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Sampling approaches for road vehicle fuel consumption monitoring

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Contents

Abstract

EU Regulations introduced in 2019 for light- and heavy- duty vehicles contain provisions requiring the European Commission to set up a mechanism to monitor the real-world representativeness of the fuel consumption determined during the type-approval tests. This study proposes a sampling based approach to collect these data. Two probability-sampling methods (simple random sampling and stratified sampling) and one non-probability sampling method (quota sampling) are discussed. We use data from three user-based datasets (IFPEN, Travelcard and Spritmonitor) and the 2018 European Environment Agency CO_2 monitoring dataset. All three user-based datasets provide fairly good representations of their respective countries' sub-fleets and to a lesser extent the whole fleet. The standard deviation of the fuel consumption gap was consistently found to be approximately 20%. For a population of 15 million vehicles, using simple random sampling, and the standard deviation of the fuel consumption set at 20%, a sample of fewer than 3000 vehicles is required for estimating the average gap with a confidence level of 99% and sampling error less than 1%. Multivariate stratification with three stratification variables (vehicle manufacturer, fuel type and engine rated power) was the optimal combination, reducing the sample size by around 28% compared to simple random sample. Requiring strata specific estimators resulted to an increase of the sample size, as the number of stratification variables increased. Non-sampling errors, such as inaccuracy of On-Board Fuel and/or energy Consumption Monitor (OBFCM) device measurements, are expected to lead to an increase of the required sample size by at least 20%. Samples using quota sampling were taken and had a sampling error less than 3.5%.

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Executive summary

The average official CO_2 emissions of new passenger cars registered in the European Union (EU) were reported to have reduced from 170 g/km in 2001 to 119 g/km in 2017, based on the New European Driving Cycle (NEDC) test procedure. However, the reduction trends observed in the real-world did not follow at the same pace, an observation that is generally known as CO_2 emissions gap. This gap was reported to widen substantially, from about 8% in 2001 to about 40% in 2017. The major reason for the gap was the unrepresentativeness of the official CO_2 certification procedure, based on the NEDC and the inherent variability of fuel consumption when operating in real-world conditions.

The European Commission (EC), acknowledging the issue, introduced the Worldwide harmonized Light vehicles Test Cycle and Procedure (WLTP) in the type-approval procedure from September 2017. For the purpose of CO_2 target compliance checking, the WLTP will be used from 2021 on. This new certification procedure will decrease the gap but does not fully eliminate it. For heavy-duty vehicles, the real-world performance is more unclear, as the lack of historical certification values and real-world emission measures have yet prevented an exact quantification of the gap.

Regulation (EU) 2019/631 for light duty vehicles (LDV) as well as Regulation (EU) 2019/1242 for heavy duty vehicles (HDV) contain similar provisions requiring the Commission to set up a mechanism to monitor the real-world representativeness of the CO_2 emissions determined during the type-approval tests. To this end, the EC shall collect real-world fuel consumption and total distance travelled data (previously stored on-board) and shall aggregate them into anonymised datasets, including categorization per manufacturer, before making them public. To that aim, technical requirements and procedures need to be determined. For light-duty vehicles, Commission Implementing Regulation (EU) 2021/392 requires manufacturers and Member States to collect this data from 2022 onwards. The expectation is that this mechanism will generate data from a statistically relevant sample of the entire fleet.

In this light, the present study aims at providing a comprehensive analysis of suitable sampling methods, focusing on optimizing and testing the methods. Sample size calculations must be performed a priori. To reach a high precision and determine the minimum sample sizes needed, knowledge of the targeted vehicles is required. For this, data from 3 user-based datasets (Geco Air, Travelcard and Spritmonitor) were used. These datasets are based on volunteering and the data do not come from the OBFCM. Geco air is a mobile app calculating the CO_2 emissions based on the vehicle characteristics and GPS measurements. Travelcard and Spritmonitor are based on self-reported data of fuelling events. CO_2 emissions data gathered by the European Environment Agency (EEA) for all new passenger cars registered in the Member States in 2018 were also utilised. The fuel consumption gap for the vehicles recorded by EEA is not available. For the purposes of this report it was simulated using the information about fuel consumption gap of the other three datasets.

The representativeness of the three datasets and the sub-fleets of their respective countries was examined in respect to fuel type, type approval CO_2 emissions, vehicle manufacturer, engine rated power and engine displacement. It was found that all datasets provide fairly good representations of their respective countries sub-fleets and to a lesser extent the EU fleet.

The fuel consumption gap was analysed firstly as a stand-alone variable, then in relation to the other variables used in this report (fuel type, transmission type, vehicle manufacturer, type approval CO_2 emissions, engine rated power, engine displacement and total distance driven). The standard deviation of the fuel consumption gap in the three user datasets was consistently found to be approximately 20%.

Two probability sampling methods (simple random sampling and stratified sampling) and one non-probability sampling method (quota sampling) were chosen and discussed in this report. In simple random sampling, the higher the variability of the fuel consumption gap, the higher the required sample size. For a fleet of 15 million vehicles, if the standard deviation of the fuel consumption gap of the whole fleet is 20% (as inferred by the data retrieved from the three sources) a sample of fewer than 3,000 vehicles is required for estimating the average fleet-wide average gap with a confidence level of 99% and sampling error less than 1%. If the standard deviation of the fuel consumption gap is 40% (an assumption that is not validated by the data received from the three sources) approximately 10,500 vehicles would be required to achieve this precision.

Stratified sampling can further reduce the required sample size for determining precisely the fleet-wide average gap and also provide sufficient representation of sub-populations of interest. Three different kinds of allocation procedures were examined, of which Neyman allocation produced the best results, but requires extensive a priori knowledge of the population. Different stratification variables were used, first separately (univariate stratification) and then combinations of them (multivariate stratification). It was found that multivariate stratification with three stratification variables (vehicle manufacturer, type-fuel type and engine rated power) was the optimal combination requiring the least sample size - about 28% less than simple random sampling. Increasing the number of stratification variables offered marginally better results while increasing the difficulty and complexity of the process.

The probability sampling methods were validated by simulating a large number of samples and calculating the population error. In all cases, when a margin of error of 1% and a confidence level of 99% was required, the sampling error was found to be in average 0.0%, with a standard deviation less or equal to 0.6% (Table ES1).

When precise estimators are demanded not only for the fuel consumption gap of the whole fleet, but also per stratum, the required sample size increases. The required sample size escalates when the number of stratification variables increases. To get precise estimators for all strata when stratifying by vehicle manufacturer, type-fuel type and engine rated power, a sample of approximately 18,000 vehicles is needed (compared to ~ 2000 vehicles with precise estimator of the whole population average fuel consumption gap only).

To understand the impact of non-sampling errors and more specifically of the OBFCM inaccuracies on the sample size, a “noise” was added to the type approval and the real world fuel consumption of all vehicles. This led to 2.5% higher standard deviation of the fuel consumption gap of EEA vehicles, which resulted in a 26% increase of sample size when using simple random sampling.

For quota sampling, it is not possible to estimate the sampling error because of the absence of randomness. However to get an indication of the method’s effectiveness a quota sample (with respect to the vehicle manufacturer, fuel type and engine rated power) was extracted from each dataset. The sampling error in all four datasets was found to be less than 3.5% (Table ES1).

Table ES1 Statistics of the sampling error

	Dataset											
	Geco air (France)			Spritmonitor.de (Germany)			Travelcard (Netherlands)			EEA (EU)		
Method	share (%)	mean (%)	sd (%)	share (%)	mean (%)	sd (%)	share (%)	mean (%)	sd (%)	share (%)	mean (%)	sd (%)
Simple random sampling	96.1	0.0	0.4	26.3	0.0	0.4	8.2	0.0	0.4	0.019	0.0	0.4
Stratified sampling by OEM	81.9	0.0	0.4	25.0	0.0	0.4	7.5	0.0	0.4	0.015	0.0	0.4
Stratified sampling by OEM & Fuel type	78.7	0.0	0.5	24.8	0.0	0.5	7.3	0.0	0.4	0.015	0.0	0.4
Stratified sampling by OEM & Fuel type & Power	82.7	0.0	0.6	21.0	0.0	0.6	6.4	0.0	0.5	0.014	0.0	0.5
Stratified sampling by OEM & Fuel type & Power & TA CO_2	94.5	0.0	0.5	18.7	0.0	0.6	5.9	0.0	0.5	0.014	0.0	0.5
Quota sampling	82.7	2.8	-	21.0	1.5	-	6.4	3.2	-	0.014	2.1	-

Note: In parenthesis the countries where the majority of vehicles come from; margin of error 1%; confidence level 99%; sd: standard deviation; TA: type-approval, OEM: manufacturer; Power: engine rated power; share: percentage of the population sampled; population sizes: [Geco air:127, Spritmonitor.de:7,218, Travelcard:26,964 and EEA:14,623,747]

Source: JRC, 2021.

1 Introduction

1.1 Background

The first set of carbon dioxide (CO_2) emission standards for passenger cars was introduced in the European Union (EU) in 2009, (Regulation (EC) No 443/2009) and revised in 2014, (Regulation (EU) No 333/2014). The emission values used for assessing compliance against the targets are the official type-approval CO_2 emissions of the vehicles. Over the course of the last 20 years, data collected from experimental testing and self-reporting provided indications of an increasing divergence between real-world CO_2 emissions and fuel consumption values and those reported officially, based on the New European Driving Cycle (NEDC). Although the average official CO_2 emissions of new passenger cars in the EU reduced from 170 g/km in 2001 to 119 g/km in 2017, rebounding to 122 g/km in 2019, the reduction trends observed in the actual operation (real-world measures) did not follow at the same pace, an observation that is generally known as CO_2 emissions gap. Most of these analyses of real-world trends relied on statistical evaluations of voluntarily self-reported consumer or fleet operator fuel consumption data. The gap was reported to widen substantially, from about 8% in 2001 to about 40% in 2017 (Tietge et al. 2019; Fontaras et al. 2017). This growth of the gap undermined the climate change mitigation efforts of the EU CO_2 standards and resulted in higher-than-expected fuel cost for consumers as well as foregone tax revenue for governments (Tietge et al. 2019).

The major reason for the gap, highlighted by many studies (Fontaras et al 2017; Ligterink et al. 2016; Tietge et al. 2019) was the unrepresentativeness of the official CO_2 certification procedure, based on the phasing-out methodology (NEDC) and the inherent variability of fuel consumption when operating in real-world conditions. It is clear that no single experimental test, no matter how complex, can capture the vast variety of a vehicle's real-world operating conditions. However, the main trends regarding emissions reduction and efficiency improvements observed over the certification test should be reflected also in real-operation, if not to their entirety, at least to a very large extent. The European Commission (EC), acknowledging the issue of the non-representativeness of the NEDC-based certification test introduced the Worldwide harmonized Light vehicles Test Cycle and Procedure (WLTC and WLTP, respectively) in the type-approval procedure from September 2017 (Regulation 2017/1151). From 2021 on, the WLTP is the only cycle used for light-duty vehicle CO_2 certification in the EU. This new certification procedure is expected to decrease the gap by more than half, to an order of about 20% when compared with the certification average CO_2 value (Pavlovic et al. 2018; Tsiakmakis et al. 2016). Dornoff et al. 2020 confirm these estimates, suggesting that WLTP closes the gap by 22% to 24% compared to the NEDC.

For heavy-duty vehicles (HDVs), the real-world performance is more unclear, the lack of historical certification values and real-world emission measures have prevented an exact quantification of the gap.

Regulation (EU) 2019/631 for passenger cars and light commercial vehicles (LDVs) as well as Regulation (EU) 2019/1242 for HDVs, set new CO_2 emission targets for 2025 and 2030. Both Regulations also contain similar provisions requiring the Commission to set up a mechanism to monitor the real-world representativeness of the CO_2 emissions determined during the type-approval or certification tests and the progression of any eventual difference between the two. Also, the EC shall ensure that the public is informed on the evolution of the gap over time and use these data to prevent the gap between type-approval and real-world emissions from growing.

To this end, the Commission will collect real-world fuel and/or energy consumption and distance travelled data from vehicles using On-Board Fuel and/or energy Consumption Monitoring (OBFCM) devices. For LDVs such devices have been introduced in the type-approval legislation through Regulation (EU) 2018/1832 (the so-called "WLTP 2nd-act"), amending Regulation 2017/1151. For HDVs the standardization of OBFCM devices and their type-approval requirements have not been introduced in a Regulation as yet. The two main parameters concerned subject to future monitoring are the accumulated (lifetime) values of fuel consumed and total distance travelled. Both these parameters shall be determined and stored on-board of the vehicle, while also being unrestrictedly accessible through the on-board diagnostics port (OBD). The data shall be then collected and transferred from the vehicles to the EC and subsequently integrated into anonymised and aggregated datasets, including per manufacturer. The EC shall assess how the collected data can be used to ensure the real-world representativeness of CO_2 emissions values determined during the type-approval or certification tests. To that aim technical requirements and procedures need to be determined. The EC has launched studies on the matter, trying to identify which solutions are technically feasible, cost-effective, and adequate to satisfy the requirements set by the Regulation.

For light-duty vehicles, Commission Implementing Regulation (EU) 2021/392 requires manufacturers and Member States (through the Periodic Technical Inspections) to collect this data from 2022 onwards. This approach shall be reviewed by the Commission by 2023, in particular regarding the number of vehicles equipped with direct data transfer devices and the need for continued monitoring and reporting of real-world data by manufacturers. For heavy-duty vehicles, the Commission is still in the process of studying various data collection options.

A sampling-based approach could give an acceptable precision and level of information for the quantification of the gap with a limited margin of error and a very high confidence level, while involving a minimum of resources. A detailed statistical analysis for determining the different sampling methods that could be implemented, could help establish approaches that will supplement the missing information and help establish a robust monitoring approach.

1.2 Objectives

The goal of this study is to provide a comprehensive analysis of sampling approaches that could support the monitoring of the CO_2 emission and fuel consumption gap of road vehicles for the fleet of new vehicles introduced in the EU. This includes:

1. Optimization of sampling i.e. minimum sample size that is representative of the whole fleet within the acceptable error limits;
2. A reliable method of sample selection;
3. Comparison between different approaches;
4. Validation of the methods using both real-world and simulated data.

1.3 Structure of the report

The report is structured as follows:

Chapter 1 is an introduction to the current situation and the technical and policy-making issues regarding the monitoring of the fuel consumption gap.

Chapter 2 provides the statistical background; describes the sampling approaches and respective sample sizes and characteristics; introduces the datasets used in the analysis and the pre-analysis performed.

Chapter 3 examines the representativeness of the datasets; the relationships between the fuel consumption gap and the rest of the variables. It includes a validation of the different sampling approaches using the datasets and presents an application for the different test cases.

Chapter 4 summarizes the main conclusions of this report.

2 Methodology

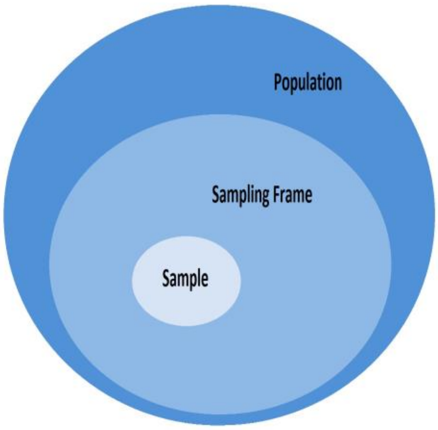
2.1 Statistical background

2.1.1 Terminology and basic concepts

The following terms are used:

- (Target) population: The entire group of vehicles that the study is intended to research and to which generalizations from samples are to be made. A measure of a characteristic of the population is a parameter.
- Sampling Unit: Any single vehicle belonging to the population. Every vehicle being regarded as individual and indivisible.
- Sample: A set of vehicles drawn from the population. Arithmetical characteristics of the sample are called sample statistics, these are used as estimates of population parameters.
- Sampling Frame: All sampling units from which those to be included in the sample are selected. The sampling frame is a subset of the population and a superset of the sample (Figure 1). Ideally, the sampling frame should be the same as the population, but often this is not feasible.
- Census: A complete enumeration of the population. The observations of all vehicles in the population are collected.

Figure 1 Depiction of relations between population, sampling frame and sample



Source: JRC, 2021.

A census does not have sampling error because all the units are measured. Yet it is easier to conduct a sample survey than a census. In practice conducting a census might not be plausible due to cost or technical limitations. By sampling it is possible to get reliable information at far less cost than a census. Additionally, it is less time consuming, enabling the publication of estimates in a timely fashion, while the sampling error from a survey can be quantified by using probability samples. In some cases, estimates based on a census can be less accurate than those based on a representative sample, because the data gathering procedure and instrument can be designed to be of higher quality.

Sampling methods can be of two types depending on whether the sample selection procedure used a probability mechanism or not:

- In probability sampling each vehicle has a predetermined non-zero chance to be included in the sample. In this way, there are no selection biases, and statistical theory can be used to extract properties of the estimators (e.g. the convergence of the sample mean to the population mean). This category includes simple random sampling, stratification, systematic sampling and cluster sampling.

- ► In non-probability sampling, vehicles are selected based on non-random criteria, and not every vehicle has a chance of being selected. This type of sampling is easier and costs less, but does not provide valid statistical inferences about the whole population. In most cases, the vehicles are chosen supposing they are representative of the population. There is subjectivity, which prevents the development of a theoretical framework for it. Because of targeted selection, bias can easily be introduced, and the possibility of generalizing and arriving at robust findings is reduced. This category includes convenience sampling, quota sampling and judgmental sampling.

Errors arising during a sampling procedure can be classified into two broad categories: sampling errors and non-sampling errors.

- ► Sampling error is a statistical error that happens because the sample selected does not represent perfectly the population of interest. The sampling error appears because of the variation between the population and the sample parameters. In probability sampling, sampling error can be quantified (by the margin of error and confidence level, see 2.2.1) and reduced by increasing the sample size. In non-probability sampling it cannot be quantified.
- ► Non-sampling error is an umbrella term which consists of all the errors, other than the sampling error. It results because of a number of reasons, i.e. error in questionnaire design, in problem definition, approach, data preparation, coverage, information provided by respondents, tabulation, collection, and analysis. Non-sampling errors can be found in all sampling methods (even in census). A non-sampling error can be either random or systematic. Random errors usually offset each other and therefore, most often, are of little concern. Systematic errors, on the other hand, affect the entire sample and therefore present a more significant issue. Non-sampling errors include: selection bias, sampling frame error, population miss-specification error, non-response error, processing error, respondent error, instrument error, surrogate error and interviewer error.

By designing properly all the steps of a statistical procedure (2.1.2) most types of error can be minimized or even eliminated. In this case of quantifying the fuel consumption gap, of great interest for the EC is to quantify and minimize the instrument error (OBFCM accuracy).

2.1.2 Designing a sampling scheme

For designing a proper sampling procedure, the following aspects should be made clear:

- ► *The purpose of the study*: define the main research question. In this report the purpose is to estimate the divergence between the real-world and the official type-approval fuel consumption values for the whole fleet of new passenger cars registered in the EU, which is quantified as the fuel consumption gap:

$$FC_{gap} = \frac{FC_{RW} - FC_{TA}}{FC_{TA}} * 100\% \tag{1}$$

where FC_{gap} is the fuel consumption gap, FC_{TA} is the type-approval fuel consumption and FC_{RW} the real-world fuel consumption.

- ► *The statement of objectives*: define the secondary objectives of this research. In this report these include :
    - o Estimate and compare the fuel consumption gap for different subpopulations defined by known variables (see Table 1).
    - o Examine the representativeness of the user datasets with respect to variables of interest (fuel type, type approval CO_2 emissions, vehicle manufacturer, engine rated power and engine displacement).

   - Find trends and relationships/correlations between the fuel consumption gap and other variables (see Table 1).

- *The target population*: specify the population of interest. The EC is interested in studying two different populations: the LDVs and the HDVs introduced in the EU from 2021 onwards. In this report, data analysis was conducted for LDVs, but the same methods can be applied for HDVs as well.
- *Access to the population*: deciding on a sampling frame and how good it is. The sampling frame should ideally be the closest possible to the whole population. If this is not feasible, the sampling frame should represent as close as possible the population. All vehicles registered in the EU are documented (section 2.3.4), however, it is not yet clear when the real-world fuel consumption will be available (see section 1.1).
- *Data gathering procedure/instrument*: determining the data collection method and the accuracy of the measurements. The OBFCM monitored quantities will be available at the on-board diagnostic (OBD) port in both LDVs and HDVs. These devices will collect the real-world consumption, while the type-approval fuel consumption will continue to be monitored by the European Environment Agency (EEA). For LDVs the required accuracy of the OBFCMs for the fuel consumption is set to 5% compared to the fuel consumption reported during WLTP type-approval tests. EC is currently working on requirements for the OBFCMs accuracy for LDVs and HDVs both at the lab and on-road (Pavlovic et al. 2021).
- *Cost/budget*: determining the cost of collecting the data, transferring them from the OBFCM devices to the EC and processing them. Considering the budget allocated from the EU and how it will be divided and if the sampling cost is the same for all vehicles across the EU countries. In this report, costs are not included in the analysis; cost-effectiveness will be one of the key factors for deciding any final solution and shaping its eventual implementation.
- *Sample size*: determining the appropriate sample size in advance. Finding the best compromise between accuracy considerations and cost/availability of the data. Observations cost money, time and effort. Increasing the sample size above a certain level gives minimal gains in terms of accuracy or representativeness.
- *Quantifying the quantity of interest*: deciding on which measures of location or variability are going to be estimated. If the gap is measured for the whole population (census) then the population measures of location and spread will be known and no estimations will be needed. In case a sampling approach is used, the result is going to be sampling measures of location and variability. These are estimators of the respective population ones. With probability samples, the sampling error can be quantified and confidence intervals can be constructed. In this report, mainly the mean value and the standard deviation are used.
- *Previous studies*: studying and using the related bibliography.
- *Sampling Technique*: A suitable sampling method can be found by taking into account the previous factors as well as the advantages and disadvantages of the various sampling techniques. In this report there is one continuous variable of interest (the fuel consumption gap), as well as information and interest for several other variables (e.g. fuel type and manufacturer). Two probability sampling methods were examined: simple random sampling and stratified sampling. Additionally, quota sampling was proposed, in case probability sampling is not feasible.

2.2 Sampling methods

Simple random sampling, stratifying sampling and quota sampling were the sampling methods investigated in this report. Simple random sampling and stratifying sampling are probability sampling methods, formulas for calculating the accuracy of the fuel consumption gap using the sample are available. Utilising these formulas the required sample size for achieving the demanded accuracy can be calculated in advance. Quota sampling is a non-probability method, hence the extent to which valid inferences for the population can be made using the sample is limited, but the criteria for choosing the sample are less strict.

2.2.1 Simple random sampling

Simple random sampling is the simplest of the probability sampling techniques. The principle is that each vehicle has the same probability of being selected. For example, for getting a sample of n vehicles from the population of N new vehicles registered in the EU, every vehicle could be assigned a number in the range from 1 to N, random numbers would be generated, and the first n numbers selected would be the sample. This unbiased random selection of vehicles is required to allow that the sample would accurately represent the population.

This type of sampling requires a complete sampling frame. Advantages are that it is free of classification error, no advance knowledge of the population is obligatory, and it is relatively easy to interpret data collected. If more information is available stratified sampling can be used. Simple random sampling can provide a benchmark for the required sample size.

To estimate the population mean μ, its unbiased estimator the sample mean $\bar{x}$ is used. The population variance σ^2 is estimated with its unbiased estimator, the sample variance s^2. The variance of the estimator $\bar{x}$ is:

$$\mathrm{Var}(\bar{x}) = \left(1 - \frac{n}{N}\right)\frac{s^2}{n} \tag{2}$$

The standard error of the estimate $\bar{x}$ is the square root of the variance of the estimate:

$$\mathrm{SE}(\bar{x}) = \sqrt{\left(1 - \frac{n}{N}\right)\frac{s^2}{n}} \tag{3}$$

where N is the population size, n the sample size. The finite population correction factor $1 - \frac{n}{N}$ adjusts the variance of the estimator to reflect the amount of information that is known about the population through the sample.

The results are presented as a confidence interval $\bar{x} \mp ME$. To construct this confidence interval a point estimate of the population mean and a quantitative measure of uncertainty associated with the point estimate is used. The margin of error is the radius (half the width) of the confidence interval constructed around the sample mean; it is calculated as a multiple of the standard error $SE(\bar{x})$, with the factor depending on the level of confidence desired. This factor presenting the confidence level is denoted by $t_{n-1,\frac{a}{2}}$ and is the upper $\frac{a}{2}$ point of the standard Student distribution with $n - 1$ degrees of freedom (α is the rate at which are Type I errors tolerated). In this way a $100(1 - \alpha)\%$ confidence interval for μ is constructed:

$$\bar{x} \mp ME = \bar{x} \mp \sqrt{\left(1 - \frac{n}{N}\right)\frac{s^2}{n}}\, t_{n-1,a/2} \tag{4}$$

Strictly speaking, the inferred confidence interval means that if the sampling procedure was repeated a hundred times, then the confidence level (confidence level is equal to $100(1 - \alpha)\%$) of times the produced confidence intervals $\bar{x} \mp ME$, would include the true population mean. After conducting the sampling only one sample exists and what is inferred is an estimate of the population mean.

The size of the sample should be determined before the sampling. When the sample size increases, the variance of the estimator decreases, which is desirable. This, though, is accompanied by increased sampling costs. A balance between these two considerable aspects has to be considered. The sample size can be determined based on prescribed values of the margin of error, i.e. by deciding on the desired multiple of the standard error. An important constraint in determining the sample size is that information about the population variance σ^2 is a prerequisite. This could be dealt with by conducting a pilot survey, i.e. collecting a preliminary sample, and use this survey's sample variance as an estimation of the population variance. It is also possible to estimate the population variance from past data, experience, prior information etc.

In practice this means the way to determine the number of sample units to measure is by establishing the degree of precision that is required for the desired estimate, i.e. to predetermine the margin of error and then solve the expression for the sample size:

$$ME = \sqrt{\left(1-\frac{n}{N}\right)\frac{\sigma^2}{n}}t_{n-1,\frac{a}{2}} \Rightarrow$$
$$n = \frac{1}{\frac{ME^2}{(z_{\frac{a}{2}})^2\sigma^2}+\frac{1}{\mathrm{N}}} \tag{5}$$

The determination of the sample size requires information on $t_{n-1,\frac{a}{2}}$ which depends on the sample size. Therefore, it is substituted by the respective value $z_{\frac{a}{2}}$ from the normal distribution. This simple substitution is applicable for this report, as, for all cases of real interest, the sample size is large ($n > 30$).

2.2.2 Stratified sampling

In cases when the population is homogeneous (the fuel consumption gap of all identifiable subpopulations does not differ substantially), simple random sampling will produce a homogeneous sample. In such a case the sample mean will be a good estimator of the population mean. If the population is heterogeneous, a sampling scheme than reduces the heterogeneity in the population is a better choice, as it would increase the precision of the estimator. Stratified sampling is such a method.

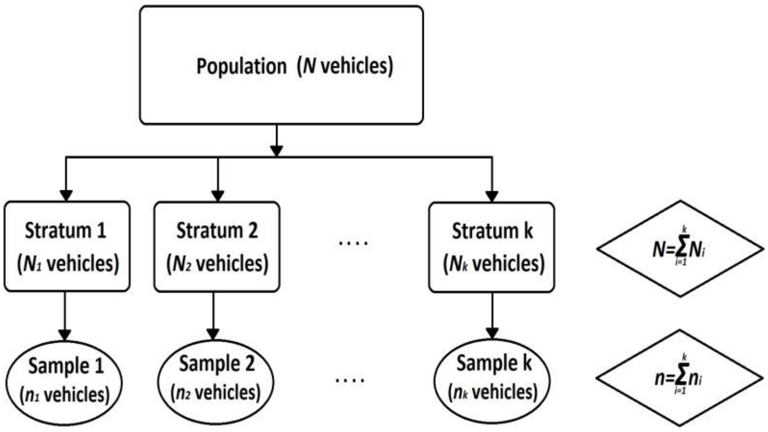
To conduct stratified sampling one has to:

- ► Break down the heterogeneous population into subpopulations, homogeneous in respect to the fuel consumption gap. These subpopulations are called strata.
- ► Consider each subpopulation as a separate population and take a sample (in this report simple random sampling will be used) from each stratum.

The procedure of stratified sampling is the following (Figure 2):

- ► Divide the population of N sampling units into k strata.
- ► Let the i^{th} stratum has N_i sampling units. Strata are constructed so that they are non-overlapping and homogeneous with respect to the characteristic under study, such that $\sum_{i=1}^{k} N_i = N$.
- ► Draw from the i^{th} stratum an independent sample of n_i vehicles.
- ► All the sampling units (vehicles) drawn from every stratum compose a stratified sample of size $n = \sum_{i=1}^{k} n_i$.

Figure 2 Stratifying sampling procedure



Source: JRC, 2021.

There are k independent samples drawn through simple random sampling of sizes $n_1, \dots, n_k$ from each stratum. Therefore, one can have k estimators of the parameter (population mean) based on these samples. The main goal is not to have k different estimators of the parameters but one single estimator. Taking into account that the final sample is a sum of k independent samples, an unbiased estimator for the population mean is:

$$\bar{x}_{st} = \sum_{i=1}^{k} \frac{N_i}{N} \bar{x}_i \qquad (6)$$

where $\bar{x}_i$ is the sample mean from the i^{th} stratum.
An estimator of the standard error of the estimate $\bar{x}_{st}$ is:

$$SE(\bar{x}_{st}) = \sqrt{\sum_{i=1}^{k} \left(\frac{N_i}{N}\right)^2 \left(1 - \frac{n_i}{N_i}\right) \left(\frac{{s_i}^2}{n_i}\right)} \qquad (7)$$

where the sample standard deviation s_i is an unbiased estimator of the population standard deviation S_i of the i^{th} stratum.

Therefore the confidence interval for estimating the population mean is:

$$\bar{x}_{st} \mp ME = \sum_{i=1}^{k} \frac{N_i}{N} \bar{x}_i \mp \sqrt{\sum_{i=1}^{k} \left(\frac{N_i}{N}\right)^2 \left(1 - \frac{n_i}{N_i}\right) \left(\frac{{s_i}^2}{n_i}\right)} \, t_{d,\frac{a}{2}} \qquad (8)$$

where d is the Satterthwaite's approximation for the degrees of freedom (Cochran 1977).

In the case of stratified sampling, as per the above formula, the precision of the estimator depends on the following factors:

- ► The confidence lever or equivalently the allowable probability (α) that type I error will occur.
- ► The stratification: The precision dependents on the strata sizes and most importantly, the margin of error is small when the strata standard deviations are small. This is suggestive of how to construct the strata. If all strata standard deviations are small then the margin of error will also be small.

- The sample allocation: The total sample size has to be allocated among the strata. Depending on the allocation, the precision varies.
- The total sample size: The higher the sample size the higher the precision of the estimator.

Sample allocation methods are usually dependent on:

- the total number of vehicles in each stratum;
- the variability of the fuel consumption gap within each stratum;
- the cost of taking an observation from each stratum.

In this report, the cost of sampling from each stratum will be considered the same and cost considerations will not be taken into account.

Three commonly used allocation procedures are:

1. Equal allocation: If the sizes of the strata are the same and there is no prior information about the population, a legitimate decision would be to assume equal sample sizes for the strata, so that:

$$n_i = \frac{n}{k} \; 1, \dots, k \tag{9}$$

2. Proportional allocation: if the sizes of the strata differ, proportional allocation would usually be better in order to maintain a steady sampling fraction throughout the population. The sample sizes per stratum are proportional to the strata sizes:

$$n_i = \frac{n}{N} N_i \; 1, \dots, k \tag{10}$$

3. Neyman allocation: In this allocation both the size and the variability in each stratum are taken into account. Larger sample size is allocated to the larger and more variable strata:

$$n_i = \frac{n N_i S_i}{\sum_{i=1}^{k} N_i S_i} \; 1, \dots, k \tag{11}$$

Choosing the sample size: Before calculating the sample size, the allocation method has to be decided. The same way as in simple random sampling (section 2.2.1) the required sample size is calculated by specifying the margin of error and confidence level in Equation (7). The determination of the sample size requires information on $t_{d,\frac{a}{2}}$ which itself depends on the sample size. Therefore, it is substituted by the respective value $z_{\frac{a}{2}}$ from the normal distribution.

- For equal allocation:

$$\mathrm{n} = \frac{k * \sum_{i=1}^{k} \frac{{N_i}^2 {S_i}^2}{\mathrm{N}^2}}{\frac{ME^2}{(z_{\frac{a}{2}})^2} + \sum_{i=1}^{k} \frac{N_i {S_i}^2}{\mathrm{N}^2}} \tag{12}$$

- for proportional allocation:

$$\mathrm{n} = \frac{\sum_{i=1}^{k} \frac{N_i {S_i}^2}{\mathrm{N}}}{\frac{ME^2}{(z_{\frac{a}{2}})^2} + \sum_{i=1}^{k} \frac{N_i {S_i}^2}{\mathrm{N}^2}} \tag{13}$$

- For Neyman allocation:

$$n = \frac{\left[\sum_{i=1}^{k} \frac{N_i S_i}{N}\right]^2}{\frac{ME^2}{(z_{\frac{a}{2}})^2} + \sum_{i=1}^{k} \frac{N_i S_i{}^2}{N^2}} \tag{14}$$

Neyman allocation is a special case of optimal allocation which is formulated to minimize the standard error of the estimate in Equation (7). This means that if the variances of the strata are specified correctly, Neyman allocation will always, for the same sample size, produce an estimator with a smaller variance than proportional allocation (Lohr 2019). When the standard deviations of the strata are equal, Equation (13) and Equation (14) are equivalent, which means that proportional and Neyman allocation requires the same sample size. The degree of which Neyman allocation is better than proportional depends on the variability of the strata standard deviations. In this report, the coefficient of variation was used to quantify this variability.

If the strata sizes are large enough to permit the approximation $\frac{N_i - 1}{N_i} \approx 1$ then for the same sample size proportional allocation always gives a smaller variance than simple random sampling (Cochran 1977). This means that the required sample size to achieve the same precision is smaller when using stratified sampling with proportional allocation. The degree of which stratified sampling with a proportional allocation is better than simple random sampling depends on how variable the strata means are. The higher the variability the bigger the difference in required sample size. The coefficient of variation of the mean values was used to quantify this variability.

To optimize the estimation of the fuel consumption gap one variable of interest: dependent variable (the fuel consumption gap) and multiple stratification variables: independent variables (see Table 1) were used. The methods which use one stratification variable are called univariate stratification methods. If more than one stratification variables are utilized they are called multivariate stratification methods. In this report cross-classification design was used for multivariate stratification methods. In this design when L variables are used, with the i^{th} having H_i strata, they form $H = \prod_{i=1}^{L} H_i$ strata.

Increasing the number of stratification variables makes the analysis more complicated and strata with less than 2 vehicles may be formed. Equations (*12)* (*13)* and (*14)* which were used for computing the sample sizes, require the strata standard deviations. Strata with only one vehicle have no standard deviation. The approach used in this report was to join strata with less than two vehicles into a superstratum. That is to say, this superstratum contains all vehicles from strata with one vehicle. If there was only one stratum with one vehicle, the vehicle was transferred to a random stratum.

2.2.3 Quota sampling

Quota sampling is a non-probability version of stratified sampling.

- In quota sampling, the entire population is divided into relevant strata using stratification variables, like country or fuel type, chosen according to their relevance to the fuel consumption gap.
- The number of vehicles that is sampled from each stratum is proportional to the stratum's vehicles, known from the EEA datasets. Thus, the sample is representative of the entire population, in respect to the stratification variables.
- Convenience or judgment sampling is practiced to choose vehicles from each stratum, both methods being subjective.
- By adhering to the stratification variables chosen, other factors contributing to variability could lead to samples biased in certain ways. The resulting sample may still have an unrepresentative combination of the stratification variables. Understanding the variable under research (fuel consumption gap) and the factors that contribute to its variability (fuel type, engine rated power, engine displacement, manufacturer etc.) is important to design an accurate quota-

sampling scheme and avoid major bias. Interrelated controls can be used to attain a correct combination of the stratification variables. A balance is desirable between the higher costs of using more detailed quota controls and the increased representativeness.

2.3 Data Sources

In this report four datasets are used, from which the three were user-based (Geco air, Spritomonitor.de and Travelcard), while the fourth was the annual CO_2 emissions monitoring data from newly registered M1 vehicles in the EU in 2018 as reported by Member States to the EEA.

- All datasets were utilized to test and validate the sampling methods. This was accomplished by considering the datasets as the population, taking samples and examining the accuracy and the required sample size for each method.
- Data from EEA were utilized to find the distributions/proportions of vehicles registered in the EU in 2018 concerning other variables (e.g. per fuel type). These were used for examining the representativeness of the user datasets.
- The user datasets were utilized to find trends, make comparisons and understand the relation between the fuel consumption gap and the other available variables.
- The real-world data from the user datasets were also used to get information about the fuel consumption gap, in particular its variability, which was required for calculating sample sizes.

Data screening was applied to the three user-based datasets to remove faulty data, data that were not in the scope of this report and to use comparable data from the different datasets. Entries with the following characteristics were removed:

- Plug-in hybrid and electric vehicles.
- Vehicles not fuelled by diesel or petrol.
- Vehicles with either type-approval fuel consumption or type approval CO_2 not available.
- Vehicles with real-world fuel consumption less than or equal to 3 l/100km (assumption that these are plug-in hybrid vehicles).
- Vehicles with type-approval, fuel consumption less than or equal to 3 l/100km (assumption that these are plug-in hybrid vehicles).
- Vehicles with fuel consumption gap greater than 200%.
- Vehicles by manufacturers with only one vehicle in the dataset.
- Vehicles with registration-year other than 2018.
- Vehicles with a minimum recorded mileage (or in the case of Travelcard the number of fuelling entries, because the distance was not available) less than a specified distance (fuelling entry) criterion. For Geco air and Spritomonitor.de it was found that vehicles with a driven distance less than 1,000 km and 1,250 km, respectively, had to be removed to ensure there would be no statistically significant difference when using vehicles with low recorded mileage. For Travelcard, vehicles with less than three fuelling entries were excluded from the analysis.

Table 1 Available variables per dataset

Variables	Dataset			
	Geco air (France)	Spritmonitor.de (Germany)	Travelcard (Netherlands)	EEA (EU)
Real-world FC or CO_2 (l/100km or g/km)	✓	✓	✓	×
Type-approval FC or CO_2 (l/100km or g/km)	✓	✓	✓	✓
Fuel type	✓	✓	✓	✓
Manufacturer	✓	✓	✓	✓
Vehicle Year	✓	✓	✓	✓
Engine Displacement (cc)	✓	×	✓	✓
Engine Rated Power (kW)	✓	✓	✓	✓
Transmission Type	✓	✓	×	×
Distance (1,000km)	✓	✓	×	×
Number of fuelling events	×	×	✓	×
Country of registration	×	×	✓	✓

Source: JRC, 2021.

2.3.1 Geco air

Geco air is a mobile application designed by IFP Energies Nouvelles to help individual users become "eco-drivers" by estimating their pollutant (NO_x and CO) and CO_2 emissions. The real-world CO_2 emissions are calculated using a physical model that uses as inputs:

- The real-world data profiles of speed and altitude, which are calculated using the GPS measurements, recorded at 1 Hz by the mobile phones;
- Technical specifications of the vehicle including those shown in Table 1, which are either manually inserted by the user or extracted by the plate number (if it is provided by the user). In the cases when the plate number is available, the type approval CO_2 value corresponds to the value appearing on the French registration document.

IFP Energies Nouvelles provided JRC anonymized data of approximately 7,500 vehicles registered from 1987 to 2019 (approximately 300 were registered in 2018) driven on real-world conditions. For each vehicle, aggregated data were provided for both its CO_2 emissions and the total distance, recorded via GPS, these data in addition to the provided type approval CO_2 emissions were used to derive the FC gap for every vehicle. Additionally, the dataset included: fuel type, manufacturer, build year, engine displacement, engine rated power and transmission type (Table 1).

After applying different selection criteria mentioned in section 2.3, a sample of 225 vehicles remained. To ensure that the vehicles were driven for an adequate distance, all vehicles with a recorded mileage less than 1,000 km were removed. This criterion of 1,000 km was chosen because it was found that there is no statistically significant difference between the subpopulations of vehicles driven for at least 1,000 km and at least 1,500 km. To find the minimum distance that could be used, hypothesis tests were performed; it was checked whether using shorter minimum driven distance would lead to a statistically significant difference to the mean value of the fuel consumption gap ($pvalue \leq 0.05$). The groups were not normally distributed, therefore unpaired two-sample Wilcoxon test was used. Tietge et al. (2019) used 1,500 km, and this was chosen as a reference and starting value and compared to shorter distances. It was also confirmed that there was no statistically significant difference between the subpopulation of vehicles driven for at least 1,500 km and vehicles driven for longer distances. After applying the distance criterion a total of 127 vehicles were used for further analysis.

2.3.2 Spritmonitor.de

Spritmonitor.de is a free web service where owners of vehicles report real-world fuel consumption. It was launched as a website in Germany in 2001, and aims to provide drivers with a simple device to help them monitor their fuel consumption. To register a vehicle on this website, the car owner provides vehicle specifications (i.e. fuel type, manufacturer, built year, engine rated power and transmission type). Also, Spritmonitor.de users can provide the type approval fuel consumption value and ″trip″ details with each entry. To start making use of the service users are requested to fill the fuel tank completely, and the first event provides the reference for calculations of fuel consumption. In every fuelling entry, the user is requested to record the mileage and the liters fueled. Fuel consumption data are added voluntarily, therefore there is a risk of self-selection bias.

Spritmonitor.de dataset had anonymized data on approximately 122,000 vehicles registered from 2014 to 2019 (approximately 20,300 were registered in 2018). For every vehicle, the real-world fuel consumption value was computed based on the total fuel consumption of the vehicle and the total mileage. Using the same methodology as for Geco air (section 2.3.1), and after applying the non-distance criteria 7,722 vehicles remained. It was then calculated that the minimum mileage that would not produce statistically significant differences was 1,250 km. Keeping only the vehicles with a recorded mileage larger than 1,250 km, 7,218 were utilised in the analysis.

2.3.3 Travelcard

Travelcard Nederland B.V. is a fuel card provider based in the Netherlands. Fuel cards are used as payment cards at gas stations and are employed by companies for tracing fuel expenses of their fleets. The Travelcard data-providers are drivers who usually drive new cars and change vehicles every few years. Usually, the expenses of Travelcard users are covered by employers. Travelcard drivers may thus have a lower incentive to drive in a fuel-conserving manner than private car owners. To compensate for this, Travelcard has a fuel-cost saving program to push drivers to be mindful of excess fuel consumption. For example, loyalty points are awarded to users with comparatively low fuel consumption and a fuel pass that can be used in public transportation.

JRC received anonymized data for around 258,000 vehicles registered from 2011 to 2019 (approximately 28,300 were registered in 2018). The real-world and type-approval fuel consumption was provided and used to calculate the fuel consumption gap. The dataset also contained information about the fuel type, manufacturer, build year, engine displacement, engine rated power transmission type and the number of fuelling events. The data pre-processing by utilizing the same criteria as for Geco air and Spritmonitor.de removed entries and 27,892 vehicles remained. Recorded mileage was not available and the number of fuelling events was used instead. A similar methodology as in section 2.3.1 was applied to find that three was the minimum number of fuelling events which would not lead to a significant difference for the average fuel consumption gap. Removing all vehicles with less fuelling events resulted in a dataset consisting of 26,964 vehicles.

2.3.4 European Environment Agency

Regulation (EU) 2019/631 (previous (EC) No 443/2009) requires the Member States to record information for each new passenger car registered in their territory. EEA documents all the vehicles registered in the EU every year and provides public datasets with anonymized data. These annual datasets include the type-approval CO_2 emission, fuel type, manufacturer, engine displacement, engine rated power, country of registration and other information not used in this report. The EEA datasets do not include real-world CO_2 emissions and fuel consumption, therefore the calculation of the fuel consumption gap was not possible. For this report, the 2018 final dataset was used. It consists of approximately 15,273,000 passenger cars; after removing electrical and plug-in hybrid vehicles and vehicles not fuelled by petrol or diesel, 14,623,747 remained. In this step, no other entries were removed because of interest was to use this dataset to get a better understanding of the census, hence removing vehicles because one variable was missing was not the suitable approach.

The fuel consumption gap for EEA vehicles was simulated to apply the sampling methods on the EEA dataset. The goal was to assign a reasonable fuel consumption gap that would allow testing the sampling methods for the census (all the vehicles registered during one year in the EU). The fuel consumption gap of Geco Air, Spritmonitor.de and Travelcard vehicles were used to make a representative simulation (at least representative for Germany, France and the Netherlands; in section 3.1 it is discussed whether these three countries can represent the whole EU) of the fuel consumption gap for EEA's vehicles. For the simulation the following procedure was performed:

- A combined dataset consisting of vehicles sampled from Geco Air, Spritmonitor.de and Travelcard was created. The number of vehicles sampled from Geco Air, Spritmonitor.de and Travelcard datasets followed the same ratios, as the ratios of vehicles registered, according to EEA dataset, in France (2,273,335), Germany (3,303,367) and the Netherlands (381,689). All 127 vehicles of Geco Air dataset were used, 185 from Spritmonitor.de and 21 from Travelcard were randomly chosen.
- The combined and the EEA dataset were stratified in respect to five stratification variables: the manufacturer, fuel type, type-approval CO_2 emissions, engine rated power and engine displacement.
- For every vehicle of the EEA dataset it was identified in which stratum it belonged. If there were vehicles in the respective stratum of the combined dataset, the fuel consumption gap was randomly sampled using the fuel consumption gap's distribution of that stratum of the combined dataset.
- If in the combined dataset there were no vehicles in that stratum, both datasets were stratified in respect to four stratification variables: the manufacturer, fuel type, type-approval CO_2 emissions and engine rated power (removing the last stratification variable). Then the stratum the vehicle belonged in respect to this second stratification was identified. If the respective stratum of the combined dataset had at least one vehicle, the fuel consumption gap was randomly sampled from that stratum's fuel consumption gap distribution. If not, the combined and the EEA dataset were stratified in respect to three stratification variables: : the manufacturer, fuel type and the type-approval CO_2 emissions and the same procedure was repeated.
- This continued until a fuel consumption gap was assigned for that vehicle (reducing by one the stratification variables, until the stratification was done only by one stratification variable: the manufacturer). If there were no vehicles of that manufacturer in the combined dataset, a new stratification using four stratification variables: the type-approval CO_2 emissions, fuel type, engine rated power and engine displacement was performed. The procedure was repeated until a fuel consumption gap was assigned. The last possible stratification was by one stratification variable: the type-approval CO_2 emissions, in which case a value is always assigned.

3 Data analysis

3.1 Dataset Representativeness

To evaluate the datasets used for testing the sampling methods utilised to support the determination of the fuel consumption gap of vehicles registered in the EU after 2021, it was investigated whether:

- ► The three datasets were representative of the fleet of EU vehicles registered in 2018;
- ► The three datasets were representative of the sub-fleets of their respective countries (Geco air for France, Sprtimonitor.de for Germany and Travelcard for the Netherlands);
- ► These three countries could represent the 2018 population of newly registered vehicles in the EU.

Representativeness was determined in respect to fuel type, type approval CO_2 emissions, vehicle manufacturer, engine rated power and engine displacement.

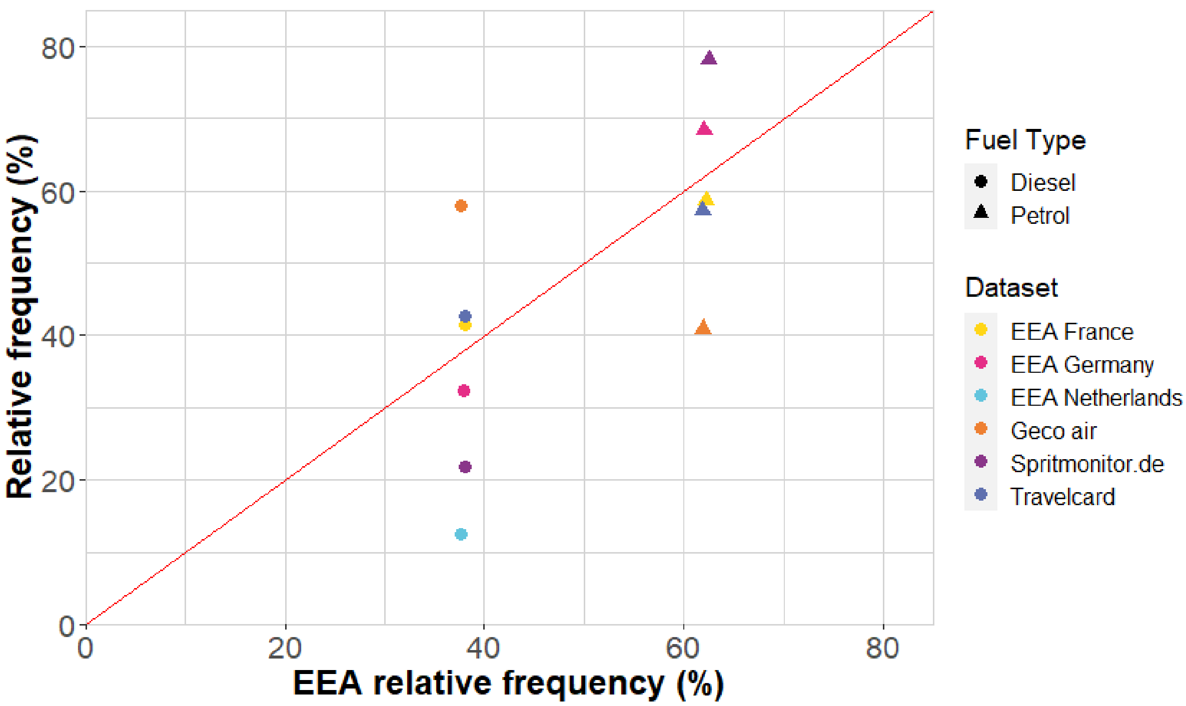
The distribution of the whole fleet of vehicles introduced in the EU market in 2018 was calculated from the EEA dataset, for the manufacturer, type-approval CO_2 emissions (g/km), fuel type, engine displacement (cc) and engine power (kW). The distributions of the country-wise sub-fleets were collected for the above five variables. For the same variables, the distribution was calculated of the Geco Air, Spritmonitor.de and Travelcard datasets.

For each of the five variables, plots were drawn where Geco Air, Spritmonitor.de and Travelcard were compared to the French, German and Dutch sub-fleets, respectively, as well as to the 2018 European fleet. It should be noted that the following analysis does not represent the whole Geco Air, Spritmonitor.de and Travelcard datasets, but only those registered in 2018 and those that passed the removal criteria as described in section 2.3. The main purpose of this section was not to evaluate the datasets but to check whether, and to what degree, it is justified to use them for getting a valid indication of the fuel consumption gap across the EU. The datasets cannot be used in the context of Regulation (EU) 2019/631 as they are not relying on data recorded using OBFCM devices.

Fuel type is a critical parameter concerning the type-approval and the real-world fuel consumption and subsequently the FC gap. These relationships have been studied in (Ntziachristos et al. 2014). For the three user datasets used in this report, results are presented in Figure 3. The relative frequencies are larger than the corresponding ones that would be calculated if all vehicles were used. Nevertheless, this does not influence the inferences made in this report. Variations exist from country to country. The share of newly registered diesel and petrol vehicles in 2018 for the German and French market is close to the share of the whole EU (Figure 3), while in the Netherlands in 2018 only 12.5% of the newly registered vehicles were diesel. Hence, the Netherlands subpopulation cannot represent the whole EU when it comes to fuel type.

In Geco Air dataset approximately 58.0% of the vehicles were diesel-powered. This is a substantial difference compared to EEA (37.8%) and EEA France (41.5%). 22.0% of Spritmonitor.de vehicles were diesel-powered, which is relatively closer to the German sub-fleet’s share (32.6%). For Travelcard, almost 42.0% of the vehicles used diesel fuel, therefore this dataset cannot be considered as representative of the Dutch fleet in respect to fuel type, but it is representative of the whole European fleet.

Figure 3 Representativeness of datasets per fuel type

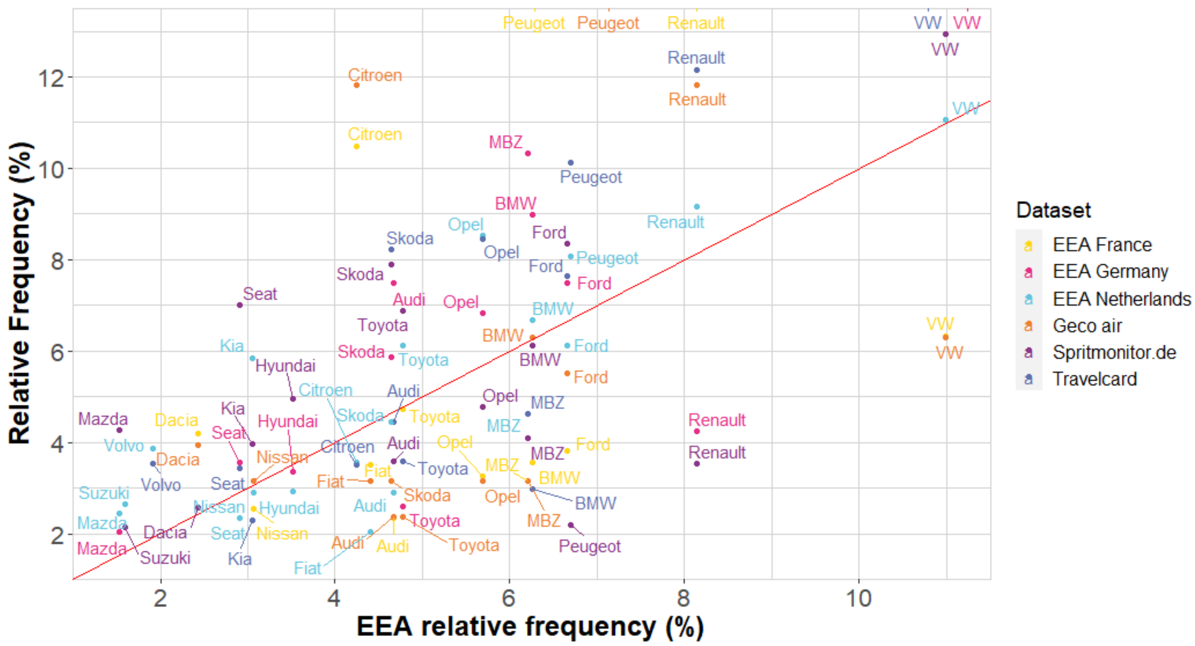


Source: JRC, 2021.

Figure 4 presents all manufacturers that have a share of a least 2% on the respective dataset. The French sub fleet is not representative of the whole European fleet, because Renault, Peugeot and Citroen share almost 50% of the French market, while their portion of the whole EU fleet is less than 26%. In Germany there is a similar situation, e.g. Audi, BMW, Mercedes-Benz and Volkswagen have a higher share of the German market (46%) in comparison to their share in the European fleet (28%). The Dutch sub-fleet exhibits the best behaviour, only two manufacturers have a difference greater than 2% (Opel and Kia).

Geco Air dataset is representative of the French market, except for Peugeot which is overrepresented by 14% in Geco air and Renault which is underrepresented by 9% in Geco air. Spritmonitor.de is not representing satisfactorily neither the German sub fleet nor the European one. Travelcard is over-representing the most popular manufacturers, reaching up to 7% for Volkswagen.

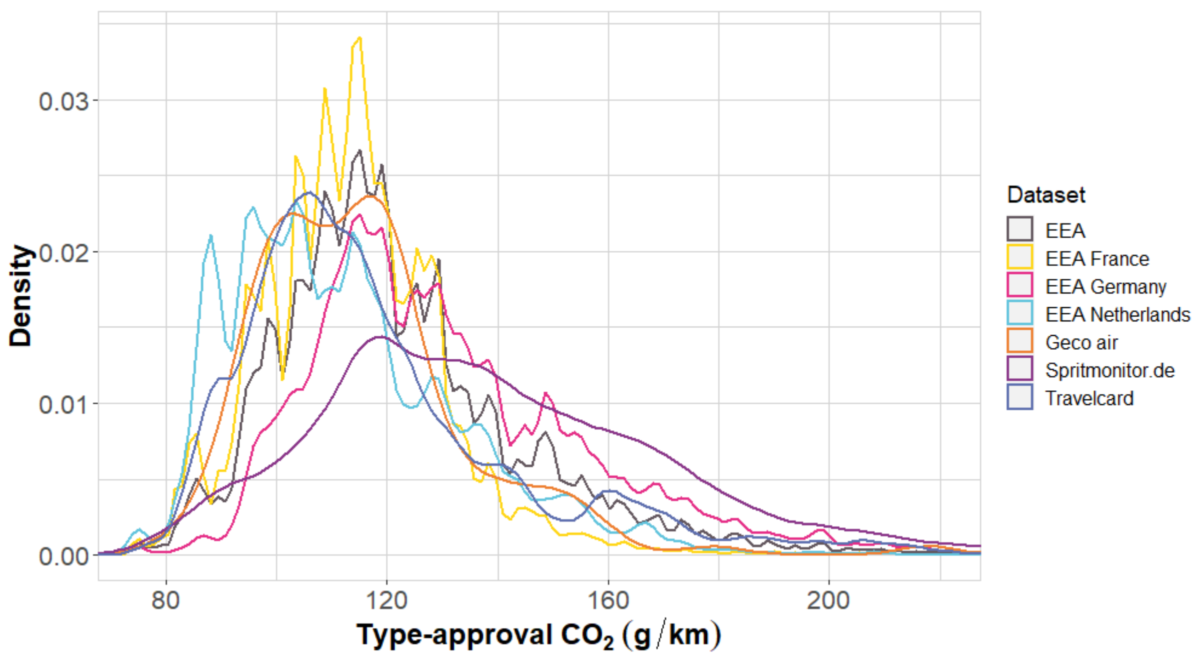
Figure 4 Representativeness of datasets per manufacturer



Source: JRC, 2021.

The CO_2 emission gap and consequently the fuel consumption gap is a function of the real-world and the type-approval CO_2 emissions. In some cases linear relationships can be found and simple linear regression models can be constructed for predicting the real-world fuel consumption only by using the type-approval fuel consumption (Ntziachristos et al. 2014). The French and Dutch sub-fleets (Figure 5) have more vehicles with low type-approval CO_2 emissions in comparison to the whole fleet. On the other hand in the German market the percentage of vehicles with high type-approval CO_2 emissions sold in 2018 was higher than the respective one of the whole EU market.

Figure 5 Representativeness of datasets per type-approval CO_2



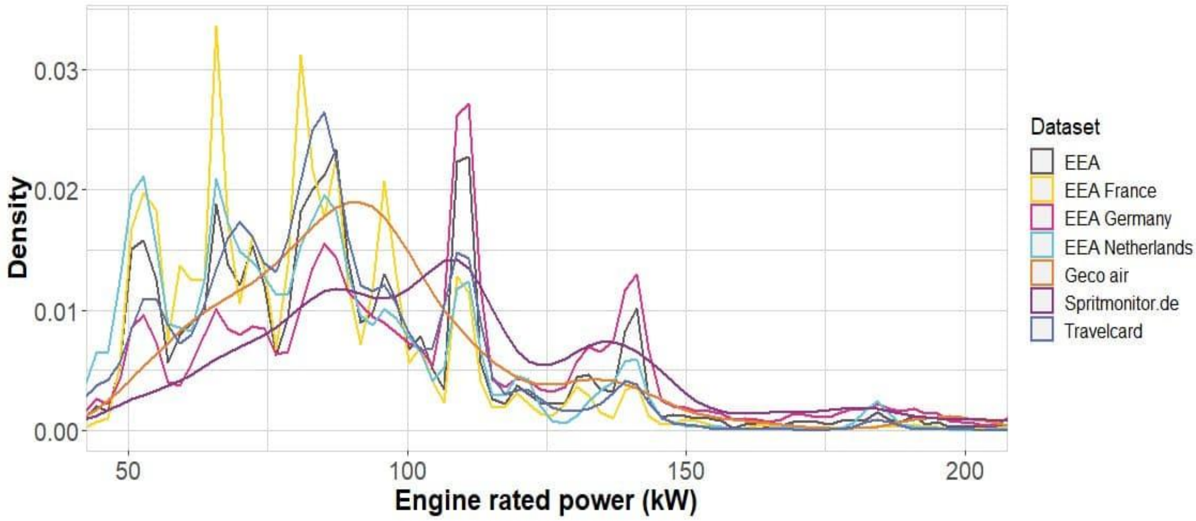
Source: JRC, 2021.

Concerning type-approval CO_2 emissions, Geco Air's density distribution was relatively close to both EEA France's and EEA's distributions. Vehicles of Spritmonitor.de with type-approval emissions around 110g/km were overrepresented. Travelcard was the best representative of the EU fleet with respect to type-approval CO_2 emissions.

Vehicles sold in France in 2018 had on average lower engine rated power compared to the average across the EU, while in Germany it was higher. The Dutch market was closer to the whole European as regards engine rated power (Figure 6).

In Geco air dataset the engine rated power was closer to the whole fleet's compared to the French fleet's. Spritmonitor.de approximates well the German market, with the only exception being vehicles with engine rated power around 110kW. Travelcard is relatively close to the Dutch sub-fleet.

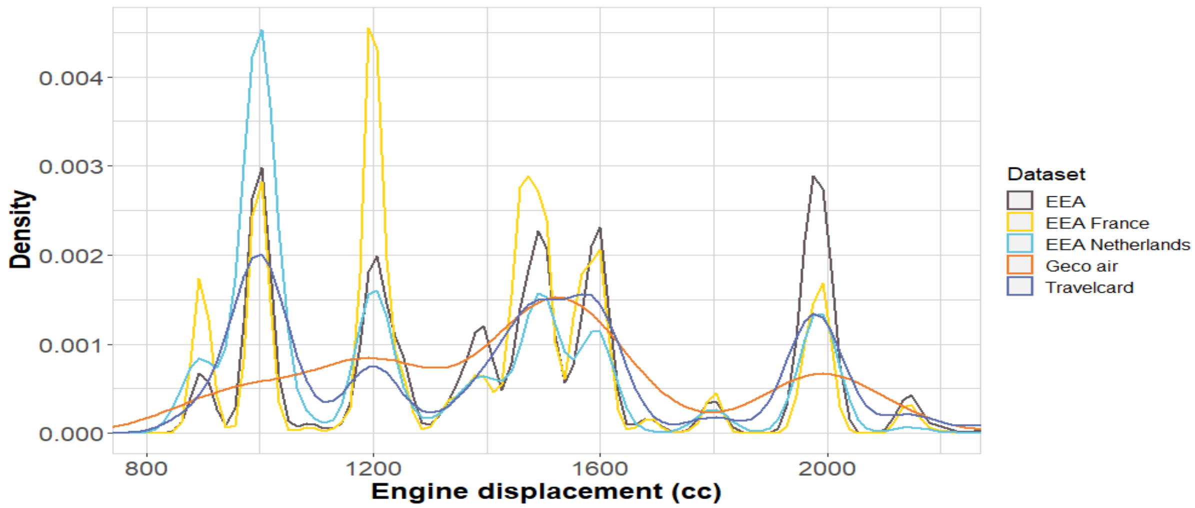
Figure 6 Representativeness of datasets per engine rated power



Source: JRC, 2021.

Engine displacement was not available for Spritmonitor.de vehicles. Both the French and Dutch vehicle's average engine displacement in 2018 were lower than across Europe. Worth mentioning is that in 2018, the Netherlands had the lowest average engine displacement in the EU for new passenger car registrations. Travelcard is representative of the Netherland's situation in all but for vehicles with low engine displacement (Figure 7).

Figure 7 Representativeness of datasets per engine displacement



Source: JRC, 2021.

Only a limited number of vehicles were used from each dataset, while the rest was removed as explained in section 2.3. The current assessment is seen from a purely scientific perspective and in this sense, a strict approach was selected. In fact, all datasets provide fairly good representations of their respective countries sub-fleets and to a lesser extend the EU fleet, particularly considering the uncertainty of other datasets and calculations. Hence, the main conclusions concerning the representativeness of the datasets can be summarised as:

- The French sub-fleet can represent the EU fleet satisfactory with respect to fuel type and engine displacement.
- The German sub-fleet can represent the EU fleet satisfactory with respect to fuel type, type-approval CO_2 emissions and engine rated power.
- The Dutch sub-fleet can represent the EU fleet satisfactory with respect to the manufacturer, type-approval CO_2 emissions and engine rated power.
- The Geco Air dataset can represent the vehicles registered in France satisfactory with respect to the manufacturer and type-approval CO_2 emissions.
- The Spritmonitor.de dataset can represent the vehicles registered in Germany satisfactory concerning type-approval CO_2 emissions and engine rated power.
- The Travelcard dataset can represent the vehicles registered in the Netherlands satisfactory in respect to type-approval CO_2 emissions, engine rated power and engine displacement.

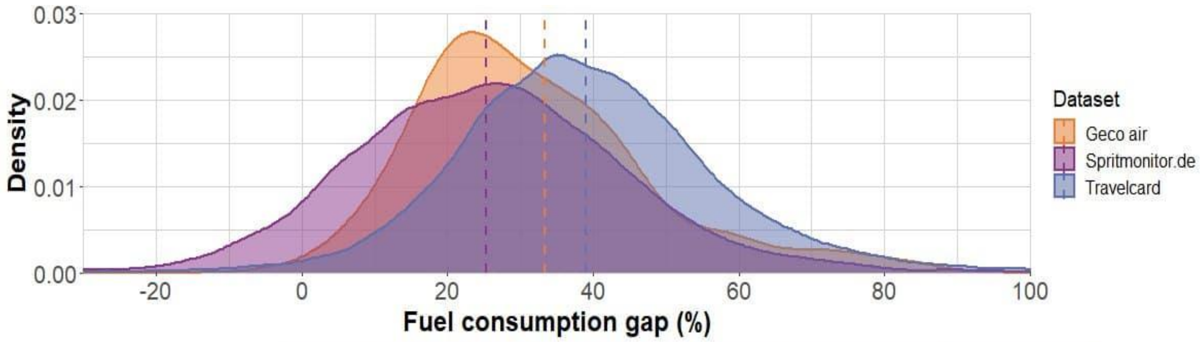
3.2 Fuel consumption gap analysis

The goal of this section was to get a better understanding of the fuel consumption gap, firstly as a stand-alone variable, then in relation to the other variables used in this report. Special emphasis was given to the variability of the fuel consumption gap because a priori knowledge of the population standard deviation is necessary for calculating the sample size required for implementing probability sampling approaches. Moreover, choosing stratification variables and optimizing a stratification sampling scheme requires choosing strata in such a way that the fuel consumption gap is more homogeneous within strata than among strata. The analysis was performed separately for each dataset.

For all three datasets the distributions of the fuel consumption gap (Figure 8) were right-skewed (most values were clustered around the left tail of the distribution; the right tail of the distribution was longer). Geco air was highly right-skewed, Spritmonitor.de and Travelcard were approximately symmetric. Vehicles of Spritomonitor.de dataset on average had the smallest fuel consumption gap (25.3%) and of Travelcard the biggest (39.1%) (Figure 8). International Council on Clean Transportation (ICCT) reported for Spritomonitor.de in 2018, an average fuel consumption gap of 39% (Dornoff et al. 2020). This difference of 13.7% could be attributed to the exclusion in the present analysis of electric and plug-in hybrid vehicles that reportedly exhibit higher gap values (Plötz et al. 2021) and to the usage of different type-approval fuel consumption values. While the ICCT research team used in their analysis an ICCT maintained dataset for linking it to Spritomonitor.de vehicles, in this report the self-reported values provided by the vehicle owners in Spritomonitor.de were utilized without any correction. As a last possible factor could be identified the different criteria used to remove vehicles during the data pre-analysis.

An important observation, for the scope of the study, because of its use in sampling methods, is the convergence of the standard deviation of all three samples. The three datasets have similar standard deviations of fuel consumption: Geco Air (20.4%), Spritmonitor.de (19.7%) and Travelcard (19.0%). Another measure of variability is the interquartile range (3rd Quartile - 1st Quartile): Geco air, Spritmonitor.de and Travelcard have interquartile ranges of 20.0%, 24.7% and 21.9%, respectively.

Figure 8 Histograms & statistics of fuel consumption gap, per dataset



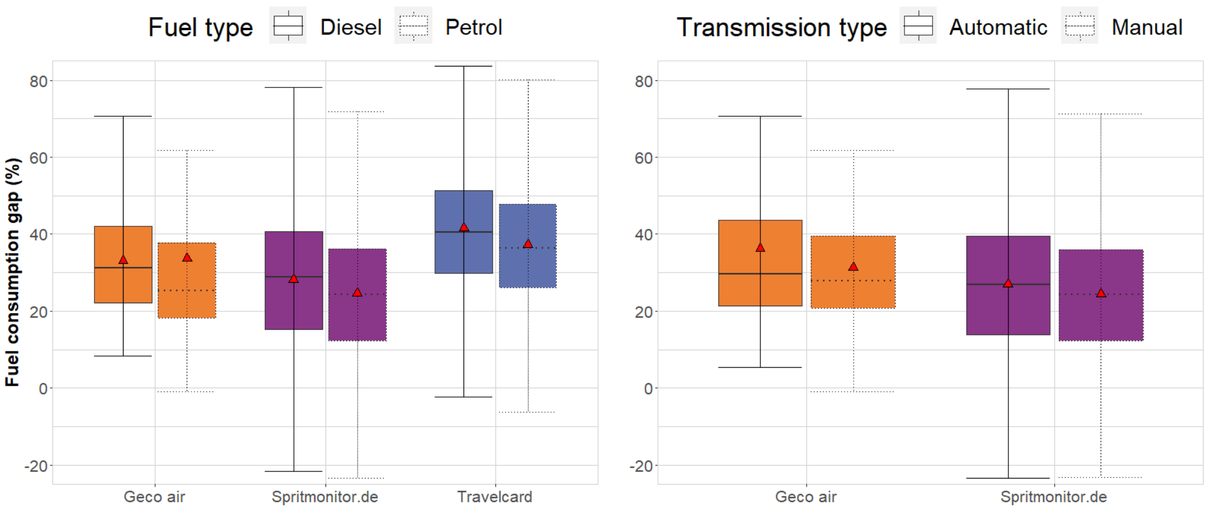
	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum	Standard Deviation	Number of Vehicles
Geco air	-0.9	21.1	29.0	33.3	41.1	152.1	20.4	127
Spritmonitor.de	-74.7	12.8	25.1	25.3	37.5	156.5	19.7	7,218
Travelcard	-66.8	27.5	38.0	39.1	49.4	186.2	19.0	26,964

Source: JRC, 2021.

The relationship between the fuel consumption gap and fuel type presents similar patterns in all three datasets (Figure 9). Petrol vehicles had on average lower fuel consumption gap, however, there was no statistically significant difference. Concerning the variability of the fuel consumption gap for Spritmonitor.de and Travelcard there was no statistically significant difference between diesel and petrol vehicles (e.g. for Travelcard the standard deviation of the fuel consumption gap for diesel and petrol vehicles was 18.8% and 18.9%, respectively. The IQR was 21.5% in both groups). Geco air petrol fuelled vehicles had a substantially larger standard deviation compared to the diesel powered ones (27.6%-13.4%). The reason is that in Geco air there were quite a few petrol vehicles with high fuel consumption gap and these 'outliers', not presented in Figure 9, strongly affected the standard deviation.

Vehicles with a manual transmission had a lower average and lower variability of the fuel consumption gap in both Geco air and Spritmonitor.de datasets (Figure 9).

Figure 9 Fuel consumption gap by fuel type and transmission type, per dataset. Red triangles depict the mean values



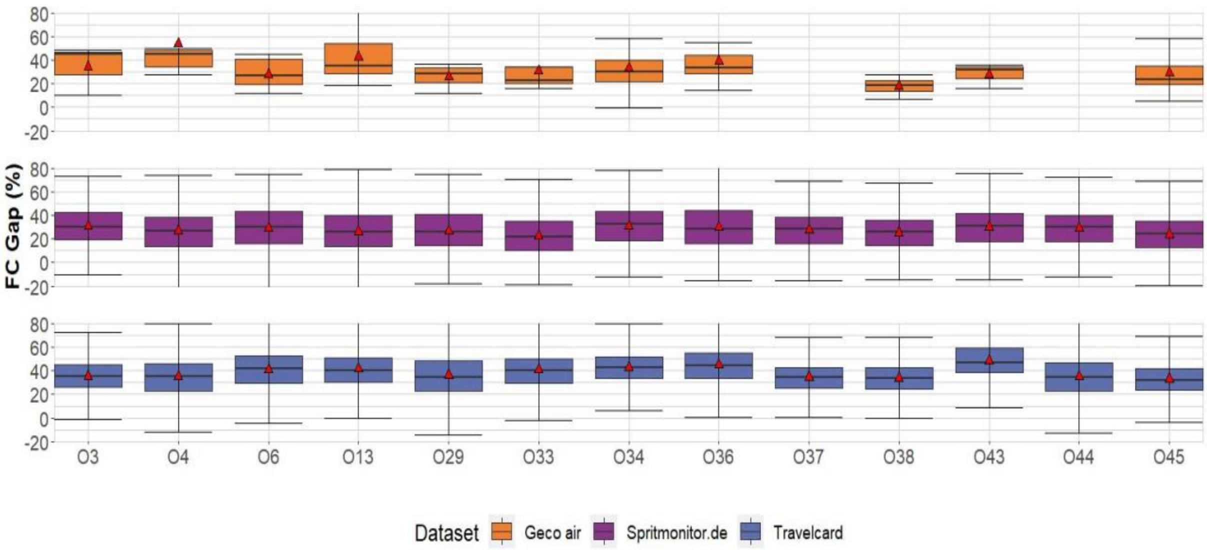
Source: JRC, 2021.

The three datasets give different results concerning the average and the standard deviation of the fuel consumption gap per manufacturer (Figure 10). In Spritmonitor.de the averages and the variabilities of the fuel consumption gap per manufacturer, do not present very large variations. The largest variations are seen in Geco air dataset, followed by Travelcard.

In Figure 11, the relation between the fuel consumption gap and the type-approval CO_2 emission, the engine rated power and the engine displacement are presented for each dataset. The curves are an estimate of the conditional mean function, i.e. it is an estimate of the mean fuel consumption gap conditional on the variable shown on the x-axis. For Geco air, which had less than 1,000 vehicles, locally estimated scatterplot smoothing was applied. For Spritmonitor.de and Travelcard a generalized additive model was fitted to the data.

Travelcard and Spritomonitor.de vehicles with low type-approval CO_2 emissions had in average the largest fuel consumption gap. For Spritmonitor.de an almost linear decreasing relationship was observed between the average fuel consumption gap and the type-approval CO_2 emissions. For Travelcard the average fuel consumption gap decreased until approximately 140g/km and then presented a slight increase. For Geco air vehicles with low and high type-approval CO_2 emissions had the lowest average fuel consumption gap.

Figure 10 Fuel consumption gap by manufacturer, per dataset. Only manufacturers with at least a share of 4% in one of the datasets are presented. Red triangles depict the mean values



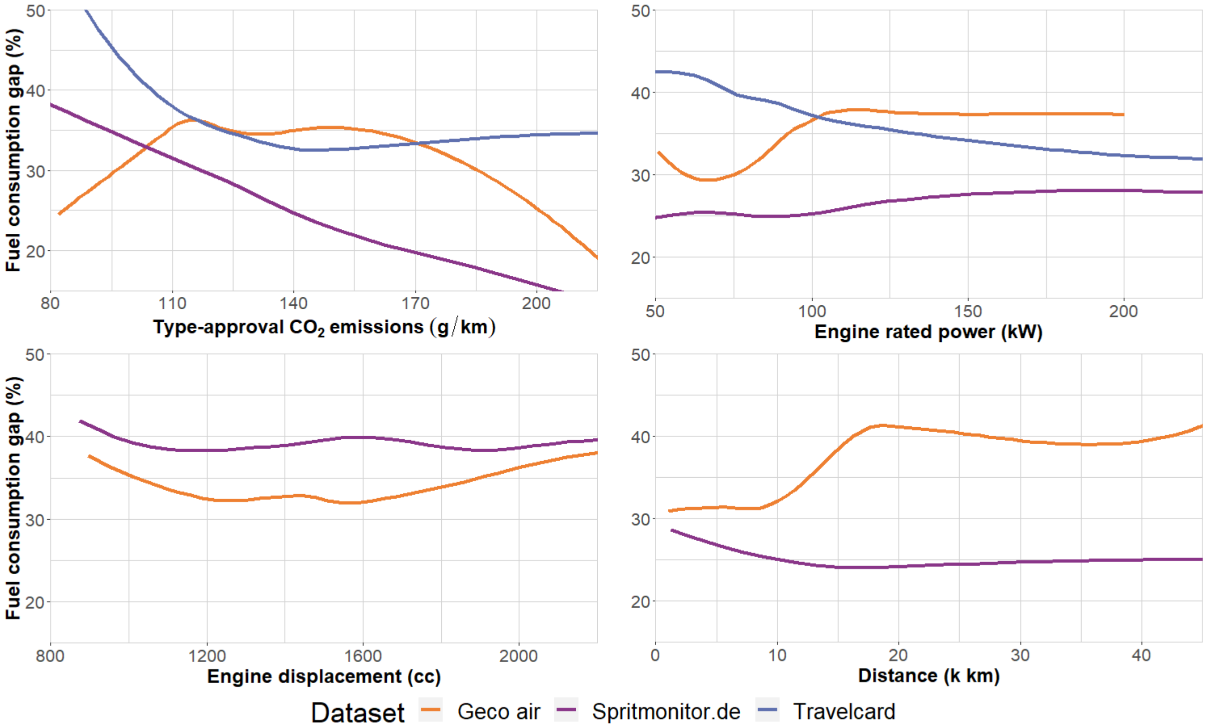
Source: JRC, 2021.

In all three datasets, the average fuel consumption did not present big divergences for vehicles with an engine rated power higher than 125 kW. Geco air and Spritmonitor.de vehicles had an average higher fuel consumption gap for vehicles with a lower engine rated power. The opposite held true for Travelcard vehicles.

Geco air and Travelcard presented similar trends in regards to the relationship between the average fuel consumption and engine displacement. In both datasets, there were no big variations in the vehicles average fuel consumption gap concerning the engine displacement. Vehicles with low and high engine displacement had a slightly higher fuel consumption gap.

The average fuel consumption of Geco air vehicles was low for vehicles with low mileage. For Spritmonitor.de, vehicles with a high mileage had in average a lower fuel consumption gap.

Figure 11 Average fuel consumption gap in relation to type-approval CO_2 emissions, engine rated power, engine displacement and distance driven, per dataset



Source: JRC, 2021.

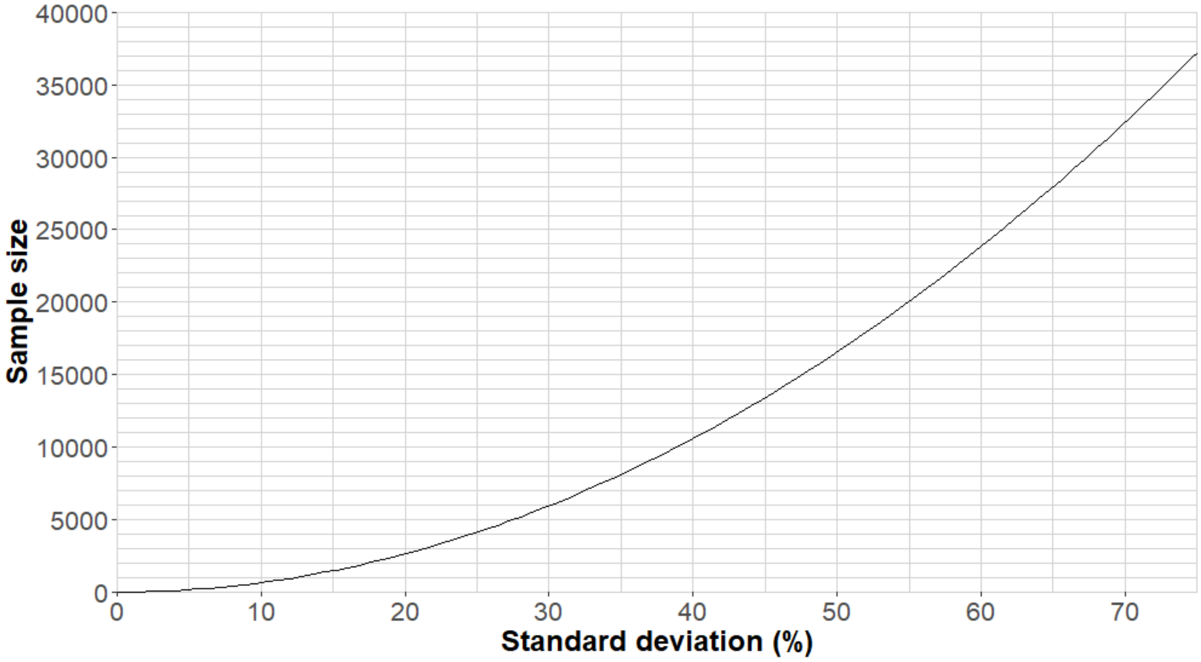
3.3 Validation of sampling methods

3.3.1 Simple random sampling

For the simple random sampling analysis, the only variable used was the fuel consumption gap (Table 2). The population sizes and the population mean values differ substantially, allowing an understanding of the impact they have on the required sample size. The standard deviations are similar; nevertheless, the impact on the sample size is shown in Figure 12. The mean value of the fuel consumption gap of EEA vehicles lies between the minimum and the maximum of the other three datasets, the standard deviation is larger. This is a consequence of the way EEA vehicles fuel consumption gap was simulated using the other three datasets vehicles' fuel consumption gap (section 2.3.4).

A preliminary estimation of the required sample size, in case of simple random sampling, for a population of 15 million vehicles and population standard deviation ranging from 0% to 75% is presented in Figure 12. The most stringent requirements for the precision examined in this report (confidence level 99% and margin of error 1%) were adopted. The three user-based datasets examined in this report had a standard deviation of the fuel consumption gap approximately 20% (Figure 8). For a standard deviation of 20%, the required sample size is 2,654. If the standard deviation was 25% the sample size would be 4,146 vehicles. Even if the population standard deviation is 75%, a sample size of less than 38,000 (0.25% of the total population) vehicles would be enough to reach the required precision.

Figure 12 Sample size in relation to standard deviation, for simple random sampling to achieve a confidence level of 99% and a margin of error of 1% for a population of 15 million vehicles



Source: JRC, 2021.

Table 2 Statistics of the fuel consumption gap, per dataset

Dataset	Population size	Population mean	Standard deviation
Geco air	127	33.3%	20.4%
Spritmonitor.de	7,218	25.3%	19.7%
Travelcard	26,964	39.1%	19.0%
EEA	14,623,747	30.5%	20.7%

Source: JRC, 2021.

The expected sampling error (the margin of error with a confidence level of 99%), for a population of 15 million vehicles and for different combinations of sampling size and standard deviation, is presented in Table 3. The general trend is that for the same standard deviation of the population (the same column in the table), when the number of sampled vehicles increases, the sampling error drops. In addition, for the same number of sampled vehicles (the same raw in the table), when the standard deviation of the population increases, the error increases. If 1,000 vehicles are sampled and the standard deviation of the population is 10%, the expected sampling error is 0.81%, while if the standard deviation of the population is 70% the expected sampling error is 5.70%. If 3,000 vehicles are sampled and the standard deviation of the population is 20% the expected sampling error would be 0.94%. In the case of a sample of 40,000 vehicles from a fleet with a standard deviation of 70%, the expected sampling error is 0.90%

Table 3 Margin of error in relation to sample size and standard deviation, for simple random sampling for a population of 15 million vehicles

Sample Size	Standard Deviation						
	10%	20%	30%	40%	50%	60%	70%
1,000	0.81	1.63	2.44	3.26	4.07	4.89	5.70
2,000	0.58	1.15	1.73	2.30	2.88	3.46	4.03
3,000	0.47	0.94	1.41	1.88	2.35	2.82	3.29
4,000	0.41	0.81	1.22	1.63	2.04	2.44	2.85
5,000	0.36	0.73	1.09	1.46	1.82	2.19	2.55
6,000	0.33	0.66	1.00	1.33	1.66	1.99	2.33
7,000	0.31	0.62	0.92	1.23	1.54	1.85	2.15
8,000	0.29	0.58	0.86	1.15	1.44	1.73	2.02
9,000	0.27	0.54	0.81	1.09	1.36	1.63	1.90
10,000	0.26	0.51	0.77	1.03	1.29	1.54	1.80
20,000	0.18	0.36	0.55	0.73	0.91	1.09	1.27
30,000	0.15	0.3	0.45	0.59	0.74	0.89	1.04
40,000	0.13	0.26	0.39	0.51	0.64	0.77	0.90

Note: confidence level 99%; in bold the lowest sample sizes to achieve a margin of error less than 1% for each population standard deviation

Source: JRC, 2021.

To calculate the required sample size and to validate the accuracy of the simple random sampling method for every dataset, the following procedure was performed:

- For each combination between the margin of error (10%, 9%, to 1%) and confidence level (90%, 95% and 99%), Equation (5) was used to calculate the required sample size (Table 4).
- For every resulting sample size, one million random samples were simulated
- For every random sample, the following were calculated:
  - The sample mean and the sampling error (the difference between the sampling and the population mean);
  - It was examined whether the absolute value of the sampling error was lower than the required margin of error;
  - For each combination of the margin of error and confidence level, the percentage of the cases for which the absolute value of the sampling error was lower than the specified margin of error was calculated (Table 5);
- Finally, these percentages were compared to the respective confidence level.

For example for Geco air, to achieve $\mathrm{ME} = 1\%$ and $\mathrm{cl} = 99\%$ a sample size of $n = 122$ was required. One million samples of 122 vehicles were randomly simulated. Of these samples, the population mean was predicted accurately 990079 times (99%). 99% is the percentage of the number of times the absolute sampling error was lower than the margin of error, or equivalently the percentage of the number of times the sample mean was inside the interval (Figure 13):

$$(mean_{pop} - ME \ , mean_{pop} + ME) = (33.3 - 1, 33.3 + 1) = (32.3, 34.3)$$

The sampling method was validated in this case, because $99\,\% \geq \ cl = 99\%$.

Table 4 Sample size required per dataset for different margins of error and confidence levels, for simple random sampling

Dataset	*cl* \ ME	10%	9%	8%	7%	6%	5%	4%	3%	2%	1%
Geco air	90%	11	13	16	20	26	34	46	64	88	115
	95%	15	18	21	27	33	43	57	75	97	118
	99%	23	27	33	40	48	60	74	90	108	122
Spritmonitor.de	90%	11	13	17	22	30	42	66	115	254	9157
	95%	15	19	24	31	42	60	92	162	355	1,236
	99%	26	32	40	53	71	102	158	276	591	1,898
Travelcard	90%	10	13	16	20	28	39	61	108	242	942
	95%	14	18	22	29	39	56	87	154	342	1,318
	99%	24	30	38	49	67	96	149	264	586	2,198
EEA	90%	12	15	19	24	33	47	73	130	291	1,163
	95%	17	21	26	34	46	67	104	184	413	1,654
	99%	29	36	45	59	80	115	179	317	713	2,851

Source: JRC, 2021.

Four factors contribute to the sample size. Two depend on the demanded accuracy: the confidence level and the margin of error. The other two are population parameters, the population size and the population standard deviation.

The calculated sample sizes for all four datasets (Table 4) confirm that the required sample size increases as the demanded confidence level increases and as the margin of error decreases. For example for Geco air, to achieve confidence level 90% and margin of error 10%, 11 vehicles were required. If the confidence level remained at 90%, while the requested margin of error was 1%, 115 vehicles would need to be sampled. In the most stringent case examined in this report, of confidence level, 99% and margin of error 1%, 122 of the total 127 vehicles would have to be sampled.

Concerning the population parameters, it holds that for both, the population size and the population standard deviation the larger they are, the larger the required sample size is. This is clear when comparing results for Travelcard and EEA datasets: EEA has a larger population size and population standard deviation, and for the same confidence level and margin of error, the required sample size for EEA is larger for all cases compared to Travelcard. On the other hand Spritmonitor.de has a smaller population size, but a higher population standard deviation than Travelcard. Consequently, for the same confidence level and margin of error, the required sample size for Spritmonitor.de is sometimes lower and sometimes higher than the required sample size for Travelcard. For example, for confidence level 99% and margin of error 10% 26 and 24 vehicles are respectively required from the datasets of Spritmonitor.de and Travelcard. For confidence level 99% and margin of error 1%, 1,898 and 2,198 vehicles are required for Spritmonitor.de and Travelcard respectively. The reason for that can be derived from Equation (5), the confidence level and the margin of error can be considered as weights for the population size and the population standard deviation. The standard deviation is multiplied by $\frac{\mathrm{ME}^2}{(z_{\frac{a}{2}})^2}$, therefore the higher this weight is the bigger the contribution of the standard deviation. This weight is higher for a larger margin of error and lower confidence level. This explains why for a large margin of error and low confidence level Spritmonitor.de needs more vehicles to reach the same accuracy as Travelcard.

As a final note, it should be mentioned that while the required sample size increases as the population size increases, there is a limit: after a certain point no matter how much the population size increases the increase of the required sample size is negligible. This behaviour is visible when looking at the datasets in Table 4, for confidence level 99% and margin of error 1%, 122 of the 127 (96.1%), 1,898 of the 7,218 (26.3%), 2,198 of the 26,964 (8.2%) and 2,851 of the 14,623,747 (0.02%) vehicles are respectively required from Geco air Spritmonitor.de, Travelcard and EEA datasets.

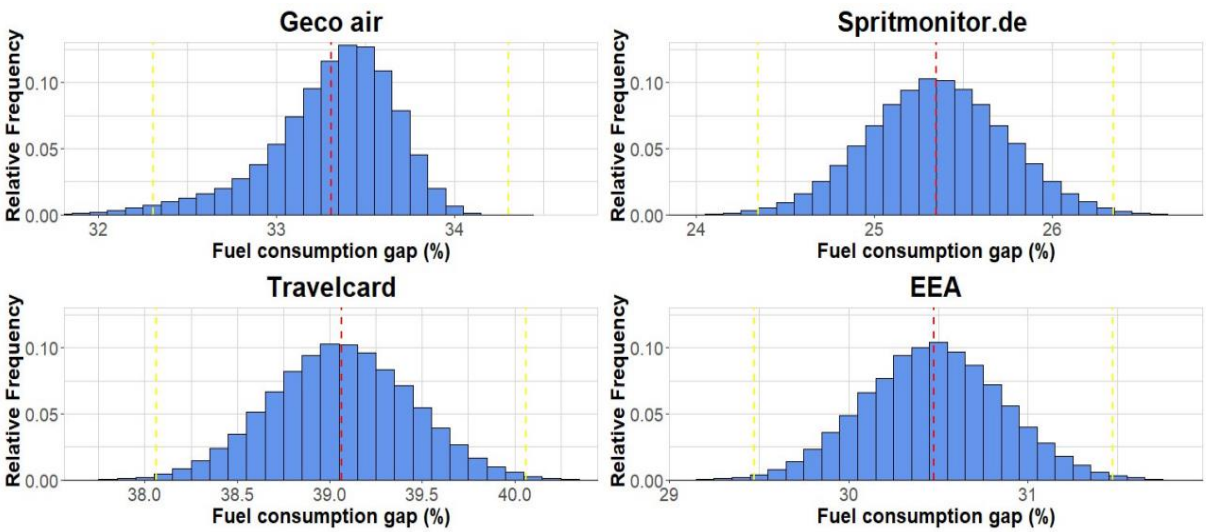
Concerning the validation of the accuracy of the simple random sampling method, for all four datasets, the results are very similar (Table 5). For required confidence levels of 95% and 90%, the percentage of accurate samples is always higher and with this result the method is validated. For confidence level equal to 99% there are cases with a percentage of accurate samples lower than the confidence level. However, even the biggest divergences are only 0.1% and these cases are only when the margin of error is high (more than 6%). It should be mentioned that in these "problematic" cases the sample size was not very large while the required accuracy (margin of error) was big (99%) and this resulted in not good enough convergence of the distribution of the mean value to the normal distribution.

Table 5 Accurate cases per dataset for different margins of error and confidence levels, for simple random sampling

Dataset	ME / cl	10%	9%	8%	7%	6%	5%	4%	3%	2%	1%
Geco air	90%	91.2	90.6	90.5	90.3	90.2	90.3	90.1	90.0	90.0	90.0
	95%	95.3	95.3	95.3	95.3	95.1	95.2	95.1	95.1	95.0	95.1
	99%	98.9	99.0	99.0	98.9	99.0	99.0	99.0	99.0	99.0	99.0
Spritmonitor.de	90%	90.3	90.9	90.2	90.0	90.0	90.4	90.2	90.0	90.0	90.0
	95%	95.4	95.0	94.9	95.2	95.2	95.1	95.0	95.0	95.0	95.0
	99%	99.0	99.0	99.0	99.0	99.0	99.0	99.0	99.0	99.0	99.0
Travelcard	90%	91.1	90.7	90.4	90.0	90.2	90.1	90.0	90.1	90.0	90.0
	95%	95.0	95.2	95.3	95.2	95.2	95.0	95.0	95.1	95.0	95.1
	99%	99.0	99.0	99.0	99.0	99.0	99.0	99.0	99.0	99.0	99.0
EEA	90%	91.0	90.7	90.3	90.1	90.2	90.1	90.2	90.2	90.0	90.1
	95%	95.0	95.3	95.2	95.1	95.1	95.0	95.1	95.1	95.0	95.1
	99%	98.9	99.0	99.0	98.9	99.0	99.0	99.0	99.0	99.0	99.0

Source: JRC, 2021.

Figure 13 Distributions of the sample mean of the fuel consumption gap, per dataset



Note: margin of error 1% and confidence level 99%; The red lines depict the population means and the yellow lines the confidence intervals around them

Source: JRC, 2021.

Some statistics of the difference between the sample mean and the population mean ($mean_{sam} - mean_{pop}$) for confidence level 99% and margin of error 1%, for the four datasets are presented in Table 6. For all datasets, except Geco air which has a small population size the differences have symmetrical distributions (Figure 13) with mean and median 0.0 and standard deviation 0.4. Half the differences (50%) are between -0.3% and 0.3%, while 99% are between -1% and 1%. The maximum and minimum difference are less than ±2%, denoting that in even the worst (less accurate) sample, the sampling error was less than 2%.

Table 6 Sampling error per dataset for margin of error 1% and confidence level 99%, for simple random sampling

Dataset	Minimum (%)	1st Quartile (%)	Median (%)	Mean (%)	3rd Quartile (%)	Maximum (%)	Standard Deviation (%)
Geco air	-1.9	-0.3	0.0	0.0	0.3	1.5	0.4
Spritmonitor.de	-1.8	-0.3	0.0	0.0	0.3	1.7	0.4
Travelcard	-1.6	-0.3	0.0	0.0	0.3	1.7	0.4
EEA	-1.6	-0.3	0.0	0.0	0.3	1.6	0.4

Source: JRC, 2021.

3.3.2 Stratified sampling

In stratified sampling, the first step required is to choose the stratification variable(s) and to determine the strata to split the population. In this section, different stratification variables were examined and conclusions and comparisons are presented. The main goal was to get a better understanding of the variables which require the smallest sample size to predict accurately the fuel consumption gap of the population. Additionally to identify the variables that are relevant to the fuel consumption gap, which were used to construct a quota sampling scheme. For each dataset, variables presented in Table 1 were used, first separately (univariate stratification) and then in combinations (multivariate stratification).

To calculate the required sample size, allocate it to the strata, and validate the accuracy of the stratified sampling method, for Geco air, Spritmonitor.de, Travelcard and EEA datasets, the following analysis was performed:

- One or more stratification variables were chosen;
- For each combination of the margin of error (10%, 9% to 1%) and confidence level (90%, 95%, 99%), the required sample size was calculated;
- This sample size was allocated to the k strata after applying different allocation methods;
- For equal allocation, if the sampling size required from a stratum was higher than the stratum size, the method was termed as unfeasible;
- For proportional and for Neyman allocation, reallocations were performed to ensure that the number of sampling units to be drawn from all strata were not more than the number of sampling units in the stratum:

$$n_i \leq N_i, \qquad i = 1, \dots, k$$

- For every resulting sample size, million ($n_{sim} = 1{,}000{,}000$) random samples were simulated.
- For every sample the following was calculated:
    - The sample mean;

- The sampling error (the difference between the sampling and the population mean);
- It was examined whether the absolute value of the sampling error was larger than the margin of error.

► The percentage of the cases for which the absolute value of the sampling error was lower than the specified margin of error was calculated for each combination of the margin of error and confidence level.

► Finally, these percentages were compared to the respective required confidence levels and the method was validated.

The sample sizes for Neyman (n_o), proportional (n_p), and equal allocation (n_e), without considerations of the sampling cost, were calculated using Equations (*14)*, (*13)* and (*12)* respectively. The parameters contributing to the sample size are related to the demanded accuracy, population and stratification. The confidence level and the margin of error determine the accuracy. Concerning the population parameters, the population size and the population standard deviation influence the sample size. The population standard deviation (S) is not directly used, the contribution to the sample size depends on the strata standard deviations (S_i). The importance of the stratification can be also seen from the use of the strata sizes (N_i), and in the case of equal allocation the number of strata (k) in the formulas.

The sample size allocation for equal, proportional and Neyman allocation was performed, using Equations (*9)*, (*10)* and (*11)* respectively. For equal allocation, when the results were not integers, they were rounded up to the next integer and the required sample size was recalculated. For proportional and Neyman allocation controlled rounding was used to round these real values to a set of integers that sum to the calculated sample sizes.

Detailed analysis and explanations for univariate stratification stratifying by the fuel type and the type-approval CO_2 emissions are provided in sections 3.3.2.1 and 3.3.2.2, respectively. Results of these two sections were used to compare the different allocation procedures. Based on the results of section 3.3.2.1 and the simple random analysis of section 3.3.1 it was decided for the analysis that follows to use a confidence level of 99% and a margin of error of 1%. To avoid repeatable and almost identical tables and conclusions, validation results for stratification sampling are presented only in section 3.3.2.1. In section 3.3.2.3 the stratification variables are compared separately. Multivariate stratification is introduced in section 3.3.2.4, combining variables of interest. In section 3.3.2.5 the sample sizes are presented when accurate estimators are also required per stratum.

3.3.2.1 Stratifying by Fuel Type

A simple univariate stratification is when stratifying by fuel type, in the sense that the populations (Geco air, Spritmonitor.de, Travelcard and EEA) were split into only two strata (diesel and petrol vehicles). Geco air had more diesel vehicles than petrol vehicles (58.3%-41.7%), the standard deviation of the fuel consumption gap was lower for diesel vehicles (13.4%-27.6%) (Table 7). Spritmonitor.de had less than one third diesel than petrol vehicles (22.0%-78.0%), standard deviation was slightly higher for the diesel vehicles (20.0%-19.5%). Travelcard had a higher number of petrol vehicles (58.1%-41.9%), the two strata had almost the same standard deviation (18.9%-18.8%). EEA also had more petrol vehicles (62.2%-37.8%), the standard deviation of the simulated fuel consumption gap was higher for petrol vehicles (23.4%-15.2%).

Table 7 Fuel consumption gap grouped by fuel type, per dataset

Fuel type	Dataset											
	Geco air			Spritmonitor.de			Travelcard			EEA		
	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i
Diesel	74	33	13.4	1,586	28.2	20.0	11,296	41.6	18.8	5,530,321	32.1	15.2
Petrol	53	33.7	27.6	5,632	24.5	19.5	15,668	37.3	18.9	9,093,426	29.5	23.4
Minimum	53	33	13.4	1,586	24.5	19.5	11,296	37.3	18.8	5,530,321	29.5	15.2
Maximum	74	33.7	27.6	5,632	28.2	20.0	15,668	41.6	18.9	9,093,426	32.1	23.4
Mean	63.5	33.4	20.5	3,609	26.4	19.8	13,482	39.5	18.9	7,311,873.5	30.8	19.3
Standard deviation	14.8	0.5	10	2,861	2.6	0.3	3,091.5	3.0	0.1	2,519,495.7	1.9	5.8
Coefficient of variation	0.23	0.01	0.49	0.79	0.10	0.02	0.23	0.08	0.00	0.34	0.06	0.30

Source: JRC, 2021.

The calculated sample sizes for all four datasets and three allocation methods confirm that as the demanded confidence level increases and the margin of error decreases, the required sample size increases (Table 8). For example for Geco air, to achieve a confidence level of 90% and margin of error of 10%, 10, 11 and 10 vehicles are required to be sampled respectively for equal, proportional and Neyman allocation. If the confidence level remains at 90%, while the requested margin of error is 1%, 106, 115 and 101 vehicles are necessary, respectively for equal, proportional and Neyman allocation. In the most stringent case with confidence level equal to 99% and margin of error equal to 1%, equal allocation does not work as more petrol vehicles are required for sampling compared to the total number of petrol vehicles that exist in the dataset. For proportional and Neyman allocation, 122 and 108 (of the total 127 vehicles) have to be sampled, respectively.

For Spritomonitor.de, Travelcard and EEA, equal allocation requires a higher sample size compared to proportional and Neyman allocation, to achieve the same confidence level and margin of error (Table 8). In contrast, for Geco air proportional allocation requires the highest sample size. This is because for Geco air, in the case of proportional allocation, less petrol than diesel vehicles are sampled. However, petrol vehicles have a higher standard deviation and as a result, a high total sample is required to reach the accuracy standards.

The variabilities of the strata standard deviations are presented in Table 7, in this stratification, the coefficient of variation of the standard deviations of the strata's fuel consumption gap was the highest for Geco air (0.49) and as a consequence, the relative difference between Neyman and proportional allocation was the highest. For Travelcard the coefficient of variation was approximately zero and subsequently the required sample sizes for the two allocation methods are the same.

As regards the simulated fuel consumption gap of the EEA dataset, for achieving the most stringent sampling conditions (margin of error 1% and confidence interval 99%) for Neyman allocation one would need to sample a total of 2,734 vehicles (772 diesel and 1962 petrol) for proportional allocation 2,840 vehicles (1,074 diesel and 1,766 petrol), and for equal allocation 3,252 vehicles (1,627 diesel powered and the same number of petrol). This agrees with the results for simple random sampling. A sample size of approximately 3,000 vehicles and the respective cost is considered reasonable. For the analysis that follows this required accuracy (margin of error 1% and confidence interval 99%) were used to keep the presentation simple and not repetitive. In the case of different precision requirements (lower or higher ones) the methodology and the inferences made would be the same, with required sample size similar to the ones presented in Table 4 and Table 8. It should be noted that increasing the number of strata and stratification variables does not result in different trends.

Table 8 Sample sizes per dataset required for different margins of error and confidence levels, with stratification variable the fuel type, per dataset

Dataset	cl \ ME	10%			5%			1%		
Geco air	90%	10	11	10	32	34	30	106	115	101
	95%	14	15	13	40	43	38	-	118	105
	99%	22	23	21	56	60	53	-	122	108
Spritmonitor.de	90%	14	11	11	55	42	42	1,190	912	912
	95%	20	15	15	78	59	59	1,604	1,230	1,230
	99%	34	26	26	132	101	101	2,466	1,890	1,889
Travelcard	90%	10	10	10	40	39	39	956	931	931
	95%	16	14	14	58	55	55	1,338	1,303	1,303
	99%	26	24	24	98	95	95	2,232	2,173	2,173
EEA	90%	14	12	12	54	47	45	1,326	1,159	1,115
	95%	20	17	16	76	66	64	1,884	1,645	1,583
	99%	34	29	28	132	114	110	3,252	2,840	2,734

Note: pink is for equal allocation, green for proportional allocation, yellow for Neyman allocation

Source: JRC, 2021.

Concerning the validation of the accuracy of the stratified sampling method, for all four datasets, the results were similar. For confidence levels 95% and 90% the percentage of accurate samples was every time higher than the confidence level validating the method. For confidence level 99% there were some cases with percentage of accurate samples lower than the confidence level. However, even the biggest divergences were only 0.3% and these cases appear when the margin of error was high (larger than 5%). This would not pose a problem if confidence level 99% and margin of error 1% were adopted. It should be mentioned that in these "problematic" cases the sample size was not very large while at the same time the required accuracy (margin of error) was big (99%). This lead to poor convergence of the distribution of the mean value to the normal distribution. The sample mean for stratifying sampling converges to the same distribution as for simple random sampling. Consequently, the results were similar to those presented in Figure 13 and Table 6.

3.3.2.2 Stratifying by type-approval CO_2 emissions

Type-approval CO_2 emissions were discretized into nine strata as shown in Table 9. For Geco air the standard deviations of different strata ranged from 3.7% to 30.9%. The coefficient of variation of the standard deviations was the highest (0.64%) compared to the other datasets. The strata sizes were from 2 to 34 vehicles. For Spritmonitor.de the standard deviations of the strata varied less (16.6% to 20.6%), and the strata sizes presented big differences (251 to 1,790 vehicles). Travelcard strata standard deviations and sizes ranged from 15.6% to 26.4% and from 779 to 7,002 vehicles, respectively. EEA's standard deviations and sizes ranged from 15.3% to 26.5% and from 556,727 to 3,408,016, respectively. It should be noted that in EEA the type-approval CO_2 emissions were not available for 387,181vehicles. The approach followed in this report was to pool them together in a separate strata, so that the population size would remain the same no matter the stratification scheme and consequently the results would be comparable.

Table 9 Statistics of the fuel consumption gap grouped by type-approval CO_2 emissions, per dataset

Type-approval CO_2 emissions (g/km)	Dataset											
	Geco air			Spritmonitor.de			Travelcard			EEA		
	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i
<90	4	25.1	6.2	251	38.4	17.7	2,235	51.4	18.0	556,828	34.3	15.3
(90,100]	21	28.6	15.1	325	33.1	16.6	3,211	45.3	17.4	1,398,299	27.9	15.9
(100,110]	31	33.0	17.1	615	32.4	18.8	7,002	39.7	15.6	2,680,338	30.2	16.7
(110,120]	34	39.4	30.9	1,046	30.6	18.3	5,223	36.5	17.0	3,408,016	37.3	26.5
(120,130]	17	28.5	12.9	866	29.1	18.1	2,959	36.3	19.1	2,264,323	29.4	18.2
(130,140]	8	33.0	13.9	1,095	25.5	18.6	2,149	33.1	17.8	1,432,206	27	21.9
(140,150]	5	40.4	12.6	612	23.0	17.1	1,001	31.1	18.9	909,277	29.2	16.9
(150,160]	5	35.0	4.1	618	21.2	17.7	779	31.2	20.0	598,727	25.6	17.7
>160	2	21.4	3.7	1,790	17.0	20.6	2,405	37.4	26.4	988,552	21.4	17.3
NA	-	-	-	-	-	-	-	-	-	387,181	29.5	21.9
Minimum	2	21.4	3.7	251	17.0	16.6	779	31.1	15.6	556,828	21.4	15.3
Maximum	34	40.4	30.9	1,790	38.4	20.6	7,002	51.4	26.4	3,408,016	37.3	26.5
Mean	14.1	31.6	12.9	802	27.8	18.1	2,996	38.0	18.9	1,581,840.7	29.2	18.8
Standard deviation	12.2	6.3	8.3	469.3	6.7	2.8	1,987.3	6.7	3.1	992,784.6	4.4	3.5
Coefficient of variation	0.86	0.20	0.64	0.59	0.24	0.15	0.66	0.18	0.16	0.69	0.15	0.19

Source: JRC, 2021.

The required sample sizes in order to achieve confidence level 99% and margin of error 1%, as well as the allocation to the strata are presented in Table 10. The differences between the required sample size for Neyman and proportional allocation and its dependence on the variability of the strata standard deviation, can be observed again. Geco air had the biggest coefficient of variation of the strata standard deviations (0.64) and, as a result, the relative difference between the required sample size for Neyman and proportional allocation was the largest. Spritmonitor.de had vehicles with the lowest variability among the strata and as a result the gain by using Neyman allocation was minimal (8 vehicles less would need to be sampled compared to using proportional allocation). Equal allocation cannot be used in the case of Geco air and Spritmonitor.de, as there are strata with a lower number of vehicles than required. For Spritmonitor.de and EEA datasets equal allocation required a higher sample size than proportional and Neyman allocation. This is also the case when using other stratification schemes. Hence, for the rest of this Report equal allocation will not be used.

Table 10 Sample sizes required and sample allocation per dataset with stratification variable the type-approval CO_2 emissions

Type-approval CO_2 emissions (g/km)	Dataset											
	Geco air			Spritmonitor.de			Travelcard			EEA		
<90	-	4	3	-	61	58	286	170	165	438	104	77
(90,100]	-	20	17	-	79	70	286	244	229	438	260	201
(100,110]	-	30	28	-	150	150	286	532	447	438	498	402
(110,120]	-	32	34	-	255	248	286	397	366	438	634	812
(120,130]	-	16	12	-	211	203	286	225	232	438	421	371
(130,140]	-	8	6	-	267	264	286	163	157	438	266	282
(140,150]	-	5	4	-	149	136	286	76	77	438	169	139
(150,160]	-	5	2	-	151	142	286	59	64	438	111	95
>160	-	2	1	-	436	480	286	183	261	438	184	154
NA	-	-	-	-	-	-	-	-	-	438	72	76
Total sample size	-	122	102	-	1,759	1,751	2,574	2,049	1,998	4,380	2,719	2,609
Sample size as % of the population	-	96.1	83.5	-	24.9	24.9	9.6	7.7	7.5	0.030	0.019	0.018

Note: margin of error 1% and confidence level 99%; pink is for equal allocation, green for proportional allocation, yellow for Neyman allocation.

Source: JRC, 2021.

It is observed that Neyman allocation analysis requires more sampling units from strata with high variability. The higher differences between Neyman and proportional allocation are observed when a stratum with many vehicles has a low variability or when a stratum with a few vehicles has a high variability. For example Travelcard has many vehicles (5,223) with type-approval CO_2 emission between 110 and 120 g/km. These vehicles are homogenous as regards the fuel consumption gap (standard deviation is small: 17.0%). As a consequence Neyman allocation would need sample less vehicles than proportional from this stratum. Neyman allocation is constructed in such a way that when the strata sizes and standard deviations are known, it will produce the optimal results. In practice, at least for the first year it will be difficult to have an accurate estimation of the variability of the fuel consumption gap. If stratification variables that are available in the EEA are used, the strata sizes can be estimated using the information from previous year(s). For stratification sampling with stratification variables the fuel type and the type-approval CO_2 emission the reduction in required sample size when using Neyman compared to proportional allocation are presented in Table 8 and Table 10, respectively. For the rest of the report results are presented only for Neyman allocation, since the variabilities per stratum are known and the relationship between proportional and Neyman allocation has been examined.

In EEA dataset, using Neyman allocation, 2,609 vehicles would be enough to reach a margin of error of 1% and confidence level of 99%. Almost one third of the vehicles (812) would have type-approval CO_2 emissions in the range from 110-120 g/km, this is because this stratum has the highest number of vehicles with the most variable fuel consumption gap. The smallest number of sampled vehicles would have type-approval CO_2 emissions below 90 g/km, as this is the smallest stratum with the lowest variability (not taking into account the vehicles with type approval CO_2 emissions not available).

3.3.2.3 Univariate stratification

Seven stratification variables are examined in this report, Table 11 presents the sample size required to achieve a margin of error of 1% with a confidence level of 99%, per dataset for each stratification variable. Table 16 (Annex 1) shows the statistics of the fuel consumption gap when stratifying per manufacturer. The statistics of the fuel consumption gap and the sample allocation when stratifying by engine rated power, engine displacement, transmission and total driven distance can be found in Table 17Table 24

(Annex 1). Stratifying by fuel type and by type-approval CO_2 emissions have been examined in detail in sections 3.3.2.1 and 3.3.2.2, respectively. The respective sample sizes for simple random sampling are also presented in Table 11. The values given in parenthesis quantify the reduction in required sample size when using stratification sampling, in comparison to simple random sampling. These percentages are comparable and were used to compare the efficiencies of the different sampling schemes for the different datasets.

For Geco air the biggest reduction was observed when engine rated power was used as stratification variable (96 vehicles would be a sufficient sample, which is an 21.3% reduction compared to simple random sampling). Stratifying by fuel type or type-approval CO_2 emissions or manufacturer also presented a reduction larger than 10%. For Spritmonitor.de and Travelcard the biggest reductions in sample sizes were with stratification variables the type-approval CO_2 emissions (7.7% and 9.1% respectively) and the manufacturer (5.0% and 7.6% respectively). For the EEA dataset the greatest reduction in required sample size was when stratifying by manufacturer (21.2%), followed by stratifying by type-approval CO_2 emissions (8.5%).

The reduction in sample size when using stratification sampling with Neyman allocation, compared to using simple random sampling, can be attributed to two contributors:

- The reduction of using stratified sampling with proportional allocation in comparison to simple random sampling. This in general is larger when the strata mean values differ more. This difference was quantified by the coefficient of variation of the strata means.
- The reduction of using stratified sampling with Neyman allocation in comparison to stratified sampling with proportional allocation. This in general is larger when the strata standard deviations differ more. This difference was quantified by the coefficient of variation of the strata standard deviations.

It can be observed (Table 11 andTable 12) that the stratification variables with high coefficients of variation were the ones which had higher efficiency. By choosing stratification variables and forming strata that maximize these two coefficients of variation it is possible to minimize the sample size.

Table 11 Sample size required, for different stratification variables, per dataset

	Stratification variable							
Dataset	Fuel type	OEM	TA CO_2 emissions	Engine rated power	Engine displacement	Transmission	Distance	Simple random sampling
Geco air	108 (11.5)	104 (14.8)	102 (16.4)	**96 (21.3)**	117 (4.1)	117 (4.1)	116 (4.9)	122 (0.0)
Spritmonitor.de	1,889 (0.5)	1,804 (5.0)	**1,751 (7.7)**	1,890 (0.4)	-	1,867 (1.6)	1,874 (1.3)	1,898 (0.0)
Travelcard	2,173 (1.1)	2,030 (7.6)	**1,998 (9.1)**	2,132 (3.0)	2,134 (2.9)	-	-	2,198 (0.0)
EEA	2,734 (4.1)	**2,234 (21.6)**	2,609 (8.5)	2,809 (1.5)	2,784 (2.4)	-	-	2,851 (0.0)

Note: margin of error 1% and confidence level 99%; in parenthesis the sample method efficiency (percentage of reduction in sample size in comparison to simple random sampling); in bold the highest efficiencies; TA: Type-approval, OEM: manufacturer

Source: JRC, 2021.

Table 12 Coefficients of variation for different stratification variables, per dataset

Dataset	Stratification variable						
	Fuel type	OEM	TA CO_2 emissions	Engine rated power	Engine displacement	Transmission	Distance
Geco air	0.0	0.3	0.2	0.3	0.1	0.2	0.1
	0.5	0.5	0.6	0.7	0.3	0.4	0.3
Spritmonitor.de	0.1	0.5	0.2	0.1	-	0.1	0.1
	0.0	0.3	0.2	0.1	-	0.1	0.0
Travelcard	0.1	0.2	0.2	0.1	0.1	-	-
	0.0	0.3	0.2	0.1	0.2	-	-
EEA	0.1	0.4	0.2	0.0	0.1	-	-
	0.3	0.3	0.2	0.2	0.2	-	-

Note: margin of error 1% and confidence level 99%; grey is for the coefficient of variation of the strata mean values and green of the strata standard deviation; TA: Type-approval, OEM: manufacturer

Source: JRC, 2021.

3.3.2.4 Multivariate Stratification

Combinations of stratification variables, which had the best results (highest efficiency) in univariate stratification and were of greater interest, were used in multivariate stratification. In this design, when L variables were used, with the i^{th} having H_i strata, they formed $\mathrm{H} = \prod_{\mathrm{i}=1}^{\mathrm{L}} \mathrm{H}_i$ strata. It should be noted that significant increase of the number of stratification variables makes the analysis more complicated and the gains do not offset the technical difficulties that arise.

The introduction of more stratification variables reduced the sample size required (Table 13 and Figure 14). For Spritmonitor.de and Travelcard, increasing the number of stratification variables to 3 and 4 resulted in a reduction of the sample size (compared to simple random sampling) approximately 20% and 30%, respectively. For Spritmonitor.de and Travelcard the highest reduction was when stratifying by type-approval CO_2 emissions and manufacturer. For EEA there was a small difference between the efficiency of using only manufacturer and manufacturer and fuel type. Introducing a third stratification variable, the engine rated power, improved the efficiency to 28.3%. Adding a fourth stratification variable (the type-approval CO_2 emissions) resulted in a marginal improvement to 28.7% (Table 13). For Geco air, because of the low number of vehicles, when stratifying using multiple stratification variables most strata had only one vehicle. As a result most vehicles were pooled together (see section 2.2.2), consequently the results shown in Table 13 concerning stratifying Geco air with more than two stratification variables are not reflecting how the method would work with a larger dataset.

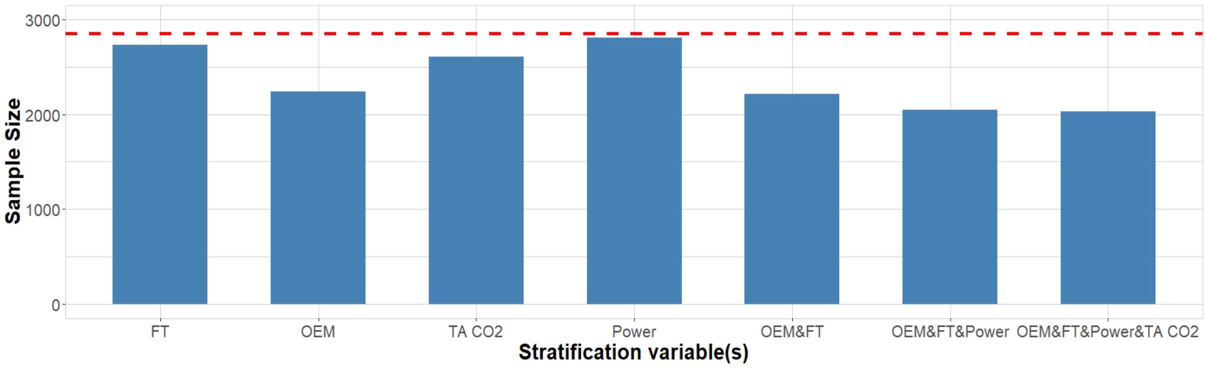
Table 13 Sample size required, for up to four stratification variables, per dataset

Dataset	Stratification variable(s)							
	Fuel type	OEM	TA CO_2	Engine rated power	OEM & Fuel type	OEM & Fuel type& Power	OEM & Fuel type& Power& TA CO_2	Simple random sampling
Geco air	108 (11.5)	104 (14.8)	102 (16.4)	96 (21.3)	86 (29.5)	100 (18.0)	105 (13.9)	122 (0.0)
Spritmonitor.de	1,889 (0.5)	1,804 (5.0)	1,751 (7.7)	1,890 (0.4)	1,787 (5.8)	1,518 (20.0)	1,347 (29.0)	1,898 (0.0)
Travelcard	2,173 (1.1)	2,030 (7.6)	1,998 (9.1)	2,132 (3.0)	1,974 (10.2)	1,723 (21.6)	1,602 (27.1)	2,198 (0.0)
EEA	2,734 (4.1)	2,234 (21.6)	2,609 (8.5)	2,809 (1.5)	2210 (22.5)	2,045 (28.3)	2,032 (28.7)	2,851 (0.0)

Note: margin of error 1% and confidence level 99%; in parenthesis the sample method efficiency (percentage of reduction in sample size in comparison to simple random sampling); TA: Type-approval, OEM: manufacturer

Source: JRC, 2021.

Figure 14 Sample size required for different stratification variables, for EEA



Note: margin of error 1% and confidence level 99%; red dash line is sample size for simple random sampling; FT: Fuel type; TA: Type-approval; OEM: manufacturer; Power: Engine rated Power

Source: JRC, 2021.

3.3.2.5 Strata specific estimators

Regulation (EU) 2019/631 requires from the EC to monitor the fuel consumption gap of each manufacturer. To accomplish this a precise estimator of the whole population average fuel consumption gap is not enough. As described in section 2.2.2, in stratified sampling unbiased estimators of each stratum mean are calculated and used to form an unbiased estimator of the population mean. So far the main goal has been to find the minimum sample size that ensures that the sample mean is a precise estimator of the population mean. This section explores additional requirements so that the sample means of all/some strata are precise estimators of their respective strata means. In this way sufficient vehicles would be sampled from each stratum of interest to ensure that a separate analysis of these strata can be performed. The higher the required precision, the higher the sample size per stratum and consequently the total sample size. In the following analysis, for the sample mean of the whole population, a margin of error of 1% with a confidence level of 99% was used. Concerning the sample mean of each stratum, the conditions were less strict, a margin of error of 2% with a confidence level of 90% was chosen.

In univariate stratification, when precise estimators are required for all strata, the higher the number of strata, the bigger the increase in sample size compared to normal stratified sampling. In multivariate stratification there are two options, either to demand precise estimators for all strata or for only some of the stratification variables. E.g. if the stratification variables are the manufacturer, the fuel type and the engine rated power, there are $1044 = 58 * 2 * 9$ strata, for EEA. If precise estimators for all 1044 strata are needed, the total sample size would be 18,243 vehicles. However if only precise estimators per manufacturer are required (58 strata) , then the sample size would be 3,094 vehicles. The number of vehicles in the case of stratifying by manufacturer, fuel type, engine rated power and requiring precise estimators only per manufacturer (3,094 vehicles) is of the same order as the number of vehicles when stratifying by manufacturer and requiring precise estimators for each manufacturer (3,068). Hence, only sample sizes for when estimators for every stratum are required are discussed.

Figure 15 shows the sample size for the EEA dataset required to get precise estimators of the mean fuel consumption gap, for different stratification schemes, when precise estimators are required for all strata. For EEA, with four stratification variables (manufacturer, fuel type, type-approval CO_2 emissions and engine rated power) the required sample size was almost 36 times larger (72,889 instead of 2,035 vehicles). When only the mean fuel consumption gap of the whole population is required to be precise, increasing the stratification variables leads to lower sample size (Table 14). On the other hand when precise estimators for all strata are required, increasing the stratification variables leads to a steep increase in sample size.

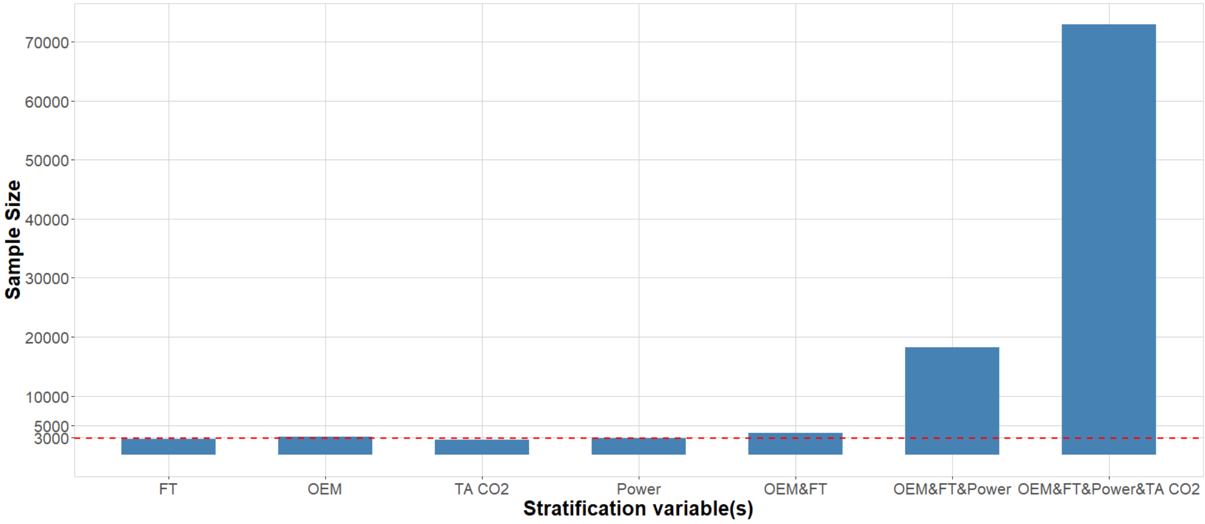
Table 14 Sample size, for up to four stratification variables, per dataset

	Stratification variable							
Dataset	Fuel type	OEM	TA CO_2	Engine rated power	OEM & Fuel type	OEM & Fuel type& Power	OEM & Fuel type& Power& TA CO_2	Simple random sampling
Geco air	108	104	102	96	86	100	120	122
	108	114	107	98	104	116	105	
Spritmonitor.de	1,889	1,804	1,751	1,890	1,787	1,518	1,347	1,898
	1,889	1,945	1,751	1,890	2,131	3,428	4,293	
Travelcard	2,173	2,030	1,998	2,132	1,974	1,723	1,602	2,198
	2,173	2,345	1,998	2,132	2,538	4,784	7,224	
EEA	2,734	2,234	2,609	2,809	2,210	2,045	2,032	2,851
	2,734	3,051	2,609	2,809	3,767	18,238	72,865	

Note: grey is for normal stratified sampling and green for stratifying sampling when the precise estimators are required for all strata; margin of error 1% and confidence level 99%; TA: Type-approval, OEM: manufacturer

Source: JRC, 2021.

Figure 15 Sample size required for different stratification variables when strata specific estimators are required for all strata



Note: EEA dataset, margin of error 1% and confidence level 99%; red dash line is sample size for simple random sampling; FT: Fuel type; TA: Type-approval; OEM: manufacturer; Power: Engine rated Power

Source: JRC, 2021.

3.3.3 Impact of non-sampling errors

The statistical approaches previously discussed and analysed are performed in such a way that the sampling error is controlled and the sample size is minimized. The datasets used are user-based with either self-reported data (Spritmonitor.de and Travelcard) or data collected through GPS measurements and real-world CO_2 emissions calculated by the model (Geco air). The vehicles composing these three datasets are mostly from three countries. As a result even though the datasets were found to represent, in respect to most vehicle characteristics, the whole fleet of vehicles in a satisfactory manner, the whole variability of the fleet, as concerns the vehicle characteristics, was not captured. To the best of the authors' knowledge there is no published research that explicitly quantifies the differences in the fuel consumption gap from country to country across the EU. Additionally the datasets suffer from self-selection bias, as in general users of these applications (Spritmonitor.de and Geco air) are more environmental friendly and conservative with fuel consumption. Users of Travelcard in general care less, since their companies provide them the vehicles and pay the fuel costs. Additionally, it is difficult to quantify the reliability of the values inserted by the users in Spritmonitor.de and Travelcard.

Most of these issues will not exist in the future as data will be extracted from the OBFCM devices whose accuracy is set to ±5% compared to the fuel consumption reported in the laboratory during WLTP type-approval test. In addition OBFCM accuracy is expected to improve as the new technologies are introduced and the requirements and tests become stricter. In this case it is of importance to quantify the measurement error of these devices and to understand the impact that it will have on the sampling scheme. According to previously published research (Pavlovic et al., 2021), in real-world conditions OBFCM devices were found to have, in respect to measuring the fuel consumption in litres per hundred kilometres (l/100km), a mean error/inaccuracy of 2.7% with a standard deviation of 5.6%, compared to values calculated by Portable Emissions Measurement Systems (PEMS). During laboratory (WLTP) tests the OBFCM devices had a mean error/inaccuracy of 1.5% with a standard deviation of 4.5%.

Taking these into account, to get an indication of the impact of the OBFCM inaccuracies on the sample size, a "noise" amounting to the respective on-road and type approval OBFCM error was added to the real world and to the type approval fuel consumption of all vehicles. It should be noted that the noise is not a cumulative addition to the fuel consumptions, but a percentage dispersion. By doing this, the average fuel consumption gap of Geco air's, Spritmonitor.de's, Travelcard's and EEA's vehicles increased by 1.9%, 1.7%, 1.8% and 1.9%, respectively. The standard deviation increased by 1.8%, 2.3%, 2.7% and 2.5%, respectively (Table 15). Therefore for simple random sampling the required sample size to have a margin of error of 1% and confidence level of 99% is increased by 1% (126->127), 17% (1898->2220), 27% (2198->2795) and 19% (2,851->3,267), respectively. For stratified sampling the increases are expected to be of the same order. To get more precise results an estimation/understanding of the OBFCM accuracy per stratum would be necessary.

Table 15 Impact of non-sampling errors in simple random sampling, per dataset

Dataset	Standard deviation increase	Sample size before	Sample size after	Sample size increase (%)
Geco air	1.8	122	123	1
Spritmonitor.de	2.3	1,898	2,222	17
Travelcard	2.7	2,198	2,798	27
EEA	2.5	2,851	3,580	26

Source: JRC, 2021.

3.3.4 Practical considerations for the implementation of quota sampling

Quota sampling is an alternative to choosing a representative sample when probability sampling is not an option. If quota sampling is used, selecting as stratification variables those that are correlated to the average fuel consumption gap gives some degree of control over selection biases.

The relationship between the fuel consumption gap and other variables was examined (section 3.2) and the efficiencies of using these variables in a univariate stratification sampling design were compared (section 3.3.2.3). In conclusion, the vehicle manufacturer, the type-approval CO_2 emissions and the fuel type are the three variables that produce better results. When using them the sample required to reach a pre-specified accuracy was the smallest, equivalently with a pre-specified sample size a higher accuracy would be reached when using them. These variables should be used if a quota sampling design is implemented.

A study in Germany (Bluthner and Schroder, 2020) showed that approximately 10% of the vehicles had performed the PTI by the first year of the vehicle's registration. For the selection of a representative sample, a feasible option could be to use vehicles from those that perform the PTI test. However, care should be taken to understand whether the fuel consumption gap is different for vehicles that do not go for an early PTI and if it varies from one country to another. In such cases, suitable adaptions have to be made.

There are no specific formulas to calculate the sample size that would suffice for estimating the fuel consumption gap with exhaustive precision. A general rule is to use at the least a sample size as big as the one stratified sampling would require.

For each of the datasets a sample respecting the proportions of the EEA dataset (with respect to the vehicle manufacturer, the type-approval CO_2 emissions and the fuel type) was chosen by selecting the first vehicles that satisfied these conditions. The sample sizes were the same as the one required for stratification sampling with those three variables. The sampling errors of the average fuel consumption were 2.9%, 2.2%, 3.4% and 2.4% respectively for Geco air, Spritmonitor, Travelcard and EEA.

4 Conclusions

- The average fuel consumption gap of new vehicles registered in the EU can be accurately estimated using a sample. Especially for the first level of analysis where only the monitoring of the global emissions trend is required.
- The standard deviation of the fuel consumption gap of conventional pure internal combustion and hybrid petrol and diesel LDVs in three user datasets was consistently found to be approximately 20%.
- In simple random sampling the higher the variability of the fuel consumption gap the more vehicles need to be sampled. For a population of 15 million vehicles, if the standard deviation of the fuel consumption is 20%, a sample of fewer than 3,000 vehicles is required for estimating the average gap with a confidence level of 99% and sampling error less than 1%. If the standard deviation of the fuel consumption is 40%, approximately 10,500 vehicles are required.
- Stratified sampling can further reduce the required sample size. Of the different allocation procedures, Neyman allocation produces the best results, but requires the most a priori knowledge.
- For EEA dataset multivariate stratification with three stratification variables (vehicle manufacturer, fuel type and engine rated power) required a sample size approximately 28% less than simple random sampling. Adding a fourth stratification variable (CO_2 emissions) reduced the sample size by less than 1%.
- When precise estimators are demanded for each stratum the sample size increases. As the number of stratification variables increases, the required sample size escalates.
- Non-sampling errors are expected to enlarge the variability of the fuel consumption gap by at least 2%-3% and consequently the sample size by ~20%.
- The quota sampling method is an alternative technique that can produce a representative sample. The three stratification variables mentioned above and at least the sample size of multivariate stratification is recommended in this case. A quota sample was selected from each dataset. The sampling error in all four datasets was found to be less than 3.5%.

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List of abbreviations and definitions

CO_2	Carbon dioxide
EC	European Commission
EEA	European Environment Agency
EU	European Union
HDVs	Heavy-duty vehicles
ICCT	International Council on Clean Transportation
JRC	Joint Research Centre
LDVs	Light-duty vehicles
NEDC	New European Driving Cycle
PTI	Periodic Technical Inspection
OBFCM	On-Board Fuel and/or energy Consumption Monitor device
OTA	Over-the Air-Transmission
WLTC	Worldwide harmonized Light vehicles Test Cycle
WLTP	Worldwide Harmonized Light Vehicles Test Procedure

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Annex 1. Allocations and statistics

Table 16 Statistics of the FC Gap grouped by manufacturer, per dataset

OEM	Dataset											
	Geco air			Spritmonitor.de			Travelcard			EEA		
	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i
Minimum	2	17.9	6.0	2	-7.1	0.0	2	14.2	8.9	2	-17.8	9.5
Maximum	41	54.0	40.6	934	45.7	29.3	4,770	58.4	33.3	1,606,461	47.1	39.5
Mean	8.5	31.0	16.4	176	24.2	18.2	728.8	38.3	18.3	252,133.6	23.3	17.1
Standard deviation	9.9	9.2	8.7	212.1	10.8	5.0	1,101.9	8.9	4.8	376,145.5	10.2	5.3
Coefficient of variation	1.16	0.30	0.53	1.2	0.45	0.28	1.51	0.23	0.26	1.49	0.44	0.31

Source: JRC, 2021.

Table 17 Statistics of the FC Gap grouped by engine rated power, per dataset

Engine rated power (kW)	Dataset											
	Geco air			Spritmonitor.de			Travelcard			EEA		
	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i
≤60	8	31.0	21.3	356	22	21.6	3,817	44.0	19.9	1767902	28.6	20.8
(60,70]	18	31.4	20.6	477	24.3	19.7	4,131	38.4	17.9	1690848	31.3	22.1
(70,80]	7	22.4	13.1	405	27.3	20.4	2,399	43.9	18.5	965798	31.7	20.6
(80,90]	32	28.9	11.0	1074	27.0	19.9	7,274	38.6	16.7	2580055	30.6	18.3
(90,100]	27	38.2	24.4	754	25.4	20.7	3,029	38.5	18.4	1306271	32.7	25.1
(100,110]	5	52.0	56.5	1455	24.6	18.4	3,529	35.5	21.1	1635021	30.9	18.0
(110,120]	12	30.0	12.1	256	23.5	19.8	548	36.2	17.9	315605	29.3	14.7
≥120	18	38.1	13.5	2441	25.6	19.5	2,237	35.2	21.5	2057343	29.5	19.8
NA	-	-	-	-	-	-	-	-	-	2304904	30.2	22.5
Minimum	5	22.4	11.0	256	22.0	18.4	548	35.2	16.7	315605	28.6	14.7
Maximum	32	52.0	56.5	2441	27.3	21.6	7,274	44.0	21.5	2580055	32.7	25.1
Mean	15.9	34.0	21.6	902.2	25.0	20.0	3,370.5	38.8	19.0	1624860.8	30.5	20.2
Standard deviation	9.8	8.9	15.0	743.4	1.8	0.9	1,940.2	3.5	1.7	692534.1	1.3	3.0
Coefficient of variation	0.61	0.26	0.69	0.82	0.07	0.05	0.58	0.09	0.09	0.43	0.04	0.15

Source: JRC, 2021.

Table 18 Sample size required and sample allocation, with stratification variable the engine rated power, for Neyman allocation, per dataset

Engine rated power (kW)	Dataset			
	Geco air	Spritmonitor.de	Travelcard	EEA
≤60	8	102	321	343
(60,70]	17	126	312	350
(70,80]	4	110	188	186
(80,90]	17	285	514	441
(90,100]	27	208	236	306
(100,110]	5	356	315	275
(110,120]	7	68	42	43
≥120	11	635	204	381
NA	-	-	-	484
Total sample size	96	1,890	2,132	2,835
Sample size as % of the population	75.6	26.2	7.9	0.019

Note: Neyman allocation, margin of error 1% and confidence level 99%

Source: JRC, 2021.

Table 19 Statistics of the FC Gap grouped by engine displacement, per dataset

Engine Displacement (cc)	Dataset								
	Geco air			Travelcard			EEA		
	N_i	m_i	sd_i	N_i	m_i	sd_i	N_i	m_i	sd_i
≤1,000	18	34.9	22.9	7215	39.2	18.2	2726237	31.5	23.3
(1,000,1,200]	24	32.8	23.4	2671	38.7	17.2	1519122	30.6	17.9
(1,200,1,400]	4	29.6	22.7	1696	32.3	17.0	1920492	26.7	23.5
(1,400,1,600]	54	31.7	21.6	8973	40.6	17.5	4257143	31.2	20.7
(1,600,1,800]	0	-	-	688	45.7	17.6	432167	33.7	11.7
(1,800,2,000]	21	37.8	13.4	4499	36.2	22.1	2748987	31.0	20.0
≥2,000	6	31.3	10.3	1222	43.5	24.0	1019503	29.0	15.4
NA	-	-	-	-	-	-	96	29.7	18.3
Minimum	4	29.6	10.3	688	32.3	17.0	96	26.7	11.7
Maximum	54	37.8	23.4	8973	45.7	24.0	4257143	33.7	23.5
Mean	21.2	33	19.1	3852	39.5	19.1	1827968.4	30.4	18.8
Standard deviation	18	2.9	5.7	3186.5	4.5	2.8	1394017.5	2.0	4.0
Coefficient of variation	0.85	0.09	0.3	0.83	0.11	0.15	0.76	0.07	0.21

Source: JRC, 2021.

Table 20 Sample size required and sample allocation, with stratification variable the engine displacement, per dataset

Engine displacement (cc)	Dataset		
	Geco air	Travelcard	EEA
≤1,000	18	555	590
(1,000,1,200]	24	194	253
(1,200,1,400]	4	122	420
(1,400,1,600]	54	667	817
(1,600,1,800]	NA	51	47
(1,800,2,000]	14	421	511
≥2,000	3	124	146
NA	-	-	0
Total sample size	117	2,134	2,784
Sample size as % of the population	92.1	7.9	0.019

Note: Neyman allocation, margin of error 1% and confidence level 99%

Source: JRC, 2021.

Table 21 Statistics of the FC Gap grouped by distance, per dataset

Distance (k km)	Dataset					
	Geco air			Spritmonitor.de		
	N_i	m_i	sd_i	N_i	m_i	sd_i
≤5	62	30.8	21.8	1,093	27.5	23.8
(5,10]	24	33.7	15.4	1,482	26.2	19.7
(10,15]	18	37.4	17.5	1,353	24.6	18.9
(15,20]	10	42.5	32.0	1,090	23.7	18.4
(20,25]	5	31.9	15.9	797	24.8	17.7
(25,30]	2	33.9	11.8	525	24.5	16.9
(30,35]	3	25.6	9.3	282	24.1	19
≥35	3	36.3	19.2	596	25.8	20.1
Minimum	2	25.6	9.3	282	23.7	16.9
Maximum	62	42.5	32.0	1,482	27.5	23.8
Mean	15.9	34.0	17.9	902.2	25.2	19.3
Standard deviation	20.3	5.0	6.9	421.4	1.3	2.1
Coefficient of variation	1.28	0.15	0.39	0.47	0.05	0.11

Source: JRC, 2021.

Table 22 Sample sizes required and sample allocation, with stratification variable the distance, per dataset

Distance (k km)	Dataset	
	Geco air	Spritmonitor.de
≤5	62	345
(5,10]	19	395
(10,15]	16	340
(15,20]	10	266
(20,25]	5	187
(25,30]	2	118
(30,35]	2	71
≥35	3	159
Total sample size	116	1,874
Sample size as % of the population	91.3	26.0

Note: Neyman allocation, margin of error 1% and confidence level 99%

Source: JRC, 2021.

Table 23 Statistics of the FC Gap grouped by transmission, per dataset

Transmission	Dataset					
	Geco air			Spritmonitor.de		
	N_i	m_i	sd_i	N_i	m_i	sd_i
Automatic	50	36.2	25.2	4,003	27.6	19.5
Manual	77	31.4	16.6	3,215	22.6	19.5
Minimum	50	31.4	16.6	3,215	22.6	19.5
Maximum	77	36.2	25.2	4,003	27.6	19.5
Mean	63.5	33.8	20.9	3,609	25.1	19.5
Standard deviation	19.1	3.4	6.1	557.2	3.6	0.0
Coefficient of variation	0.30	0.10	0.29	0.15	0.14	0.00

Source: JRC, 2021.

Table 24 Sample sizes required and sample allocation, with stratification variable the transmission, per dataset

Transmission	Dataset	
	Geco air	Spritmonitor.de
Automatic	50	1,042
Manual	67	833
Total sample size	117	1,875
Sample size as % of the population	92.1	26.0

Note: Neyman allocation, margin of error 1% and confidence level 99%

Source: JRC, 2021.

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