HACETTEPE UNIVERSITY

INSTITUTE OF POPULATION STUDIES

DEMOGRAPHY PROGRAM

THE EFFECT OF A NEW BORN ON HOUSEHOLD POVERTY IN TURKEY: THE CURRENT SITUATION AND FUTURE PROSPECTS BY SIMULATIONS

BARIŞ UÇAR

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Doctor of Philosophy Degree

in Demography at Hacettepe University

Institute of Population Studies

ANKARA, MAY 2017

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Supervisor

Prof. Dr. İSMET KOÇ

ANKARA, MAY 2017

ACCEPTANCE AND APPROVAL

This is to certify that we have read and examined this thesis and that in our opinion it is fully adequate, in scope and quality as a thesis for the degree of Doctor of Philosophy in Demography.

<u>Examining Committee Members:</u>

Member (Chair):...
Prof. Dr. Meltem Dayıoğlu, Middle East Technical University, Department of Economics
Member (Supervisor): ....
Prof. Dr. İsmet Koç, Hacettepe University, Institute of Population Studies
Member: ....
Assoc. Prof. Dr. Mehmet Ali Eryurt, Hacettepe University, Institute of Population Studies
Member: ....
Assoc. Prof. Dr. Emel Memiş Parmaksız, Ankara University, Department of Economics
Member: ....
Assist. Prof. Dr. M. Aykut Attar, Hacettepe University, Department of Economics

This thesis has been accepted by the above-signed members of the Jury and has been confirmed by the Administrative Board of the Institute of Population Studies, Hacettepe University.

Date: …. / …. / 2017

....
Prof. Dr. Banu Ergöçmen
Director

Bu tez Türkiye Bilimsel ve Teknolojik Araştırma Kurumu (TÜBİTAK)'nun 2214-A - Yurt Dışı Doktora Sırası Araştırma Burs Programı kapsamında desteklenmiştir.

This thesis has been supported by the Scientific and Technological Research Council of Turkey through its International Research Fellowship Program for Doctorate Students.

ABSTRACT

THE EFFECT OF A NEW BORN ON HOUSEHOLD POVERTY IN TURKEY: THE CURRENT SITUATION AND FUTURE PROSPECTS BY SIMULATIONS

This study aims to analyze the causal relationship between fertility and poverty in Turkey. This study basically focuses on micro level analysis. The relationship is analyzed at household level.

Such a study requires monitoring households throughout time to analyze the differences in their well-being occurring after the birth of a child. Their well-being will be examined by using various indicators. In addition to income and consumption expenditure, conventional poverty indicators based on consumption expenditure and income will be used along with fuzzy measures of poverty and deprivation index in a comparative way.

The analysis throughout time is possible by making use of data from a panel survey where households are interviewed regularly at different times. For the case in Turkey, this type of data is only available from SILC (Statistics on Income and Living Conditions) Survey. From SILC survey it is possible to monitor households within a four years of time span. Since SILC lacks consumption expenditure variable, this will be made available by statistical matching from the Household Budget Survey where such information exists.

There are different suggested methods to analyze the causal effect of fertility on household well-being. The most widely used approach depends on using propensity scores, either running a regression or applying propensity score matching (PSM). The causal relationship analyses in this study employ methods with propensity scores. The findings indicate the households that had

a child between the beginning and the end of the panel are worse-off in economical well-being, compared to households that did not have a child. Most of the indicators used in the analyses support this finding.

ÖZET

TÜRKİYE'DE YENİ BİR DOĞUMUN HANEHALKI YOKSULLUĞU ÜZERİNDEKİ ETKİSİ: MEVCUT DURUM VE SİMÜLASYONLARLA GELECEK DURUM ANALİZİ

Bu çalışma Türkiye'de doğurganlık ve yoksulluk arasındaki nedensel ilişkiyi analiz etmeyi amaçlamaktadır. Çalışma temel olarak mikro düzey analizlere odaklanmaktadır. Söz konusu ilişki hanehalkı düzeyinde incelenmektedir.

Böyle bir çalışma, doğumun ardından hanehalkının durumunda meydana gelen değişimi ölçebilmek için hanehalklarını zaman içerisinde takip edebilmeyi gerektirmektedir. Hanehalkının ekonomik durumu çeşitli göstergelerle incelenecektir. Gelir ve tüketim harcaması dışında, bunlara dayalı yoksulluk göstergeleri ile fuzzy yoksulluk göstergeleri ve yoksunluk göstergesi karşılaştırmalı bir şekilde kullanılacaktır.

Zaman içerisinde bir analiz ancak hanehalkları ile düzenli olarak farklı zamanlarda yapılan görüşmeler neticesinde derlenen panel veri kullanımı ile mümkündür. Türkiye'de, bu amaçla kullanılabilecek veri olarak Gelir ve Yaşam Koşulları Araştırması (GYKA) mevcuttur. GYKA verileri ile bir hanehalkını dört yıllık bir süre boyunca takip etmek mümkündür. GYKA verileri içerisinde tüketim harcaması yer almadığı için, bu değişken, Hanehalkı Bütçe Araştırması (HBA) verilerinden istatistiksel eşleştirme yöntemi ile elde edilerek kullanılmıştır.

Yeni bir doğumun hanehalkının ekonomik durumu üzerindeki etkisini ölçmek için farklı yöntemler mevcuttur En çok kullanılan yöntem regresyon veya eşleştirme yöntemi aracılığıyla eğilim skoru hesaplanmasına dayalıdır. Bu çalışmadaki nedensel ilişki analizleri propensity skorlara dayalı yöntemler

kullanılması ile gerçekleştirilmiştir. Elde edilen sonuçlar panel süresince bir çocuk sahibi olmuş hanehalklarının, çocuk sahibi olmayan hanelerle karşılaştırıldığında ekonomik olarak daha kötü bir duruma geçtiklerini göstermektedir. Kullanılan bir çok gösterge bu bulguyu desteklemektedir.

ACKNOWLEDGEMENTS

This work was carried out during the years 2011-2017 at the Hacettepe University Institute of Population Studies (HUIPS) including a 1-year visit to Siena University Department of Economics and Statistics between April 2016 and April 2017.

It is a pleasure to thank those who made this thesis possible. I would like to thank to my supervisors Prof. İsmet Koç and Prof. Gianni Betti, for their advice and time at every stage of this thesis.

I would like to thank Prof. Meltem Dayıoğlu and Assoc. Prof. Mehmet Ali Eryurt, who have been members of my Thesis Monitoring Committee for their valuable comments and contributions to this work through our meetings.

I would like to thank Gabriella Donatiello and Marcello D’Orazio for meeting me and answering my questions regarding statistical matching.

I would like to thank to the staff of TurkStat, who conducted the surveys and made the data sets available. I would like to thank especially to Özlem Sarıca for her support. I would like to thank to Süheyla Tulumbacı and Hakan Yazıcıoğlu for their proofreading.

I would like to thank Havva Yiğiter, Taşkın Özkütük and Seyhan Özkütük for their support before my transfer to Siena University.

Finally, I would like to thank my friends, Can Yücesoy, Seda Nihal Yücesoy and Çınar Yücesoy and those in my family, Ayşen Uçar, Mevlüt Uçar and Hayriye Çolak.

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INTRODUCTORY NOTE

In the beginning of the new millennium, fertility started to fall towards replacement level in Turkey and this declining fertility was seen as a threat. The European experience of ageing triggered worries within the country. These worries further increased when the comparative situation with Europe was considered. The ageing process took about 150 years in Europe, but it was taking only 30-40 years in Turkey. This very fast pace of ageing has increased the worries more and more.

Consequently, declining fertility in Turkey triggered calls for at least three children by the governing authorities, recently. Related to these calls or not, there is an upward movement in fertility which can be monitored by latest statistics. In the light of the fear from ageing and declining population, now there are ongoing studies in order to implement policies to increase fertility in Turkey such as support systems and incentives. The discussion is mostly going on how to increase fertility in order to prevent or cut down on the negative effects on ageing. In this regard, the effects of high fertility should also be on the table for discussion. Only then, the trade-offs between ageing and high fertility would be brought out into the open and the implications of policies would be more visible.

For contribution to the discussion under question, this study analyzes the effects of fertility on household economic well-being. How the birth of a new born affects the economic well-being of households and its relationship with household poverty is studied with different tools and available datasets.

In literature, there are various methods which attempt to analyze this causal relationship. This study basically focuses on micro level analysis. The relationship is analyzed at household level.

Micro level research of poverty and fertility at household level is relatively recent and most of this literature depends on the relationship between household size as the indicator of fertility. Sinding (2009) attribute this inadequate literature to scarcity of longitudinal datasets that would enable such research. Recently, there are studies which measure the effect of fertility through analyzing the difference before and after the birth of a child in a household which facilitate dynamic analyses, but the literature is not rich in studies targeting to examine the effect of fertility on poverty in a dynamic perspective. Kim et al. (2009) and Arpino and Aassve (2013) are the most prominent studies in the very rare literature in this respect.

Such a study requires monitoring households throughout time to analyze the differences in their well-being occurring after the birth of a child. Their well-being is examined by using various indicators. In addition to income and consumption expenditure, conventional poverty indicators based on consumption expenditure and income will be used along with fuzzy measures of poverty and deprivation index in a comparative way.

The analysis throughout time is possible by making use of data from a panel survey where households are interviewed regularly at different times. For the case in Turkey, this type of data is only available from SILC (Statistics on Income and Living Conditions) Survey. From SILC survey it is possible to monitor households within a four years of time span.

There are different suggested methods to analyze the causal effect of fertility on household well-being. The most widely used approach depends on using propensity scores either running a regression or applying propensity score matching (PSM). The causal relationship analyses in this study employ methods with propensity scores.

This thesis consists of three main chapters. The first two chapters are organized as completely independent papers. Their structures reflect this characteristics. They contain all the sections of an independent paper, including the references and appendices. Chapter III is closely related to Chapter II and serves as a complement. Therefore, it does not have sections that are devoted to methodology or data set explanation, since these are available in Chapter II they are not repeated once again.

The first chapter occupies with the creation of a synthetic data set to be used in the second chapter. In the analysis of the effect of a new born on household economic well-being, among others, consumption expenditure is used as an indicator. This indicator is not available in the main data set to be used. Therefore, the first chapter serves to this end.

The aim is to create a synthetic longitudinal data set, which includes the consumption expenditure variable in addition to the other variables in Turkish Income and Living Conditions (SILC) Survey Data Set, in which information on consumption expenditure does not exist. Consumption expenditure is available in another data set, which is the Household Budget Survey (HBS). The targeted synthetic data set is achieved by statistically matching SILC and HBS Data Sets, which have many variables in common. The 2010-2013 longitudinal data set of SILC is used in the process and data from each year is matched with the corresponding year's data set of HBS.

In the second and third chapters, the core targets of the thesis are handled. The second chapter focuses on the effect of a new born on household economic well-being. To this end, first the methodology is explained in detail. Then the analyses are made by using multiple indicators of household well-being.

The findings of the second chapter indicate the households that had a new born between the beginning and the end of the panel are worse-off in economic well-being, compared to households that did not have a new born during the panel. Most of the indicators used in the analyses support this finding.

The third chapter focuses on some more detailed analyses regarding the effect of a new born on household well-being along with some ideas about how to compensate for the loss of household monetary well-being. In this regard, some propositions are made by making use of the available data. These propositions could be used as a basis for further analyses that would be realized in this regard.

The first target of the third chapter is to detect the effect of a new born more proximately by limiting the analysis to only one year, instead of four year span, by making use of only one of the indicators, namely, the deprivation index.

In addition to this, the analysis that is done for all households with PSM is repeated for different household sizes and according to households' monetary well-being. The indicators that are used as outcome in this chapter are income, fuzzy monetary and fuzzy supplementary measures. An analysis is made for poorer half of the sample in order to estimate a compansation of the forgone income following the childbirth, and a proposition for support is made. In this chapter also the cost of an additional child for different household types are computed by making use of equivalence scales.

At the end of this chapter, simulations are conducted to demonstrate the possible effects of new borns on the overall poverty rates. This is realized by taking into consideration the probabilities of having a new born for each household.

The core target of the study is to reveal the effect of a new born on household economic well-being. Whether the households are capable of compensating according to various indicators on economic well-being of households after the enlargement of the household is questioned. The expectation was that the new born would have a decreasing effect on household economic well-being as also suggested by Kim et. al (2009) and Arpino and Aassve (2013). The findings are in line with the expectations. The main finding of this thesis is that households that had a new child between the beginning and the end of the panel are worse-off in their well-being, compared to households that did not have a new child, which calls for further support for childbirth if pro-natal policies are considered.

CHAPTER I

TRANSFERRING CONSUMPTION EXPENDITURE VARIABLE FROM HOUSEHOLD BUDGET SURVEY DATA TO INCOME AND LIFE CONDITIONS SURVEY (SILC) PANEL DATA: A STATISTICAL MATCHING EXERCISE FOR TURKISH DATA

I.1. INTRODUCTION

Statistical matching (SM), in broad terms, is the name of the procedure for merging two or more different data sets, in order to make use of the variables, which are not simultaneously available in either data set. It enables exploiting more from the available data sets to produce more information for inference. Instead of implementing a survey or a census in which all required variables are available, a statistical procedure is put to work which is less costly and more feasible. The data sets to be fused should refer to the same population (D'Orazio, 2016) and the files should be combined in such a way that the distributions of the related variables stay unchanged as much as possible (Kum and Masterson, 2008).

In statistical matching method, the idea is to fuse variables in two data sets by making use of a common set of variables, which are available in both data sets. X denotes variables available in both data sets, and Y and Z denote variables that are only available in one of the data set respectively. The aim is to obtain a data set including X, Y and Z. Data fusion, data combination, micro data set merging, synthetic matching are other names given to this method (van der Putten et al., 2002; Kum and Masterson, 2008; Leulescu and Agafitei, 2013). In general, one of the data sets is the **recipient** and the other one the

donor. The matching is realized by transferring variables from the donor to the recipient by making use of the matching variables.

Record linkage should not be confused with statistical matching while at some aspects and at some implementations they have similar prospects. The difference is identified with regard to the units in question. Record linkage is used in case of overlapping units where one-to-one direct matching can be realized. Similar units are the subject of statistical matching. On the other hand, identical units are the subject of record linkage. (Leulescu and Agafitei, 2013)

I.1.1. Aim

This paper came out for the need of longitudinal consumption expenditure data in Turkey to be used in research with regard to the relationship between childbirth and poverty.

In Turkey, there is a longitudinal data set of a four-year span from SILC survey, which comprises information on family formation throughout time that includes the presentation of a new born in the household, as well as other information with regard to household characteristics. Unfortunately, this data set lacks information on household consumption expenditure, which is available in Household Budget Survey (HBS). Since no such data is available, creating a synthetic data set by fusing available data sets demonstrates itself as a feasible solution. Therefore, this necessity of an ad hoc data set lead to the efforts provided in this paper.

The incorporation of the two surveys will be executed by using **statistical matching method**. Further specifications, requirements and formation of the new data set will be discussed in the following sections in detail.

As pointed out earlier, the main target of this study is to create a data set, which will be used in further research on the relationship between childbirth and poverty in Turkey, for which there is need for longitudinal consumption data. The literature is scarce with regard to studies that target statistical matching with longitudinal data. This study has the property of being one of the few in such effort.

I.1.2. Organization of the Chapter

This chapter is organized as follows. After the brief introduction, which also comprises the main objective of the study, literature review on statistical matching will be put forward in section 2, which comprises of general literature on statistical matching as well as literature specific to the matching of cross-sectional and longitudinal data and literature specific to Turkey in the subsections. Then the methodology will be put forth in section 3. In section 4, the data sets will be defined briefly and descriptive tables will be presented. In section 5 how data sets are prepared for matching will be explained. In section 6, the statistical matching procedures gone through will be explained step by step with full detail. In section 7, the results will be presented and discussed. The quality of the match will be evaluated in section 8 and section 9 will conclude the paper.

I.2. LITERATURE REVIEW ON STATISTICAL MATCHING

I.2.1. General Literature on Statistical Matching

Statistical matching is relatively a new area of research. Okner (1972) is regarded to be the first one to produce academic research in this regard. Okner (1972) merged two files namely the 1967 Survey of Economic

Opportunity and 1966 Tax File in order to obtain income distribution with regard to demographic characteristics, which was not available in any available data sets. He used “equivalence classes” which is defined as comparable characteristics available in both files. The following paragraph by Okner (1972) defines the procedure as costly and time-consuming. All the same, he thinks the effort is worth it. In this era, where computers are much more powerful and capable to carry out procedures much faster, the value of statistical matching outshines compared to its alternatives such as conducting a new survey.

> *“Creating the MERGE data file was a costly and time-consuming operation. It took well over a year and involved several man-years of labor input and computer time. Although it involved a tremendous investment of resources, we feel that the effort was worthwhile and that the file is an extremely useful analytical tool.”* Okner (1972)

Because of the advantages it presents today with the help of computers, statistical matching is being used widely all over the world. Many studies have been conducted in this regard. Varieties of new techniques have been developed and studies have been conducted on every detail of the matching process.

Kum and Masterson (2008) indicate the use of statistical matching in different areas such as medical research as follows:

> *“Statistical matching (or data fusion, as it is called in Europe) is by now a widely used technique in producing empirical studies. The method is used in many observational studies in **medical literature** (Little and Rubin, 2000; Rubin and Thomas, 1992, 1996; Rosenbaum and Rubin, 1983). In addition to the numerous examples in the field of **economics** cited by Rässler (2002),*

> *there are studies by Radner (1981), Wolff (2000), Wolff and Zacharias (2009), Greenwood (1983, 1987), Wagner (2001), Brodaty, Crépon, and Fougère (2001), Keister (2000, 2003), the Urban-Brookings Tax Microsimulation (Rohaly, Carasso, and Saleem, 2005), and the 2003 Congressional Budget Office report on income tax burdens (CBO, 2003).“* Kum and Masterson (2008)

Statistical matching methods have been classified in various ways by some researchers, according to the different characteristics they hold. D’Orazio et al. (2006) have summarized the classifications of these approaches as macro and micro; and parametric, nonparametric and mixed methods. Statistical matching could be realized to obtain joint distributions of variables from two different data sources. In this case, a **macro** level matching would be in question. If the aim is to obtain a new synthetic data set via the fusion of the data sets then it is a **micro** level matching. **Parametric** models could be used for the matching as well as **nonparametric** methods. There are also cases when both are used in the same process, which are the so-called **mixed** methods.

The matching at micro level could be realized with distance functions, predictive mean matching or by making use of propensity scores (Kum and Masterson, 2008). Methods using distances include **nearest neighbour**, **random** or **rank** hot deck procedures (D’Orazio, 2016).

The procedure can be realized with a **constrained** statistical matching (CM) where each item can be matched only for once or with an **unconstrained** statistical matching (USM) where the matching is more disengaged. In USM, a distance function is used for finding the nearest neighbour. When this method is used, it is possible that there are multiple selections or no selection of records from donor data set. The result of this could be different marginal distributions of X (matching variables) or joint distributions of X and Y (variables in the recipient data set), in the statistically matched file compared with those in the original donor file (Kum and Masterson, 2008). On the other hand, CSM does not allow for multiple selection. The records are matched with regard to their rank. The disadvantage of the CSM approach is that matches are possible even with unacceptably large distances. However, in the final synthetic data set all marginal distributions are the same as they are in the original files.

One main issue when dealing with the statistical matching problem is the so-called **Conditional Independence Assumption** (CIA). When matching is realized by using relationship of X and Y; and X and Z respectively, to obtain an estimate for the relationship between Y and Z, it is assumed that Y and Z are independent conditional on X. This situation, which is not true in most of cases, is called the CIA. Unless there is additional information from another source, this cannot be tested and acceptance of this assumption is one of the weaknesses of SM procedures.

When there is **auxiliary information** from another source, this assumption can be relaxed and this information can be used to obtain higher quality SM results.

I.2.1.1. Statistical Framework

In order to prevent complications that could arise due to differences in the statistical framework and notations that are coming from different studies, the statistical framework and notations will be borrowed from the same source. The statistical framework and notations to be used in this study are based on D’Orazio et al. (2006) and are summarized as follows.

Let X, Y, Z be a random variable with density f (x, y, z)

Let

$X = (X_1, \ldots\ldots, X_P)'$,

$Y = (Y_1, \ldots\ldots, Y_Q)'$, and

$Z = (Z_1, \ldots\ldots, Z_R)'$

Be vectors of random variables of P, Q and R respectively.

Assume that A and B are two samples consisting of n_A and n_B independent and identically distributed (i.i.d.) observations generated from f (x, y, z).

Furthermore, let the units in A have Z missing and the units B have Y missing.

Let

$(x_a^A, y_a^A) = (x_{a1}^A, \ldots\ldots, x_{aP}^A, y_{a1}^A, \ldots\ldots.., y_{aQ}^A)$

$A=1, \ldots\ldots, n_A$, be the observed values of the units in sample A, and

$(x_b^B, y_b^B) = (x_{b1}^B, \ldots\ldots, x_{bP}^B, z_{b1}^B, \ldots\ldots.., z_{bR}^B)$

$B=1, \ldots\ldots, n_B$, be the observed values of the units in sample B

When the objective is to gain information on the joint distribution of (X, Y, Z) from the observed samples of A and B, we are dealing with the statistical matching problem.

I.2.2. Statistical Matching for Consumption Expenditure

Recently, there are statistical matching applications of HBS and SILC data sets where consumption expenditure variable in HBS is imputed into SILC. Donatiello et al. (2014) has carried out this task with Italian HBS and SILC data sets. The consumption expenditure was categorized in this study.

Data set of SILC with reference year 2011 for income and 2012 for other variables was matched with HBS 2011. The reason for this choice was to enable comparative analysis of expenditure and income in the synthetic data file. In this study, use of auxiliary information in order to avoid Conditional Independence Assumption (CIA), which is a critical issue in SM, was evaluated. The auxiliary information relied on the monthly household income, which was derived from HBS.

Another study for this kind of matching is by Baldini et al. (2015). This study also concentrates on imputing expenditure information in HBS into SILC data set in Italy. This time all expenditure items are imputed with a two-stage procedure by making use of expenditure-income relationship which is derived from another data set (Survey on Household Income and Wealth (SHIW)) where joint information on both expenditure and income variables is available where all data sets correspond to 2012. The method in this study consists of three steps. In the first step, in SHIW data set expenditure is regressed on income with other variables, which are also available in SILC. Then, in the second step, estimates of expenditure is obtained in SILC data set. In an intermediate step, households are sorted by per centiles of imputed expenditure in SILC and sorted by original overall expenditure in HBS. Finally, in the last step distance function matching is applied.

A recent study by Webber and Tonkin (2013) also integrated expenditure data in HBS with SILC for UK, 2005. They used three different methods, namely, parametric, nonparametric and mixed methods and found that the mixed methods were slightly better in the matching. EU-SILC in the UK measures current income unlike to other European countries. In HBS, also current income and expenditure is collected, but the reference period, on other hand, is the 2005/2006 financial year. However, these values are deflated to 2005 for coherence.

I.2.3. Literature on Matching of Longitudinal Data sets

Up to the present, the literature on statistical matching of cross-sectional and longitudinal data sets is scarce compared to the vast literature on statistical matching.

Betti (1998) imputed consumption expenditure into British Household Panel Study data set by making use of a consumption model created in Family Expenditure Survey for years 1991 to 1994. The matching method was completely parametric.

Rasner et al. (2007) described the preparatory steps for matching administrative data, Completed Insurance Biographies with German Socio-Economic Panel (SOEP). Rasner et al. (2011) discusses the realization of this matching. Mahalonobis distance matching was used in this study.

One conference paper has considered the issue where a statistical matching was exercised between a cross-sectional and longitudinal data sets using propensity matching method (Thiede et al., 2010). For further analysis of the main issue of this paper, a sample of longitudinal data comprising of insured people with monthly career changes was matched with a cross-sectional data set, which contained information on the diagnosis, which led to premature retirement. As this diagnosis information was not available in the longitudinal data set and it was required for the analysis, such a statistical matching was considered. The paper lacks the details of the quality of the match.

Simonson et al. (2012) German Aging Survey (DEAS) with a sample of administrative data from Active Pension Accounts (VSKT). In this study, they used Mahalonobis distance for the matching procedure. Both data sources in this study are longitudinal. The matching was realized between the corresponding years.

Zacharias et al. (2014) statistically matched South Korean Time Use Survey (KTUS 2009), and the South Korean Welfare Panel Survey of 2009. The matching is realized for one year of the panel, therefore longitudinal analysis was not targeted in this study.

I.2.4. Literature Review on Statistical Matching in Turkey

Use of statistical matching methods in Turkey is very new. So far, there is only one study explicitly using statistical matching method in Turkey. It is "Time Deficits and Poverty" study by Zacharias et al. (2014). In this study, there was need for information on time spent on household production, time spent on employment and household consumption expenditures, but in maximum two of these were available in a single data set. In Household Budget Survey (HBS), time spent on employment and household consumption expenditures were variable, but there was no information on time spent on household production. This variable was available in Time Use Survey (TUS). Therefore, time spent on household production for each individual aged 15 years and older in TUS was fused into HBS data. Moreover, Masterson (2013) analyzed the quality of the match in another article where the match was found to be of high quality.

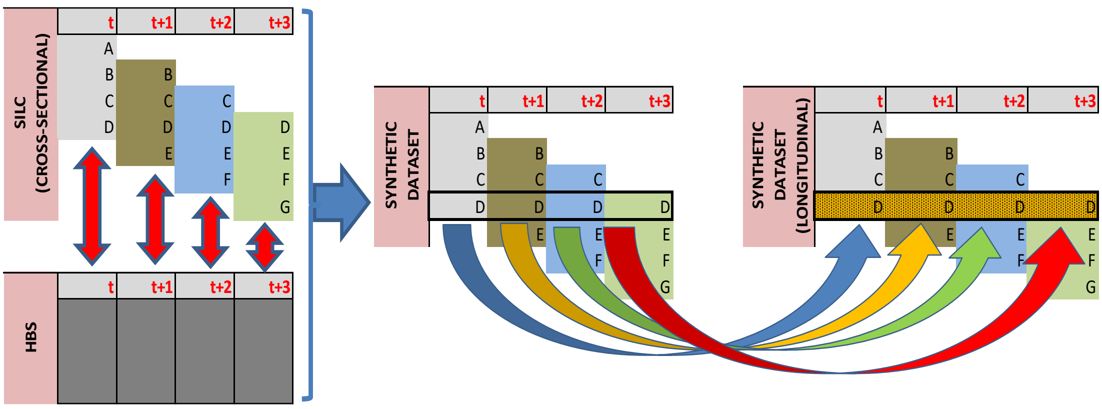
I.3. METHODOLOGY

For the creation of a synthetic longitudinal data set, including household consumption expenditure, longitudinal SILC data and cross-sectional HBS data from Turkey will be incorporated using statistical matching method. In the final synthetic data set, there will be variables (Y) from SILC, variables common in both data sets (X) and household consumption expenditure variable (Z) from HBS.

For this study, there will be need for more than one matching application. There is need for a matching for each year of SILC data with the corresponding year of HBS data.

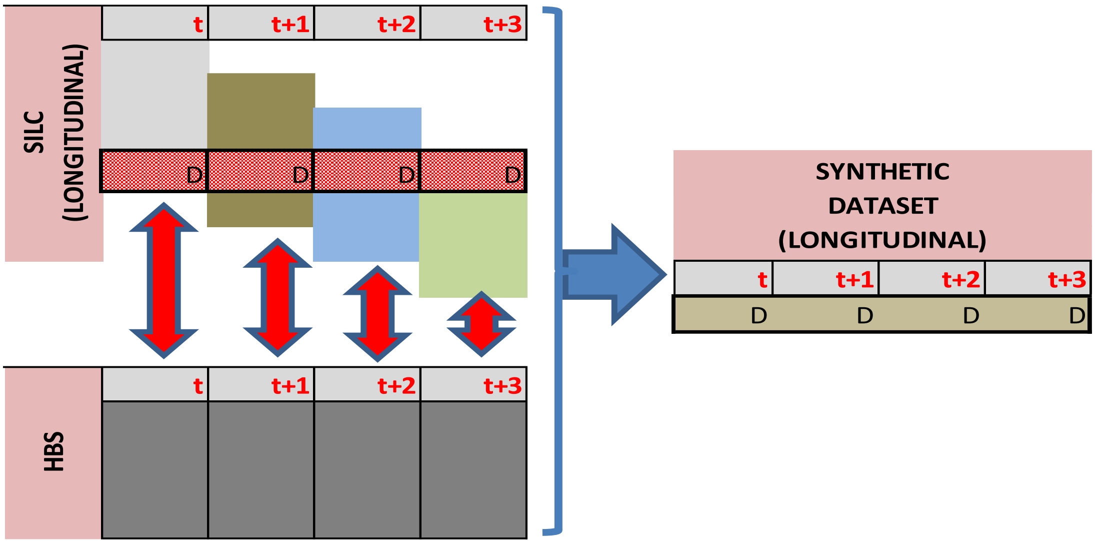
The more information we have, the more will be inferred from it. Having more information available at hand would make the matching process more reliable, consistent and precise. The available information can be maximized by carrying out the statistical matching for the cross-sectional data sets of SILC with HBS (Figure I.3.1) and following this step, the synthetic data set that is created can be matched (not statistical matching, direct record matching) with the corresponding records in the longitudinal data set only to select the longitudinal final data set (Figure I.3.1). This way it will be secured that, a data set which is around four times greater than the section (each data part regarding to one year in the data set) of the longitudinal data set could be used for a better statistical matching implementation.

Figure I.3.1. Schema for longitudinal statistical matching (first approach)



When this is accomplished, a longitudinal data set will be available which is realized by the utmost information available for use. However, unfortunately this cannot be realized for Turkish data, which obstructs such use by concealing the necessary identification number that would be used to link the records in the cross-sectional and longitudinal data sets of SILC. Therefore, it is only possible to realize the statistical matching procedure only by the corresponding section of the SILC longitudinal data set (Figure I.3.2).

Figure I.3.2. Schema for longitudinal statistical matching (second approach)



This study will employ the method provided in StatMatch package in R, which is provided by D'Orazio (2016) as a framework. The steps suggested in this study will be followed and these steps will constitute the subsections of the "Procedure Steps" section. After a brief introduction of the data sets to be used, each step of the SM procedure will be put forth in detail. Therefore, further details regarding the methodology are available in the corresponding sections of the study.

I.4. DATA

The main sources of data are the Household Budget Survey and SILC Survey as mentioned above. Both data sets have stratified and clustered sampling designs. Moreover, SILC includes a rotating structure with regard to its longitudinal design. Twenty five per cent of the sample is replaced with new ones each year. Although the cross-sectional sample of SILC has a similar population with HBS, the longitudinal data set has a different population due to its panel structure. The rotational sampling design, entries and exits are the main reason for this divergence.

I.4.1 Household Budget Survey

Household budget survey provides information on socio-economic structures, standards of living, and consumption patterns of the households. With this survey, it is possible to produce information on consumption habits, types of consumption expenditures and diversity of spending for goods and services according to socio-economic characteristics of households, employment status of household members, total income of households, and source of income.

For the first time, Household Income and Consumption Survey was conducted to cover overall Turkey in 1987, the second one was conducted in 1994. Afterwards, Turkstat started to conduct Household Budget Survey every year since 2002, of which the name was Household Income and Consumption Expenditure Survey in 2002 and was converted to Household Budget Survey starting from 2003.

Geographical coverage of the survey is all settlement areas within the territory of Turkey. There is also information for urban areas and rural areas until 2013, where this distinction was cancelled due to the new administrative formation.

The survey covers all household members living in Turkey. Population living in institutional places, such as elderly houses, rest homes, correction facilities, military barracks, etc. is not covered.

The survey is conducted between January 1 and December 31, where sample households change every month. Interviewers visit households about 8 times a month. Sampling frame is obtained from National Address Database since 2009. As sampling method, stratified two-stage cluster sampling method is used. Blocks, covering 100 address units, are selected by the probability proportional to size sampling (pps). The sample units are systematically selected from each block. Final sample unit is the household that live at the selected address.

A diary is kept by households in which they record all their daily expenditures they make in the survey month. The information gathered from the diary is coded according to COICOP/HBS classification.

Three basic groups of variables are obtained from the survey:

- Variables regarding socio-economic status of the households: type of dwelling, ownership status of property, heating system, dwelling facilities, durables, premises and vehicles owned etc.,
- Variables regarding consumption expenditures: type of expenditure and the total value of expenditure,
- Variables regarding household members: variables related to individuals' age, gender, educational background, marital status, employment

(occupation, economic activity, employment status etc.), activity and non-activity and incomes received during last 12 months, etc.

I.4.2. SILC Survey

Starting from 1987 to 2005, TURKSTAT used Household Budget Survey (HBS) to produce statistics on income distribution. Income and Living Conditions (SILC) Survey has been conducted every year since 2006. SILC Survey is carried out yearly by using panel survey technique for displaying the income distribution between individuals and households, measuring the living conditions of the people, social exclusion and poverty with the income dimension. The aim of the survey is to produce comparable data with the EU Countries, on income distribution, relative poverty, living conditions and social exclusion. It is carried out in accordance with the European Union Compliance Programme.

Respondents in the sample are monitored for four years in this survey. Panel survey technique is used and field application is carried out every year regularly. Twenty-five per cent of the households are changed every year. Panel data as well as cross-sectional data are obtained from the survey for each year.

Until 2013, the data set provides information at urban and rural levels as well as the country as a whole. Cross-sectional data set is large enough to provide information at NUTS1 level.

All household members living in the country are included in the sampling frame. Those living in military barracks, prisons, nursing homes, childcare centers, private hospitals and hotels are excluded from the sample frame. Immigrants are also excluded. Address Based Population Registration

System and the National Address Database, which were established in 2007, constitute the basis for the sampling frame. The sampling design of SILC Survey is a two stage stratified cluster sampling. First, clusters (blocks), which are comprised of approximately 100 dwelling addresses (80 to 120) are constructed. Then households, which are the final sampling unit, are selected.

The Primary Sampling Unit is a Block. These blocks are comprised of approximately 100 household addresses. A locality that doesn’t have a municipality (i.e. village) is also considered as a block. In the first stage, primary sampling units (PSU), namely blocks are selected from the sampling frame. The selection is made with probability proportional to address size. The Secondary Sampling Unit constitute twelve household addresses for urban, eight for rural from each selected block.

The longitudinal weights of SILC are calculated by taking into account the non-responses and the base weights over the related year of the individuals, who participate in the panel. These weights are achieved by assigning 2, 3 and 4 year multiplier factors to the base weights of the individuals.

Income and Living Conditions Survey is carried out regularly each year. Data compilation is performed between April-July, in two stages. In the first stage, interview is accomplished with the households who continue to live in the same address as in previous application and with the new households. In the second stage, interview is carried out for the sample persons that moved out to another dwelling and for households that moved to another address.

I.4.3. Descriptives for the data sets

The data sets to be used are 2010-2013 longitudinal data of SILC and data sets of HBS for four corresponding years. There are a total of 9 244 individuals in the panel with a four year weight. The number of households which have at least one member of such individuals is 2 958. In the following table, number of households and individuals present in the HBS data set are demonstrated for each year.

Table I.4.3.1. Number of records in HBS (unweighted)

	Number of Households	Number of Individuals
2010	10 082	38 206
2011	9 918	37 121
2012	9 987	36 343
2013	10 060	36 812

In Table I.4.3.2 and Table I.4.3.3, the weighted values from the data sets are provided. The ones from HBS and SILC Cross-sectional correspond to the total number of households and total number of individuals (population). The number of households and population derived from the panel data are meaningless due to the sampling design and weighting structure of the panel. All the same, figures obtained by longitudinal weights are presented in the following tables. They are used in the calibration stage when the populations are adjusted for the two base data sets. The population of SILC panel is the same for each year, since the weights are derived from individuals which are present every year. The number of households differ because it is derived from individual weights and household size and because the household structure is different for each year.

Table I.4.3.2. Number of households in the data sets (weighted)

	Number of Households		
	HBS	SILC (Panel)	SILC (Cross-sectional)
2010	18 808 172	13 052 553	19 321 205
2011	19 311 637	13 214 787	19 658 387
2012	20 051 454	13 496 609	20 220 578
2013	20 476 409	13 623 565	20 625 072

Table I.4.3.3. Number of individuals in the data sets (weighted)

	Population		
	HBS	SILC (Panel)	SILC (Cross-sectional)
2010	71 342 749	49 531 667	71 342 760
2011	72 376 233	49 531 667	72 376 677
2012	73 603 548	49 531 667	73 603 527
2013	74 456 551	49 531 667	74 456 554

I.5. DATA SET PREPARATION

Before everything else, there is need for a step zero for the preparation of the data sets to be matched. At this stage, the framework suggested by van der Laan (2000) will be used as a basis which is also suggested by Leulescu and Agafitei, (2013) and D'Orazio (2016). The data preparation stage requires harmonization between the two data sets to be matched. The two data sets should be in accordance with each other as much as possible to enable a good quality match. The issues suggested by van der Laan (2000) to be considered, are presented and explained with respect to the statistical matching exercise handled in this study.

“a. harmonization of definition of units: are the statistical units defined uniformly in all sources? (special reference to comparability in space and time)
b. harmonization of reference periods: do all data refer to the same period or the same point in time?
c. completion of populations (coverage): do all sources cover the same target population?
d. harmonization of variables: are corresponding variables defined in the same way? (special reference to comparability in space and time);
e. harmonization of classifications: are corresponding variables classified in the same way? (special reference to comparability in space and time);
f. adjusting for measurement errors (accuracy): after harmonizing definitions, do the corresponding variables have the same value?
g. adjusting for missing data (item non-response): do all the variables possess a value?
h. derivation of variables: are all variables derived using the combined information from different sources?”

I.5.1. Harmonization of the definition of units

I.5.1.1. Households and Individuals

Both surveys use the same household definition, which is an important issue to be considered in a statistical matching application. On the other hand, the panel structure of SILC creates some complications.

In HBS data sets, the issue regarding the relationship between households and individuals is straightforward. Every household and individual in the corresponding data sets have a weight and could be used directly. In SILC, selecting the individuals and households for each year of the panel is a little more complicated, since these are different for each year although we have weights attached to individuals only for the final year. For this purpose, the individuals that have a four-year panel weight are selected and afterwards the households that they belong are selected. And for each year **all individuals** that are members of these households in the corresponding year are selected and these individuals and households constitute the population of that year. With this process, some of the households - that are left with no members in the final year, but have an ex-member with a weight who moved out from these households - are neglected. Because these households do not have a member with a weight in the four-year panel, they will not appear in the final synthetic data set, so they are deleted in advance. Number of such households are quite few and they only correspond to 0.5 per cent of all households.

I.5.1.2. Age

There is a major difference between the survey periods of SILC and HBS and how the age information is collected. The SILC survey is realized in a period between April and July. On the other hand, HBS is carried out in the course of the whole year. Every month, a fraction of the households is interviewed in HBS in order to have data that represents the year average. Because HBS is a consumption expenditure survey, which necessitates exhaustive data recording within a full month, collecting information throughout the year is important for gathering data, which would represent the whole year, for eliminating the seasonal effects that could occur. This is a problematic case with respect to periods especially when a matching application will be carried out. All the same, this situation will be ignored and will be classified as one of the flaws of the study and the information collected will be regarded as corresponding to the midyear situation.

In the special case of age, there are further complications. In HBS, like most of the other variables, age corresponds to the completed age at the time of the survey. Like the other variables, this will be ignored and no action will be taken in this regard. On the other hand, there is yet more complications concerning the age variable in SILC. In SILC, the age corresponds to a specific time period, which is the end of the income period, more precisely, the month of December preceding the survey year. This creates individuals that are of -1 age for those born between December of preceding year and the survey time. As will be explained in detail later in subsection 5.3, a weight calibration will be conducted. When such calibration is carried out at Turkstat, those at age -1 are considered in the 0-4 age group. Although this is not the perfect solution, in order to prevent further complications with regard to age, this study will also consider those at age -1 in the first age group which will be 0-14 in this case. In order to give some figures regarding observations at age -1, it can be said that in 2010, which is the starting year of the four year panel, less than 0.6 per cent of the observations are at age -1. This also corresponds to 2 per cent of the 0-14 age group.

I.5.1.3. Reference Person

The characteristics of the reference person could be used as common variables. However, there is a difference between SILC and HBS about how they define and handle the reference person. The definitions for the reference person are as follows:

<u>In SILC:</u>

The reference person is defined as an adult household member, who manages the household and who has the most information on the characteristics of the household and other members of the household.

<u>In HBS:</u>

It is defined as a member of the household with the highest income.

For this reason, there is need for creating consistent variables. In this respect, a new variable was created in SILC according to the income information of individuals. For those households where it was not possible to determine the individual with the highest income (this corresponds to only 4 per cent of the households) the original reference person in the data set was accepted. The original reference person in SILC and the new one created are consistent with an 80 per cent match.

I.5.2. Harmonization of the Reference Periods

Obstacles in the first place present themselves with regard to the reference periods of the variables in the two data sets. First of all, SILC survey is conducted in a limited time period compared to HBS. Data collection is performed between April-July, in two stages. In the first stage, interview is accomplished with the households who continue to live in the same address as in previous application and with the new households. In the second stage, interview is accomplished with the sample persons moved out to another dwelling and households moved to another address. The information collected generally corresponds to the situation at the time of the survey except for income and age. There are also others, such as working status, which correspond to the week prior to the survey. Therefore, in SILC, there is a major disharmony among the reference periods of some variables. While almost all other variables refer to the survey year, income variable, which is of great account, since it is the major variable in SILC, refers to the previous year.

HBS is conducted throughout the year. Every month a proportion of the households are interviewed. The situation at the time of the survey is reflected for most of the variables. On the other hand, similar to SILC, the reference period for the disposable income is the previous year, which is corrected with CPI index in order to provide some harmonization. The corresponding reference date is the survey year. The reference period for consumption expenditures on the other hand correspond to the survey month and no harmonization is realized. The survey month is not made available in the data set therefore the consumption expenditure information will be used as is without any reconciliation. This is one of the flaws of the study for which there is no way of overcoming with the data set at hand. Therefore, after being noted here, this situation will be ignored throughout the text as if the consumption expenditure for all households correspond to the same period.

For a certain year, the variables in HBS with regard to household characteristics including the household consumption expenditure refer to the survey year.

As can be seen from Figure I.5.2.1, while all the variables in both data sets are pertinent to the survey year t, t+1, etc., the income variable in SILC corresponds to year t-1 for survey year t, to year t for survey year t+1, etc. However, the incompatibility with regard to income and other variables in SILC requires some touch for harmonization, since it is a basic variable in targeted data set.

One way to overcome this could be to follow Donatiello et al. (2014). The matching of the SILC data set of year t could be carried out with HBS of t-1. In that way, it will be possible to have all variables except for income and consumption expenditure, corresponding to year t and for income and consumption expenditure, the corresponding year will be t-1. This will harmonize income and consumption expenditure, but they will not be in accordance with all other variables. The final data set will contain some information that correspond to the previous year. The household and individual characteristics reflect the current year where consumption expenditure and income reflect the previous year.

In addition, the matching will be less precise because the matching is realized with common variables, which correspond to two different time periods. It is obvious that data relating to two different years would yield less accurate results.

For a cross-section application, this seems to be the most logical solution as it facilitates the matching application by avoiding complications that may arise in harmonizing periods. However, since the disadvantages brought by such an approach are numerous, other ways could be investigated making use of panel structure as an advantage.

Figure I.5.2.1. Reference periods of variables

SILC					
	t	**t+1**	**t+2**	**t+3**	**t+4**
	X_t	X_{t+1}	X_{t+2}	X_{t+3}	X_{t+4} (na)
	Y_t	Y_{t+1}	Y_{t+2}	Y_{t+3}	Y_{t+4} (na)
	INC_{t-1}	INC_t	INC_{t+1}	INC_{t+2}	INC_{t+3} (na)
HBS	X_t	X_{t+1}	X_{t+2}	X_{t+3}	X_{t+4} (na)
	Z_t	Z_{t+1}	Z_{t+2}	Z_{t+3}	Z_{t+4} (na)

This inconsistency of periods could be better overcome by relating each year's SILC data set with the following year's income (Figure I.5.2.2). When this is accomplished the income variable for the year t+3 cannot be obtained because it is unavailable in the longitudinal data of the range (t – t+3). It is only obtainable from the year t+4 which is not available (na).

Figure I.5.2.2. An approach to overcome reference period inconsistency

SILC					
	t	**t+1**	**t+2**	**t+3**	**t+4**
	X_t	X_{t+1}	X_{t+2}	X_{t+3}	X_{t+4} (na)
	Y_t	Y_{t+1}	Y_{t+2}	Y_{t+3}	Y_{t+4} (na)
	INC_t	INC_{t+1}	INC_{t+2}	INC_{t+3} (na)	←
HBS	X_t	X_{t+1}	X_{t+2}	X_{t+3}	X_{t+4} (na)
	Z_t	Z_{t+1}	Z_{t+2}	Z_{t+3}	Z_{t+4} (na)

In this case, in the final data set, it is only possible to have a panel data set of three years instead of four years (Figure I.5.2.3). Unfortunately, this limits the data available for further research, but it seems to be one of the few ways of overcoming the existing problem.

Figure I.5.2.3. Synthetic data set for three years

SYNTHETIC DATA SET			
	t	**t+1**	**t+2**
	X_t	X_{t+1}	X_{t+2}
	Y_t	Y_{t+1}	Y_{t+2}
	INC_t	INC_{t+1}	INC_{t+2}
	Z_t	Z_{t+1}	Z_{t+2}

In some cases at individual level, some income items might be missing for some of the individuals. Even if this is the case, such information is imputed for those individuals, so making the overall income information for the household already available at hand in the existing SILC data set.

There is one problem with this approach though. There are entries into and exits from the household, so the income information of year t does not exactly correspond to the household composition in year t because it is collected in year t+1 and more likely to represent the household composition in year t+1. For year t+1, there is no income information for those who have left the household between t and t +1. And those who have attended the household between t and t + 1, the household information and income information will not be coherent since income information collected in t + 1 (which actually corresponds to year t) for the new attendee will not be relevant to the household in year t.

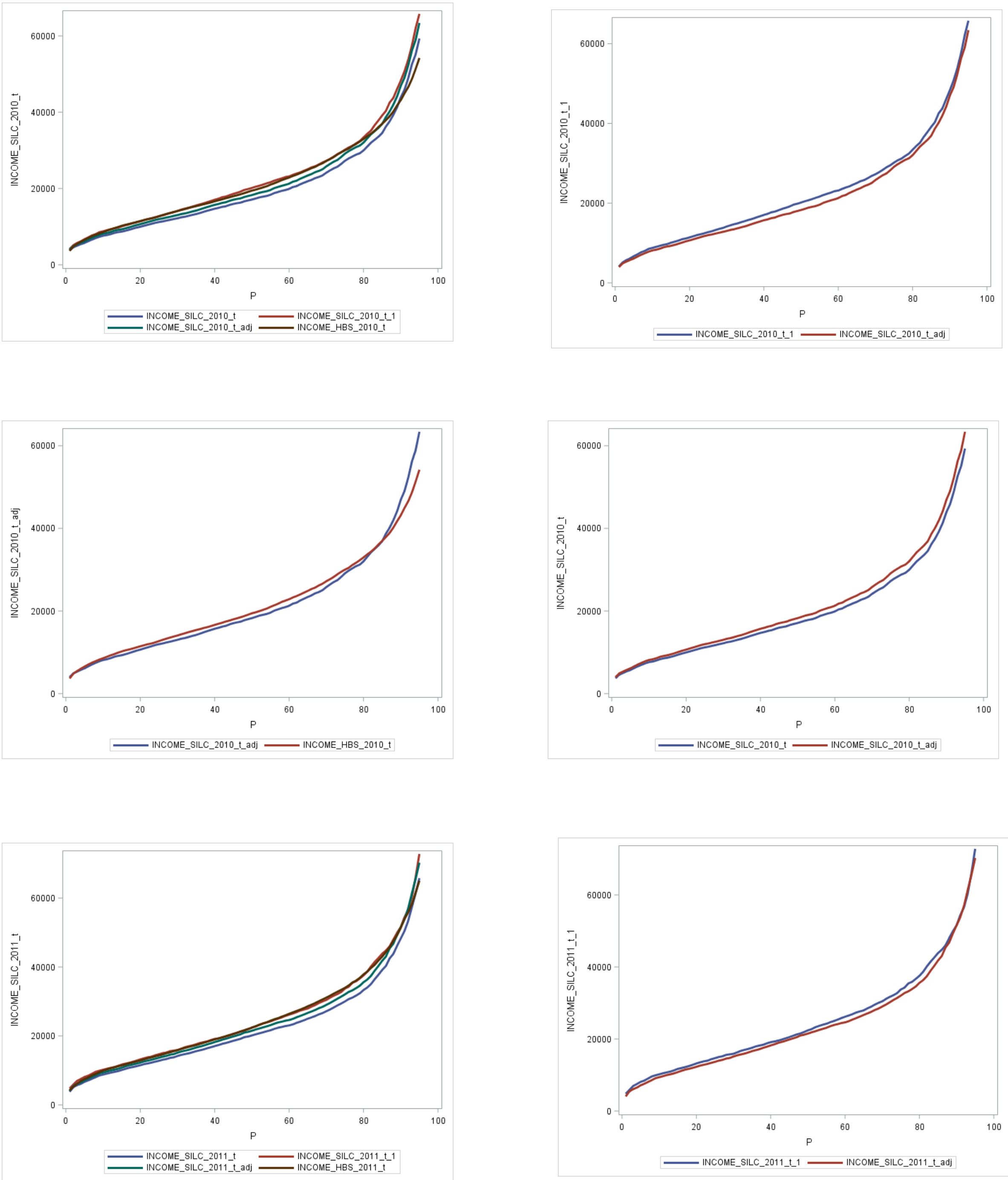
Individuals that have entries and exits are around 10 per cent for each year. Although this solution is not perfect, this approach could be used by disregarding such households, using the household size of the following year as well as income or excluding observations in such households from the data set.

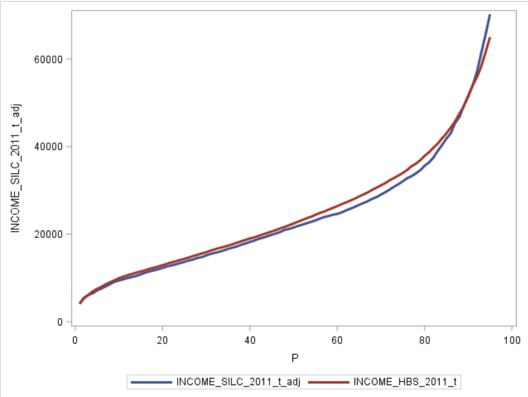
One alternative could be to transfer the equivalized income from year t+1, using an equivalence scale to adjust for household composition, and then by using scales for adults and children, income could be rescaled according to the household composition in year t. Here, there is also a problem with the entries and exits. Using this method for consumption would not cause many complications, on the other hand, when income is in question, the changes in household compositions do not necessarily indicate the same situation. The entrants and outgoings could be income earner in one situation and not an income earner in the other one, which would cause inconsistencies in the achieved values. This could be overcome by making use of personal income variables. All the same, an equivalence scale is used to standardize monetary variables at household level for comparison, and it never perfectly represents all household compositions. There are major differences among household types and using such a tool for the purpose of transferring a variable from one data set to another especially when it is used for two times could lead to further deviations from the targeted outcome.

Another alternative option could be to bring the income of year t-1 to year t by using consumer price index (CPI). This could reduce the number of complications that are faced. In the following graphs income per centile values are compared for different sources. “t” corresponds to the survey year. Comparisons are made for income values in SILC at the survey year (SILC_t), the following year (which actually corresponds to the income of the survey year, (SILC_t_1)), adjusted income value which is the value of income variable collected in the survey year adjusted with CPI (SILC_t_adj), and income value from HBS which is collected with a reference period one year prior to the survey year, but then inflated to the survey year (HBS_t).

The analyses of the graphs show that there are not major differences between the variables. The values are not very dispersed from each other and the distributions are alike. The focus is on the adjusted income variable in SILC. It is very closely located to the income value of SILC from year t+1. Considering to use any of the procedures explained does not appear to be worthwhile when the complications coming with them are taken into account. At this point, best option to continue with is the simplest one, which requires adjusting the income of SILC data set with CPI to get the income of the current year. This method also provides another very important advantage by enabling use of four-year panel instead of three, by preventing the loss of one year of panel that would arise as a result of procedures that are followed in other methods.

Figure I.5.2.4. Comparison of cumulative distributions of income from different sources

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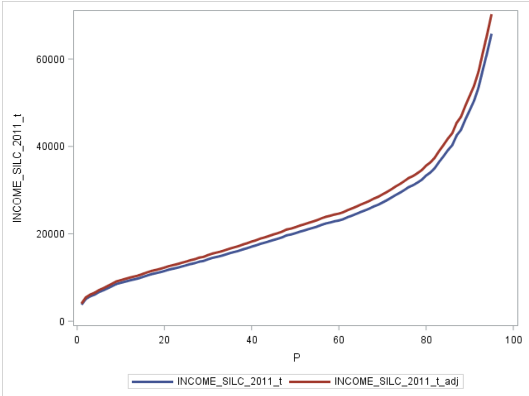
INCOME_HBS_2011_t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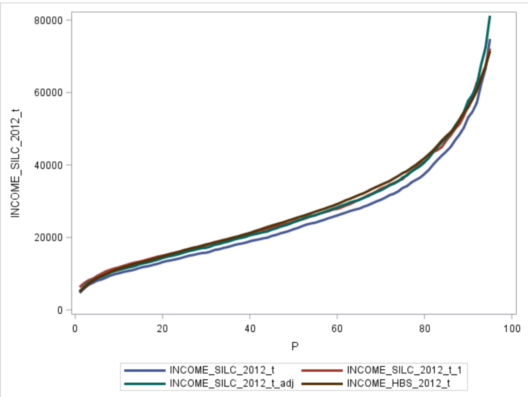
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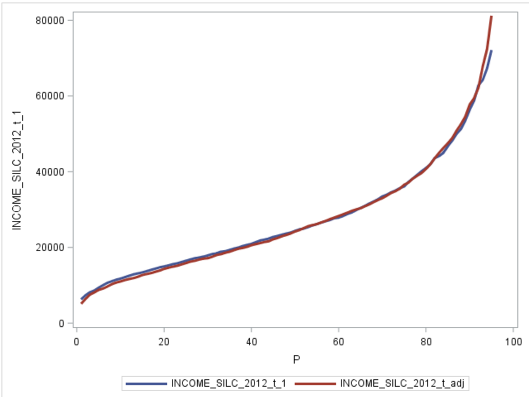
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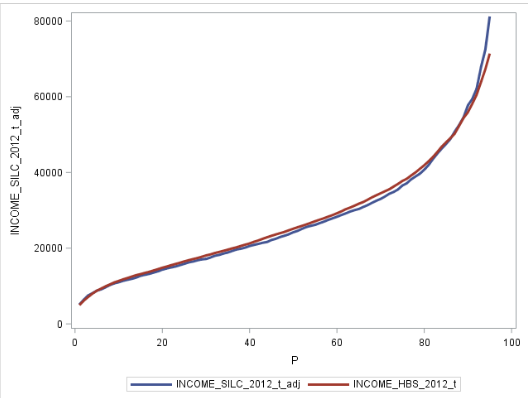
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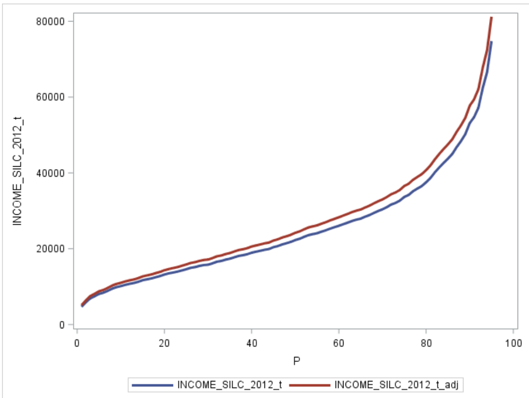
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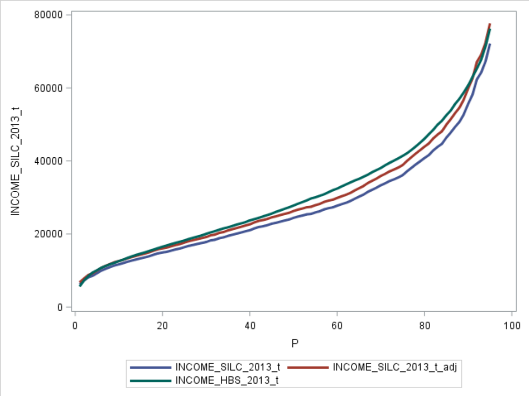
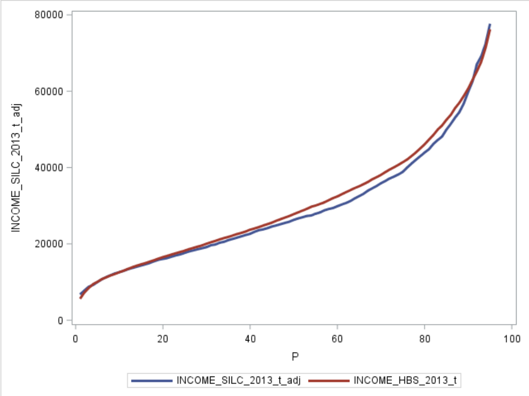
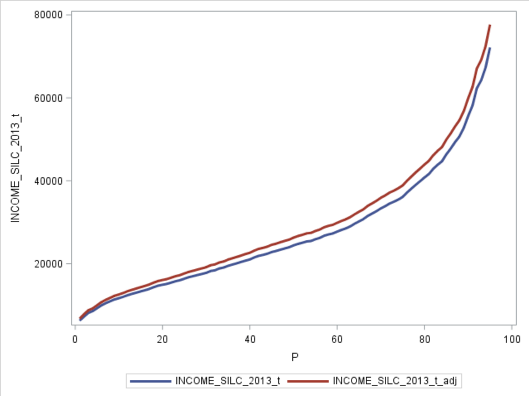






I.5.3. Completion of Populations (Coverage)

I.5.3.1. Weight Calibration

Since the overall population and its distribution with regard to age, sex and household size is different for the two data sets at hand; first of all, there is need for reconciliation. Normally, in both SILC and HBS, a calibration is carried out to adjust the survey population to the projected Turkish population figures. For the survey years in question, this calibration is done for age and sex distribution of the population as well as the population total. Although their implementation periods and how they deal with calculation of ages are not the same, both SILC cross-sectional and HBS populations are calibrated to the same population total, and age and sex distribution. On the other hand, the longitudinal data set has a major divergence from the other data set populations due to its panel structure. Unlike the cross-sectional data set, the weights are only given at individual level in the longitudinal data set and because there are exits and entries to the households between two waves, neither the population total, nor its age and sex distribution is comparable to that of cross-sectional SILC and HBS data set.

At this point, the adjustment is realized by calibrating the sections of SILC panel data set populations to the corresponding year of HBS data set. Because SILC cross-sectional data and HBS data are calibrated to same totals, this study will take this into consideration and behave accordingly in order to prevent further complications. Besides age and sex, household size is also an important calibration item, and because these are different for SILC cross-sectional data set and HBS data set, the calibration will be realized towards HBS data set, which will enable similar populations with regard to age, sex and household size between the two matching data sets.

The problem here is that a simple calibration will provide an individual data set and when matching is realized at individual level there will be individuals with different consumption expenditure values in the same household. It can be considered that, in the panel it is individuals who are followed and not the households, so this could be ignored since the persons have their own weights and although having variables with regard to household characteristics attached to them, they can be analyzed independently. However, for some individuals that are considered to be in the same household, while having all other variables, including income, of the same value; having different values for consumption would be a problematic issue.

An option to overcome this situation, could be to use integrated calibration technique to attach the same weights to each household member in a household. However, in SILC survey individuals are followed, not households. Individuals with a weight in the data set do not necessarily have the same household compositions throughout the panel. They might even be in a completely different household if they have moved out and joined another household. In this respect, there is no straightforward method for such calibration.

Another way to deal with this problem could be to select the households that did not have a change in their composition throughout the panel. This way an integrated calibration could be realized and a weight could be attached to the household. This solution also comes with problems. First, there will be a definite limitation in the available data set and maybe more importantly this will lead to a biased data set where dynamic households will be ignored and most important of all, such a household wouldn’t include any new borns which constitutes the basic motive of this study.

As mentioned above, there is no straightforward method for overcoming this issue, but, a method which enables the use of integrated calibration seems to be the reasonable solution. This would make the most desired outcome by providing a weight also at household level. Nevertheless, to start an integrated calibration for the panel sections there is need for a household weight to calibrate. In this case, this is acquired by the mean value of total household individual weights with regard to household size. For each year, those that are a member of the household are taken into consideration disregarding whether they have a four-year weight or not.

The original SILC panel data set (2010-2013) for individual registers is split into four. In addition, four data sets are created for each year. First of all, the data set for 2013 is created, because the weights are attached to the last year. For year 2013, the individuals which have a four-year panel weight are selected and then the households they belong to are determined. These households constitute the basis of the study. For each year, these households are selected and then individuals who are a member of these households in the respective year are selected and these individuals constitute the population in the associated year. The calibration is realized at the following levels:

- Age groups
- Sex
- Household size

Household distribution and structure is unique to each year. The result of this procedure is an age, sex and household size distribution in SILC section, which is the same with those of HBS. After the calibration, there is need for one more step to obtain the final weights. The resulting total population is different from HBS; the calibration enables to get the desired age, sex and household size distribution, but not the desired population. Therefore, a final rescaling step is used to adjust the matching data sets. At this final stage, weights are obtained for each year of the 2010-2013 SILC panel data set.

I.5.4. Harmonization of Variables

The variables, which are not consistent, were made to be consistent with the required methods. Whenever there was need, reclassifications were made and new variables were created.

I.5.5. Harmonization of Classifications

For dwelling type, the classifications in the data sets were different, so they were both reclassified in order to get consistent categories. Current rent related to occupied dwelling (including imputed rent, total space available to the household (m^2), lowest monthly income to make ends meet and total disposable household income are all continuous variables. These were categorized in both data sets and consistent categories were created.

I.5.6. Adjusting for Measurement Errors (Accuracy)

There are no known measurement errors in the data sets. Therefore, no action was taken in this regard.

I.5.7. Adjusting for Missing Data (Item Non-response)

The variables to be used in this study did not have any missing items. Missing items were already imputed into the data sets before use.

I.5.8. Derivation of Variables

Some new variables were created to be included in the matching variables. It was possible to create these variables in both data sets, which could act as matching variables. Therefore, the following variables were derived from the existing variables in both data sets:

Number of children (0-17) in the household
Number of adults (18-64) in the household
Number of elderly (65+) in the household
Number of women in the household
All household members are adults
All household members are elderly
All household members are women
Number of employed people

Number of individuals with employee income

Number of individuals with self-employed income

Number of individuals with retired income

Since longitudinal SILC data does not include household size variable this was also derived as mentioned in the calibration section.

I.6. PROCEDURE STEPS

In this section, the procedures that are implemented will be presented in detail. The steps are formed mainly as suggested in D'Orazio (2016) as listed as follows:

1. Choice of the variables (Y, Z) that are distinctly available in SILC (A) and HBS (B)
2. Identification of common variables (X)
3. Choice among X
4. Choice of matching framework
5. Implementation of the application
6. Evaluation of results

I.6.1. Choice of the Variables (Y, Z)

For the targeted data set, only household consumption expenditure will be used as a distinct variable from HBS. Thus, Z consists of only one variable. Y will be income variable in SILC, so it also consists of one variable.

I.6.2. Identification of Common Variables (X)

Both data sets were analyzed and a total of 40 variables were selected and created that could serve as matching variables. The categories of the variables were recoded to have compatible categories. The continuous variables were categorized and some of the variables with several categories were recategorized in order to have less categories to increase the similarities between the two data sets. The recoding is realized in a way that does not allow any missing values for any of the variables. Some variables are derived from the same variables, so are definitely exposed to multicollinearity, but they will be filtered in the following phases according to their explanatory power in the models.

Table I.6.2.1. List of common variables

#	Name of Variable	Variable
1.	hsize	Household size
2.	num_ch	Number of children (0-17) in the household
3.	num_adu	Number of adults (18-64) in the household
4.	num_eld	Number of elderly (65+) in the household
5.	num_wom	Number of women in the household
6.	all_adu	All household members are adults
7.	all_eld	All household members are elderly
8.	all_wom	All household members are women
9.	num_emp	Number of employed people
10.	num_emp_inc	Number of individuals with employee income
11.	num_self_emp_inc	Number of individuals with self-employed income
12.	num_ret_inc	Number of idividuals with retired income
13.	ref_sex	Reference person's sex
14.	ref_age	Reference person's age group
15.	ref_mar	Reference person's marital status
16.	ref_edu	Reference person's education
17.	ref_pro	Reference person's professional status
18.	ref_occ	Reference person's occupation
19.	ref_eco	Reference person's economic activity of work
20.	ref_whrs	Reference person's number of weekly working hours
21.	dwe	Dwelling type
22.	tenure	Tenure status
23.	rent_cat	Current rent related to occupied dwelling (including imputed rent)
24.	room_num	Number of rooms (except for kitchen, bathroom and toilet) available to the household
25.	tot_ar	Total space available to the household (m2)
26.	heat_sys	Heating system of the dwelling
27.	bath	Bath or shower in dwelling
28.	toilet	Indoor flushing toilet for sole use of household
29.	piped_wat	Piped water
30.	hot_wat	Hot water
31.	mobile	Mobile
32.	comp	Computer
33.	internet	Internet
34.	wash_m	Washing machine
35.	refrig	Refrigerator
36.	dish_w	Dishwasher
37.	air_con	Air conditioner
38.	car	Car
39.	low_mon_inc	Lowest monthly income to make ends meet
40.	dis_inc_cat	Total disposable household income

I.6.3. Choice Among X

The first step to choose among the common variables is to analyze the distributions in both data sets. It is important to have matching variables with similar distributions. A simple comparative analysis of the distributions could be performed (see the appendix for the distributions), but such a comparison is better performed with a distance function, which enables to detect the similarities and differences between the distributions of variables. In this study, Hellinger Distance (HD) is used as suggested by Donatiello et al. (2014). The formula for the Hellinger Distance is given below.

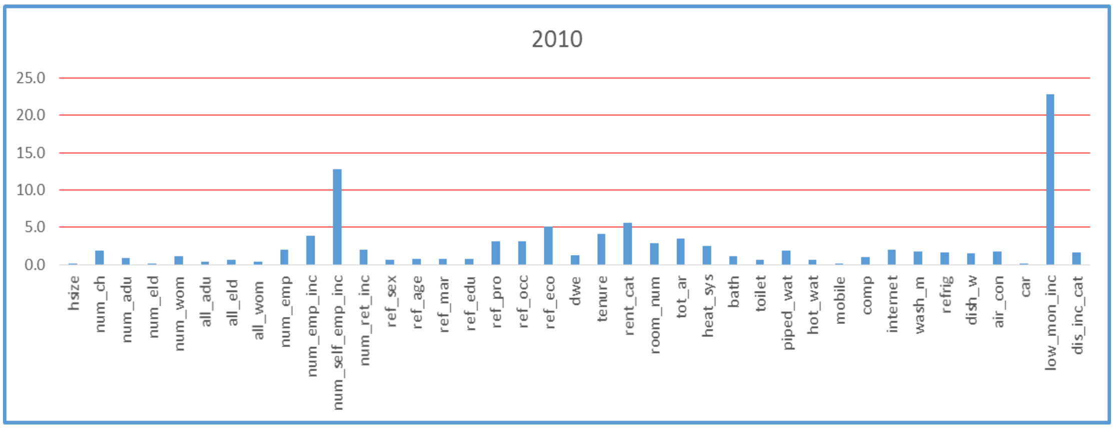
$$\text{HD (P,Q)} = \frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{k}(\sqrt{p_i}-\sqrt{q_i})^2}\ ,$$

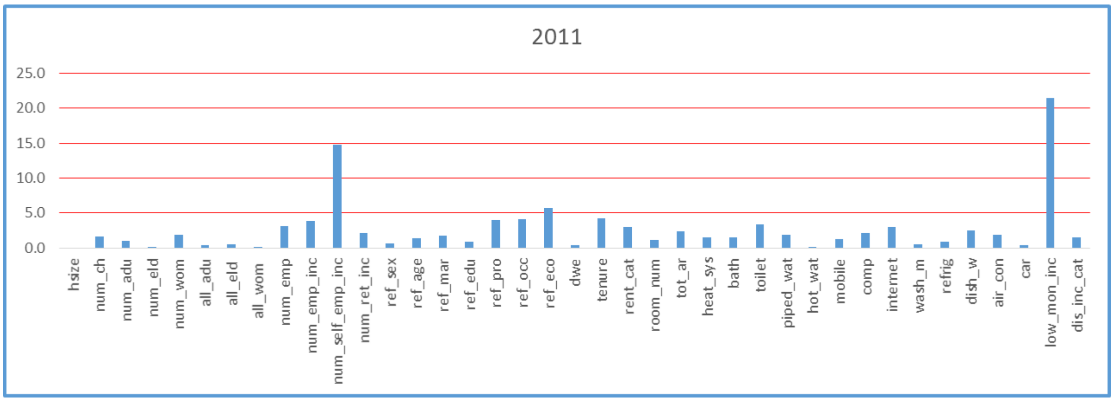
where p and q are the respective percentages of frequencies for each category. The indicator takes a value between 0 and 1. 0 indicates a perfect similarity and 1 indicates exact dissimilarity.

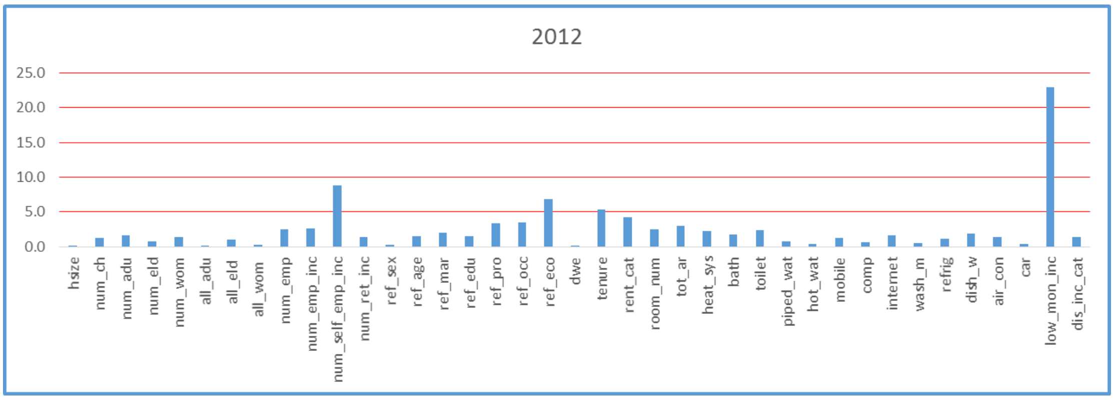
There is also need for a selection criterion of a good fit. In literature, 5 per cent is mostly used as a cutoff line (Donatiello et al., 2014). Variables with HD values that are less than 5 per cent are considered to have very similar distributions.

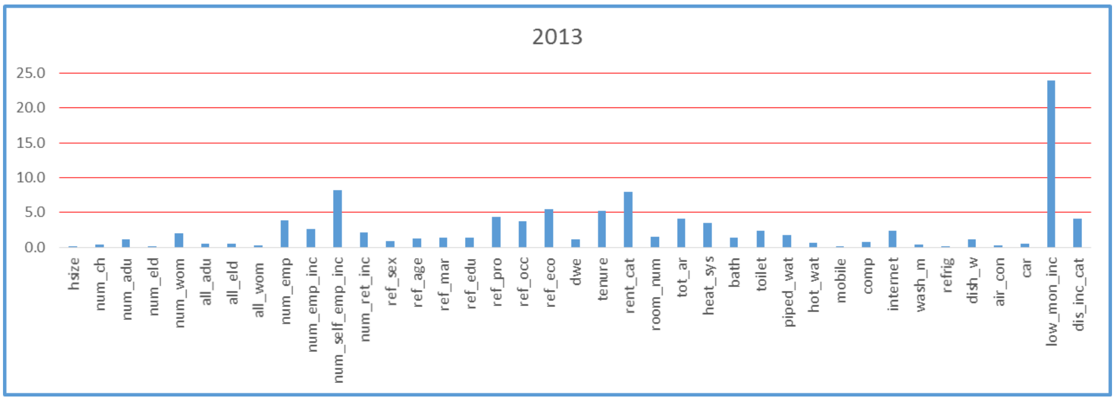
Hellinger Distance is a simple tool to be used for detection of similarities of variables between two data sets; on the other hand, it does not take into consideration the sampling design. For this purpose, as indicated by Leulescu and Agatifie (2013) other tests, such as, Chi square, Kolmogorov Smirnov, Rao-Scott, Wald-Wolfowitz tests could be used, but because these tests require relevant variables with regard to sampling design, they cannot be used in this study.

Figure I.6.3.1. Hellinger distance analyses:









Note: the reference person's number of weekly working hours is not covered in the figures because its high value as an outlier deteriorates the observation of other variables.

The analyses with HD demonstrates that four variables have a Hellinger distances that are higher than 5 per cent for all years of the panel. These variables are the reference person's number of weekly working hours, reference person's economic activity at work, number of self-employed persons in the household and the lowest monthly income considered by the household to make ends meet. Among these, the reference person's economic activity at work is recoded into four categories as agriculture, manufacturing construction and service sectors instead of 18 main categories and this way the Hellinger distance is smaller than 5 per cent for all years and therefore could be used in the further stages. The other three variables have different distributions probably due to poor data collection in either or both data sets, and are not considered as matching variables.

In addition, two other variables have a value greater than 5 per cent for two years. These variables are the tenure status of the household and rent (either paid or imputed). The tenure status is recoded into two main categories as owning the dwelling that is lived in or not; and the rent is recoded into two categories instead of four, by collapsing the last three categories into one category. These recoding operations allow the distributions for both variables to have Hellinger distances smaller than 5 per cent, so these variables are eligible for further analysis. After the HD analyses three variables are omitted and there are a total of thirty-seven variables remaining that are considered to have similar distributions.

There should be further selection among the common variables to perform the statistical matching. In the matching stage, models will be formed for the income variable in SILC and consumption expenditure variable in HBS using the common variables selected. Both response variables are continuous and all the common variables are categorical. In this regard, spearman2 function in Hmisc package (Harrell, 2016) in R is used to observe the pairwise correlations between the response variables (income in SILC and consumption expenditure in HBS) and the common variables.

> *"Spearman2 computes the square of Spearman's rho rank correlation and a generalization of it in which x can relate non-monotonically to y. This is done by computing the Spearman multiple rhosquared between (rank(x), rank(x)2) and y. When x is categorical, a different kind of Spearman correlation used in the Kruskal-Wallis test is computed (and spearman2 can do the Kruskal Wallis test). This is done by computing the ordinary multiple R^2 between k-1 dummy variables and rank(y), where x has k categories." (Harrell, 2016)*

The adjusted ρ^2 values are presented in Table I.6.3.1. Around 12 to 14 variables have an explanatory power over 10 per cent for different years of SILC and HBS. low_mon_inc is the variable with the highest value for all years in both data sets. It is generally followed by computer ownership in HBS and reference person's educational attainment in SILC. Ownership of dishwasher, car and internet, paid or imputed rent and heat system are among the first in rho2 value for all years of both data sets. The only exception is that car ownership is replaced with hot water in SILC 2010. In order to be consistent between different years of the synthetic data file, the selection of the variables will be realized accordingly and same matching procedure with the same matching variables will be followed for each year. It is profitable to have models with the same explanatory variables for all years. Therefore, with this in mind, in addition to the abovementioned variables with the highest explanatory power, hot water and dwelling type are included in the models. Total area available to the household and room number variables both have strong explanatory powers, but since these are closely related, the one with higher explanatory power, which is the total area available to the household is selected for further analyses.

Table I.6.3.1. Pairwise relationship between response and common variables (adjusted rho2 values)

	HBS				SILC			
	2010	2011	2012	2013	2010	2011	2012	2013
hsize	0.062	0.058	0.070	0.074	0.049	0.052	0.056	0.072
num_ch	0.022	0.022	0.026	0.027	0.033	0.027	0.024	0.023
num_adu	0.108	0.088	0.104	0.111	0.070	0.087	0.102	0.111
num_eld	0.028	0.022	0.043	0.032	0.018	0.018	0.014	0.015
num_wom	0.013	0.013	0.017	0.018	0.005	0.003	0.005	0.011
all_adu	0.004	0.002	0.003	0.001	0.015	0.012	0.013	0.010
all_eld	0.054	0.050	0.072	0.067	0.038	0.046	0.056	0.068
all_wom	0.038	0.029	0.029	0.039	0.029	0.036	0.043	0.050
num_emp	0.059	0.062	0.071	0.083	0.069	0.104	0.094	0.130
num_emp_inc	0.092	0.090	0.073	0.080	0.081	0.084	0.087	0.090
num_self_emp_inc	0.020	0.020	0.023	0.022	0.000	0.006	0.009	0.012
num_ret_inc	0.012	0.009	0.009	0.006	0.040	0.036	0.046	0.044
ref_sex	0.014	0.008	0.006	0.013	0.005	0.007	0.007	0.007
ref_age	0.043	0.033	0.059	0.054	0.037	0.045	0.042	0.047
ref_mar	0.027	0.019	0.026	0.035	0.021	0.024	0.022	0.025
ref_edu	0.212	0.218	0.237	0.229	0.270	0.256	0.241	0.263
ref_pro	0.074	0.068	0.086	0.085	0.077	0.080	0.063	0.076
ref_occ	0.052	0.062	0.060	0.058	0.058	0.081	0.068	0.097
ref_eco2	0.090	0.091	0.111	0.108	0.112	0.102	0.083	0.100
ref_whrs	0.041	0.040	0.051	0.053	0.048	0.063	0.044	0.059
dwe	0.154	0.141	0.136	0.125	0.182	0.154	0.148	0.141
tenure2	0.003	0.001	0.000	0.001	0.006	0.013	0.022	0.016
rent_cat2	0.202	0.211	0.199	0.168	0.210	0.189	0.192	0.192
room_num	0.113	0.112	0.114	0.114	0.155	0.141	0.145	0.138
tot_ar	0.126	0.127	0.122	0.131	0.173	0.160	0.169	0.161
heat_sys	0.191	0.196	0.203	0.197	0.246	0.233	0.225	0.209
bath	0.046	0.033	0.033	0.030	0.068	0.029	0.025	0.021
toilet	0.092	0.074	0.074	0.077	0.098	0.056	0.051	0.054
piped_wat	0.014	0.005	0.012	0.010	0.032	0.022	0.022	0.013
hot_wat	0.134	0.110	0.129	0.108	0.185	0.155	0.141	0.121
mobile	0.077	0.072	0.080	0.060	0.063	0.063	0.061	0.059
comp	0.230	0.229	0.242	0.230	0.255	0.224	0.218	0.236
internet	0.208	0.203	0.224	0.196	0.229	0.203	0.207	0.218
wash_m	0.064	0.045	0.054	0.049	0.096	0.075	0.078	0.051
refrig	0.015	0.014	0.011	0.017	0.039	0.024	0.025	0.013
dish_w	0.219	0.230	0.214	0.205	0.253	0.235	0.237	0.225
air_con	0.046	0.046	0.047	0.047	0.058	0.060	0.057	0.044
car	0.205	0.222	0.211	0.224	0.166	0.185	0.183	0.166
low_mon_inc	0.255	0.259	0.287	0.289	0.392	0.423	0.436	0.445

Afterwards, dummy variables are created for these 11 variables and regression is run for all on the log of consumption expenditure in HBS. The total explanatory power of these variables is adj-R^2=0.5138 (see appendix for the tables). After deselecting ownership of dishwasher and internet, heat system and dwelling type from the model, explanatory power only decreases to 0.5052. Therefore, these four variables can be omitted from the model. Similar results are obtained for all years and also when income (adjusted with CPI) is regressed against the same regressors in SILC.

When adjusted disposable income classes are introduced in the consumption expenditure model in HBS, for 2010, the explanatory power increases up to 0.6273 with all other regressors included. Even when only computer, car ownerships, rent categories and hot water availability in the dwelling are kept as regressors with the income categories the adjusted R^2 is 0.6034.

Having less number of matching variables is preferable for the quality of the match since as the number variables are higher the procedure is exposed to complications more (Kum and Masterson, 2008). Among these imputed rent, which is used to form rent categories, is known to be calculated with a model, so this is also dropped from the model and besides disposable income categories, computer, car ownerships and hot water availability are kept as final regressors. The adjusted R^2 in this model is 0.5950. Thus, without losing much from the explanatory power it was possible to omit rent categories.

I.6.4. Choice of Matching Framework

I.6.4.1. Micro-Macro

The first choice regarding the matching framework is to choose between micro and macro level matching. The micro approach enables to obtain a synthetic data set, but the macro approach only allows for certain contingency tables and correlations between the variables. The macro approach is not appropriate when there is need for a data set for further analysis. In this case, since there is need for a data set at the end of the study the SM will performed at micro level.

I.6.4.2. Parametric-Nonparametric-Mixed

Moreover, a choice should be made between parametric, nonparametric and mixed methods. The parametric method enables use of a model where relationships can be estimated among variables with parametrical indicators. On the other hand, model misspecification would cause further problems. In addition to that, the nonparametric method allows for use of live values. In this regard, use of a mixed method, which involves both parametric and nonparametric methods, sustain the advantages of these approaches concurrently (D’Orazio, 2016). The findings of Webber and Tonkin (2013) also suggest that use of a mixed method yields better results.

The mixed method in (D’Orazio et al., 2016) is comprised of two consequent steps. In the first step a model is fit in each data set and in the second step, by making use of parameters from the first step, the two data sets are matched with nonparametric matching methods.

Step 1. Parametric:

Following the StatMatch package, in the first step a model is fitted either by maximum likelihood method (ML) or by the method suggested by Moriarity and Scheuren (2001, 2003) (MS).

Step 2. Nonparametric:

In the second step, hot deck imputation procedures are carried out, and missing values are filled with observed ones (D'Orazio et al., 2006).

I.6.4.3 Choosing the Donor and the Recipient

A choice should be made between the data sets to determine which one will be the recipient and which one will be the donor file. One of the very first criteria is reliability. If the data sets are deemed to be equally reliable then sample size is taken into consideration. When one file has significantly greater number of records, in this case, the smaller file is selected as the recipient. When it is done otherwise and the selected donor is the smaller file, the variability of the imputed variable's distribution would be higher in the synthetic file because some records in the donor file would be imputed more than once in the recipient, (D'Orazio et al., 2016).

In this study, because the main target is to match consumption expenditure into longitudinal SILC data set. The recipient is definitely the SILC data set and the donor HBS. Even if this was not the case and the target was to match equal number of variables on each size, with regard to the criteria mentioned above the same choice would have been made. The two data sets are more or less equal in reliability issues, since they are both carried out by the same institute. Also HBS sample size is greater than sections of SILC, which would be another reason to make the same choice.

I.6.4.4. Conditional Independence Assumption

When dealing with the SM problem, one of the very first issues is the Conditional Independence Assumption (CIA). The mutually exclusive variables in the two data sets are assumed to be independent since no information on this issue can be deduced from the matching data sets. It is a strong assumption and rarely holds in reality as also suggested by D'Orazio (2016). This assumption can be relaxed and a SM of better quality could be realized if there is any information available in another data set where the variables in question can be found simultaneously or there is any other source of information is available suggesting the correlation of the variables.

D'Orazio (2016) suggests another alternative in the case of uncertainty regarding the relationship between mutually exclusive variables (Y and Z) in the two data sets. In this case, ranges of values are calculated by making use of the properties of the correlation matrix.

$$\rho_{XY}\,\rho_{XZ} - \sqrt{(1-\rho_{YX}^2)(1-\rho_{XZ}^2)} \leq \rho_{YZ} \leq \rho_{XY}\,\rho_{XZ} + \sqrt{(1-\rho_{YX}^2)(1-\rho_{XZ}^2)}$$

In our case, there is existing information on the correlation of income and consumption expenditure from HBS data where these two variables are available at the same time. Then, this information will be used in the StatMatch package and CIA will be relaxed.

I.6.4.5. Complex Sample Design

D'Orazio (2016) explains the problem with regard to complex design as follows:

> *"The SM techniques presented in the previous sections implicitly or explicitly assume that the observed values in A and B are i.i.d. Unfortunately, when dealing with samples selected from a finite population by means of complex sampling designs (with stratification, clustering, etc.) it is difficult to maintain the i.i.d. assumption: it would mean that the sampling design can be ignored. If this is not the case, inferences have to account for sampling design and the weights assigned to the units (usually design weights corrected for unit nonresponse, frame errors, etc.)"*

Both of the data sets that are used in this study for SM have complex sampling designs. Both use stratification and clustering in the sample design. Moreover, the SILC survey also includes a rotating sample. Therefore, if possible this complex design features should be taken into consideration. Also, the weights are considerably different from each other, therefore ignoring this, will pave the way for different marginal and joint distributions in the final synthetic data set from those of the original matched data sets.

D'Orazio (2016) suggests two approaches for dealing with the complex survey design issue. One way to deal with the issue is the naïve approach and the other one is explicitly taking into account the complex survey design and the survey weights.

I.6.4.5.1. Naïve Approach

The naïve approach in principle ignores the sampling design and the weights. One of the nonparametric micro methods is used. The sampling design and the weights of the recipient data set are used in the subsequent work with the newly created synthetic data set (D'Orazio, 2016).

D'Orazio et al. (2012) conducted a study in order to compare naïve procedures. Their findings suggest that when rank and random hot deck procedures use the weights, in the synthetic data set the marginal distribution of the imputed variables and its joint distribution with the matching variables are well preserved. On the other hand, the nearest neighbor procedure presents good results only when constrained matching is used and a design variable is used in the formation of donation classes.

I.6.4.5.2. Explicitly Taking into Consideration

There are mainly three methods for overcoming the complex design issue when the decision is to explicitly take the complex design into consideration (D'Orazio, 2016). These are Renssen's calibrations based approach (Renssen, 1998), Rubin's file concatenation (Rubin, 1986), and Wu's approach based on empirical likelihood methods (Wu, 2004). Renssen's (1998) method is employed in StatMatch application. The method is based on calibration technique to obtain consistency between population totals with regard to the variables at hand. This method requires use of only a number of continuous joint variables (X). It also allows one of the mutually exclusive variables (in Y or Z) to be continuous.

Donatiello et al. (2015) studied the extension of the use of Renssen's method to continuous variables. They used a two-step procedure. In the first step, they predicted consumption in Italian SILC (IT-SILC) by applying a linear model taking into consideration the survey harmonized weights and in the same way, they predicted consumption in HBS. In the second step, they performed a nearest neighbor distance hot deck procedure on these predictions and imputed the “observed” values for consumption into IT-SILC.

The advantages of Renssen method are several. First, it starts from available data and weights and harmonizes marginal and joint distributions of the matching variables. It provides a synthetic data set that preserves the marginal distribution of the imputed variable and its joint distributions with the matching variables. It also allows introducing auxiliary data sources easily. (Donatiello et al., 2015)

On the other hand, Renssen’s method has a few weaknesses. First, there is a probability that the calibration fails. Another issue in this regard is that heteroskedasticity and residuals are not normally distributed. (Donatiello et al., 2015)

I.7. PROCEDURE AND RESULTS

In order to take into consideration the complex survey design as much as possible and in order to make use of auxiliary information, this study employs the Renssen (1998) method available in StatMatch R package by D’Orazio (2016). The method is employed with its extension suggested by Donatiello et. al (2015).

Before the above-mentioned steps, there is need for harmonizing the matching variables. In this case, the harmonization is realized for the joint distributions of four variables. The harmonization actually means calibrating the two data sets jointly with respect to the four matching variables by adjusting the weights of the data sets accordingly. It is similar to the procedure conducted previously in order to make the two data sets coherent with respect to age, sex and household size of the population. It is true that this second procedure will dislocate the first one, but necessary operations were carried out to select the matching variables between the two procedures. There is need for adjusting the four variables, and adding others (age, sex, and household size) would be too demanding and would result much poorer results. In addition, there is no need for age, sex and household size to be recalibrated because they will not be used in the matching process. Even if recalibration with all seven variables were conducted, because of too many constraints, the weights would have extreme values, which would inflate the variation of any estimation (Kish, 1965). In order to avoid further complications, the procedure will be carried out for the four common variables as suggested by D'Orazio (2016).

The first analysis in Table I.7.1 for 2010 data shows the overlapping of the two data sets with respect to the four common variables by making use of various indicators. The indicators suggest that the data sets are already in good harmony with respect to those four variables.

Table I.7.1. Overlap of data sets (1)

tvd	overlap	Bhatt	Hell
0.059	0.941	0.996	0.064

All the same, further harmonization will be looked for by using "harmonization" function in StatMatch package.

"harmonize.x: Harmonizes the marginal (joint) distribution of a set of variables observed independently in two sample surveys referred to the same target population. This function harmonizes the totals of the X variables, observed in both survey A and survey B, to be equal to given known totals specified via x.tot. When these totals are not known

(x.tot=NULL) they are estimated by combining the estimates derived from the two separate surveys. The harmonization is carried out according to a procedure suggested by Renssen (1998) based on calibration of survey weights (for major details on calibration see Sarndal and Lundstrom, 2005). The procedure is particularly suited to deal with categorical X variables." (D'Orazio, 2016)

The function first requires the survey designs to be attached. The data sets do not include information on survey design such as strata variables. Only the survey weights are available which are to be used in this case.

The following commands are used to attach the survey designs (where cal_w4 and FAKTOR are the weight variables in the respective data sets, and AA and BB are SILC and HBS data sets respectively):

svy.A <- svydesign(~1, weights=~cal_w4, data=AA)
svy.B <- svydesign(~1, weights=~FAKTOR, data=BB)

The calibration in the "harmonize" operation could be carried out with three different methods, namely, "linear", "raking" and "poststratify". "Linear" option could lead to negative weights. There is a risk of convergence and the calibration may not result in "linear" and "raking" methods. "Poststratification" on the other hand avoids problem of convergence. The downside of "poststratification" is that it may produce final weights with higher variation.

With regard to x.tot, which refers to the total population, since the exact population totals of the variables are not known x.tot is taken as "NULL". Otherwise, population totals for each variables were to be reached.

With the "linear" method, using the following command calibration is carried out:

out.hz <- harmonize.x (svy.A=svy.A, svy.B=svy.B, form.x=~car:comp:hot_wat:dis_inc_cat-1 ,cal.method="linear")

The same action was repeated for "raking" and the same results in Table I.7.2 were obtained. The results indicate that the calibration operation did not take place as suggested that could happen by D'Orazio (2016).

Table I.7.2. Overlap of data sets (2)

tvd	overlap	Bhatt	Hell
0.059	0.941	0.996	0.064

The poststratification did not provide results with joint distribution of the four variables either, displaying the following error message, indicating that joint calibration would not be possible with the method.

Error in xtabs(as.formula(ff.xA), data = data.A) : interactions are not allowed

So, result with marginal distribution was looked for. This time the results were again the same with the ones with the other methods, indicating that there are too many calibration variables. Availability of hot water was dropped from the calibration and the following indicators were obtained and the operation was continued with the weights acquired by this last process, which would lead to the best approximation that could be attained at this point. The following indicators were obtained:

Table I.7.3. Overlap of data sets (3)

tvd	overlap	Bhatt	Hell
0.0374	0.9626	0.9986	0.0372

After the matching variables are harmonized to the highest possible proximity by “harmonization” function, “comb.samples” function is used to carry out the matching by Renssen (1998) method.

comb.samples: Statistical Matching of data from complex sample surveys

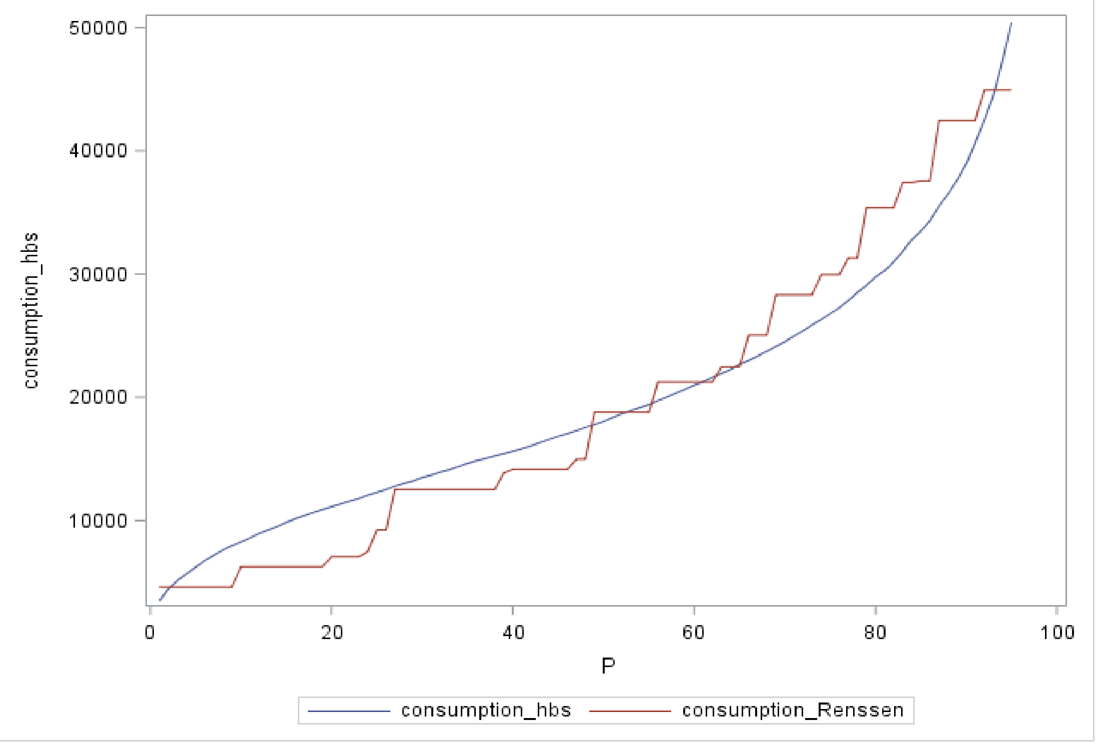
In the function, there is an opportunity for using auxiliary information if available. In our case because there is available information in HBS data set regarding the relationship between consumption expenditure and income as well as other common variables we make use of it. All variables including income categories are set as common variables in SILC and in HBS. Only consumption expenditure is the extra one. Among the methods, Synthetic Two-Way Stratification is the one that is suitable to the data sets at hand, so this is used.

comb.samples(svy.A=out.hz$cal.A,svy.B=out.hz$cal.B,svy.C=svy.C, y.lab="dis_inc_cat",z.lab="harcama_yil",form.x=~car:comp:hot_wat: dis_inc_cat-1,estimation="STWS",micro="TRUE")

After the results are obtained with the Renssen method, a comparison of cumulative density functions of consumption expenditure is made between the two data sets, original HBS data set and SILC after Renssen method is applied. Because of the method used, a total of 27 different consumption values are available in SILC. The variation is extremely low. A glance at the figure shows the overall distributions in the two data sets are similar although the distribution acquired by Renssen method does not demonstrate a smooth graph and the observations are gathered at some values.

Figure I.7.1. Cumulative distribution of consumption expenditure (HBS and

Renssen method), 2010



NND.hotdeck:

For a more approximate distribution of the matched variable (consumption expenditure), one other step is required as suggested by Donatiello et al. (2015). In this step Donatiello et al. (2015) suggests use of estimates from the Renssen method application. In the Renssen application, consumption expenditure is estimated in both SILC and HBS, by making use of common variables and auxiliary information. Then these estimates are used in this step by nearest neighbor distance function in order to get more approximate distributions among the data sets. In our case, because we already have the live values of consumption expenditure from HBS, in addition to all other variables that are existent in the SILC data set to be matched, we preferred to use these live values instead of estimates.

NND.hotdeck function is described as follows:

"This function implements the distance hot deck method to match the records of two data sources that share some variables." (D'Orazio, 2016)

First, the function was applied with constrained model. In this case, a register from the donor data set can be used only for once. The results indicated huge differences between the estimate in the recipient file and the matched value. This time, unconstrained model was applied. In this case, a register from the donor file could be matched to the recipient file more than once.

Figure I.7.2 shows the comparison of cumulative distributions of consumption expenditure in HBS, after the application of Renssen method and after the finalization with NND method with unconstrained matching. The figure shows that the distribution in the final synthetic data set is quite similar to the original distribution. Another check was made, and it was seen that also, the numbers of those having consumption expenditure higher than their disposable income are very close.

Figure I.7.2. Cumulative distribution of consumption expenditure (HBS, Renssen method and NND), 2010

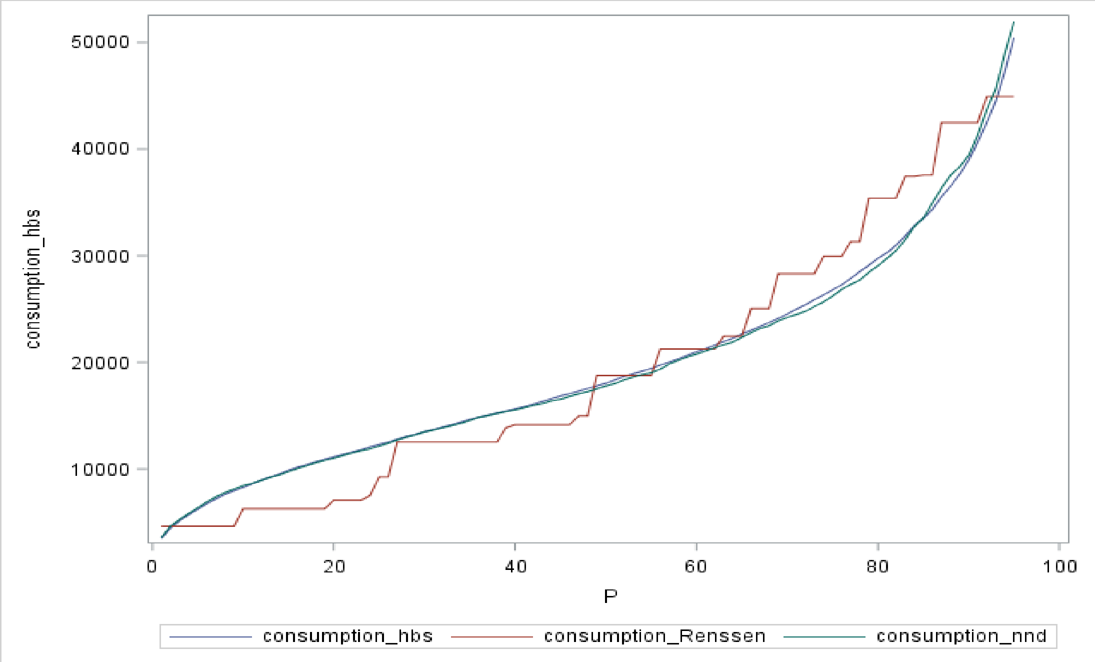


Figure I.7.3. Cumulative distribution of consumption expenditure (HBS, Renssen method and NND), 2011

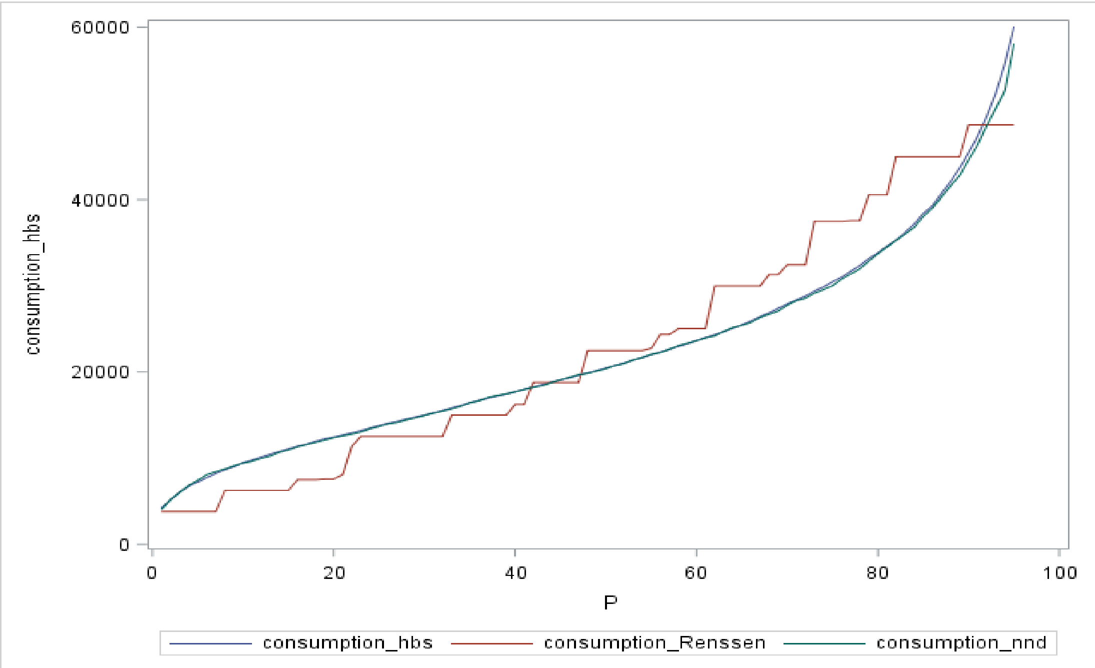


Figure I.7.4. Cumulative distribution of consumption expenditure (HBS, Renssen method and NND), 2012

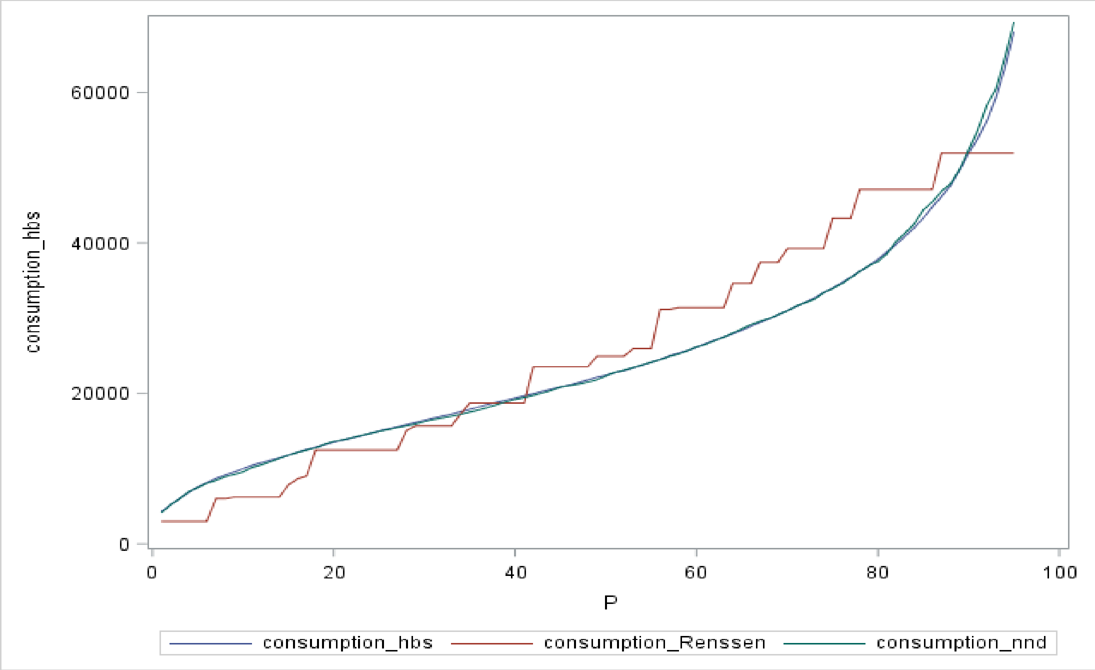
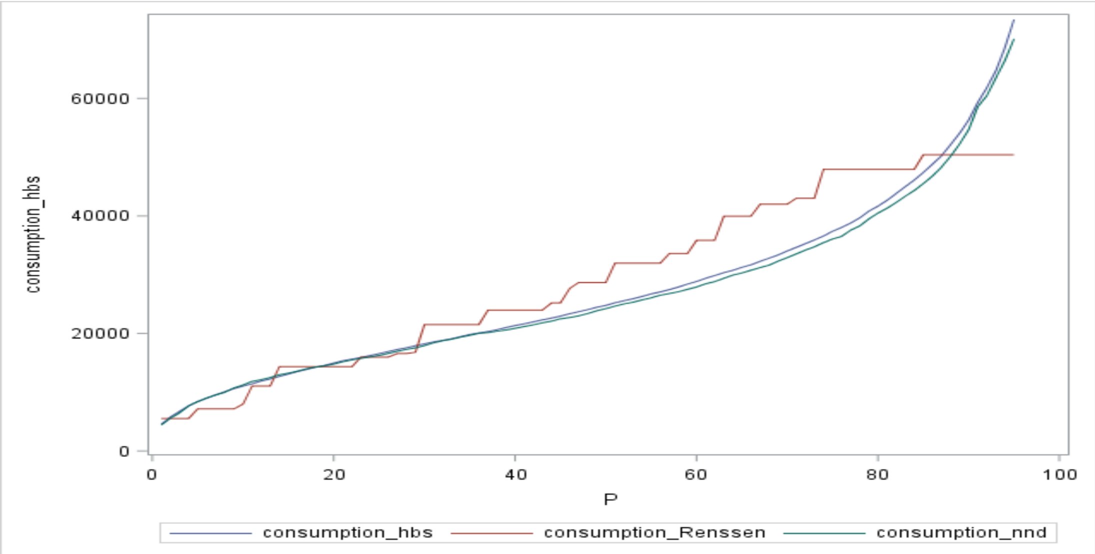


Figure I.7.5. Cumulative distribution of consumption expenditure (HBS, Renssen method and NND), 2013



I.8. VALIDATION (QUALITY CONTROL)

The quality of the synthetic data file obtained by the SM procedure determines whether the goal of the effort is achieved. The quality depends on two main conditions. The marginal and joint distributions in the synthetic file should be as close as possible to the respective distributions in the original files (Kum and Masterson, 2008). Special attention is given to the relationship between income and consumption expenditure.

Main indicators created by consumption expenditure, such as poverty measures are also used to validate the quality of the matching procedures. These indicators are created in both HBS and the synthetic data files and compared according to different household characteristics.

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."*

The quality control will be realized in three main steps. In the first step, marginal distributions of matching variables will be compared. In the second step, joint distributions matching variables and consumption groups will be compared. And in the final step, poverty head count ratios will be compared at household size level.

As will be seen at the end of this section, quality control results referred to a change in the model. With regard to marginal and joint distributions of variables and with regard to overall poverty indicators there weren't significant differences between the synthetic file and HBS. On the other hand, poverty head count ratios at household size level were significantly different from each other. Therefore the model was changed and the statistical matching procedure was repeated. The results provided below refer to the finalized data set. The differences between the two models are insignificant for the first two analyses. On the other hand, there are major differences in the third analysis, therefore a comparison of the two matching models are provided for this analysis.

1. **Marginal distributions of matching variables:**

Table I.8.1. Availability of car

Car	Synthetic Data set				HBS			
	2010	2011	2012	2013	2010	2011	2012	2013
1	31.9	33.5	36.5	38.5	32.0	33.4	36.4	38.7
2	68.1	66.5	63.5	61.5	68.1	66.6	63.6	61.4

Table I.8.2. Availability of computer

Comp	Synthetic Data set				HBS			
	2010	2011	2012	2013	2010	2011	2012	2013
1	42.4	45.6	49.3	49.5	42.1	45.0	49.1	49.3
2	57.6	54.4	50.7	50.5	58.0	55.0	50.9	50.7

Table I.8.3. Disposable income categories

Dis inc cat	Synthetic Data set 2010	2011	2012	2013	HBS 2010	2011	2012	2013
1	24.2	18.4	13.8	10.6	24.1	18.2	13.7	10.9
2	23.5	20.9	19.1	17.4	23.4	21.0	19.0	16.7
3	17.4	17.4	17.5	17.0	17.5	17.2	17.4	16.6
4	11.2	13.2	14.0	13.9	11.4	13.3	13.9	13.6
5	8.2	9.3	10.4	10.7	8.3	9.4	10.5	11.0
6	15.5	20.8	25.3	30.4	15.3	21.0	25.6	31.2

2. Joint distributions of matching variables with consumption categories:

For all years, the joint distributions are similar between the synthetic data set and HBS. Only the results for 2010 are presented for demonstration as no significant differences were observed between years.

Table I.8.4. Availability of car by consumption categories, 2010

	Synthetic Data set Consumption categories			HBS Consumption categories		
Car	>=1500	1500-3000	>3000	>=1500	1500-3000	>3000
1	14.4	41.4	77.8	14.6	41.5	72.5
2	85.6	58.6	22.2	85.5	58.5	27.5

Table I.8.5. Availability of computer by consumption categories, 2010

	Synthetic Data set Consumption categories			HBS Consumption categories		
Comp	>=1500	1500-3000	>3000	>=1500	1500-3000	>3000
1	22.9	57.6	78.5	21.8	56.6	79.0
2	77.1	42.4	21.5	78.2	43.4	21.0

Table I.8.6. Disposable income categories by consumption categories, 2010

Dis inc cat	Synthetic Data set Consumption categories >=1500	1500-3000	>3000	HBS Consumption categories >=1500	1500-3000	>3000
1	43.5	5.1	1.0	44.0	5.3	1.0
2	32.5	17.1	4.8	33.4	16.7	4.2
3	14.8	24.2	7.4	14.3	25.1	7.4
4	5.1	19.9	9.7	4.6	20.5	11.3
5	2.3	15.0	12.5	2.4	14.5	13.2
6	1.8	18.8	64.5	1.3	18.0	63.0

3. Poverty measures by household size

Overall poverty head count ratios are not very different from each other. On the other hand, especially for single households the differences are substantial. For households with 1 and 2 members, the poverty ratios are underestimated demonstrating overestimation for such households. On the other hand, households with 3 or more members generally have higher poverty ratios in the synthetic file compared to HBS, which indicates an underestimation for such households.

Main reason for this substantial divergence at household breakdown could be the lack of household size among the matching variables. For this purpose, household size was included among the matching variables instead of availability of hot water and estimation was repeated for the data. Availability of hot water was chosen because it was the least related to income and consumption compared to other matching variables. Although household size demonstrated even lower relationship in the pairwise analyses, after the divergence of poverty head count ratio between HBS and the synthetic file was observed at household size breakdown, it was decided to include it in the matching variables. This condition appears as a necessity when the target is to carry out further research on poverty measures based on the matched consumption expenditure, especially at household size breakdown. Although there was a decrease, the explanatory power of the model did not change much. The one with hot water availability has an adjusted R^2 value of 0.5950 and the one with household size has an adjusted R^2 value of 0.5892.

The results with the new model generated good results with respect to poverty head count ratio comparison between HBS and the synthetic file. Now the estimates are more reliable, and could be used for further analyses with more confidence.

Table I.8.7. Poverty head count ratios by household size, 2010-2013

Year	HHS	hbs	cons_M1	cons_M2
2010	**1**	14.8	6.9	16.2
2010	**2**	11.3	7.4	9.2
2010	**3**	10.5	9.9	11.6
2010	**4**	15.5	19.9	16.7
2010	**5**	39.5	45.0	42.5
2010	**Total**	19.9	21.2	20.9
2011	**1**	14.6	5.6	15.4
2011	**2**	8.9	5.9	7.0
2011	**3**	8.6	12.2	9.1
2011	**4**	15.2	14.9	16.0
2011	**5**	35.0	37.6	36.0
	Total	17.6	17.8	17.8
2012	**1**	14.1	4.6	13.9
2012	**2**	11.3	8.5	10.1
2012	**3**	9.2	9.3	11.2
2012	**4**	11.5	15.9	13.8
2012	**5**	34.2	37.7	32.5
	Total	16.6	17.4	17.0
2013	**1**	13.0	7.1	12.6
2013	**2**	10.3	6.9	7.3
2013	**3**	7.8	10.6	8.3
2013	**4**	11.9	14.7	14.1
2013	**5**	32.4	39.9	33.7
2013	**Total**	15.5	17.6	15.9

I.9. CONCLUSION

This study aims to create a consumption expenditure variable in longitudinal SILC survey data set via statistical matching of SILC and HBS. Conditional independence assumption is considered to be confirmed by use of auxiliary information. Income variable which is also available in HBS serves in this regard.

The study used the approach by D’Orazio (2016) and its extension by Donatiello et al. (2015) where the procedure is extended to continuous variables. StatMatch R package is used for the matching procedure. The matching procedure actually consists of two main steps. In the first one statistical matching is realized with Renssen (1998) methodology. In the second step, nearest neighbor distance function is applied to the results achieved in the first step to get the final results.

The first results indicated a good match at aggregated levels. On the other hand, poverty head count ratios were substantially divergent at household size breakdown. In this regard, household size was substituted into the matching variables instead of hot water availability. The results improved to a considerable extent.

This showed that even if household size is not selected in the first place as a matching variable because it is not one of the best predictors of the response variables, it should definitely be added among the matching variables, if the target is to pursue further study at disaggregated level.

For further research on the statistical matching of consumption expenditure, another option could be to use equivalized measures of consumption expenditure and income. Hereby household size will be intrinsic in the matched variables. This way an extra variable could be added to increase the quality of the match.

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Appendix I.1. List of common variables

#	Name of Variable	Variable
1.	hsize	Household size
2.	num_ch	Number of children (0-17) in the household
3.	num_adu	Number of adults (18-64) in the household
4.	num_eld	Number of elderly (65+) in the household
5.	num_wom	Number of women in the household
6.	all_adu	All household members are adults
7.	all_eld	All household members are elderly
8.	all_wom	All household members are women
9.	num_emp	Number of employed people
10.	num_emp_inc	Number of individuals with employee income
11.	num_self_emp_inc	Number of individuals with self-employed income
12.	num_ret_inc	Number of idividuals with retired income
13.	ref_sex	Reference person's sex
14.	ref_age	Reference person's age group
15.	ref_mar	Reference person's marital status
16.	ref_edu	Reference person's education
17.	ref_pro	Reference person's professional status
18.	ref_occ	Reference person's occupation
19.	ref_eco	Reference person's economic activity of work
20.	ref_whrs	Reference person's number of weekly working hours
21.	dwe	Dwelling type
22.	tenure	Tenure status
23.	rent_cat	Current rent related to occupied dwelling (including imputed rent)
24.	room_num	Number of rooms (except for kitchen, bathroom and toilet) available to the household
25.	tot_ar	Total space available to the household (m2)
26.	heat_sys	Heating system of the dwelling
27.	bath	Bath or shower in dwelling
28.	toilet	Indoor flushing toilet for sole use of household
29.	piped_wat	Piped water
30.	hot_wat	Hot water
31.	mobile	Mobile
32.	comp	Computer
33.	internet	Internet
34.	wash_m	Washing machine
35.	refrig	Refrigerator
36.	dish_w	Dishwasher
37.	air_con	Air conditioner
38.	car	Car
39.	low_mon_inc	Lowest monthly income to make ends meet
40.	dis_inc_cat	Total disposable household income

Appendix I.2. Distributions of common variables

#	NAME OF VARIABLE	VARIABLE	SILC (%) 2010	SILC (%) 2011	SILC (%) 2012	SILC (%) 2013	HBS (%) 2010	HBS (%) 2011	HBS (%) 2012	HBS (%) 2013
1	hsize	Household size								
	1		6.1	6.3	6.9	6.9	6.1	6.3	6.9	6.9
	2		18.0	19.5	19.6	20.5	18.0	19.5	19.6	20.5
	3		23.5	23.1	23.8	23.5	23.5	23.1	23.8	23.5
	4		26.0	25.1	25.4	25.7	26.0	25.1	25.4	25.7
	5+		26.4	26.0	24.3	23.5	26.4	26.0	24.3	23.5
2	num_ch	Number of children (0-17) in the household								
	0		41.0	42.4	42.1	42.7	40.0	41.2	42.5	43.2
	1		22.4	22.6	23.4	23.3	24.1	23.9	23.8	23.1
	2		22.1	20.9	22.0	21.5	21.7	21.7	20.6	21.2
	3		9.3	9.0	7.6	7.9	8.4	8.1	8.1	8.0
	4+		5.3	5.1	4.9	4.7	5.7	5.1	5.0	4.5
3	num_adu	Number of adults (18-64) in the household								
	0		6.9	6.9	7.5	7.3	6.3	6.5	6.7	6.9
	1		8.4	8.8	8.9	9.8	8.9	9.2	9.9	9.4
	2		52.2	52.3	53.0	52.1	52.2	52.9	52.5	53.4
	3		18.9	18.7	17.3	18.1	18.6	17.7	18.1	17.5
	4+		13.5	13.5	13.3	12.6	14.0	13.8	12.9	12.8
4	num_eld	Number of elderly (65+) in the household								
	0		79.6	79.6	79.9	80.0	79.5	79.6	79.6	80.0
	1		14.3	14.2	13.8	13.7	14.5	14.1	14.5	13.8
	2+		6.2	6.2	6.3	6.4	6.1	6.3	5.9	6.3
5	num_wom	Number of women in the household								
	0		2.5	2.7	3.0	3.1	2.6	3.4	3.3	3.3
	1		41.1	42.2	42.7	43.0	42.2	41.6	43.5	44.4
	2		32.9	32.3	33.2	33.4	31.5	31.8	31.4	31.1
	3		15.2	14.5	13.9	13.4	14.9	14.9	14.1	13.2
	4+		8.3	8.3	7.3	7.1	8.9	8.4	7.7	8.0
6	all_adu	All household members are adults								
	No		73.4	72.2	72.4	71.9	73.8	72.7	72.3	71.2
	Yes		26.6	27.8	27.6	28.1	26.2	27.3	27.7	28.8
7	all_eld	All household members are elderly								
	No		93.2	93.2	92.6	92.8	93.8	93.7	93.4	93.2
	Yes		6.8	6.8	7.4	7.2	6.2	6.3	6.7	6.8
8	all_wom	All household members are women								
			94.0	93.8	93.4	93.4	93.8	93.7	93.6	93.6
			6.0	6.2	6.6	6.6	6.2	6.3	6.4	6.4

#	NAME OF VARIABLE	VARIABLE	SILC (%) 2010	SILC (%) 2011	SILC (%) 2012	SILC (%) 2013	HBS (%) 2010	HBS (%) 2011	HBS (%) 2012	HBS (%) 2013
9	**num_emp**	**Number of employed people**								
	0		20.2	19.7	19.0	20.2	18.5	17.4	17.2	17.4
	1		44.8	44.9	44.9	45.7	44.3	43.4	43.7	44.1
	2		25.4	25.7	26.7	25.8	27.2	28.3	28.7	28.1
	3		6.5	6.6	6.5	5.6	6.9	7.5	7.6	7.2
	4+		3.2	3.0	2.9	2.7	3.2	3.4	2.8	3.2
10	**num_emp_inc**	**Number of individuals with employee income**								
	0		35.1	33.5	32.3	31.9	40.7	38.0	31.2	31.7
	1		44.1	41.9	43.0	42.6	40.4	40.7	40.9	40.3
	2		16.6	19.6	19.5	20.3	15.4	17.6	21.7	21.8
	3		3.2	3.7	4.1	4.4	2.8	3.0	4.8	4.7
	4+		0.9	1.4	1.1	0.8	0.8	0.8	1.4	1.4
11	**num_self_emp_inc**	**Number of individuals with self-employed income**								
	0		68.3	67.5	69.2	69.3	83.6	84.9	80.0	79.3
	1		30.1	30.4	29.0	28.8	15.7	14.4	18.7	19.2
	2+		1.6	2.2	1.9	1.9	0.7	0.7	1.4	1.4
12	**num_ret_inc**	**Number of idividuals with retired income**								
	0		66.9	66.7	66.9	66.4	67.9	67.4	67.6	68.1
	1		27.7	28.0	27.7	28.1	28.0	28.7	28.0	27.6
	2+		5.3	5.3	5.4	5.5	4.2	4.0	4.4	4.2
13	**ref_sex**	**Reference person's sex**								
	Male		84.5	84.6	83.9	83.3	83.9	84.1	83.6	84.3
	Female		15.5	15.4	16.2	16.7	16.1	15.9	16.4	15.7
14	**ref_age**	**Reference person's age group**								
	<25		5.7	5.9	4.9	5.6	5.8	5.2	5.6	5.5
	>=25 and <35		26.3	24.6	24.3	24.0	25.6	25.8	25.2	25.0
	>=35 and <45		25.5	26.1	25.7	24.8	26.1	26.2	25.7	25.5
	>=45 and <65		31.3	32.4	33.4	34.0	31.7	31.9	32.2	32.8
	>=65		11.3	11.1	11.8	11.6	11.0	10.9	11.3	11.2
15	**ref_mar**	**Reference person's marital status**								
	Married		81.1	81.5	81.2	80.7	81.8	80.7	80.7	80.6
	Never married		9.1	8.8	8.2	8.8	8.8	9.4	9.1	9.3
	Widow		7.5	7.3	8.0	7.7	7.1	7.0	7.0	6.9
	Divorced		2.2	2.5	2.6	2.8	2.4	3.0	3.2	3.1

#	NAME OF VARIABLE	VARIABLE	SILC (%) 2010	SILC (%) 2011	SILC (%) 2012	SILC (%) 2013	HBS (%) 2010	HBS (%) 2011	HBS (%) 2012	HBS (%) 2013
16	**ref_edu**	**Reference person's education**								
	No formal education		11.6	11.4	10.9	10.3	11.0	10.8	10.8	10.5
	Less than high school		54.9	54.4	53.4	53.9	55.8	54.6	52.6	53.5
	High school		19.0	19.4	20.0	19.8	19.1	19.2	19.4	18.7
	Higher education		14.5	14.8	15.6	16.0	14.2	15.4	17.2	17.3
17	**ref_pro**	**Reference person's professional employment status**								
	Doesn't work		26.3	25.7	25.1	26.9	24.6	22.9	22.9	23.6
	Regular employee		44.2	44.8	46.3	45.9	43.8	44.9	45.6	45.8
	Casual employee		5.5	5.8	5.8	5.5	6.4	7.2	6.6	5.8
	Employer		5.3	5.2	5.4	5.3	4.4	4.3	4.6	4.4
	Own account worker		18.1	17.9	17.0	16.0	20.4	20.5	19.9	20.0
	Unpaid family worker		0.7	0.6	0.4	0.4	0.4	0.3	0.3	0.4
18	**ref_occ**	**Reference person's occupation (ISCO-88)**								
	Doesn't work		26.3	25.7	25.1	26.9	24.6	22.9	22.9	23.6
	Legislators, senior, officials and managers		8.9	8.6	5.4	5.1	10.4	10.3	7.2	6.6
	Professionals		6.3	6.2	7.0	7.0	5.3	5.9	6.8	6.8
	Technicians and associate professionals		4.3	4.9	4.3	4.2	4.9	5.4	4.7	4.2
	Clerks		4.0	4.1	4.1	4.2	4.2	4.4	4.1	4.2
	Service workers and shop and market sales workers		8.3	8.3	13.0	13.0	7.6	8.5	12.9	14.0
	Skilled agricultural, and fishery workers		11.7	11.7	11.4	10.5	11.8	12.8	12.0	12.0
	Craft and related trades workers		12.2	12.5	12.7	12.2	12.2	10.7	12.0	11.9
	Plant and machine operators and assemblers		9.2	9.2	8.8	9.3	9.9	9.4	9.5	8.7
	Elementary occupations		8.9	8.9	8.3	7.6	9.2	9.7	7.8	8.0
19	**ref_eco**	**Reference person's economic activity of work (NACE Rev.2)**								
	Doesn't work		26.3	25.7	25.1	26.9	24.6	22.9	23.0	24.0
	Agriculture, forestry and fishing (A)		12.9	12.5	12.0	11.3	12.7	13.8	12.9	12.5
	Mining and quarrying (B)		0.6	0.7	0.7	0.6	0.5	0.4	0.6	0.9
	Manufacturing (C)		14.7	14.8	15.1	15.2	15.4	14.2	15.0	14.0
	Electricity, gas, steam, water supply, sewerage etc. (D+E)		1.2	1.0	1.0	1.1	0.8	0.7	0.8	1.1
	Construction (F)		5.5	6.1	6.0	6.4	6.3	7.1	6.9	6.1
	Wholesale and retail trade (G)		11.5	12.0	11.8	10.9	12.2	12.1	10.9	11.5
	Transportation and storage (H)		4.5	4.5	4.9	4.3	3.5	3.8	3.5	4.0
	Accommodation and food service activities (I)		3.4	3.3	3.0	3.1	4.9	5.1	4.6	4.4
	Information and communication (J)		0.7	0.6	0.9	0.9	0.6	0.8	0.6	0.7
	Financial and insurance activities (K)		1.3	1.3	1.2	1.0	0.8	1.0	1.2	1.2
	Real estate activities (L)		0.2	0.6	0.3	0.3	0.2	0.7	0.9	0.6
	Professional, scientific and technical activities (M)		1.1	1.4	1.2	1.1	1.3	1.6	1.5	1.7
	Administrative and support service activities (N)		3.0	2.7	3.5	3.2	2.5	2.4	2.4	2.7
	Public administration and defence (O)		4.4	4.2	4.3	4.2	5.5	5.4	6.0	5.7
	Education (P)		3.8	3.6	4.4	4.3	3.4	3.4	3.9	3.6
	Human health and social work activities (Q)		2.0	2.2	2.3	2.5	2.0	1.9	2.5	2.7
	Arts, entertainment and recreation (R)		0.5	0.5	0.4	0.6	0.3	0.3	0.3	0.4
	Other social, community and personal service activities (S+T+U)		2.6	2.3	2.2	2.1	2.7	2.5	2.5	2.3

#	NAME OF VARIABLE	VARIABLE	SILC (%) 2010	SILC (%) 2011	SILC (%) 2012	SILC (%) 2013	HBS (%) 2010	HBS (%) 2011	HBS (%) 2012	HBS (%) 2013
20	**ref_whrs**	**Reference person's number of weekly working hours**								
	Doesn't work		26.3	25.7	25.1	26.9	24.6	22.9	22.9	23.6
	<20		1.7	1.5	1.6	1.4	61.5	63.3	63.5	62.8
	>=20 and <40		19.1	17.7	18.4	17.8	11.9	12.2	11.8	11.9
	>=40 and <60		36.9	37.8	37.4	37.6	2.0	1.6	1.7	1.7
	>=60		16.1	17.3	17.5	16.3	0.1	0.1	0.1	0.0
21	**dwe**	**Dwelling type**								
	Detached or semidetached		46.3	44.7	43.4	42.9	44.4	44.1	43.6	44.4
	Apartment		53.7	55.3	56.6	57.1	55.6	55.9	56.5	55.6
22	**tenure**	**Tenure status**								
	Owner occupied		60.0	59.9	59.9	59.7	60.0	60.2	57.5	59.8
	Rented		21.1	21.3	20.6	21.4	23.8	23.9	24.9	23.3
	Owned by governmental or private organizations		1.3	1.3	1.1	1.0	2.0	2.0	2.3	2.4
	Not owner occupied, but no rent is paid		17.7	17.5	18.4	18.0	14.2	13.8	15.3	14.5
23	**rent_cat**	**Current rent related to occupied dwelling (including imputed rent)**								
	<250		49.5	43.5	38.1	43.1	46.9	43.4	38.6	36.9
	>=250 and <500		36.2	42.0	47.8	44.6	42.8	44.2	44.5	42.8
	>=500 and <750		10.0	10.6	10.7	8.7	7.3	8.2	11.3	13.5
	>=750		4.3	3.9	3.5	3.6	3.0	4.3	5.7	6.8
24	**room_num**	**Number of rooms available to the household**								
	1		1.0	1.0	0.9	0.8	1.0	0.9	0.8	0.9
	2		9.1	8.8	8.3	8.1	8.0	8.2	8.8	7.8
	3		42.4	41.8	42.0	42.2	39.8	41.0	38.7	40.4
	4+		47.6	48.4	48.9	48.9	51.2	49.8	51.7	50.9
25	**tot_ar**	**Total space available to the household (m^2)**								
	<=60		7.8	7.6	7.1	6.9	7.5	7.3	7.6	7.7
	>60 and <=80		17.3	16.8	16.9	17.0	15.7	15.8	14.7	14.8
	>80 and <=100		38.9	38.5	37.7	37.2	36.3	36.8	36.2	35.4
	>100 and <=120		20.0	20.2	20.6	21.0	22.1	21.3	21.5	20.3
	>120		16.0	16.9	17.8	17.9	18.3	18.8	20.1	22.0
26	**heat_sys**	**Heating system of the dwelling**								
	Stove (coal, gas, natural gas, electricity, etc.)		62.9	59.2	56.7	53.7	65.3	60.1	56.3	55.6
	Central heating for one or more buildings		10.1	10.3	10.8	10.5	9.7	10.6	11.2	10.9
	Central heating for one dwelling		22.9	26.0	29.0	32.3	20.8	25.5	28.1	29.0
	Air conditioner		4.0	4.2	3.3	3.2	3.8	3.5	4.3	4.5
	Other		0.2	0.2	0.2	0.2	0.4	0.3	0.1	0.1
27	**bath**	**Bath or shower in dwelling**								
	Yes		95.9	97.5	97.8	97.9	96.5	96.8	97.0	97.3
	No		4.1	2.5	2.2	2.1	3.5	3.2	3.0	2.7

#	NAME OF VARIABLE	VARIABLE	SILC (%) 2010	SILC (%) 2011	SILC (%) 2012	SILC (%) 2013	HBS (%) 2010	HBS (%) 2011	HBS (%) 2012	HBS (%) 2013
28	**toilet**	**Indoor flushing toilet for sole use of household**								
	Yes		89.2	92.7	92.9	93.3	89.8	90.0	91.1	91.5
	No		10.8	7.3	7.1	6.7	10.2	10.0	8.9	8.5
29	**piped_wat**	**Piped water**								
	Yes		98.0	98.4	98.9	99.0	98.7	99.0	98.6	99.5
	No		2.0	1.6	1.1	1.0	1.3	1.0	1.4	0.6
30	**hot_wat**	**Hot water**								
	Yes		82.1	83.6	85.5	87.1	82.8	83.6	85.0	87.6
	No		17.9	16.4	14.5	12.9	17.2	16.4	15.0	12.4
31	**mobile**	**Mobile**								
	Yes		94.0	94.9	95.4	95.7	93.9	94.1	94.6	95.8
	No		6.0	5.1	4.6	4.3	6.1	5.9	5.4	4.2
32	**comp**	**Computer**								
	Yes		43.5	47.9	50.1	50.4	42.1	45.0	49.1	49.3
	No		56.5	52.1	49.9	49.7	58.0	55.0	50.9	50.7
33	**internet**	**Internet**								
	Yes		34.2	37.5	39.3	39.9	31.3	33.6	37.0	36.6
	No		65.8	62.5	60.7	60.1	68.8	66.5	63.0	63.4
34	**wash_m**	**Washing machine**								
	Yes		92.9	94.8	95.4	96.6	94.1	95.1	95.6	96.4
	No		7.1	5.2	4.7	3.4	5.9	4.9	4.4	3.6
35	**refrig**	**Refrigerator**								
	Yes		98.0	98.9	99.0	98.9	98.6	98.7	98.6	98.9
	No		2.0	1.1	1.0	1.2	1.4	1.3	1.4	1.1
36	**dish_w**	**Dishwasher**								
	Yes		44.2	49.8	54.4	58.0	42.1	46.3	51.8	56.4
	No		55.8	50.2	45.6	42.0	57.9	53.7	48.2	43.6
37	**air_con**	**Air conditioner**								
	Yes		15.8	17.2	18.0	20.9	14.0	15.2	16.6	21.3
	No		84.2	82.8	82.0	79.1	86.0	84.8	83.4	78.7
38	**car**	**Car**								
	Yes		31.8	34.0	36.9	37.9	32.0	33.4	36.4	38.7
	No		68.2	66.0	63.1	62.1	68.1	66.6	63.6	61.4

#	NAME OF VARIABLE	VARIABLE	SILC (%) 2010	2011	2012	2013	HBS (%) 2010	2011	2012	2013
39	**low_mon_inc**	**Lowest monthly income to make ends meet**								
	<=1000		25.7	22.8	15.2	11.8	52.0	47.0	38.8	32.2
	>1000 and <=1500		24.2	25.3	23.9	18.8	24.6	25.1	25.0	26.3
	>1500 and <=2000		22.3	21.9	22.1	23.3	13.9	16.2	19.3	21.3
	>2000 and <=2500		8.7	9.6	9.5	12.2	3.4	3.9	5.5	6.2
	>2500 and <=3000		9.1	9.0	12.6	14.4	3.7	4.5	6.4	8.0
	>3000		10.0	11.4	16.8	19.6	2.4	3.3	5.0	6.0
40	**dis_inc_cat**	**Total disposable household income**								
	<=1000		24.7	19.2	14.1	9.7	24.1	18.2	13.7	10.9
	>1000 and <=1500		23.6	20.8	19.6	19.6	23.4	21.0	19.0	16.7
	>1500 and <=2000		17.2	17.9	17.7	18.2	17.5	17.2	17.4	16.6
	>2000 and <=2500		10.1	12.9	14.3	14.9	11.4	13.3	13.9	13.6
	>2500 and <=3000		8.1	9.0	10.1	9.7	8.3	9.4	10.5	11.0
	>3000		16.3	20.2	24.2	27.9	15.3	21.0	25.6	31.2

Appendix I.3. Regression tables

HBS, MODEL 1, 2010-2013

	2010		2011		2012		2013	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
Intercept	7.63	0.04***	7.82	0.03***	7.84	0.03***	7.88	0.03***
low_mon_inc_1	-0.51	0.03***	-0.59	0.03***	-0.61	0.02***	-0.57	0.02***
low_mon_inc_2	-0.35	0.03***	-0.43	0.03***	-0.47	0.02***	-0.43	0.02***
low_mon_inc_3	-0.24	0.03***	-0.35	0.03***	-0.35	0.02***	-0.35	0.02***
low_mon_inc_4	-0.20	0.04***	-0.31	0.03***	-0.29	0.03***	-0.26	0.03***
low_mon_inc_5	-0.16	0.04***	-0.23	0.03***	-0.23	0.03***	-0.20	0.02***
comp_1	0.08	0.02***	0.09	0.02***	0.10	0.02***	0.13	0.01***
dish_w_1	0.07	0.01***	0.10	0.01***	0.08	0.01***	0.09	0.01***
ref_edu_1	-0.34	0.02***	-0.30	0.02***	-0.33	0.02***	-0.33	0.02***
ref_edu_2	-0.10	0.02***	-0.09	0.02***	-0.11	0.01***	-0.13	0.01***
ref_edu_3	-0.07	0.02***	-0.06	0.02***	-0.08	0.02***	-0.08	0.02***
internet_1	0.12	0.02***	0.11	0.02***	0.11	0.02***	0.07	0.02***
car_1	0.30	0.01***	0.34	0.01**	0.33	0.01***	0.32	0.01***
rent_cat2_1	-0.14	0.01**	-0.16	0.01***	-0.14	0.01***	-0.11	0.01***
heat_sys_2	0.11	0.02***	0.07	0.02***	0.08	0.02***	0.09	0.02***
heat_sys_3	0.09	0.01***	0.11	0.01***	0.09	0.01***	0.14	0.01***
heat_sys_4	0.06	0.02**	0.06	0.03**	0.01	0.02	0.04	0.02*
heat_sys_5	-0.02	0.07	0.10	0.08	-0.02	0.16	-0.38	0.14***
dwe_1	0.01	0.01	0.03	0.01**	0.03	0.01**	0.03	0.01***
hot_wat_1	0.17	0.01***	0.11	0.01***	0.17	0.01***	0.14	0.02***
tot_ar_1	-0.34	0.02***	-0.31	0.02***	-0.30	0.02***	-0.33	0.02***
tot_ar_2	-0.19	0.02***	-0.19	0.02***	-0.19	0.02***	-0.18	0.02***
tot_ar_3	-0.14	0.01***	-0.15	0.01***	-0.16	0.01***	-0.15	0.01***
tot_ar_4	-0.07	0.01***	-0.10	0.01***	-0.12	0.01***	-0.11	0.01***

* significant at 90% level
** significant at 95% level
*** significant at 99% level

SILC, MODEL 1, 2010-2013

	2010		2011		2012		2013	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
Intercept	10.39	0.06***	10.43	0.05***	10.45	0.05***	10.57	0.05***
low_mon_inc_1	-0.75	0.04***	-0.85	0.04***	-0.81	0.04***	-0.79	0.04***
low_mon_inc_2	-0.62	0.04***	-0.72	0.04***	-0.66	0.03***	-0.65	0.03***
low_mon_inc_3	-0.47	0.04***	-0.53	0.04***	-0.52	0.03***	-0.52	0.03***
low_mon_inc_4	-0.38	0.04***	-0.39	0.04***	-0.45	0.04***	-0.38	0.03***
low_mon_inc_5	-0.30	0.04***	-0.34	0.04***	-0.32	0.03***	-0.33	0.03***
comp_1	0.09	0.03***	0.02	0.03	0.04	0.03	0.05	0.03**
dish_w_1	0.09	0.02***	0.11	0.02***	0.11	0.02***	0.10	0.02***
ref_edu_1	-0.36	0.04***	-0.30	0.04***	-0.31	0.04***	-0.37	0.04***
ref_edu_2	-0.23	0.03***	-0.18	0.03***	-0.17	0.03***	-0.23	0.03***
ref_edu_3	-0.20	0.03***	-0.19	0.03***	-0.22	0.03***	-0.25	0.03***
internet_1	0.08	0.03**	0.12	0.03***	0.13	0.03***	0.10	0.03***
car_1	0.18	0.02***	0.21	0.02***	0.20	0.02***	0.18	0.02***
rent_cat2_1	-0.11	0.02***	-0.09	0.03***	-0.01	0.03	-0.04	0.03
heat_sys_2	0.19	0.04***	0.14	0.04***	0.18	0.04***	0.20	0.03***
heat_sys_3	0.13	0.03***	0.13	0.03***	0.12	0.03***	0.11	0.02***
heat_sys_4	0.06	0.05	0.10	0.05**	0.06	0.05	0.11	0.05**
heat_sys_5	0.23	0.21	0.43	0.18**	0.56	0.19***	0.73	0.17***
dwe_1	0.04	0.02	0.06	0.03**	0.03	0.03	0.07	0.02***
hot_wat_1	0.23	0.03***	0.20	0.03***	0.15	0.03***	0.11	0.03***
tot_ar_1	-0.36	0.04***	-0.28	0.04***	-0.33	0.04***	-0.29	0.04***
tot_ar_2	-0.29	0.03***	-0.17	0.03***	-0.17	0.03***	-0.19	0.03***
tot_ar_3	-0.22	0.03***	-0.13	0.03***	-0.14	0.03***	-0.14	0.02***
tot_ar_4	-0.12	0.03***	-0.07	0.03***	-0.07	0.03**	-0.10	0.03***

* significant at 90% level
** significant at 95% level
*** significant at 99% level

HBS, MODEL 2, 2010-2013

	2010		2011		2012		2013	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
Intercept	7.78	0.04***	7.98	0.03***	7.98	0.03***	8.03	0.03***
low_mon_inc_1	-0.57	0.03***	-0.63	0.03***	-0.65	0.02***	-0.61	0.02***
low_mon_inc_2	-0.40	0.03***	-0.47	0.03***	-0.51	0.02***	-0.46	0.02***
low_mon_inc_3	-0.28	0.03***	-0.37	0.03***	-0.38	0.02***	-0.37	0.02***
low_mon_inc_4	-0.22	0.04***	-0.32	0.03***	-0.31	0.03***	-0.27	0.03***
low_mon_inc_5	-0.18	0.04***	-0.24	0.03***	-0.24	0.03***	-0.21	0.02***
comp_1	0.18	0.01***	0.19	0.01***	0.20	0.01***	0.19	0.01***
ref_edu_1	-0.38	0.02***	-0.34	0.02***	-0.36	0.02***	-0.37	0.02***
ref_edu_2	-0.13	0.02***	-0.12	0.01***	-0.14	0.01***	-0.16	0.01***
ref_edu_3	-0.09	0.02***	-0.08	0.02***	-0.10	0.02***	-0.10	0.02***
car_1	0.31	0.01***	0.35	0.01***	0.34	0.01***	0.33	0.01***
rent_cat2_1	-0.19	0.01***	-0.21	0.01***	-0.18	0.01***	-0.16	0.01***
hot_wat_1	0.19	0.01***	0.13	0.01***	0.20	0.01***	0.17	0.02***
tot_ar_1	-0.36	0.02***	-0.34	0.02***	-0.31	0.02***	-0.35	0.02***
tot_ar_2	-0.21	0.02***	-0.21	0.02***	-0.20	0.02***	-0.20	0.02***
tot_ar_3	-0.16	0.01***	-0.16	0.01***	-0.17	0.01***	-0.16	0.01***
tot_ar_4	-0.08	0.01***	-0.11	0.01***	-0.12	0.01***	-0.11	0.01***

* significant at 90% level
** significant at 95% level
*** significant at 99% level

SILC, MODEL 2, 2010-2013

	2010		2011		2012		2013	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
Intercept	10.59	0.05***	10.65	0.05***	10.67	0.05***	10.79	0.04***
low_mon_inc_1	-0.79	0.04***	-0.90	0.04***	-0.86	0.04***	-0.82	0.04***
low_mon_inc_2	-0.66	0.04***	-0.77	0.04***	-0.71	0.03***	-0.68	0.03***
low_mon_inc_3	-0.50	0.04***	-0.57	0.04***	-0.56	0.03***	-0.54	0.03***
low_mon_inc_4	-0.40	0.04***	-0.42	0.04***	-0.48	0.04***	-0.40	0.03***
low_mon_inc_5	-0.31	0.04***	-0.36	0.04***	-0.34	0.03***	-0.35	0.03***
comp_1	0.16	0.02***	0.12	0.02***	0.14	0.02***	0.14	0.02***
ref_edu_1	-0.42	0.04***	-0.35	0.04***	-0.37	0.04***	-0.43	0.04***
ref_edu_2	-0.29	0.03***	-0.23	0.03***	-0.22	0.03***	-0.28	0.03***
ref_edu_3	-0.23	0.03***	-0.21	0.03***	-0.25	0.03***	-0.27	0.03***
car_1	0.19	0.02***	0.23	0.02***	0.21	0.02***	0.19	0.02***
rent_cat2_1	-0.16	0.02***	-0.13	0.02***	-0.08	0.02***	-0.09	0.02***
hot_wat_1	0.25	0.03***	0.22	0.03***	0.18	0.03***	0.14	0.03***
tot_ar_1	-0.37	0.04***	-0.30	0.04***	-0.36	0.04***	-0.33	0.04***
tot_ar_2	-0.32	0.03***	-0.21	0.03***	-0.21	0.03***	-0.23	0.03***
tot_ar_3	-0.23	0.03***	-0.15	0.03***	-0.17	0.03***	-0.17	0.02***
tot_ar_4	-0.13	0.03***	-0.08	0.03***	-0.07	0.03***	-0.12	0.03***

* significant at 90% level
** significant at 95% level
*** significant at 99% level

HBS, MODEL 3, 2010-2013

	2010		2011		2012		2013	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
Intercept	7.96	0.03***	8.09	0.03***	8.14	0.03***	8.16	0.03***
dis_inc_cat_1	-0.90	0.02***	-0.85	0.02***	-0.91	0.02***	-0.98	0.02***
dis_inc_cat_2	-0.58	0.02***	-0.54	0.01***	-0.58	0.02***	-0.61	0.01***
dis_inc_cat_3	-0.43	0.02***	-0.40	0.01***	-0.43	0.01***	-0.45	0.01***
dis_inc_cat_4	-0.31	0.02***	-0.30	0.01***	-0.29	0.01***	-0.31	0.01***
dis_inc_cat_5	-0.23	0.02***	-0.19	0.02***	-0.22	0.02***	-0.23	0.01***
low_mon_inc_1	-0.32	0.03**	-0.39	0.02**	-0.41	0.02***	-0.36	0.02***
low_mon_inc_2	-0.24	0.03***	-0.30	0.02***	-0.34	0.02***	-0.28	0.02***
low_mon_inc_3	-0.18	0.03***	-0.28	0.02***	-0.28	0.02***	-0.26	0.02***
low_mon_inc_4	-0.17	0.03***	-0.25	0.03***	-0.24	0.03***	-0.22	0.02***
low_mon_inc_5	-0.14	0.03***	-0.21	0.03***	-0.21	0.02***	-0.18	0.02***
comp_1	0.04	0.01***	0.06	0.01***	0.06	0.01***	0.06	0.01***
dish_w_1	0.02	0.01**	0.05	0.01***	0.03	0.01***	0.03	0.01***
ref_edu_1	-0.16	0.02***	-0.14	0.02***	-0.15	0.02***	-0.14	0.02***
ref_edu_2	0.00	0.01	-0.02	0.01	-0.01	0.01	-0.04	0.01***
ref_edu_3	0.01	0.01	0.00	0.01	-0.02	0.01	-0.03	0.01*
internet_1	0.05	0.01***	0.06	0.01***	0.06	0.01***	0.04	0.01***
car_1	0.20	0.01***	0.24	0.01***	0.23	0.01***	0.23	0.01***
rent_cat2_1	-0.08	0.01***	-0.11	0.01***	-0.08	0.01***	-0.08	0.01***
heat_sys_2	0.05	0.02***	0.04	0.02**	0.03	0.02*	0.05	0.02***
heat_sys_3	0.03	0.01**	0.06	0.01***	0.04	0.01***	0.08	0.01***
heat_sys_4	0.01	0.02	0.03	0.02	-0.01	0.02	0.01	0.02
heat_sys_5	-0.06	0.06	0.10	0.07	-0.01	0.14	-0.27	0.12**
dwe_1	0.00	0.01	0.02	0.01	0.01	0.01	0.03	0.01***
hot_wat_1	0.12	0.01***	0.05	0.01***	0.09	0.01***	0.06	0.01***
tot_ar_1	-0.23	0.02***	-0.18	0.02***	-0.19	0.02***	-0.19	0.02***
tot_ar_2	-0.1	0.01***	-0.11	0.01***	-0.12	0.01***	-0.11	0.01***
tot_ar_3	-0.07	0.01***	-0.08	0.01***	-0.12	0.01***	-0.1	0.01***
tot_ar_4	-0.03	0.01***	-0.08	0.01***	-0.09	0.01***	-0.08	0.01***

*   significant at 90% level
** significant at 95% level
*** significant at 99% level

HBS, MODEL 4-5, 2010

	Model-4		Model-5	
	est.	s.e.	est.	s.e.
Intercept	7.69	0.02***	7.61	0.02***
dis_inc_cat_1	-1.06	0.02***	-1.11	0.02***
dis_inc_cat_2	-0.68	0.01***	-0.71	0.01***
dis_inc_cat_3	-0.51	0.01***	-0.53	0.01***
dis_inc_cat_4	-0.37	0.02***	-0.38	0.02***
dis_inc_cat_5	-0.27	0.02***	-0.27	0.02***
comp_1	0.12	0.01***	0.15	0.01***
car_1	0.23	0.01***	0.23	0.01***
hot_wat_1	0.16	0.01***	0.20	0.01***
rent_cat2_1	-0.14	0.01***	-	-

*   significant at 90% level
** significant at 95% level
*** significant at 99% level

CHAPTER II

THE EFFECT OF A NEW BORN ON HOUSEHOLD POVERTY IN TURKEY: THE CURRENT SITUATION

II.1. INTRODUCTION

Approach to fertility is not constant throughout time and among cultures. Some saw fertility as a threat to the future of a country where others favored it with different motives.

In Turkey, during the first years of the republic high fertility was favored. After long years of consecutive wars the low level of population was seen as a problem. There were efforts to increase fertility. The population of Turkey almost doubled within 30 years and as a result, in the 1960s high fertility was considered as a problem and antinatalist policies were put in action. (Franz, 1994; Koç et al., 2010).

In the beginning of the new millennium, fertility started to fall towards replacement level and this time falling fertility was seen as a threat. The European experience of ageing triggered worries within the country. These worries further increased when the comparative situation with Europe was considered. The ageing process took about 150 years in Europe, but it was taking only 30-40 years in Turkey. This very fast pace of ageing has increased the worries more and more.

Consequently, declining fertility in Turkey triggered calls for at least three children by the governing authorities, recently. Related to these calls or not there is an upward movement in fertility which can be monitored by latest statistics. According to Turkish Statistical Institute (Turkstat) figures which are based on registers, total fertility rate (TFR) increased from 2.10 to 2.17 between 2013 and 2014 (Turkstat, 2015). Also according to Turkish Demographic Health Survey (TDHS-2008), TFR was 2.16, and TDHS-2013 results indicate that TFR is 2.26 (HUIPS, 2009; HUIPS, 2014). Although these figures don't prove an increase because that the confidence intervals are overlapping, when considered with Turkstat figures it's likely that an increase has occurred. Therefore, this increase shows that the effects of high fertility should still be on the table for discussion.

There are several reasons for taking low fertility as a problem. The main rationale behind this approach is that as the population is ageing, a declining fertility is conceived as a threat to the social security system because within a few decades the old age dependency ratio will rise to very high levels and it will be harder for the economically active population to pay for the pensions and the increasing health expenditures of the elderly.

This justification is already criticized by some researchers. Sayan (2013) agrees that there is need to take some measures, but these measures should be related to increasing insurance premiums. Instead of increasing insurance premiums through increasing fertility, this should be accomplished by struggling against informal (off the record) employment and increasing the labor force participation rate especially for women. Another perspective is presented by Lee and Mason (2014) whose study's result indicate that fertility below replacement and modest population decline favor higher material standards of living.

At this point, it should also be taken into consideration that there is still time for the opportunity window to be closed and maximum benefit should be made of this duration. Increasing fertility would offset the potential benefits of the opportunity window because it will increase the dependency ratio and available resources will be dedicated to more children which will decrease the quality of education dedicated to these children. Lee and Mason (2014) put forward the case indicating that "*the gains from this demographic window of opportunity may be made permanent if they are invested in physical capital and human capital. With good planning, this demographic dividend can be used to transform economies such that their growth potential remains high after the window has closed"*.

Also, ageing itself is considered as a problem related to various reasons. Labor force will diminish as the population ages. There will be more people in labor force dedicated to working in old age health issues related posts instead of working for more productive jobs for increasing the overall level of the economy.

Besides ageing, another issue is that low fertility might also lead to depopulation. In this case, the country will have fewer reserves for the military. Civil political power will also be affected by depopulation. Population has a role in determining the representation of a country in international bodies, such as the European Commission and the European Parliament. Also the size of the overall economy is directly related to population size. The size of the economy on the other hand is another criteria in being represented in the world. Representation in Group of 8 (G8) and Group of 20 (G20) depends on the size of the national economy which as mentioned above is related to population size (Coleman and Rowthorn, 2011). One last issue was brought into discussion by Simon. According to Simon (1977), as population gets greater, number of geniuses in that population will be more and these geniuses will contribute to the overall improvement in technology which will positively affect productivity and economic development.

In the light of the fear from ageing and declining population, now there are ongoing studies in order to implement policies to increase fertility in Turkey such as support systems and incentives. The discussion is mostly going on how to increase fertility in order to prevent or cut down on the negative effects on ageing. Although it is unarguable that ageing has negative effects on the economy, there are also numerous reasons to be suspicious about the relevancy of these policies regarding the well-being of the Turkish citizens and the economy as a whole.

Before implementing policies to enhance fertility, other dimensions should also be taken into consideration and discussed. Accepting that ageing is detrimental to the economy and finding the cure as increasing fertility, restrict the improvement of other approaches. The issue should be discussed on a broader perspective as it implies a multidimensional characteristic. This would enable better understanding of the issue and enhance flexibility for future actions.

The potential negative effects of ageing are being discussed thoroughly. At this point the effects of high fertility also should be discussed. The effects of high fertility and what higher fertility would lead to, if the pro-natal policies were effective should also be on the table for discussion.

There are a few studies which indicate that ageing is preferable to high population growth. Elgin and Tumen (2012) suggest that a declining population is not a worry for modern economies, if endogenously induced mechanisms are sufficiently effective. Attar (2013) indicate that a hypothetical rise in fertility rate in 2015 to the 1995 level will lead to a substantial lower per capita output.

There are several dimensions of a discussion regarding effects of high fertility, and starting with a framework of these dimensions would be profitable for putting the question right.

First, it should be discussed that whether it is logical and possible to increase the population continuously. Malthusian perspective indicates that, given that the country is bounded with a geographical area to be lived on and given that the available natural resources are not unlimited, the population increase would be restricted at some point. Although today some implications of Malthus have been falsified especially with regard to technological improvements, one cannot argue that while the country has its limits, it’s not possible to increase its population forever. The opponents of Malthus, such as Simon (1981) and Kahn et al. (1976), while opposing the approach indicated by Malthus emphasized there were expandable limits for food production instead of infinitely flexible boundaries. Today, the human carrying capacity is still under discussion. Therefore it is arguable that the ageing of the population could be delayed forever by boosting population growth through increased fertility.

According to the population projections conducted by Turkish Statistical Institute (2013a), under the scenario that the total fertility rate will rise up to 3 in 2050 and stay constant throughout 2050 to 2075, the population of Turkey will be 140.7 million by 2075, which is almost the twice of the population today.

In line with these, Attar’s (2013) findings could be mentioned once again. After indicating that the main source of economic growth of Turkey in the 21st century will be technological progress, he emphasizes that although ageing will lead to a slowdown in economic growth, a hypothetical rise in fertility rate in 2015 to the 1995 level will lead to a substantial lower per capita output, a considerably high dependent population and a permanently low share of working age population.

Increasing population also has implications regarding sustainability as mentioned by Attar (2013). The increasing population is likely to result in adverse effects on the economy. Besides this, the resources of the country are not endless, either. According to a World Bank scenario, even if the world population remained at its 2005 level, agricultural productivity has to increase 25 per cent by 2055 to meet the growing demand for food. This increase should be up to 80 per cent when the rise in population and the effects of climate change are taken into account (World Bank, 2010). Moreover, an increased population will obviously be less likely to experience sustainable growth, which indicates an intergenerational dimension of the issue. Therefore, this first dimension for discussion can be defined as the **sustainability of ever increasing population and intergenerational aspects**.

The second dimension is the **direct negative effects of high fertility on the economy with regard to high child dependency rate**. As mentioned above, if the total fertility rate rises up to 3 in 2050 and stays constant throughout 2050 to 2075, the population of Turkey would increase to 140.7 million by 2075 (Turkstat, 2013a). Even such a great increase in population will not be enough to offset ageing, where the old age dependency ratio will increase to 31 per cent in this scenario. In the most probable scenario, where total fertility rate decreases in its natural flow and reaches to its lowest value 1.65 in 2050, and then increases after this year and reaches the value 1.85 in 2075, the old age dependency ratio will increase to 48 per cent. On the other hand, there will be an increase in the child dependency ratio which would be 45 per cent in the high fertility scenario and 25 per cent in the low fertility scenario, which shows that the choice is actually between making a trade-off between old age dependency rate and child dependency rate. Even more, such a high increase in fertility will have a slightly unfavorable effect on the total age dependency ratio where this ratio will increase to 76 per cent which is about 2 points higher than the rate according to the low fertility scenario.

It is obvious that increase of children dependency rate would lead to increased demand for child care, education and such. Also higher number of children would also lead to lower labor force participation for women. Therefore, the extent and details of the effect of child dependency rate should be discussed with regard to old age dependency rate.

The third dimension is the **negative effects of high fertility at household level**. As well as having a direct effect on the economic well-being of households, the effects on the households also have an indirect effect on the economy as a whole via smaller amount of human capital. So this dimension can be studied under two sub-dimensions. First is the **direct effects of high fertility on the well-being of households** and the second is the **indirect effects of high fertility on the economy depicted as the human capital accumulation**.

So far, a framework was put forward for the discussion of effects of increased fertility with regard to preventing ageing in Turkey. These issues should be studied thoroughly for the sake of profitable policies for the future of Turkey. Only then, the trade-offs between ageing and high fertility would be brought out into the open and the implications of policies would be more visible.

It is hard to carry out an in-depth study covering all the aspects of the issue under discussion. For better understanding, in-depth studies should be carried out regarding every dimension. For contribution to the discussion under question, **this study will analyze the effects of fertility on household economic well-being**. How more children affect the well-being of households and its relationship with household poverty will be studied with different tools and available datasets.

II.1.1. The Effects of Fertility on Household Well-being

The increased fertility would lead to diminishing financial means provided to the extra children, which in turn would lead to lower quantity and quality of nutrition, education, etc. provided to those children.

It is necessary to understand the potential negative impacts of higher fertility especially at household level. Whether higher fertility leads to higher poverty and the degree of the lessened economic well-being of the households resulting from more children are important issues which must be dealt with. The analysis of these issues would contribute to the implementations of policies regarding both fertility and poverty which are two of the core policy targets.

As argued in Becker (1960), when child is considered as a normal consumption good, an increase in income would lead to an increase in the amount of consumption of that good which means a decision to have more children or an increase in the amount to be spent on the existing children which incurs higher quality children which means children with better nutrition and education. Becker (1960) argues that the quantity elasticity of having a child is relatively small, but positive and quality elasticity is large meaning that rather than having more children people prefer to increase their spending on the existing children.

There is abundant literature on the trade-off between quantity and quality of children where quality is mostly associated with the nutrition and education provided to the children. If Turkish population chooses to increase the quantity of children and have more children, obviously a decrease would occur in the quality of the existing children due to the increased number of children. The implication of this situation would be multidimensional. Some households would be pushed into poverty as a result of having more children because their resources wouldn’t be enough to compensate for the increased family size. Moav (2005) denotes that there is risk of poverty trap when the fertility of the low-wage families is considered. For such families the opportunity cost of time is low so that children of minimal quality are "cheap". Therefore there is a comparative advantage for the poor in child quantity. This advantage in child quantity leads to low level of investment in education of these children and thus these children are more likely to be poor in the future as well.

This study analyzes the relevance whether families are poorer because of having more children and the extent of the situation which is to say, the extent of change in average income and consumption expenditure, how many households are pushed to poverty and and for those who are already poor how exit rate from poverty is different between households with or without a new born.

It is known that poverty is more likely to be encountered in more crowded households especially in those with many children. Higher the number of household members, more probable is that the household is poor. For Turkey, this matter is supported by the poverty statistics provided by the Official Statistics Office. As can be seen from Table 1.1, poverty rate is much higher for larger households compared to less crowded households. When a household is larger than four persons the probability of being poor increases significantly. There are further major increases in poverty rate of households which are greater than seven persons.

Table II.1.1. Poverty rates by household size

	2002	2003	2004	2005	2006	2007	2008	2009
Total	**22.5**	**23.0**	**20.7**	**15.4**	**14.0**	**13.6**	**13.5**	**14.5**
1-2	16.5	13.4	14.5	8.4	11.0	9.4	9.9	11.5
3-4	16.4	17.1	13.7	9.2	8.3	8.1	8.2	9.4
5-6	29.0	31.7	27.4	22.4	17.5	20.8	21.1	21.8
7+	46.0	48.4	51.1	44.1	41.8	39.8	37.7	38.5

Source: Turkstat, 2009, Poverty Study Results
Note: the figures are up to 2009 because the official absolute poverty measures are only available until that year

The rising risk of poverty would incur negative returns to the economy and society as a whole. To provide the extra children a reasonable life quality with the available financial constraints of households, will be a challenge for those households. The burden of the extra children also includes the risk of pushing the household to poverty.

The UNFPA report "The Cairo Consensus at Ten: Population, Reproductive Health and the Global Effort to End Poverty" indicate that *"there is clear evidence that enabling people to have fewer children, if they want to, helps to stimulate development and reduce poverty, both in individual households and at the macro-economic level"* (UNFPA, 2004).

As defined in UNFPA (2004):

"• Smaller families share income among fewer people, and average income per capita increases. A family of a certain size may be below the poverty line, but with one less member may rise above the poverty threshold.
• Fewer pregnancies lead to lower maternal mortality and morbidity, and often to more education and economic opportunities for women. A mother's death or disability can drive a family into poverty. Her ability to earn income can lead the family out of poverty.

• *High fertility undermines the education of children, especially girls. Larger families have less to invest in the education of each child. In addition, early pregnancy interrupts young women's schooling, and in large families mothers often remove daughters from school to help care for siblings. Less education typically implies increased poverty for the family as well as the inter-generational transmission of poverty.*

• *Families with lower fertility are better able to invest in the health of each child, and to give their children proper nourishment. Malnourishment leads to stunted growth, cerebral underdevelopment and subsequent inability to achieve high levels of productivity in the labour force."* UNFPA (2004)

II.1.2. Aim

The relevance and target of this study is that it searches whether and to what extent, birth of a child leads to lower economic well-being of households.

Objective of this study is as follows:

To determine the causal effects of fertility on economic well-being at household level

The contribution of this study to the literature is that this subject is put forward for the first time in Turkey. There is no study explicitly addressing the relationship between fertility and poverty in Turkey. Also, the causal relationship between fertility and poverty has not been thoroughly discussed in the existing literature. There are only a few articles directly addressing the issue (Kim et al., 2009; Arpino and Aassve, 2013). The effect on income has not been studied, either. The study is unique in the variety of the well-being indicators employed. This study uses consumption expenditure and income which is not used in previous studies as well as different conventional poverty meaures along with monetary and supplementary fuzzy poverty measures and deprivation index which enable comparison with regard to the chosen indicator. Moreover, supplementary fuzzy measures and deprivation index are equivalence scale-free indicators which gives the opportunity for analyses in this regard.

II.1.3. Organization of the Chapter

After this introduction section, in section 2, theoretical framework on the relationship between fertility and economic well-being will be presented. In section 3, literature review will be demonstrated. In section 4, background information on Turkey with regard to economy, poverty measures and demographic transition, will be given. Section 5 and section 6 will present the methodology and the data respectively. In section 7, an analysis will be realized by adjusting the equivalence scales as if some of the births did not take place. In section 8 the results of the application of the analyses with propensity score methods will be demonstrated and finally section 9 will conclude.

II.2. THEORETICAL FRAMEWORK

The literature on the relationship between fertility and poverty is bidirectional. The causal effect is studied in both directions. There are several issues pointed out so far in literature while examining the relationship between economic well-being and fertility. There is economic theory as well cultural theory. There are also other breakdowns such as macro level theory and micro level theory. The macro level theory focuses on the economy as a whole where micro level theory focuses on economic agents, especially households in our case.

The fertility and economic well-being relationship is dependent on the main mode of production in that economy and the development level of the country.

The vast literature on the economic theory of fertility is depending on the benefit of having children as a means of production and old age security of the parents (Caldwell, 1976). Especially in traditional societies where agriculture is the main mode of production, children are seen as future income earners. In such societies social security system is not improved either, which causes children to be seen as security for their parents in their old ages. According to this theory family as a rational economic agent decides on the number of children taking into consideration the present and future costs and benefits of the children. The cost item also includes opportunity cost, such as the income forgone that would be acquired by the mother in case the child was not born. This is, of course, also related with the employment opportunities available for the mother. In such traditional societies infant mortality rate would be expected to be high which also affects the demand for children. This is the demand side of the story. The supply side is also important such that the availability of contraception would also have an effect on the number of children. The family is not always able to balance their fertility without unlimited access to contraception.

Another point regards to the cost and benefits of the child which are interfered by legal regulations. Free education lowers the cost of children, thus has an increasing effect on fertility and regulations restricting child labor decrease the benefits to be acquired from the child thus has a decreasing effect on fertility. The child labor restrictions are found to be less effective because of hardship in monitoring such activities. On the other hand, compulsory education is more effective because it's easier to take measures to keep children at school. (Doepke, 2004)

In more developed societies or in richer families, on the other hand, children are not seen as a means of production and old age security. In this case, quality of children is mostly favored to quantity of children (Becker, 1960). The quality is defined as the nutrition and education opportunities provided to the children.

The other side of the relationship is less exploited by researchers. When a household is bounded with limited resources one would expect that average consumption of household members would decrease with an increase in household size. Households at higher economic well-being levels are more likely to compensate an increase in household size with their existing resources, but this wouldn't be possible for households with lower levels of well-being. So, at lower levels of household well-being a decrease in average consumption of household members following an increase in household size seems inevitable. But, of course, there are other dimensions to be taken into consideration. In an economy where child labor is exploited at very early ages, the income created by the children might offset the costs borne by them. Also the subsidies provided by the government for the caring of children might also offset, at least some of the burden on the households.

In the case of Turkey this is not very relevant. Recent figures for Turkey indicate quite low levels of child labor. In Turkey, percentage of children in 6-17 age group who are employed in economical activities is 5.9 per cent in 2012. The employment level has not changed between 2006 and 2012. The employment rates are 2.6 and 15.6 per cent respectively for 6-14 age group and 15-17 age group (Turkish Statistical Institute, 2013b). This figure also emphasizes that even if children are seen as breadwinners, this is happening after the age of 15 which is a very late return for such an investment. The very low level of employment rate of children at early ages demonstrate that the cost effect of having children is much higher than the income effect.

Moav (2005) argues that as quantity cost of children increases which means the cost of additional children are higher, the families will reallocate resources to child quality which will increase economic growth and release the economy from poverty trap. Policies which target decreasing the quantity cost of children, such as, tax discounts for large families, child allowances, subsidized day care and meals and unregulated child labour will have a negative effect on income in the long run. Cancelling or even reversing such policies will contribute to per-capita income in the long run.

Malthus (1798), on the other hand, has discussed this issue at macro level. When population increases which means that fertility is high, the food prices will increase. Moreover, because now there is higher labor supply, the labor income will decrease. This dual effect will decrease the economic well-being especially of those depending on labor income. Therefore, this Malthusian perspective indicates a direct positive relationship between fertility and poverty.

II.3. LITERATURE REVIEW

The relationship between population dynamics and economic well-being has been a matter of interest since old times. Malthus was one of the first to bring out the issue and his theories have been discussed extensively by many researchers. Malthus (1798) suggested that food production increases arithmetically where population increases geometrically resulting in over increasing of population. There are two mechanisms to stop this increase. These mechanisms are preventive checks and positive checks. Preventive checks are those applied by the society such as increase in the age of marriage or use of contraceptives that have a reducing effect on fertility and thus population growth. If these preventive checks are not applied by the society then positive checks come up. Positive checks are explained as famine, diseases and wars that especially increase the mortality within a society and stop the population growth.

Malthus was criticized because he didn't take into consideration the pace of technological improvements. These critiques went in line with the apparent situation in the world. Unlike Malthus' views, technological improvements in food production exceeded the population growth in the 20th century and although there was an unprecedented population growth in this century the population was increasing ceaselessly. In spite of this growth some researchers such as Simon (1981); Kahn et al. (1976) indicated that this increase is not limitless, but unlike Malthus' opinion there were expandable limits on population growth.

II.3.1. Macro Level

Most of the literature on population and economic well-being are at macro level. Sinding (2009), indicates that after World War II, the macro level relationship between rapid population growth and economic performance can be classified into three stages. The first one is the neo-Malthusian views represented by Coale and Hoover (1958), Myrdal (1968) and Enke (1970). These researchers argue that *“only by bringing rapid population growth under control could countries hope to achieve improved economic performance and high standards of living”*. The second stage is the revisionist period named by Kelley (1986). According to Sinding (2009) this period is symbolized by the publication, "Population growth and economic development: policy questions" prepared by US National Research Council (NRC). Citing from Sinding (2009):

> *“Birdsall (1988) put it, ‘rapid population growth can slow development, but only under specific circumstances and generally with limited or weak effects’. The third stage is represented by the "demographic bonus" and "opportunity window" concepts. So, by looking at a changing age structure in addition to declining fertility, economists were now able to discern a highly plausible causal connection between demographic change and economic growth—a connection that was much more difficult to see in the less sophisticated analysis of the 1986 NRC study and the prior revisionist research on which it reported (Merrick 2001; Greene and Merrick 2005).”*

Coale and Hoover (1958) studied the relationship between population growth and economic growth in Mexico and India. They suggest the negative effects of population growth in these countries as decreasing ratio of worker per capita, increasing dependency ratio, especially high child dependency ratio, and because of high dependency ratio higher household consumption expenditure which leads to lower savings. Besides these, public expenditures for education and health drive out expenditures for more productive and growth targeting investments.

Boserup (1981), has a more optimistic view of population growth. She suggests that higher population density stimulates technological improvement in a region. She indicates that every individual is a potential source of creativity and genius and societies with greater population are more likely to grow because they have more potential for higher number of scientits, inventors and creative minds.

Eastwood and Lipton (1999) found negative impact of fertility on well-being measured by consumption based poverty. They carried out a cross-national study and the results of the study indicated that higher fertlity increased poverty by retarding economic growth and skewing distribution against the poor.

II.3.2. Micro Level

Micro level research at household level is relatively recent and most of this literature depends on the relationship between household size as the indicator of population. Sinding (2009) attribute this scarce literature to scarcity of longitudinal datasets that would enable such research.

The economic well-being is generally measured by economic growth at macro level. Micro level studies use income, consumption expenditure and poverty indicators. There are also studies which use stunting and wasting as indicators of child well-being in the household (Lanjouw and Ravaillon, 1995).

Household size has been seen as an important factor of well-being of households. Besides household size, number of children in the household is also used in various studies. Most of the time, these studies are bound to be static analyses at one specific time and are not capable of indicating the change in household composition.

In one such study Desta (2014) found that the effect of a large number of children on consumption expenditure of households is negative for rural households, whereas results for urban households are not as clear.

Among studies that use child birth as fertility indicator, Gupta and Dubey (2003) found that fertility has a significant positive effect on poverty, which is halved when endogeneity of fertility in poverty is taken into account. Mussa (2014) analyzed the relationship between fertility with objective and subjective poverty using IV method based on son preference and concluded that fertility has a positive effect on objective poverty and a negative effect on subjective poverty in Malawi.

Aassve et al. (2005) analyzed the effect of fertility on overall poverty levels for Albania, Ethiopia, Indonesia and Vietnam. In their study, they used dynamic models besides static ones. In their dynamic model for poverty, they used a probit regression of entry into and exit from poverty between the two waves of the longitudinal data. Their findings suggest that households with many children (i.e. high fertility) tend to have a higher rate of entering poverty and lower rate of exiting poverty.

Aassve et al. (2006) used simultaneous and dynamic random effects models to analyze the causal relationship between fertility and poverty in both directons. Their study indicate that poverty itself has little effect on fertility, whereas there is evidence of state dependence in poverty and important feedback from fertility on future poverty. In the study they use both consumption expenditure and poverty status as indicators of economic well-being.

Recently, there are studies which measure the effect of fertility through analyzing the difference before and after the birth of a child in a household which facilitate dynamic analyses, but the literature is not rich in studies targeting to examine the effect of fertility on poverty in a dynamic perspective. Kim et al. (2009) and Arpino and Aassve (2013) are among these studies in the very rare literature in this respect.

Kim et al. (2009), "Does Fertility Decrease Household Consumption: An Analysis of Poverty Dynamics and Fertility in Indonesia", analyzes the effect of fertility on household consumption by using propensity matching method. The findings assert that when per capita consumption measure is used, household consumption decreases 20 per cent. On the other hand, the magnitude of the effect is rather sensitive to the equivalence scale in use. When different equivalence scales are used instead of per capita measures the magnitude of the effect of fertility on household consumption is found 20 to 65 per cent of the effect found by using per capita measures.

Arpino and Aassve (2013) used different methods for analyzing the causal relationship between fertility and consumption expenditure in Vietnam and found that "*those households having children between the recorded waves have considerably worse outcomes in terms of changes in consumption expenditure by using methods based on the unconfoundedness assumption"*. With the instrumental variable approach which relies on son preference, they estimated "*a negative impact of fertility on poverty with a magnitude not dramatically different from that obtained by methods based on the unconfoundedness assumption"*.

II.3.3. Literature from Turkey

In Turkey, the literature regarding fertility and poverty relationship is also scarce. Because of this, in this section, some indirectly related articles are also assessed. Most of the existing studies are at macro level. One recent article by Öztürk (2012) analyzes the relationship between fertility and poverty at province level using macro variables for provinces. Due to lack of data the analysis is limited to out-of-date data of 1990 and 2000. Öztürk's findings indicate that the income levels of provinces are negatively associated with total fertility rate, dependency ratio and average household size.

Kabaş and Kandır (2013) have studied the relationship between demographic transition and poverty. They suggest that household size is one of the most important determinants of poverty. When demographic transition is in progress with falling fertility, there will be an opportunity window until 2040, and to benefit the most from this opportunity window emphasis should be given to education, health and employment policies. (Kabaş and Kandır, 2013)

Attar (2013) has carried out a hypothetical study and his findings indicate that that although ageing will lead to a slowdown in economic growth, a hypothetical rise in fertility rate in 2015 to the 1995 level will lead to a substantial lower per capita output, a considerably high dependent population and a permanently low share of working age population.

Attar (2015) also conducted another study and computed the minimum child allowances (bonuses) that would lead rational households to have one more child. The finding assert that if a household that normally would have two children transits to three children they remain below some poverty lines.

Sayan (2013) objected to those favoring pronatalist policies stressing that it's not wise to increase insurance premiums through increased fertility and population at working age. Instead, informal economy should be shrinked and labor force participation rate should be increased especially for women. (Sayan, 2013)

Mumcu and Çağlar (2006) also suggest similar paths with Sayan (2013). To make the highest benefit from opportunity window it is suggested that employment rate should be increased, education system should be improved, skills in employment should be transformed and institutional structure should be improved. (Mumcu and Çağlar, 2006)

Kırdar et al. (2007) studied the relationship between sibship size, birth order and sex composition with school enrollment. Their results indicate that *"the negative correlation observed between sibship size and school enrollment among urban Turkish households does not have a causal interpretation. The exogenous variation in sibship size brought about by multiple births has no* *impact on school enrollment of children. On the other hand, birth order of children does matter for their educational outcomes. Middle born children are found to fare worse for all household income groups except for roughly the top 15 per cent of the income distribution”.* (Kırdar et al., 2007)

Akça and Ela (2012) suggest that policies regarding education especially targeting females would have a reducing effect on fertility. Reduced fertility in return will remove the negative effect of population growth on unemployment and lead to an improved human capital. (Akça and Ela, 2012)

II.3.4. Poverty-Fertility Relationship

So far, in the literature review, the focus was on how fertility has an effect on poverty. It is also worthwhile to discuss the reverse side of the relationship briefly. The literature in general demonstrate that the poor are more likely to have higher fertility rates. There are various reasons for this. First of all, especially in tarditional societies children are considered as important contributors to the household economy through their inclusion in economic activities as laborers. Therefore, poorer families are more likely to have higher number of children to put into labor. (Caldwell, 1976). Besides this, poorer families tend to consider their children as a security to contribute for them in their old ages. Higher mortality rates in poorer families also lead to higher fertility. They increase their fertility to reach their ideal number of children, which is affected by the high early-age mortality rates.

Education has an important intervening role in the context, with different aspects. The increase in education of women increases the opportunity cost of having a child and leads to lower fertility (Willis, 1973). Education of women also pave the way for empowerment of women, which give the women the opportunity to opt for less children. Knowledge on and access to contraceptives is another issue in this regard. Poorer and less educated are less likely to have knowledge on contraceptives and are less likely to reach contraceptives.

One other perspective is presented by Becker (1960). He asserts that as families are richer they prefer having less children with better quality (that have better education and nutrition) rather than having more children.

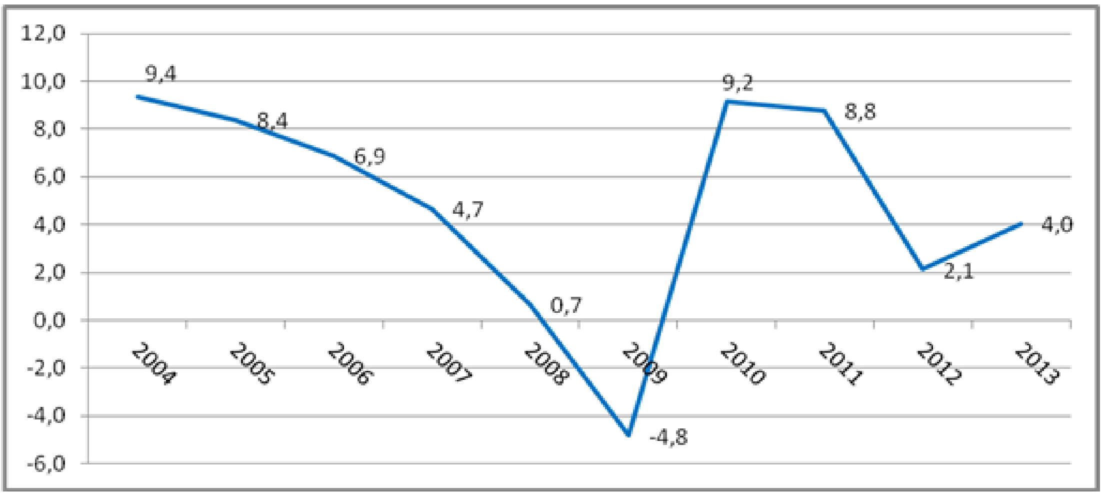
II.4. BACKGROUND INFORMATION ON TURKEY

This section provides background information on Turkey with regard to economy, poverty measures and demographich transition.

II.4.1. Economy

Turkey is the 18th largest country with respect to its population (UN, 2012). With regard to economy, Turkey is the 17th greatest in the world with a 1.6 trillion TL of GDP which is about 750 billion US dollars (World Bank, 2014). In the last ten years, GDP growth rate of Turkey demonstrated an unstable profile. Starting from a very high growth rate in 2004, a decline was observed which was followed by a high growth rate for two more successive years in 2010 and 2011 after a negative growth rate in 2009 (Turkstat, 2014a).

Figure II.4.1.1. GDP Growth Rates, 2004-2013



Although Turkish economy is among the first 20 economies, GDP per capita is at a moderate level, which is around 10 000 US dollars (World Bank, 2014). This is less than one third of OECD average. For the last five years GDP per capita did not change much depicting a situation which can be regarded as middle income trap.

Turkey’s economic improvements are not in line with its position in the Human Development Index rankings. The rank of Turkey in HDI ranking is 90 (UNDP, 2013). Recent developments in the economy were not adequate for compensation in the components of the HDI.

One of the most significant characteristics of the Turkish economy is its low level of labor force participation rate which is especially typical among women. Labor force participation rate is 70 per cent among men and 29 per cent among women (Turkstat, 2014b). Overall unemployment rate is around 10 per cent.

II.4.2. Poverty

In Turkey there are mainly two official sources for poverty measurement, Household Budget Survey (HBS) and Income and Living Conditions (SILC) Survey. By HBS, poverty is measured with cost of basic needs approach using consumption expenditure as the well-being indicator. This measurement was stopped in 2009 due to problems with the methodology in order to improve the measurement methodology. There are still ongoing studies for the implementation of the new methodology. From HBS, also dollar based poverty measures are produced with World Bank’s methodology using a poverty line based on puchasing power parity (PPP).

Table II.4.2.1. Poverty rates according to poverty lines based on purchasing power parity, Turkey, 2007-2013

Poverty lines	Percentage of poor individuals (%)						
	2007	2008	2009	2010	2011	2012	2013
Below 2.15 $ per capita per day (1)	0.52	0.47	0.22	0.21	0.14	0.06	0.06
Below 4.3 $ per capita per day (1)	8.41	6.83	4.35	3.66	2.79	2.27	2.06

Source: TurkStat, Poverty Study, 2015

(1) Here 0.926 TL, 0.983 TL, 0.917 TL, 0.990 TL which were the equivalents of 1 $ purchasing power parity (PPP), were used for 2007, 2008, 2009 and 2010 respectively; 1.004 TL was used for years 2011 and 2012; 1.10 TL was used for 2013 and 1.20 TL was used

SILC as the second source of official statistics on poverty in Turkey contains a variety of poverty related measures. One of them is the poverty measure based on household disposable income. Equivalized household disposable income is compared to a certain percentage value of the median household disposable income to obtain poverty rates.

Table II.4.2.2. Poverty rate by equivalized household disposable income (%), 2006-2013

Percentage of median income	2006	2007	2008	2009	2010	2011	2012	2013
40%	12.8	9.9	10.1	10.6	10.3	10.1	10.0	9.1
50%	18.6	16.3	16.7	17.1	16.9	16.1	16.3	15.0
60%	25.4	23.4	24.1	24.3	23.8	22.9	22.7	22.4
70%	32.0	30.1	30.9	31.1	30.6	30.0	30.2	29.5

Source: TurkStat, Income and Living Conditions Survey
Note: Reference period of incomes is the previous calendar year.

Another poverty related indicator is material deprivation or severe deprivation. "*The material deprivation rate is an indicator in EU-SILC that expresses the inability to afford some items considered by most people to be desirable or even necessary to lead an adequate life. The indicator distinguishes between individuals who cannot afford a certain good or service, and those who do not have this good or service for another reason, e.g. because they do not want or do not need it (Eurostat, 2016).*" The household is considered as deprived or severely deprived according to the number of deprivations. When at least three or four of the items cannot be afforded then the unit is considered as deprived. At least three items means deprived and at least four means severely deprived. Turkstat publishes the percentage of the severely deprived.

Table II.4.2.3. Severe material deprivation rate (%)

2009	2010	2011	2012	2013
63.0	63,5	60,4	59,2	49,7

Source: TurkStat, Income and Living Conditions Survey

II.4.3. Demographic Transition in Turkey

The first census of the Turkish Republic was conducted in 1927, four years after the foundation of the Republic. By 1927, the population of the country was about 13.6 millions. This was a population which has lost much of its young population due to many years of ongoing wars. Especially there was a shortage of male population. The sex ratio, which is defined as the number of men per 100 women, was found to be 93 in 1927 census which shows there were fewer men compared to women.

The republic encouraged higher fertility and fertility increased to 7 births per woman in the middle of 1930’s. Fertility rate was more or less the same until the 1950’s and then started to decline continuously from then on. Total fertility rate (TFR) declined to 6 in the beginning of the 1960’s, to 5 at the end of the 1970’s and to 3 at the end of the 1980’s. According to TDHS-2008 TFR was 2.16 which is just above replacement level which was followed by an increase to 2.26 in 2013 (TDHS, 2013). Although some of this change could be related to the variance because it is derived by a sample survey,the official statistics published by Turkstat which are based on registers support this information on upward movement in fertility (Turkstat, 2015).

The decline in fertility rate was also encouraged by the government. In 1965 an antinatalist law was introduced which marked the deliberate efforts of the government to reduce fertility. In 1983, this law was revised and more effective methods for reducing fertility were introduced such as legalization of induced abortion until the 10th week of pregnancy as well as legalization of sterilization for women and men.

The changes in TFR do not reflect similar levels for all regions in Turkey. For example in the Western Anatolia region TFR has fallen to replacement level in the beginning of the 1990’s. Most of the regions have followed and in the following years their TFR also has declined to replacement level. On the other hand, in the Eastern region, TFR is still over replacement level.

Recently there also been a change in age specific fertility rates (ASFR). Until 2008, ASFR was highest in 20-24 age group. This was changed with 25-29 age group in 2008 which reflect a postponement of births. Here also, Eastern Anatolia region differs from other regions. In this region ASFR was highest in 20-24 age group contrary to other regions.

The history of the republic also witnessed major changes in mortality. In the beginning of the 1940's life expectancy at birth was about 30 years for men and 33 years for women. Life expectancy increased continuously and rose to 75 years for men and 81 years for women by 2013. This increase was mostly related to improvements in infant and child mortality. For many years, especially infant mortality was very high in Turkey which demonstrated a contradiction with its economic improvement level. This was regarded as the Turkish puzzle in literature. By 2013, infant mortality rate has declined to 13 per thousand which is more compatible with the development level of Turkey.

Subject to major changes in fertility and mortality levels, Turkish population has changed significantly in its level and composition. The population has increased to 24 millions in the middle of the 1950's which is almost twice the population in 1927. The population of Turkey almost doubled within 30 years. The increase in population continued and today the population of Turkey is more than 75 millions.

The age composition has changed remarkably during the republic period. The share of the elderly was about 4 per cent for many years. By 2013, it is 8 per cent and was expected to increase very fast since TFR was declining.

Today, this recent development is the main issue under discussion regarding the demographic transition of Turkey.

II.5. METHODOLOGY

This study particularly aims to analyze the causal relationship between fertility and poverty. The main issue is to reveal the effect of fertility on poverty. In literature there are various methods which attempt to analyze such causal relationships. The analyses are made both at macro level and micro level. **This study will basically focus on micro level analysis.** The relationship will be analyzed at household level. This will enable discovering the mechanisms more directly and proximately in further studies.

Most of the studies in literature focus on a relationship at one point in time mostly due to lack of data availability. This static analysis limits the quality of the findings of the studies. As Aassve et al. (2005) indicates "*studies concerned with the dynamic side of poverty are few and none of these have explicitly considered the link with the fertility behaviour".* Only after the study of Aassve et al. (2005) and Kim et al. (2005) there are dynamic analyses focusing on the causal relationship between fertility and poverty, but only a few studies are realized. **The main target of this study is to explore the effect in a dynamic perspective.** Such a study requires monitoring households throughout time to analyze the differences in their well-being.

For analyzing causal relationships there are various methods in literature. In this study, mainly propensity score matching method is used. Some analyses are also made by regression methods based on propensity scores. Instrumental variable (IV) methods for analyzing causal relationships are also abundant in literature, but this method was not preferred to be used in this study. One reason being that the outcome measured by PSM and IV methods are different. In PSM methods the outcome is either average treatment effect on the treated (ATT) or average treatment effect (ATE). On the other hand, the outcome is usually the local average treatment effect (LATE) for IV methods (Arpino and Aassve,2013). Moreover, valid instruments are generally hard to find. Our data is not rich in this regard. Community level variables that could be used as instruments are not available. Use of twins and son preference that are observed in literature as instruments are not very feasible in our case. In the twins case, the number of observations are very low. Son preference cannot be used without hesitation, since birth history is not available in the data.

This study utilises many indicators of well-being in order to demonstrate the relationship in a multidimensional perspective. Among the well-being indicators that are used are consumption expenditure, income, poverty indicators based on consumption expenditure and income, fuzzy measures of poverty and material deprivation index. The variety of analyzed indicators will enable more robust inferences along with variety in the acquired results. Supplementary fuzzy measures and material deprivation index are independent from equivalence scale size effects. Therefore the analyses with these indicators will enable further robust results for the study.

Regarding the fertility measure, in literature there are studies which use household size and number of children. This is mostly due to lack of data (Sinding, 2009). This study uses the new born as an indicator of fertility throughout time. Multiple births between waves could create complications in the measurement of the effect, therefore the sample is restricted to households which have only one child between the waves.

II.5.1. Measuring the Causal Effect

As mentioned above, there are several methods to analyze the causal effect of fertility on household well-being. Aassve and Arpino (2013) have summarized these methods. There are two main approaches. The first approach depends on **unconfoundedness assumption (UNA)**. Unconfoundedness assumption suggests that there are enough controls in the analysis of causal inference. There aren't unobservable variables in the model used for estimation, which indicates that there is no selection bias. It is also known as Conditional Independence Assumption (CIA), selection on observables or the exogeneity assumption.

Under this assumption either a **regression** can be run or **propensity score (PS) matching method** can be applied. Using this method with sensitivity analysis relaxes the UNA to a certain level (Ichino et al., 2008). Also, when the outcome is a difference-in-differences type, which would be in our case, the potential bias would be minimised (Arpino, 2008). The estimates obtained by these methods are called Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATT).

The alternative which doesn’t rely on UNA are intrumental variable IV methods. Estimates obtained by IV methods are usually the Local Average Treatment Effect (LATE) and depend on the instrumental variable used. When treatment effects are heterogeneous, LATE is generally different from ATE and ATT, which are the the preferred estimates in general (Arpino and Aassve, 2013).

This study will use methods that rely on UNA with supplementary sensitivity analysis. Rubin’s Causal Model presents a useful framework for the application of analyses for causal inferences which will be the main approach in this study.

II.5.2. Rubin's Causal Model

Holland (1986) draws a valuable framework for the understanding of the terminology on causal effects in statistics. He explains Rubin's Causal Model and suggests using terminology of an experiment setting which is the basic framework of the method. First of all, he mentions that the effect of a cause is always relative to another cause. When it is mentioned that A causes B, this means that A causes B relative to other causes. In this regard, the experiment terminology is introduced by saying that these causes are seperated as treatment and control indicating the one cause versus another cause.

The population of units under analysis is denoted by U and units in the population are denoted by u. There are only two causes in this framework for simplicity, namely the treatment and control, as mentioned above. Treatment is denoted by t and control by c. A variable S, indicates the cause is exposed to either t or c. In a controlled study, the scientist sets the values for S. In an observational study this is not the case. Y is the response variable, for which the effect of the cause is to be explained. A denotes the characteristics of u.

Variables are divided into two groups with regard to exposure to cause. Before exposure they are called pre-exposure, and after the exposure they are post-exposure. Y is required to be a post-exposure variable to measure its effect. Potentially there are two values for Y for each unit; $Y_t(u)$, when the unit is exposed to treatment and $Y_c(u)$ when the unit is exposed to control. The difference between the two gives the effect that is looked for. Unfortunately, these two outcomes cannot be observed at the same time for the same unit. This is addressed as the **fundamental problem of causal inference** by Holland (1986). Fortunately, this can be overcome in a statistical context, by measuring the average causal effect T, which is expected value of the difference between $Y_t(u)$- $Y_c(u)$. This can be denoted as,

$E(Y_t - Y_c) = T$ (1), which can also be written as,

$T = E(Y_t) - E(Y_c)$ (2)

Although Y_t and Y_c cannot be observed for the same unit, information can be derived from observed values from different units. Hereby,

> *"…the statistical solution replaces the impossible-to-observe causal effect of t on a specific unit with the possible-to-estimate average causal effect of t over a population of units." (Holland, 1986)*

When this is the case, the causal indicator variable S determines whether Y_c or Y_t is observed for a given unit.

if $S(u)=t$ then $Y_t(u)$ is observed,
if $S(u)=c$ then $Y_c(u)$ is observed,

The model contains three variables, S, Y_t and Y_c, on the other hand there are only two observable variables, S and Y_s. Hereby,

$E(Y_s \mid S = t) = E(Y_t \mid S = t)$, (3)

$E(Y_s \mid S = c) = E(Y_c \mid S = c)$ (4)

$E(Y_t)$ refers to the average treatment effect (ATE) and $E(Y_t \mid S = t)$ refers to the average treatment effect on the treated (ATT). According to unconfoundedness assumption the process is randomized which means that the treatment is independent of all other variables. In this case ATE is equal to ATT. So, under this assumption the effect of treatment can be computed by the following equation:

$E(Y_s \mid S = t) - E(Y_s \mid S = c)$ (5)

The model relies also on other assumptions. Stable Unit Treatment Value Assumption (SUTVA) implies that the potential outcomes for a given unit do not vary with the treatments assigned to any other unit, and that there are no different versions of treatment Rubin (1980). In our case, the implication is that fertility behaviours in other households do not have an effect on the outcome of other households. The “different versions” refer to different characteristics of the new born. The effect of differences in sex, weight and other characteristics of the new born on the outcome is assumed to be null.

Temporal stability assumes that the effect of the treatment does not depend on when it is applied, and causal transience assumes that the exposure to control at time t does not affect the result of the exposure to treatment at succeeding times, or vice versa (Holland, 1986).

II.5.3. Propensity Scores

For computation of the treatment effect there is need for specifying the treated and control groups. In order to ensure the plausability of UNA the treatment and control groups in the process are selected so that their pretreatment characteristics are the same and thus the experiment is fully randomized. When this is accomplished UNA is no more a strong assumption. The treatment effect now depends also on the pretreatment variables (X).

$$E(Ys \mid S = t, X) - E(Ys \mid S = c, X) \qquad (6)$$

If a model that guarantees the two groups are matched according to pretreatment characteristics can be provided then UNA would be more plausible. When this is done by using many variables the so called curse of dimensionality is faced. There are computational problems while trying to match treatments with controls. A solution to this problem was found by creating propensity scores based on the characteristics of the observations. Propensity score is the conditional probability of receiving a treatment given pretreatment characteristics (Rosenbaum and Rubin, 1983). By making use of propensity scores the dimensions are reduced to a scalar therefore the treatment and control groups can be matched on this.

There are various ways to use propensity scores for estimating treatment effects. In literature there are applications with propensity score matching, regression methods and stratification.

II.5.3.1. Stratification

Stratification rests on dividing observations into subclasses according to their propensity score values (Rosenbaum and Rubin, 1983). "*The optimal number of strata depends on the sample size and the amount of overlap between the propensity scores of the treatment and control groups. However, five subclasses, claimed to remove 90 per cent of the bias due to measured confounders, have been used by the majority of propensity score studies*." (Laneheart et al., 2012)

II.5.3.2. Regression Methods

There are different ways to use regression with propensity scores. In Inverse Probability of Treatment Weights (IPTW), individuals are weighted by the inverse probability of receiving the treatment they received. Treated individuals receive a weight of 1/ps and controls receive a weight of 1/(1-ps) (Harder et al., 2010). The weights are then used in a weighted least squares (WLS) regression model along with the pretreatment variables. The IPTW method includes all subjects in a study, therefore no loss of sample occurs as in matching (Laneheart et al., 2012).

Another regression method is ANCOVA, by using the propensity score as a covariate. "*In this method the propensity score and treatment status are used to predict the potential outcome (Austin, 2011; Shadish and Steiner, 2010). If the outcome is continuous, then an OLS regression model is selected and the treatment effect is estimated by the adjusted difference in means. If the outcome is dichotomous, a logistic regression model is used and the treatment effect is estimated by the adjusted odds ratio (Austin, 2011). Since there are no subjects discarded because of non-overlap, generalizability is maintained, assuming that the relationship between the propensity score and the outcome has been correctly specified*." (Laneheart et al., 2012)

II.5.3.3. Propensity Score Matching Method

In propensity score matching method treated and control units are matched on the propensity scores. Since in most of the cases it is not possible to find a perfect match between the treated and the controls an interval or a distance is used instead. There are various ways to apply propensity score matching (PSM). Such matching methods will be clarified in the following sections.

PSM method is mainly based on a five steps process (Caliendo and Kopeinig, 2008).

1. Propensity score estimation
2. Choice of matching algorithm
3. Checking overlap / common support
4. Matching quality / effect estimation
5. Sensitivity analysis

In the following subsections these steps are explained.

II.5.3.3.1. Propensity Score Estimation

The propensity scores are derived through a regression model application. While constructing the model to be used in the estimation of propensity scores, there are two main choices to be made. The type of model and the variables to be used in the model should be considered.

The purpose of a model is classification rather than estimating structural coefficients. Therefore any discrete choice model could be used for obtaining propensity scores. In general logit and probit models are used for the estimation of propensity scores when the treatment is binary. Both models produce similar results (Caliendo and Kopeinig, 2008).

On the other hand, the choice of variables is more controversial. There are contradicting views in literature. The basic idea of propensity score estimation is that because the matching is based on UNA, the outcome variable should be independent of the treatment conditional on propensity score. Therefore the variables to be chosen for the construction of the model and computation of propensity scores should serve to this end.

Omitting important variables increase the bias (Heckman, Ichimura and Todd, 1997). Therefore all important variables should be included in the model. Variables that influence simultaneously the treatment and the outcome variable should be included in the model. Moreover, knowledge on the theory of the research area and literature and also information about the institutional should guide the researcher in the construction of the model (Caliendo and Kopeinig, 2008).

Another important issue is that the variables that are unaffected by treatment assignment should be chosen. In order to ensure this, variables should either be fixed over time or measured before treatment. If the variable is a pretreatment measure also the anticipation effect should be considered and it should be made sure that the variable is not affected by an anticipation of treatment (Caliendo and Kopeinig, 2008).

The number of the variables included in the model is also a matter of concern. Bryson et al. (2002) Augurzky and Schmidt (2000) argue that over-parameterised models should be avoided. Such models could lead to problem in the common support and increase the variance of the estimates. All the same, they wouldn't lead to bias. On the other hand, Rubin and Thomas (1996) recommend against decreasing the number of variables. They argue that "*a variable should only be excluded from analysis if the variable is either unrelated to the outcome or not a proper covariate. If there are doubts about these two points, they explicitly advise to include the relevant variables in the propensity score estimation"*. Black and Smith (2003) indicate that when the model is constructed in a minimal setting there are problems with regard to the plausability of UNA. Austin, (2011) also argues more covariates are better. Because propensity score reduces information from many dimensions into a single score it is less sensitive to model misspecification Therefore concerns about collinearity and model fit do not apply in the context of the propensity score model. Accuracy of propensity score model is less important than the balance on covariates obtained and model misspecification is an iterative process with balance checking.

Arpino (2013) has used community level variables as well as regional dummies in addition to household level variables, in the model construction. Since, our data set lacks such variables, the variables of the model comprise of household level variables of which some are derived from individual level.

II.5.3.3.2. Choice of Matching Algorithm

In literature, the taxonomy of matching algorithms for propensity score matching have an intertwined characteristic.

The most commonly used and straightforward matching estimator is nearest neighbor (NN) matching. An observation from the treatment group is matched to an observation in the control group that is closest in terms of propensity score. This can be implemented with or without replacement. In the former case, a control can be used more than once as a match, whereas in the latter case it is considered only once. *"Matching with replacement involves a trade-off between bias and variance. If replacement is allowed, the average quality of matching will increase and the bias will decrease"* (Caliendo and Kopeinig, 2008). Also more than one nearest neighbour could be used. Such matching algorithms are called 1:N instead of 1:1 matching, where N is the decided number of neighbours to be selected for each treatment. This also involves a trade-off between variance and bias. As N increases the matches are of less quality, hence the bias increases. On the other hand, variance decreases.

Nearest neighbour matching could be conducted by making use of a caliper. The magnitude of the caliper decides the distance of the match and hence the quality of each match. Radius matching is also a type of caliper matching where all of the comparison members within the caliper are matched.

"Kernel matching (KM) and local linear matching (LLM) are non-parametric matching estimators that use weighted averages of all observations in the control group to construct the counterfactual outcome. One major advantage of these approaches is the lower variance achieved with more information and the drawback of these methods is that possibly bad matches are generated" (Caliendo and Kopeinig, 2008). The scheme on the effect of

matching algorithm choice on bias and variance prepared by (Caliendo and Kopeinig, 2008) is presented below:

Table 1: Trade-Offs in Terms of Bias and Efficiency

Decision	Bias	Variance
Nearest neighbour matching:		
multiple neighbours / single neighbour	(+)/(-)	(-)/(+)
with caliper / without caliper	(-)/(+)	(+)/(-)
Use of control individuals:		
with replacement / without replacement	(-)/(+)	(+)/(-)
Choosing method:		
NN-matching / Radius-matching	(-)/(+)	(+)/(-)
KM or LLM / NN-methods	(+)/(-)	(-)/(+)
Bandwidth choice with KM:		
small / large	(-)/(+)	(+)/(-)

KM: Kernel Matching, LLM: Local Linear Matching
NN: Nearest Neighbour
Increase: (+), Decrease: (-)

II.5.3.3.3. Checking Overlap / Common support

Overlap or common support is an important issue in PSM. By common support it is ensured that for every treated unit there are control units with similar propensity scores. Various methods are suggested in the literature. Visual analysis of the density distribution of the propensity score in both groups, comparing the minima and maxima of the propensity score in both groups are among the most straightforward ones. Minima and maxima analysis is based on deleting all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group (Caliendo and Kopeinig, 2008). A different method for checking common support is suggested by Smith and Todd (2005), which is trimming to determine the common support

II.5.3.3.4. Matching Quality / Effect Estimation

After the matching is realized in the common support the quality of the matching should be checked. The distributions of the matching variables in the model should be similar. In this study, we use the the methodology in Psmatch2 application in STATA. The common support is determined and balancing hypothesis is tested through this algorithm*: "1. Split the sample in k equally spaced intervals of e(x) 2. Within each interval test that the average e(x) of treated and untreated do not differ 3. If the test fails, split the interval and test again 4. Continue until, in all intervals, the average e(x) of treated and untreated units do not differ 5. Within each interval, test that the means of each characteristic do not differ between treated and untreated"* (Leuven and Sianesi, 2003).

Besides this quality is checked also by calculating the absolute standardized bias (ASB). ASB is defined as the absolute difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups (Rosenbaum and Rubin, 1985).

$$ASB = \left| 100 \frac{\left(\overline{X}_T - \overline{X}_C\right)}{\sqrt{0.5\left(s_T^2 - s_C^2\right)}} \right|$$

II.5.3.3.5. Sensitivity Analysis

Regression and matching methods based on propensity scores involve Unconfoundedness Assumption which is also known as the Conditional Independence Assumption or Selection on Observables. It assumes that the model for estimation of propensity scores, includes every variable that explains the treatment and the outcome variables and no nonobservable variables are left. UNA is not informed by the data which means it is untestable by the data set. Since it is a strong assumption, sensitivity tests were generated for the inspection of the assumption. Such sensitivity analyses provide valuable information to draw conclusions on reliability of the estimates. By realizing these tests inference could be made to what degree this assumption holds. There are some indirect and direct tests.

One of the ways to assess the UNA is using multiple control groups. In this method another control group is created and the causal effect of belonging to one of the control groups which is expected to have a zero effect, is estimated (Rosenbaum, 1987). If the effect is found to be different than zero this means at least one of the control groups is invalid (Arpino, 2008).

Another indirect method suggests estimating the causal effect of the treatment on variables which are expected to be unaffected by it. In this case pretreatment variables are useful for testing. If the effect is not different from zero, it means that UNA is more likely to hold (Imbens, 2004).

In this respect a major contribution was made by Ichino et al. (2008) who suggested a more direct method. The sensitivity analysis proposed by them builds on Rosenbaum and Rubin (1983) and Rosenbaum (1987), and it is based on a simple idea. Parametrization is not necessary in this sensitivity analysis. They suggest that when unconfoundedness is not satisfied given observables but would be satisfied if we could observe an additional binary variable, U.

$$Y_s \perp S \mid (X, U).$$

This binary variable can be simulated in the data and used as an additional matching factor. A comparison of the estimates obtained with and without matching on this simulated variable shows the extent of robustness of the estimator to this specific source of failure of the UNA. This simulation is done in two ways in practice. In the first one a binary variable which is significant in the model is used by mimicking this variable. In the second method no such variable is required, but some parameter values are attached which simulate the unobserved variable's (U) distribution and the sensitivity analysis is carried out accordingly. The analysis tests to what extent unobservables impose a threat to the baseline ATT.

$$\Pr(Y=1 \mid S, X, U) \neq \Pr(Y=1 \mid S, X) \qquad (7)$$

U values that would drive the treatment effects to zero are looked for. These are called "killer confounders" or "dangerous confounders". After this the plausability of the configuration of parameters that generate such a U value is assessed. If it is not found to be likely, then the PSM is considered to be robust (Nannicini, 2007). For the sensitivity analysis Sensatt module of STATA is used.

II.5.4. Instrumental Variable (IV)

IV method can be considered as an alternative to methods using propensity scores. As was mentioned earlier, IV methods usually measure LATE instead of ATE or ATT. *"If treatment effects are heterogenous, LATE is generally different from ATE and ATT, which are usually the parameters of interest."* (Arpino and Aassve, 2013). The chosen instrumental variable definitely makes a difference in the obtained results.

We are also restricted with the data set for the application of IV method. For IV application community level variables could be used. Such variables are not available in our data set, therefore it couldn't be applied. Some other options for using IV method is use of twins or sex preference. For the case of twins, only twenty-four twins are identified by considering the year and month of births in the same household. This is the number for the whole data set not even selecting for households that are followed for four years. The number is too low to pursue any reliable. Son preference is a frequently used instrumental variable in literature. In our case this is also not a very feasible method since birth history data is not available in the data. Thus, an IV method was not preferred for the application in this study.

II.5.5. Well-being Indicators for Analyses (Outcomes)

II.5.5.1. Consumption Expenditure

Consumption expenditure is seen as one of the most important indicators of household economic well-being in literature. For this reason, an extra effort was realized to make use of this indicator.

II.5.5.1.1 Statistical Matching of Consumption Expenditure

Information on consumption expenditures is not available in SILC data. Detailed information on consumption expenditures is collected with another survey, the Household Budget Survey. In this case, to make use of consumption expenditure in this study, the most suitable method is to incorporate information on consumption expenditures in HBS to SILC data. The incorporation of the two surveys is executed by using ***statistical matching method*** and consumption expenditure is fused into SILC data set to be used in this study.

II. 5.5.2. Income

The effect on income is one of the basic indicators. To some extent, it demostrates the resources available for the household. Whether the household would be able to enlarge its resources after the birth a child is an issue especially important for poorer households.

II. 5.5.3 Conventional Poverty Measures with Cost of Basic Needs Approach

For the analyses with regard to poverty, the choice should be made for the method of poverty measurement, indicator of poverty, and construction of poverty line. To this end, when conventional poverty measures are calculated this study will utilize the previous poverty measurement methodology of Turkey which was used until 2009. This allows for a fixed poverty line, which is calculated according to Cost of Basic Needs Approach (Ravallion and Bidani, 1994).

In this methodology, a minimum level of food consumption expenditure is calculated based on a minimum calorie level. By multiplying this value with the food consumption expenditure share in total consumption expenditure of a reference household type, a poverty line is calculated. Poverty measures will be calculated with this methodology at household level. The ratio of the poor refers to the percentage of households that are poor.

II.5.5.3.1 Poverty Line

For the conventional measures of poverty, a **poverty line** for the distinction of poor from non-poor is necessary for the analyses. This is a crucial point since, whether a household is poor or non-poor will be decided according to the comparison of its consumption expenditure and income level with the poverty line. The poverty line for each year will be the adjusted values of poverty line from 2009, which is the last year when official conventional poverty measures were presented, using CPI.

II.5.5.3.2 Equivalence Scales

For comparing consumption expenditures and incomes with the poverty line there is need for adjustment according to household characteristics, so that the households with different characteristics can be made comparable with the same poverty line. Most widely used is the household size for such adjustment. The adjustment is realized by using equivalence scales. This study will utilize recently computed equivalence scales for Turkey (Betti et al., 2017). These equivalence scales are the most recent measures derived from Turkish data. Each additional adult corresponds to 0.65 of the first adult and each child correspond to 0.35 of the first adult.

II.5.5.3.3. Consumption Poverty and Income Poverty

Conventional poverty measures are based on both consumption expenditure and income. The measures are produced for both indicators.

II.5.5.4. Fuzzy Poverty

Relatively recent literature on measures of poverty other than conventional ones are now widely found in poverty literature. Fuzzy poverty measures are among these. When dealing with fuzzy poverty measures every unit has a degree of poverty, which generally has a value between 0 and 1, rather than being classified as poor and non-poor.

There are two separate use of fuzzy poverty measures in general. One, that is based on monetary indicators is called fuzzy monetary measure and the other is called the fuzzy supplementary measure, which is a multidimensional poverty measure.

The fuzzy monetary measure in this study is constructed by the following formula by Betti and Verma (2008):

$$FM_i = \left(\frac{\sum_{\gamma=i+1}^{n} w_\gamma \mid y_\gamma > y_i}{\sum_{\gamma=2}^{n} w_\gamma \mid y_\gamma > y_1} \right)^{\alpha-1} \left(\frac{\sum_{\gamma=i+1}^{n} w_\gamma y_\gamma \mid y_\gamma > y_i}{\sum_{\gamma=2}^{n} w_\gamma y_\gamma \mid y_\gamma > y_1} \right) \tag{8}$$

Here, y is the equivalized income and w is the sample weight. γ shows the rank of the individual in the income distribution in the ascending order. α is estimated in a way that the head count ratio based on the poverty line corresponding to 60 per cent of the median income is equal to the mean of the fuzzy monetary measure (Betti and Verma, 2008).

Fuzzy supplementary is a multidimensional poverty measure based on specific characteristics of households and individuals. The list of variables used to derive the fuzzy supplementary poverty measure is presented in the appendix. The fuzzy supplementary measure in this study is constructed by the following formula by Betti and Verma (2008):

$$FS_{hi} = \left[\frac{\sum_{\gamma=i+1}^{n} w_{h\gamma} \mid s_{h\gamma} > s_{hi}}{\sum_{\gamma=2}^{n} w_{h\gamma} \mid s_{h\gamma} > s_{h1}} \right]^{\alpha-1} \left[\frac{\sum_{\gamma=i+1}^{n} w_{h\gamma} s_{h\gamma} \mid s_{h\gamma} > s_{hi}}{\sum_{\gamma=2}^{n} w_{h\gamma} s_{h\gamma} \mid s_{h\gamma} > s_{h1}} \right], \tag{9}$$

$$h = 1, 2, ..., m; i = 1, 2, ..., n; \mu_{hn} = 0$$

Here s is a computed score for deprivation in one of the components of the fuzzy supplementary measure and w is the sample weight. h corresponds to dimension and j corresponds to deprivation variable. Similar to fuzzy monetary measure, it is estimated in a way that the head count ratio based on the poverty line corresponding to 60 per cent of the median income is equal to the mean of the fuzzy monetary measure (Betti and Verma, 2008).

II.5.5.5. Material Deprivation Index

"The material deprivation rate is an indicator in EU-SILC that expresses the inability to afford some items considered by most people to be desirable or even necessary to lead an adequate life. The indicator distinguishes between individuals who cannot afford a certain good or service, and those who do not have this good or service for another reason, e.g. because they do not want or do not need it. The indicator adopted by the Social Protection Committee measures the percentage of the population that cannot afford at least three of the following nine items" (Eurostat, 2016):

- to pay their rent, mortgage or utility bills;
- to keep their home adequately warm;
- to face unexpected expenses;
- to eat meat or proteins regularly;
- to go on holiday;
- a television set;
- a washing machine;
- a car;
- a telephone.

II.5.6. Measuring the Differences of Outcomes

In order to measure the differences of outcomes between the control and treatment groups it is important to take into consideration that the two samples to be contrasted are dependent, therefore a correlated means test is required. Use of a paired test is necessary instead of testing the two samples independently. In our case, this is also accomplished by using the psmatch2 package in STATA considering the paired characteristic of the sample at hand.

The differences of outcomes refer to the differences between treatment and control groups. Because the changes between two periods are considered the indicators are regarded as diference-in-difference indicators. Using this, also enables to decrease the potential bias (Arpino, 2008).

There are three main reasons for the change in consumption expenditure and income in consecutive years as formulized in this study. The first is economic growth in the country which increases the well-being of the average household. The second is inflation which increases the monetary elements in nominal terms. And in our case the third is the birth of a child. Since our target is single out the effect of child birth we make use of the dynamic approach. The monetary terms are all equivalized with regard to inflation and all monetary values refer to 2013 level. For comparison of treated and control households we take differences between the first period and the following or the last period, so because we are comparing the differences, the outcome under investigation will be the comparison of differences in change of well-being (which could also be defined as economic growth for solely monetary indicators) between two periods.

II.5.6.1. Timing of the Birth

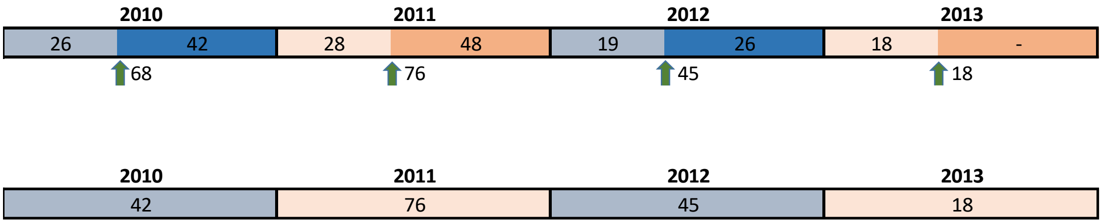
In causal inference the role of time is profoundly important (Holland, 1986). Contrary to this fact, the literature analyzing the causal effect of fertility on well-being lacks the discussion on timing of the birth and compare births between two periods without considering when the birth has occurred. In general, births between panels waves of four or five years are analyzed with regard to their effect on well-being. On the other hand, all births are considered the same disregarding the time of the birth. Doubtlessly these births have different effects according to the time when the birth took place. This study will try to distinguish the difference that depends on the time of the birth. The shortcoming for this analysis is that as the births are stratified according to time periods, there will be less observations left for examination. An alternative could be to focus on a shorter panel, such as the two-years panel. This exercise is realized in Chapter III.

The births in the four-year panel are presented in Figure II.5.6.1. The first part of the figure shows number of births with regard to year of birth as well as whether its occurrence is before or after the survey date. For instance, in 2011, there are a total of 76 births, of which 28 are before the survey in 2011 and 48 are after the survey is realized. The second part of the figure shows the births that are considered in the analyses.

Because there is no available pre-treatment information for the 26 households that had a child before the interview in 2010, we exclude these households from the analyses. They are not kept in the controls either, in order to be consistent and not to include the effects of these very recent births.

The household size is based on the household roster and determined at the time of the interview. There are two reasons why this is accepted as it is and no action is taken. Firstly, because almost all other collected variables regarding household and individuals refer to the time of interview and secondly the births are spread within the year so their effect does not apply directly to the year after the birth, so the interview date also provides an approximately average effect. In Turkey, recently infant mortality rate is around as low as 10 per thousand, so any such case that would exist in the data is ignored.

Figure II.5.6.1. The timing of births



The timing of changes in consumption expenditure and income with regard to child birth also require a closer look. It is hard to tell the exact time a change would commence. The household could be starting to increase its consumption before the birth and this would mean a smaller amount of change after the birth which is hard to tell with the data at hand. Income as well as consumption expenditure could be affected by pregnancy rather than birth. Such analyses in depth, requires longer panels with bigger samples.

II.5.6.2. Unit of Analysis, Sample restrictions and Weights

The measurements of well-being are at household level and the measured effect will be at household level. Since the analyses will be made at household level the unit of analysis will be households. The SILC longitudinal survey follows individuals and provides weights at individual level. But in this case, because there is need for household level measurements, individual level weights are not very convenient for use. Household weights can be derived by making use of individual weights, but since there entries to and exits from households which lead to household splits and formation of new households there is no way to follow all households throughout the panel waves. Also, the child birth, which is the main point of issue in this study requires a change in the household structure between the waves.

The analyses will be restricted to households which include only one married woman of age between 15 and 49, and in which there were no other changes, with regard to its formation between the waves, with the exception of a child birth. This way the households are restricted to those having exactly one woman that are subject to risk of child bearing.

Also the treated households will be restricted to those which have only one child between the waves. When such restrictions are made household weights could be derived for the last wave of the panel and the analyses could be made accordingly. But the weights will no more be representative of the whole population, therefore such effort would be unnecessary. Taking all these issues into consideration, the use of weights will be dropped. Restricting the sample and dropping of weights cause bias which can’t be measured. This will be one of the shortcomings of the study. On the other hand, dealing with complexity of household formation and deriving household weights from individual weights for a sample which is no more representative of the whole population will be more problematic an issue than the otherwise.

Another restriction was made at this point to reduce the outlier effect and households with either consumption expenditure or income over 100 000 TL were excluded from the subsample. This choice is arbitrary and decreasing the level would lead to further cuts in the sample which is not desired. After this restriction, total number of households were 947 and households with a child birth between 2010 and 2013 were 181. The number of the treated in the analyses is 181 and the control is 766.

II.6. DATA

The main data source for this study is the Turkish Income and Living Conditions (SILC) Survey, which is conducted since 2006 on a yearly basis. Both, cross-sectional and panel datasets are produced from this survey. The core concepts of the survey are income and living conditions of individuals and households, which could also be inferred from the name of the survey. Social exclusion and poverty indicators are also produced from the survey. The survey is conducted in accordance with EU regulations and comparable data with the EU countries is produced.

The panel is comprised of four years. Each year 25 per cent of the households are switched with new ones.

Until 2013, the data set provides information at urban and rural levels as well as the country as a whole. Cross-sectional data set is large enough to provide information at NUTS1 level.

All household members living in the country are included in the sampling frame. Those living in military barracks, prisons, nursing homes, childcare centers, private hospitals and hotels are excluded from the sample frame. Immigrants are also excluded. Address Based Population Registration System and the National Address Database, which were established in 2007, constitute the basis for the sampling frame. The sampling design of SILC Survey is a two stage stratified cluster sampling. First, clusters (blocks), which are comprised of approximately 100 dwelling addresses (80 to 120) are constructed. Then households, which are the final sampling unit, are selected.

The Primary Sampling Unit is a Block. These blocks are comprised of approximately 100 household addresses. A locality that doesn’t have a municipality (i.e. village) is also considered as a block. In the first stage, primary sampling units (PSU), namely blocks are selected from the sampling frame. The selection is made with probability proportional to address size. The Secondary Sampling Unit constitute twelve household addresses for urban, eight for rural from each selected block.

The longitudinal weights of SILC are calculated by taking into account the non-responses and the base weights over the related year of the individuals, who participate in the panel. These weights are achieved by assigning 2, 3 and 4 year multiplier factors to the base weights of the individuals.

The survey takes place between April-July each year, in two stages. In the first stage, interview is accomplished with the households who continue to live in the same address as in previous application and with the new households. In the second stage, interview is accomplished with the sample persons moved out to another dwelling and households moved to another address.

The main source of data is SILC Survey which is a panel survey that provides panel data of four years. At the beginning of the study, microdata was available until 2013 for SILC panel data. Therefore this was used for the study.

Besides this, for information on the entire population cross-sectional SILC data was used for descriptive analysis in section 8.

In section 7, in order to make use of the original consumption variable in the Household Budget Survey, the data was acquired from this survey.

II.7. ANALYSIS WITH EQUIVALENCE SCALE MODIFICATION

In this subsection the effect of the new born will be analyzed by modifying the equivalence scale in a resrospective “what if” approach perspective. The assumption here is that when the consumption expenditure and the income level of the household is preserved, how would the the poverty status of the households change if the new borns were not added to the household. By altering the equivalence scale the value of adult equivalent consumption expenditure and income values will be increased and some of the households will rise above the poverty line and the aim is to observe the number of such households.

The consumption expenditure and income variables from HBS will be used because there are more observations available in HBS and it's better to use the original consumption expenditure variable instead of the estimated one SILC whenever it's possible. Therefore the data set used in this subsection is HBS, 2013. The households that are under poverty line are assumed to be using all their available resources in order to reach a consumption level as high as possible since they are under the poverty line. These households might have obtained transfers related to the new born. However, this will be ignored because this means there are resources available to these households which are under the poverty line and these transfers could have been made to pull them out of poverty instead. Therefore the analysis is made with this approach.

As mentioned before, the national equivalence scale values computed by Betti et al. (2017) will be used. In this scale, the value for children is 0.35. The equivalence scale value will be revised according to the number of children of age 0, 1, 2 and 3 in the household. Accordingly equivalized consumption expenditure and income will be revised and these revised values will be compared with the poverty line.

This simple analysis aims to serve as a premise for the further analyses. The confidence intervals are not considered and some of the differences might be insignificant. All the same, the central values gives an idea how the poverty rates could have changed.

The results indicate that both consumption poverty and income poverty decrease 0.4 points when children of age 0 are excluded from the household. The difference is almost 2 points when children up to age 3 are excluded. The number of the poor would have been more than 1 million lower than the actual number, without these recent births.

Table II.7.1. Number and percentage of poor when the new born are excluded

		All	- 0 year	- 0,1 year	- 0,1,2 year	- 0,1,2,3 year
Number of people	Consumption Poor	15 176 552	14 878 766	14 553 781	14 158 900	13 909 196
	Income Poor	13 759 151	13 486 387	13 080 990	12 724 028	12 361 213
%	Consumption Poor	20.4	20.0	19.5	19.0	18.7
	Income Poor	18.5	18.1	17.6	17.1	16.6

The analyses at household size level show that as household size increases, also the difference between the actual poverty rate and the poverty rate that would be when the children are excluded, increases. This is an expected result since larger households include more children and the method we use is based on altering the equivalence scale, which is related to the number of children.

Table II.7.2. Percentage of consumption poor when the new born are excluded, by household size (HHB)

	Consumption Poverty				
HHB	All	- 0 year	- 0,1 year	- 0,1,2 year	- 0,1,2,3 year
1	13.0	13.0	13.0	13.0	13.0
2	10.3	10.3	10.3	10.3	10.3
3	7.8	7.6	7.4	7.3	7.2
4	11.9	11.8	11.4	11.1	10.6
5	21.9	21.1	20.8	20.0	19.7
6	35.0	34.7	33.5	32.1	31.4
7+	54.2	53.1	52.1	50.8	50.2

Table II.7.3. Percentage of income poor when the new born are excluded, by household size (HHB)

	Income Poverty				
HHB	**All**	**- 0 year**	**- 0,1 year**	**- 0,1,2 year**	**- 0,1,2,3 year**
1	9.4	9.4	9.4	9.4	9.4
2	7.1	7.1	7.1	7.1	7.1
3	6.7	6.6	6.4	6.3	6.1
4	11.2	10.8	10.2	9.6	9.2
5	20.6	20.2	19.4	18.5	18.3
6	32.3	31.4	31.1	29.8	28.6
7+	49.6	49.0	47.7	47.5	46.3

II.8. APPLICATION OF THE ANALYSES USING PROPENSITY SCORES AND RESULTS

In order to demonstrate the effect of fertility there is need for selecting households that are more likely to have children. In this respect, the households with married women aged between 15-49 are selected. As also suggested by Aassve and Arpino (2007) this is a useful selection as it eliminates units that are unlikely to experience child birth.

II.8.1 Descriptives for the Data Sets

After the restrictions are applied in the data set, the sample is decreased to 947 observations. Among these 181 are treatments, meaning that there was exactly one birth in these households after the first interview in 2010 and before the last interview in 2013.

Table II.8.1.1. Entries and exits in the sample households

	Frequency	%
Household that don't have entries or exits (except for child birth)	1654	56.2
Household that have entries or exits	1287	43.8
Total	2941	100

Table II.8.1.2. Number of eligible women in the sample households

Number of married women of age group 15-49 in 2010	Frequency	%
0	622	37.6
1	1016	61.4
2	15	0.9
4	1	0.1
Total	1654	100.0

Table II.8.1.3. Number of births in households with eligible women

Number of child births during the panel	Frequency	%
0	806	48.7
1	189	11.4
2	21	1.3
Total	1016	61.4

After these selections are made there are 995 observations left. Among these further selections are made, such as those households where there were births without a woman with the given criteria, those with incomes over 100 000 TL as outliers were deleted from the data set. Moreover, some observations which were coded incorrectly were deleted, and finally 947 total cases are obtained. In 766 of these there is no birth and in the 181 there is a birth. The following tables demostrate the distributions of household size and number of children for the two groups, namely the treatment and the control group.

Table II.8.1.4. Household size in 2010

Household size	Control	Treatment	Cross-sectional
1	-	-	7.3
2	8.6	14.4	21.1
3	24.4	39.2	21.7
4	39.4	22.1	22.9
5	16.2	12.7	12.6
6+	11.4	11.6	14.5
Total	100.0	100.0	100.0

Table II.8.1.5. Number of children in 2010

Number of children (0-14)	Control	Treatment	Cross-sectional
0	18.1	17.1	48.1
1	28.2	43.1	22.2
2	36.4	26.0	17.9
3	11.1	8.8	6.6
4+	6.1	5.0	5.3
Total	100	100	100

Similar to whole population, around 30 per cent of the women are employed in both groups. In our restricted sample there are only 51 women who are employed one week prior to the survey in 2010. Among these 16 are unpaid family workers and only 35 are income earners of any kind. Of the 51 women, 34 still declares to have worked in the last week at the end of the panel in 2013. This low number of observations restricts for further analysis on the employment, income and fertility relationship for these women.

The cross-sectional figures refer to all women in the data set, regardless of their age or marriage status. But it should be taken into consideration that the question is addressed only to those at age 15 or over.

Table II.8.1.6. Working status of women one week preceding the survey, 2010, 2013

%

	Worked last week	Control	Treatment	Cross-sectional	Control	Treatment	Cross-sectional
2010	**Yes**	242	51	4 693	31.6	28.2	27.6
	No	524	130	12 325	68.4	71.8	72.4
Total		**766**	**181**	**17 018**	**100.0**	**100.0**	**100.0**
2013	**Yes**	256	42	7 609	33.4	23.2	27.5
	No	510	139	20 024	66.6	76.8	72.5
Total		**766**	**181**	**27 633**	**100.0**	**100.0**	**100.0**

Below in Table II.8.1.7 all income related items in the data set are presented seperately for treatment and control groups, for the beginning and the end of the panel. The years are those which correspond to the reference period of income information.

Table II.8.1.7. Income items by reference periods (2013 price level)

Income item	2009 Treatment	2009 Control	2012 Treatment	2012 Control
n	181	766	181	766
Imputed rent	1 226	1 343	1 102	1 205
Income received by people aged under 15	0	2	9	3
Child allowances (in cash)	38	42	31	23
Child allowances (in kind)	1	1	0	0
Housing allowances	5	0	0	0
Other cash transfers	2	12	9	6
Other non-cash transfers	23	19	6	13
Regular inter-household cash transfer received	164	224	208	220
Regular inter-household transfer received (in kind)	79	55	35	47
Alimonies received (compulsory + voluntary)	6	16	0	1
Income from rental of a property or land	60	262	72	295
Interest, dividends, profit from capital investments in unincorporated business	463	460	175	369
Value of goods produced for own consumption	23	18	25	11
Regular inter-household cash transfer paid	49	176	104	188
Regular inter-household non-cash transfer paid	8	35	8	15
Alimonies paid (compulsory + voluntary)	41	10	27	4
Regular taxes	75	83	103	104
Imputed income for nonresponding individuals	0	0	0	0
Total household disposable income	**12 218**	**12 228**	**11 177**	**13 415**
Personal income				
Employee cash or near cash income	7 445	6 287	7 060	6 870
Non-Cash employee income	499	431	436	483
Cash benefits or losses from self-employment	1 729	2 351	1 801	2 612
Non-cash benefits or losses from self-employment	27	40	22	37
Unemployment benefits	49	77	29	41
Retirement, old-age, private retirement allowances	297	732	315	1 166
Retirement benefits	168	106	0	216
Survivor' benefits	93	62	102	95
Sickness benefits	8	10	2	3
Disability benefits	7	23	12	33
Education-related allowances	0	3	0	24
Private insurance premium paid	22	45	33	45
Total personal income	**10 323**	**10 124**	**9 779**	**11 580**

When the differences of income and consumption expenditure between the first and last year are compared, it can be seen that there is a loss for the treatment group and a gain for the control group (Table II.8.1.8). The subsequent analyses are made for all births that occurred during the four-year panel.

Table II.8.1.8. Differences in income and consumption expenditure for treatment and control groups (in 2013 prices)

		Income			Consumption		
	n	**2009**	**2012**	**diff**	**2010**	**2013**	**diff**
Treatment	181	12 218	11 177	-1 041	11 618	10 639	-980
Control	766	12 228	13 415	1 187	11 756	12 967	1 211

The descriptives for deprivation index items show that the decrease in the proportion of the deprived is not as strong among the treatment group compared to those in the control group. For some items, the proportion of the deprived is even increasing among the teatment group while it is decreasing for the control group.

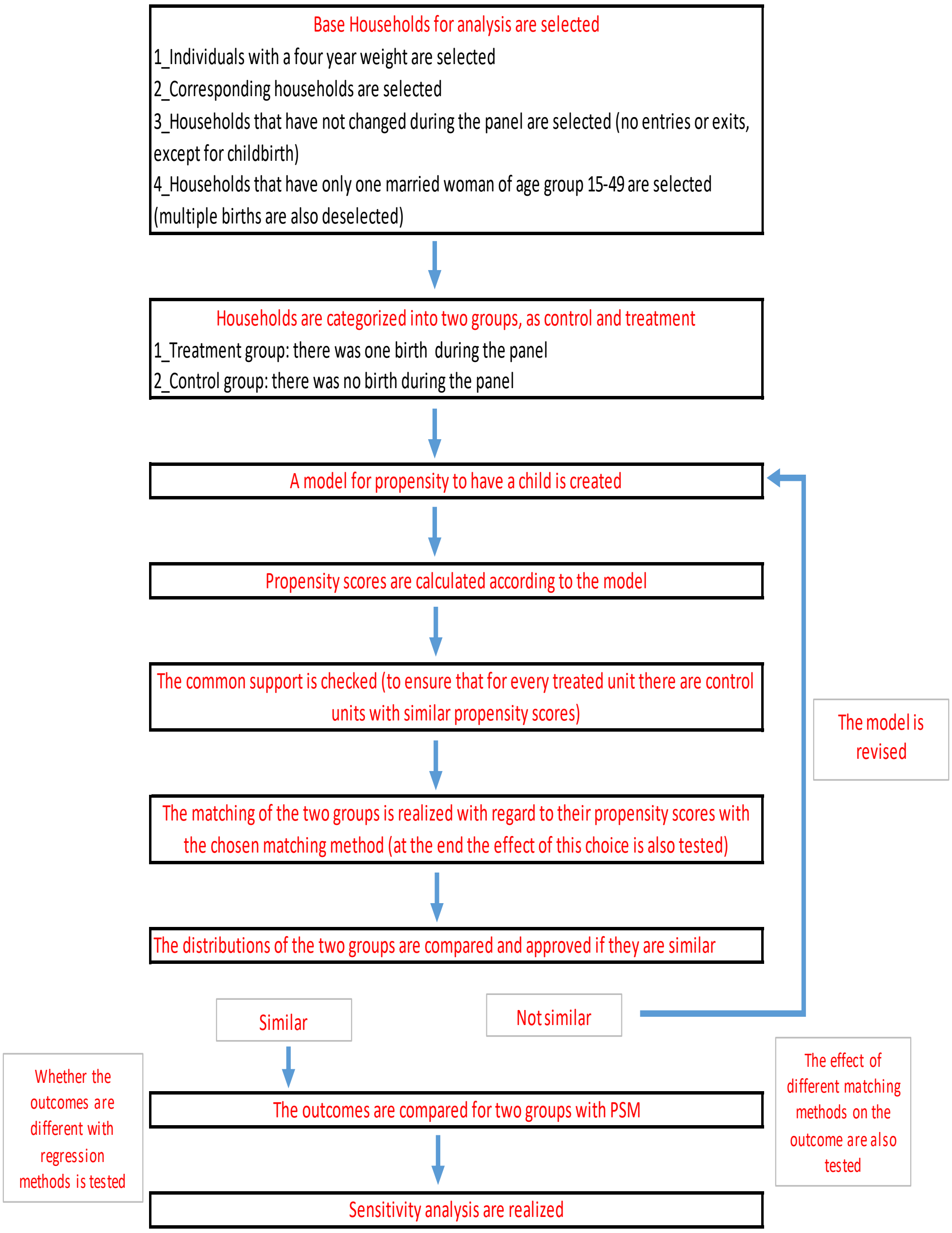
Table II.8.1.9. Deprivation items

	2010		2013	
	Control	Treatment	Control	Treatment
to pay their rent, mortgage or utility bills				
Deprived	44.9	39.2	37.6	41.4
No	55.1	60.8	62.4	58.6
to keep their home adequately warm				
Deprived	35.4	28.2	25.1	32.0
No	64.6	71.8	74.9	68.0
to face unexpected expenses				
Deprived	64.9	63.0	46.2	53.0
No	35.1	37.0	53.8	47.0
to eat meat or proteins regularly				
Deprived	60.4	55.8	43.6	44.8
No	39.6	44.2	56.4	55.3
to go on holiday				
Deprived	85.1	81.2	76.8	79.0
No	14.9	18.8	23.2	21.0
a television set				
Deprived	0.8	0.0	0.3	0.0
No	99.2	100.0	99.7	100.0
a washing machine				
Deprived	5.5	5.5	2.0	1.7
No	94.5	94.5	98.0	98.3
a car				
Deprived	58.9	59.7	49.1	55.8
No	41.1	40.3	50.9	44.2
a telephone				
Deprived	23.4	23.2	16.5	22.7
No	76.6	76.8	83.6	77.4
deprivation index				
Deprived	71.2	65.8	56.4	60.2
No	28.9	34.3	43.6	39.8
Total	**766**	**181**	**766**	**181**

II.8.2. Analyses with PSM

This subsection presents the propensity score estimation and analyses with PSM. First, the algorithm of the estimation method is demonstrated.

Figure II.8.2.1. The algorithm for the PSM method



II.8.2.1. Model Selection

A logit model is used for the propensity score estimation. The dependent variable is the treatment which means occurrence of a birth during the four-year panel. Treatment variable takes a value of one when there is a birth and zero in the absence of a birth. The independent variables refer to the beginning of the panel, in other words, they are all pretreatment variables, so that similar households are matched from the treatment and control groups according to their characteristics at the beginning of the panel. And the difference in the outcomes are calculated accordingly. The independent variables include the sex of the reference person and age of the reference person, where reference person is the person with the highest personal income, household size, dummy variables for whether there is at least one child between ages 0 and 4, 5 and 9, and 10 and 14 respectively, percentage of those in the household with educational attainment of high school or more multiplied by percentage of those has worked last week, a dummy variable for whether there is at least one man who has educational attainment of high school or more, a dummy variable for whether there is at least one woman who has educational attainment of high school or more, a dummy variable for whether there is at least one woman who has worked last week, logarithm of consumption and logarithm of income.

Our data set lacks some variables such as rural-urban variable, region and ethnicity, which were used in similar studies and could have been used in this study.

Table II.8.2.1.1. Model for propensity score estimation

	coeff.	s.e.	
Intercept	1.471	1.846	
Gender of reference person	0.010	0.387	
Age of reference person	-0.698	0.131	***
Household size	0.066	0.103	
Children of age 0-4 dummy	0.307	0.221	
Children of age 5-9 dummy	-0.200	0.215	
Children of age 10-14 dummy	-0.793	0.260	***
Percentage of household members with high school education or more * Percentage of household members that worked last week	2.444	0.697	***
Men with high school education or more dummy	0.243	0.220	
Women with high school education or more dummy	-0.675	0.270	**
Women that worked last week dummy	-0.302	0.230	
Log of consumption expenditure in 2010 (with 2013 prices)	-0.049	0.209	
Log of income in 2009 - measured in 2010 (with 2013 prices)	-0.097	0.216	

II.8.2.2. Common Support

The graphical analysis shows that the overlap is sufficient (Figure II.8.2.2.1). The balancing property is satisfied and the region of common support is [0.0406, 0.764]. At the end of the common support analysis with minima-maxima criteria 2 observations from the treated sample is dropped from the matching sample (Table 7.3.2.1). Further trimming is not desired in order not to lose observations.

Figure II.8.2.2.1. Common support / overlap

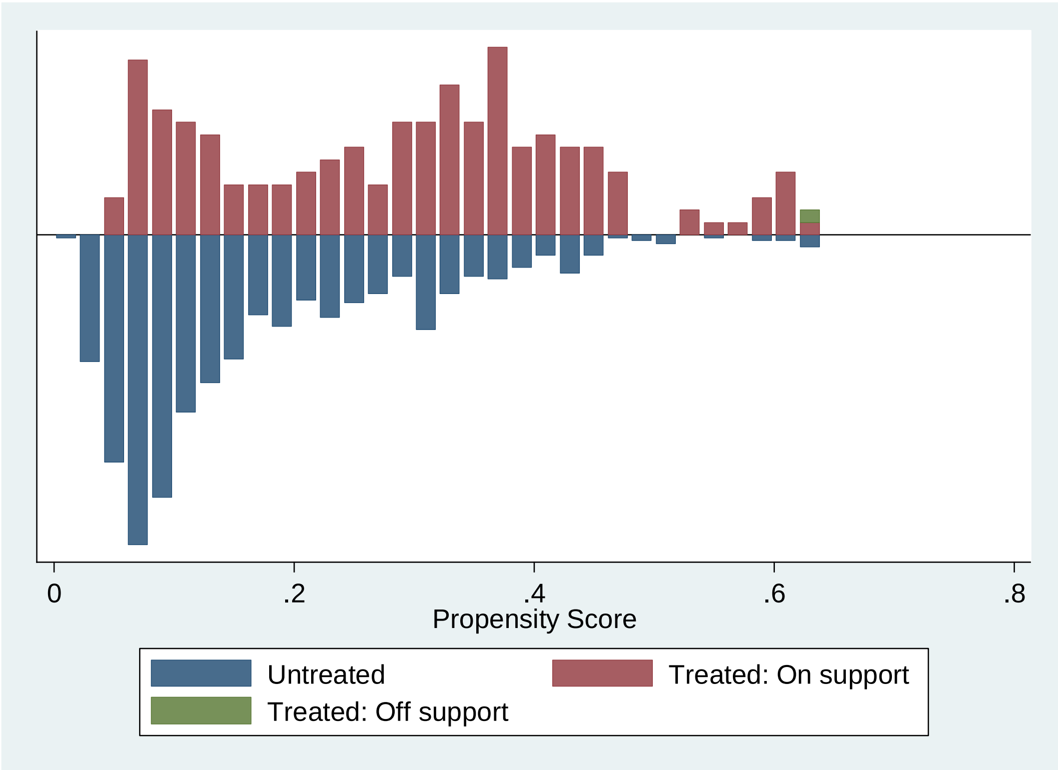


Table II.8.2.2.1. Common support

	Off support	On support	Total
Untreated	0	766	766
Treated	2	179	181
Total	2	945	947

8.2.3. Matching Quality

Matching quality is assessed by the standardized bias. There is only one variable (child of age 0-4 dummy) which has an absolute value slightly over 5 per cent. The matching quality is considered to be high. Because the labels of the variables are already given above, here for simplicity, the names of the variables are given.

Table II.8.2.3.1. Absolute standardized bias (ASB)

Variable	Sample	Mean Treated	Mean Control	% bias
ref_sex_1_0	Unmatched	0.94	0.93	2.9
	Matched	0.94	0.94	-2.3
ref_age	Unmatched	2.29	2.84	-70.1
	Matched	2.30	2.32	-2.1
hsize_orj	Unmatched	3.77	4.08	-22.1
	Matched	3.79	3.82	-2.0
child_0_4_dummy	Unmatched	0.60	0.41	39.4
	Matched	0.61	0.64	-5.7
child_5_9_dummy	Unmatched	0.39	0.48	-18.1
	Matched	0.40	0.42	-4.5
child_10_14_dummy	Unmatched	0.17	0.42	-55.8
	Matched	0.17	0.16	2.5
perc_edu_worked	Unmatched	0.15	0.09	31.7
	Matched	0.14	0.14	1.7
men_edu_high_dummy	Unmatched	0.54	0.40	27.0
	Matched	0.53	0.52	2.3
women_edu_high_dummy	Unmatched	0.31	0.29	6.0
	Matched	0.31	0.30	1.2
women_worked_dummy	Unmatched	0.29	0.33	-8.4
	Matched	0.28	0.27	2.4
log_cons	Unmatched	9.14	9.14	0.5
	Matched	9.14	9.14	0.4
log_inc	Unmatched	9.15	9.14	1.3
	Matched	9.15	9.14	0.2

II.8.2.4. Results

The results of the PSM analyses for different types of outcomes are presented in this section.

II.8.2.4.1. Income, Consumption Expenditure and Fuzzy Poverty

Both income and consumption expenditure behave similarly for treatment and control groups. There is a decrease in the treated and an increase in the controls. Fuzzy monetary poverty measure decrease for both groups, but the decrease is 0.05 points greater for the controls which supports the finding that control group is better off compared to the treatment group. Fuzzy supplementary poverty measure increases for the treatment group showing that they are worse than they used to be in absolute terms, without even comparing to the control group, but this estimate is not very significant.

It can also be seen that the average treatment effect is generally similar to the average treatment effect on the treated.

Regarding the standard errors, there isn’t a consensus in literature. Bootstrapping is used in some studies. Abadie and Imbens (2008), on the other hand, argue that bootstrapping is inappropriate for the matched data. In this study, unadjusted standard errors are presented. Only specific to the sensitivity analyses tables, are between-imputation standard errors are used as these are provided by the Sensatt package.

Table II.8.4.1.1. ATT and ATE for income, consumption expenditure and fuzzy poverty

		ATT				
	n	Treated	Controls	Difference	s.e.	ATE
income	179	-979	1 347	-2 326	786	-2 516
consumption expenditure	179	-944	2 326	-3 270	1 267	-2 654
fuzzy monetary	179	-0.013	-0.062	0.049	0.022	0.032
fuzzy supplementary	179	0.009	-0.026	0.035	0.029	0.032

An interesting idea would be view the income of the woman seperately to assess its effect on the overall loss in income. At the beginning of the panel there are only 51 women in the treatment group who earn an income of any kind. This figure decreases to 42 at the end of the panel. It should also be mentioned that not all of these working women are income earners. Some analyses were made in this regard such as looking for the difference in income of women during the panel, the results were not significantly different from 0, which indicates there isn't a difference between the treatment and control groups in this regard. An important issue here is that with such small number of observations the PSM method is not reliable any more. Even using different models, such as using a probit or a logit model generates differences. With logit model as suggested above, no difference between the groups was observed. On the other hand, probit model suggested a difference, which is not a reliable outcome.

II.8.2.4.2. Conventional Poverty Measures and Deprivation

For those households which were not income poor in the beginning of the panel there is not considerable difference with regard to their entrance into poverty. Around 8.5 per cent of the treatment group and 7.7 per cent of the control group enter into poverty at the end of the panel. On the other hand, consumption poverty demonstrate a difference among the groups indicating the control group is better off in general. Deprivation index shows the opposite.

All the same, it is seen that the difference is not statistically significant for income poverty and deprivation.

Table II.8.4.2.1. Entrance into poverty (for those who were not poor or deprived in 2010)

		ATT			
	n	**Treated**	**Controls**	**Difference**	**s.e.**
income poverty	130	0.085	0.077	0.008	0.043
consumption poverty	144	0.174	0.069	0.104	0.041
deprivation	60	0.283	0.367	-0.083	0.105

When exit from poverty is considered, the results for income poverty indicate that 60 per cent of income poor in the beginning of the panel among the treatment group, was still poor at the end of the panel. This percentage was 46 per cent for the control group. Consumption poverty shows the opposite, but the results are not significant for both estimators. The analysis of deprivation shows that the treatment group is worse-off. This estimate is nearly significant at 90 per cent confidence level.

Table II.8.4.2.2. Exit from poverty (for those who were poor or deprived in 2010)

		ATT			
	n	**Treated**	**Controls**	**Difference**	**s.e.**
income poverty	48	0.604	0.458	0.146	0.116
consumption poverty	32	0.344	0.469	-0.125	0.141
deprivation	119	0.773	0.639	0.134	0.067

II.8.2.4.3. Sensitivity to Matching Algorithm

The analyis shows that choice among logit and probit models and matching algorithm does not have a significant impact on the estimated treatment effect.

Table II.8.4.3.1. Sensitivity to matching algorithm

Model type and matching algorithm	n	ATT	s.e.
logit / nnd / with replacement	179	-2 326	786
probit / nnd / with replacement	179	-2 559	746
logit / nnd / without replacement	179	-2 297	634
logit / nnd / without replacement / caliper (0.1)	174	-2 209	645
logit / nnd / without replacement / caliper (0.01)	167	-2 475	663
logit /radius	179	-2 166	466
logit /kernel	179	-2 482	544

II.8.2.4.4. Sensitivity for UNA

When PSM method, which relies on UNA is applied it is utmost important to carry out sensitivity analysis to account for robustness. In this respect indirect and direct tests are carried out for analysis.

II.8.2.4.4.1. Indirect Tests

The indirect tests with different outcomes show that these outcomes are not significantly different for the treatment and control groups.

Table II.8.2.4.4.1.1. Indirect Tests

Name of variable	ATT	s.e.
income in 2010	-721	1 321
consumption expenditure in 2010	-434	1 084
hot water	0.04	0.04
internet	0.07	0.06
household size	-0.03	0.16

II.8.2.4.4.2 Direct Tests

The direct tests for the change in income are presented in this section. Using variables from the model to mimic the unobserved variable is the first direct test. The baseline ATT value is -2 326 and none of the ATT with tested variables are significantly different from the baseline ATT. G refers to outcome effect which is the effect of unobserved variable on the outcome variable, that is the difference in income in this case and A refers to selection effect, which refers to the effect of unobserved variable on the treatment variable. pij refers to the distribution of the variable where both i and j take values of 0 and 1. i refers to the treatment variable and j refers to a transformed form of the outcome variable which takes a value of 1 if the outcome is greater than the median and 0 otherwise.

Table II.8.2.4.4.2.1. Direct Tests 1

Unobserved variable simulated according to	p11	p10	p01	p00	Outcome effect (G)	Selection effect (A)	ATT	s.e.
none							-2 326	786
child_0_4_dummy	0.71	0.54	0.38	0.44	0.79	2.28	-2 534	901
child_5_9_dummy	0.35	0.41	0.47	0.49	0.91	0.70	-2 632	829
child_10_14_dummy	0.20	0.16	0.39	0.45	0.77	0.30	-2 696	908
women_edu_high_dummy	0.32	0.31	0.31	0.27	1.23	1.16	-2 551	822
women_worked_dummy	0.31	0.28	0.35	0.31	1.23	0.82	-2 551	817
men_edu_high_dummy	0.58	0.51	0.45	0.35	1.48	1.80	-2 581	853

Note: Standart errors are between-imputation standard errors

The second direct test is presented below. In this test, d refer to (p01 − p00) and s refer to (p1.− p0.), respectively (Ichino et al., 2008). At some extremes the ATT value is different from the baseline value (benchmark) or close to zero. Even so, in general the ATT’s obtained with the test are not significantly different from the baseline ATT and the they always have a value which is negative and generally significantly different from zero. The results indicate that the PSM is not robust only in the case of an unreasonably effective unobserved variable.

Table II.8.2.4.4.2.2. Direct Tests 2

						G < 1 and A < 1						
	s = -0.1				s = -0.3				s = -0.5			
	ATT	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**
d = -0.1	-2 661	450	0.67	0.68	-2 808	512	0.67	0.21	-3 007	609	0.59	0.11
d = -0.3	-2 756	500	0.28	0.74	-3 153	538	0.29	0.31	-3 669	576	0.25	0.11
d = -0.5	-2 810	498	0.07	0.76	-3 530	521	0.07	0.33	-4 222	616	0.07	0.11
						G > 1 and A < 1						
	s = -0.1				s = -0.3				s = -0.5			
	ATT	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**
d = +0.1	-2 570	447	1.54	0.70	-2 399	468	1.52	0.23	-2 082	560	1.75	0.12
d = +0.3	-2 385	489	3.65	0.68	-1 986	500	3.61	0.28	-1 511	504	4.17	0.10
d = +0.5	-2 185	489	15.20	0.64	-1 524	491	15.03	0.28	-789	446	14.70	0.09
						G < 1 and A > 1						
	s = +0.1				s = +0.3				s = +0.5			
	ATT	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**
d = -0.1	-2 468	432	0.58	1.82	-2 347	543	0.59	4.16	-2 173	589	0.58	10.86
d = -0.3	-2 297	463	0.24	1.76	-1 820	474	0.25	4.73	-1 550	554	0.25	13.87
d = -0.5	-2 123	478	0.07	1.80	-1 326	469	0.07	4.94	-734	506	0.07	14.57
						G > 1 and A > 1						
	s = +0.1				s = +0.3				s = +0.5			
	ATT	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**	**ATT**	**s.e.**	**G**	**A**
d = +0.1	-2 721	476	2.39	2.02	-2 964	558	2.42	5.02	-3 169	718	2.38	10.42
d = +0.3	-2 760	483	6.41	1.49	-3 388	555	6.29	3.90	-3 814	622	6.29	8.67
d = +0.5	-3 028	519	14.73	1.55	-3 631	516	14.50	3.62	-4 397	576	15.04	12.48

Note: Standart errors are between-imputation standard errors

In the following table, the comparisons of ATTs to the benchmark value (- 2 326) in each case are presented.

Table II.8.2.4.4.2.3. Direct Tests 2 (comparison to benchmark)

				G < 1 and A < 1					
	s = -0.1			s = -0.3			s = -0.5		
	ATT/Benchmark	**G**	**A**	**ATT/Benchmark**	**G**	**A**	**ATT/Benchmark**	**G**	**A**
d = -0.1	1.14	0.67	0.68	1.21	0.67	0.21	1.29	0.59	0.11
d = -0.3	1.18	0.28	0.74	1.36	0.29	0.31	1.58	0.25	0.11
d = -0.5	1.21	0.07	0.76	1.52	0.07	0.33	1.82	0.07	0.11
				G > 1 and A < 1					
	s = -0.1			s = -0.3			s = -0.5		
	ATT/Benchmark	**G**	**A**	**ATT/Benchmark**	**G**	**A**	**ATT/Benchmark**	**G**	**A**
d = +0.1	1.10	1.54	0.70	1.03	1.52	0.23	0.90	1.75	0.12
d = +0.3	1.03	3.65	0.68	0.85	3.61	0.28	0.65	4.17	0.10
d = +0.5	0.94	15.20	0.64	0.66	15.03	0.28	0.34	14.70	0.09
				G < 1 and A > 1					
	s = +0.1			s = +0.3			s = +0.5		
	ATT/Benchmark	**G**	**A**	**ATT/Benchmark**	**G**	**A**	**ATT/Benchmark**	**G**	**A**
d = -0.1	1.06	0.58	1.82	1.01	0.59	4.16	0.93	0.58	10.86
d = -0.3	0.99	0.24	1.76	0.78	0.25	4.73	0.67	0.25	13.87
d = -0.5	0.91	0.07	1.80	0.57	0.07	4.94	0.32	0.07	14.57
				G > 1 and A > 1					
	s = +0.1			s = +0.3			s = +0.5		
	ATT/Benchmark	**G**	**A**	**ATT/Benchmark**	**G**	**A**	**ATT/Benchmark**	**G**	**A**
d = +0.1	1.17	2.39	2.02	1.27	2.42	5.02	1.36	2.38	10.42
d = +0.3	1.19	6.41	1.49	1.46	6.29	3.90	1.64	6.29	8.67
d = +0.5	1.30	14.73	1.55	1.56	14.50	3.62	1.89	15.04	12.48

II.8.3. Analyses with Stratification and Regression

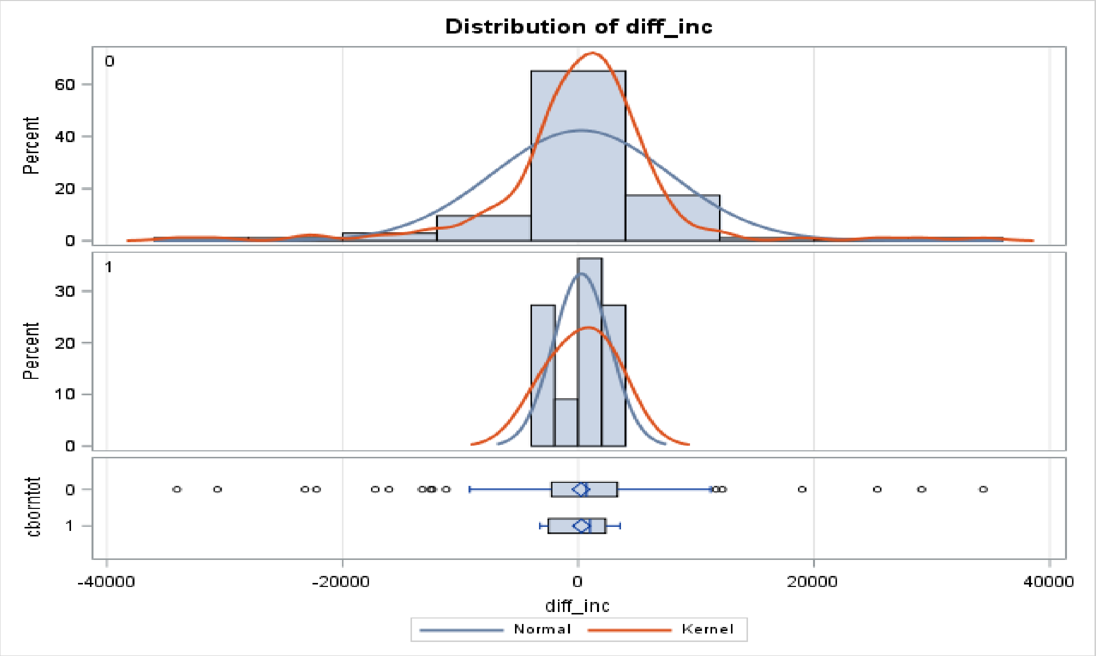
The analyses with stratification and regression methods return similar results with PSM. In the stratification, the observations are divided into stratas according to their propensity scores. The results show that there is a difference between the control and treatment groups with regard to the difference in income between 2010 and 2013. This difference is in line with findings from PSM method. Only in the first strata we don't observe any difference. In this strata, there are only 11 treatment observations, which is probably the cause of this situation.

Table II.8.3.1. Stratification

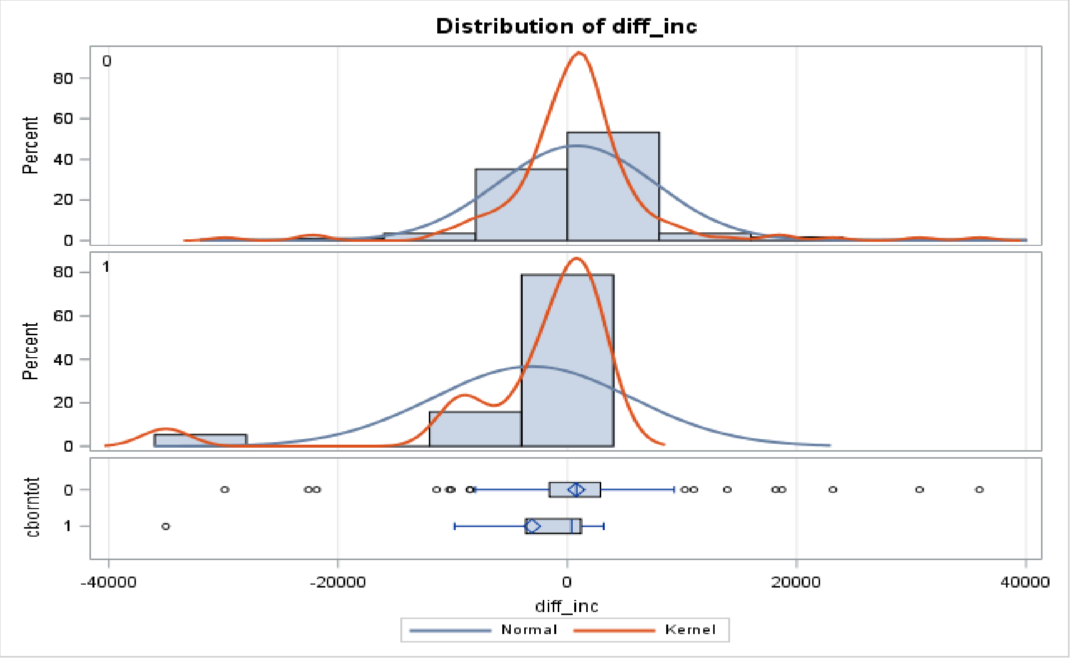
	1		2		3		4		5	
	mean	**s.e.**	**mean**	**s.e.**	**mean**	**s.e.**	**mean**	**s.e.**	**mean**	**s.e.**
Control	232	565	776	523	2 294	487	1 224	548	1 678	460
Treatment	278	721	-3 080	1 993	-1 396	950	-2 411	805	33	589
Difference	46	2 285	-3 856	1 702	-3 690	1 357	-3 635	1 104	-1 645	736

Figure II.8.3.1. Stratification

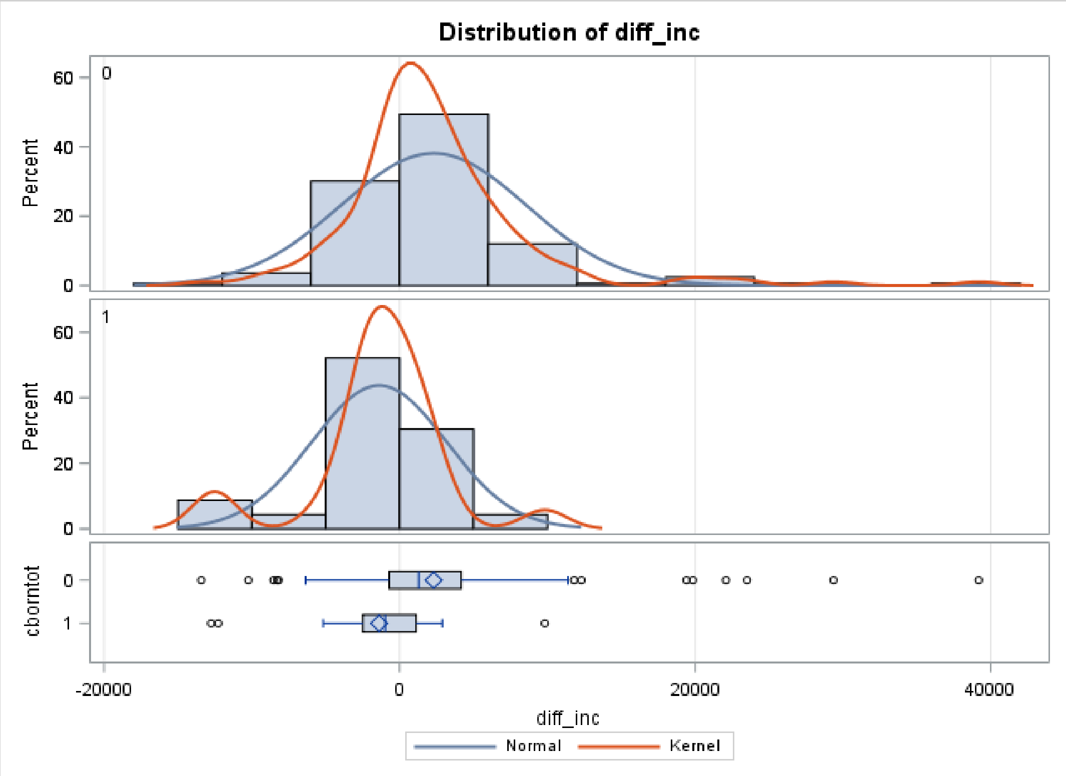
Strata 1



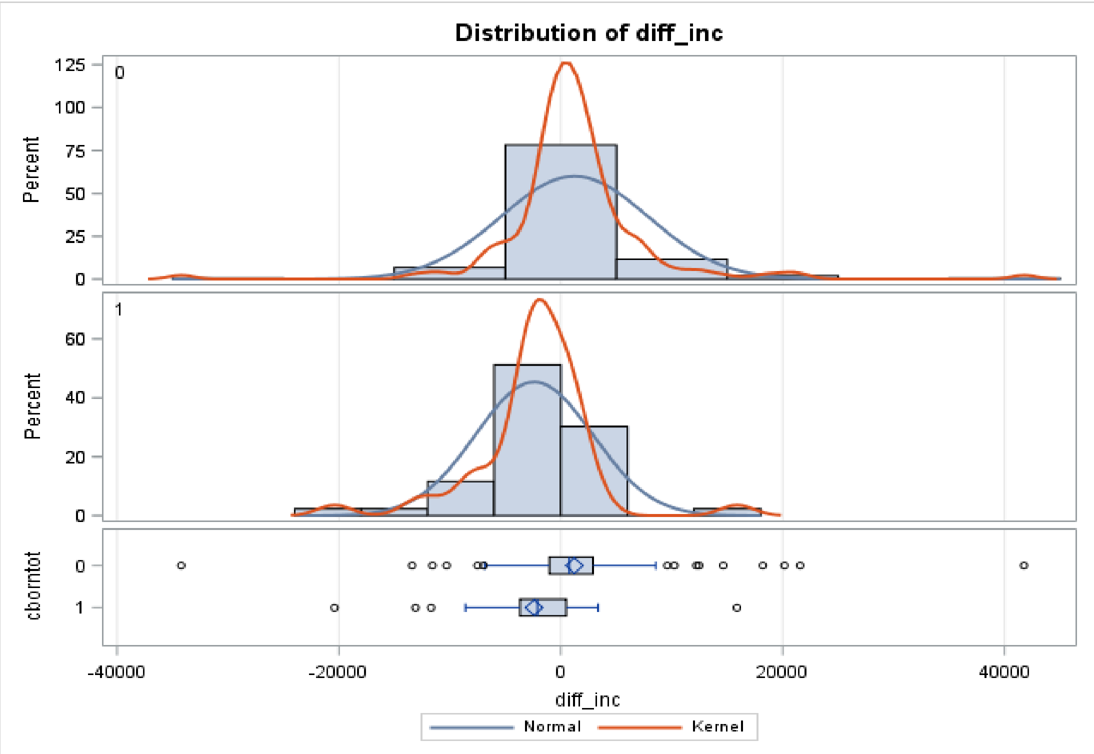
Strata2



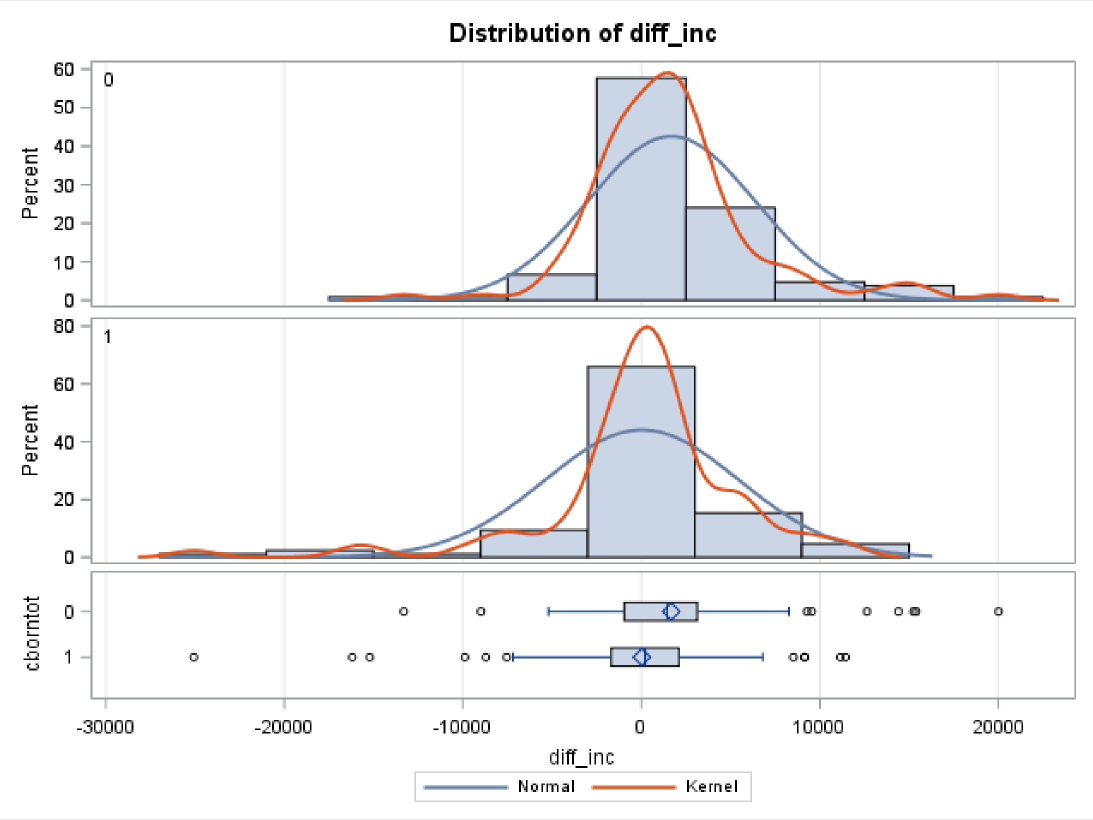
Strata 3



Strata 4



Strata 5



The analysis with ANCOVA and regression with inverse weights present results similar to PSM method. The difference in income between the two periods are analysed for treatment and control groups and the findings are very close to the findings with PSM method.

Table II.8.3.2. ANCOVA

Control	1 274
Treatment	-1 408
Difference	-2 681

Figure II.8.3.2. ANCOVA

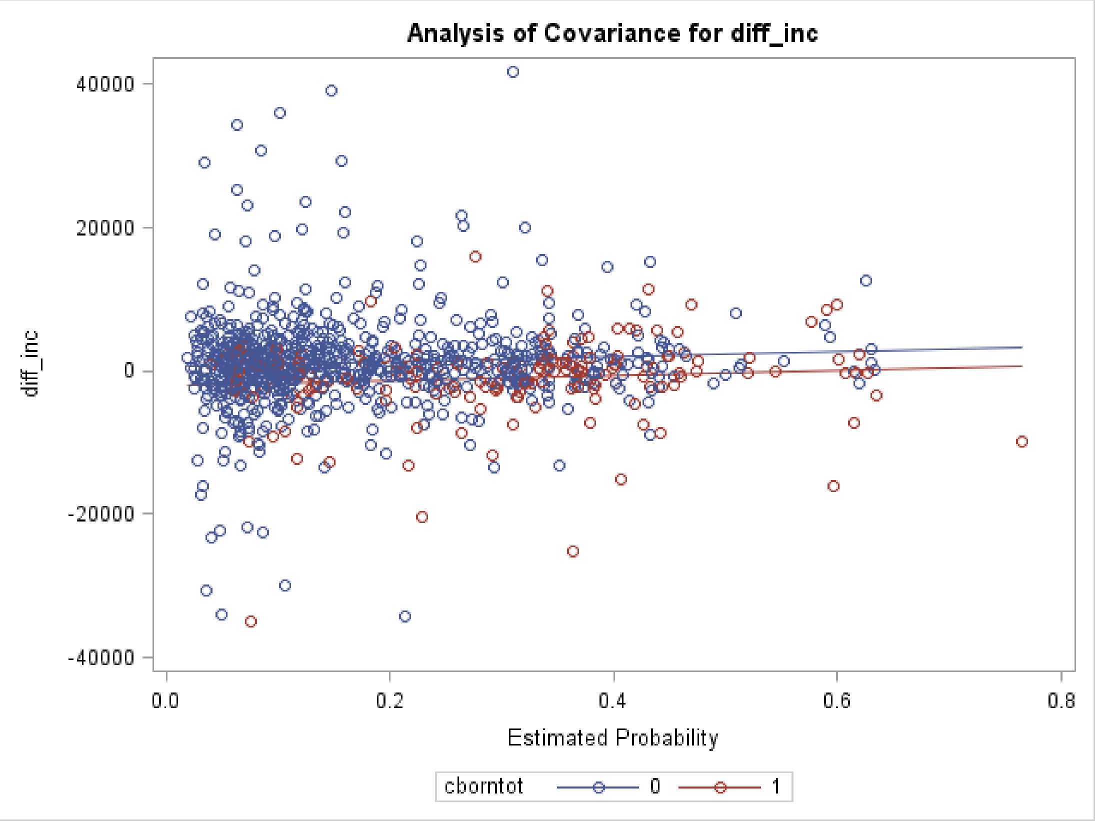


Table II.8.3.3. Regression with inverse weights

Parameter	Estimate	s.e.
Intercept	-1 399	287
Control	2 660	407
Treatment	0	.

II.9. CONCLUSION

Economic growth by itself wouldn't be adequate for increasing well-being of all households and decreasing poverty. In order to struggle with poverty, specific groups should be targeted. Especially when there is a pronatal policy in action, the extent of the effect of child birth on household economic well-being should be well analyzed and understood. Only by this way, anti poverty policies could be put in action and poverty could be avoided.

Establishing policy targets requires information on the issues to be dealt with. Information on causality is particularly important in this regard. Knowing causal relationships enables better understanding of socio-economic structures and in this way provides a basis for better targeting for policy makers. In the case of the relationship between fertility and poverty, the acquired information would provide useful tools for policy makers to compansate for the households if there is a risk of decreased well-being depending on having an extra child.

The results indicate the negative effect of having a new born in the household on well-being. Analyses using propensity scores either with PSM method, stratification or regression methods bring out similar results.

The sensitivity analyses demonstrate the unconfoundedness assumption is not a strong one. There is negative effect of a new born on household well-being with most of the measures used to analyze. This finding calls for further support for households having a child, in the context of pronatal policies. Such support, by providing the necessary funds for households, would encourage pronatal policies as well.

The effect is mostly generated by the expanding household size. When another person is included in the household without increasing the resources or consumption expenditures with the available resources, the equivalized household disposable income and consumption is lower, which makes households having a new born relatively poorer with respect to other households. When income is considered, this might not be a concern for households living high above the poverty line, since they could make use of their available income which would be adequate for the expanding family. On the other hand, for those with lower incomes, it would be a concern. Their resources would not be adequate to compensate for keeping the living standard relatively at the same level with those who don’t have a new born. Because of this, pronatal policies should be supported well with poverty policies in order to compensate for the loss of households that opt to have a child. In this study, it was observed that the income is relatively decreasing for households after having a new born. The finding for the whole population does not have a direct policy implication. Further analyses should be made to detect the effect especially on poorer households in order to look for compensation to support such households.

The finding regarding consumption is more prominent with respect to policy implication. The study indicates that the equivalized consumption is relatively lower for households with a new born during the panel. Failing to attain the increase acquired by the control group suggests that these households which had a new born are not able to expand their consumption level as large as the control group.

Besides the effect of growing household size, another effect might be caused by the effect of fertility on employment of women. This study is not analyzing this issue. One reason being for this is the low number of observations for such analysis. However, this issue has already been studied by Abbasoğlu Özgören (2015). The findings indicate a negative effect of fertility on women’s employment. They are more likely to exit employment because of pregnancy. Also among the ones who are not employed, pregnancy and having a child makes such women less likely to enter employment.

Equivalence scale used in the study might raise questions since the level of the equivalence scale affect the results substantially. Using per person scale would exaggerate the results since it assumes no economies of scale and considers the adults and children at equal weight. For this reason, an equivalence scale, which is computed for the Turkish population with recent representative data set was used. Not using any equivalence scale was not considered because an addition of another member to the household definitely decreases the resources available to its members. All the same, to observe the situation with indicators that are not directly affected by the use of equivalence scales, fuzzy supplementary measure and deprivation index are employed. Among these indicators, only exit from deprivation demonstrated nearly significant outcomes and the result obtained with this indicator also suggest similar results.

Some of the indicators in the analyses do not return significant results. The ones that are significant demonstrate that the treatment group is worse-off when compared to the control group.

The utility obtained by the birth of the child is another issue that may have relevance in our context. There is an economical loss demonstrated by monetary and supplementary measures, but this loss may well be compensated by the utility that arises with having a child and therefore the overall well-being of households may be affected less or even even be affected positively in total. Whether the utility provided by the child compensates for the economical is an issue that should be taken into consideration in further studies.

In this study, the shortcoming with regard to use of consumption expenditure is that it is a derived variable via statistical matching. The procedure to obtain this variable could have caused a variation which cannot be measured. Although using income which is closely related to consumption expenditure in its estimation provided more reliable outcomes, the results associated with this variable should be treated with caution.

On the other hand, the income variable in SILC has low variability between successive years. High imputation process in SILC links one year to another decreasing the variability between them. In this regard, use of relatively new poverty measures such as fuzzy measures of poverty and deprivation index, demonstrates itself as a dominant alternative over conventional measures.

One target of the study was to carry out the analyses by considering the year of birth. Due to the low number of observations, this exercise didn't return results that are consistent and interpretable. However, since this is an important issue, it should be considered in further research agenda whenever bigger samples are available.

The birth of a child is expected to affect also the intrahousehold allocation of income and consumption expenditure. Such analysis would enable to understand the change in well-being of different household members instead of the whole household.

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Appendix II.1. The list of variables used to derive the fuzzy supplementary poverty measure

Dimension	Items of deprivation
1 Basic lifestyle	Meals with meat, fish or chicken
	Household adequately warm
	Holiday away from home
	Ability to make ends meet
2 Consumer durables	Car
	PC
	Telephone
	Washing Machine
	TV
3 Housing amenities	Bath or Shower
	Indoor flushing toilet
	Leaking roof and damp
4 Financial situation	Inability to cope with unexpected expenses
	Arrears on mortgage or rent payments
	Arrears on utility bills
	Arrears on hire purchase instalments
5 Work & Education	Low education
	Worklessness
6 Health related	General health
	Chronic illness
	Mobility restriction

CHAPTER III

The Effect of a New Born on Household Poverty in Turkey: One-Year Analysis, Analysis at Household Size and Income Level Distinction, and Simulations for Future Prospects

III.1. INTRODUCTION

The findings from our analysis of the causal relationship between childbirth and household economic well-being with Propensity Score Matching (PSM) method showed that after the birth of a new born the well-being of the household is relatively worse-off compared to households that did not have a new born. The analysis was conducted with many well-being indicators and the results were similar.

This study has several targets. The first target of this study is to detect the effect of a new born more proximately by limiting the analysis to only one year. This is accomplished by making use of two year weights in the 2010-2013 SILC panel. Therefore only 2012 and 2013 survey data are used. The reference period of income is not in line with other household characteristics. On that account, simply the deprivation index is used for this analysis.

Moreover, in this study, the analysis that was done for all households with PSM is repeated for different household sizes and according to households' monetary well-being. The small sample size limits the decomposition that could be made. In this respect, the household size is classified into 2 categories. Households with 2 or 3 members in the beginning of the panel are compared to those with 4 or more members. The composition of the household is not taken into consideration because further decompositions lead to very small sample size that decreases the reliability and quality of the obtained results.

The analysis is made for poorer half of the sample in order to estimate a compensation of the forgone income following the childbirth, and a proposition for support is made.

The findings of Arpino (2008) suggest that the effect of a new born is highest in small households followed by large households. It is lowest in medium size households, therefore demonstrating a U-shape pattern. All the same, it should be mentioned that the values are not statistically different from each other.

The indicators that are used as outcome in this study are income, fuzzy monetary and fuzzy supplementary measures. This choice of indicators is related to keep the sample size as large as possible. When an entry or exit is considered, the sample size is divided and gets smaller returning less reliable results.

Households with income less than 9 000 TL (equivalized and adapted to 2013 values) constitute nearly half of the sample (483 households vs. 464). In order to observe the effect of childbirth on poorer households this bottom half is used. Our focus will be relatively poorer households while making the proposition for compensation of the cost of the new born.

In this study also the cost of children are computed by making use of equivalence scales. The computations are made for various types of households, according to the number of adults and children in the household. The results show the marginal effect of one child on the monetary indicators of the households.

Finally, simulations are conducted to demonstrate the possible effects of new borns on the overall poverty rates. This is realized by taking into consideration the probabilities of having a new born for each household.

III.2. ONE-YEAR ANALYSIS

The timing of pre-treatment characteristics and income periods are not congruent (Figure 1). The reference period of income for 2012 survey refers to 2011 calendar year, and for 2013 it is 2012 calendar year.Therefore we don’t utilize income along with conventional and fuzzy poverty measures, which are based on income, in the one-year analysis.

Deprivation index is a simple tool for such analysis at this point. It perfectly matches the survey period since its reference period is the time of the survey.

Figure III.2.1. SILC survey reference periods

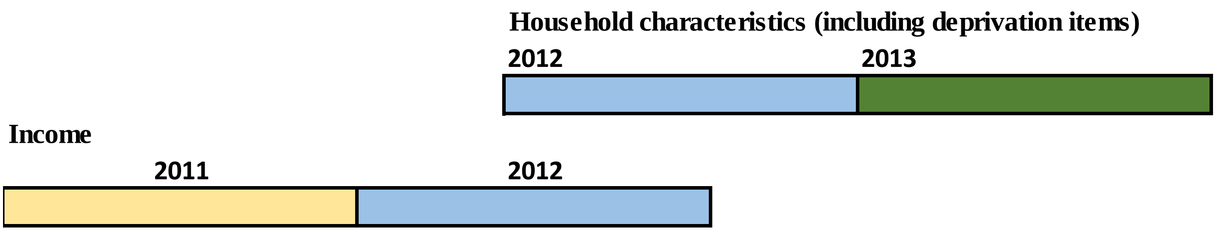

Table III.2.1. Entries and exits in the sample households

	Frequency	%
Household that don't have entries or exits (except for child birth)	11 813	86.7
Household that have entries or exits	1 813	13.3
Total	13 626	100

Table III.2.2. Number of eligible women in the sample households

Number of married women of age group 15-49 in 2010	Frequency	%
0	4 356	36.9
1	7 208	61.0
2	224	1.9
3	24	0.2
4	1	0.0
Total	11 813	100.0

Table III.2.3. Number of births in households with eligible women

Number of child births during the two-year panel	Frequency	%
0	6 629	92.0
1	569	7.9
2	10	0.1
Total	7 208	100.0

When treatment and control groups are simply compared according to different deprivation items and deprivation index, it can be seen that the treatment group is generally worse-off compared to the control group. The deprivation index demonstrates a 4.4 percentage points difference between the two. The difficulty in paying rent, mortgage and utility bills is especially drawing atttention. For households having a child the percentage of those declaring such difficulty increased where it decreased for others.

Table III.2.4. Deprivation items

	2012		2013		Change (percentage points)	
	Control	Treatment	Control	Treatment	Control	Treatment
to pay their rent, mortgage or utility bills	45.0	43.8	41.9	48.3	-3.1	4.6
to keep their home adequately warm	34.0	39.4	27.9	30.6	-6.1	-8.8
to face unexpected expenses	59.9	62.6	49.4	55.4	-10.5	-7.2
to eat meat or proteins regularly	54.2	52.4	47.4	47.8	-6.9	-4.6
to go on holiday	84.1	83.8	78.9	82.1	-5.2	-1.8
a television set	0.5	0.5	0.4	0.0	-0.1	-0.5
a washing machine	3.5	5.8	2.3	3.5	-1.2	-2.3
a car	52.9	59.9	50.9	57.3	-2.0	-2.6
a telephone	20.8	23.0	19.6	22.3	-1.2	-0.7
deprivation index	67.6	69.2	59.4	66.4	-8.2	-2.8
Total	**6 629**	**569**	**6 629**	**569**	**6 629**	**569**

The PSM analysis for deprivation index as the outcome shows that households that had a child are worse-off with regard to both, exit from deprivation and entry into deprivation. However, in neither case of we obtain very significant results.

Table III.2.5. ATT for entrance into and exit from deprivation

		ATT			
	n	Treated	Controls	Difference	s.e.
deprivation-exit	394	0.850	0.810	0.041	0.029
deprivation-entry	173	0.243	0.197	0.046	0.048

III.3. ANALYSIS AT HOUSEHOLD SIZE AND INCOME LEVEL DISTINCTION

The results with household income distinction show that the difference of change in income between control and treatment groups is higher for the upper income group. This is mainly because of the higher total income in this group, as would be expected.

Table.III.3.1. Difference in income between 2010 and 2013, by household income

equivalized income in 2010	n	ATT			
		Treated	Controls	Difference	s.e.
All	179	-979	1 347	-2 326	786
< 9 000	87	872	1 884	-1 012	477
>=9 000	88	-3 077	-715	-2 362	1 331

When the analysis is conducted with fuzzy monetary indicator it is seen that the effect is higher in the lower income households. This is not in line with the finding by using difference in income as an indicator and shows the importance of using multiple indicators especially those having a characteristic other than absolute monetary scales. Here, those with lower incomes do not provide very significant results.

Table.III.3.2. ***Difference in fuzzy monetary indicator between 2010 and 2013, by household income***

equivalized income in 2010	n	ATT			
		Treated	Controls	Difference	s.e.
All	179	-0.013	-0.062	0.049	0.022
< 9 000	87	-0.061	-0.117	0.055	0.039
>=9 000	88	0.038	0.009	0.029	0.012

The findings using fuzzy supplementary measure is in line with the findings with fuzzy monetary measure. Poorer households are worse-off when compared to richer households, but the results are not very significant.

Table.III.3.3. Difference in fuzzy supplementary measure between 2010 and 2013, by household income

		ATT			
equivalized income in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
All	179	0.009	-0.026	0.035	0.029
< 9 000	87	0.011	-0.074	0.085	0.057
>=9 000	88	0.009	-0.003	0.013	0.023

When the whole population is taken into consideration it is seen that smaller households are worse-off in terms of income compared to larger households. This pattern is not supported by the fuzzy monetary measure. The finding asserts an opposite result. The finding with fuzzy supplementary also support the findings from fuzzy monetary, but the results are not statistically significant.

Table.III.3.4. Difference in income between 2010 and 2013, by household size

		ATT			
Household size in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
2-3	96	-1 301	3 650	-4 951	1 367
4 or more	81	-662	739	-1 401	862

Table.III.3.5. Difference in fuzzy monetary indicator between 2010 and 2013, by household size

		ATT			
Household size in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
2-3	96	-0.020	-0.014	-0.006	0.027
4 or more	81	-0.003	-0.100	0.098	0.038

Table.III.3.6. Difference in fuzzy supplementary measure between 2010 and 2013, by household size

		ATT			
Household size in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
2-3	96	0.007	0.010	-0.003	0.033
4 or more	81	0.015	-0.033	0.048	0.049

As would be expected, due to the use of equivalence scales, the effect on difference in income is higher in households where there are no children or only one child at the beginning of the panel. Use of fuzzy monetary measures shows the opposite, but the results are not significant. On the other hand, fuzzy supplementary measures show that the households with two or more children are worse of compared to other households. The results are not significant for this indicator either.

Table.III.3.7. Difference in income between 2010 and 2013, by number of children in 2010

		ATT			
Number of children (0-14) in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
0-1	107	-1 366	1 447	-2 813	1 306
2 or more	69	-500	838	-1 338	589

Table.III.3.8. Difference in fuzzy monetary measure between 2010 and 2013, by number of children in 2010

		ATT			
Number of children (0-14) in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
0-1	107	-0.019	-0.020	0.002	0.026
2 or more	69	-0.001	-0.045	0.044	0.035

Table.III.3.9. Difference in fuzzy supplementary measure between 2010 and 2013, by number of children in 2010

		ATT			
Number of children (0-14) in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
0-1	107	0.010	-0.016	0.026	0.029
2 or more	69	0.016	-0.051	0.068	0.047

When we concentrate on poorer households, the analysis with income also shows that larger households are worse-off. The fuzzy monetary measure shows that poverty increases more in larger households. The findings from fuzzy supplementary measure shows that poverty increase in smaller households is higher than larger households. Due to the very low number of observations nearly all of the indicators in this analysis return insignificant results.

Table.III.3.10. Difference in income between 2010 and 2013, among the poor (<9 000), by household size

		ATT			
Household size in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
2-3	27	1 620	1 705	-86	898
4 or more	54	368	1 156	-789	464

Table.III.3.11. Difference in fuzzy monetary measure between 2010 and 2013, among the poor (<9 000), by household size

		ATT			
Household size in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
2-3	27	-0.097	-0.110	0.013	0.059
4 or more	54	-0.036	-0.086	0.051	0.047

Table.III.3.12. Difference in fuzzy supplementary measure between 2010 and 2013, among the poor (<9 000), by household size

		ATT			
Household size in 2010	**n**	**Treated**	**Controls**	**Difference**	**s.e.**
2-3	27	0.015	-0.218	0.233	0.075
4 or more	54	0.014	0.012	0.002	0.062

III.3.1. Proposition for Compensation

Taking the findings into consideration, it is hard to make a precise proposition for compensation of the loss in income that is caused by childbirth. The number of observations are too low to obtain significant results in most of the cases. There should be further analysis for different household types to make use of the public resources efficiently. All the same, a proposition is made taking into consideration the average loss in income of poorer households. This will at least compensate for any poverty creating effect of childbirth to an extent.

We didn’t take into consideration the magnitude of any support readily provided for families. The proposition made here is an extra support on any support that is already being made. Since around 1 000 TL is the average loss in incomes of poorer households that is related to childbirth, this can be used as a baseline for compensation. Because this value is in 2013 price level, it should be converted into 2017 prices. When this is converted into 2017 values, it is roughly 1 300 TL which corresponds to around 110 TL per month.

III.4. COST OF CHILD

The cost of child to the household is an important issue when dealing with the relationship between fertility and household well-being. The additional effect of a child on the household will be computed from the equivalence scales calculated for Turkey. The estimations of Betti et al. (2017) demonstrate that after the first adult in the household, every additional adult has a weight of 0.65 and every child has a weight of 0.35. Adults are defined as those at age 14 or over and children are defined as those at age 13 or younger.

Making use of these estimations, effect of one child for different types of households are calculated. As would be expected, as number of adults and children increase in the household the relative cost of one child gets lower.

Table III.4.1. Cost of child computed from equivalence scales for Turkey

Household type	Original level	Level after the addition of one child	Relative effect of one child
1 adult	1.00	1.35	**0.35**
2 adults	1.65	2.00	**0.21**
2 adults + 1 child	2.00	2.35	**0.18**
2 adults + 2 child	2.35	2.70	**0.15**
2 adults + 3 child	2.70	3.05	**0.13**
3 adults	2.30	2.65	**0.15**
3 adults + 1 child	2.65	3.00	**0.13**
3 adults + 2 child	3.00	3.35	**0.12**
3 adults + 3 child	3.35	3.70	**0.10**
4 adults	2.95	3.30	**0.12**
4 adults + 1 child	3.30	3.65	**0.11**
4 adults + 2 child	3.65	4.00	**0.10**
4 adults + 3 child	4.00	4.35	**0.09**

III.5. SIMULATIONS FOR FUTURE PROSPECTS

In this section, some simulations are conducted with respect to different scenarios. The same model which was used for the propensity score estimation in the previous chapter is used in this section as well, with some modifications. It is better to make use of cross-sectional data, since it has more observations. Here, since analysis are made for future prospects, it is more important to have the more recent data set. In this respect, SILC 2014 cross-sectional data set is used in this study. In this data set we have not inserted consumption variable, therefore it is not available in the model. On the other hand, number of women of age 15-49, and region dummies which are available in the cross-sectional data set are made use of. In order to observe the probability of having a child in 2014, the dependent variable is a dummy variable whether there is a child of age 0 or -1 (because age refers to December, 2013) in the household. For number of children, numbers are used instead of dummies and the first age group is 1-5.

Table III.5.1. Model for childbirth

	Estimate	Standard Error	Pr > ChiSq
Intercept	-2.54	0.02	<.0001
ref_sex_1_0	0.45	0.00	<.0001
ref_age	-0.06	0.00	<.0001
hsize	0.67	0.00	<.0001
num_child_1_5	-0.61	0.00	<.0001
num_child_6_10	-0.54	0.00	<.0001
num_child_11_15	-1.19	0.00	<.0001
perc_edu_worked	1.22	0.01	<.0001
men_high_edu	-0.48	0.00	<.0001
women_high_edu	0.06	0.00	<.0001
women_worked	-0.81	0.00	<.0001
num_mar_wom_15_49	1.31	0.00	<.0001
log_eq_dis_inc	-0.11	0.00	<.0001
region2	-0.24	0.01	<.0001
region3	-0.08	0.00	<.0001
region4	-0.18	0.00	<.0001
region5	0.06	0.00	<.0001
region6	0.01	0.00	<.0001
region7	0.10	0.00	<.0001
region8	-0.05	0.00	<.0001
region9	0.09	0.01	<.0001
region10	0.31	0.01	<.0001
region11	-0.45	0.01	<.0001
region12	0.25	0.00	<.0001

After the model is estimated, the effect of having one more child for all households are simulated. The question is: “What would be the effects of this change on the poverty indicators of the country as a whole?”. This analysis is simply conducted by adding one or more children for households and cross tabulating the new dataset by using equivalence scales.

The first step after the model estimation is to compare random numbers having a value between 0 and 1 with the propensity to have a child.

If the propensity is higher than the random number then a child is added to the household as can be seen in Table III.5.2.

Table III.5.2. Adding a child

Prob. of having a child	Random number	Child
0.5	0.6	0
0.4	0.3	1
0.6	0.7	0
0.3	0.4	0
0.6	0.5	1

This is also done by increasing the probability of having a child 10 per cent, in order to assess the situation in case of an increase in fertility. In the final step, the equivalence scale is revised accordingly, followed by a revision in the equivalized income and poverty rates are recalculated and compared.

In the analysis the confidence intervals are not considered. There might be overlapping in some cases and the differences could be insignificant. The target is rather to see the potential effects, so the interpretations are made considering only the central values.

As can be seen from Table III.5.3, in about 350 thousand households the births from the model and data coincide. We add one child to the 1 143 thousand households, which are more likely to have a childbirth according to the model.

Table III.5.3. Childbirth in the model and in the data

Childbirth in the model	**Number of children of age 0,-1**				
	0	**1**	**2**	**3**	**Total**
0	18 780 000	1 077 529	24 786	0	19 880 000
1	1 142 580	323 595	33 178	2 743	1 502 096
Total	19 920 000	1 401 124	57 964	2 743	21 380 000

Adult equivalent poverty line is around 380 TL for 2010. When this is adjusted with CPI, it is around 515 TL. This poverty line is used in the analysis. The analysis shows that there isn't a considerable change when there is a birth in the households determined by the model. The poverty rate for households increase from 11 per cent to 11.3 per cent in this analysis, which make an increase of around 50 thousand in the number of the poor households.

Table III.5.4. Simulated number of poor

Poor	Poor (revised)		
	0	1	Total
0	18 970 000	49 782	19 020 000
1	0	2 360 643	2 360 643
Total	18 970 000	2 410 425	21 380 000

We repeat the same analysis with another poverty line, in order to observe the effect of change in the poverty line. This time, 60 per cent of the median income is used as the poverty line, which corresponds to around 8 200 TL. In this case, the poverty rate increase from 20.8 to 21.2 returning a similar increase in percentage points, but the number of the poor because of the potential births are almost doubled.

Table III.5.5. Simulated number of poor according to poverty line with 60 per cent of median income

Poor	Poor (revised)		
	0	1	Total
0	16 850 000	81 836	16 930 000
1	0	4 452 226	4 452 226
Total	16 850 000	4 534 062	21 380 000

Afterwards, another exercise is conducted by increasing the probality of having a child. Propensity to have a child is increased by 0.10 points for every household and the following tabulation is obtained.

Table III.5.6. Childbirth with increased probability

Childbirth in the model	Number of children of age 0,-1				
	0	1	2	3	Total
0	16 750 000	927 928	17 092	0	17 700 000
1	3 165 845	473 195	40 872	2 743	3 682 655
Total	19 920 000	1 401 124	57 964	2 743	21 380 000

This time the equivalence scale is revised again with the new propensities, as if there is a childbirth, like has been done in the previous exercises. 60 per cent of the equivalized median income is used as poverty the poverty line. The result shows that poverty rate increases from 20.8 per cent to 21.8 per cent depicting the effect of increased fertility. This makes an increase of over 200 thousand in the number of poor households.

Table III.5.7. Simulated number of poor in case of increased probability

Poor	Poor (revised)		
	0	1	Total
0	16 700 000	226 815	16 930 000
1	0	4 452 226	4 452 226
Total	16 700 000	4 679 041	21 380 000

III.6. CHILD SUPPORT

In the previous analyses child support was not taken into consideration. In the following, this is also considered. Both, cash and noncash child support are regarded. Among over 20 million households, it is seen that around 1.2 million get cash or noncash child support or both. This is much lower than expected, since those who work under the social security scheme get child support. Also, there is support for those who don’t have insurance and who are in need. So, most of the families with children are expected to have some kind of support. The reason might be the difficulty in collecting this information, which is hard to collect, since generally it is given with the income and also because it refers to a small amount in income.

For government employees child support for each child is 48 TL for 2017. This is for the 0-6 age group. When the child is older the value is 24 TL. For employees in private sector there is child support for families with children under 18 years old. The support is 33 TL in 2016. There is a one time payment called “breast-feeding payment”. This is paid for once after the birth and it is 132 TL for 2017.

There is also a support which is paid at once at the time of the birth. This is 300 TL for the first child, 400 for the second and 600 for the third.

The employed women are also allowed for a total of 16 weeks of paid maternity leave. There is an additional one and a half hours daily breast-feeding time allowed, until the new born is one year old.

In the data set, among the households who obtained child support, the mean value is around 900 TL and median value is 700 TL per year. If the mean value of child support is added to the households to which one child is added, although lower this time, the poverty still increases from 20.8 to 21.1. There are still more than 50 thousand households that would be poor (according to the poverty line based on 60 per cent of median income). Only when the amount is higher than 2 500 TL per year, does the effect converge to zero. This is higher than the finding of monthly 110 TL in the first section (even more higher when 2017 price level is considered). So this monthly 110 can be regarded as a minimum limit to compensate for the effect of a new born on poverty measures.

Table III.6.1.Simulation where poverty is compensated for

Poor	Poor (revised)		
	0	1	Total
0	16 880 000	51 819	16 930 000
1	0	4 452 226	4 452 226
Total	16 880 000	4 504 044	21 380 000

III.7. CONCLUSION

A more proximate analysis was made by using the last two years' data from the survey and the immediate effect after the birth of the child was analysed. The results show that both entry into deprivation and exit from deprivation are different for control and treatment groups. The treatment group is relatively worse-off in both situations, demonstrating the poverty creating effect of a new born. But, it should be kept in mind that the findings are not very significant.

For the four year panel data, the changes in income are significantly different for the treatment and control groups. The control group has a relative increase of 2 326 TL which is about half of the poverty line in 2013. When the population is divided into two as poorer and richer groups, it is seen that the magnitude of the difference is mostly due to higher income households, but poorer households are also worse-off and when their level of income is considered they are substantially affected by the childbirth. Fuzzy monetary and supplementary measures show that the poorer households are more affected compared to richer households.

When the analysis is made at household size level, it is seen that smaller households (with 2 or 3 members in the beginning of the panel) have a higher loss compared to larger households (with 4 or more members). This finding with income is not supported by fuzzy measures. When poorer households were considered with respect to household size, the results are mostly insignificant and contradictory. The low number of observations affect the quality and diversity of the analysis.

Nevertheless, a propositon for extra support for poorer households is made. It is true that the proposition is not based on precise results considering the diversity in household structures, but it can still be considered as a reference point. The proposed amount is 110 TL for one additional child with 2017 price level.

In the simulations we used cross-sectional SILC data in order to increase the sample size and make use of regional variables. We were not able to use the statistically matched consumption expenditure variable in this case, but it is not a significant variable in the model, but rather serves as a control variable to make the starting point similar for the treatment and control groups. Therefore its loss did not make a difference in the significance of the model, but increasing the sample size enabled a better estimation.

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CONCLUDING REMARKS

This last section of the thesis focuses on the main findings and inferences obtained from the realized studies. The methods that are employed are briefly summarized as well.

The main issue of this study is to analyze the effect of fertility on household economic well-being. For this purpose, Turkish Income and Living Conditions (SILC) Data Set, which contains information for a four year span is utilized. The effect of birth of a new born on economic well-being of households is studied with this data set by making use of a variety of indicators. Consumption expenditure, which is among these indicators is not available in the SILC data set. Therefore, it is created by statistical matching method. The creation of a synthetic data set including the consumption expenditure variable is the secondary target of the thesis. First, this secondary target is accomplished and then the main issue is dealt with.

The first chapter focuses on issues regarding the creation of the synthetic data set via statistical matching of SILC data set and Household Budget Survey (HBS) data set. The second chapter focuses on the effect of a new born on household economic well-being and the third chapter focuses on further analyses at a shorter time span and diaggregated levels. From here on methodologies and findings of each chapter is presented briefly.

In the first chapter, a consumption expenditure variable in longitudinal SILC survey data set is created via statistical matching of SILC and Household Budget Survey (HBS). Income variable which is also available in HBS was used as auxiliary information, which relaxed the conditional independence assumption in this regard.

The approach by D’Orazio (2015) and its extension by Donatiello et al. (2015), was employed. StatMatch R package is used for the matching process. The matching procedure actually consists of two main steps. In the first one statistical matching is realized with Renssen (1998) methodology. In the second step, nearest neighbor distance function is applied to the results achieved in the first step and the final data set is obtained.

The quality analysis after the synthetic data set was obtained indicated a good match at aggregated levels. Meanwhile, poverty head count ratios were substantially different at household size breakdown. There is an intention to carry out the analysis at household size as well. We would like to have synthetic data set, which is similar to the HBS with respect to consumption expenditure distribution at household size level. Because of this, the matching procedure was repeated, this time including the household size among the matching variables. One of the previous matching variables, namely, hot water availability was deleted from the matching variables. The repeated quality analysis demostrated an improvement to a considerable extent at disaggregated levels. This showed that if the target is to pursue further study at disaggregated level, the variable for breakdown should definitely be added among the matching variables, even if it is not one of the best predictors of the response variables.

Chapter II deals with the primary target of the study. The relationship between fertility and poverty is a two-sided issue. The majority of existing literature deals with the effect of poverty on fertility. Our approach is to study the reverse relationship at a micro level setting. The birth of a child is used as an indicator of fertility.

The need for understanding the extent of the effect of child birth on household economic well-being is particularly crucial when there is a pronatal policy in action. Providing such information would enable knowledge for policies to prevent more poverty. Policies regarding fertility and poverty should be used simultaneously in order to obtain the desired policy effects.

The study is realized at micro level with a dynamic perspective, by considering the changes during the panel. Such studies that analyze the effect of child birth on household economic well-being rare in the literature. Kim et. al (2009) and Arpino and Aassve (2013) are the most significant ones in this respect.

The main method used in the study is propensity score matching method. The application of the method is based on a quasi experimental setting, mainly developed by Rubin (1980) and regarded as the Rubin's Causal Model. The households are separated as treatment and control groups based on whether they had a child between the beginning and the end of the panel. In order to prevent further complications that could arise from the mobility of the households, such households that did not have any entries or exits of individuals are considered. The only exception is the birth of a child. Another restriction implied on the data set is that only households that include only one married woman of age group 15-49 are considered. Multiple births are not considered, either and the treatment group consists of households that had only one child during the panel.

After the creation of the treatment and control groups, these groups are matched and balanced with respect to pre-treatment variables, which regard to characteristics that refer to the beginning of the panel. Balancing means that the similar distributions of the pre-treatment variables of treatment and control groups are attained after the matching on propensity scores. Afterwards, the difference between the treatment and control groups are compared. The comparison is made for the change of values for various indicators. The change refers to variation between the beginning of the panel (pre-treatment) and the end of the panel. By this way, we used difference-in-differences estimators. The indicators that are used to measure the household economic-well-being are income, consumption expenditure, conventional poverty measures based on these two indicators, fuzzy monetary and supplementary measures and deprivation index.

The findings indicate that a new born has a decreasing effect on household economic well-being. Those with a new born during the panel are worse-off according to many indicators. In the context of pro-natal policies this finding has direct policy implications. It asserts that the households are not able to compensate for the enlarging household size. Therefore, further policies should be implemented in order to prevent poverty that would arise accordingly.

In this regard, the third chapter occupies with disaggregated data in order to shed more light into the finding and to make efforts to present a proposition for the compensation of the loss due to the presence of a new born. Among others, one other aim of this chapter is to provide efforts for more proximate analysis. For this purpose, a one-year analysis is carried out. In this chapter, also, some simulations are conducted to demonstrate the would-be effects of potential new borns.

The one-year analysis employs entry into deprivation and exit from deprivation as outcome indicators. The results show that the treatment group is relatively worse-off in both situations, demonstrating the poverty creating effect of a new born. Nevertheless, the findings are not very significant.

The disaggregated level analyses are mostly restricted with insignificant results. The disaggregation leads to smaller subsamples, which disables reaching robust inferences. The disaggregated analyses are carried out for three indicators, namely, income, fuzzy monetary and fuzzy supplementary measures.

When the population is divided into two as poorer and richer groups, it is seen that the magnitude of the difference in change in income is mostly due to higher income households, but poorer households are also worse-off and when their level of income is considered they are substantially affected by the childbirth. Fuzzy monetary and supplementary measures show that the poorer households are more affected compared to richer households. However, these findings should be handled with care because some of the results are not significant.

When the analysis is made at household size level, it is seen that smaller households (with 2 or 3 members in the beginning of the panel) have a higher loss compared to larger households (with 4 or more members). This finding with income is not supported by fuzzy measures. When poorer households were considered with respect to household size, the results are mostly insignificant and contradictory. The low number of observations affect the quality and diversity of the analysis.

Nevertheless, a propositon for extra support for poorer households is made. The relative loss in income of poorer households is set as a basis for the proposition. It is true that the proposition is not based on precise results considering the diversity in household structures, but it can still be considered as a reference point. The proposed amount is 110 TL for one additional child with 2017 price level.

Finally, some simple simulations are carried out in order to observe the potential effects of fertility on poverty. In these simulations, cross-sectional SILC data is used in order to increase the sample size and make use of regional variables. A model that includes these regional variables is used to estimate the propensity to have a child. The propensities are compared with random numbers and a child is added to those households that have propensities greater than the random number. In this case, the number of the would-be poor households increase by around 50 thousand when the extended official poverty line is used. The increase is around 80 thousand when 60 per cent of the median income is used as the poverty line. In a final attempt, the propensity to have a child obtained from the model is increased arbitrarily 10 per cent to demonstrate the potential effect. The increase in the number of the poor is more than 200 thousand households in this situation. This analysis shows to some extent, how an increase in fertility would lead to an increase in the number of the poor.

After summarizing the general methodology and the obtained results, at this point, it is worthwhile to mention some of the shortcomings of the study. The main shortcoming regarding the method in use, the propensity score matching method, is that it relies on unconfoundedness assumption. It is assumed that there are no unobservables in the model, which is used to balance the treatment and control groups. We use a difference-in-differences estimator. The difference between two time periods and the difference of those between control and treatment groups are considered. This relaxes the unconfoundedness effect with regard to time invariant unobservables, but does not remove the bias completely. Besides the use of difference-in-differences estimator, we employed sensitivity analysis. By this analysis the consequence of the violation of unconfoundedness assumption is tested (Arpino, 2008). Although the analysis returned favorable results it should be kept in mind that this assumption is not completely testable with the available information at hand. So, it should be considered as one of the weaknesses of the study.

An alternative to the employed method could be the instrumental variable (IV) approach. This approach is not free of shortcomings, either. First of all, it is hard to find a valid instrument. Secondly, the finding from the IV approach is dependent on the used instrument, since usually it regards to a subpopulation and measures the local average treatment effect (LATE). Our data set lacks community level variables, therefore, it is not possible use such variables as instruments. Among other instruments used as instruments, there are twins and son preference, where this exists. Using twins as instruments is unattainable in our case, due to the low number of such observations. Using son preference as an instrument is not very feasible, either, due to the lack of birth history data. All the same, household roster could be used as a proxy and son preference could be used as an instrument after carrying out validation studies for its use. Bearing in mind the shortcomings of the data and the IV approach, a similar study could be carried out with this method in the future.

In this study, the most recent data sets that were available at the beginning of the study were utilized. The study could be replicated with more recent data and changes could be monitored throughout time. Also the study could be replicated for other countries with similar data sets. EU-SILC provides a tool to be used for all European countries.

Increasing the sample size would enable better outputs in the future. In many cases, the results were insignificant because of the low number of observations at lower levels. Similar studies made use of regional, urban-rural and ethnicity variables. Including such variables in the data sets would enable better results.

Such study is realized for the first time for Turkish data. It could be a pioneer to enhance further studies in this regard. The issue has direct policy implication and could be used as a starting point for studies in the future. Unlike previous studies in literature, this study makes use of multiple indicators. Making use of indicators that are not affected by equivalence scales is a particular novelty in this regard.

APPENDIX A:

THESIS/DISSERTATION ORIGINALITY REPORT

HACETTEPE UNIVERSITY
INSTITUTE OF POPULATION STUDIES
THESIS/DISSERTATION ORIGINALITY REPORT

HACETTEPE UNIVERSITY
INSTITUTE OF POPULATION STUDIES
TO THE DEPARTMENT OF DEMOGRAPHY

Date: 08/05/2017

Thesis Title / Topic: **The Effect of a New Born on Household Poverty: The Current Situation and Future Prospects and by Simulations**

According to the originality report obtained by myself/my thesis advisor by using the *TURNITIN* plagiarism detection software and by applying the filtering options stated below on 04/05/2017 for the total of 187 pages including the a) Title Page, b) Introduction, c) Main Chapters, and d) Conclusion sections of my thesis entitled as above, the similarity index of my thesis is 7 %.

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I respectfully submit this for approval.

Date and Signature
08/05/2017

Name Surname: Barış Uçar

Student No: N11144127

Department: Demography

Program: Demography

Status: ☐ Masters X☐ Ph.D. ☐ Integrated Ph.D.

ADVISOR APPROVAL

APPROVED.

Prof. Dr. İsmet Koç
Thesis Supervisor
(Title, Name Surname, Signature)