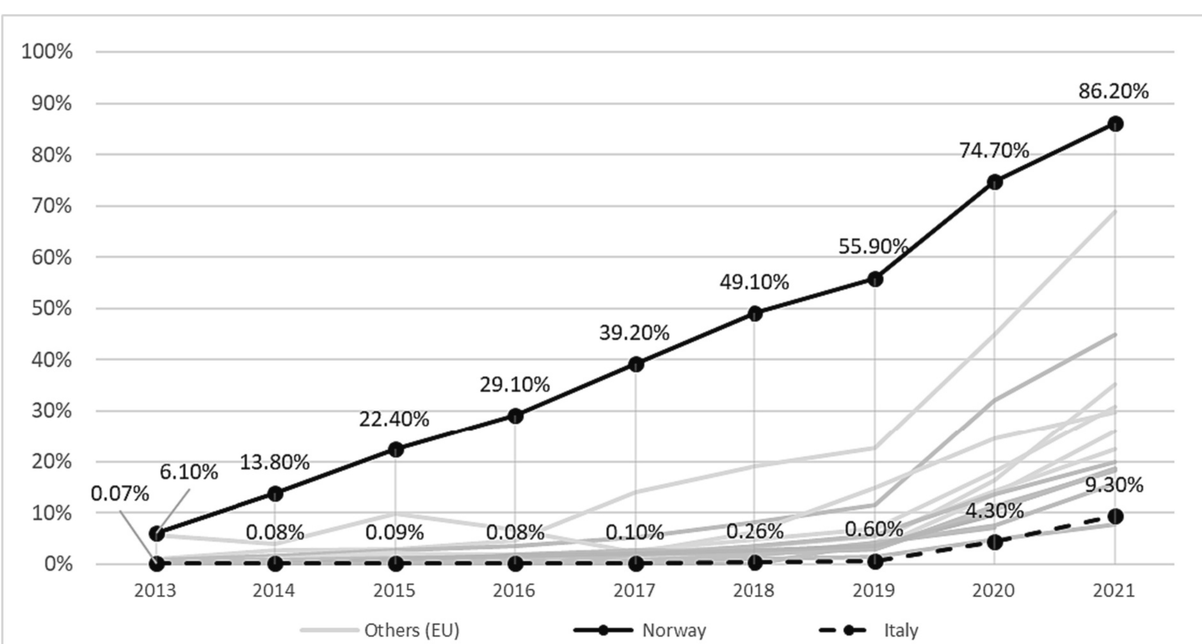


**Fig. 1.** Passenger EV market share of total new car sales for selected countries since 2013.
*Source:* Statistics Norway (2022), UNRAE (2022), ACI (2022)

ICEVs. Specifically, so far BEVs enjoyed VAT exemption, generally 25%; no registration tax, instead of the considerable $CO_2$ and weight graduated, one-off registration tax levied on ICEVs; lower rates on the annual circulation (ownership) tax; fully or partially exemption from road toll; lower rates on ferry fares; and reduced public parking fees. In Italy, instead, Scorrano et al. (2019) found that the EV competitiveness was largely dependent on the purchase subsidies.

In this paper, we compared car choices made by Italian and Norwegian car drivers. Thanks to a survey recently carried out among 1144 respondents in the two countries, we collected data on their actual car choices (henceforth called "revealed", in accordance with the discrete choice literature) and on the car choices that they stated they would make under a set of hypothetical scenarios (i.e., the "stated" choices). Differently from Fevang et al. (2021), our units of analysis are individual respondents, although we collected information also on the fleet composition of their household. The revealed choice data allowed us to estimate the revealed preferences (RP), while the stated choices captured the stated preferences (SP) of the two national samples. The two datasets have different pros and cons, as highlighted in the literature (Bhat & Castelar, 2002; Brownstone, Bunch, & Train, 2000; Cherchi & De Dios Ortúzar, 2011; Morikawa, 1994). An advantage of the former is that they do not suffer from the hypothetical bias, being based on the actual choice behavior, and incorporate all real-world constraints and opportunities (income, garage availability, public charging network, access privileges, reduced parking fees, and so on). The disadvantage is that such choices were made in the past (from 2010 onwards), hence, some of them might neither reflect the actual market condition nor fully incorporate the current expectations regarding the future developments of the car market. A potential solution is to pool the two datasets to exploit advantages of each (Helveston, Feit, & Michalek, 2018; Guzman, Arellana, Cantillo-García, & Ortúzar, 2021).

We analyzed the choice among five powertrain alternatives: petrol vehicle (PV), diesel vehicle (DV), BEV, HEV, and PHEV. We applied the same specification, the random parameter logit (RPL) model to the three datasets: the RP, the SP and the pooled RP\SP dataset. We used as explanatory variables the attributes purchase price, driving range and fuel costs, which are considered as the most important ones in the previous literature. We interacted them with the car segment (small vs large cars) covariate to explore whether the attributes' sensitivity depends on the car segment, as suggested by Jensen, Thorhauge, Mabit, and Rich (2021). In fact, as documented below, Italian car drivers bought mostly small cars while Norwegian drivers bought larger cars in larger quantities than small cars. Since different car segments play different roles in satisfying the users' mobility needs and they have different charging requirements, we considered important to explore whether car preferences are car segment-specific. The model specification was enriched by a series of socio-demographic determinants (age, gender, income, charging availability, place of residency). The estimates provided us with interesting information on the preference structure of the Norwegian and Italian car buyers.

The paper is structured as follows. Section 2 presents some statistics concerning the fleet composition, new registrations and the EV charging network in the two countries. Section 3 explains the modeling framework. Section 4 describes the survey. Section 5 illustrates the econometric results of the models estimated using the revealed and stated choice data. Section 6 concludes.

## 2. Italy vs. Norway: fleet composition, new car registrations, EV penetration and charging network

### 2.1. Fleet composition

Italy is characterized by a growing number of cars (39.7 million, 670 cars per a thousand inhabitants), mainly fueled by petrol (45.5%), diesel (43.8%), LPG (6.7%) and CNG (2.5%) (Fig. 2). HEVs and PHEVs represent 1.4% of the total fleet and BEVs only 0.1%. In Norway, the fleet of private cars consists of 2.82 million cars, equal to 520 cars per a thousand inhabitants. In 2020, the Norwegian fleet was quite different from the Italian one, and from that of many European countries. It consisted of diesel cars (44.6%), petrol cars (33.7%), BEVs (12%), PHEVs (5.2%) and HEVs (4.5%) (Fig. 2). The large share of EVs, relative to other European countries, is the result of more than a decade of EV penetration in the Norwegian car market. In fact, already in 2013, the EV's market share for new sales was equal to 6.1%, doubling in 2014, reaching almost 50% in 2018, 74.7% in 2020 and 86.2% in 2021 (Fig. 1).

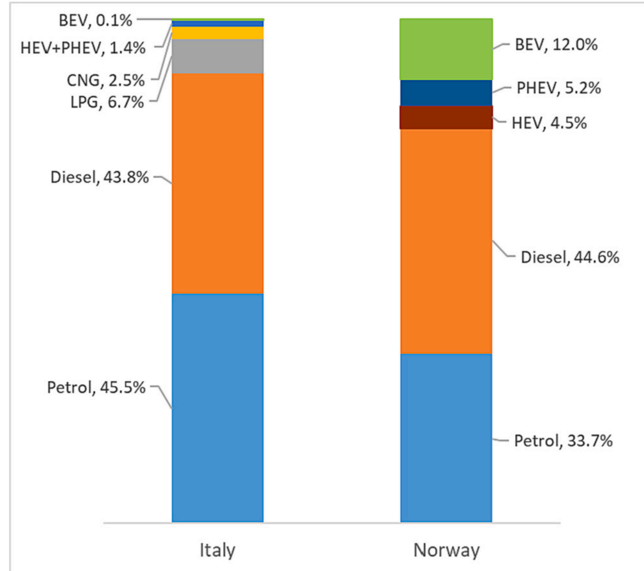


**Fig. 2.** Fleet composition by powertrain in Italy and Norway in 2020.
*Source:* Statistics Norway (2022), UNRAE (2022), ACI (2022)

### 2.2. New car registrations

In 2021, petrol, diesel and hybrid cars make up the large majority (81.3% of the total registrations) of the Italian passenger car market (Fig. 3). Other fossil fuel-based cars, such as LPG and CNG, had a market share of 7.3%, and 2.1%, respectively. In the last years, the major change has been the growth of HEVs (from 5.7% in 2019 to 29% in 2021), substituting both petrol (down from 44.3% to 29.7%) and diesel cars (down from 40% to 22.6%). The second development has been the modest but steady growth of EVs, which represent in 2021 9.3% of the market (from 0.5% in 2019), equally divided between PHEVs and BEVs

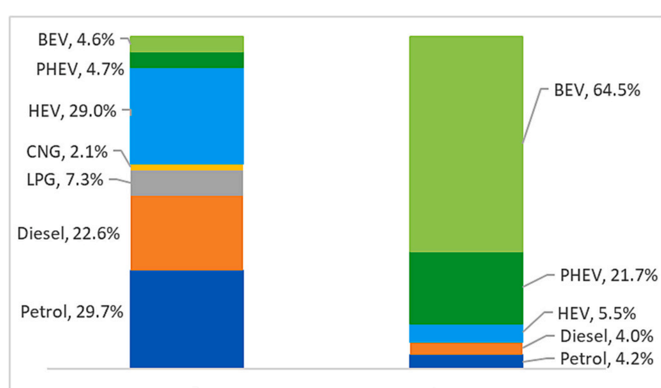


**Fig. 3.** New registrations by powertrain in Italy and Norway in 2021.
*Source:* Statistics Norway (2022), UNRAE (2022), ACI (2022)

(Fig. 3). In Norway, BEVs and PHEVs dominated the car market in 2021, with a share of 64.5% and 21.7%, respectively, while the remaining powertrains played a marginal role.

### 2.3. Small and large car segments

In the Italian statistics, cars are classified by size in terms of engine capacity (cubic centimeters, c.c.). From the data made available by ACI (2022), it results that 24% of the car fleet has an engine smaller than 1200 c.c., 50.5% in the range 1201–1600 c.c., 19.4% in the range 1601–2000 c.c., and the remaining 6.1% above 2000 c.c. Hence, we can conclude that the majority of the Italian car fleet consists of small or medium engine size cars (Fig. 4). In Norway, cars are classified by segment, denoted by the letters A, B, C, D, etc., based on weight and size parameters, similar to the ones used at European level (see supplementary material SM 3.0). Identifying the small cars as the ones belonging to the segments A, B and C, it results that large cars prevail (1,769,133 vs 1,025,312 in 2020), i.e. they represented 63.3% of the total fleet. In the small car segment, petrol is the most common powertrain (42.5%), while diesel makes up more than half of the larger cars (55.4%). BEVs represent a large and growing share of the total fleet of small cars (22.6%), while they are only 6% of the fleet in the large car segment (see supplementary material SM 2.0). Thanks to the recent trends, BEV shares in both segments are rapidly growing.

### 2.4. EV penetration and charging network

Because of these different EV penetration levels between the two countries, in 2020 in Italy there was one EV for every thousand inhabitants, while in Norway the ratio of EVs per thousand inhabitants was equal to 63. Of course, Italy was also lagging behind in terms of number of charging points: 0.3 every thousand inhabitants versus 3.4 every thousand inhabitants in Norway.

## 3. Modeling framework

In order to analyze revealed and stated choices of the consumers, we used a random parameter logit (RPL) model that accounts for random heterogeneity in preferences.

Since our goal is to compare the consumers' preferences in the two countries, a separate estimate for each country would not be appropriate because the scale parameter, capturing the unspecified attributes, might differ between the two countries. Along the lines suggested by Train (2009, p. 25), a solution is to normalise the scale parameter with respect to one of the countries. Therefore, denoting with $U_{njt}$ the (relative) utility individual $n$ receives from choosing alternative $j \in J$ in the choice task $t$, we specified the model as follows:

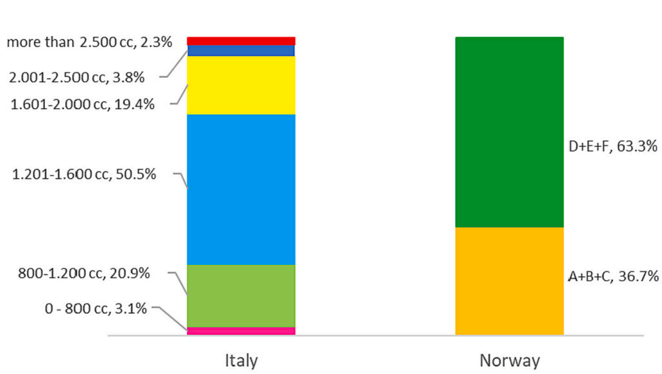


**Fig. 4.** Fleet by car segment in Italy and Norway in 2020.
*Source:* Statistics Norway (2022), UNRAE (2022), ACI (2022)

$$\begin{cases} U_{njt}^{NOR} = \left(V_{njt}^{NOR} + \varepsilon_{njt}^{NOR}\right) = \left(ASC_{nj}^{NOR} + \beta_{nj}^{NOR} X_{njt}^{NOR} + \gamma_{nj}^{NOR} Z_{n}^{NOR} + \varepsilon_{njt}^{NOR}\right) \\ U_{njt}^{IT} = \theta\left(V_{njt}^{IT} + \varepsilon_{njt}^{IT}\right) = \theta\left(ASC_{nj}^{IT} + \beta_{nj}^{IT} X_{njt}^{IT} + \gamma_{nj}^{IT} Z_{n}^{IT} + \varepsilon_{njt}^{IT}\right) \end{cases} \tag{1}$$

where $\theta = \theta^{IT} / \theta^{NOR} = \sigma^{NOR} / \sigma^{IT}$.

For each country, NORway and ITaly, ASC is the alternative-specific constant, X is a vector of the attributes proposed in the choice experiment (net purchase price, driving range, fuel/energy cost), $\beta_{nj}$ is the corresponding vector of coefficients that differ across individuals, reflecting respondents' tastes, and follow a distribution that is up to the researcher to choose testing which one best fits the data (e.g., normal, lognormal, uniform, triangular, etc.). Z is a vector of socioeconomic characteristics, $\gamma_{nj}$ being its vector of coefficients. $\varepsilon_{njt}$ is a random term IID extreme value type 1. $\theta^{NOR}$ and $\theta^{IT}$ are scale parameters equal to the ratio of the standard deviations of the error terms ($\theta^{NOR} = 1/\sigma^{NOR}$; $\theta^{IT} = 1/\sigma^{IT}$).

However, the parameters of the equation for Italy are over-specified. One cannot simultaneously estimate $\theta$ and the remaining parameters of the equation which are multiplied by $\theta$ (any product might result from an infinite combination of factors). At least one parameter of the equation for Italy should be set generic, that is, equal to one of the parameters of the equation for Norway, so as 'to anchor' that parameter to the Norwegian dataset. A similar procedure has been applied by Jensen, Cherchi, and Mabit (2013) to compare preferences and attitudes before and after experiencing an EV and by Noel et al. (2019) to compare preferences among Nordic countries.

The cumulative distribution function of $\beta$ in the population is $F(\beta|\vartheta)$ which depends on parameters $\vartheta$ (e.g., mean and variance). The distribution can be continuous or discrete, different elements in $\beta$ may follow different distributions (including some being fixed), and the elements of $\beta$ may be correlated with each other. With continuous F, the probability of an individual $n$ choosing alternative $j$ can be calculated as the weighted average of the logit formula evaluated at different values of $\beta$, with the weights given by the density $f(\beta|\vartheta)$:

$$P_{nj} = \int \frac{e^{V_{nj}(\beta)}}{\sum_{j} e^{V_{nj}(\beta)}} f(\beta|\vartheta) d\beta \tag{2}$$

Since such a probability is not a closed form, the probabilities are approximated through simulation for any given value of $\vartheta$.

We firstly estimated two different RPL models, with the RP and the SP dataset separately, to capture the differences between the determinants of actual and stated choices. We then estimated a joint model considering both RP and SP data to take advantage of their complementary characteristics.

As discussed in the literature, RP and SP data have different properties. Morikawa (1994) underlined that RP data are cognitively congruent with actual behavior while SP data might be incongruent. RP choices are made among all real-world alternatives, whereas SP choices consider only the ones presented in the scenarios, with the advantage of developing alternatives not yet available in the market place. With reference to the attributes, the ones used for RP data may include measurement errors, be correlated and present limited intervals. On the contrary, the ones used in the SP scenarios are defined by the analysis, multicollinearity can be avoided by design and the attribute levels can be extended. Other limitations of the RP data are that the choice set considered by the individuals might be difficult to identify, only one response can be obtained for each respondent and the only preference information available is the choice. On the contrary, with the SP experiments the choice set is prespecified by the analyst, more than one choice scenario can be collected from each respondent and various response formats can be considered (e.g., choice, rank, rate). As a result, RP datasets are often much smaller than the SP ones (Cherchi & De Dios Ortúzar, 2011), RP data is more prone to multicollinearity issues (Brownstone et al., 2000), and it is more difficult to explore respondents' heterogeneity among individuals. On the other hand, SP data might suffer from a hypothetical bias, anchoring effects and strategic behavior (Fosgerau, Hjorth, & Lyk-Jensen, 2010; Schmid et al., 2019).

A way out to overcome the limitations of both datasets and potentially obtain a better picture of the respondents' preference structure is to pool the two datasets. Pooling information from different sources is considered a data enrichment technique (Cherchi & De Dios Ortúzar, 2011). Schmid et al. (2019) argued that pooling the two datasets ensures robustness and efficiency in parameters estimation, overcoming the limitations of pure RP or SP models. Brownstone et al. (2000) showed that a joint RP\SP model might provide more reliable forecasting results. The challenge for the researcher is to find the best specification of a RP \SP model.

The issue of pooling RP and SP datasets has been studied both from the theoretical and the empirical point of view. Axsen, Mountain, & Jaccard (2009) compared three alternative techniques to jointly estimate choice models from SP and RP data. The first pooling technique consists in assigning equal weighting to the SP and RP data, estimating joint beta coefficients for vehicle attributes, and unique ASCs for the RP data, assigning a weight to SP data to limit influence to be equivalent with the RP data. The second pooling technique is similar to the first one, but without "corrective" weights. The third technique, defined "sequential", consists in directly extracting beta coefficients from the SP model and calibrating the ASCs to fit the RP data. They propose to choose the resulting model with the least maximum likelihood. Yan et al. (2019) opted for a RP\SP model with data-specific coefficients for all ASCs and generic coefficients for all common variables. The adjusted McFadden's pseudo R-square value for the model is used to demonstrate the improved model fit of the joint model over the separate one. Guzman et al. (2021) proposed a set of rules to test which parameters should be treated as common and which one as database-specific. The methodology comprises a visual analysis and a statistical analysis based on the LR test formulated as follows:

$$LR = -2[LogLikelihood_{RP-SP} - LogLikelihood_{RP} - LogLikelihood_{SP}]$$

where LR distributes asymptotically $\chi 2$ with degrees of freedom equal to the number of parameters assumed to be common minus one. The null hypothesis is that the common utility parameters are equal.

Helveston et al. (2018) performed a theoretical analysis testing their conclusions with a synthetic database. They acknowledged that pooling has the potential to improve the model by adding additional information about the parameters, reducing multicollinearity, and allowing the incorporation of attributes that do not appear in the market. However, they proved that the statistical justification of the superiority of the pooled model over two separate models, usually tested by the LR test, might fail in two specific circumstances: when there is potential for endogeneity problems in the RP data and when consumer willingness to pay for attributes from the survey context differ from that of the market context.

## 4. The survey

In the following subsections, we illustrate the questionnaire and the characteristics of the respondents who participated to the survey. We paid special attention to representativeness of the samples.

### 4.1. The questionnaire

We collected data via a web-based survey, administered between November and December 2021 on a sample of Italian ($N = 643$) and Norwegian ($N = 501$) respondents using a CAWI (Computer Assisted Web Interviewing) questionnaire. We entrusted the data collection to two companies specialized in market surveys: SWG for the Italian sample and Norstat for the Norwegian one. The samples were randomly drawn from the two companies' communities so that only persons with a driving license were eligible to fill in the questionnaire.

The questionnaire consisted of three main parts. The first part consisted of 10 hypothetical choice scenarios, as the one reported in Fig. 5.

Since preferences may be different and attributes may be perceived differently across car segments, we proposed five hypothetical choice exercises focusing on the small car segment and five referred to the large car segment. For each choice task, respondents were asked to choose among five labelled alternatives: petrol car, diesel car, BEV, HEV, PHEV. Despite the large number of attributes that could be used to characterize car choice scenarios (for a discussion see Liao, Molin, & van Wee, 2017; Coffman, Bernstein, & Wee, 2017; Greene, Hossain, Hofmann, Helfand, & Beach, 2018; Danielis et al., 2020), we opted to restrict our selection to the three main attributes that from our previous experience have a strong influence on car choice: net purchase price, fuel/energy costs, and driving range. We explained respondents that net purchase price is to be intended as net of subsidies and including VAT and registration taxes. Fuel/energy costs are the ones incurred to travel 100 km, while driving range is the maximum distance in km with a full tank/battery (tank plus battery for PHEVs). The choice of focusing on only three attributes had the obvious advantage of reducing respondents' fatigue thus allowing us to submit them five different choice scenarios for each car segment. The attribute levels are reported in the supplementary material SM 1.0. Using the Ngene software, we developed an efficient design of the choice tasks (Bliemer & Rose, 2011). The survey was preceded by a pre-test carried out with 200 respondents interviewed in Italy and Norway to obtain our a-priori estimates.

In the second part of the questionnaire, we collected information on the respondents' real-world car choices. We asked for the number of cars owned in the household, and, for each car, we enquired about the powertrain, car segment to which they belong, year of registration, main use and annual distance travelled. We constructed RP dataset for the last car chosen only, considering the available alternative powertrains depending on the year of registration[2] and the prevailing average purchase prices, driving ranges, and fuel costs in that year.

In the third part, we asked them socio-economic data, such as gender, age, educational level, occupation, household composition and income, house type (apartment vs. detached house), house ownership (for rent or as an owner), garage availability, home charging availability, and area of residence (urban, suburban, rural).

### 4.2. The sample

Due to budget constraints, we were able to interview 1144 respondents, 501 Norwegians and 643 Italians. The absolute number is rather small in relation to similar car surveys. However, we devoted great care to achieve a good sample representativeness along various dimensions.

The reference population are the driving license holders who have or plan to buy a passenger car. In the absence of disaggregate information on this specific population target, we checked the representativeness with reference to population above 18 years of age. Descriptive statistics for the two subsamples and a detailed discussion of their representativeness for each country are reported in supplementary material SM 2.0. We achieved a good level of representativeness in both countries in

[2] For instance, if a person bought a PV in 1995, it is assumed to have chosen between PVs and DVs only, since the newer powertrains (HEVs, PHEVs and BEVs) were not available (note that CNG-, LPG-fueled cars and other minor powertrains are excluded from our analysis). From the respondents' data on their fleet composition and the manufacturer's reports, we observed that HEVs were available in significant numbers in Norway and in Italy from 2009 onwards, BEVs from 2011, and PHEVs after the year 2012.

| | PETROL | DIESEL | BEV | HEV | PHEV |
|---|---|---|---|---|---|
| Price (net of taxes and subsidies) | €12,000 | €27,000 | €34,000 | €26,000 | €22,000 |
| Driving range | 700 km | 1000 km | 300 km | 1100 km | 1300 km |
| Fuel/energy costs (per 100 km) | €9 | €10 | €7 | €9 | €14 |
| **YOUR CHOICE** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Fig. 5.** Example of a choice task (for the small segment) proposed to the Italian respondents.

terms of gender and geographical area. In terms of age, household type, educational attainment, type of housing, place of residency, some classes are slightly over-represented. More specifically, the under-30 age class, the highly educated groups, the people living in apartment and in cities are slightly over-represented. The representativeness by income, number of cars per household and commuting distance is difficult to check because there are no official data on these topics. Finally, we consider the samples' representativeness in terms of car segment. Overall, the degree of representativeness is satisfactory.

## 5. Econometric estimates

Using the Apollo package in R (Hess & Palma, 2019), we estimated a RPL model with the RP data only, with the SP data only and combining the RP and SP dataset.

The main goal of the econometric estimation was to detect preference differences between the two countries concerning the valuation of the trade-offs between the vehicles' attributes, the alternative specific constants (ASCs) and observed and unobserved preference heterogeneity. The previous literature estimating discrete choice models using both RP and SP data showed that the two datasets, because of their inherent differences, tend to generate different results (Morikawa, 1994; Brownstone et al., 2000; Cherchi & De Dios Ortúzar, 2011; Schmid et al., 2019; Coote, Swait, & Adamowicz, 2021 ).

In order to compare also among datasets, we searched for the best model specification which can be applied across datasets in terms of data fitting. Moreover, since Norwegians and Italians buy cars of different segments, as illustrated in Section 2.3, we interacted the main vehicle attributes and ASCs with the car segment covariate $\gamma_s^c$, with s = (small, large) and c = (Norway, Italy). The model that produced the best goodness of fit is illustrated in Eq. 3.

be more appropriate (e.g., a lognormal distribution). Unfortunately, using such a specification resulted in much lower data fitting and in convergence issues, hence, we opted for using the normal distribution for all parameters. The estimate distortions should not be large since the coefficients of the vehicles attributes are highly statistically significant, hence, the relevant confidence interval is defined either below or above zero.

Only for BEVs, we tested the impact of the following socioeconomic variables: gender, age, income, place of residence, charging availability, BEV density. They are assumed to be normally distributed to account for individual heterogeneity. We tested also a richer specification by interacting all powertrains with the available socioeconomic variables, but the estimates resulted in a large number of statistically insignificant coefficients, a greater use of the degrees of freedom and a significantly lower overall adjusted statistical fit of the model.

Since we have accounted for the scale difference between the two countries, and assumed a common price parameter for identification purposes, as explained in Section 3, the coefficients are comparable not only in terms of their sign but also in terms of their absolute value.

### 5.1. Estimates with the RP dataset

Table 1 reports the econometric results obtained using the RP database in the first three columns. The third column illustrates whether the coefficients estimates of the two countries are statistically significantly different (we will use this term throughout the paper, although a more appropriate one could be "compatible with the data", as suggested by Amrhein, Greenland, and McShane (2019)). As we will see in detail, most attributes are significant and have the expected sign. This is not an obvious result, given the multicollinearity issue that usually troubles RP datasets (Brownstone et al., 2000; Morikawa, 1994).

The preference for a given powertrain is estimated against the petrol

$$
\begin{cases}
V_{n,PV}^{c} = \left(1+\gamma_s^c\right)\left(ASC_{n,PV}^{c} + \beta_{n,Price}\cdot Price_{PV}^{c} + \beta_{n,Range}^{c}\cdot Range_{PV}^{c} + \beta_{n,F/E\ costs}^{c}\cdot F\Big/E\ costs_{PV}^{c}\right) \\
V_{n,DV}^{c} = \left(1+\gamma_s^c\right)\left(ASC_{n,DV}^{c} + \beta_{n,Price}\cdot Price_{DV}^{c} + \beta_{n,Range}^{c}\cdot Range_{DV}^{c} + \beta_{n,F/E\ costs}^{c}\cdot F\Big/E\ costs_{DV}^{c}\right) \\
V_{n,HEV}^{c} = \left(1+\gamma_s^c\right)\left(ASC_{n,HEV}^{c} + \beta_{n,Price}\cdot Price_{HEV}^{c} + \beta_{n,Range}^{c}\cdot Range_{HEV}^{c} + \beta_{n,F/E\ costs}^{c}\cdot F\Big/E\ costs_{HEV}^{c}\right) \\
V_{n,PHEV}^{c} = \left(1+\gamma_s^c\right)\left(ASC_{n,PHEV}^{c} + \beta_{n,Price}\cdot Price_{PHEV}^{c} + \beta_{n,Range}^{c}\cdot Range_{PHEV}^{c} + \beta_{n,F/E\ costs}^{c}\cdot F\Big/E\ costs_{PHEV}^{c}\right) \\
V_{n,BEV}^{c} = \left(1+\gamma_s^c\right)\left(ASC_{n,BEV}^{c} + \beta_{n,Price}\cdot Price_{BEV}^{c} + \beta_{n,RangeBEV}^{c}\cdot Range_{BEV}^{c} + \beta_{n,F/E\ costs}^{c}\cdot F\Big/E\ costs_{BEV}^{c}\right) + \beta_{Age}^{c}\cdot \mathrm{AgeClass}^{c} + \beta_{Gender}^{c}\cdot \mathrm{Gender}^{c} + \beta_{Income}^{c}\cdot \mathrm{Income}^{c} \\
\qquad + \beta_{EVdensity}^{c}\cdot \mathrm{EVdensity}^{c} + \beta_{BEVowner}^{c}\cdot \mathrm{BEVowner}^{c}
\end{cases}
\tag{3}
$$

All variables are assumed to be normally distributed to capture the respondents' heterogeneity. The normality assumption is justified for the ASC variables since we have no a-priori about their signs. On the contrary, for the variables price, range and fuel cost our a-priori is that they have either a positive (range) or negative sign (net purchase price or fuel cost), hence, a distribution allowing only negative\positive signs would

one. In technical terms, the alternative specific constant (ASC) of the petrol cars is set to zero. The ASCs capture the preference of an alternative *ceteris paribus*, i.e., when all the other variables specified in the model are equal (in our case, purchase price, driving range and fuel cost). Hence, they reflect previous experience with a given drivetrain, car performance, the existence of a reliable supply network, engine

**Table 1**
RPL estimates with the RP or the SP dataset.

| | RP dataset | | | SP dataset | | |
|---|---|---|---|---|---|---|
| | NORWAY | ITALY | | NORWAY | ITALY | |
| | Coeff. (t-ratio) | Coeff. (t-ratio) | Diff | Coeff. (t-ratio) | Coeff. (t-ratio) | Diff |
| *ASC (relative to petrol)* | | | | | | |
| $ASC_{Diesel}$ | −10.543 (−7.507) | −5.248 (−5.238) | *** | −0.555 (−2.579) | −0.343 (−3.147) | |
| SD of $ASC_{Diesel}$ | 1.327 (3.307) | 1.455 (4.831) | | 2.668 (13.763) | 1.759 (11.916) | *** |
| $ASC_{Diesel}$*Large cars | 0.645 (1.434) | 1.716 (5.176) | *** | 0.225 (1.258) | 0.03 (0.34) | |
| $ASC_{HEV}$ | −11.855 (−4.549) | −6.83 (−3.965) | *** | −0.734 (−2.945) | 0.536 (5.649) | *** |
| SD of $ASC_{HEV}$ | 8.489 (3.532) | 3.792 (3.179) | *** | 3.416 (16.279) | 1.496 (12.699) | *** |
| $ASC_{HEV}$*Large cars | −6.899 (−4.938) | 0.89 (1.752) | *** | 0.095 (0.52) | −0.02 (−0.225) | |
| $ASC_{PHEV}$ | −7.317 (−4.614) | −10.859 (−3.02) | | −0.039 (−0.189) | −0.637 (−4.427) | ** |
| SD of $ASC_{PHEV}$ | 2.85 (2.434) | 5.317 (3.414) | | 3.623 (16.963) | 1.434 (9.567) | *** |
| $ASC_{PHEV}$*Large cars | 4.012 (3.038) | 5.479 (3.704) | | 0.09 (0.472) | 0.573 (5.086) | ** |
| $ASC_{BEV}$ | −2.391 (−0.549) | −5.756 (−1.195) | | −4.742 (−3.671) | −1.629 (−3.264) | ** |
| SD of $ASC_{BEV}$ | 0.449 (0.239) | 0.504 (0.435) | | 0.83 (4.384) | 0.078 (0.461) | *** |
| *Socio-economic characteristics* | | | | | | |
| $ASC_{BEV}$*Gender | 0.049 (0.04) | −0.161 (−0.114) | | −0.39 (−1.278) | 0.139 (0.817) | |
| SD of $ASC_{BEV}$*Gender | 0.345 (0.454) | 0.223 (0.231) | | 0.709 (6.475) | 0.01 (0.1) | *** |
| $ASC_{BEV}$*Age | −1.291 (−3.451) | −0.787 (−1.15) | | −0.325 (−3.842) | −0.242 (−3.975) | |
| SD of $ASC_{BEV}$*Age | 0.214 (0.328) | 0.773 (2.324) | | 0.998 (13.233) | 0.283 (8.115) | *** |
| $ASC_{BEV}$*Income | 1.639 (2.19) | 2.592 (2.475) | | 0.945 (3.412) | 0.034 (0.286) | *** |
| SD of $ASC_{BEV}$*Income | 1.215 (3.787) | 0.365 (0.776) | | 0.125 (0.958) | 0.388 (6.78) | * |
| $ASC_{BEV}$* Charging availability | 3.37 (1.727) | 0.217 (0.095) | | 1.3 (2.774) | 0.174 (0.901) | ** |
| SD of $ASC_{BEV}$* Charging availability | 0.391 (0.266) | 2.225 (1.756) | | 1.526 (6.98) | 0.244 (1.94) | *** |
| $ASC_{BEV}$*Urban resident | −2.942 (−2.165) | −0.3 (−0.145) | | 0.784 (1.989) | 0.361 (1.946) | |
| SD of $ASC_{BEV}$*Urban resident | 0.095 (0.037) | 0.951 (0.775) | | 1.885 (3.082) | 1.061 (5.021) | |
| $ASC_{BEV}$*BEV density | 0.072 (2.666) | −0.713 (−1.613) | * | 0.023 (3.867) | 0.38 (2.716) | ** |
| SD of $ASC_{BEV}$*BEV density | 0.009 (0.516) | 0.145 (0.412) | | 0.009 (4.038) | 0.066 (0.764) | |
| *Vehicle attributes* | | | | | | |
| Net $Price_{All\ cars}$ (in €1000) | −0.405 (−7.008) | −0.405 (−7.008) | | −0.077 (−18.316) | −0.077 (−18.316) | |
| SD of Net price | 0.00005 (0.01) | 0.00005 (0.01) | | 0.083 (18.084) | 0.083 (18.084) | |
| Fuel/energy $cost_{All\ cars}$ | −2.315 (−7.395) | −0.696 (−4.614) | *** | −0.329 (−15.251) | −0.206 (−13.058) | |
| SD of Fuel/energy $cost_{All\ cars}$ | 0.753 (5.345) | 0.295 (4.248) | *** | 0.265 (13.236) | 0.163 (11.992) | |
| $Range_{All\ but\ BEVs}$ (in km) | 0.041 (8.041) | 0.023 (6.409) | *** | 0.001 (4.763) | 0.001 (6.874) | |
| SD of $Range_{All\ but\ BEVs}$ | 0.001 (0.525) | 0.0002 (0.531) | | 0.001 (6.44) | 0.001 (6.476) | |
| $Range_{BEV}$ | 0.067 (6.391) | 0.05 (4.397) | | 0.005 (4.129) | 0.004 (4.969) | |
| SD of $Range_{BEV}$ | 0.0003 (0.087) | 0.0004 (0.186) | | 0.003 (6.333) | 0.002 (3.241) | |
| $Range_{BEV}$*Large cars | −0.028 (−6.125) | 0.011 (2.417) | *** | −0.001 (−1.891) | −0.001 (−2.469) | |
| ITA-to-NOR scale parameter§ | 2.291 (7.434) | | | 1.255 (3.125) | | |
| *Goodness of fit statistics* | | | | | | |
| LL(0) | −2508 | | | −15,965 | | |
| LL(final) | −1083 | | | −10,634 | | |
| Adj.Rho-square (0) | 0.47 | | | 0.52 | | |
| Estimated parameters | 63 | | | 63 | | |

Age: coded in age classes:1: 18–29 years old; 2: 30–39 years old; 3: 40–49 years old; 4: 50–59 years old; 5: more than 60 years old. Gender: coded as 0 for males and 1 for females. Income, coded in income classes. For the Italian sample, 1: less than €30,000; 2: from €30,000 to €70,000; 3: from €70,000 to €100,000; 4: more than €100,000. For the Norwegian sample, 1: Less than NOK 400,000; 2: Between NOK 400,001 and NOK 800,000; 3: Between 800,001 and NOK 1,200,000; 4: More than NOK 1,200,001. BEV density, expressed as number of BEVs per 1000 inhabitants. Urban resident coded as 1 if the respondent lives in an urban area, 0 if s/he lives in a suburban or rural area.
***, **, * indicate significance at 1%, 5% and 10% respectively, § *t*-test with respect to 1.

efficiency, air emission technology, peers' imitation, social image, car knowledge, confidence towards new technology, and so on. Since RP choice data consist into actual past choices, they depend on the past history of the respondent.

Regarding DVs, respondents assign them a lower utility compared to PVs in both countries, but to a significantly larger extent in Norway than in Italy. The result reflects the decline of the actual DV shares and their reputation loss caused by the “diesel gate”. In both countries, we detect high preference heterogeneity. In Italy, some of the preference heterogeneity can be explained by the car segment, in the sense that the DVs' lower preference relative to PVs is less strong for large cars. Norwegians assign HEVs a much lower utility than PVs, statistically significantly more so than Italians. They exhibit also a higher heterogeneity and their aversion increases in the large car segment, differently from the Italians whose aversion relative to HEVs decreases for larger cars. With regards to PHEVs, both countries value them less than PVs, in particular the Italians but the difference between the two countries is not statistically significant. The negative sign is partially offset when considering the large car segment, especially in the case of the Italian respondents.

The ASC for BEVs is interacted with the socioeconomic variables and, therefore, by itself is less meaningful. The first variable interacted with the $ASC_{BEV}$ is gender (coded zero for males). Norwegian women assign a higher utility to BEVs than men, while the opposite seems to be true for Italy. But none of the coefficients is statistically significant, meaning that there is a large number of cases in which the opposite is true. Hence, we can conclude that gender is not an unequivocal determinant of the preference for BEVs.

The variable age indicates that younger respondents have a stronger preference for BEVs than older ones. Such a result is shared by both countries, but it is statistically significant only in Norway. However, the difference between the two countries is not significant. An interesting result is that the coefficient of income is positively related to the choice of a BEV instead of a PV, i.e., higher income individuals are more likely to buy a BEV in both countries and both coefficients are statistically significant. This indicates that income played a role in the choice of a BEV, more so in Italy, although the difference between the two countries is not statistically significant. A potential explanation of the higher relationship with income of the Italians is that in Italy BEVs are more expensive to buy relative to comparable cars with different powertrains than in Norway, as a result of the different fiscal policies on car acquisition (Scorrano et al., 2019).

One of much discussed determinants of the choice of a BEV is the availability of a private parking potentially equipped with a car charger. Our results indicate the existence of a positive relationship using the RP database for both countries, but the t-statistic is low, signaling that such a conclusion is only weakly statistically significant.

Next, we tested the impact of two external determinants: the place of residency of the respondent (urban vs non-urban) and the density of BEVs in the region. Regarding the former variable, BEVs appear to be chosen more by non-urban residents in Norway, while in Italy the coefficient is not statistically significant different from zero. Longer daily driving distances and higher car use (due to lower public transport availability) are most likely the main reasons behind this result. The latter variable, BEV density as a proxy of the peer effect, is consistently positive and statistically significant in Norway. On the contrary, in Italy the coefficient is negative in the RP dataset and not significant. The difference is 90% statistically significant.

Let us now turn to the sensitivity to the car attributes purchase price, driving range and fuel costs. As expected, the purchase price is a strong choice determinant. By construction, the size of such coefficient is set equal between the two countries, as explained in Section 3. The standard deviation of the coefficient indicates that there is very little heterogeneity, as to be expected from an RP dataset. Fuel cost coefficients are also always negative and statistically significant. Fuel costs appear to play a stronger role in Norway than in Italy, and the difference is statistically significant. A possibly explanation is that, as illustrated in Section 2.3, Norwegian cars are on average larger cars (less fuel-efficient) than the Italian ones and that Norwegian car drivers travel longer annual distances than Italians (12,480 km for Norway in 2016 vs 11,200 in Italy).

The role of the driving range has been evaluated distinguishing between non-BEVs and BEVs. A potential drawback of our analysis is that PHEVs share some features with BEVs since they can potentially drive in the battery-only mode. However, according to recent studies (Plötz et al., 2022), PHEVs are driven most of the times using the internal combustion engine, because the battery-only driving range is limited. Our estimates indicate that the driving range coefficient of non-BEVs has the expected positive sign in both countries with very limited heterogeneity. The Norwegian coefficient is statistically significantly higher than the Italian one.

Regarding BEVs, the driving range coefficients are also both positive, with no statistically significant difference between the two countries. Note also that the driving range coefficients are higher for BEVs than for non-BEVs, indicating that range is perceived as a problem more for BEVs than for non-BEVs. Comparing the size of the coefficients between the two countries, we observed that the $\text{Range}_{\text{BEV}}$ coefficient is higher in Norway, but the difference is not statistically significant. We will provide an interpretation of the different coefficients size in Section 5.4. We also tested the impact of the car segment. We found that in Norway the sensitivity to the driving range decreases when large cars are considered, while the opposite is true in Italy. The explanation might be related to the development of the public charging infrastructure which is quite dense in Norway while still in the initial phase in Italy. In fact, at the time of the writing of the paper (May 2023) Norway has 4.6 charging points per thousand inhabitants (25,091 charging points), a large part of them fast or ultrafast chargers, while Italy has 0.7 charging points per thousand inhabitants (41,173 charging points), with a relatively lower proportion of fast charging ones.

The ITA-to-NOR scale parameter (setting the Norwegian scale parameter to 1) is equal to 2.291, significantly higher than 1, implying that the stochastic variance of the Italian data is lower than that of the Norwegian data.

### 5.2. Estimates with the SP dataset

Within the controlled experiment set up in designed scenarios, the respondents stated choices reflecting their preferences when they filled up the questionnaire, irrespective of their actual past choices. The resulting preference structure is somewhat, but not radically different, from that resulting from the RP dataset. We will underline the main differences between the two countries and between the RP-based and the SP-based parameters.

The lower utility associated with DVs relative to PVs is confirmed also with SP data, with almost equal parameters in the two countries, the unobserved heterogeneity is high (significantly higher in the Norwegian sample than in the Italian one) and not explained by the car segment. Similar results can be found for HEVs within the Norwegian dataset: the coefficient is statistically significantly worse than PVs, and there is high unexplained heterogeneity. Italians, on the contrary, significantly prefer HEVs to PVs, irrespective of the car segment. Such a difference between the two countries did not appear with RP dataset. The preference of the Italian car owners for HEVs is also documented by the sales data reported in Section 2.2.

Norwegian respondents showed no specific preference for PHEVs relative to PVs. The negative coefficient is not statistically significant and there is high unexplained heterogeneity. On the contrary, Italian respondents assigned PHEVs a statistically significant negative value relative to PVs, but such attitude is partially offset when it comes to large cars. Concerning BEVs, we detected statistically significant differences between the respondents of the two countries, as the impact of BEV density on the preference for BEVs where the negative coefficient of the RP Italian dataset is reversed in the SP dataset. SP data confirmed that gender plays no significant role while age does, in the sense that younger respondents have a stronger preference for BEVs relative to older ones. As it could be expected given the hypothetical nature of the data, in the SP dataset the coefficient for income in the Italian sample is positive but not significant, while it was in the RP dataset. Charging availability plays a statistically significant role only in the Norwegian sample. The place of residency (urban vs non-urban) has a positive and statistically significant coefficient both in Norway and in Italy, reversing the sign detected with RP data.

With reference to the vehicle attributes, the higher attention of the Norwegian respondents to the fuel\energy costs is confirmed but the magnitude of the coefficient is much lower than that found with the RP dataset. No difference between the two countries can be detected with reference to the driving range of the non-BEVs, while there is a difference in the case of BEVs, but not statistically significant. However, the Italian dataset indicated higher random heterogeneity. Note also that all range coefficients have a lower magnitude than those obtained from the RP dataset. We will provide further comments on this result in Section 5.4.

The ITA-to-NOR scale parameter (setting the Norwegian scale parameter to 1) is equal to 1.255, significantly higher than 1, implying that the stochastic variance of the Italian data is lower than that of the Norwegian data. Note that the country scale parameter is higher in RP dataset than with the SP dataset indicating a stronger impact of the unspecified variables on actual choices than on stated choices.

### 5.3. Estimates with the RP\SP dataset

As suggested by Guzman et al. (2021), we started by visually inspecting the coefficients resulting from the two datasets, trying to identify which coefficients are equal after adjusting for the scale factor. Similar coefficients are expected to fall in an elliptical region close to the line that passes through the origin with slope equal to the scale factor. The visual inspection, however, did not provide us with a clear cut picture. In the case of Norway, the SP parameters are on average 20% the size of the RP ones. Generally, the sign is the same, but the scale difference varies from 1% to 150% with no clear cut groupings. In a

**Table 2**
RPL estimates pooling the RP and SP datasets.

| | NORWAY | | ITALY | |
|---|---|---|---|---|
| | Coeff. (t-ratio) | Coeff. (t-ratio) | Coeff. (t-ratio) | Coeff. (t-ratio) |
| | RP-specific | SP-specific | RP-specific | SP-specific |
| *ASC (relative to petrol)* | | | | |
| $ASC_{Diesel}$ | −1.23 (−4.428) | −0.816 (−1.282) | 0.29 (1.943) | −1.404 (−4.183) |
| SD of $ASC_{Diesel}$ | 0.158 (1.045) | 8.193 (9.338) | 0.062 (0.474) | 4.429 (7.627) |
| $ASC_{Diesel}$*Large cars | 1.68 (7.014) | 0.41 (0.775) | 0.082 (0.579) | −0.303 (−1.286) |
| $ASC_{HEV}$ | −1.454 (−4.654) | −1.859 (−3.005) | −0.915 (−4.961) | 1.128 (4.473) |
| SD of $ASC_{HEV}$ | 0.124 (0.33) | 8.712 (9.385) | 0.399 (1.761) | 4.156 (7.93) |
| $ASC_{HEV}$*Large cars | −1.791 (−3.502) | −0.329 (−0.627) | −0.261 (−1.001) | −0.469 (−1.942) |
| $ASC_{PHEV}$ | −0.732 (−1.908) | −0.808 (−1.411) | −1.573 (−2.701) | −2.892 (−5.074) |
| SD of $ASC_{PHEV}$ | 0.07 (0.208) | 8.957 (9.532) | 0.73 (1.861) | 4.519 (7.244) |
| $ASC_{PHEV}$*Large cars | 2.572 (4.765) | −0.576 (−1.101) | 1.467 (2.687) | 1.328 (4.163) |
| $ASC_{BEV}$ | −2.28 (−1.659) | −6.971 (−2.29) | −3.484 (−1.424) | −2.209 (−1.938) |
| SD of $ASC_{BEV}$ | 0.166 (0.643) | 0.948 (2.126) | 1.598 (2.205) | 0.051 (0.112) |
| *Socio-economic characteristics* | | | | |
| $ASC_{BEV}$*Gender | −0.106 (−0.274) | −3.073 (−3.675) | −0.867 (−1.019) | −0.523 (−1.155) |
| SD of $ASC_{BEV}$*Gender | 0.065 (0.394) | 3.464 (8.167) | 0.75 (1.679) | 0.887 (3.984) |
| $ASC_{BEV}$*Age | −0.382 (−3.166) | −0.979 (−3.82) | −0.372 (−1.005) | −0.273 (−1.991) |
| SD of $ASC_{BEV}$*Age | 0.199 (2.6) | 1.929 (8.067) | 0.005 (0.032) | 1.359 (6.828) |
| $ASC_{BEV}$*Income | 0.54 (2.291) | 0.386 (1.034) | 2.044 (2.542) | 0.536 (2.479) |
| SD of $ASC_{BEV}$*Income | 0.094 (1.253) | 2.709 (8.744) | 0.655 (2.294) | 0.231 (1.405) |
| $ASC_{BEV}$* Charging availability | 0.753 (1.037) | 2.264 (2.044) | −0.226 (−0.184) | 0.523 (1.045) |
| SD of $ASC_{BEV}$* Charging availability | 0.418 (1.643) | 2.294 (4.193) | 0.757 (1.279) | 2.115 (5.591) |
| $ASC_{BEV}$*Urban resident | −1.122 (−2.379) | 1.07 (1.193) | −0.52 (−0.652) | 0.664 (1.52) |
| SD of $ASC_{BEV}$*Urban resident | 0.943 (1.845) | 3.303 (4.853) | 0.927 (1.57) | 0.181 (0.416) |
| $ASC_{BEV}$*BEV density | 0.017 (1.819) | 0.181 (7.371) | −0.301 (−1.368) | 0.487 (1.688) |
| SD of $ASC_{BEV}$*BEV density | 0.002 (0.468) | 0.111 (8.265) | 0.039 (0.304) | 1.142 (4.284) |
| *Vehicle attributes* | Joint RP\SP | | Joint RP\SP | |
| Fuel/energy $cost_{All\ cars}$ | −0.508 (−9.841) | −0.978 (−9.338) | −0.053 (−2.042) | −0.518 (−7.782) |
| SD of Fuel/energy $cost_{All\ cars}$ | 0.0003 (0.021) | 0.787 (8.714) | 0.003 (0.391) | 0.361 (7.148) |
| Net $Price_{All\ cars}$ (in €1000) | −0.198 (−11.129) | | −0.198 (−11.129) | |
| SD of Net price | 0.101 (11.75) | | 0.101 (11.75) | |
| $Range_{All\ but\ BEVs}$ (in km) | 0.007 (7.971) | | 0.004 (6.253) | |
| SD of $Range_{All\ but\ BEVs}$ | 0.00004 (0.287) | | 0.0003 (2.655) | |
| $Range_{BEV}$ | 0.013 (4.951) | | 0.008 (3.851) | |
| SD of $Range_{BEV}$ | 0.001 (1.272) | | 0.003 (2.823) | |
| $Range_{BEV}$*Large cars | −0.004 (−4.038) | | −0.001 (−1.349) | |
| ITA-to-NOR scale parameter§ | 1.508 (9.9) | | | |
| SP-to-RP scale factor§ | 0.292 (24.389) | | | |
| *Goodness of fit statistics* | | | | |
| LL(0) | −18,474 | | | |
| LL(final) | −11,726 | | | |
| Adj.Rho-square (0) | 0.50 | | | |
| Estimated parameters | 114 | | | |

Age: coded in age classes:1: 18–29 years old; 2: 30–39 years old; 3: 40–49 years old; 4: 50–59 years old; 5: more than 60 years old. Gender: coded as 0 for males and 1 for females. Income, coded in income classes. For the Italian sample, 1: less than €30,000; 2: from €30,000 to €70,000; 3: from €70,000 to €100,000; 4: more than €100,000. For the Norwegian sample, 1: Less than NOK 400,000; 2: Between NOK 400,001 and NOK 800,000; 3: Between 800,001 and NOK 1,200,000; 4: More than NOK 1,200,001. BEV density, expressed as number of BEVs per 1000 inhabitants. Urban resident coded as 1 if the respondent lives in an urban area, 0 if s/he lives in a suburban or rural area.
***, **, * indicate significance at 1%, 5% and 10% respectively, § t-test with respect to 1.

similar fashion, the Italian SP parameters are 8% the size of the RP ones, generally with consistent sign but varying from 1% to 35% and no clear groupings. Hence, we proceeded by a combination of theoretical a-priori and statistical testing. We grouped the coefficients into three main types: (i) ASCs, (ii) socio-economic interactions with the $ASC_{BEV}$ and (iii) vehicle attribute coefficients, and tested various specifications. Our a-priori was that the ASCs are context-specific: the ones derived from the real market data are very different from those resulting from hypothetical choices (Yan, Levine, & Zhao, 2019). Regarding the parameter interactions with the $ASC_{BEV}$ and the socio-economics, we did not have specific a-priori, hence they could be either data-specific or jointly estimated. As for vehicle attribute coefficients, the literature (Brownstone et al., 2000; Helveston et al., 2018) suggests to take advantage of the data enrichment property of the joint RP\SP estimation.

After testing alternative specifications, it resulted that the one with the highest model fit includes: a) data-specific parameters for the ASCs, the interaction between the $ASC_{BEV}$ and the socio-economic variables and fuel/energy cost parameter, while b) pooled RP\SP parameters for the other vehicle attributes (Table 2).

When comparing the model fitness of the two separate models versus the pooled one, the likelihood ratio test applied to the separate RP and SP models and to the joint one gives a value equal to 17.02 for 12 degrees of freedom, which needs to be compared with the critical $\chi 2$ value for a 95% confidence level (21.03). Since the LR test statistic is smaller, we cannot reject the null hypothesis that the combined RP-SP specification is appropriate at the 95% confidence level. Hence, the pooling technique is justified and the RP\SP model should produce better forecasting results.

For forecasting purposes, Guzman et al. (2021) identified two situations: 1) specific parameters for both domains (RP and SP) might have adequate signs and significance, or 2) one specific parameter might be not significant or with inconsistent sign from the theoretical point of view. In the former case, they suggested to prefer the RP parameters since they are derived from real market situations; while in the latter case, the significant parameter is the most appropriate regardless of the domain (if a SP-specific parameter is selected for forecasting, multiplied by the scale parameter since forecasting always refers to the RP environment). In our specific case, if the model is to be used for forecasting, since we do not have a theoretical a-priori concerning the signs of the ASCs and their interactions with the socio-economic variables, the parameters of the RP domain should be selected. Regarding fuel\energy costs, since both parameters are significant and have the correct sign, the RP should be preferred. The parameters of the other vehicle attributes (price and ICEV and BEV driving range) are the ones derived from the RP \SP model since they benefitted from the data enrichment technique.

When comparing the parameter estimates across models (the results from the RP model with those of the RP-specific parameters in the RP\SP model, and the results from the SP model with those of the SP-specific parameters in the RP\SP model), one notes the following. The absolute values of the parameters for the three groupings described above are different but they provide similar behavioral interpretations. The main exception is the $ASC_{Diesel}$ parameter that is positive and weakly significant in the pooled dataset, while it is negative and significant when estimated with RP data only.

The vehicle attributes with the pooled dataset have both absolute value and statistical significance intermediate between the one obtained in the separate models. Therefore, while maintaining a sufficiently high statistical significance, they incorporate information from the actual and the stated choices. In the case of the interaction between the $Range_{BEV}$ parameter and the large car segment, since the estimates derived from the RP and SP data had opposite signs and were both significant, the pooled version maintained the negative sign but with low statistical significance.

The SP-to-RP scale factor (setting the RP scale parameter to 1) is equal to 0.292, significantly lower than 1, implying that the stochastic variance of the SP data is larger than that of the RP data. This result is in line with most but not all previous studies (Bhat & Castelar, 2002) and may result from the SP experimental design effects and the hypothetical nature of SP responses (Yan et al. 2019).

### 5.4. The implied willingness to pay (WTP) for the driving range

In order to appreciate the difference between the three datasets, we estimated the willingness to pay (WTP) implied by the range coefficients for non-BEVs, BEVs and their interaction with the dummy identifying the large car segment (Table 3).

We underline the following results. The WTPs derived from the RP dataset are much higher than the ones derived from the SP dataset. For instance, a Norwegian car owner is estimated to be willing to pay €102.3 for an additional km of driving range for a non-BEV and €166.1 for a BEV, which is reduce by €69.6 if the BEV belongs to the large car segment. When estimated with the SP dataset, the implied WTP is lower. This is not a new result. In a modal choice model, Morikawa (1994) found a 4.6 times higher value of time when estimated with RP data than when estimated with SP data. Bhat and Castelar (2002) found an almost twice higher value of time analyzing data on the San Francisco Bay area. The result is attributed to the limited variation in cost within the RP sample as well as multi-collinearity between time and cost. In our case, the RP dataset might suffer from multi-collinearity because of the relationship between purchase price and driving range. With the pooled dataset, the WTP values generally (but not in all cases) lie between the RP upper bounds and the SP lower bounds.

**Table 3**
Implied WTP (in euro) for the driving range attribute from the RP, SP and pooled RP/SP dataset.

| | | NOR | | ITA | |
|---|---|---|---|---|---|
| | | WTP | t-ratio | WTP | t-ratio |
| RP | Non-BEVs | 102.3 | 7.4 | 57.7 | 13.1 |
| | BEVs | 166.1 | 4.7 | 123.5 | 9.7 |
| | BEVs *Large cars | −69.6 | −4.6 | 26.6 | 4.9 |
| SP | Non-BEVs | 18.9 | 3.5 | 11.9 | 6.4 |
| | BEVs | 69.3 | 3.0 | 54.3 | 4.4 |
| | BEVs *Large cars | −11.2 | −1.6 | −13.5 | −2.2 |
| RP/SP | Non-BEVs | 32.9 | 10.7 | 19.4 | 5.5 |
| | BEVs | 63.5 | 5.1 | 40.0 | 3.4 |
| | BEVs *Large cars | −20.6 | −4.0 | −6.6 | −1.3 |

Norwegian respondents have consistently higher WTP for an additional km of driving range than Italian respondents. This might depend on the fact that Norwegian drivers travel higher annual distances by car than Italian drivers, since Norway has a lower population density (14.3/$km^2$ vs 195.41 ab./$km^2$) and a higher number of people living in rural areas (28.4% vs 18.3%). Another explanation is the higher purchasing power of the average Norwegian household relative to the Italian one.

Our WTP estimates are in line with the previous estimates. With regards to Norway, Fridstrøm & Østli (2022) used RP data up to May 2019. They estimated a diminishing return-to-range function and found that in a car with an initial range of 150 km, the revealed willingness-to-pay for an additional 100 km is €24,000 (i.e. €240 for an additional km) but that value drops to €5100 where the reference range is 500 km. Our estimates are €166 for a car of the small segment and €96.5 for the large segment. To be best of our knowledge, there are no RP-based estimates concerning Italy.

Instead, there are various SP-based estimates derived from Italian samples. Valeri and Danielis (2015) found a value of €50 per additional km of driving range, Valeri and Cherchi (2016) reported a value of €42, Giansoldati et al. (2018) a value ranging from 37 to 106 €/km, and Danielis et al. (2020) a value of 29–66 €/km. Our estimates are €54 for a small car, reduced to €41 for a larger car. With regards to Norway, Noel et al. (2019) found values starting at €300 per additional km for an initial driving range of 150 km, and declining at less than €100 when the driving range is equal to 400 km. Our estimates are €69 for a small car, reduced to €58 for a larger car.

## 6. Conclusions

Thanks to the collection of a joint survey carried out in Norway and Italy, we compared the car users' preferences on the basis of a RP, a SP and a joint RP\SP dataset. Actual choices indicate that in Norway DVs, HEVs and PHEVs are not preferred to PVs. The BEVs preference relative to PVs is decomposed in the socio-economic determinants. While neither gender nor the charging availability at home seem to play a role, the preference for BEVs is higher by higher income respondents, non-urban residents and in BEV dense counties. Relative to the Norwegian respondents, the Italian car drivers dislike less DVs and have a higher preference for HEVs relative to PVs. Stated choices provide a similar picture, but the difference in magnitude between the coefficients of the Norwegian respondents and those of the Italian respondents is lower.

Since both RP and SP datasets have pros and cons, we have estimated a joint model pooling the two datasets in a model where the ASCs are based on the RP data only and the trade-offs between the vehicle attributes are estimated with the pooled RP\SP dataset. The model provides statistically significant estimates, which provided us an estimate of the implied WTP for the driving range in the two countries. The two main results are that the WTP is generally higher in Norway than in Italy, both for non-BEVs and BEVs, motivated by the longer travel distances and the higher per capita income. However, when the large cars are considered, the WTP declines in both countries and to a larger extent in Norway, indicating that in Norway the range anxiety issue has been gradually overcome, while that is not yet the case in Italy.

All in all, we do not feel that the two countries present major differences in the car preference structure. The main differences are associated with longer car driving habits of the Norwegian drivers associated with the lower population density and the share of rural population, the different mix of car type ownership (with a higher percentage of large cars in Norway), and the more developed public charging infrastructure. Since the supply of cars is quite similar, such a consideration leads us to believe that the huge difference in BEV uptake is due to the policy setting. In fact, over the last decade and a half Norway enacted a large array of BEVs incentivizing policies such as no purchase/import taxes, exemption from 25% VAT on purchase, no or reduced annual road tax, no charges on toll roads or ferries (1997–2017), free municipal parking (1999–2017), access to bus lanes (2005-), and other advantages. In addition, non-BEVs were subject to expensive $CO_2$ and NOx taxes according to the polluters' paying principle, which made the after-tax purchase costs of a BEV convenient with respect to non-BEVs. On the contrary, Italy issued a much weaker financial support for low emission cars without taxing the fossil fuel ones in proportion to their air emissions, so that BEVs remained unattractive from the economic point of view. Currently, Norway is considering reducing the preferential fiscal system granted to BEVs. It will be interesting to see whether and by how much the relative market shares will be altered. Since no major difference in the car drivers' preference structure could be detected, the evolution of the policy setting and of the technology will determine whether Italy will follow the Norwegian model of gradual BEV uptake. As of the time of the writing of this paper (August 2023), there are little signs that Italy has embraced such a path.

As any other empirical research, our study suffers several limitations. With reference to the specification of the model, our model is restricted to the car technical and economic properties and the measurable socio-economic determinants. The model does not include psychological, sociological, or experience factors with the exception of the peer effect captured by the BEV density indicator. Other model specifications, for instance, the integrated choice and latent variable model, would allow a more detailed description of the choice process (Ben-Akiva et al., 2002). A second limitation is that the sample size does not allow a finer spatial analysis. For instance, it is quite possible that there are regional differences in BEV acceptance. At least in Italy, the North-South divide is still quite strong and it is reflected in differences in public charging density, which might slow down BEV acceptance in some regions. A third limitation is that the question we asked ("what car would you buy?") is highly general and does not specify the type of use (for short urban travel vs longer intercity trips) or the use of the car, within the family fleet (only car, second family car, etc.).

## CRediT authorship contribution statement

**Mariangela Scorrano:** Conceptualization, Data curation, Formal analysis, Software, Methodology, Writing – original draft, Writing – review & editing. **Terje Andreas Mathisen:** Conceptualization, Supervision, Validation, Writing – review & editing. **Romeo Danielis:** Conceptualization, Supervision, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Ozlem Simsekoglu:** Investigation, Writing – review & editing. **Giuseppe Marinelli:** Investigation, Writing – review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rtbm.2023.101041.

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