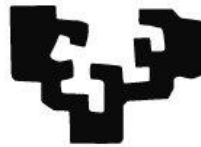


MASTER THESIS
MASTER IN ECONOMICS: EMPIRICAL APPLICATIONS AND POLICIES
UNIVERSITY OF THE BASQUE COUNTRY UPV/EHU
FACULTY OF ECONOMICS AND BUSINESS

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MASTER IN ECONOMICS



**Empirical Applications
and Policies**



**THE EFFECT OF A NEWBORN ON THE
HOUSEHOLD LABOUR SUPPLY**

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Academic year: 2019-2020

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ABSTRACT

This master's thesis investigates the effect of a newborn on household members' labour market status. With this goal in mind, we use data from the Spanish Household Budget Survey and causal inference methods to estimate the effect of a newborn on couples' participation in the labour force. In particular, we focus on the effect on the main breadwinner of the household and the spouse. The results indicate that spouses reduce their labour participation in about 5% while main breadwinners labour supply is not affected significantly. The same effect is obtained when the analysis is carried out by gender, with women reducing their labour force participation in about the same figure and men having no significant response.

KEY WORDS

Employment, newborn, birth, household, labour status, causal inference, treatment, estimation, Average Treatment Effect on the Treated, semiparametric differences-in-differences.

1. INTRODUCTION

The news of a pregnancy is always a decisive moment in every couple's life, for better or worse. Likewise, the arrival of a new member into a household is a reason to celebrate. However, for the newborn's parents, this moment will condition their lives for ever, or at least until their child becomes independent. But until that moment occurs, parents should provide their child education, health care, clothing, food, and everything that they can need until they are able to make their living. But what happens with parent's labour when their child comes to life? Parent's and their children's future will depend on parent's labour situation. Thus, the previous question is quite important. Previous articles such as Angrist and Evans (1996) or Alba and Álvarez (2004) found that, when a newborn arrives into the household, it produces a negative effect on parents' labour supply, especially on mothers.

Following this idea, the aim of this thesis is to assess the effect that a newborn causes on household members' labour status in Spain. So, this thesis is an observational study in which use causal inference methods to assess the effect of a newborn on the labour status.

The arrival of a new member in the household is taken as the treatment, so the allocation into treatment and control groups is not random.

The thesis is organised as follows. First, in Section 2 we describe the data we use, where it comes from and what information contains, and how we process it in order to create our own panel data with the information of the sample that we analyse. In Section 3, we explain how we restrict the sample and why we restrict it. In Section 4, we explain the method of estimation we use for the analysis. In Sections 5 and 6, we explain how we define the treatments and the outcomes, and we explain the reason why we impose different treatments and outcomes. In Section 7, we carry out the estimation and we comment on the obtained results. Lastly, in Section 8 we make our own conclusions.

2. DATA

For carrying out our analysis, we make use of the data provided by the Household Budget Survey (Encuesta de Presupuestos Familiares, from now on, EPF) which is conducted by the Spanish National Institute of Statistics (Instituto Nacional de Estadística, from now on, INE). These are public data which can be downloaded for free from INE webpage. This survey provides annual information about households' expenditure, but also about the labour situation of the household members, which is the outcome we are interested in. Households are chosen using stratified random sampling from Spanish census.

We use the surveys held in 2014 and 2015. Exactly, 22,146 households were interviewed in 2014 and 22,130 households were interviewed in 2015. About half of the sample rotates each year, so that each household participates twice, in two consecutive years. This is, most households did not participate in the survey both years. For our purpose, we need to know which households did, as they are our sample. After matching households which participated in both waves, we obtain a total number of 9,246. Now we explain in detail the process we have followed.

1. Downloading the required data from INE webpage (Download link: https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176806&menu=resultados&idp=1254735976608#!tabs-1254736195147).

We select years 2014 and 2015, as we have previously said. Each year contains three different files: one containing information about households' expenditure, another containing information on households' characteristics and another one

containing information about households' members. Also, when downloading the data, INE provides us with a guide describing the variables contained in the three files and the possible values that variables can take.

2. Each file provided by INE is unformatted. So, in order to be able to read the files with our software (STATA), we create dictionaries to instruct STATA how to read the unformatted files and create the variables. Once we have created the dictionaries, we command STATA to read them, reshape them (in order to create a panel data set) and save the created databases in our desired format.
3. There are three databases for each year, this is, six databases in total. We then merge the three databases for each year, and obtain only two databases, one for 2014 and another for 2015.
4. An identification number is given for each household (introduced as the variable "numero"), but it differs across years for each household. Now that we have both databases, we must match the households that took part on the survey both waves. Given a household matching file, this file tells us the households that took part on the survey both waves and the identification number (value of the variable "numero") that they had in 2014 and 2015. We create a variable called "id", which identifies the households that appear both years. Then, we merge 2014 and 2015 databases with the household matching. Finally, we delete all households that participate only once, either in 2014 or 2015.
5. Lastly, once we have the household matched databases for 2014 and 2015, we merge their observations, resulting in a single database that takes the form of a panel data including the sample that we use for our analysis.

3. SAMPLE RESTRICTION

We also want to restrict our sample to those households in which their components are likely to have children. We keep in our sample all household with at least one member of the household being 45 years or less. Thus, eliminating households with only elderly people.

We retain those 5,952 households with at least one member less than 45 years.

Lastly, for our purpose of analysis we keep in the sample only those households in which the main breadwinner and the spouse are the same person in both years. We apply this

second restriction by keeping in the sample those households in which there is no change in the sex of the main breadwinner and the spouse between 2014 and 2015 and the age of the main breadwinner and spouse increases by one between 2014 and 2015. In the end, our sample is composed by a total number of 4,266 households. Table 1 summarizes the number of households included as units of observation each case.

Table 1: Summary of the number of households included each time.

	Number of households
Complete survey (year 2014)	22,146
Complete survey (year 2015)	22,13
Unrestricted sample	9,246
First restriction (age)	5,952
Second restriction	4,266

4. METHOD OF ESTIMATION

For calculating the effect that a newborn causes on employment, we make use of the semiparametric difference-in-differences method of estimation introduced in Abadie (2005). This method of estimation parts from the difference-in-differences method but relaxing the parallel trends assumption. We now explain both.

4.1. Differences-in-differences method

In some observational studies and natural experiments, we have to deal with individuals for which we have observations in two different periods of time. One period would be previous to the application of the treatment and the other period would be after the application of the treatment. The difference-in-differences method of estimation, also called diff-in-diff or DD, allows us to compare the change in the average outcome of the treatment group (post-treatment minus pre-treatment) with the change in the average outcome of the control group (post-treatment minus pre-treatment). This is, it evaluates the difference (treatment minus control) of two differences (post-treatment minus pre-treatment). This method of estimation has been used in many studies and experiments, but also in many public policy evaluation programmes. One of the most well known studies in which difference-in-differences is applied is on the evaluation of the effect of the rise in the minimum wage on employment conducted by Card and Krueger in 1994. For carrying out a difference-in-differences estimation the parallel trends assumption must hold. This assumption states that, in absence of the treatment, the average outcome for the treatment and the control groups will follow a parallel trend in time.

In a diff-in-diff estimation, the model we want to estimate would be the following:

$$Y_{it} = \alpha + \beta D_i + \gamma D_t + \delta(D_i D_t) + X'_{it}\pi + \varepsilon_{it},$$

where:

- Y_{it} is the outcome variable we are interested in. Subindex “i” stands for individual and subindex “t” stands for time period.
- D_i is the treatment status variable. It is a dummy variable that takes the value 1 if the individual receives the treatment and 0 otherwise.
- D_t is the period indicator variable. It is a dummy variable that takes the value 1 if the observations are in a post-treatment period and 0 otherwise.
- X'_{it} is a vector of covariates introduced in the model to give robustness to the analysis.
- ε_{it} is a disturbance term with zero mean
- $\alpha, \beta, \gamma, \delta,$ and π are the regression coefficients of the model.

We must say that in a diff-in-diff estimation, the regression coefficients of the model are estimated by Ordinary Least Squares (OLS). In a diff-in-diff estimation, regression coefficient δ expresses the treatment effect. We show this making use of conditional expectations and omitting the covariates (the interpretation of the regression coefficients are the same if adding covariates or not, but as we said before, we add covariates in the estimation to give robustness to the analysis).

$$\begin{aligned} \delta &= \{E(Y_{it}|D_i = 1, D_t = 1) - E(Y_{it}|D_i = 1, D_t = 0)\} \\ &\quad - \{E(Y_{it}|D_i = 0, D_t = 1) - E(Y_{it}|D_i = 0, D_t = 0)\} \\ &= \{(\alpha + \beta + \gamma + \delta) - (\alpha + \beta)\} - \{(\alpha + \gamma) - \alpha\} \end{aligned}$$

We can see that the Average Treatment Effect on the Treated (ATET) is obtained by a difference between two differences as we have said before. The first difference ($E(Y_{it}|D_i = 1, D_t = 1) - E(Y_{it}|D_i = 1, D_t = 0)$) captures the post-treatment minus pre-treatment difference for the treatment group, whereas the second difference ($E(Y_{it}|D_i = 0, D_t = 1) - E(Y_{it}|D_i = 0, D_t = 0)$) captures the post-treatment minus pre-treatment difference for the control group.

4.2. Semiparametric difference-in-differences method

We have said that for carrying out a difference-in-differences estimation, in absence of the treatment, the average outcome for the treatment and the control groups will follow a

parallel trend in time. This is, the parallel trends assumption must hold. An explanation why the parallel trends assumption fails to hold is that the characteristics X'_{it} are not evenly distributed between treatment and control groups. For these cases when the parallel trends assumption does not hold, Abadie (2005) proposed a semiparametric solution to estimate the Average Treatment Effect on the Treated (also called ATET or ATT). This ATET calculates the effect that the treatment causes in those who receive the treatment. It can be defined as:

$$ATET = E(Y_{i1}^1 - Y_{i1}^0 | D_i = 1),$$

Where Y_{i1}^1 and Y_{i1}^0 stand for the potential outcome under treatment and under no treatment respectively. The semiparametric solution that Abadie proposed is based on the use of propensity scores. The propensity score is defined as the probability of receiving the treatment given the pre-treatment covariates X . We can define it as:

$$P(D_i = 1|X)$$

Also, we must say that the common support assumption must hold. This assumption states that:

$$0 < P(D_i = 1|X) < 1 \text{ for all } X.$$

Abadie (2005) shows that:

$$ATET = E(Y_{i1}^1 - Y_{i1}^0 | D_i = 1) = E\left(\frac{Y_{i1}^1 - Y_{i0}^0}{P(D_i = 1)} \times \frac{D_i - P(D_i = 1|X)}{1 - P(D_i = 1|X)}\right)$$

To estimate these quantities, we need the fitted values of the propensity score for each unit of observation and use sample averages in the treatment and the control groups. We express these fitted values as $\hat{P}(D_i = 1|X = x_i)$. We now show the math.

First, let's define:

$$\Omega = \frac{Y_{i1}^1 - Y_{i0}^0}{P(D_i = 1)} \times \frac{D_i - P(D_i = 1|X)}{1 - P(D_i = 1|X)}$$

By conditional expectation:

$$E(\Omega) = E(\Omega|D_i = 1) \times P(D_i = 1) + E(\Omega|D_i = 0) \times (1 - P(D_i = 1))$$

This way we can work separately with treatment groups and control groups. First, in the treated:

$$\begin{aligned}
E(\Omega|D_i = 1) \times P(D_i = 1) &= P(D_i = 1) \times E \left[\frac{Y_{i1} - Y_{i0}}{P(D_i = 1)} \times \frac{1 - P(D_i = 1|X)}{1 - P(D_i = 1|X)} | D_i = 1 \right] \\
&= E(Y_{i1} - Y_{i0} | D_i = 1)
\end{aligned}$$

And, in the control group:

$$\begin{aligned}
E(\Omega|D_i = 0) \times (1 - P(D_i = 1)) &= E \left[\frac{Y_{i1} - Y_{i0}}{P(D_i = 1)} \times \frac{-P(D_i = 1|X)}{1 - P(D_i = 1|X)} | D_i = 0 \right] \\
&= -\frac{1 - P(D_i = 1)}{P(D_i = 1)} \times E \left[Y_{i1} - Y_{i0} \times \frac{P(D_i = 1|X)}{1 - P(D_i = 1|X)} | D_i = 0 \right]
\end{aligned}$$

Combining them:

$$\begin{aligned}
E(\Omega) &= E[Y_{i1} - Y_{i0} | D_i = 1] \\
&\quad - \frac{1 - P(D_i = 1)}{P(D_i = 1)} \times E \left[Y_{i1} - Y_{i0} \times \frac{P(D_i = 1|X)}{1 - P(D_i = 1|X)} | D_i = 0 \right]
\end{aligned}$$

Assume, for simplicity, that only half of the individuals are treated. In that case, we have that:

$$E(\Omega) = E[Y_{i1} - Y_{i0} | D_i = 1] - E \left[Y_{i1} - Y_{i0} \times \frac{P(D_i = 1|X)}{1 - P(D_i = 1|X)} | D_i = 0 \right]$$

So, we only need the average change in the outcomes among the treated units and the weighted average change in outcomes among the control units. The weights are defined as $\frac{\hat{P}(D_i=1|X=x_i)}{1-\hat{P}(D_i=1|X=x_i)}$. The way the weights are defined make those units with higher $\hat{P}(D_i = 1|X = x_i)$ to get more weight, and those units with lower $\hat{P}(D_i = 1|X = x_i)$ to get less weight.

5. DEFINITION OF THE TREATMENT

Treatment is defined as the arrival of one newborn (or more) in the household. We consider two different treatments. The first treatment captures the arrival of the first (or more due to multiple births) child in the household. Households that receive the treatment are those in which there are no members less than 18 years in 2014, and the number of members in the 0-4 years interval in 2015 increases. The second treatment captures the arrival of the second (or more due to multiple births) child in the household. Treated

households are those with one member less than 18 years in 2014, and the number of members in the 0-4 years interval in 2015 increases.

The reason why we consider two different treatments is to allow for comparisons. The effect of having the first child might have the same sign as that of having the second child, but the strength of the effect could differ from the first to the second child for some reasons such as having more experience taking care of children, more disposability for remaining taking care of the child or loss of the fear of leaving the child with a caregiver.

Once we have defined the outcome variables and included them in the database, we can know how many individuals received the treatment or not. Note that both treatments can only be received in the time period $t = 1$, this is, in year 2015.

Table 2: Number treated and untreated individuals.

	Frequency	Percentage
Treatment 1		
Treated	55	1.29%
Untreated	4,211	98.71%
Total	4,266	100%
Treatment 2		
Treated	54	1.27%
Untreated	4,212	98.73%
Total	4,266	100%

As we can see in table 2, there are just a few households that received treatment 1 and treatment 2, and they are almost of the same magnitude. There exist only 55 households in which the first child was born (treatment 1) and only 54 households in which the second child was born (treatment 2), representing just 1.29% and 1.27% respectively of the sample of 4,266 households.

6. DEFINITION OF THE OUTCOMES

The outcome is the labour market status. For estimation, the “absdid” command looks at the change in the labour market status, but the outcome is the status, not the change. We define four different outcomes for the estimation. All the outcomes are the labour status, but the difference between them is the household member they are referred to. We observe a change in the labour status shows if the household member passed from an active labour situation to an inactive labour situation or viceversa.

- Outcome 1: labour status of men.
- Outcome 2: labour status of women.
- Outcome 3: labour status of the main breadwinner, regardless of gender
- Outcome 4: labour status of the spouse of the main breadwinner, regardless of gender

Remember that we have shaped our database as a panel data where the units of analysis are households, not its members. This is, the observational unit is the household instead of a person. We must say that our database contains certain variables with information of the main breadwinner specifically, but not from its spouse. But also contains variables with information for any single member without specifying the role of the household member they are referred to. We explain this better with a little example. Imagine we want to know the gender of certain member. The gender of the main breadwinner is collected in a variable named “sexosp”. Then we have another variables named “sexo1”, “sexo2”, “sexo3”, ..., identifying the gender of the first household member, the second, the third... Variables “relasp1”, “relasp2”, “relasp3”, ..., identify the relationship of the first, second, third, ..., household member with the main breadwinner. With the help of these variables we can create a variable containing information of the spouse of the main breadwinner.

Following this procedure, we have created the variable containing the gender of the spouse of the main breadwinner. The same process is followed for creating the variable containing the labour situation of the spouse.

Analysing four different outcomes we are able to compare the effect between men and women and between main breadwinner and spouse and see which household member is the most affected by the treatment. We must say that because of the imposition of the second sample restriction, there not a single parent household in our sample, so we have the same number of main breadwinners and spouses of the main breadwinner in our sample, and they coincide with the number of individuals included in the sample, 4,266. It is interesting then to know how our sample is distributed by the gender of the main breadwinner and the spouse of the main breadwinner.

Table 3: Distribution of the main breadwinner and the main breadwinner's spouse by gender.

	Principal sustainer	Spouse	Total
Men	3,544	729	4273
Women	722	3,537	4259
Total	4266	4266	

In table 3 we can see that in our sample, women are mostly included as the spouse of the main breadwinner. From the total of 4,266 households, women are included as the spouse of the main breadwinner in 3,537 households, which represent 82.91% of the sample, and they are the main breadwinner in 722 households, which represent only 16.92% of the sample. Notice that these two percentages do not add up to 100%. This is so because we have in our sample some cases where the main breadwinner and the spouse were persons of the same sex. If we take a look to the last column of table 3 we can notice that the total number of men and women being included in the sample are different from 4,266, being the number of men in the sample 4,273 and being the number of women in the sample 4,259. More precisely, there are 13 cases where both the main breadwinner and its spouse are men, and 6 cases where the main breadwinner and its spouse were women.

7. ESTIMATION AND RESULTS

In this section we report and discuss the results we obtained. But first, we are going to discuss how we defined the propensity score that we mentioned in section 4.2 and show some differences in the values of the covariates included in the propensity score between the treated and the control groups.

7.1. Propensity score

As we mentioned in section 4.2, the propensity score is the probability that an individual has of receiving treatment given its pre-treatment values of the covariates. Mathematically we express it as $P(D_i = 1|X)$. We must include it in pre-treatment terms, this is, the values that they took in year 2014. The list of covariates is the following:

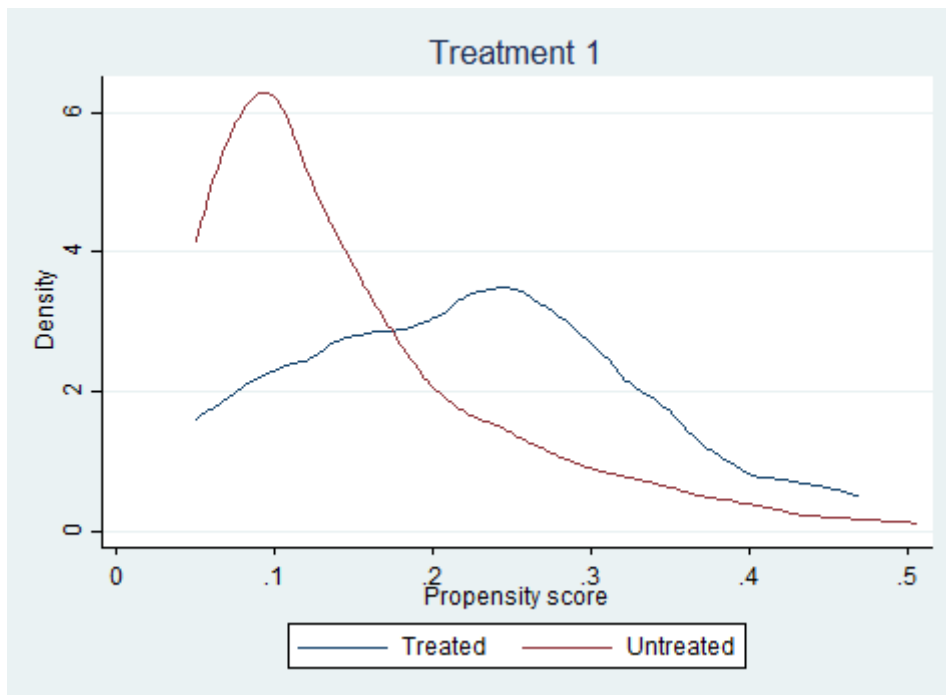
- Autonomous community of residence. (*)
- Size of the municipality. (*)
- Population density of the municipality. (*)
- Age of the main breadwinner.
- Age of the spouse of the main breadwinner. (**)

- Nationality of the main breadwinner. (*)
- Nationality of the spouse of the main breadwinner. (*) (**)
- Tenure regime of the living place. (*)
- Net monthly income of the household.
- Total expenditure of the household.
- Whether the main breadwinner was occupied the week before the survey. (*)
- Highest educational level achieved by the main breadwinner. (*)
- Highest educational level achieved by the spouse of the main breadwinner. (*) (**)
- Number of members of the household.
- Labour situation of the main breadwinner. (*)
- Labour situation of the spouse of the main breadwinner. (*) (**)

First, we must say that those variables marked with (**) are referred to the spouse of the main breadwinner and we have created them following the same process that we mentioned in section 6. Second, those variables marked with (*) are categorical variables, in which the number associated with each possible response does not have any meaning per se, but they only identify pre-fixed response options. So, we have transformed these variables into factor variables. This transformation into factor variables implies that each possible value of a qualitative variable is treated as a dummy variable.

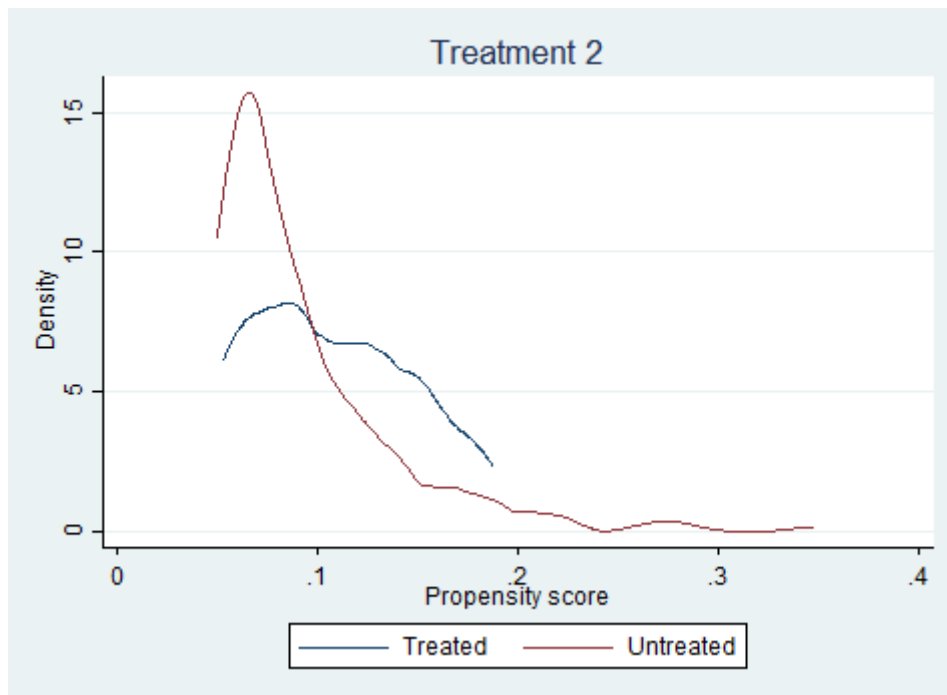
We show, in the following graphs, how the propensity score is distributed between treated and untreated:

Graph 1: Distribution of the propensity score of the first treatment.



In graph 1 we can see the distribution of the propensity score for the first treatment between treated and untreated. The differences between them are the point where the peak is reached, and that the slope of the lines is higher for the treated than for the untreated. For the treated, the peak of the distribution of the propensity score is around 0.25 and for the untreated the peak of the distribution is around 0.1. This means that most households where the first birth occurred in 2015 had a probability of that birth to occur of 25%, whereas most households where the first birth did not occur in 2015 had a probability of that birth to occur of 10%.

Graph 2: Distribution of the propensity score of the second treatment.



In graph two we can see the distribution of the propensity score for the second treatment between the treated and the untreated. Again, they differ in where the peak of is reached and the slope of the lines. As in graph 1, the slope of the line for the treated is higher than for the untreated. For the treated, the peak is reached in around 0.095 and for the untreated is reached in around 0.075. This means that most households where the second birth occurred in 2015 had a probability of that birth to occur of 9.5%, whereas most households where the first birth did not occur in 2015 had a probability of that birth to occur of 7.5%.

7.2. Differences in covariate values between treated and untreated

In the following table we show the values of the covariates that we have included in the estimation of the propensity score for the whole sample, treatment group and control groups for both treatments. We must say that these values are the ones that the covariates took in 2014, as it is a requirement for the estimation.

Table 4: Distribution of the values of the covariates.

Variables	Whole sample	Treatment 1 = 0	Treatment 1 = 1	Treatment 2 = 0	Treatment 2 = 1
Autonomous community of residence					
Andalucía	0.1214	0.1209	0.1817	0.1226	0.037
Aragón	0.0458	0.0449	0.0909	0.0456	0.037
Asturias	0.0309	0.0313	0	0.0306	0.0556
Baleares	0.0328	0.0332	0	0.033	0.0185
Canarias	0.0413	0.0413	0.0364	0.0413	0.037
Cantabria	0.0347	0.0349	0.0182	0.0344	0.0556
Castilla y León	0.0605	0.0606	0.0545	0.0613	0
Castilla La Mancha	0.0626	0.0634	0	0.062	0.1111
Cataluña	0.0872	0.0869	0.1091	0.0869	0.1111
Comunidad Valenciana	0.0839	0.0836	0.1091	0.0843	0.0556
Extremadura	0.0438	0.0442	0.0182	0.0434	0.0741
Galicia	0.0553	0.0551	0.0727	0.0556	0.037
Madrid	0.0778	0.0772	0.1273	0.0772	0.1296
Murcia	0.0429	0.0432	0.0182	0.043	0.037
Navarra	0.0361	0.0366	0	0.0359	0.0556
País Vasco	0.0987	0.0983	0.1273	0.0988	0.0926
La Rioja	0.0333	0.0335	0.0182	0.033	0.0556
Ceuta	0.0047	0.0045	0.0182	0.0047	0
Melilla	0.0063	0.0064	0	0.0064	0
Size of the municipality					
>=100,000 inhabitants	0.3483	0.3486	0.3272	0.349	0.2959
>=50,000 and <100,000 inhabitants	0.1247	0.1242	0.1636	0.1249	0.1111
>=20,000 and <50,000 inhabitants	0.1601	0.1603	0.1455	0.16	0.1667
>=10,000 and <20,000 inhabitants	0.1313	0.1313	0.1273	0.1308	0.1667
<10,000	0.2356	0.2356	0.2364	0.2353	0.2596
Population density					
High density	0.4379	0.4381	0.4182	0.4381	0.4444
Medium density	0.2628	0.2622	0.3091	0.2623	0.2963
Low density	0.2993	0.2997	0.2727	0.2996	0.2593
Age of the breadwinner	47.86	48	36.87	48	36.87
Age of the spouse	45.9	46.05	34.85	46.04	34.67
Nationality of the breadwinner					
Only Spanish	0.9236	0.9235	0.9273	0.9243	0.8704
Only foreigner	0.0558	0.0556	0.0727	0.0553	0.0926
Both Spanish and foreigner	0.0206	0.0209	0	0.0204	0.037
Nationality of the spouse					
Only Spanish	0.9008	0.9007	0.9091	0.9017	0.8333
Only foreigner	0.0748	0.0746	0.0909	0.0736	0.1667
Both Spanish and foreigner	0.0244	0.0247	0	0.0247	0
Tenure regime					
In property without mortgage	0.4020	0.4039	0.2545	0.4065	-0.1109
In property with mortgage	0.4414	0.4396	0.5818	0.4392	0.6111
Rent	0.1060	0.1057	0.1273	0.1042	0.2407
Reduced rent	0.0077	0.0078	0	0.0078	0
Semi-free cession	0.0227	0.0228	0.0182	0.0228	0.185
Free cession	0.0202	0.0202	0.0182	0.0195	0.0741
Net monthly income	2,283.35	2,282.63	2,338.67	2,286.15	2,064.96
Total expenditure	33,734.51	33,768.30	31,146.99	33,759.25	31,804.70
Breadwinner occupied the previous week					
Yes	0.7916	0.7896	0.9455	0.7899	0.9259
No	0.2084	0.2104	0.0545	0.2101	0.0741
Educational level of the breadwinner					
No studies or primary studies	0.0947	0.0952	0.0545	0.0954	0.037
Secondary studies, first cycle	0.3458	0.3465	0.2909	0.3469	0.2593
Secondary studies, second cycle	0.1957	0.1966	0.1273	0.1954	0.2222
Superior studies	0.3638	0.3617	0.5273	0.3623	0.4815
Educational level of the spouse					
No studies or primary studies	0.0996	0.1004	0.0364	0.1006	0.0119
Secondary studies, first cycle	0.3451	0.3460	0.2727	0.345	0.3585
Secondary studies, second cycle	0.2114	0.2128	0.1091	0.2125	0.1296
Superior studies	0.3439	0.3408	0.5818	0.3419	0.5
Number of members of the household	3.5900	3.6100	2.1800	3.5957	3.2500
Labour situation of the breadwinner	0.8715	0.8706	0.9454	0.8701	0.9815
Labour situation of the spouse	0.7098	0.7077	0.8727	0.7089	0.7778
Total number of households	4,266	4,211	55	4,212	54

In table 4, we can see that the values covariates take for the whole sample and those untreated individuals in both treatment 1 and treatment 2 are almost the same, but they differ from the values of treated individuals. This phenomenon has a simple explanation. As we had seen in table 2, most households are untreated in our sample, so it is logical that the characteristics of the whole sample and the characteristics of the control groups are almost the same, as the most of the sample is included in the control group. But due to the not random allocation of households into treatment and control groups the characteristics of the treatment group, which is a small part of the whole sample, may differ from the characteristics of the sample. And this is exactly what it happens.

Table 4 shows the pre-treatment values and is interesting for analysing the differences in the characteristics between treatment and control groups. For instance, we can see that for those untreated households or, in other words, those households where no birth occurred in 2015, the total expenditure in 2014 was on average around 33,700€ while for those treated households, the total expenditure was on average around 31,000€. So, we can say that those households where a birth occurred in 2015 spent less in 2014 than those households where no birth occurred in 2015. We can find more examples of this, such as the monthly income of the household, which was on average around 2,280€ for the untreated, near 2,500€ on average for those treated in treatment 1 and near 2,050€ on average for those treated in treatment 2, so we can say that those households where the first birth occurred in 2015 earned more than those where no birth occurs in 2015 and that those households where the second birth occurred in 2015 earned less than the other two kind of households. We can find more examples like this just by looking to table 4.

7.3. Estimation results

In this section we show the results of the estimation. As we have said, we use a semiparametric differences-in-differences method to estimate the Average Treatment Effect on the Treated. We must say that, for being included in the estimation, households must have a propensity score of at least 0.5%. By imposing this restriction, we are imposing common support. Intuitively, we are eliminating from the control group those households with very little chances of having a child. The estimations are done using a logistic specification of the propensity score. Also, we have specified that the estimations should be done using polynomial functions of order two. Now we show the estimations of the ATET.

Table 5: Estimation of the ATET, first treatment.

	ATET	Std. Deviation	p-value
Labour status of men (1 = active)	-0.0027	0.004801	0.570
Labour status of women (1 = active)	-0.0577	0.025712	0.025
Labour status of the breadwinner (1 = active)	0.0011	0.003443	0.743
Labour status of the spouse (1 = active)	-0.0588	0.025623	0.022

In table 5 we can see the Average Treatment Effect on the Treated for the first treatment (the first birth). We obtain two statistically significant ATETs for a significance level of at least 5%. The first is the change in the labour status of women, with an ATET value of -0.0577. This means that 5.77% of women in our sample passed from being in an active labour situation to be out of the labour force after giving birth to the first child in 2015. The second is the change in the labour situation of the spouse of the main breadwinner, with an ATET value of -0.0588. This means that 5.88% of spouses in our sample passed from being in an active labour situation to be out of the labour force when the first birth occurs. These two values turn to be very similar. As we have seen in table 3, most women are included as spouses. It is logical then that the effects are quite similar.

Table 6: Estimation of the ATET, second treatment.

	ATET	Std. Deviation	p-value
Labour status of men (1 = active)	0.0006	0.002935	0.825
Labour status of women (1 = active)	0.0002	0.033926	0.996
Labour status of the breadwinner (1 = active)	0.0004	0.002306	0.845
Labour status of the spouse (1 = active)	0.0006	0.034002	0.987

In table 6 we can see the Average Treatment Effect on the Treated for the second treatment (the second birth). No statistically significant ATETs are found, so we have to say that the second birth does not have effect on labour status for any one of the four categories that we have specified.

So, we have found a negative effect on the labour status of women and spouses when the first birth occurs, but not when the second birth occurs. We should provide an explanation for this. Intuition suggests that if a mother or a spouse quits her job and gets into an inactive labour situation when the first birth occurs, they will still be on an inactive labour situation when the second birth takes place. As they remain out of the labour force, there is no change in their labour market status, because the effect was caused when the first birth and remains in time until the second birth.

Lastly, and returning to the two statistically significant ATETs, we must say that it would be interesting to know whether those women or spouses that were still in the maternity/paternity leave when they answered the survey, or if they decided to leave the workforce but still they are categorized as active population because they didn't register as being out of the labour force. The Household Budget Survey does not provide us with that information and nor does it provide information on the labour market situation two or more years after the birth occurred. Therefore, we take those negative effects for women and spouses when the first birth happens not as the exact effect, but as the lower bound of the effect.

8. CONCLUSIONS

We end up this report drawing our own conclusions of what we have done. First of all, we want to say that carrying out an investigation of this nature is essential to have a good and reliable source of data. In our case, the data is provided by the Spanish National Institute of Statistics for free. We should be grateful to INE for allowing anybody to use such a rich source of information.

Fortunately, we have left behind that kind of society or that kind of social belief that the principal task of a women was to be a housewife and that if they develop a job it should be jobs as caregiver, nurse or office clerk. That kind of mentality is, by fortune, disappearing and nowadays the only ones that still think like that are elder people who were raised with those beliefs. We interpret the fact that most women are included as spouses of the main breadwinner as the remainder of that expired old-fashioned kind of mentality where men obtained all the households' earnings and women just had to take care of the house. At present gender should not be source of discrimination as it used to be in the past, but we know that some may still remain. It is our generation the one who must fight to end up with this mentality and not just in our homeland, but all over the globe.

Also, we want to say that the negative effect on labour market status can have negative effects on family planning, as individuals do not want to ruin their career. In Spain, the country we are analysing, this is not good news. Spanish population is really aged, we are seeing that our public retirement system is now unsustainable, as there are not enough taxpayers to cope with the retirement expenses. We should provide the incentives for

Spanish population to have children, not the other way around, because otherwise in the near future the public retirement grants will be in danger

Lastly, we want to say that it would be interesting to know if the reason why a woman left the workforce was because of her own decision or if it was because she was fired just because of motherhood. Although in Spain this is illegal, sometimes it still happens, where the employer searches for any excuse for firing a woman when her notices that one employee is pregnant. As said before, fortunately this is disappearing but we should work on making it completely disappear. And also, we should work on making the negative effect to disappear. For instance, one solution that we can find is that governments should design policies that allow mothers to reconcile motherhood with labour, so they do not have any incentive to leave the workforce when they have children.

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