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Introduction

Recent initiatives highlighted the growing importance of new indicators and statistical surveillance tools that cover cross-cutting needs and go beyond aggregates to capture key distributional issues. In particular, the 'GDP and beyond' Commission communication and the Stiglitz-Sen-Fitoussi Commission' Report raised awareness about the need to review and update the current system of statistics in order to address new societal challenges and to support policy-making. This urges for integrated statistical information that covers several socio-economic aspects.

The social statistical infrastructure is organised around specific surveys covering many relevant aspects of the users demand: income, consumption, health, education, labour market, social participation. However, no single survey can cover all the requested aspects. Against this backdrop the current process of modernisation of social surveys is focused on increasing the overall efficiency of social surveys, the responsiveness to user needs and the analytical potential of the data collected via a better integrated system of social surveys.

Statistical matching (also known as data fusion, data merging or synthetic matching) is a model-based approach for providing joint statistical information based on variables and indicators collected through two or more sources. The potential benefits of this approach lie in the possibility to enhance the complementary use and analysis of existing data sources (e.g. cross-cutting statistical information that encompasses a broad range of socio economic aspects), without further increasing costs and response burden. However, statistical matching is a complex operation which requires specific technical expertise and raises several methodological issues.

Therefore, in December 2010 in Eurostat started a feasibility study that carried out methodological work with a view to checking whether statistical matching could be used in the framework of social surveys as a tool to integrate extensive information from several existing sources.

The project focused on the ex post integration of existing micro data sets and it had a strong practical focus on specific needs in social statistics. This first publication aims to provide a general overview on the statistical matching methodology and its implementation requirements in a practical context. It has three main objectives: (1) to provide a general introduction to statistical matching with an emphasis on implementation in an applied context, namely within the European system of social surveys; (2) to present the main results and practical highlights from two pilot studies on matching implemented in Eurostat (e.g. producing joint information on quality of life indicators based on EU-SILC[1]and EQLS[2]; study the feasibility of the technique for production of tabulated LFS data enhanced with SILC-matched wages); (3) to draw conclusions on the quality of results obtained through statistical matching given the status–quo and translate into recommendations for addressing limitations in the design stage. A second volume on statistical matching is forthcoming. It explores a new approach to statistical matching based on the incorporation of ex-ante requirements in the current process of redesign of social surveys.

[1] EU Statistics on Income and Living Conditions

[2] European Quality of Life Survey

Chapter 1 reports on the general methodological framework and guidelines for the implementation of matching techniques. Chapters 2-3 document in detail the first empirical case studies conducted in the matching project in Eurostat.

1

A methodological overview and implementation guidelines

1 A methodological overview and implementation guidelines

1.1 Short introduction to statistical matching

Statistical matching (also known as data fusion, data merging or synthetic matching) is a model-based approach for providing *joint information on variables and indicators* collected through multiple sources (surveys drawn from the same population). The potential benefits of this approach lie in the possibility to enhance the complementary use and analytical potential of existing data sources (e.g. cross-cutting statistical information that encompasses a broad range of socio economic aspects). Hence, statistical matching can be a tool to increase the efficiency of use given the current data collections.

Most often the aim of a matching exercise is to enlarge the information scope, but matching techniques have been used also for *alignment of estimates* observed in multiple surveys and for improving the *precision* of these estimates by integration with larger surveys.

Two main approaches can be delineated in terms of outputs that can be obtained through matching:

(1) *the macro approach* refers to the identification of any structure that describes relationships among the variables not jointly observed of the data sets, such as joint distributions, marginal distributions or correlation matrices (D’Orazio, 2006)

(2) *the micro approach* refers to the creation of a complete micro-data file where data on all the variables is available for every unit. This is achieved by means of the generation of a new data set from two data sets that are based on an informative set of common variables between two ‘synthetic micro records’.

An essential feature of statistical matching is that, although the units in the concerned data sets should come from the same population, they are usually not overlapping. You identify and link records from different sources that correspond to similar units. This is the basic difference compared with record linkage, where units included in the data sets overlap that allows to link records from the different data sets that correspond to the same unit. Therefore, **record linkage** deals with **identical** units, while **statistical matching,** or synthetic linkage, deals with ‘**similar**’ units.

In practice, matching procedures can be regarded as an imputation problem of the target variables from a donor to a recipient survey. Y, Z are collected through two different samples drawn from the same population; X variables are collected in both samples and they are correlated with both Y and Z. The relation between these common variables with the specific variables observed only in one of the data sets - **the donor data set**- will be explored and used to impute to the units of the other data set - **the recipient**

data set - the variables not directly observed. Thus a synthetic dataset is generated with complete information on X,Y and Z.

Box 1-1 Statistical matching situation

Sample A (donor)	***Sample B (recipient)***	*Synthetic dataset*
X,Y		
	X,Z	***X,*** $\hat{Y}$ ***,Z***

However, this view is rather simplistic and one important methodological concern has been raised regarding the validity of results. The origins of statistical matching can be traced back to the mid- 1960s, when the 1966 US Tax File and the 1967 Survey of Economic Opportunities were matched in order to provide a synthetic data set on socio-demographic variables. Then, in the early 1970s different matching techniques were applied to social surveys in the US (Ruggles 1974), but these techniques were severely criticized on the grounds that they rely on assumptions neither justified nor testable (Kadane 1978, Rodgers 1984). In particular, measures of association between Y and Z conditional on X cannot be estimated and they are usually assumed to be 0. This is the so called *conditional independence assumption (CIA*), a reference point for assessing the quality of estimates based on matching.

When this condition holds, matching algorithms will produce accurate estimates that reflect the true joint distribution of variables that were collected in multiple sources. It will give the same results as a perfect linkage procedure. Unfortunately, this assumption rarely holds in practice and it cannot be tested from the data sets. In case the conditional independence does not hold, and no additional information is available, the model will have identification problems and the artificial datasets produced may lead to incorrect inferences.

The critical question that arises is: *what can we learn from a matched dataset about the joint distribution of (Y, Z)*, which are not jointly observed? There are two main approaches proposed in current studies on statistical matching that take into account these inherent limitations.

The first one focuses on uncertainty analysis techniques that assess the sensitivity of estimated results to different assumptions (Rubin, 1980; Raessler 2002, D'Orazio et al., 2006). In this case the focus is typically on macro objectives (e.g. estimation of specific contingency tables) rather than the creation of micro-datasets. The second one explores the possibility of overcoming the conditional independence assumption by using auxiliary information. In order to overcome the conditional independence assumption, two main types of solutions were put forward. One is the use of additional information in the form of a small sub-set of units with complete information on the joint distributions (Paass, 1986). The other, which covers cases when the joint collection of specific variables is not feasible, explores the use of proxy ‘variables’ with very high predictive power. These variables can mediate the relationship between Y and Z, and can make plausible the conditional independence assumption.

In all cases, the focus is on the specific estimators of interest and not on the creation of synthetic datasets (Schaffer, 1998). The matched datasets will not usually preserve individual level values, so the exercise should aim to preserve data distributions and multivariate relations between target variables (Rubin 1986). Therefore, it is essential both to control for dimensions relevant in the analysis and to properly reflect uncertainty associated with implicit models.

In the framework of European official statistics, relevant methodological expertise on statistical matching was developed in the frame of the ESSnet on Data Integration[3]. The aim of the ESSnet on Data Integration was to promote knowledge and practical application of sound statistical methods for the joint use of existing data sources in the production of official statistics, and at disseminating this knowledge within the European Statistical System. The outputs[4] of the project comprise methodological papers and case studies on statistical matching as well as software tools for data integration (Relais for record linkage and StatMatch[5] for statistical matching). These tools are written with open source software (mainly R) and are freely available.

1.2 Statistical matching – a stepwise approach in an applied context

The application of statistical matching in a practical context usually implies a set of key steps, related to various stages of a survey process. The selection of an appropriate matching technique is only one of these steps and often not the most essential.

First of all, statistical matching relies on certain pre-requisites of harmonisation and coherence of data sources to be matched. Therefore, in practice, it often requires a data reconciliation process that enables the joint analysis of multiple data sources. Secondly, multivariate analysis and modelling techniques need to be implemented for the selection of matching variables. Finally, the application of matching techniques and related quality assessment can be implemented. Every step of the process has to be monitored carefully in order to produce accurate results.

1.2.1 Harmonisation and reconciliation of multiple sources

In order to understand whether data from two different surveys can be matched it is necessary to evaluate if they are coherent. Coherence of the statistics produced by a survey process is an important feature that refers to the adequacy of the data to be reliably combined in different ways and for various uses.

The first step in a data matching process is the harmonisation of multiple sources. An extensive methodological work on harmonisation methods and reconciliation of

[3] http://www.cros-portal.eu/content/data-integration-1

[4] http://www.cros-portal.eu/sites/default/files//WP2.pdf

[5] http://www.cros-portal.eu/sites/default/files//WP3.2%20D%27Orazio%20-%20Updating%20StatMatch%20%28slides%29.pdf

multiple sources was done in the framework of the ESSnet on Data Integration. D'Orazio et al (2006) mention the following eight types of reconciliation actions:

(a) harmonisation on the definition of units

(b) harmonisation of reference period

(c) completion of population

(d) harmonisation of variables

(e) harmonisation of classifications

(f) adjustment for measurement errors (accuracy)

(g) adjustment for missing data

(h) derivation of variables

Discrepancies can emerge at different levels: in the data collection (e.g. different household definitions, different variables or filters applied to similar variables), but also downstream in the surveys methods (calibration factors or reference sources) and in the derived information disseminated to users (e.g. complex concepts such as household composition, dependent child are calculated based on different criteria).

The empirical studies done in Eurostat showed that in an applied context these standardization issues can hamper the successful application of matching methods. Practical issues, which might arise, and their impact on the quality of matching results are presented in the following sections, based on the different case studies. The single analysis of metadata is not sufficient to understand if data from two surveys can be compared and integrated. This analysis should be followed by data processing of the two surveys.

For example, in sample surveys on households, usually the definition of the household should be deepened in order to understand whether the two surveys share the same definition or not. It is very important to ascertain if all the household members are surveyed or not (e.g. data collected only for member with age >= 18, etc.). These comparisons (e.g. of the household definition) should be accompanied by a comparison of the estimated number of households and their distribution by region, size etc.

An essential point for the quality of results from the matching procedures is the existence of a common set of variables that should be homogeneous in their statistical content. In other words, the two samples A and B should estimate the same distribution for each common variable: the two sample surveys should represent the same population. Common variables selected as matching variables should show similar joint and marginal empirical distributions in the two datasets.

There are different possibilities to quantify the degree of similarity/dissimilarity for different distributions. The first and simplest one is to compute, in the two data sources involved, the weighted frequency distributions for each variable of interest and to calculate the differences. The maximum value of these differences can be taken as a criterion for comparison. Coherence of the variable in the two surveys will be rejected if this maximum difference is higher than a certain threshold. Obviously, this is simply a rule of thumb without much theoretical background, and the threshold established is arbitrary.

Another possibility is to quantify similarity of two distributions so that we could give a relative measure of differences in the distributions of various common variables at different levels. Distance metrics are used to measure distortion of distributions. Thus, we chose the Hellinger distance (see equation below) to quantify the similarity between probability distributions of donor and recipient data. It lies between 0 and 1 where a value of 0 indicates a perfect similarity between two probabilistic distributions, whereas a value of 1 indicates a total discrepancy. Unfortunately, it is not possible to set up a threshold of acceptable values of the distance, according to which the two distributions can be said close. However, a rule of thumb, often recurring in literature, considers two distributions close if the Hellinger distance is not greater than 0.05.

$$HD(V,V^{'}) = \sqrt{\frac{1}{2}\cdot\sum_{i=1}^{K}\left(\sqrt{p(V=i)}-\sqrt{p(V^{'}=i)}\right)^{2}} = \sqrt{\frac{1}{2}\cdot\sum_{i=1}^{K}\left(\sqrt{\frac{n_{Di}}{N_D}}-\sqrt{\frac{n_{Ri}}{N_R}}\right)^{2}}$$

where K is the total number of cells in the contingency table, n_{Di} is the frequency of cell i in the donor data D, n_{Ri} is the frequency of cell i in the recipient data R and N is the total size of the specific contingency table.

We applied Hellinger distance because it is easy to interpret and allows for comparisons across variables, surveys and countries. However, Hellinger distance shall be used with cautions since it does not take into account variability due to sampling design or a large number of categories and the thresholds are also set up on arbitrary basis.

The third group refers to statistical tests for the similarity of distributions (Chi square; Kolmogorov Smirnov, Rao-Scott, Wald-Wolfowitz tests). These methods could give a stronger base to the conclusions on similarity/discrepancy between distributions coming from the two sources as they take into account the complex sampling designs applied in social surveys. We have not applied such statistical test because, in Eurostat, the sampling design information is not available for all surveys.

Additionally, when dealing with a continuous X variable, hypothesis testing for comparing of means/totals can be done by considering the usual t-test when an estimate of the sampling errors is available.

When the empirical distributions show substantial differences, some harmonisation procedures can then be applied in order to improve the similarity of the distributions, such as re-categorisations of variables or more complex calibration techniques. There are several studies that focus on the alignment of estimates for common variables in two or more sample surveys based on calibration and re-weighting techniques (Sarndal et al 1992; Renssen and Nieuwenbroek, 1997; Merkouris, 2004). Some of these actions may be difficult to implement, and in some cases, no amount of work can produce satisfactory results.

Inconsistencies between surveys can be more prevalent in some countries due to operational differences: similar concepts or common guidelines can be implemented differently in the various countries. Therefore, in the framework of social surveys, the need for coherence must be addressed at different levels of the statistical process.

The best possibility of matching occurs when a survey, with a common questionnaire providing some basic information for all the units, is divided into subsamples, each of them containing a module with specific questions answered by the units of that subsample (nested surveys). In this case all the conditions previously mentioned are fulfilled: the population and reference period are the same and the definitions and classifications of the common variables are also identical. Thus, the different modules can be safely matched.

Although good coherence is a necessary pre-condition for matching, it does not address limitations related to the conditional independence assumption. The modelling stage is essential for the quality of estimates obtained in the matching procedure.

1.2.2 Analysis of the explanatory power for common variables

The choice of the matching variables is a crucial point in statistical matching. It was often emphasised (Adamek, 1994) that the choice of suitable matching variables among common variables has a greater impact on the validity of the matching exercise than the matching technique effectively used.

The conditional independence assumption is the reference point. The fulfilment of this condition guarantees that the joint distribution of matched variables Y and Z will be the same as the one obtained from a perfect linkage procedure. This assumption will, consequently, validate inference procedures about the actually unobserved association and induce a strong predictive relationship between the common matching variables and the recipient-donor measures.

This means that the validity of a matching exercise depends to a great extent on the power of the matching variables to behave as good predictors of the specific information to be transferred from the donor to the recipient file.

Optimally, the common variables should contain all the association shared by Y and Z. From this point of view, inclusion of all the common variables in A and B that show some significant relation with the variables to impute would look like a reasonable decision. But it is good to take into account the fact that each additional variable complicates the computational procedure and it can have a negative impact on the quality of results. So, a moderate parsimony in the selection of the matching variables is recommended for practical purposes.

A number of methods can be applied in order to find the optimum set of predictors. Among these methods, multivariate techniques play a fundamental role: stepwise regression as it allows selecting the variables with higher explanatory power for each of the variables in the donor file that will be imputed in the recipient one; factor analysis, that provides rules for the selection of the variables and, finally, the derivation of new common variables with the highest possible explanatory power.

The quality of the variables is a second selection criterion. According to Cibella (2010), it is important to choose as matching variables those with a high level of quality, with no errors and no missing data. On the same line, Scanu (2010) states that it is advisable to avoid the use of highly imputed variables as matching variables. For the implementation of a successful matching process it is fundamental to have good quality reporting on the datasets to be integrated and on the specific procedures of imputation and calibration implemented. It is also necessary to have the imputed values in the dataset appropriately flagged.

The specific analysis to be performed with the matching files can make advisable the inclusion of a small number of variables, called the critical variables, which will be used for the separation of data into groups, the so called “matching classes”, or strata. Then, matching is done independently within strata.

One other issue to consider is that sometimes we need to impute several variables from one dataset to another. However, it is very unlikely that the common variables should have equal explanatory power for each of the specific variables. A common practice is to split the variables to be matched into more or less homogeneous groups, and to perform a statistical matching in each of the groups by using the common variables with the highest explanatory power for that particular group. That generally means using different matching variables, or different weights of these variables for each group. This practice is known as “matching in groups”. It implies that a unit of the recipient set will be most probably matched to a different unit of the donor file for each group of imputed variables.

1.2.3 Matching methods

Many different techniques have been used for statistical matching over more than forty years since these exercises have been implemented. Several strands can be differentiated according to some relevant criteria:

- First, there is a clear difference between the techniques that assume conditional independence in the matching data set and those that do not assume it: the techniques belonging to the first group will need only the information contained in the data sets to be matched. If some additional information is available, it will be useful only for checking purposes. On the contrary, the techniques applied to matching exercises in which the conditional independence cannot be assumed are based on the incorporation and use of additional information from the very beginning.

- The second classification criterion is connected with the parametric features of the model. If it can be assumed that the joint distribution of variables belongs to a family of known probability distributions (i.e. normal multivariate, multinomial), the matching problem will mainly consist of parameter estimations. That means that it can be solved with parametric techniques, among which the maximum likelihood principle will usually play a fundamental role. If no underlying family of distributions can be specified, non-parametric techniques will have to be used.

- Then a third source of classification is the scope given to the concept of statistical matching. Often the goal is to obtain a complete synthetic micro data file through effective imputation of values to the unobserved variables. However, the use of synthetic datasets should be done with caution as imputation approaches have limited ability to recreate individual level values. Therefore, imputed data should be used at a sufficient level of aggregation and for specific estimates, defined and controlled for a priori in the imputation procedure. When only the relationship existing among the two sets of variables is to be explored, macro-matching techniques can be adopted.

Based on these considerations we provide a synthesis of the main matching methods and issues related to their application in a practical context. For more details on the different methods please refer to the outputs of the ESSnet on Data Integration (Working Package 1 of ESSnet-DI , page 42-62) and D'Orazio et al 2006 .

a. Hot deck methods

The most popular matching techniques are, by far, the non-parametric micro-matching methods- to be used under the assumption of conditional independence- known as hot-deck imputation procedures. A common feature of these methods is that they will impute the non-observed variables in the recipient file with "live" values, that is, values really existing in the donor file. A definition of distance is established, and calculated for the common variables. Then each record of the recipient file is associated with the nearest record in the donor file, that is, the record that shows a smallest distance. When two or more donor records are equally distant from the recipient record, one of them is chosen at random. Distance can be defined in many ways. The definitions of distance more frequently employed are the Euclidian distance, the city-block metric or the Mahalanobis distance. A weighted distance can also be adopted, reflecting the relative relevance attributed to each of the matching variables (according to their explanatory power or to any other consideration).

This method is known as unconstrained distance hot deck, unconstrained matching or generalized distance method, and provides the closest possible match. Its main problem is that each record in the donor file can be used as donor more than once, a result that is known as polygamy. Also, some donors can remain unused. The multiple choices of donors can reduce the information and the effective sample size. Also, the empirical distribution of the imputed Z variable in the statistical matching file will usually not be identical to the corresponding distribution in the donor file.

In order to limit the number of times a donor is taken, a penalty weight can be placed on donors already used, while establishing an algorithm that avoids the factor of dependence introduced by the order in which the donor units are taken. Alternatively, a tolerance extra distance can be added to the observed minimum distance, and any units within this distance can be considered as possible matches. Then several devices can be applied for the selection of the final donor. For example, it can be selected at random among the possible choices. It is also usual to impute to the recipient record the average values of all the matches within the established distance, although this method will most probably produce imputed values that will not be "live", that is, really existing values. The disadvantage of these alternatives to distance hot deck is that they usually increase the average matching distance. Also, when averages are taken, variances and covariances can be underestimated.

Another alternative is the constrained distance hot deck, which allows each record in the donor file to be used only once, provided that the donor file is larger or equal to the recipient file. It consists in finding the best donor for each record by minimizing the distance between records conditioned to the preservation of the weights in both data sets. This ensures that the empirical multivariate distribution of the variables observed only in the donor file is exactly replicated in the synthetic file. When there are more donors than recipients, this method leads to a typical linear programming problem, and its solution usually requires a considerable computational effort.

b. Regression based methods

In a parametric framework, the assumption of conditional independence ensures that data are sufficient to estimate the parameters of the model. Under this assumption the likelihood function of the joint distribution can be calculated as a product of the conditional likelihood functions for each of the data sets and the likelihood function of the marginal distribution of the common variables. Then, maximum likelihood (ML) methods can be employed for the estimation of parameters and the identification of the distribution. Sometimes least square estimators have been employed (Rässler, 2002), which in fact results in a very small difference with the ML estimations for large samples. These methods have several disadvantages: regression towards the mean and sensitivity towards misspecifications of the models. Regression based imputation underestimates the variance of estimates and the results can be very different in comparison with hot deck imputations.

c. Mixed methods

Also, parametric and non-parametric methods are sometimes combined in a two stage process, trying to add to the parsimony of the parametric approach the robustness of non-parametric techniques. Such is the case of the predictive mean matching imputation method (Rubin, 1986) in which, in a first step, the regression parameters of Z on X are estimated on the donor database B. These parameters are used to estimate an intermediate value of Z for each register in the recipient file A. Then, with a suitable distance function, a hot deck method is applied, and the record in B that is nearer to the intermediate value in A is the one used for the final matching. Predictive mean matching is more likely to preserve original sample distributions than expected values. One minor drawback of PPM in this situation is that only "observed" rather than "possible" values can be imputed.

Another interesting mixed method is the propensity score, as described in Rässler (2002). Both data sets are extended with an additional variable taking value 1 for all the records in file A and value 0 for all the records in data set B. Putting both files together, a logit or probit model is estimated, taking as dependent variable the added one, and as independent variables the common variables X (and including the regression constant). The propensity score is defined as the estimated conditional probability of a unit to belong to one of the groups, given X. Then a matching is performed on the basis of the estimated propensity scores: for each recipient record a donor unit is searched with the same or the nearest estimated propensity score.

d. Multiple imputation methods

Multiple imputation techniques are often used in the matching framework in order to address the identification problem of the model. First proposed by Rubin in the 1970′s, the method imputes several values (N) for each missing value, to represent the uncertainty about which values to impute. The pooling of the results of the analyses performed on the multiply imputed datasets implies that the resulting point estimates are averaged over the N implicates and the resulting standard errors and p-values are adjusted according to the variance of the corresponding N sub-samples. This variance called the ‘between imputation variance’, provides a measure of the extra inferential uncertainty due to missing data.

In matching, multiple imputation methods were used to build complete datasets. Used in a Bayesian framework, multiple imputation methods rely on a model for variables with missing data, conditional on both observed variables and some unknown parameters. In these cases, different partial correlations between the two not jointly observed variables are used (CIA is not assumed). These explicit models generate a posterior predictive distribution from which imputations are drawn.

Multiple imputation has been applied mainly in a parametric setting (Moriarty and Scheuren, 2001; Raessler, 2002). It has been used by Rässler (2002) to estimate lower and upper bounds of the unknown parameters. More complex techniques, such as Sequential Regression Multiple imputation account also for complex rooting and different filters in the matched surveys, as well as different models for estimating the missing data (Raghunathan, Reiter and Rubin 2003; Raiter 2004). Some applications for the fully Bayesian model were developed based on several models: normal linear regression model, logistic regression, a Poisson loglinear model, a two stage model for truncated data (the case of wage). These give the flexibility in handling each variable on a case by case basis. The disadvantage is that they can be computationally intense.

1.2.4 Quality assessment

The quality assessment in the context of matching needs a process approach. Each of the steps (the quality and the coherence of data sources, modelling techniques, matching/imputation algorithms) has a large impact on the quality of results. However, given certain pre-requisites in terms of coherence and integration, results obtained through statistical matching have still to be validated in terms of their potential to provide reliable and accurate estimates.

Rässler (2002) proposes a framework for the evaluation of quality in a statistical matching procedure. She establishes four levels of validity for a matching procedure: (1) the marginal and joint distributions of variables in the donor sample are preserved in the statistical matching file; (2) the correlation structure and higher moments of the variables are preserved after statistical matching; (3) the true joint distribution of all variables is reflected in the statistical matching file; (4) the true but unknown values of the Z variable of the recipient units are reproduced.

It is most often straightforward to reach level 1, if you use robust methods and pre-conditions of coherence are met. This level actually measures the matching noise that can depend both on the amount of the sampling and non-sampling errors of the source data sets and on the effectiveness of the chosen matching method. The second and third levels can be checked either through simulation studies, the use of auxiliary information or more complex techniques that reflect properly the uncertainty of the estimates. Current studies on uncertainty analysis and multiple imputation techniques focus on the sensitivity of parameter estimates (e.g. correlation coefficient) to different prior assumptions. The fourth level will not be usually attained, unless the common variables determine the variables to be imputed through an exact functional relationship. In any case, since the true values of the variables are unknown, only simulation studies will allow an assessment that this condition is satisfied.

Most traditional methods focus on level 1: the comparison of marginal and joint distributions in the matched /real datasets. This is considered a minimum requirement of a statistical matching procedure, and can be easily ascertained by specific tests/ indexes for similarity of distributions (e.g Hellinger distances). However, this condition is not sufficient to validate the estimates for the joint distribution of variables not collected together. In the typical situation for matching we assume that Y and Z are statistically independent conditional on X. P(Y,Z/X)=P(Y/X) P(Y/Z). Several papers (Kadane 1978, Barr et al 1981, Rodgers de Vol, 1981) emphasised the limits of the conditional independence assumption and the implications it has on the quality and usability of estimates obtained through matching. Whenever it is not possible to justify this assumption, as most often happens, the use of auxiliary information is needed.

For example, the purpose is to have joint information on income (from source A) and consumption (from source B) that are never observed together based on a set of common variables. We impute consumption in A and the new synthetic dataset should preserve the marginal distributions of this variable as well as the cross tabulations or correlation structure with the common variables. Good results in the reproduction of joint distributions of consumption with the common variables can provide a measure of robustness for the techniques applied, but they alone cannot validate the results obtained in terms of the joint distribution of income and consumption. The creation of synthetic micro datasets, which satisfy the first level of validity, does not automatically imply that we can estimate the joint distribution of variables not collected together through standard methods applied to observed datasets.

Another issue to consider is the level for which we aim to obtain estimates via statistical matching. Traditional techniques do not consider the multilevel structure of the data (e.g. region level). If we ignore the structure and use a single-level model (e.g. individual effect) our analyses may be flawed because we have ignored the context in which processes may occur. One assumption of the single-level multiple regression model is that the measured individual units are independent while in reality the individuals in clusters (areas) have similar characteristics. We have missed important area level effects — this problem is often referred to as the atomistic fallacy. Therefore, the multilevel structure of the data has to be accounted for in the imputation procedure: the compatibility of the distributions observed for the whole sample does not translate automatically to all domains.

In a matching exercise it is essential to properly reflect uncertainty including those associated with prior assumptions implicit in the model. In light of these methodological limitations there are two main approaches in terms of quality evaluation:

a) the first one focuses on methods to estimate the uncertainty in the final estimates and it is usually focused on macro objectives (e.g. estimation of correlation coefficients and contingency tables). However, multiple imputation procedures with different correlation for the variables not jointly observed can be used for the creation of multiple synthetic micro-datasets. Methods for variance estimation in the framework of missing data can be employed for assessing the sensitivity of results to estimations based on the different datasets

b) the second one focuses on the identification of auxiliary information that can reduce uncertainty and can relax the conditional independence assumption. This can lead to partially synthetic/observed datasets and can therefore enhance the analytical potential.

a. Uncertainty analysis

In the context of matching we do not usually obtain point estimates for the target quantities — inherently related to the absence of joint information for the variables not observed together (Raessler 2002, Kiesl and Raessler, 2009). There is a region in the parametric space such that any of its points defines a parametric set compatible with the information in the data sets. This indetermination in the context of matching is known as ‘uncertainty’. The greater the explanatory power of the matching variables the less uncertainty remains for creating the fused dataset. Marginal distributions can reduce even further the set for feasible target quantities. There are two streams of work on uncertainty analysis:

a) Interval estimates which are usually applied in a non-parametric setting. Once again, methodologies and tools developed within the frame of the ESSnet on data integration can help to make an assessment of quality for results based on matched datasets. When dealing with categorical variables, the Fréchet classes can be used to estimate plausible values for the distribution of the random variables (Y,Z/X) compatible with the available information. Fréchet bounds can be used as an instrument to build a measure of the degree of uncertainty in the problem. For example, in D'Orazio et al, 2006 they provide lower and upper bounds for the contingency table that crosses income and consumption quintiles. These intervals contain all the values compatible with the observed data in the two files. The more informative the common socio-demographic variables in the two data sets are, the narrower the interval will be.

b) Multiply imputed datasets can be produced according to different values describing the conditional association (Kiesl and Raessler, 2009). We choose a plausible initial value for the conditional parameter on X from the parametric space and generate m independent values for each missing record. This process is repeated as many times as convenient with different initial values, in order to fix bounds for the unconditional parameter. From these datasets, we can reveal sensitivity to different assumptions about the correlation structure. An added advantage of multiple imputation is that you can get point and interval estimates under a fairly general set of conditions (Rubin 1987). Multiple imputation is the natural way to reflect uncertainty about the values to impute. In general, standard errors and mean square errors are computed based on methods specific to the variance estimation in case of missing errors, on the line of bootstrap and Monte Carlo simulations.

b. Auxiliary information and partially synthetic datasets

Another approach for tackling the conditional independence assumption is the use of auxiliary information. Auxiliary information usually comes in one of the following possible types:

a) Auxiliary parametric information, obtained from “hook” variables (e.g. a short set of variables used as a proxy for a complex concept that is usually measured through an extensive battery of questions);

b) A third data set (C) or an overlap of the two samples (A, B) that provides complete information on (X,Y,Z).

In a macro-matching parametric approach the auxiliary information, generally collected from hook variables, or through previous samples, archives or collection of data, can be particularly useful. Hook variables can contribute to significantly increasing the explanatory power of the common variables and therefore decrease the degree of uncertainty, and can eventually eliminate it completely in some cases. One example in D’Orazio et al. (2006) is the use of net monthly income deciles that prove to improve results for the estimation of the joint distribution of more detailed income and consumption variables.

Auxiliary datasets can also be of use in the macro matching approach. The likelihood function can be split into two factors, and the data files A, B and C can be merged into one file. The final report of the ESSnet on Data Integration identifies three main methodologies that focus on the use of auxiliary datasets with complete information:

- Singh et al (1993) proposes a two-step procedure for the use of auxiliary dataset in the context of hot deck methods. First, a live value of the variable Z from the data set C is imputed to each unit in data set A using one of the hot deck procedures. Secondly, for each record in A, a final live value from B will be imputed: the one corresponding to the nearest neighbour in B with a distance calculated on the previously determined intermediate value.

- Another methodology for the use of auxiliary information which takes into account complex sample designs is provided by Renssen (1998). Renssen identifies two approaches for providing estimates from the joint dataset, mainly focused on the adjustment of weights:

    a) The ‘calibration approach’ that is obtained under the incomplete two way stratification. This approach consists in calibrating the weights in the complete file (C) constraining them to reproduce in C the marginal distributions of Y and Z estimated from files to be matched.

    b) A ‘matching approach’ where a more complex estimate of P (Y, Z) can be obtained under the synthetic two way stratification. Roughly speaking it consists in adjusting the estimates computed under the conditional independence assumption using residuals computed in C between predicted and observed values for Y and Z respectively.

- The third approach was proposed by Rubin (1986) and consists in appending the two data sources A and B. In the case of an overlap of samples, difficulties in estimating the concatenated weights can limit the applicability of this approach. Ballin et al. (2008) suggest a Monte Carlo approach in order to estimate the concatenated probabilities.

The use of auxiliary datasets and hook variables was proposed also in the ‘split questionnaire design’ literature. Raghunathan and Grizzle (1995) tested the split questionnaire design in a simulation environment where the original questionnaire was divided into several components of variables. This approach requires that any combination of variables, which are to be evaluated, must be jointly observed in a small sub sample (to avoid estimation problems due to non-identification). The allocation of variables in components was not random but done so that highly correlated variables are in different components. This can facilitate the multiple imputation of missing information, based on good explanatory models and without relying on the conditional independence assumption. Using existing data from the full questionnaire, they assessed the quality of the multiple imputation method by comparing point estimates of proportions and the associated standard errors of variables of interest from the full questionnaire to the multiple imputation method and the available case method (the available case method uses only the data collected from that small sample without imputation). They found that, in general, the estimates obtained using either the available case method or the multiple imputation method were very similar to those obtained from the full questionnaire. Overall, the standard error estimates from both of these methods were larger than those obtained from the full questionnaire, but the multiple imputation method resulted in smaller standard error estimates than the available case method for all variables of interest. Raessler 2004 shows that in a split questionnaire design data can be quite successfully multiply imputed.

In terms of national statistical institutes both Canada and US apply matching techniques for creating synthetic datasets (SPSD -Canada and SIPP -US). However, they do not rely solely on matching but on a combination of linking and matching. First of all, a set of linking procedures are applied and then the missing data is multiply imputed based on a model. They refer to partially synthetic datasets as there is always a limited set of observations for which complete data is observed. This means that they do not have to impose assumptions about the relationship between variables" and therefore conditional independence assumption is not implicit in the imputation procedure. Confidence intervals are computed based on both between and within imputation: the variance between imputations reflects variability due to modelling assumptions, the variance within imputations reflects sample variability. Therefore more than one random draw should be made under each model to reflect sample variability.

1.3 Concluding remarks

1) A first challenge in any applied matching exercise is the harmonisation of different data sources. Discrepancies related to different sampling designs, different concepts and common variables as well as survey methods in terms of weighting, calibration and treatment of missing variables can hamper the matching exercise. The reconciliation of multiple sources is an iterative time consuming process that requires feedback loops between existing documentation of variables, data analysis and methodology. Actual matching occurs at the end of this integration process.

   A practical requirement of matching is the existence of an analytical system designed for joint data sources. This should provide both harmonised structures for different datasets and validated analytical tools (e.g. for imputation and calibration).

2) Quality evaluation in the framework of matching needs to take into account several critical factors: the quality and the coherence of the sources, the explanatory power of common variables, the matching/imputation methods applied and methods used to compute estimates based on the matched datasets. Once the pre-requisites of harmonisation are met, there are several quality criteria that need to be checked:

   a) Model diagnostics: variables used for matching should accumulate as much explanatory power as possible on the variables to impute, in order to approach the fulfilment of the conditional independence assumption.

   b) Comparison of marginal distributions in the real/matched datasets: this can provide a first quality measure of the matching process and of the robustness of the method used for imputation. However, this is just the basic requirement, a necessary but not sufficient condition.

   c) Uncertainty analysis: An assessment of uncertainty should be included in any matching exercise. The insight provided by the uncertainty analysis can be useful to assess the plausibility of the conditional independence assumption. This can open the way for defining ‘accuracy’ measures for the results obtained through matching. This allows to better validate results, but will most probably characterise a phenomenon in terms of trends or interval estimates, and not point estimates. This direction can be further explored as a follow up of the work of the ESSnet on data integration.

d) Use of auxiliary information: The existence of auxiliary information is an essential point for any matching procedure in order to address the potential non-fulfilment of the CIA, which is often the case. Auxiliary information can help to address the main limitations of matching techniques, namely the reliance on implicit models.

e) Multiple imputation methods: This stream of research developed significantly and has several advantages: it includes exercises based on explicit models (not hidden assumptions), complex data structures and models, incorporation of auxiliary information and use of standard tools for the data analysis. Quality measures can be computed, such as variance estimates and mean square error. These measures take into account both model and sample variability.

3) In conclusion, matching applied in an ex post perspective (in the current ESS system) needs to undertake several initial steps of reconciliation of sources before the actual application of matching techniques. However, this process can provide detailed documentation on existing differences at both metadata and data level and can lead to further improvements in current processes.

A critical factor is the possibility to address the limitations inherent in statistical matching, related to the non-fulfilment of the conditional independence assumption and provide a measure of quality for estimates based on matched datasets.

When this assumption holds a robust matching algorithm produces valid inferences. In this case, the preservation of marginal distributions can be considered as a measure of quality for matching. But in practice it does not usually hold. In order to validate the analytical potential of matched datasets we need to check its plausibility. Hence, uncertainty analysis needs to be an integrative part of a matching exercise in order to validate the estimates based on matched datasets.

4) Given the current process of streamlining social surveys, several steps are foreseen for a better integration and coordination of surveys. This can provide the opportunity to enhance the potential for matching, if planned in advance. Not only surveys will be better harmonised, but also several aspects can be designed ex ante:

a) the choice of common variables between surveys, which can favour the imputation in relation to specific objectives. Some studies in the frame of split questionnaire designs have addressed the optimal ex-ante allocation of questions between the various components of the questionnaire, so as to allow matching and imputation

b) consider matching jointly with other options for micro-integration (linking and use of administrative data). They are usually seen as substitutes: statistical matching is applied when no common identifiers enable linking. However, these alternative integration methods can often complement each other (the US SIPP dataset)

c) consider possibilities to use auxiliary information, mainly small datasets with common information on the two variables of interest and/or a small set of proxy variables with high predictive power as an integrative part of the system.

d) more integrated survey models (nested surveys, split questionnaire design) are recommended by several authors as solutions that can foster the application of matching techniques in practice (D'Orazio et al, 2006, Raessler, 2002).

2

Case study 1: Quality of life

2 Case study 1: Quality of Life

2.1 Background

There is a growing societal and policy demand to measure well-being and quality of life in a comprehensive way. The importance and urgency of this demand is demonstrated by recent European initiatives. In particular, the GDP and beyond communication[6] and the Stiglitz-Sen-Fitoussi Report[7] raised awareness about the need to review and update the current system of statistics in order to support specific recommendations on the measurement of quality of life.

- *Steps should be taken to improve measures of people's health, education, personal activities and environmental conditions. In particular, substantial effort should be devoted to developing and implementing robust, reliable measures of social connections, political voice, and insecurity that can be shown to predict life satisfaction;*

- *Surveys should be designed to assess the links between various quality-of-life domains for each person, and this information should be used when designing policies in various fields;*

- *Measures of both objective and subjective well-being provide key information about people's quality of life. Statistical offices should incorporate questions to capture people's life evaluations, hedonic experiences and priorities in their own survey.*

Ideally, all quality of life indicators should be captured by a single statistical instrument in order to enable the analysis of links across dimensions and the identification of multiply disadvantaged sub-groups. In practice, such an instrument does not currently exist in the European Union.

In this context, statistical matching appears as a very useful technique for the integration of several independent sources of information on quality of life, as an alternative to implementing new surveys or extending the questionnaires of the current ones. Therefore, a first pilot study focused on testing the feasibility of using matching techniques in order to obtain joint distributions for various dimensions of quality of life, drawing on variables collected through two main sources: the European Union Statistics on Income and Living Conditions (EU-SILC) and the European Quality of Life Survey (EQLS).

[6] http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=com:2009:0433:FIN:EN:PDF

[7] http://www.stiglitz-sen-fitoussi.fr/documents/rapport_anglais.pdf

EU-SILC was devised by the European Commission and the Member States in order to provide statistics and indicators for monitoring poverty and social exclusion. It therefore covers extensively the dimension on economic well-being and it combines three main indicators ─ at-risk-of-poverty, severe material deprivation, and low-work intensity ─ into an overall index (AROPE[8]).

Box 2-1 Main target indicators in EU-SILC

- **At-risk-of-poverty rate:** Share of persons with an equivalised disposable income below the risk-of-poverty threshold, which is set at 60% of the national median equivalised disposable income after social transfers.
- **Severe material deprivation rate:** Share of population with an enforced lack of at least four out of nine material deprivation items[9] in the 'economic strain and durables' dimension that represent basic living standards in most of EU Member States.
- **Low work intensity rate:** Share of people living in households where adults work less than 20% of their potential during the income reference year

Nevertheless, EU-SILC is a multi-dimensional instrument covering not only economic aspects but also housing conditions, labour, health, demography and education to enable the multidimensional approach of social exclusion to be studied. This raised interest within the European Statistical System (ESS) for a possible extension of EU-SILC towards a more comprehensive coverage of quality of life dimensions, namely subjective concepts on the overall experience with life[10], such as emotional well-being, social participation and trust in institutions. EQLS[11] is carried out by EuroFound and collects and disseminates 160 statistical indicators of well-being covering a broad range of topics: work and social networks; life satisfaction, happiness and sense of belonging; social dimensions of housing; participation in civil society; quality of work and life satisfaction; time use and work–life options. Hence, EQLS provides valuable subjective indicators, complementary to EU-SILC variables.

In the frame of this pilot study we focus on matching into EU-SILC, individual level estimates for subjective well-being variables from EQLS (see Box 2-2). The main purpose of matching information from EQLS into EU-SILC is to provide integrated statistics on economic and subjective well-being aspects of people's life when these indicators are collected through different surveys. An important added value of matching is to assess how particular policy relevant sub-groups (AROPE) score on various dimensions of quality of life (e.g. life satisfaction, perceptions of social exclusion etc.). The matching exercise is based on the EQLS survey collected in 2007.

[8] People at-risk-of-poverty and social exclusion

[9] 1) arrears on mortgage or rent payments, utility bills, hire purchase instalments or other loan payments; 2) capacity to afford paying for one week's annual holiday away from home;3) capacity to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day; 4) capacity to face unexpected financial expenses [set amount corresponding to the monthly national at-risk-of-poverty threshold of the previous year];5) household cannot afford a telephone (including mobile phone); 6) household cannot afford a colour TV; 7) household cannot afford a washing machine; 8) household cannot afford a car and 9) ability of the household to pay for keeping its home adequately warm.

[10] http://epp.eurostat.ec.europa.eu/portal/page/portal/pgp_ess/0_DOCS/estat/SpG_progress_wellbeing_report_after_ESSC_adoption_22Nov1.pdf

[11] http://www.eurofound.europa.eu/areas/qualityoflife/index.htm

Box 2-2 Main target variables in EQLS ─ considered for matching into EU-SILC

- **Overall life satisfaction**: All things considered, how satisfied would you say you are with your life these days?
- **Trust in institutions**: Please tell me how much you personally trust each of the following institutions: the press/government/legal system/parliament/police/political parties;
- **Recognition**: I don't feel the value of what I do is recognised by others.
- **Social exclusion:** I feel left out of society; Life has become so complicated today that I almost can't find my way; Some people look down on me because of my job situation or income.
  …

This pilot study provides in detail the methodology for two selected countries: Finland (FI) and Spain (ES). They represent two very different typologies of countries both for their characteristics and the data collections methods employed. Following a standard matching approach we produce results for EU-27, but these results should be interpreted with caution. While there are advantages to a "one solution fits all" approach (economies of scale in the analysis, better comparability of estimates), the detailed analysis for the two selected countries shows that optimal solutions at national level often require tailored approaches.

2.2 Statistical matching: methodology and results

This chapter provides in detail the methodology and results obtained from matching EU-SILC and EQLS for the two selected countries (ES, FI), including a general overview of results for EU-27. It follows the main four stages of the matching algorithm described in Chapter1.

2.2.1 Harmonisation and reconciliation of sources

The first step in matching EU-SILC and EQLS consisted in analysing the two data-sources and assessing the fulfilment of the pre-conditions for matching. The main condition required is the existence, in both surveys, of a set of common variables both coherent and with a high explanatory power in relation to our specific imputation needs.

In theory, the two surveys have a large number of variables in common that touch upon several areas: demographics, household composition, labour, health, dwelling, material deprivation, environment, income. In order to test their coherence, a detailed analysis was carried out in terms of wording of questions, definition of concepts, measuring scales and guidelines. Then, a careful comparison of marginal distributions and appropriate statistical tests were implemented in order to select consistent variables for the two countries. Comparisons have been carried out, for the marginal distributions of each potential matching variable, between the 95% confidence intervals calculated for EU-SILC and those in EQLS (see Annex II-2). Overlapping of these intervals for every category implies that there are no grounds for rejecting the hypothesis of coherence of variables.

Several issues were encountered in this first stage that proved the need for a better harmonisation of variables across social surveys:

- The harmonisation at meta-data level is sometimes difficult to ascertain due to the fact that concepts that are basically equivalent are expressed with different wording in each of the surveys. For example, the variable that refer to the 'capacity to afford a one week holiday' includes the possibility to stay with relatives in the case of EU-SILC, while in EQLS this situation is specifically excluded. This might induce different answers from the respondents. Moreover, the categorisations of common variables are often different and sometimes it is very difficult to find a common structure (See Annex II-1 for a detailed comparison of common variables).

- The analysis of marginal distributions for the common variables resulted in a very limited set of coherent variables. When confidence intervals don't overlap the variables are considered inconsistent. Several essential variables were excluded, both socio-demographic variables (e.g. *highest level of education completed*) and economic conditions related questions (*ability to make ends meet, material deprivation items*). As further analysis will show, the omission/inclusion of these variables has an important impact on the results and conclusions based on matched datasets. We can also notice that different variables are selected in the two countries.

- An additional quality check was done to detect variables with a high item non-response and/or small un-weighted sample size for some categories. The small sample size of EQLS was one of the limitations of the matching exercise: many relevant categories of the main variables are insufficiently represented in the un-weighted sample so that estimates are not accurate or representative. For some variables presenting a good level of consistency at metadata level, one of the categories accumulates a very high proportion of the total sample size, consequently leaving a very sparse sample for estimation in the other categories. Variables that show a real un-weighted sample of less than 30 units for at least one of the categories are considered unfit for our matching exercise. Some of the potential matching variables have to be rejected on this ground, irrespective of the consistency of definitions. Some other variables have to be redefined by merging some of their categories. More specifically, for EQLS in Finland the following variables had to be rejected: c*ountry of birth; country of citizenship; afford to keep house adequately warm; afford a meal with meat, chicken or fish every second day; amenities: lack of bath or shower in accommodation; amenities: Lack of indoor flushing toilet in accommodation.*

  For others, we aggregated several categories: e.g. *ability to make ends meet (with great_difficulty +with_difficulty+some_difficulty vs. fairly_easily+easily+ very easily); general health status (very good+good+fair vs. bad+very bad).*

When the data from Spain are considered, only two variables had to be rejected on the grounds of scarce sample: a*menities: lack of bath or shower in accommodation;*

amenities: lack of indoor flushing toilet in accommodation. Some others had to be re-categorised: *Spain NUTS 2 Region; general health status.*

Table 2-1 summarises the coherence analysis step and identifies, for each country, the common variables that meet the pre-conditions for the selection in the matching process: they have adequate quality and coherent marginal distributions between EQLS and EU-SILC 2007.

Table 2-1 Coherence common variables between EU SILC and EQLS, Spain/Finland–2007

Variables	*Quality/coherence good (ES)*	*Quality/coherence good (FI)*
Gender	✓	✓
Age in completed years	✓	✓
Country of citizenship at time of data collection	✗	✗
NUTS2 Region of residence	✓	✓
Country of birth	✗	✗
Economic sector in employment	✗	✗
Highest level of education completed	✗	✗
Hours usually worked per week in main job	✗	✓
General health status	✗	✓
Legal marital status	✗	✗
De facto marital status (consensual union)	✗	✗
Household composition	✗	✗
Degree of urbanisation	✗	✗
Self-declared labour status	✓	✗
Status in employment	✓	✓
Ability to make ends meet	✗	✗
Net monthly income of the household	✗	✓
Afford to keep home adequately warm	✗	✗
Afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day	✓	✗
Afford paying for a week's annual holiday away from home	✗	✗
Arrears on mortgage or rent payment	✓	✗
Arrears on utility bills	✓	✗
Financial burden of the total housing cost	✗	✗
Amenities in dwelling: bath or shower	✗	✗
Amenities in dwelling: indoor flushing toilet	✗	✗
Problems with dwelling: violence, crime and vandalism	✗	✗
Problems with dwelling: noise	✗	✗
Problems with dwelling: pollution, grime or other environmental problems	✗	✗
Problems with dwelling: litter or rubbish in the street	✗	✓
Longstanding physical or mental illness	✗	✗
Tenure status of household	✓	✗

2.2.2 Analysis of the explanatory power for common variables

A second criterion for the selection of the common variables, besides coherence, is that they should show a good association with the target variables (variables in both surveys not collected together for which we need to estimate the joint distribution). The optimal situation, when the common variables contain all the association shared by the target variables and thus fulfil the conditional independence assumption (CIA), is rarely attainable.

So, in order to make a further selection of common variables to be used in the matching process, their association with a broader set of target variables from EQLS (life satisfaction, trust in institutions, perceived quality of accommodation, job satisfaction, and social exclusion variables) was analysed using several methods.

A first method focused on pairwise correlations. We relied mainly on Rao-Scott tests, which are a generalisation of the standard Pearson chi-squared and likelihood-ratio chi-squared tests for testing the null hypothesis of no association/independence in categorical variables (Agresti, 2007). Annex II-3 documents in detail the results for each combination of variables, for both countries. It also indicates in bold variables that show a significant association at the 5% level (p-values[12]<0.05). The Rao-Scott tests have the advantage that they incorporate complex design effects. Still, they do not provide a measure of the strength of the association between variables. Thus, as a complement, two traditional measures of association were calculated: the adjusted Pearson contingency coefficient (Pearson contingency coefficient adjusted by the number of files and columns of the table); the Cramer's V coefficient (D' Orazio et al., 2006), derived from the Pearson chi-square test, adjusted by the minimum of the degrees of freedom. They are scaled between 0 (absence of association) and 1 (perfect association). The two coefficients of association tend to confirm the results of the Rao-Scott tests.

In general, the results for both countries show that several common variables tend to be strongly associated with a considerable proportion of target variables and appear as good candidates for matching purposes. Table 2-2 provides a summary overview of a synthetic index of the global explanatory power of each common variable (the average of the measures of association with all variables to be imputed). We can also note that some variables have a higher predictive power in only one country (e.g. Material deprivation 3: A meal with meat, chicken or fish every second day), which leads to slightly different scenarios across Member States.

[12] Probability to reject the null hypothesis of no association

Table 2-2 Explanatory power common variables for Spain/Finland, EQLS – 2007

Variables	Spain		Finland	
	Average adjusted contingency coefficient	Average Cramer's V	Average adjusted contingency coefficient	Average Cramer's V
Gender	0.17	0.12	0.11	0.08
Age	0.30	0.14	0.25	0.12
Country of citizenship	0.18	0.13	0.16	0.11
Country of birth	0.17	0.12	0.14	0.10
NUTS 2 Region (or equivalent)	0.55	0.24	0.23	0.12
Highest level of education completed (ISCED)	0.31	0.13	0.29	0.12
General health status	0.37	0.18	0.28	0.13
De facto marital status (consensual union)	0.20	0.12	0.16	0.09
Household composition	0.16	0.12	0.18	0.13
Degree of urbanisation	0.25	0.15	0.17	0.10
Self-declared labour status	0.36	0.15	0.29	0.12
Status in employment	0.12	0.07	0.28	0.23
Ability to make ends meet	0.40	0.17	0.40	0.17
Net monthly income of household	0.33	0.17	0.31	0.16
Material deprivation 1: home adequately warm	0.34	0.25	0.11	0.08
Material deprivation 3: A meal with meat, chicken or fish every second day	0.33	0.24	0.19	0.14
Material deprivation 2: Paying for a week's annual holiday away from home	0.25	0.15	0.20	0.12
Arrears on rent or mortgage payments	0.18	0.11	0.20	0.12
Arrears on utility bills, such as electricity, water, gas	0.20	0.12	0.21	0.12
Financial burden of total housing cost	0.28	0.15	0.23	0.12
Amenities: Lack of bath or shower	0.20	0.14	0.17	0.12
Amenities: Lack of indoor flushing toilet	0.16	0.11	0.11	0.08
Problems with dwelling. Violence, crime and vandalism	0.27	0.21	0.21	0.15
Problems with dwelling. Noise	0.26	0.19	0.19	0.14
Problems with dwelling: pollution, grime or environmental problems	0.27	0.20	0.17	0.12
Problems with dwelling. Litter or rubbish in the street	0.27	0.20	0.21	0.15
Long-standing physical or mental health problem	0.29	0.18	0.22	0.13
Limitations due to a long standing illness	0.48	0.30	0.27	0.16
Tenure status of household	0.23	0.12	0.28	0.15

An important aspect to consider is that most of these variables didn’t meet the conditions of quality and coherence required (highlighted in blue in Table 2-2). Another variable with a high level of explanatory power, net monthly income, had to be rejected for Spain for lack of quality. Thus, the strict selection of common variables, which meet the criteria for coherence and predictive power, results in a very narrow set of matching variables with a low potential to obtain valid results (see Box 2-3).

Box 2-3 Final matching variables for Spain/Finland (method1), EQLS – 2007

Spain	Finland
• Gender	• Gender
• Age	• Age
• NUTS 2 Region	• NUTS 2 Region
• Afford a meal with meat, chicken or fish every second day (yes/no)	• Status in employment
• Self-declared labour status	• Net monthly income of the household
• Tenure status of household	• General health status (with a re-categorisation)

A second method for selecting the best predictors was based on logistic regressions to account for multivariate relationships. The selected model was used for imputation in the next stage. The focus in this case was on addressing the limitations related to the conditional independence assumption for a specific pair of target variables: life satisfaction in EQLS and AROPE indicators in SILC. Results (for ES, FI) indicate that even if we have some good predictors for the subjective variables to be imputed, the overall predictive power of the model it is not very high: “Percentage concordant” which measures the fit between predicted probabilities and observed values is around 65%. However, for the CIA to hold, it is important not only the absolute level of explanatory power of common variables, but most of all, the extent of mediation[13] relative to the relationship between imputed variables and AROPE indicators.

For example, Table 2-3 reports the odds ratio for the ordinal logit with life satisfaction as a dependent variable. Several variables have a strong effect on the likelihood to be satisfied with your life: health status, relationship status and activity status. However, even when controlling for these dimensions, we find a strong correlation between life satisfaction and ‘bad’ economic conditions (e.g. a few selected items on ‘material deprivation’ or ‘make ends meet’ which are collected in both SILC and EQLS). This implies that the CIA does not hold and thus we cannot correctly estimate the relationship between life satisfaction and AROPE indicators under this assumption.

[13] the extent to which the common variables capture (mediate) the relationship between the imputed information (e.g. life satisfaction) and the target variable(s) in the recipient survey (e.g. material deprivation index).

Table 2-3 Final matching variables for Spain/Finland (dependent variable=life satisfaction), EQLS — 2007

Matching variable		ES-Odds Ratio Estimates			FI - Odds Ratio Estimates		
	Base category	Point Estimate	95% Wald Confidence Limits		Point Estimate	95% Wald Confidence Limits	
Age		0.996	0.984	1.007	1.003	0.991	1.015
Age-square		0.999	0.993	1.004	1.009	0.998	1.02
Gender	male	1.052	0.81	1.367	1.446	1.14	1.833
Low education (ISCED 5-6)	ISCED (3-4)	0.968	0.677	1.384	0.911	0.851	1.472
High education (ISCED 0-2)	ISCED (3-4)	1.123	0.835	1.512	1.139	0.811	1.601
Tenure status-Owner	rent	1.317	1.003	1.728	1.115	0.844	1.474
Material deprivation 2	not deprived	0.69	0.511	0.934	0.884	0.623	1.256
Material deprivation 1	not deprived	0.681	0.328	1.415	0.409	0.144	1.166
Material deprivation 3	not deprived	0.835	0.565	1.234	0.706	0.219	2.275
Living alone	not living alone	0.878	0.535	1.442	1.007	0.617	1.643
(Bad) general health status	good	0.655	0.482	0.891	0.396	0.297	0.529
(In)Ability to make ends meet	yes	0.549	0.421	0.714	0.36	0.261	0.496
Labour- employed	unemployed	1.909	1.14	3.195	2.881	1.426	5.82
Labour- in education		9.261	4.135	20.74	1.747	0.57	5.355
Labour- retired		1.934	0.99	3.778	2.352	1.122	4.933
Rel_status-couple	widowed/ separated	2.651	2.357	3.189	1.604	1.374	1.976
Rel_status- single		1.941	1.371	2.746	1.638	1.035	2.592

Following the approach suggested by D'Orazio et al. (2006), in cases where the CIA doesn't hold, the use of auxiliary information is recommended. As no sample containing joint information on our target variables is available, the only solution possible would be the use of 'proxy variables' that can improve estimations if included in the imputation model. Thus, the few selected items on material deprivation or the single question on net monthly income can be instrumental for our specific purpose: analysing subjective variables for the AROPE sub-group.

For example, even if we cannot test directly with the data at hand, we can reasonably assume that the use of the three items on 'material deprivation' (which are collected in EQLS) can help us to improve estimations for the joint distributions of life satisfaction and the overall indicator. In order to confirm this hypothesis some further analysis were performed in EU-SILC for the indicator on material deprivation. This showed that the three common items between EU-SILC and EQLS have a high predictive power in relation to the overall indicator (based on 11 items): >90% of concordance (between observed and predicted probabilities for the SMD indicator).The quantity "c", which is equivalent to the well-known ROC curve (where 0.5 corresponds to the model randomly predicting the response, and a 1 corresponds to the model perfectly discriminating the response), is also higher than 0.95. These diagnostics show that the three items work relatively well in predicting the overall indicator and that they will therefore tend to mediate the relationship between the indicator and imputed information.

As the two criteria of coherence and predictive power lead often to divergent results, in the next stage we performed the imputation based on two different sets of variables: 1) a restricted one based on the set of variables both coherent and with high explanatory power; 2) an extended set in which we relaxed the coherence requirements and we gave prevalence to the particular significance of some variables for the fulfilment of the CIA (*general health status, ability to make ends meet and material deprivation items*). Several sensitivity tests were employed to test the effects of the different sets of predictors and methods on the final results. Moreover, a unique model (tested for ES and FI) was selected to be used for imputation in all EU27 countries, but allowing for different coefficients across countries. On the one hand, a "one solution fits all" approach across countries should be implemented with caution, as it usually does not provide optimal results for specific countries. On the other hand, the harmonisation and reconciliation for 27 countries is an extremely intensive and time consuming task.

2.2.3 Matching methods

Both distance unconstrained hot deck and model based methods were employed for the imputation of variables (life satisfaction, trust in institutions and social exclusion variables) from EQLS into EU-SILC.

For the hot deck method, a limited set of covariates that met all the coherence and quality pre-requisites (see Table 2-3) was used. For the model based imputation, an extended set of predictors (see Annex II-3) was chosen, mainly on the basis of their ability to capture the relationship between imputed variables and AROPE indicators.

Both are micro-matching methods which finally provide a synthetic file containing the complete set of variables (X, Y, Z). We assign an imputed value to every unit of the recipient file (EU-SILC in our case) for the subjective well-being variables (Z) collected only in EQLS.

The hot-deck method of imputation assigns to each unit of the recipient file the values of the nearest unit in the donor file, measured with a certain definition of distance. The standard distances (Euclidean, Manhattan or Mahalanobis) are used for continuous variables. But in our exercise all variables are qualitative, and each of them has been transformed, for matching purposes, into a set of binary variables. For this reason we have considered more appropriate to work with a distance specifically built for this type of variables. So, we have selected the distance for binary variables defined on the similarity coefficient of Dice (also known as the Czekanowski or Sorensen similarity coefficient). This distance (Gower, 1986) is defined as

$$D_{ij} = \sqrt{1 - S_{ij}}$$

Where

$$S_{ij} = \frac{2a}{2a + b + c}$$

a being the number of indicators for which *i=1* and *j=1, b* the number of indicators for which *i=1* and *j=0* and *c* the number of indicators for which *i=0* and *j=1* (Cox and Cox, 2001).

For model based methods, we tested both imputations based on logistic regressions and the predictive mean matching method. The covariates selected in the modelling stage, both socio-demographic characteristics and economic variables that are correlated to poverty measures, were used in the imputation algorithm:

- Age, gender, education, marital status
- Tenure status
- Activity, health status
- Material deprivation items (3); ability to make ends meet

The matching exercise has been implemented mostly in SAS, but for non-parametric methods the R package Statmatch[14] developed by ISTAT was used.

2.2.4 Results and quality evaluation

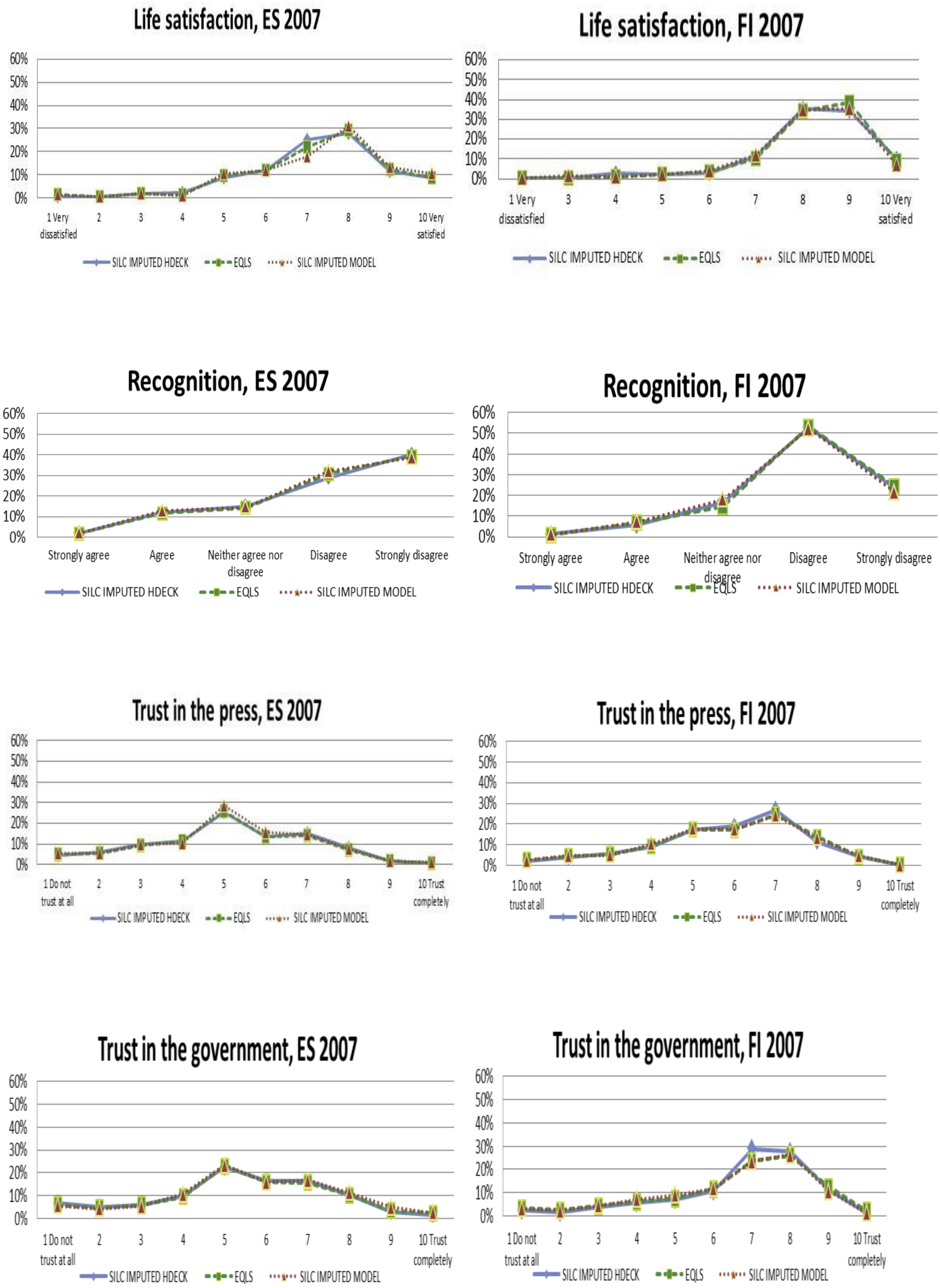
We analyse in detail the quality of results based on four main target variables imputed into EU-SILC: life satisfaction, meaning in life, trust in the press, and trust in the government. The results show that both methods of imputation presented above preserved reasonably well the marginal distributions of the variables before and after imputation.

However, the results tend to differ in terms of joint distributions of variables not collected together. The inclusion in the model of a very limited number of variables makes difficult to capture the dependence relationship between poverty indicators and the more subjective variables to be imputed. In order to better illustrate the differences in conclusions that are drawn from the two matching approaches we first transform the four ordinal variables (on a scale 1-10) imputed in EU-SILC into binary indexes (e.g. low/high quality of life -if life satisfaction =</>6). We report in Figure 2-1 for the four binary indexes the differences between the whole population and the sub-group of people materially deprived[15] in SILC.

[14] http://cran.r-project.org/web/packages/StatMatch/index.html.

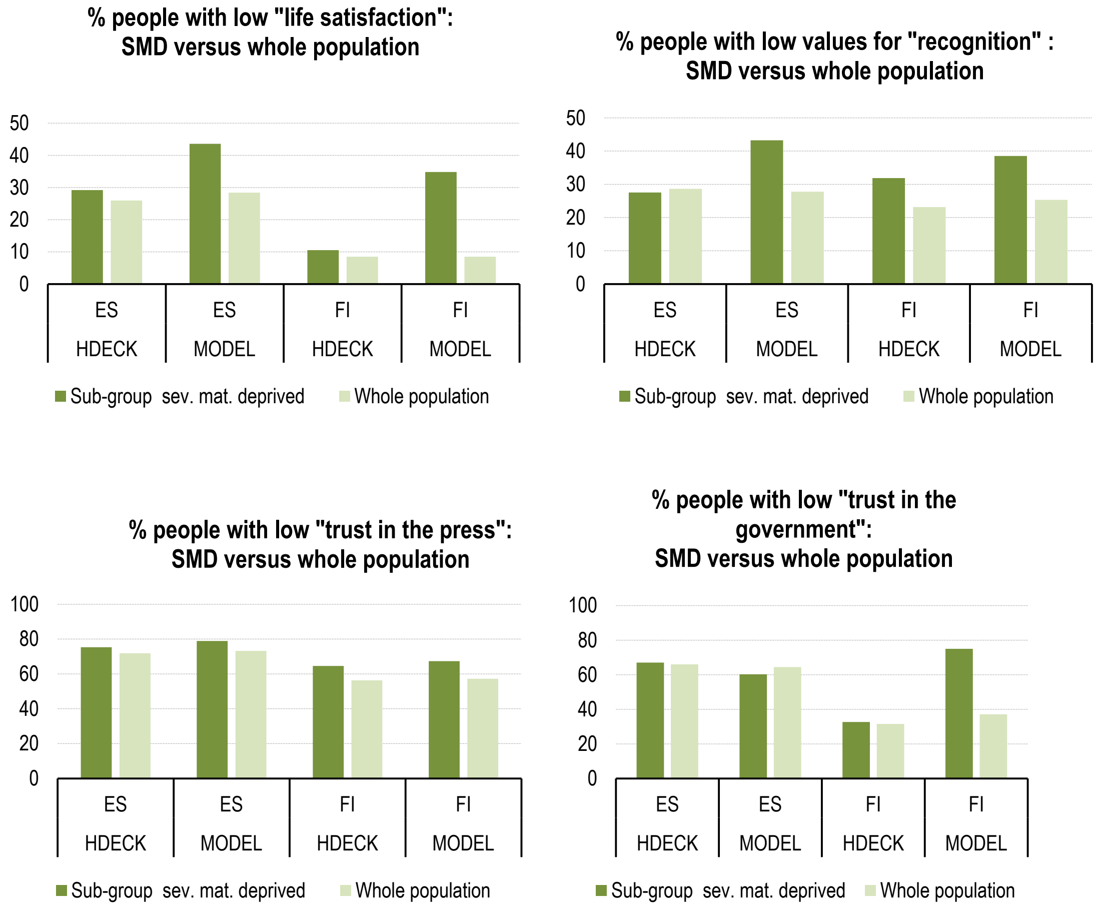
[15] based on the full set of 9 items.

Figure 2-1 Preservation of marginal distributions: observed EQLS versus imputed (%)



We can note that for Spain, the first results showed no significant differences in terms of *life satisfaction* or *recognition in life* between the whole population and the materially deprived sub-group. This is likely to be related to the prior assumptions of conditional independence, rather than a real lack of association. In a second stage, when we included proxies for the poverty indicators in the model, estimates show that people materially deprived tend to cumulate negative scores also on more subjective life assessments.

Figure 2-2 Joint distributions severe material deprivation & imputed subjective well-being variables



Finally, we selected the model based method to impute life satisfaction and social exclusion variables for EU-27. For social exclusion we computed binary micro-indexes that identify people that tend to cumulate negative scores on various items (the social exclusion index is 1 if people declare to agree with at least 2 out of 4 negative statements[16]). Figure 2-3 and 2-4 show the results in terms of life satisfaction and social exclusion for two specific vulnerable sub-groups: the AROPE[17] sub-population and the

[16] I feel left out of society/Life has become so complicated today that I almost can't find my way/I don't feel the value of what I do is recognised by others/Some people look down on me because of my job situation or income.

[17] At risk of poverty and social exclusion – see section 2

subset of people materially deprived. In both cases, we can observe that people that face poverty and/or material deprivation have lower scores on questions related to their quality of life, and this holds in all member states.

Figure 2-3 Average life satisfaction: whole population versus AROPE

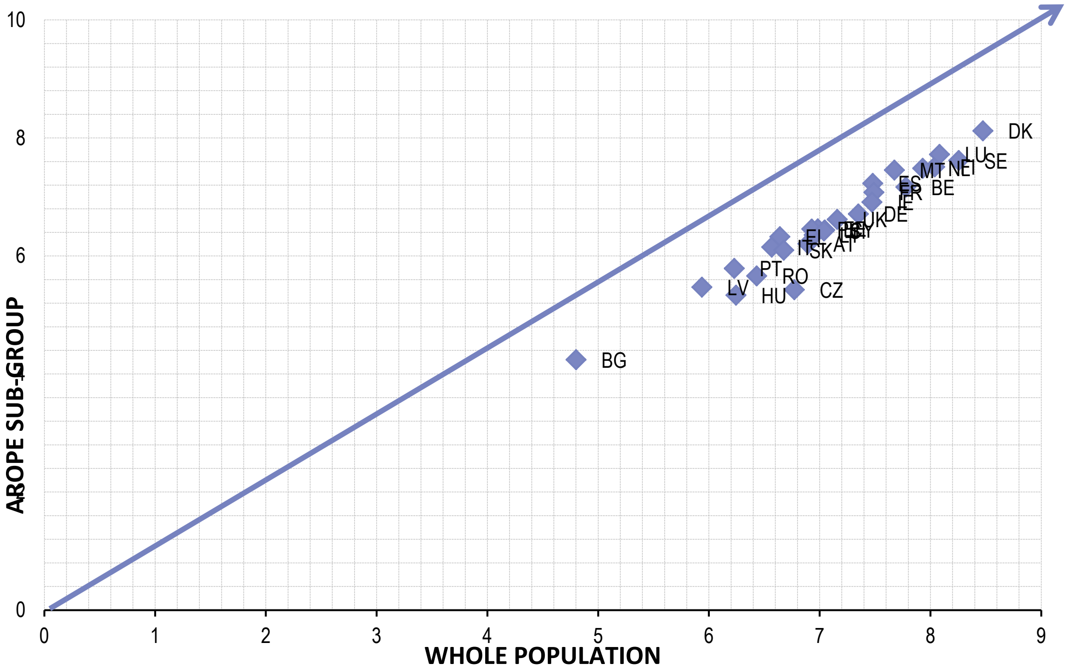
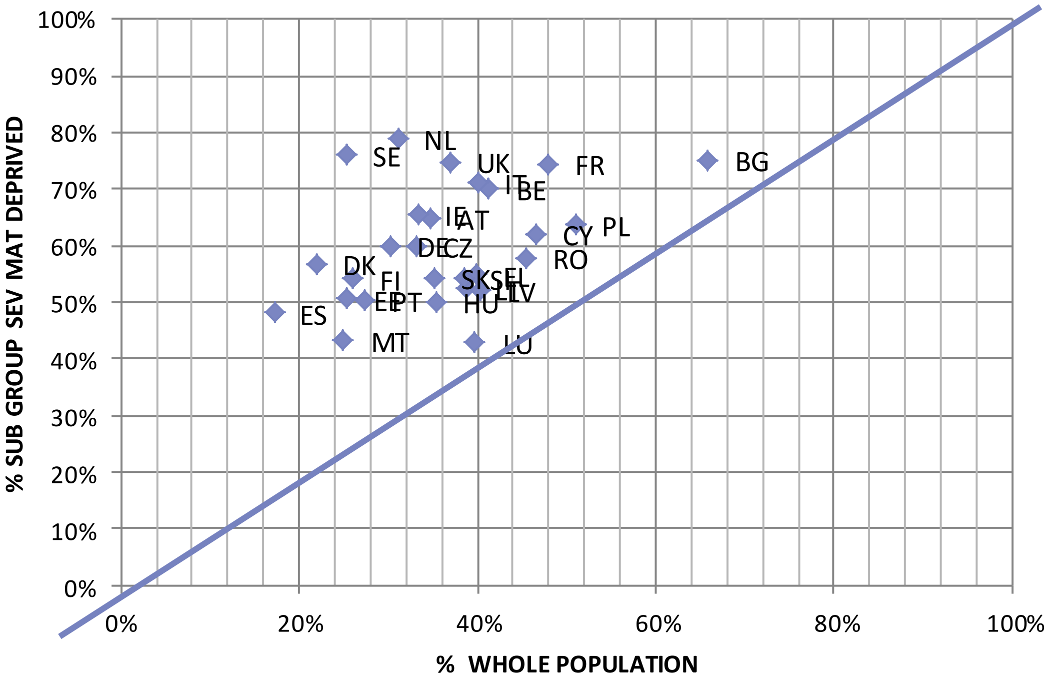


Figure 2-4 % people that feel socially excluded: whole population versus materially deprived



However, results based on matched datasets should be interpreted with caution and in relation to specific, well-defined objectives: e.g. the joint distribution of life satisfaction and AROPE indicators. As our results show, they tend to be very sensitive to the variables included in the imputation process. We also implemented the quality measure proposed and developed within the frame of the ESSnet on Data Integration that refer to the uncertainty of estimates for the relationship between variables not collected together: uncertainty intervals based on the Frechet bounds[18]. For example, these intervals give all possible values for the joint distributions of life satisfaction and severe material deprivation compatible with the available observed data in both EQLS and EU-SILC. We can observe in Table 2-4 the Frechet bounds based on the enlarged set of common variables. While in general the size of the uncertainty space is reasonable, it is very difficult to draw conclusions for small groups, such as the materially deprived people. In this case the intervals are often not informative and rather sensitive to slight variations in the common variables used.

Table 2-4 Frechet bounds for the joint distribution of life satisfaction and severe material deprivation

		ES			FI		
Life satisfaction	**Severe material deprivation**	**Lower bound**	**CIA**	**Upper bound**	**Lower bound**	**CIA**	**Upper bound**
1	**0**	0.79%	0.92%	1.00%	0.38%	0.50%	0.51%
2	**0**	0.83%	0.85%	0.86%	0.00%	0.00%	0.00%
3	**0**	2.18%	2.36%	2.46%	0.28%	0.34%	0.36%
4	**0**	2.51%	2.58%	2.63%	1.28%	1.55%	1.58%
5	**0**	7.95%	8.42%	8.64%	1.37%	1.75%	1.87%
6	**0**	8.75%	9.35%	9.70%	1.12%	1.86%	2.02%
7	**0**	20.32%	20.76%	21.01%	8.19%	9.19%	9.48%
8	**0**	29.54%	29.97%	30.20%	30.28%	31.37%	32.05%
9	**0**	11.91%	13.22%	13.30%	37.77%	38.71%	39.35%
10	**0**	8.51%	8.79%	8.92%	8.78%	9.43%	9.55%
1	**1**	0.11%	0.19%	0.33%	0.00%	0.01%	0.13%
2	**1**	0.00%	0.01%	0.03%	0.00%	0.00%	0.00%
3	**1**	0.00%	0.10%	0.28%	0.00%	0.10%	0.18%
4	**1**	0.00%	0.06%	0.22%	0.03%	0.23%	0.32%
5	**1**	0.20%	0.42%	0.89%	0.09%	0.30%	0.58%
6	**1**	0.06%	0.40%	1.00%	0.10%	0.46%	1.01%
7	**1**	0.16%	0.51%	0.85%	0.16%	0.46%	1.45%
8	**1**	0.12%	0.36%	0.79%	0.30%	0.98%	2.07%
9	**1**	0.04%	0.32%	0.42%	0.23%	0.87%	1.81%
10	**1**	0.10%	0.22%	0.50%	0.06%	0.18%	0.83%

One important conclusion of the exercise is that the preservation of marginal distributions for the variables imputed is rather straightforward in a matching exercise but is not a sufficient criterion for assessing quality. Whenever micro datasets enhanced

[18] See description in Chapter 1

through matching are used, the focus should be on estimations of the joint distributions for variables not collected together which gives the real value added. When important predictors are omitted, the imputation under CIA can lead to the under-estimation of the association between the variables not jointly observed. In this particular case study, a better harmonisation and improved sample size for a few selected variables in EQLS (which are highly related to both subjective measures of well-being and poverty aspects), are essential for improving the quality of estimates based on matching.

2.3 Conclusions and Recommendations

In general, this pilot study raised several problems when matching EU-SILC with EQLS. Two important lessons can be drawn which concern the application of statistical matching in practice:

- *A very careful review of the metadata should be carried out for each of the common variables to be used in the matching process. Often, even if similar, we cannot establish exact equivalence of concepts and small differences can translate in large discrepancies in the data.*

- *The preservation of marginal distributions for the variables imputed is not a sufficient criterion for assessing quality in statistical matching. It is essential both to control for the dimensions relevant for the aim of the analysis and to properly reflect uncertainty associated with implicit models. When important predictors are omitted, the imputation under CIA, can lead to the under-estimation of the association between the variables not jointly observed.*

The lack of harmonisation for most of the variables and the low quality for particularly relevant predictors (e.g. small sample size for material deprivation items) lead to difficulties that cannot be tackled in the ex-post integration. The problems experienced in the implementation of this matching exercise, and the results obtained, lead us to suggest also a number of recommendations that, if applied to the social surveys involved, could contribute to a better integration of surveys that cover different aspects of quality of life.

Recommendation 1*: When possible, standardization of the wording of similar questions in all the social surveys currently collected – or to be collected – in the EU in order to guarantee total consistency of meaning and to propitiate comparable responses should be considered.*

Recommendation 2*: The inclusion of a small module with common questions in the future waves of the two surveys considered could be very useful as auxiliary information in order to reduce uncertainty and for checking purposes.*

Recommendation 3: *A better harmonisation with EU- SILC and improved sample size for a few relevant variables in EQLS, which are highly related to both subjective measures of well-being and monetary aspects, are essential for improving the quality of estimates based on matching.*

Recommendation 4: *The insight provided by the uncertainty analysis can come up useful to assess the plausibility of assumptions but the uncertainty intervals are usually very large, as it is the case for this particular exercise. Therefore, these methods can provide a quality indicator, but unless we have a very exhaustive model they are generally not precise enough to be informative. The development of proper quality measures needs to continue as a follow up of the work of the ESSnet on data integration.*

Annex 2-1 Common variables- metadata analysis

A. Core social variables

<table>
<tr><th></th><th>EU-SILC 2007</th><th>EQLS 2007</th><th>Common aggregation</th></tr>
<tr><td>Age in completed years</td><td><table><tr><td>Month of birth</td><td>RB070</td></tr><tr><td>Year of birth</td><td>RB080</td></tr></table></td><td>Age at last birthday.<table><tr><td>Age</td><td>HH2b Aggregated in datafile</td></tr><tr><td></td><td>CVhh2b Microdata variable with label “CONTINUOUS VARIABLE HH2b: AGE OF RESPONDENT”</td></tr></table></td><td>Every aggregation is possible</td></tr>
<tr><td>Sex</td><td><table><tr><td>Sex</td><td>PB150</td></tr></table></td><td><table><tr><td>Sex</td><td>HH2a</td></tr></table></td><td>1 Male
2 Female</td></tr>
<tr><td>Country of birth</td><td>Country of birth is defined as the country of residence of the mother at the time of birth<table><tr><td>Country of birth</td><td>PB2010</td></tr></table>Categorisation can be seen in Common aggregation cell</td><td>The question about country of birth (Q70) -In which country were you born?<table><tr><td>Country of birth</td><td>Q70</td></tr></table>Categorisation can be seen in Common aggregation cell</td><td><table><tr><td>Common</td><td>EU-SILC</td><td>EQLS</td></tr><tr><td>In this country</td><td>Country</td><td>Country</td></tr><tr><td>European Union</td><td>Aggregation of countries</td><td>Aggregation of countries</td></tr><tr><td>Rest of Europe</td><td>Aggregation of countries</td><td>Aggregation of countries</td></tr><tr><td>Asia, Africa or Latin America</td><td>North Africa
West Africa
Other Africa
Central and South America
Near and Middle East
Other Asia</td><td>Asia, Africa or Latin America</td></tr><tr><td>Northern America or Oceania</td><td>USA
Canada
Australia and Oceania</td><td>Northern America or Oceania</td></tr></table></td></tr>
<tr><td>Country of citizenship at time of data collection</td><td>When a person has multiple citizenships, the two main citizenships should be collected. For persons with multiple citizenships and where one of the citizenship is the one of the country of residence, that citizenship should be coded.<table><tr><td>Citizenship 1</td><td>PB220A</td></tr><tr><td>Citizenship 2</td><td>PB220B</td></tr></table>Categorisation can be seen in Common aggregation cell</td><td><table><tr><td>Citizen of [country]</td><td>Q69</td></tr><tr><td>Country of citizenship</td><td>Q70</td></tr></table></td><td>The same as Country of birth
In case of two citizenship in EU-SILC one of them must be chosen</td></tr>
</table>

<table>
<tr><th></th><th>EU-SILC 2007</th><th>EQLS 2007</th><th>Common aggregation</th></tr>
<tr>
<td>Legal marital status</td>
<td><table><tr><td>MARITAL STATUS</td><td>PB190</td></tr></table>
EU-SILC recommends that Civil partnership should be treated as marriage</td>
<td><table><tr><td>Current marital status</td><td>Q30</td></tr></table>
The question mixes legal and de facto marital status.</td>
<td>Not possible</td>
</tr>
<tr>
<td>De facto marital status (consensual union)</td>
<td><table><tr><td>CONSENSUAL UNION</td><td>PB200</td></tr></table>
1 yes, on a legal basis
2 yes, without a legal basis
3 no</td>
<td><table><tr><td>Current marital status</td><td>Q30</td></tr></table>
The question mixes legal and de facto marital status, it is not possible to differentiate legal and consensual union.</td>
<td><table>
<tr><td>EU-SILC</td><td>EQLS</td></tr>
<tr><td>1 yes, on a legal basis
2 yes, without a legal basis</td><td>1 Married or living with partner</td></tr>
<tr><td>3 no</td><td>2 Separated or divorced and not living with partner
3 Widowed and not living with partner
4 Never married and not living with partner</td></tr>
</table></td>
</tr>
<tr>
<td>Self-declared labour status</td>
<td><table><tr><td>SELF-DEFINED CURRENT ECONOMIC STATUS</td><td>PL030</td></tr></table>
1 Working full time
2 Working part-time
3 Unemployed
4 Pupil, student, further training, unpaid work experience
5 In retirement or in early retirement or has given up business
6 Permanently disabled or/and unfit to work
7 In compulsory military community or service
8 Fulfilling domestic tasks and care responsibilities
9 Other inactive person</td>
<td>-
<table><tr><td>Which of these best describes your situation?</td><td>HH2D</td></tr></table>
1 at work as employee or employer/self-employed
2 employed, on child-care leave or other leave
3 at work as relative assisting on family farm or business
4 unemployed less than 12 months
5 unemployed 12 months or more

6 unable to work due to long-term illness or disability
7 retired
8 full time homemaker/ responsible for ordinary shopping and looking after the home
9 in education (at school, university, etc.) / student
10 other</td>
<td><table>
<tr><td>EU-SILC</td><td>EQLS</td></tr>
<tr><td>1 Working full time
2 Working part-time</td><td>1 at work as employee or employer/self-employed
2 employed, on child-care leave or other leave
3 at work as relative assisting on family farm or business</td></tr>
<tr><td>3 Unemployed</td><td>5 unemployed 12 months or more
6 unable to work due to long-term illness or disability</td></tr>
<tr><td>4 Pupil, student, further training, unpaid work experience</td><td>9 in education (at school, university, etc.) / student</td></tr>
<tr><td>5 In retirement or in early retirement or has given up business</td><td>7 retired</td></tr>
<tr><td>6 Permanently disabled or/and unfit to work</td><td>6 unable to work due to long-term illness or disability</td></tr>
<tr><td>8 Fulfilling domestic tasks and care</td><td>8 full time homemaker/ responsible for ordinary shopping and looking after the home</td></tr>
<tr><td>7 In compulsory military community or service
9 Other inactive person</td><td>10 other</td></tr>
</table></td>
</tr>
</table>

<table>
<tr><th></th><th>EU-SILC 2007</th><th>EQLS 2007</th><th>Common aggregation</th></tr>
<tr>
<td>Region of residence</td>
<td><table><tr><td>Region</td><td>DB040</td></tr></table>NUTS 2 digits
From 2008 operation onwards, it was agreed by the Working Group (meeting in June 2008) to use the classification NUTS-08 (to replace the former classification NUTS-03). No double reporting and no back-casting are required.</td>
<td>Classification NUTS 2
There exists a variable by country. For example:
P7ES (Spain) and P7FI (Finland)</td>
<td><table>
<tr><td>EU-SILC</td><td>EQLS</td></tr>
<tr><td>FI18 Etelä-Suomi
FI20 Åland</td><td>1 Southern Finland and Aland</td></tr>
<tr><td>FI19 Länsi-Suomi</td><td>2 Western Finland</td></tr>
<tr><td>FI13 Itä-Suomi</td><td>3 Eastern Finland</td></tr>
<tr><td>FI1A Pohjois-Suomi</td><td>4 Northern Finland</td></tr>
</table></td>
</tr>
<tr>
<td>Degree of urbanisation</td>
<td><table><tr><td>DEGREE OF URBANISATION</td><td>DB100</td></tr></table>1 densely populated area
2 intermediate area
3 thinly populated area

-Densely populated area: This is a contiguous set of local areas, each of which has a density superior to 500 inhabitants per square kilometers, where the total population for the set is at least 50,000 inhabitants.

-Intermediate area: This is a contiguous set of local areas, not belonging to a densely-populated area, each of which has a density superior to 100 inhabitants per square kilometers, and either with a total population for the set of at least 50,000 inhabitants or adjacent to a densely-populated area.

-Thinly-populated area: This is a contiguous set of local areas belonging neither to a densely-populated nor to an intermediate area</td>
<td>Q52 is provided by the respondent and the alternatives do not correspond to the definition. Variable DOMICIL<table><tr><td>Domicile, respondent's description</td><td>Q52</td></tr></table>1 The open countryside
2 A village/small town
3 A medium to large town
4 A city or city suburb</td>
<td><table>
<tr><td>EU-SILC</td><td>EQLS</td></tr>
<tr><td>1.Densely populated area</td><td>4.City or city suburb</td></tr>
<tr><td>2.Intermediate populated area</td><td>3.A medium to large town</td></tr>
<tr><td>3.Thinly populated area</td><td>1. The open countryside
2. A village/small town</td></tr>
</table></td>
</tr>
</table>

<table>
<tr><th></th><th>EU-SILC 2007</th><th>EQLS 2007</th><th>Common aggregation</th></tr>
<tr>
<td>Status in employment</td>
<td>Status in main employment
<table><tr><td>STATUS IN EMPLOYMENT</td><td>PL040</td></tr></table>
1 self-employed with employees
2 self-employed without employees
3 employee
4 family worker

This variable refers to the main job. If multiple jobs are held or were held, the main job should be the one with the greatest number of hours usually worked.</td>
<td>Question Q2 can distinguish between Employed and Self-employed
Question HH2D from household grid can show when respondent is a family worker
<table><tr><td>Current occupation</td><td>Q2</td></tr><tr><td>Activity status</td><td>HH2D</td></tr></table>
QUESTION Q2- SELF EMPLOYED
1. Farmer
2. Fisherman
3. Professional (lawyer, medical practitioner, accountant, architect etc.)
4. Owner of a shop, craftsmen, other self-employed person
5. Business proprietors, owner (full or partner) of a company
EMPLOYED
6. Employed professional (employed doctor, lawyer, accountant, architect)
7 General management, director or top management (managing directors, director general, other director)
8. Middle management, other management (department head, junior manager, teacher, technician)
9. Employed position, working mainly at a desk
10. Employed position, not at a desk but travelling (salesman, driver, etc.)
11. Employed position, not at a desk, but in a service job (hospital, restaurant, police, fireman, etc.)
12. Supervisor
13. Skilled manual worker
14. Other (unskilled) manual worker, servant</td>
<td><table>
<tr><th>EU-SILC</th><th>EQLS Q2</th><th>EQLS HH2D</th></tr>
<tr><td>1 self-employed with employees
2 self-employed without employees</td><td>1-5 Self-employed</td><td>1 at work as employee or employer/self-employed
2 employed, on child-care leave or other leave</td></tr>
<tr><td>3 employee</td><td>6-14 Employed</td><td></td></tr>
<tr><td>4 family worker</td><td></td><td>3 at work as relative assisting on family farm or business</td></tr>
</table></td>
</tr>
</table>

<table>
<tr><th></th><th>EU-SILC 2007</th><th>EQLS 2007</th><th>Common aggregation</th></tr>
<tr>
<td>Type of contract</td>
<td>Type of contract in the main job
This variable refers to the main job. If multiple jobs are held or were held, the main job should be the one with the greatest number of hours usually worked.
This question is addressed only to employees

1 permanent job/work contract of unlimited duration
2 temporary job/work contract of limited duration</td>
<td>Question Q4 can distinguish between permanent/temporary job/work contract.
Question HH2D from household grid can show when respondent has actually a paid work
<table>
<tr><td>Type of contract</td><td>Q4</td></tr>
<tr><td>Activity status</td><td>HH2D</td></tr>
</table>
1 On an unlimited permanent contract
2 On a fixed term contract of less than 12 months
3 On a fixed term contract of 12 months or more
4 On a temporary employment agency contract
5 On apprenticeship or other training scheme
6 Without a written contract
7 Other</td>
<td>
<table>
<tr><th>EU-SILC</th><th>EQLS Q4</th><th>EQLS HH2D</th></tr>
<tr><td>1 permanent job/work contract of unlimited duration</td><td>1 On an unlimited permanent contract</td><td>1 at work as employee or employer/self-employed
2 employed, on child-care leave or other leave</td></tr>
<tr><td>2 temporary job/work contract of limited duration</td><td>2 On a fixed term contract of less than 12 months
3 On a fixed term contract of 12 months or more
4 On a temporary employment agency contract
5 On apprenticeship or other training scheme</td><td></td></tr>
</table>
</td>
</tr>
<tr>
<td>Occupation in employment</td>
<td>PL050: Occupation (ISCO-88 (COM))

This variable refers to the main job (current main job for people at work or last main job for people do not have a job). If multiple jobs are held or were held, the main job should be the one with the greatest number of hours usually worked.</td>
<td>Question Q2 shows the occupation, but does not correspond to ISCO--88(COM)
Question HH2D from household grid can show when respondent has actually a paid work
<table>
<tr><td>Current occupation</td><td>Q2</td></tr>
<tr><td>Activity status</td><td>HH2D</td></tr>
</table>
QUESTION Q2
SELF EMPLOYED
1. Farmer
2. Fisherman
3. Professional (lawyer, medical practitioner, accountant, architect etc.)
4. Owner of a shop, craftsmen, other self-employed person
5. Business proprietors, owner (full or partner) of a company
EMPLOYED
6. Employed professional (employed doctor, lawyer, accountant, architect)
7 General management, director or top management (managing directors, director general, other director)
8. Middle management, other management (department head, junior manager, teacher, technician)
9. Employed position, working mainly at a desk
10. Employed position, not at a desk but travelling (salesman, driver, etc.)
11. Employed position, not at a desk, but in a</td>
<td>Not available</td>
</tr>
</table>

	EU-SILC 2007	EQLS 2007	Common aggregation
		service job (hospital, restaurant, police, fireman, etc.) 12. Supervisor 13. Skilled manual worker 14. Other (unskilled) manual worker, servant	
Economic sector in employment	The economic activity of the local unit of the main job for respondents who are currently at work. This variable refers to the main job. If multiple jobs are held, the main job should be the one with the greatest number of hours usually worked. Coded according to NACE Rev.1.1	Not available	Not available
Highest level of education completed	Highest ISCED level attained Educational attainment of a person is the highest level of an educational programme the person has successfully completed and the study field of this programme. The educational classification used is the International Standard Classification of Education (ISCED 1997) coded according to the seven ISCED-97 categories. 0 pre-primary education 1 primary education 2 lower secondary education 3 (upper) secondary education 4 post-secondary non tertiary education 5 first stage of tertiary education (not leading directly to an advanced research qualification) 6 second stage of tertiary education	Q49 corresponds to ISCED(1) 1 None education completed (ISCED 0) 2 Primary education (ISCED 1) 3 Lower secondary education (ISCED 2) 4 Upper secondary education (ISCED 3) 5 Post-secondary including pre-vocational or vocational education but not tertiary (ISCED 4) 6 Tertiary education – first level (ISCED 5) 7 Tertiary education – advanced level (ISCED 6) 8 (Don't know/no answer)	ISCED(1)

	EU-SILC 2007	EQLS 2007	Common aggregation	
Net monthly income of the household	It can be used HY020: Total disposable household income divided by 12 HY020 = HY010 – HY120G – HY130G – HY140G Where HY010 is TOTAL HOUSEHOLD GROSS INCOME HY120G is REGULAR TAXES ON WEALTH HY130G is REGULAR INTER-HOUSEHOLD CASH TRANSFER PAID HY140G is TAX ON INCOME AND SOCIAL CONTRIBUTIONS Another possibility is (HY020+ HY130G)/12	Q67. Please can you tell me how much your household's NET income per month is? If you don't know the exact figure, please give an estimate Q68 In case the respondent does not know the figure or want to provide it there is a scale with ranges.	EU-SILC	EQLS
			Less than €50	D
			€ 50 to €99	B
			€100 to €149	I
			€ 150 to €199	O
			€ 200 to €299	T
			€ 300 to €449	G
			€ 450 to €549	P
			€ 550 to €674	A
			€ 675 to € 899	F
			€ 900 to € 1.124	E
			€ 1.125 to € 1.349	Q
			€ 1.350 to € 1.574	H
			€ 1.575 to € 1.799	C
			€ 1.800 to €2.024	L
			€ 2.025 to €2.249	N
			€ 2.250 to € 2.699	R
			€ 2.700 to € 3.149	M
			€ 3.150 to € 3.599	S
			€ 3.600 to € 4.049	K

B. Not core social variables

<table>
<tr><th></th><th>EU-SILC 2007</th><th>EQLS 2007</th><th>Common aggregation</th></tr>
<tr><td>Tenure status of household</td><td><table><tr><td>Tenure Status</td><td>HH020</td></tr></table></td><td><table><tr><td>Which of the following best describes your accommodation?</td><td>Q16</td></tr></table></td><td><table><tr><th>EU-SILC</th><th>EQLS</th></tr><tr><td>1 Owner</td><td>1 Own without mortgage (i.e. without any loans)
2 Own with mortgage</td></tr><tr><td>2. Tenant or subtenant paying rent at prevailing or market rate</td><td>3 Tenant, paying rent to private landlord</td></tr><tr><td>3 Accommodation is rented at a reduced rate (lower price that the market price)</td><td>4 Tenant, paying rent in social/voluntary/municipal housing</td></tr><tr><td>4 accommodation is provided free</td><td>5 Accommodation is provided rent free</td></tr></table></td></tr>
<tr><td>Material deprivation: Ability to keep home adequately warm</td><td><table><tr><td>Ability to keep home adequately warm</td><td>HH050</td></tr></table></td><td><table><tr><td>For each of the following things on this card, can I just check whether your household can afford it if you want it?
Keeping your home adequately warm</td><td>Q19-1</td></tr></table></td><td><table><tr><th>EU-SILC</th><th>EQLS</th></tr><tr><td>1 Yes</td><td>1 Yes, can afford it</td></tr><tr><td>2 No</td><td>2 No, cannot afford it</td></tr></table></td></tr>
<tr><td>Material deprivation: Capacity to afford paying for one week annual holiday away from home</td><td><table><tr><td>Capacity to afford paying for one week annual holiday away from home</td><td>HS040</td></tr></table></td><td><table><tr><td>For each of the following things on this card, can I just check whether your household can afford it if you want it?
2. Paying for a week's annual holiday away from home (not staying with relatives)</td><td>Q19-2</td></tr></table></td><td><table><tr><th>EU-SILC</th><th>EQLS</th></tr><tr><td>1 Yes</td><td>1 Yes, can afford it</td></tr><tr><td>2 No</td><td>2 No, cannot afford it</td></tr></table></td></tr>
<tr><td>Material deprivation: Capacity to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day</td><td><table><tr><td>Capacity to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day</td><td>HS050</td></tr></table></td><td><table><tr><td>For each of the following things on this card, can I just check whether your household can afford it if you want it?
4. A meal with meat, chicken or fish every second day if you wanted it</td><td>Q19-4</td></tr></table></td><td><table><tr><th>EU-SILC</th><th>EQLS</th></tr><tr><td>1 Yes</td><td>1 Yes, can afford it</td></tr><tr><td>2 No</td><td>2 No, cannot afford it</td></tr></table></td></tr>
<tr><td>Ability to make ends meet</td><td><table><tr><td>Ability to make ends meet</td><td>HS120</td></tr></table></td><td><table><tr><td>Thinking of your household's total monthly income: is your household able to make ends meet....?</td><td>Q57</td></tr></table></td><td>With great difficulty
With difficulty
With some difficulty
Fairly easily
Easily
Very easily</td></tr>
</table>

<table>
<tr><th></th><th>EU-SILC 2007</th><th>EQLS 2007</th><th>Common aggregation</th></tr>
<tr><td>Arrears on mortgage or rent payments</td><td><table><tr><td>In the last twelve months, has the household been in arrears, i.e. has been unable to pay
on time due to financial difficulties for:
(a) rent
(b) mortgage repayment
for the main dwelling?</td><td>HS011</td></tr></table></td><td><table><tr><td>Has your household been in arrears at any time during the past 12 months, that is, unable to pay as scheduled any of the following?
(a) Rent or mortgage payments for accommodation</td><td>Q58-a</td></tr></table></td><td><table><tr><td>EU-SILC</td><td>EQLS</td></tr><tr><td>1 Yes, once
2 Yes, twice or more</td><td>1 Yes</td></tr><tr><td>2 No</td><td>2 No</td></tr></table></td></tr>
<tr><td>Arrears on utility bills</td><td><table><tr><td>In the last twelve months, has the household been in arrears, i.e. has been unable to pay
on time due to financial difficulties for utility bills (heating, electricity, gas, water, etc.)
for the main dwelling?</td><td>HS020</td></tr></table></td><td><table><tr><td>Has your household been in arrears at any time during the past 12 months, that is, unable to pay as scheduled any of the following?
(b) Utility bills, such as electricity, water, gas</td><td>Q58-b</td></tr></table></td><td><table><tr><td>EU-SILC</td><td>EQLS</td></tr><tr><td>1 Yes, once
2 Yes, twice or more</td><td>1 Yes</td></tr><tr><td>2 No</td><td>2 No</td></tr></table></td></tr>
<tr><td>Financial burden of the total housing cost</td><td><table><tr><td>Financial burden of the total housing cost</td><td>HS140</td></tr></table></td><td><table><tr><td>Is total housing cost a financial burden to the household?</td><td>Q59</td></tr></table></td><td>1 A heavy burden
2 Somewhat a burden
3 Not burden at all</td></tr>
<tr><td>Amenities in dwelling: lack of bath or shower.</td><td><table><tr><td>Is there a shower unit or a bathtub in your dwelling?</td><td>HH080</td></tr></table></td><td><table><tr><td>Do you have any of the following problems with your accommodation?
(e) Lack of bath or shower</td><td>Q17-e</td></tr></table></td><td><table><tr><td>EU-SILC</td><td>EQLS</td></tr><tr><td>1 Yes, for the sole use of the household
2 Yes, shared</td><td>1 No</td></tr><tr><td>3 No</td><td>2 Yes</td></tr></table></td></tr>
<tr><td>Amenities in dwelling Indoor flushing.</td><td><table><tr><td>Is there an indoor flushing toilet in your dwelling?</td><td>HH090</td></tr></table></td><td><table><tr><td>Do you have any of the following problems with your accommodation?
(d) Lack of indoor flushing toilet</td><td>Q17-d</td></tr></table></td><td><table><tr><td>EU-SILC</td><td>EQLS</td></tr><tr><td>1 Yes, for the sole use of the household
2 Yes, shared</td><td>1 No</td></tr><tr><td>3 No</td><td>2 Yes</td></tr></table></td></tr>
<tr><td>Problems with dwelling.
Noise</td><td><table><tr><td>Noise from neighbours or from the street</td><td>HS170</td></tr></table></td><td><table><tr><td>Please think about the area where you live now – I mean the immediate neighbourhood of your home. Do you have very many reasons, many reasons, a few reasons, or no reason at all to complain about each of the following problems?
(a) Noise</td><td>Q54-a</td></tr></table></td><td><table><tr><td>EU-SILC</td><td>EQLS</td></tr><tr><td>1 Yes</td><td>1 Very many reasons
2 Many reasons
3 A few reasons</td></tr><tr><td>2 No</td><td>4 No reasons at all</td></tr></table></td></tr>
</table>

	EU-SILC 2007		EQLS 2007		Common aggregation	
Problems with dwelling. Pollution, grime or other environmental problems	Pollution, grime or other environmental problems	HS180	Please think about the area where you live now – I mean the immediate neighbourhood of your home. Do you have very many reasons, many reasons, a few reasons, or no reason at all to complain about each of the following problems? (b) Air pollution (c) Lack of access to recreational or green areas (d) Water quality (f) Litter or rubbish in the street	Q54-b Q54-c Q54-d Q54-f	EU-SILC 1 Yes 2 No	EQLS (any variable) 1 Very many reasons 2 many reasons 3 A few reasons 4 No reasons at all
Problems with dwelling. Crime, violence or vandalism	Crime, violence or vandalism in the area	HS180	Please think about the area where you live now – I mean the immediate neighbourhood of your home. Do you have very many reasons, many reasons, a few reasons, or no reason at all to complain about each of the following problems? (e) Crime, violence or vandalism	Q54-e	EU-SILC 1 Yes 2 No	EQLS 1 Very many reasons 2 many reasons 3 A few reasons 4 No reasons at all
General health	General health	PH010	In general, would you say your health is …	Q43	1 very good 2 good 3 fair 4 bad 5 very bad	
Chronic (long-standing) illness or condition	Suffer from any a chronic (long-standing) illness or condition	PH020	Do you have any chronic (long-standing) physical or mental health problem, illness or disability?	Q44	Not Available –different filtering questions	
Limitation in activities because of health problems	Limitation in activities because of health problems	PH030	Are you hampered in your daily activities by this physical or mental health problem, illness or disability?	Q45	EU-SILC 1 Yes, strongly limited 2 Yes, limited 3 No, no limited	EQLS (any variable) 1 Yes, severely 2 Yes, to some extent 3 No

Annex 2-2 Coherence analysis: comparison confidence intervals for marginal distributions of common variables (EQLS-SILC 2007)

Gender

		EQLS	95% Confidence Interval		SILC	95% Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Male	48.4	44.9	51.9	48.4	47.5	49.3	ES	Male	48.9	45.1	52.8	49.0	48.6	49.5
	Female	51.6	48.1	55.1	51.6	50.7	52.5		Female	51.1	47.2	54.9	51.0	50.5	51.4
	N	1,002	100.0	100.0	20609	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

Age

		EQLS	95 Confidence Interval			95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper	SILC	Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	18-24	11.0	8.3	14.3	10.7	10.1	11.2	ES	<24	10.2	8.2	12.6	10.3	9.8	10.8
	25-34	15.5	12.8	18.5	15.6	14.9	16.2		25-34	20.5	17.3	24.0	20.8	20.0	21.7
	35-49	26.0	22.8	29.6	26.2	25.5	26.9		35-49	28.4	25.2	31.8	28.6	27.7	29.4
	50-64	26.7	23.5	30.2	27.0	26.2	27.8		50-64	20.5	17.6	23.8	20.4	19.7	21.1
	65+	20.8	18.1	23.8	20.6	20.1	21.2		65+	20.4	17.8	23.4	19.9	19.1	20.7
	N	1,002	100.0	100.0	20609	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

Country of birth

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Yes	98.4	97.1	99.1	96.7	96.3	97.0	ES	Yes	88.5	85.5	90.9	93.6	93.0	94.3
	No	1.6	.9	2.9	3.3	3.0	3.7		No	11.5	9.1	14.5	6.4	5.7	7.0
	N	1,002	100.0	100.0	20609	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

Country of citizenship

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Yes	99.3	98.5	99.7	98.2	98.0	98.5	ES	Yes	91.0	88.1	93.3	95.6	94.9	96.1
	No	.7	.3	1.5	1.8	1.5	2.0		No	9.0	6.7	11.9	4.4	3.9	5.1
	N	1,002	100.0	100.0	20609	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

De facto marital status (consensual union)

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Yes	69.9	66.2	73.2	65.1	64.1	66.0	ES	Yes	69.8	66.3	73.0	63.8	63.0	64.7
	No	30.1	26.8	33.8	34.9	34.0	35.9		No	30.2	27.0	33.7	36.2	35.3	37.0
	N	1,002	100.0	100.0	20608	100.0	100.0		N	992	100.0	100.0	27,820	100.0	100.0

Household size

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	1	21.5	18.4	24.9	23.1	22.2	24.0	ES	1	8.6	7.3	10.2	7.7	7.2	8.2
	2	34.9	31.7	38.3	40.1	39.2	41.0		2	20.9	18.7	23.4	25.2	24.2	26.2
	3	18.2	15.3	21.4	15.6	15.1	16.2		3	22.8	20.0	25.7	26.1	25.0	27.2
	4	16.3	13.5	19.6	13.4	12.8	13.9		4	33.0	29.3	36.9	31.1	29.9	32.4
	5 or more	9.1	5.9	14.6	7.8	7.2	8.5		5 or more	14.6	10.0	19.2	10.0	8.6	11.6
	N	1,002	100.0	100.0	20609	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

Household composition

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	No children under 18 in household	57.0	53.0	60.9	70.9	70.1	71.6	ES	No children under 18 in household	59.3	55.7	62.8	67.8	66.6	68.9
	Children under 18 present in household	43.0	39.1	47.0	29.1	28.4	29.9		Children under 18 present in household	40.7	37.2	44.3	32.2	31.1	33.4
	N	1,002	100.0	100.0	20609	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

FI NUTS 2 Region (or equivalent)

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval	
			Lower	Upper		Lower	Upper
% del total	Southern FI	50.2	48.2	52.2	49.8	48.9	50.7
	Western FI	25.5	24.2	26.8	25.8	25.0	26.6
	Eastern FI	12.7	11.1	14.6	12.6	12.1	13.2
	Northern FI	11.7	10.4	13.0	11.8	11.2	12.4
	N	100.0	100.0	100.0	20609	100.0	100.0

		EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper	SILC	Lower	Upper
ES	Andalucia	17.3	15.1	19.6	17.4	15.3	19.5
	Aragon	3.0	1.9	4.7	2.9	2.3	3.6
	Asturias	2.6	2.3	3.0	2.5	2.0	3.2
	Baleares	2.2	2.0	2.4	2.3	1.8	2.9
	Cantabria	1.3	1.0	1.7	1.3	1.0	1.7
	Castilla/Leon	5.9	5.0	7.1	5.8	4.8	6.9
	Castilla/La Mancha	4.2	3.2	5.6	4.4	3.5	5.3
	Cataluna	16.0	13.7	18.6	16.0	14.1	18.1
	Extremadura	2.4	2.2	2.6	2.4	1.9	3.0
	Galicia	6.5	4.5	9.3	6.4	5.4	7.6
	Madrid	13.6	11.1	16.6	13.6	11.7	15.5
	Murcia	2.9	2.3	3.8	3.0	2.3	3.8
	Navarra	1.4	.8	2.4	1.3	1.0	1.7
	Pais Vasco	5.0	3.6	6.8	4.9	4.0	5.9
	Rioja	.7	.7	.7	0.7	.5	.9
	Valencia	10.6	9.0	12.5	10.8	9.2	12.6
	Canarias	4.4	3.5	5.5	4.4	3.5	5.5
	N	1,015	100.0	100.0	27,856	100.0	100.0

Degree of urbanisation

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Densely populated area	16.8	12.5	22.2	27.5	26.6	28.3	ES	Densely populated area	25.8	22.0	30.0	52.7	50.8	54.7
	Intermediate populated area	26.0	21.3	31.3	16.4	15.7	17.1		Intermediate populated area	27.6	23.5	32.1	20.0	18.1	22.0
	Thinly populated area	57.2	51.9	62.4	56.2	55.2	57.1		Thinly populated area	46.6	42.4	50.9	27.3	25.6	29.1
	N	1,001	100.0	100.0	20609	100.0	100.0		N	1,014	100.0	100.0	27,856	100.0	100.0

Highest level of education

		ESS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Less than lower secondary education (ISCED 0-1)	20.2	18.8	21.6	19.1	18.5	19.8	ES	Less than lower secondary education (ISCED 0-1)	35.8	33.6	38.1	29.5	28.5	30.6
	Lower secondary education completed (ISCED 2)	14.4	13.1	15.8	10.4	9.8	10.9		Lower secondary education completed (ISCED 2)	21.0	19.2	22.9	22.7	21.8	23.7
	Upper secondary education completed (ISCED 3)	35.4	33.5	37.3	41.7	40.8	42.6		Upper secondary education completed (ISCED 3)	16.6	15.0	18.2	21.9	21.1	22.7
									Post-secondary non-tertiary education completed (ISCED 4)	8.7	7.4	10.1	.7	.6	.9
	Tertiary education completed (ISCED 5-6)	30.0	28.3	31.9	28.8	28.0	29.6		Tertiary education completed (ISCED 5-6)	18.0	16.2	20.0	25.1	24.1	26.2
	N	1,894	100.0	100.0	20502	100.0	100.0		N	1,870	100.0	100.0	26,128	100.0	100.0

Tenure status of household

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Owner	81.7	77.0	85.7	72.6	71.8	73.4	ES	Owner	81.6	78.0	84.7	84.2	83.1	85.2
	Payng rent at prevailing or market rate	9.3	6.8	12.7	10.5	9.9	11.2		Payng rent at prevailing or market rate	15.1	12.1	18.6	7.2	6.5	8.0
	Rented at reduced rate or free	8.9	7.7	10.1	16.8	16.0	17.6		Rented at reduced rate or free	3.3	1.7	4.2	8.6	7.7	9.8
	N	998	100.0	100.0	20609	100.0	100.0		N	1,009	100.0	100.0	27,856	100.0	100.0

Material deprivation 1: home adequately warm

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Yes, can afford if want	99.0	98.0	99.5	98.9	98.7	99.1	ES	Yes, can afford if want	87.7	84.6	90.2	92.4	91.6	93.2
	No, cannot afford it	1.0	.5	2.0	1.1	.9	1.3		No, cannot afford it	10.9	8.5	13.9	7.6	6.8	8.4
									[Don't know]	1.4	.7	2.6	0.0	.0	.0
	N	1,002	100.0	100.0	20554	100.0	100.0		N	1,015	100.0	100.0	27,848	100.0	100.0

Material deprivation 2: a week's annual holiday away from home

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Yes, can afford if want	84.9	82.2	87.3	82.7	82.0	83.4	ES	Yes, can afford if want	70.0	66.2	73.5	63.8	62.4	65.2
	No, cannot afford it	14.9	12.6	17.7	17.3	16.6	18.0		No, cannot afford it	28.1	24.5	31.9	36.2	34.8	37.6
	[Don't know]	.1	.0	.5	.0	.0	.0		[Don't know]	1.9	1.0	3.5	0.0	.0	.0
	N	1,002	100.0	100.0	20528	100.0	100.0		N	1,015	100.0	100.0	27,850	100.0	100.0

Material deprivation 3: A meal with meat, chicken or fish every second day

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes, can afford if want	98.7	97.6	99.3	97.0	96.6	97.3	ES	Yes, can afford if want	96.7	95.1	97.7	97.7	97.3	98.1
	No, cannot afford it	1.3	.7	2.4	3.0	2.7	3.4		No, cannot afford it	2.8	1.9	4.3	2.3	1.9	2.7
									[Don't know]	.5	.2	1.5	0.0	.0	.0
	N	1,002	100.0	100.0	20584	100.0	100.0		N	1,015	100.0	100.0	27,851	100.0	100.0

Ability to make ends meet

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Very easily	13.4	11.1	16.2	14.2	13.6	14.8	ES	Very easily	5.7	3.7	8.7	1.3	1.0	1.5
	Easily	32.9	29.7	36.2	26.8	26.0	27.6		Easily	26.0	22.5	29.8	15.0	14.1	16.0
	Fairly easily	33.9	30.8	37.1	35.0	34.1	35.9		Fairly easily	25.8	22.2	29.6	26.7	25.5	27.9
	With some difficulty	16.1	13.7	18.8	17.2	16.5	17.9		With some difficulty	29.6	25.8	33.8	30.6	29.4	31.8
	With difficulty or great difficulty	2.9	1.8	4.8	6.9	6.2	7.6		With difficulty	10.4	7.5	13.5	26.5	15.7	17.6
	[Don't know]	.8	.4	1.6					[Don't know]	2.6	1.6	4.3	0.0	9.1	10.8
	N	1,002	100.0	100.0	20527	100.0	100.0		N	1,015	100.0	100.0	27,835	100.0	100.0

Arrears on rent or mortgage payments

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	9.0	6.9	11.8	5.3	4.7	5.8	ES	Yes	6.2	4.6	8.3	6.6	5.7	7.7
	No	90.1	87.1	92.4	94.7	94.2	95.3		No	92.1	89.9	93.8	93.4	92.3	94.3
	[Don't know]	.9	.3	2.8					[Don't know]	1.7	1.0	2.9	0.0	.0	.0
	N	1,002	100.0	100.0	11909	100.0	100.0		N	1,015	100.0	100.0	9,705	100.0	100.0

Arrears on utility bills, such as electricity, water, gas

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	9.4	7.2	12.2	4.2	3.8	4.6	ES	Yes	8.0	6.0	10.7	3.9	3.4	4.4
	No	90.4	87.6	92.6	95.8	95.4	96.2		No	90.8	88.0	93.0	96.1	95.6	96.6
	[Don't know]	.2	.1	.9					[Don't know]	1.2	.6	2.2	0.0	.0	.0
	N	1,002	100.0	100.0	20538	100.0	100.0		N	1,015	100.0	100.0	27,737	100.0	100.0

Financial burden of the total housing cost

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes, a heavy burden	3.9	2.7	5.5	16.6	15.9	17.3	ES	Yes, a heavy burden	16.1	12.8	20.0	48.1	46.7	49.5
	Yes, somewhat a burden	34.3	31.0	37.8	56.2	55.3	57.1		Yes, somewhat a burden	34.9	30.8	39.3	48.8	47.4	50.1
	No burden at all	60.8	57.0	64.5	27.2	26.4	28.0		No burden at all	44.1	39.9	48.3	3.1	2.7	3.6
	[Don't know]	1.0	.4	2.3					[Don't know]	4.9	3.3	7.3	0.0	.0	.0
	N	1,002	100.0	100.0	20521	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

Amenities in dwelling: bath or shower

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	2.2	.9	5.4	1.5	1.3	1.7	ES	Yes	1.4	.8	2.5	0.3	.2	.4
	No	97.8	94.6	99.1	98.5	98.3	98.7		No	98.6	97.5	99.2	99.7	99.6	99.8
	N	1,002	100.0	100.0	20602	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

Amenities in dwelling: indoor flushing toilet

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	1.6	.6	4.4	1.0	.8	1.2	ES	Yes	.9	.4	1.9	0.3	.2	.4
	No	98.4	95.6	99.4	99.0	98.8	99.2		No	99.1	98.1	99.6	99.7	99.6	99.8
	N	1,002	100.0	100.0	20602	100.0	100.0		N	1,015	100.0	100.0	27,856	100.0	100.0

Problems with dwelling. Noise

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	25.6	22.1	29.5	16.3	15.6	17.0	ES	Yes	53.1	48.7	57.5	26.1	24.8	27.3
	No	74.4	70.5	77.9	83.7	83.0	84.4		No	46.9	42.5	51.3	73.9	72.7	75.2
	N	1,002	100.0	100.0	20587	100.0	100.0		N	1,015	100.0	100.0	27,848	100.0	100.0

Problems with dwelling. Air pollution, grime or other environmental problems

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	22.5	19.1	26.4	14.2	13.6	14.9	ES	Yes	48.8	43.9	53.8	16.3	15.2	17.5
	No	77.5	73.6	80.9	85.8	85.1	86.4		No	51.2	46.2	56.1	83.7	82.5	84.8
	N	1,002	100.0	100.0	20576	100.0	100.0		N	1,003	100.0	100.0	27,848	100.0	100.0

Problems with dwelling. Recreational or green areas

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	6.3	4.6	8.6	14.2	13.6	14.9	ES	Yes	46.1	41.8	50.6	16.3	15.2	17.5
	No	93.7	91.4	95.4	85.8	85.1	86.4		No	53.9	49.4	58.2	83.7	82.5	84.8
	N	998	100.0	100.0	20576	100.0	100.0		N	1,011	100.0	100.0	27,848	100.0	100.0

Problems with dwelling. Litter or rubbish in the street

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	28.5	25.2	32.0	14.2	13.6	14.9	ES	Yes	38.7	34.3	43.2	16.3	15.2	17.5
	No	71.5	68.0	74.8	85.8	85.1	86.4		No	61.3	56.8	65.7	83.7	82.5	84.8
	N	999	100.0	100.0	20576	100.0	100.0		N	1,001	100.0	100.0	27,848	100.0	100.0

Problems with dwelling. Crime or vandalism

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	30.3	26.4	34.4	13.1	12.4	13.7	ES	Yes	45.1	41.0	49.3	18.2	17.1	19.5
	No	69.7	65.6	73.6	86.9	86.3	87.6		No	54.9	50.7	59.0	81.8	80.5	82.9
	N	1,002	100.0	100.0	20585	100.0	100.0		N	1,008	100.0	100.0	27,847	100.0	100.0

General health status

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Very good	17.7	15.0	20.8	22.2	21.1	23.3	ES	Very good	23.3	20.1	26.9	15.5	14.6	16.4
	Good	49.1	45.6	52.7	43.7	42.4	45.0		Good	52.3	48.4	56.1	51.3	50.3	52.4
	Fair	25.2	22.4	28.1	24.5	23.3	25.7		Fair	17.5	14.7	20.7	21.3	20.6	22.1
	Bad or very bad	8.0	6.0	10.0	9.6	8.5	10.9		Bad or very bad	6.9	4.8	10.1	11.9	11.1	12.6
	N	1,002	100.0	100.0	9007	100.0	100.0		N	1,015	100.0	100.0	27,853	100.0	100.0

Long standing illness

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Yes	39.4	36.0	43.0	44.6	43.3	45.9	ES	Yes	15.6	13.1	18.6	25.7	24.8	26.5
	No	60.1	56.5	63.6	55.4	54.1	56.7		No	83.7	80.8	86.2	74.3	73.5	75.2
	[Refusal]	.5	.2	1.1					[Refusal]	.4	.1	1.0	0.0	.0	.0
									[Don't know]	.3	.0	1.9	0.0	.0	.0
	N	1,002	100.0	100.0	9008	100.0	100.0		N	1,015	100.0	100.0	27,852	100.0	100.0

Self-declared labour status

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	At work	54.4	50.3	58.4	53.9	53.2	54.7	ES	At work	49.4	45.6	53.2	51.9	52.1	54.0
	Unemployed	2.9	2.0	4.2	5.5	5.1	5.9		Unemployed	5.6	3.9	7.8	6.2	4.9	5.7
	In education	8.1	5.9	11.1	8.3	7.8	8.7		In education	6.5	4.6	9.1	7.1	5.7	6.6
	Retired	31.5	28.1	35.0	22.5	21.9	23.0		Retired	15.1	12.8	17.6	15.3	2.0	2.4
	Long term illness or disability	1.0	.5	1.9	6.0	5.5	6.5		Long term illness or disability	.9	.5	1.8	2.1	15.0	16.3
	Full time home maker	2.2	1.0	4.4	3.4	3.1	3.7		Full time home maker	22.6	18.5	27.6	17.5	17.2	18.3
	Other	.4	.1	1.0	0.5	0.4	0.6								
	N	1,002	100.0	100.0	21773	100.0	100.0	N	184	100.0	100.0	28,65	100.0	100.0	

Net monthly income of household

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
% FI	Less than 900€	11.2	8.5	14.8	7.6	7.0	8.1	ES	Less than 900€	26.6	22.1	31.6	14.4	13.1	14.7
	900-1800€	19.4	16.4	22.9	22.3	21.5	23.1		900-1800€	31.6	27.1	36.4	30.7	28.9	31.1
	1800-2700€	21.6	18.6	24.9	23.3	22.5	24.0		1800-2700€	26.5	21.9	31.8	25.9	24.2	26.3
	More than 2700€	47.8	42.8	52.8	46.9	46.1	47.6		More than 2700€	15.3	10.8	21.3	31.6	29.6	32.3
	N	673	100.0	100.0	100.0	100.0	100.0		N	571	100.0	100.0	28,656	100.0	100.0

Status in employment

		EQLS	95 Confidence Interval		SILC	95 Confidence Interval				EQLS	95 Confidence Interval			95 Confidence Interval	
			Lower	Upper		Lower	Upper				Lower	Upper	SILC	Lower	Upper
FI	Self-employed	13.8	10.3	18.1	14.0	13.4	14.7	ES	Self-employed	18.9	14.7	23.8	15.2	14.6	16.0
	Employed	85.0	80.6	88.6	85.6	85.0	86.3		Employed	81.1	76.2	85.3	83.6	82.8	84.3
	Family worker	1.2	.4	3.5	.3	.2	.5		Family worker	.0	.0	.0	1.2	1.0	1.3
	N	492	100.0	100.0	16,329	100.0	100.0		N	475	100.0	100.0	23,682	100.0	100.0

Annex 2-3 Analysis explanatory power of common variables: Rao-Scott tests results (EQLS, 2007)

Target variables		Subjective wellbeing (ES)				Subjective wellbeing (FI)			
Common variables		Overall life satisfaction	Recognition	Trust in the media	Trust in the government	Overall life satisfaction	Recognition	Trust in the media	Trust in the government
		q29	q28-6	q27-3	q27-5	q29	q28-6	q27-3	q27-5
Gender	Pearson	.286	.630	.676	.525	.164	.549	.459	.800
	Likelihood Ratio	.255	.628	.669	.522	.159	.547	.450	.793
Age	Pearson	.081	.150	**.010**	.115	.258	.231	.753	.031
	Likelihood Ratio	.070	.086	**.015**	.160	.175	.147	.707	**.011**
Country of birth	Pearson	.054	.079	.297	.163	**.002**	.969	.857	.671
	Likelihood Ratio	**.023**	.117	.223	.096	.100	.951	.669	.513
Country of citizenship	Pearson	.101	**.008**	.071	.104	.979	**.001**	**.045**	**.003**
	Likelihood Ratio	.055	**.015**	**.041**	.077	.929	.298	.232	.472
De facto marital status	Pearson	.054	**.014**	.101	.404	**.000**	**.017**	.581	.370
	Likelihood Ratio	.063	**.022**	.115	.437	**.000**	**.020**	.585	.389
Household type	Pearson	**.003**	.499	.798	.502	**.007**	.238	.782	.613
	Likelihood Ratio	**.003**	.493	.802	.496	**.006**	.220	.750	.532
NUTS 2 Region	Pearson	**.000**	**.000**	**.000**	**.000**	.432	**.044**	**.020**	.120
	Likelihood Ratio	**.000**	**.000**	**.000**	**.000**	.381	**.036**	**.015**	.148
Net monthly income of household	Pearson	**.003**	.213	**.026**	.129	**.000**	**.000**	**.022**	**.006**
	Likelihood Ratio	**.003**	.102	**.017**	.089	**.000**	**.000**	**.020**	**.008**
Degree of urbanisation	Pearson	.304	**.000**	.281	.509	.846	**.035**	.400	.854
	Likelihood Ratio	.302	**.000**	.184	.449	.815	**.018**	.370	.839
Highest level of education (ISCED)	Pearson	.084	.307	.136	**.017**	**.000**	**.000**	.227	.094
	Likelihood Ratio	.068	.169	.224	**.025**	**.005**	**.001**	.184	.091
Tenure status of household	Pearson	**.005**	.124	.266	.369	**.014**	.795	.804	.498
	Likelihood Ratio	**.027**	.206	.374	.356	**.037**	.655	.712	.465

Target variables		Subjective wellbeing (ES)				Subjective wellbeing (FI)			
Common variables		Overall life satisfaction	Recognition	Trust in the media	Trust in the government	Overall life satisfaction	Recognition	Trust in the media	Trust in the government
		q29	q28-6	q27-3	q27-5	q29	q28-6	q27-3	q27-5
Material deprivation1: home adequately warm	Pearson	**.000**	**.000**	**.001**	**.003**	.100	.367	.604	.828
	Likelihood Ratio	**.001**	**.000**	**.046**	**.046**	.459	.338	.640	.760
Material deprivat ion 2:Paying for a week's annual holiday away from home (not staying with relatives)	Pearson	**.000**	**.000**	**.007**	.633	.070	.568	.110	.065
	Likelihood Ratio	**.000**	**.000**	**.005**	.543	.137	.571	.169	.137
Material deprivation 3: A meal with meat, chicken or fish every second day i	Pearson	**.000**	**.002**	**.000**	**.000**	**.000**	.955	.383	.154
	Likelihood Ratio	**.045**	.233	**.040**	**.011**	**.030**	.941	.533	.231
Ability to make ends meet	Pearson	**.000**	**.000**	.192	**.000**	**.000**	**.000**	**.000**	**.001**
	Likelihood Ratio	**.000**	**.000**	.099	**.001**	**.000**	**.000**	**.001**	**.000**
Arrears on rent or mortgage payments for accommodation	Pearson	.341	.622	.266	.251	.362	**.044**	.805	.073
	Likelihood Ratio	.376	.375	.384	.414	.421	.064	.719	.194
Arrears on utility bills, such as electricity, water, gas	Pearson	.133	.523	.580	.682	.116	**.000**	.801	.289
	Likelihood Ratio	.124	.429	.538	.657	.390	**.000**	.787	.567
Financial burden of the total housing cost	Pearson	.405	.342	**.004**	**.015**	**.000**	.330	**.006**	**.002**
	Likelihood Ratio	.538	.475	**.007**	**.014**	**.002**	.317	**.017**	**.027**
Amenities: Lack of indoor flushing toilet	Pearson	**.012**	.898	**.040**	**.010**	.897	.569	.356	.787
	Likelihood Ratio	**.043**	.774	.092	.070	.807	.725	.453	.744
Amenities: Lack of bath or shower	Pearson	**.000**	.860	.149	**.001**	.523	.173	.477	.805
	Likelihood Ratio	**.011**	.807	.183	**.019**	.426	.562	.502	.767
General health status	Pearson	**.000**	.078	**.018**	**.000**	**.000**	**.000**	**.048**	**.008**
	Likelihood Ratio	**.000**	.164	**.037**	**.004**	**.000**	**.000**	.080	**.032**
Long-standing health problem	Pearson	**.001**	.441	.205	.223	**.000**	**.000**	**.034**	.485
	Likelihood Ratio	**.031**	.469	.512	.291	**.000**	**.000**	.083	.547
Limitations in daily activities due to physical or mental health problem	Pearson	.091	.407	.103	.875	**.000**	**.021**	.404	.478
	Likelihood Ratio	**.041**	.445	.288	.858	**.001**	**.047**	.381	.507
Self-declared labour status	Pearson	**.000**	**.000**	**.050**	.285	**.001**	**.015**	.314	**.002**

Target variables / Common variables		Subjective wellbeing (ES)				Subjective wellbeing (FI)			
		Overall life satisfaction	Recognition	Trust in the media	Trust in the government	Overall life satisfaction	Recognition	Trust in the media	Trust in the government
		q29	q28-6	q27-3	q27-5	q29	q28-6	q27-3	q27-5
	Likelihood Ratio	**.002**	**.005**	.081	.227	**.017**	**.026**	.495	**.010**
Problems with dwelling. Noise	Pearson	**.014**	**.000**	.114	.845	.063	.180	.287	.090
	Likelihood Ratio	**.012**	**.000**	.096	.844	.068	.091	.166	.069
Problems with dwelling. Air pollution	Pearson	.052	**.000**	.239	.370	.577	.105	.171	.607
	Likelihood Ratio	.050	**.000**	.214	.343	.527	.103	.134	.510
Problems with dwelling. Recreational or green areas	Pearson	.378	**.008**	**.017**	.555	.071	.258	.315	.665
	Likelihood Ratio	.370	**.008**	**.012**	.551	.282	.318	.354	.621
Problems with dwelling. Water quality	Pearson	.675	**.000**	**.040**	.231	.070	.286	.823	.606
	Likelihood Ratio	.669	**.000**	**.041**	.224	.081	.317	.801	.445
Problems with dwelling. Crime or vandalism	Pearson	**.000**	**.011**	**.003**	.258	.226	.109	.344	**.033**
	Likelihood Ratio	**.000**	**.011**	**.002**	.252	.200	.073	.299	**.016**
Problems with dwelling. Litter or rubbish in the street	Pearson	**.001**	**.000**	**.002**	.438	.293	**.033**	.540	.240
	Likelihood Ratio	**.001**	**.000**	**.002**	.439	.184	**.017**	.455	.256
Status in employment	Pearson	.541	.539	.620	.552	**.021**	.375	.574	.747
	Likelihood Ratio	.389	.431	.672	.518	**.025**	.415	.442	.681

3

Case study 2: Wage and labour statistics

3 Case study 2: Wage and labour statistics

3.1 Background

There is an important policy need to analyse together labour market information and employment-related income. Within the European Statistical System (ESS) there are two key social surveys that address these topics: EU-SILC (European Statistics on Income and Living Conditions) and LFS (Labour Force Survey). On the one hand, EU-SILC is the reference source at EU level for the collection of extensive income statistics, including wage information for employees. On the other hand, LFS collects a large range of variables relevant for labour market analysis and has a larger sample size that can improve the precision of estimates for specific groups and domains.

In order to provide joint information on these two aspects, from 2009 onwards, LFS has been collecting wage deciles. The exercise aims to test the use of alternative model based techniques for matching wage information from EU-SILC into LFS. It also provides a good opportunity to assess the quality of the data on wage deciles currently collected via the LFS. Therefore, a second case study for the statistical matching exercise had a two-fold objective:

Box 3-1 Objectives

Objective 1 — Analyse the coherence between wage statistics based on currently collected LFS wage deciles and EU-SILC based estimates. This comparative overview of LFS coherence with EU-SILC shall provide important insights on the quality of the information collected in LFS.

Objective 2 — Assess the quality of wage statistics obtained through statistical matching in combination with variables collected in LFS.

The exercise and results presented are based on the analysis of data for seven countries: Greece, Spain, France, Austria, Poland, Portugal and Slovakia. Section 2 follows the main implementation steps[19] of matching highlighting the main results in relation to the two objectives. Section 3 summarises the main conclusions and recommendations for the application of statistical matching techniques in this pilot study.

3.2 Statistical matching: methodology and results

3.2.1 Harmonisation and reconciliation of sources

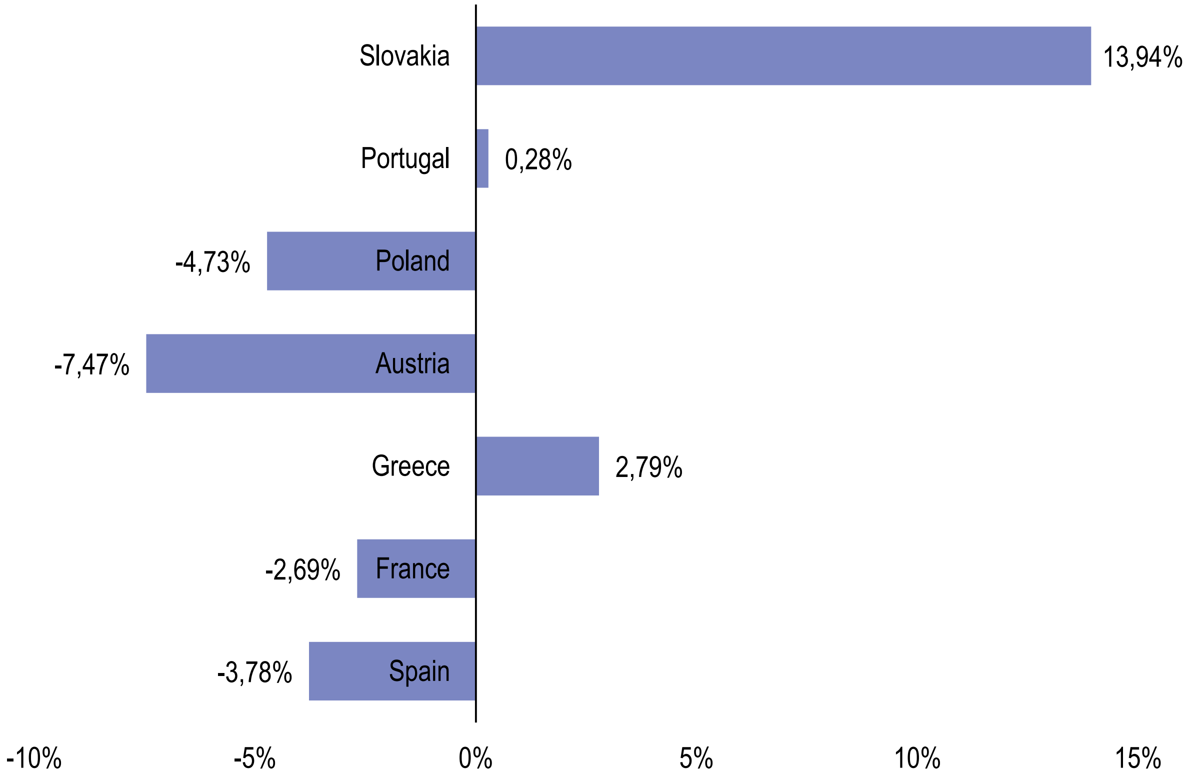
The two data sources — EU-SILC as donor and LFS as recipient — share a large common set of variables consistent in terms of definitions, classifications and marginal and joint distributions. Still, we identified two main sources of possible inconsistencies: the impossibility to use a common set of criteria to identify the target population (self-declared activity status versus ILO status), differences in wage concepts (gross versus net wages and current versus previous calendar year).

[19] See Chapter 1

a. Target population: difference in employment definition

The employment definition, used to define the target population (employees) from whom data on wages is collected, differs between the two data sources: in EU-SILC the self-declared activity status is used, while in the LFS the target population of employees is selected based on the ILO (International Labour Office) status[20]. The solution adopted is to define the population on a common basis by using the self-declared activity status (collected in both surveys). In Figure 3-1 we note that after applying the same definition of population the differences are not significant with two exceptions: (1) for Austria the estimated population in EU-SILC is 7.47% lower compared to LFS[21] (14% when the ILO concept was used for LFS), (2) for Slovakia, the selected population is 13.94% larger in EU-SILC than in the LFS (the difference was 11% when the ILO concept was used for LFS). For most countries (except EL and SK) the use of a harmonised concept for the definition of employees (based on the self-declared activity status) results in better aligned target populations.

Figure 3-1 Relative difference in size of target population (employees) between SILC and LFS based on the self-declared activity status



b. Wage concept: gross versus net and reference period

[20] http://epp.eurostat.ec.europa.eu/portal/page/portal/employment_unemployment_lfs/methodology/definitions

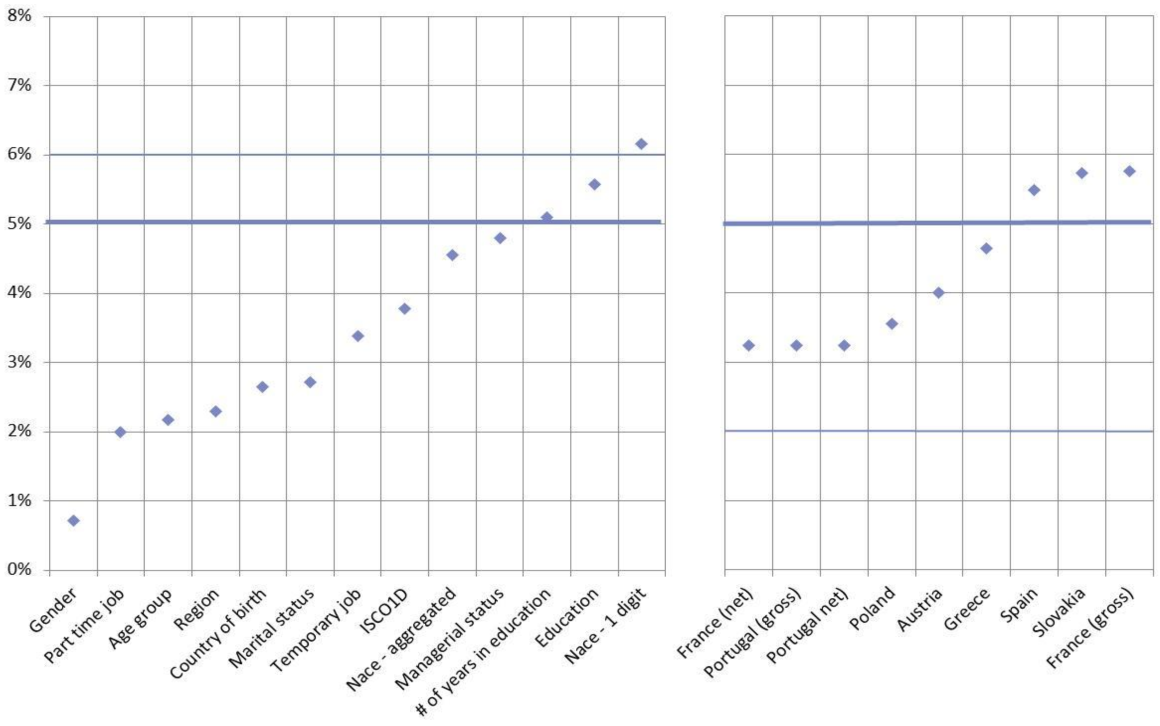
[21] In addition given that the wage information is filtered by the ILO status when we align the target population we distort the distribution of wage deciles by cutting out 40% of the first decile

The concept of current wage is slightly different in the two data sources and the main difference refers to the net/gross distinction. EU-SILC collects basically the current gross monthly earnings for employees while, in LFS, the variable is collected as ‘net’ (except for Spain). In addition, the current wage in EU-SILC is collected by a limited number of countries (in our case EL, ES, AT). For countries not collecting the current wage in EU-SILC (FR, PL, PT, SK), the yearly employee income was used, which raises other differences in comparison with the LFS concept: (1) the reference period is the previous calendar year and (2) it includes income from both main and secondary jobs.

c. Comparison of distributions for common variables

On the basis of the selected target population (employees), the consistency of the marginal distributions of common variables is analysed. The Hellinger distance[22] metric (HD) has been applied as a yardstick of similarity of distributions for all common variables (in EU-SILC and LFS) used in the matching process. Table 3-1 presents the HD values by ascending order of average across countries (rows) and across common variables (columns). Given the limitations related to conceptual differences, we note that although the range is large, the variables show, on average, a good consistency[23] (from 2% to 5%) for all countries analysed. Calibration techniques applied may explain an almost perfect similarity for some variables (e.g. age group, gender) and may induce a smaller similarity for others, but without affecting substantially their coherence.

Figure 3-2 The average Hellinger distance by main common variables and by country, in ascending order



[22] See Chapter 1 for details

[23] A rule of thumb often occurring in the literature considers two distributions as close if the Hellinger distance is not greater the 5%

In order to improve the consistency, we applied some aggregations. For instance, we merged some activities (NACE — 1 digit) into broader activity groups. Also, some variables — like tenure with employer –are eliminated from further analysis due to their lack of harmonisation and/or consistency. The variable 'number of years since educational level' was used in the matching algorithm instead of the 'actual work experience' for which no harmonised measurement can be defined between the two surveys.

Table 3-1 Hellinger distance values (%) by country and common variables, in ascending order of average across countries (columns) and common variables (countries)

Variable	France (net)	Portugal (gross)	Portugal (net)	Poland	Austria	Greece	Spain	Slovakia	France (gross)	Average
Gender	0.60	0.60	0.60	0.80	0.10	1.10	0.90	1.20	0.60	**0.70**
Part time job	1.00	1.00	1.00	3.10	1.30	3.60	3.90	2.10	1.00	**2.00**
Age group	2.60	2.60	2.60	1.40	3.10	0.90	2.20	2.20	2.10	**2.20**
Region	1.50	1.50	1.50	3.90	1.70	2.70	1.90	1.80	4.30	**2.30**
Country of birth	1.70	1.70	1.70	0.20	1.40	3.40	9.90	2.30	1.70	**2.60**
Marital status	4.50	4.50	4.50	0.40	3.70	1.80	0.70	3.60	0.90	**2.70**
Temp. job	0.50	0.50	0.50	0.20	2.10	11.40	2.40	11.20	1.90	**3.40**
ISCO 1digit	2.70	2.70	2.70	1.80	3.90	2.50	6.90	8.00	2.70	**3.80**
NACE agg.	3.10	3.10	3.10	1.70	2.20	4.30	6.40	7.80	9.30	**4.60**
Supervisory position	1.70	1.70	1.70	1.00	12.50	5.20	7.20	2.40	9.80	**4.80**
Proxy tenure	3.40	3.40	3.40	6.80	5.50	5.30	4.70	4.80	8.70	**5.10**
Education	1.40	1.40	1.40	17.10	3.60	5.90	7.20	10.10	2.10	**5.60**
NACE2	3.80	3.80	3.80	2.80	3.00	5.50	8.50	8.00	16.50	**6.20**
# of worked hours	17.10	17.10	17.10	8.70	12.00	11.40	14.20	15.00	19.00	**14.60**
Average	**3.30**	**3.30**	**3.30**	**3.60**	**4.00**	**4.60**	**5.50**	**5.70**	**5.80**	

3.2.2 Analysis of the explanatory power for common variables

In the second stage, multivariate analysis and modelling techniques were applied for the selection of matching variables. In general, all common variables show a high predictive power for the individual's earning capacity. Therefore, an Ordinary Least Square regression with stepwise selection was applied to select those characteristics that affect most the individual's earning capacity. Because truncation[24], skewness and rounding are important features of wage, we also applied a logarithmic transformation of wage in order to approximate normality.

The R-square varies between 0.65 and 0.75 according to the country, number of covariates included and stratification variables (some key variables were tested in order to separate the population within sub-groups and to allow imputation only within these sub-groups). In the

[24] As the sample is left truncated and wages are only available for people in employment, the coefficients can be biased. One further step would be to consider, namely a two stage regression to be implemented in the imputation procedures. In a first stage, the probability as an individual being employee is predicted. In a second stage, the wage is modelled using only those individuals which were predicted as employees in the first stage.

end, the stratification based on part-time/full-time workers was kept in order to control for important differentials related to the hours worked and focus on explaining differences in average earnings. Some further checks were done for selected countries[25] and additional interaction effects were included to improve the estimates, especially for specific sub-groups. For instance, we noted that low education has very strong significant negative effects but in some activity sectors and occupations these relations do not hold. The set[26] of common variables finally selected for imputation is:

- basic socio-demographic variables (age, gender, country of birth, education attainment level, marital status);
- region of residence;
- characteristics of the main job (occupation, economic activity, full-time or part-time status, temporary job, supervisory position)
- work experience (proxy used: number of years since educational level was attained).

3.2.3 Matching methods

We tested several imputation methods[27]: hot deck, regression based methods, predictive mean matching method and probabilistic decision algorithms. This last approach allocates LFS individuals into wage deciles through a probabilistic decisional tree based on the conditional probability that an individual is in a specific decile. These conditional probabilities are produced based on a logistic regression performed in EU-SILC.

Because imputation approaches have usually limited ability to recreate individual level values, results are assessed in terms of preservation of important data distribution aspects and multivariable relationships (Rubin 1996). Therefore, to assess the robustness of different methods applied, we compare the extent to which the observed distributions in the donor (EU-SILC) are preserved in the recipient (LFS) files. Hellinger distances are used again to measure the level of similarity of the joint distributions of wage deciles with key variables. The mixed methods[28] perform the best (see Annex III-3). This is because they use a more comprehensive model where several interactions are included and stratification by part time and full time employees is applied.

3.2.4 Results and quality evaluation

When assessing results based on matched datasets, the final aim of the analysis should be considered. Thus, results have to be interpreted in relation to the two-fold objective of the exercise.

Three main criteria were considered throughout the analysis:

[25] A model diagnostics analysis was performed after each model tested and outliers were excluded in order to reduce their effect on the regression parameters. No substantial effects on the final results were detected.

[26] Table 1 in the end of the chapter shows as an example the model used for Spain, 2009.

[27] See Chapter 1 for details.

[28] The predictive mean matching method was used in two main stages (1) estimates wage on both surveys based on the model coefficients obtained in EU-SILC and (2) 'the closest' real donor from EU-SILC, calculated based on a distance measure between the model based wage estimates in the two surveys, is imputed in LFS . See Chapter 1 for details.

(1) the consistency of joint distributions (of wage deciles with matching variables) among EU-SILC observed, LFS imputed and LFS observed;

1. a) The comparison between EU-SILC observed and LFS observed helps for checking the coherence of common variables. In this particular case study, it helps also to assess the quality of wage information collected in LFS with EU-SILC as a benchmark *(objective 1);*

1. b) The comparison between EU-SILC observed and LFS imputed serves as a quality criterion of matching *(objective 2);*

1. c) The comparison between LFS observed and LFS imputed helps to compare how matching performs in comparison with collected information in LFS. However, in order to draw conclusions it is essential the concurrent comparison of the three types of distribution and the premise of using EU-SILC as a benchmark.

(2) the consistency of different parameters such as totals, means and more complex distributional parameters (objective2);

(3) test the CIA29 for specific target variables: wage deciles and LFS variables not collected in EU-SILC (objective2).

a. Objective 1 — assess the quality of wage information in LFS with EU-SILC as benchmark

In order to assess the quality of wage deciles collected in LFS, the cross-distributions of LFS wage decile with the main demographic variables were compared to:

- cross-distributions based on observed EU-SILC wage information (horizontal axis in Figure 3-3) and
- cross-distributions based on imputed wages from the matching exercise (vertical axis in Figure 3-4).

Results show two main clusters of countries: Spain, France and Austria score very well for most of the variables analysed while for Greece, Poland, Portugal and Slovakia we have large inconsistencies. The average ‘dissimilarity’ of wage statistics between LFS and EU-SILC is very high mainly due to distorted wage decile distribution. We can observe that the two types of ‘dissimilarity’ are very highly correlated as estimates based on matching follow the same trend as EU-SILC observed. However, we have a slightly higher similarity between LFS observed and LFS imputed as we can control for differences in the distributions of the main demographic variables.

Indeed, the most severe problem for LFS wage deciles proved to be the use of predefined wage bands (countries in the upper right corner) instead of collecting the wage and calculating the deciles afterwards. An erroneous approximation of cut-off points leads to distorted[30] wage deciles distribution in LFS.

[29] Conditional independence assumption means that the measures of association between relevant labour variables collected only in LFS and the variable wage (decile) is assumed to be 0, conditional on the common variables used in the imputation process.

[30] The target population is not equally distributed among the 10 intervals.

We used data for Greece to illustrate the impact of using misleading cut-off points. Thus, we applied the predefined LFS cut-off points (from the questionnaire) to EU-SILC observed and imputed wages in LFS. Figure 3-5 shows a good consistency of wage decile distributions among EU-SILC observed, LFS imputed and LFS observed, given similar thresholds. Thus, the last column shows the wage distribution according to LFS data collection and the thresholds used in the questionnaire. We note that the collected LFS wage decile distribution is very distorted and the population is not equally distributed in deciles. The first/ middle column shows the wage decile distribution based on EU-SILC observed / LFS imputed wage but using the pre-defined cut-off points (used in the LFS questionnaire) instead of calculating them. We can see that both distributions remain distorted and follow the same pattern as LFS collected distribution. This also highlights that, matching functions well as it provides similar wage distribution no matter how cut-off points are fixed.

Figure 3-3 Average similarity for joint distributions of wage deciles with main socio-demographical variables, by country

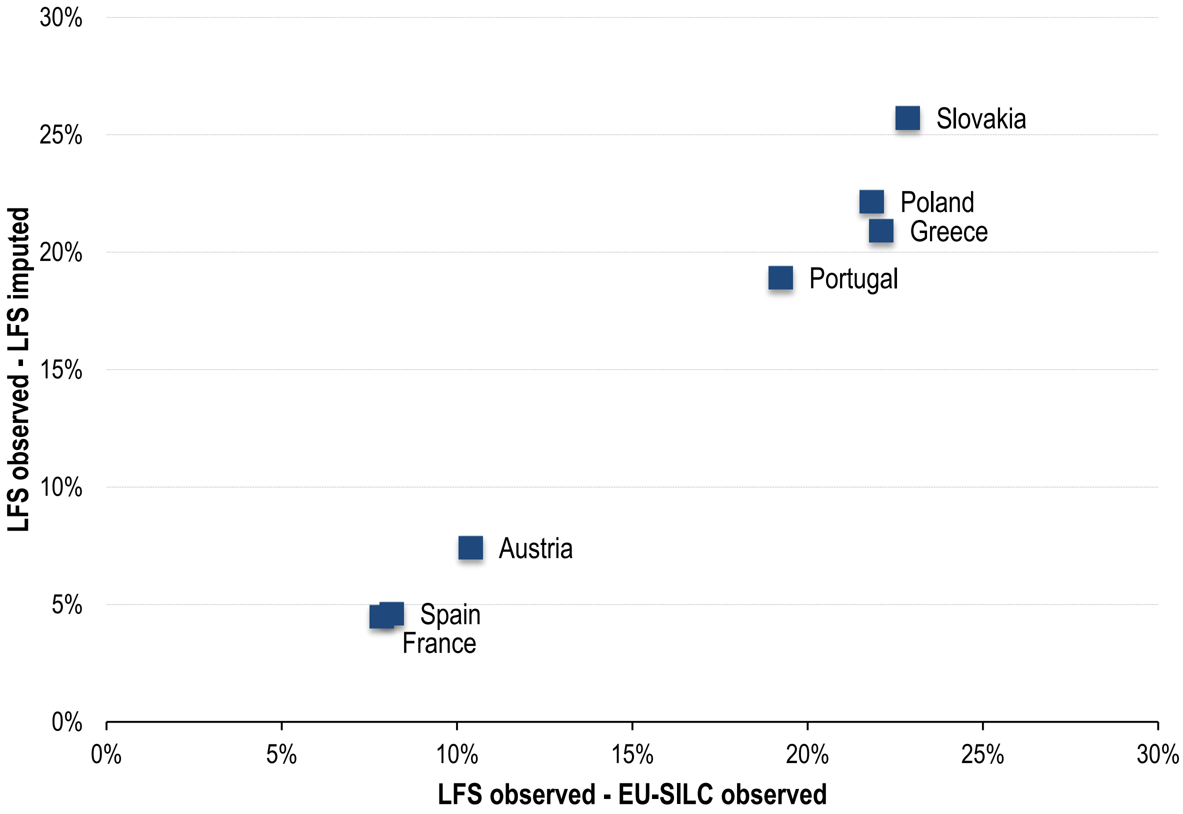
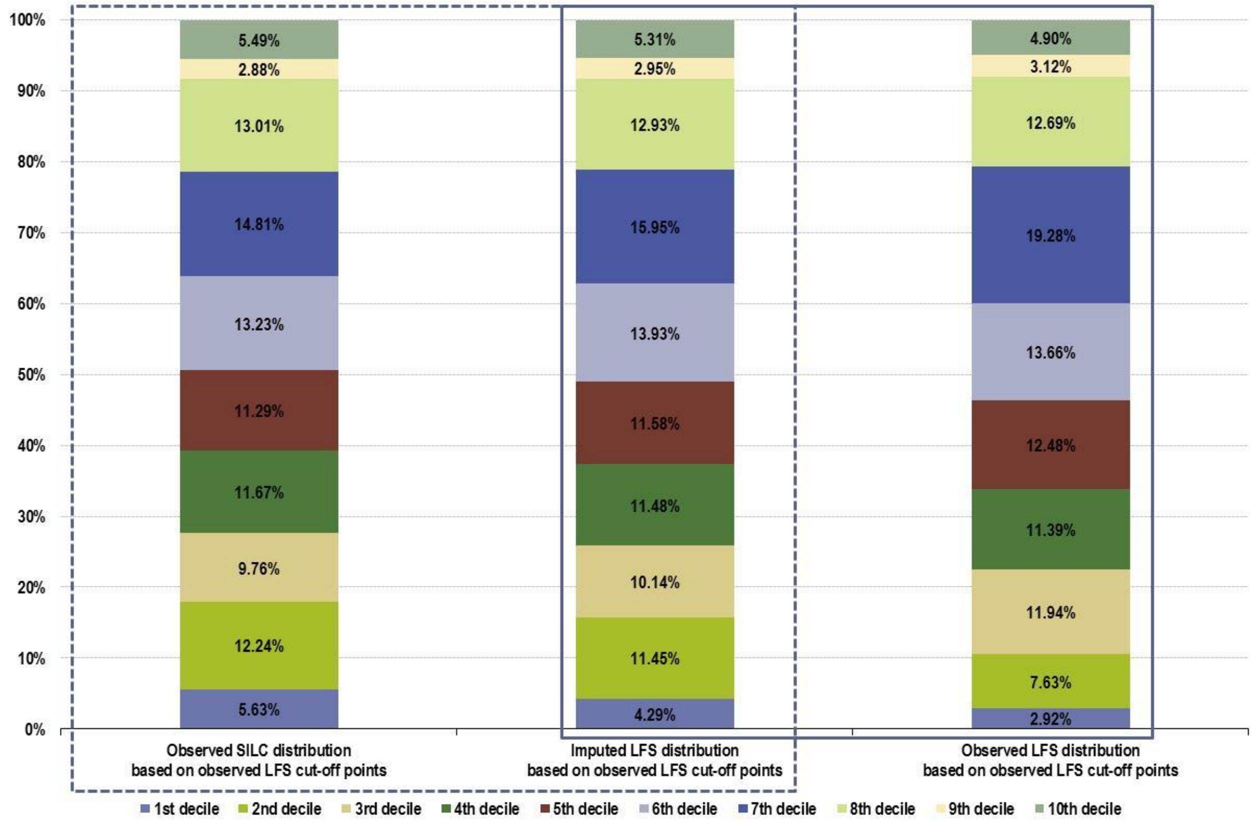


Figure 3-4: Impact on predefined cut-off points on wage decile distributions, Greece 2009

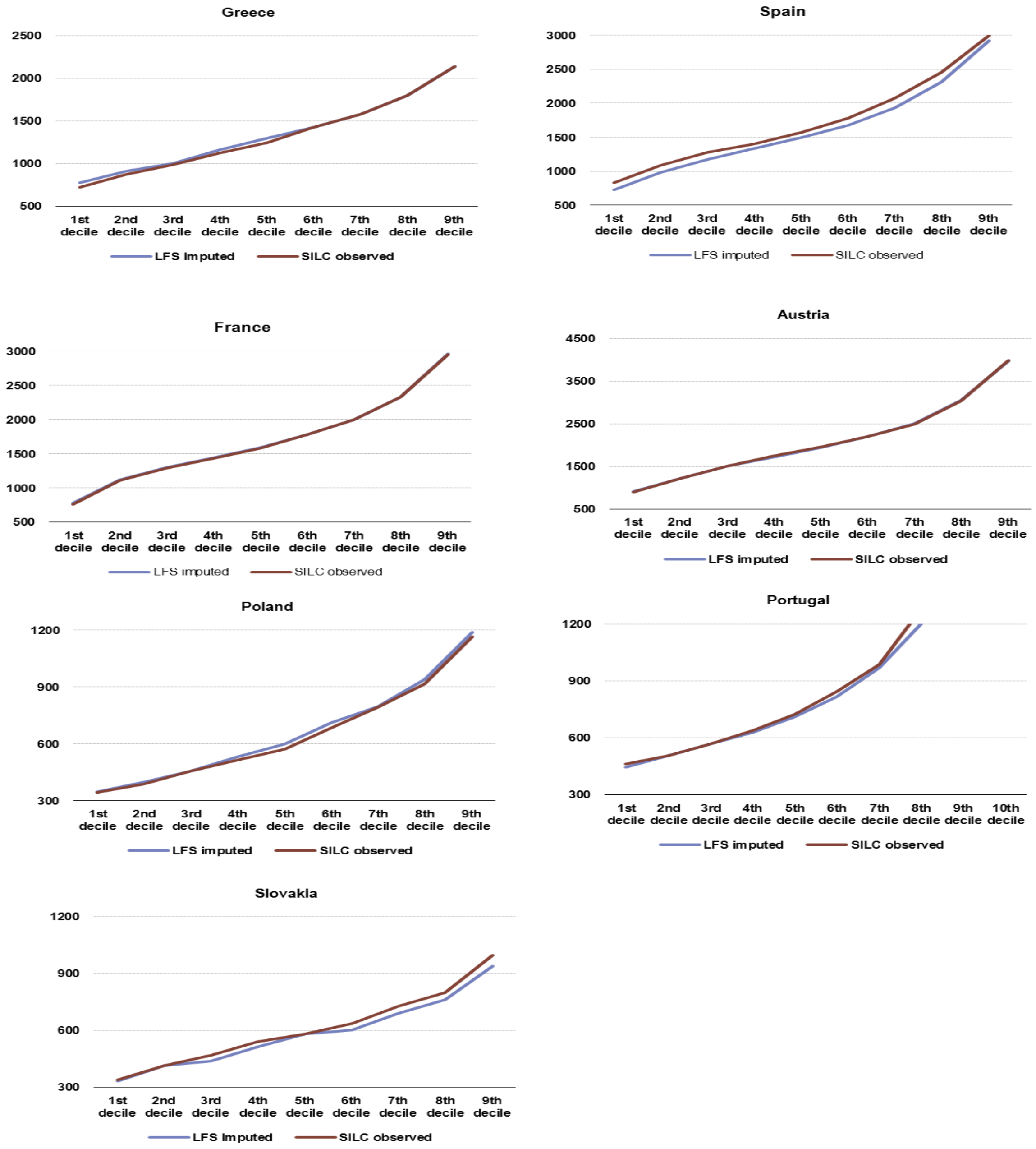


b. Objective 2 — assess the quality of LFS wage statistics obtained through matching

To assess the quality of results obtained through statistical matching we refer to two main criteria:

- Preservation of distributions and main parameters between the donor and the recipient;
- Capture the real joint distributions and correlations for variables not collected together.

Figure 3-5: The cut-off points for wage deciles



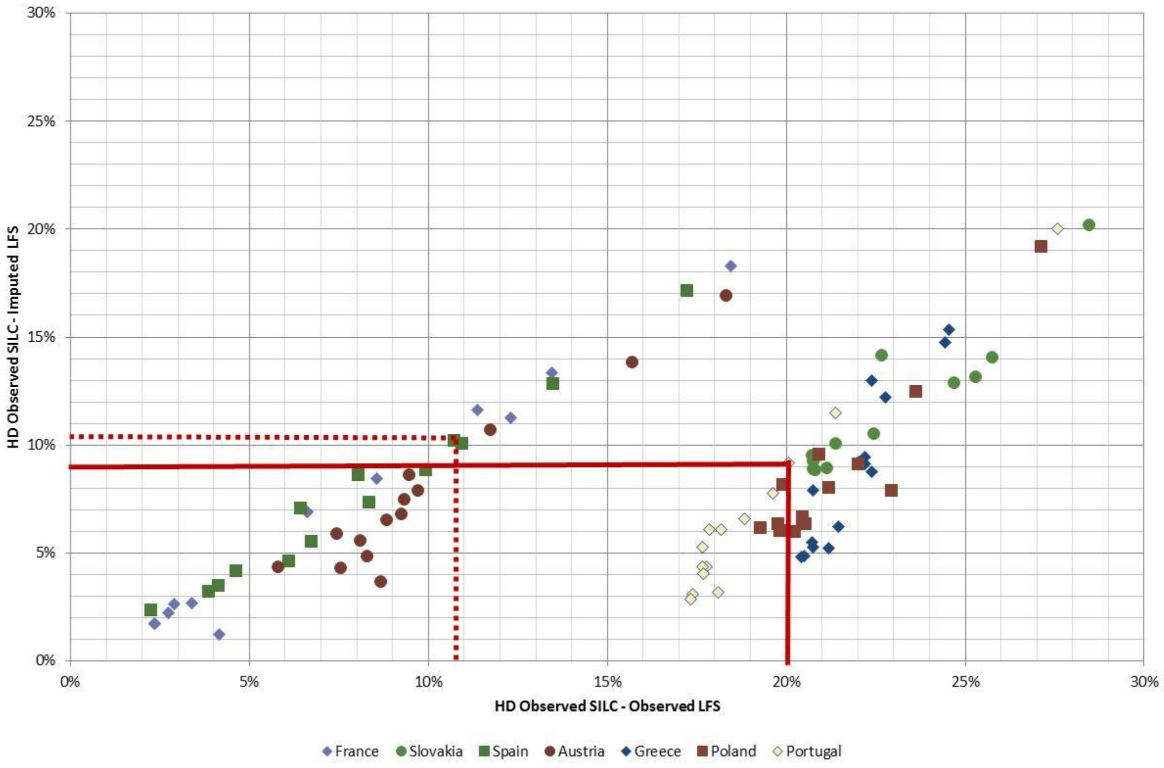
We did an in-depth analysis of the imputed wage information. In general, we note that the distributional parameters for the wage variable (e.g. means, deciles), as well as its joint distribution with matching variables, are usually consistent between the donor (EU-SILC observed) and the recipient (LFS imputed). For instance, Figure 3-5 compares the cut-off points for wage deciles between EU-SILC observed (blue line) and LFS observed (red line).

Using EU-SILC wage statistics as a benchmark, Figure 3-6 illustrates how the results obtained with matching perform in comparison with the collected wage deciles in LFS. Thus, only one criterion is considered here for comparison, namely the coherence with EU-SILC measured with the Hellinger distance. There are two main groups of countries:

- Spain, France and Austria with similar results both from matching and data collection. For instance in Spain, the joint LFS distribution of wage decile with industry has the same similarity with its corresponding EU-SILC observed distribution, no matter if we use observed LFS data (10.94%) or imputed LFS data (10.09%).

- Greece, Poland, Portugal and Slovakia with lower "similarity" for the wage deciles collected in LFS (mainly due to pre-defined thresholds). For instance in Portugal, the the Hellinger distance for the joint LFS distribution of wage decile with industry based on observed LFS data (20.07%) is two times larger than the joint LFS distribution based on imputed LFS data (9.17%).

Figure 3-6: Similarity of joint distributions: comparing EU-SILC with LFS observed/imputed wage data

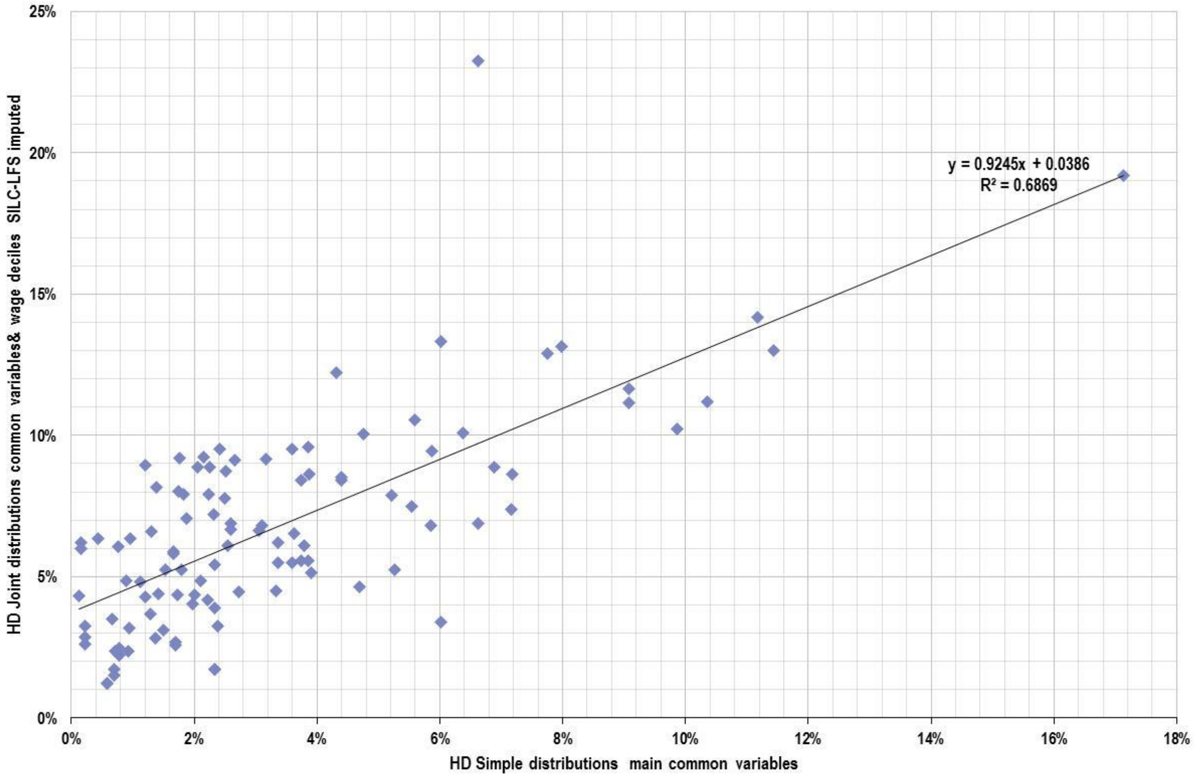


Specific matching methods[31] proved to be more robust and it is also important to control for differences in demographic structures between the two sources. Figure 3-7 captures the relationship between two pairs of distributions:

- on the horizontal axis we have the HD that measure the similarity EU-SILC-LFS for simple distributions of the main common variables used in matching;
- on the vertical axis we have the HD that measure the similarity of joint distributions of common variables with wage deciles.

The graph illustrates that there is a strong relation between the two measures. Hence, the results of matching are strongly dependent on the coherence of the common variables. Even small inconsistencies in demographic variables tend to inflate the dissimilarity indexes (HD) when wage deciles are crossed with two or more dimensions.

Figure 3-7: Impact of discrepancies in the distribution of main common variables on matching results



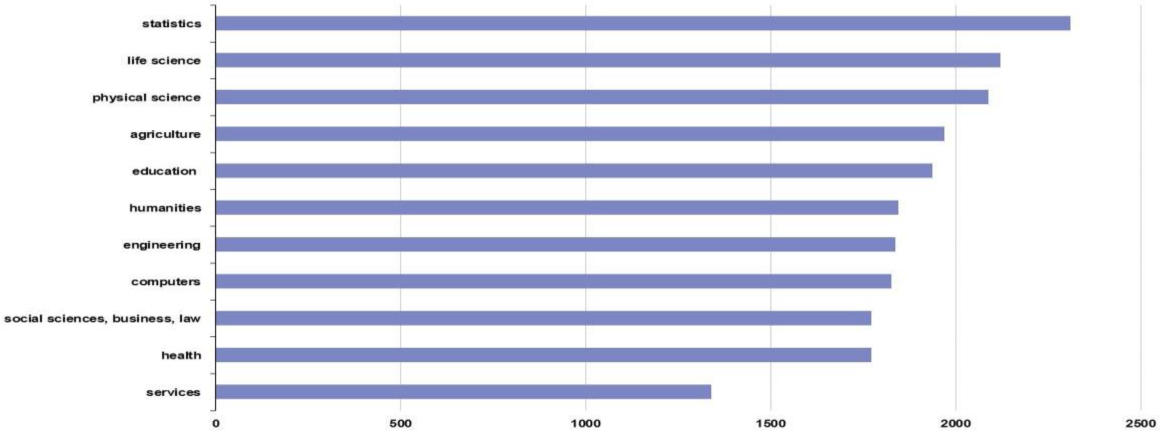
These checks can be performed as long as the imputed wage is analysed with demographic variables that are common between EU-SILC and LFS. Additional analysis is needed when the focus is on the joint distributions of imputed wage information and variables collected only in LFS. One example is the analysis of wage statistics in relation to the field of education collected only in LFS (see Figure 3-8).

The major limitation of statistical matching is its reliance on implicit assumptions[32]. When imputed wages need to be analysed with additional variable collected solely in LFS, one

[31] Predictive mean matching method

essential condition for success is the existence of good explanatory variables that mediate the relation between these variables. It is important to check the sensitivity of estimates to different assumptions.

Figure 3-8: Mean wage by field of education and age group, ES-2009

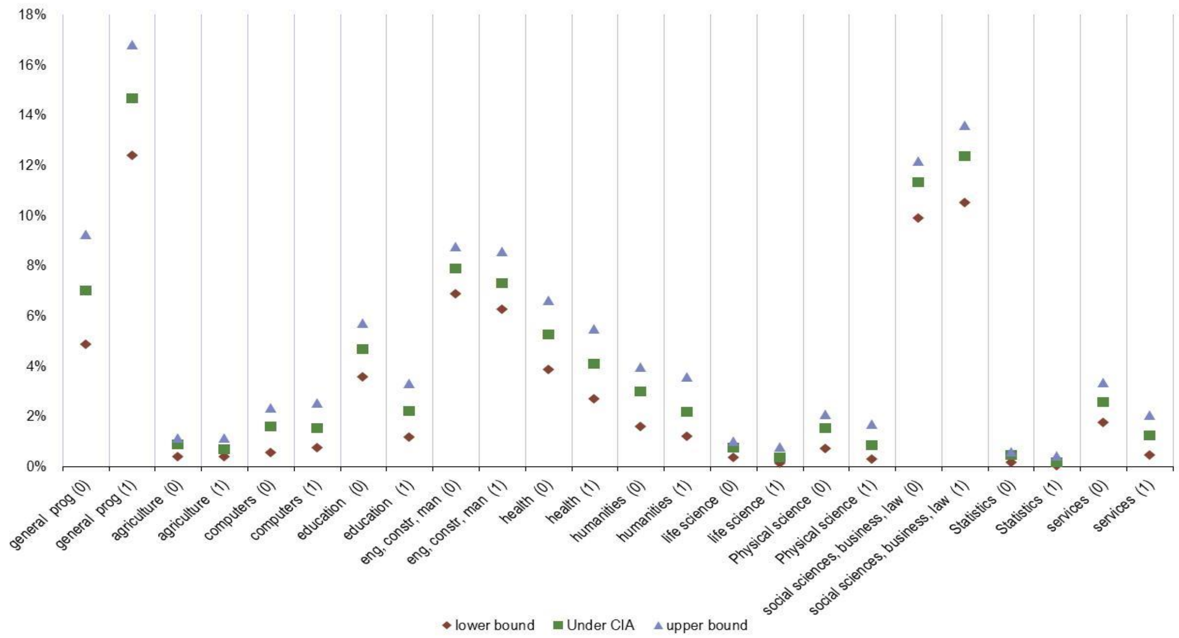


In our exercise, we apply one approach developed in the framework of the ESSnet on Data integration. The Fréchet classes[33] are used to estimate the set of all plausible values for the contingency table between wage variable and the field of education. As the Fréchet bounds work only for categorical variables, the wage variables was dichotomised by taking value 0 if the wage is below the mean wage and 1 otherwise. The results for Spain 2009 show (see Figure 3-9) that the uncertainty intervals are rather narrow in this. However, when wage deciles are used instead of the dichotomous indicators the intervals are much larger and hence, less informative. We also note that the cross distribution of wage deciles with the field of education between LFS imputed and LFS observed are very similar.

[32] See Chapter 1 for details

[33] See the ESSnet on Data Integration for more details

Figure 3-9: Frechet Bounds: % of people with wage below the mean by field of education (ES, 2009)



3.3 Conclusions and Recommendations

- *Objective 1:* For some countries, the LFS wage decile distribution is distorted mainly due to the misleading placement of the 'predefined' cut-off points. Thus, for countries such as Greece and Poland, it would be important to communicate and explain the predefined thresholds and not use them under the assumption they correspond to the true cut-offs points for deciles. Once thresholds are controlled for, the coherence with both EU-SILC and imputed wage information is good.

- *Objective 2:*

    - An important factor for the joint analysis and matching of EU-SILC and LFS is a better coherence of labour variables, including those for delimitation of the target populations. Differences and misalignment of distributions for the common variables used in the matching algorithm can cause discrepancies for wage related estimates.

    - Even if there are small inconsistencies in demographic variables, they tend to inflate the dissimilarity indexes (HD) when wage deciles are crossed with more dimensions (two and more).

    - Specific matching methods[34] proved to be more robust. However, results tend to be similar and in general estimates from matching are more sensitive to coherence pre-requisites and variables used in the model than the actual matching method employed.

    - Results show that, when pre-requisites of coherence are met matching provides good results for marginal distributions and joint distributions that involve dimensions controlled in the model. For the variables not observed together more complex quality checks such as the uncertainty analysis based on Frechet bounds are needed. However, when model assumptions hold, statistical matching can provide good inferences for specific estimates (e.g. wage and field of education).

    - Given the current system, pre-requisites for matching are not met to the same extent across countries. The existence of different patterns, coherence problems and different wage/population concepts across countries requires tailored approaches and fine-tuning for different countries.

[34] Predictive mean matching method that performs the imputation in two stages: first computation of estimates and then real values are imputed based

Annex 3-1Common variables- metadata analysis

Matched dataset	EU-SILC		LFS	
Description of variable	Codification	Description of variable	Codification	Description of variable
Gender	**RB090**	**Gender**	**SEX**	**Gender**
Male	1	Male	**1**	Male
Female	2	Female	**2**	Female
Age in completed years	**AGE**	**Age in completed years**	**AGE**	**Age in completed years**
Country of birth	**C_BIRTH**	**Country of birth**	**COBGROUP**	**Country of birth**
Native born	1	National	**0**	Born in the same country
Born in another EU MS	2	Within EU27	**1**	Born in another EU15 country
			2	Born in another EU10 country
			3	Born in another EU02 country
Born in a non-EU country	3	Outside EU27	**900**	Born in a non-EU27 country
Country of citizenship	**CIT_SHIP**	**Citizenship**	**NATGROUP**	**Nationality**
Nationals	1	National	**0**	National
Nationals of another EU MS	2	Within EU27	**1**	Citizen of another EU15 country
			2	Citizen of another EU10 country
			3	Citizen of another EU02 country
Nationals of a non-EU country	3	Outside EU27	**900**	Citizen of non-EU27 country
Marital status/de jure status	**PB190**	**Marital status**	**MARSTAT**	**Marital status**
Unmarried	1	Never married	**1**	Single
Married (including registered partnership	2	Married	**2**	Married
Widowed	4	Widowed	**3**	Widowed
Divorced	3	Separated	**4**	Divorced or legally separated
	5	Divorced		

Matched dataset	EU-SILC		LFS	
Description of variable	Codification	Description of variable	Codification	Description of variable
De facto marital status (consensual union)	**PB200**	**Consensual union**	**HHPARTNR**	**The spouse, or cohabiting partner of the person is or NOT in the same household**
Person living in a consensual union	1	Yes, legal	**1**	The spouse, or cohabiting partner of the person is in the same household
	2	Yes, without legal		
Person NOT living in a consensual union	3	No	**2**	The spouse, or cohabiting partner of the person is not in the same household
Country of residence	**DB020**	**Country**	**COUNTRY**	**Country**
Region of residence	**DB040**	**Region (according to NUTS at 2 digits)**	**REGION**	**Region**
Degree of urbanisation	**DB100**	**Degree of urbanisation**	**DEGURBA**	**Degree of urbanisation**
Densely-populated area	1	Densely	**1**	densely
Intermediate populated area	2	Intermediate	**2**	intermediate
Thinly population area	3	Thinly	**3**	thinly
Self-declared labour status	**PL030**	**Self-defined current economic status**	**MAINSTAT**	**Main labour status**
			FTPT	**Full-Time/Part-Time distinction**
Carries out an activity FULL-time	1	Work fulltime	**1**	Carries out a job or profession, including unpaid work for a family business or holding, including an apprenticeship or paid traineeship, etc, FTPT=1 (Full-time job)
Carries out an activity PART-time	2	Work part-time	**1**	Carries out a job or profession, including unpaid work for a family business or holding, including an apprenticeship or paid traineeship, etc, FTPT=2 (Part-time job)
Unemployed	3	Unemployed	**2**	Unemployed
Pupil, student, further training, unpaid work experience	4	Pupil, student, further training, unpaid work experience	**3**	Pupil, student, further training, unpaid work experience
In retirement or early retirement or has given up business	5	In retirement or in early retirement or has given up business	**4**	In retirement or early retirement or has given up business
Permanently disabled o/and unfit to work	6	Permanently disabled o/and unfit to work	**5**	Permanently disabled
In compulsory military or community service	7	In compulsory military or community service	**6**	In compulsory military service

Matched dataset	EU-SILC		LFS	
Description of variable	**Codification**	**Description of variable**	**Codification**	**Description of variable**
Fulfilling domestic tasks	8	Fulfilling domestic tasks and care responsibilities	**7**	Fulfilling domestic tasks
Other inactive persons	9	Other inactive persons	**8**	Other inactive person
Status in employment	**PL040**	**Status in employment**	**STAPRO**	**Professional status**
	PL140	**Type of contract**	**TEMP**	**Permanency of the job**
Self-employed	1	Self-employed with employees	**0**	Self-employed with or without employees
	2	Self-employed without employees	**1**	Self-employed with employees
	4	Family worker	**2**	Self-employed without employees
			4	Family worker
Employee with a permanent job or work contract with unlimited period	3	Employee and PL140=1 (permanent job/work contract of unlimited duration)	**3**	Employee + TEMP=1 (Person has a permanent job or work contract of unlimited duration)
Employee with a temporary job or work contract with limited period	3	Employee and PL140=2 (2 temporary job/work contract of limited duration)	**3**	Employee + TEMP=2 (Person has temporary job/work contract of limited duration)
Occupation in employment	**PL050**	**Occupation (isco-88 (com))**	**ISCO4D**	
Managers (4 positions)	11 to 14	Managers (4 positions)	**1**	Legislators, senior officials and managers
Professionals (6 positions)	21 to 26	Professionals (6 positions)	**2**	Professionals
Technicians and associate professionals (5 positions)	31 to 35	Technicians and associate professionals (5 positions)	**3**	Technicians and associate professionals
Clerical support workers (4 positions)	41 to 44	Clerical support workers (4 positions)	**4**	Clerks
Service and sales workers (4 positions)	51 to 54	Service and sales workers (4 positions)	**5**	Service workers and shop and market sales workers
Skilled agricultural, fishery and forestry workers (3 positions)	61 to 63	Skilled agricultural, fishery and forestry workers (3 positions)	**6**	Skilled agricultural and fishery workers
Craft and related trades workers (5 positions)	71 to 75	Craft and related trades workers (5 positions)	**7**	Craft and related trades workers
Plant and machine operators and assemblers (3 positions)	81 to 83	Plant and machine operators and assemblers (3 positions)	**8**	Plant and machine operators and assemblers
Elementary occupations (6 positions)	91 to 96	Elementary occupations (6 positions)	**9**	Elementary occupations
Armed forces (3 positions)	01 to 03	Armed forces (3 positions)	**10**	Armed forces

Matched dataset	EU-SILC		LFS	
Description of variable	Codification	Description of variable	Codification	Description of variable
Economic sector in employment, /according to NACE(1level)/	**PL111**	**Nace rev.2**	**NACE1D**	**NACE REV2 - 1 DIGIT**
Agriculture(A+B)	1 to 3	Agriculture(A+B)	**A**	Agriculture, forestry and fishing
			B	Mining and quarrying
Industry (C+D+E)	5 to 39	Industry (C+D+E)	**C**	Manufacturing
			D	Electricity, gas, steam and air conditioning supply
			E	Water supply; sewerage, waste management and remediation activities
Construction (F)	41 to 43	Construction (F)	**F**	Construction
Wholesale and retail trade (G+H+I)	45 to 56	Wholesale and retail trade (G+H+I)	**G**	Wholesale and retail trade; repair of motor vehicles and motorcycles
			H	Transportation and storage
			I	Accommodation and food service activities
Financial (J+K)	58 to 66	Financial (J+K)	**J**	Information and communication
			K	Financial and insurance activities
Other services activities (L+M+N+O+P+Q+R+S+T)	68 >	Other services activities (L+M+N+O+P)	**L**	Real estate activities
			M	Professional, scientific and technical activities
			N	Administrative and support service activities
			O	Public administration and defence; compulsory social security
			P	Education
			Q	Human health and social work activities
			R	Arts, entertainment and recreation
			S	Other service activities
			T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Matched dataset	EU-SILC		LFS	
Description of variable	**Codification**	**Description of variable**	**Codification**	**Description of variable**
Highest level of education completed,	**PE040**	**Highest ISCED level attained**	**HATLEVEL**	**Highest level of education or training successfully completed**
No formal education or below ISCED1	0	Pre-primary education	**0**	No formal education or below ISCED 1
Primary education	1	Primary education	**11**	ISCED 1
Lower secondary education	2	Lower secondary education	**21**	ISCED 2
			22	ISCED 3c (shorter than 3 years)
Upper secondary education	3	(Upper) secondary education	**31**	ISCED 3c (3 years and more)
			32	ISCED 3 a,b
			30	ISCED 3 (without distinction a, b or c possible, 2 y+)
Post secondary education but not tertiary	4	Post-secondary non tertiary education	**41**	ISCED 4a,b
			42	ISCED 4c
			43	ISCED 4 (without distinction a, b or c possible)
Tertiary education, first stage	5	First stage of tertiary education	**51**	ISCED 5b
			52	ISCED 5a
Tertiary education, second stage	6	Second stage of tertiary education	**60**	ISCED 6
Number of hours worked per week	**PL060**	**'Number of hours usually worked per week in main job'**	**HWACTUAL**	**Number of hours actually worked during the reference week in the main job**
		'Total number of hours usually worked in second, third …jobs'	**(+ HWACTUAL2)**	
	PL100			
Managerial position	**PL150**	**Managerial position**	**SUPVISOR**	**Supervisory responsibilities**
Yes, the persons has managerial tasks	1	Yes, the persons has managerial tasks	**1**	Yes
No, the persons has NOT managerial tasks	2	No, the persons has NOT managerial tasks	**2**	No

Annex 3-2Model log(wage) as dependent variable, Spain 2009

Independent Variables	Base category	Parameter Estimate	Standard Error	Pr > F
Intercept		5.97866	0.00154	<.0001
Age		0.01267	0.00007	<.0001
Age square		-0.00007	0.00000	<.0001
Gender	Female	0.13989	0.00020	<.0001
Education	ISCED 0-1			
	ISCED2	0.08967	0.00033	<.0001
	ISCED3	0.17306	0.00037	<.0001
	ISCED4	0.19105	0.00110	<.0001
	ISCED5	0.26815	0.00043	<.0001
	ISCED6	0.37464	0.00105	<.0001
Part time		-0.46045	0.00039	<.0001
Temporary contract		-0.13280	0.00023	<.0001
Number hours worked		0.01167	0.00001	<.0001
Supervisory position		0.13307	0.00022	<.0001
Proxy for work experience		0.00154	0.00015	<.0001
Sector-NACE1d aggregated	Agriculture			
	Industry	0.18421	0.00086	<.0001
	Construction	0.23483	0.00095	<.0001
	Trade	0.07089	0.00070	<.0001
	Financial	0.16441	0.00075	<.0001
	Real estate	0.07158	0.00135	<.0001
	Professional, scientific and technical activities	0.05973	0.00084	<.0001
	Administrative and support services	0.01899	0.00078	<.0001
	Public administration	0.23403	0.00073	<.0001
	Education	0.16231	0.00077	<.0001
	Other	0.01696	0.00076	<.0001
Occupation	Elementary occupations			
	Managers	0.53985	0.00071	<.0001
	Professionals	0.45952	0.00043	<.0001
	Technicians	0.24321	0.00039	<.0001
	Clerical support workers	0.15697	0.00036	<.0001
	Service and sales workers	0.06543	0.00034	<.0001
	Skilled agricultural workers	0.03747	0.00091	<.0001
	Craft workers	0.07585	0.00037	<.0001
	Plant/machine operators	0.11369	0.00042	<.0001
Country of birth	Native born			
	Born in another EU country	-0.07207	0.00054	<.0001
	Born in a non-EU country	-0.05614	0.00038	<.0001

Independent Variables	Base category	Parameter Estimate	Standard Error	Pr > F
Degree of urbanisation	Thinly			
	Densely	0.05445	0.00022	<.0001
	Intermediate	0.03078	0.00026	<.0001
Marital status	Single			
	Married	0.07894	0.00023	<.0001
	Widowed	0.00554	0.00080	<.0001
	Separated/divorced	0.02904	0.00043	<.0001

Annex 3-3 Comparison of joint distributions (based on HD) of matching variables with wage deciles (LFS imputed versus EU-SILC observed) for Spain, 2009;

COUNTRY	YEAR	VARIABLE	REG1	PMM1	REG2	PMM2	HOT DECK 1	HOT DECK 2	PROB ALG
ES	2009	GENDER	3.45%	2.91%	2.84%	2.15%	6.21%	6.84%	4.74%
ES	2009	AGEGR	6.81%	3.47%	7.34%	3.01%	5.68%	7.43%	8.27%
ES	2009	EDU	7.88%	3.43%	8.01%	3.10%	4.67%	8.32%	9.01%
ES	2009	PARTJOB	7.42%	4.36%	6.51%	3.62%	13.27%	9.93%	6.50%
ES	2009	TEMPJOB	6.72%	2.44%	5.99%	2.16%	3.31%	7.03%	7.40%
ES	2009	NBYYEXP	5.22%	2.69%	5.87%	2.32%	10.74%	10.89%	6.33%
ES	2009	URBAN	2.17%	2.25%	2.15%	1.67%	3.24%	7.02%	4.45%
ES	2009	NACE1D	10.70%	10.00%	10.74%	8.38%	11.49%	12.34%	11.75%
ES	2009	ISCO1D	14.92%	7.02%	13.59%	6.72%	9.11%	12.23%	14.21%

Legend:

REG1: multiple imputation based on regression model without interactions but with stratification

PMM1[35]: multiple imputation via predicted mean matching using a regression model without interactions but with stratification

REG2: multiple imputation based on regression with interactions and stratification

PMM2[17]: multiple imputation via predicted mean matching using a regression with interactions and stratification

HOT DECK1: single imputation based on Euclidian distance

HOT DECK2: single imputation based on Gower distance

PROB ALG: tailor-made algorithm of allocations into deciles based on probabilities

[35] Mixed method (see Chapter 1 for details)

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