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Cash Transfer impacts on Labour supply for People Living in Poverty

Evidence from Peru with “Juntos”

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Abstract

In this paper, one can find a study of the Income effect and “reallocation effect” of a Conditional Cash Transfer called “Juntos”, implemented in Peru. The transfer is subject to conditions linked to health and education, it targets people living in poverty. The focus also lies on a subsample where the conditionalities are not a constraint in order to get “pure income effects”. The results show that the “pure income effect” caused by the transfer is consistent to the theory for men (men decrease their labour supply) but not for women. Results show that the “reallocation effect” is consistent to the theory for women (women increase their labour supply).

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1. Introduction

In this paper, I analyse the impacts of a Conditional Cash Transfer in Peru called “Juntos” on **labour supply**. The Conditional Cash Transfer “Juntos” is a social program that gives a Conditional Cash Transfer to eligible households for an amount of 100 soles every month. The conditions are linked to health, education, nutrition and citizenship development. The objective is not only to decrease short term poverty, but also to enable more mobility to the poor in the long run.

The reason why I chose “Juntos” in Peru is that the program already exists since 2005 and that there are national datasets gathering all needed information for this social program. This welfare program is one of the biggest in Peru in terms of number of households and of amount of money. The Dataset is based on household surveys on national level in Peru named ENAHO. It is a continuous annual survey with data on a household’s employment situation, their income, their consumption behaviours, education, health, and this survey includes information about “Juntos” program since 2009.

The econometrical methodologies used are the First Differences and the Propensity Score Matching. After robustness checks, only the results found via the Propensity Score Matching are used. All estimations were made on the whole sample but also on a subsample where the conditionalities are not a constraint in order to get the “pure income effects”. This also enables the analysis of the difference between having Conditional Cash Transfers and Unconditional Cash Transfers in terms of labour supply reaction. Results show that the transfer given by “Juntos” decreases the number of hours of work for men and increases the number of hours of work for women, but not for those who only have children in primary school (the subsample). The results for men are in accordance with the theoretical considerations and can prove that there is a “pure income effect” of the transfer on men. The results for women could be explained by the “reallocation effect” (section 3.2). However, the results for women does not match with the theory concerning the “pure income effect”.

When these results are brought to light regarding literature over Unconditional and Conditional Cash Transfers, it could be said the sign of the outcome for men does not differ between the two times of transfer. However, the outcomes on labour supply for women when the transfer comes with the conditions are an increase of their number of hours of work while when no conditions, there is no impact on their labour supply. Concerning the best option for Peru, between Conditional or Unconditional Cash Transfer, I prefer not to give my opinion. Firstly, because the results of this paper are not perfectly unbiased. Secondly because the paper focused on the impacts of “Juntos” on labour supply, but the transfer has many other implications such as improving education and health, but also having less

intergenerational poverty traps and even improving women empowerment. If one wants to build a structured opinion, all these different dimensions should be taken into account.

The framework of the paper will be the following. In section 2, one can find all important pieces of information about the Conditional Cash Transfer “Juntos”. Going from a brief description and historic of the program, to the eligible population, the conditions that need to be fulfilled in order to receive the social transfer and de components of this transfer. In section 3 one can find many empirical evidences and the theoretical considerations. In section 4 one can find descriptions of the data, its provenance and a summary of the statistics of the sample. Section 5 describes the chosen methodologies, their robustness checks and possible further research and improvements. Section 6 is a review of the results. Section 7 discusses and interprets the results, and finally, section 8 is the conclusion of the paper.

2. A brief description of “Juntos”

“Juntos” is a social program giving Conditional Cash Transfers (CCT) to eligible households. The conditions are linked to health, education, nutrition and citizenship development. The objective is not only to decrease short term poverty via safety nets, but also to enable more mobility to the poor in the long run. In other words, delete any kind of intergenerational poverty trap by the enhancement of education for children and the enhancement of health for women and children. This welfare program is one of the biggest in Peru in terms of number of households and of amount of money. The program has been expanding ever since its beginning in 2005. The project went from almost 22,500 households living in 26 different municipalities to covering 612 more municipalities and more than 400,000 households!²

Historically, the creation of this Conditional Cash Transfer (CCT) program “Juntos” can be associated to four key factors (*Pedro & Mendoza 2006*). **(i)** The United Nations Millennium Declaration in September 2000 and its Millennium development goals. **(ii)** The call for a National Plan of overcoming poverty. **(iii)** The establishment of a Peruvian institution “conjunto de manifestos y propuestas del Acuerdo Nacional” (2002) that aims to enable meetings and discussions related to the different goals of Peru, this with different political and social groups (parties, labour unions, associations, ...). **(iv)** the Peruvian economic environment in 2005, with unequally redistributed positive economic growth leading to an increase of absolute poverty in Peru. This trend had plausible impacts on political stability because of social disruption. Therefore, the welfare program “Juntos” also aimed to strengthen government presence in remote areas of the country.

² <http://www.juntos.gob.pe> ; Francke, P. & Mendoza, A. (2006)

The realization of the program was based on previous / already existing programs in Latin America. This to avoid mistakes that were made in pre-existing programs and instead use their strengths. The main inspiration of “Juntos” conditionalities was the Conditional Cash Transfer (CCT) “PROGRESA” in Mexico. One big difference however, is that PROGRESA was randomized (besides targeting the poor, there was no targeting of the population) while “Juntos” is not (targets households having specific characteristics). There was an agreement between the two social programs (“Juntos” and “PROGRESA”) to have a permanent cooperation and exchange of experiences. The same collaboration was implemented with Brazil and the program “Bolsa-Família”. Other welfare programs of south America were used as inspiration in the creation of “Juntos”: “Familias en Acción” in Colombia, “Puente-Chile Solidario” in Chile and “Superémonos” in Costa Rica.

2.1. Eligibility ³

The eligibility to the welfare program “Juntos” is no random draw, there are three levels of population targeting. To have access to the transfer, the three need to be fulfilled.

- **Geographic targeting**

The geographic targeting is not random. To better understand it, it is important to have a perfect understanding of the administrative division of Peru. Peru is divided into 25 regions. Each region is then sub-divided in provinces. Finally, each province is sub-divided in districts.⁴ The eligibility to the welfare program “Juntos” is on the district level. This means that a region / province can appear as receiving “Juntos” but only some of the districts of this region/province are receiving the welfare program. There are five different characteristics that makes a district eligible or not.

- (1) Exposure to violence during the late 1980s and early 1990s terrorism era;
- (2) poverty level measured as the proportion of population with unsatisfied basic needs;
- (3) poverty gap ratio⁵;
- (4) level of under-five chronic malnutrition;
- (5) presence of extreme income poverty (implemented after in 2006)

The eligible districts must fulfil all characteristics, this via pre-determined thresholds. It could be that some districts, for whom almost all conditions are fulfilled, try to adjust in order to become eligible. More information on how the program avoids this kind of responses would have been

³ <http://www.juntos.gob.pe>; Francke, P. & Mendoza, A. (2006)

⁴ <https://www.citypopulation.de/php/peru-admin.php>

⁵ The poverty gap ratio measures the national intensity of poverty via the mean distance separating the population from the poverty line. The poverty line can be based on income or consumption levels.

welcomed. Unfortunately, non-have been found on the web and all attempts for contact with a representative of “Juntos” were unaccomplished.

When “Juntos” started, only the eligible districts were treated. More districts were gradually introduced thanks to changes on the required characteristics. Already in 2006, more districts became eligible thanks to modifications in the thresholds of the four already existing conditions and the creation of the fifth condition specified above. In 2007 the information used to calculate the five criteria were updated which also resulted into more districts getting included. These three years, from 2005 to 2007, is called the first “Juntos” expansion.

A second expansion period began in 2010. Between 2010 and 2013. Some of the definitions mentioned above were modified, in part because poverty had fallen considerably in recent years and to introduce regions of the country that had not benefited during the first expansion. Since 2013, the criteria have remained stable. Still, more districts are gradually becoming eligible. All gathered information would lead to assume that this expansion is due to increasing financial capacity of “Juntos”. Still, more information on how the districts were chosen would have been welcomed. Again, non-have been found on the web and all attempts for contact with a representative of “Juntos” were unaccomplished.

- **Household characteristics**

The targeted households are those declared as poor by INEI thanks to the “Sistema de Focalización de Hogares (SISFOH)”⁶. The eligibility of a households is based on an estimation of the probability of living in poverty via the following characteristics:

- (1) percentage of illiterate women in the household;
- (2) percentage of children between ages 6- and 14-years attending school;
- (3) access to industrial sources of fuel (gas, oil, kerosene);
- (4) number of appliances;
- (5) access to public services (drinking water, electricity, and sanitation);
- (6) material used in floors, walls, and ceiling.

Each of these characteristics was given an implicit weight, and those households above a certain threshold were considered poor. Only households classified as poor under these criteria, with children younger than 19 years old or that still have not finished secondary school and are located in eligible districts were eligible for the program.

⁶ <https://www.gob.pe/588-programa-juntos>

- **Community validation**⁷

The last step to become officially eligible is by passing through the “community validation”. This is carried out by assemblies composed of local authorities and representatives of the Ministry of Education and Ministry of Health. The aim of this last step is to minimize inclusion and exclusion errors. Meaning, including districts/households that are not eligible⁸ into the welfare program and vice versa.

2.2. Conditions⁹

There are 4 conditions that households need to fulfil to receive the transfer.

(1) Education

Children between 6 and 14 are enrolled in school and attend school at least 85% of their classes during one school year. Since 2010, the condition changed to pre-school attendance being required as well. In 2013, school attendance became compulsory up to the age of 19, or until the child completes school.

(2) Health

Children under 5 also need to go for check-ups following the protocols of the Ministry of Health (twice during the first month; six times during the first 12 months; ten times between ages 1 and 4; and annually thereafter. This to have their growth, nutrition and development monitored. They must get vaccinated (immunisation), take iron supplements and vitamin A supplements. Some advises are given to mothers during these check-ups.

(3) Health

Pregnant women must attend pre-natal check-ups. Since 2018, pregnant women and children must attend check-ups to combat Anemia.

(4) Identification Document

The mother and her child(ren) must have a valid national ID.

To make sure beneficiaries fulfil all conditions, there is bi-monthly monitoring by “Juntos” fieldworkers, who have access to school and health centres for information. If conditions are not fulfilled, beneficiaries stop receiving the transfer for 3 months but can get back into the program if they fulfil the conditions once more. If the unfulfillment persists, the household is taken out of the program.

⁷ J Vargas & E Villar. 2006.

⁸ Eligible: follow all the conditions.

⁹ <http://www.juntos.gob.pe>; Francke, P. & Mendoza, A. (2006)

2.3. Components ¹⁰

Once selected, the head of the household and the other members must sign a letter in which the households commit to meet the co-responsibilities and select a health centre. Once enrolled, transfers are given to the female head of the household with a payment schedule pre-defined by the program's administration (defined at the village level). Within a district, all payments occur in the same week. Since 2009, two payment methods are available for beneficiaries, via a local branch of the Peruvian National Bank or going to the main square of the village and receive the money in cash. Once the cash has been transferred, beneficiaries are free to choose how they spend the money, but they must keep the conditions in mind. "Juntos" was initially intended as a program of temporary assistance for families, with a duration of 4 years, only for households escaping from poverty. Yet, impoverished households can renew their participation for 4 more years with a benefit reduction of 20%.

Yet, more information would be welcomed on whether there is a monitoring of the households that stop receiving the transfer. Also, there should be information on whether the program takes in account the fact that some households, close to the fulfilment of the eligibility conditions, might change their behaviours in order to become eligible. But also, how the program prevents this kind of reactions. Unfortunately, once more, non-have been found on the web and all attempts for contact with a representative of "Juntos" were unaccomplished.

The given amount is equivalent to 100 soles monthly. Since 2010, it became 200 soles bi-monthly to minimize the travel distance of beneficiaries (some of them can live far away from the money withdrawal). To have an idea of the importance of the transfer, people considered as poor in Peru (in 2018) have an individual income below 338 soles. For these, a transfer of a hundred soles per month is almost equal to one third of their income. Someone is considered as extremely poor when the individual income is below 183 soles (in 2018). Therefore, for extremely poor, the transfer represents more than half of their individual income. ¹¹ For both situations, the transfer is important.

¹⁰ Blundell, R., & Macurdy, T. (1999).

¹¹ <https://www.alainet.org>. Statistics for 2018

3. Empirical evidence and theoretical considerations

3.1. General discussion, Conditional Cash Transfer VS Unconditional Cash Transfer

A Conditional Cash Transfer is a social policy designed to reach specific objectives such as well-being improvements or economic growth. These transfers are given under behavioural conditions. To make sure all conditions are followed, there is need of good administrative resources. Conditional Cash Transfers are mostly, introduced by government social policies. The cons of this type of transfer are the administrative costs to supervise the constraints and it can sometimes be considered as unethical because it is paternalistic to give conditions, one might argue it is not the role of government to tell people how they should spend their money. Another negative point is that it might exclude some groups that can not follow the conditions. Finally, if the administration/ institutions are not good enough (presence of corruption), the Conditional Cash Transfer will be more negatively affected than Unconditional Cash Transfers. The pros of having conditions on the other hand, is that it solves time inconsistency¹² (people taking bad decisions for their future utility maximization) which is better for utility maximization on the long run. This is mostly for situations where the underinvestment is not only due to lack of liquidity (underinvestment's can occur because of risk aversion and lack of insurance, lack of altruism or underestimation of returns). The Conditional Cash Transfer makes it is easy to explain for what the taxes are used. CCT also enables multidimensional effects¹³ (UCT also) and reduces next generation inequality.

An Unconditional Cash Transfer is also a social policy but with no conditionalities that need to be followed to have access to the transfer. These transfers also enable positive multidimensional effects. UCT's are mostly used when the underinvestment is due to lack of liquidity. Which means that there is lack of investment (in education or health for example) because of lack of financial resources.

The key to success of these transfers (CCT and UCT) is the good targeting of the population. One problem linked to both transfers is that they both focus only on the demand side of the services. Meaning that they focus on increasing the demand for education or health for example but not on the quality of the services themselves. To make these welfare programs better there should be an act on the supplying side of the services. But also, a good targeting of the vulnerable population, a reduction on transaction

¹² Time inconsistency is also called dynamic inconsistency and describes the phenomenon of agent's preferences changing over time. It can explain how some agents prefer a certain decision in advance but a different one when the time to implement arrives.

¹³ A transfer with multidimensional effects is a transfer that has impacts on different dimensions such as education, health, women empowerment, labour supply, ...

costs, an increase in the accountability of providers and an analysis of all possible perverse effects before the implementation. It is always recommended to have a good comprehension of already existing programs with their failures and achievements before implementation. Always keeping in mind, the importance of the cultural, demographical, geographical and economical context.

Before focusing on the CCT “Juntos” in Peru, I was mainly interested by working on a basic income experiment. This desire was not accomplished because of a lack of available datasets on the topic. The basic income is more and more trendy in welfare policies and it can be considered as an Unconditional Cash Transfer with no targeting of the population and given to everyone. But an UCT is not necessarily a basic income. For example, if an UCT is given only to the mother of each household, then it is not a basic income because it is not given to everyone. *Maniquet, F. and Neumann, D. (2016)* clearly defined what can be considered as a basic income (four conditions):

- (1) the transfer is given without any conditions linked to the resources of the agent;
- (2) the transfer is given without any conditions linked to the work supply of the agent;
- (3) the transfer is given to everyone (individually and not to the household as with “Juntos”);
- (4) the amount of the transfer and the taxation if revenues are modified (fiscal reform).

The basic income could avoid numerous administration costs and if well performed (via the choice of taxation), enable a vertical redistribution. But its possible impacts on labour supply need to be identified before implementing this kind of policy in a country. Let’s leave this to other researchers and focus on the CCT transfer “Juntos” in Peru.

Here, in the context of Peru, the question is whether a Conditional Cash Transfer such as “Juntos” is efficient and whether introducing an Unconditional Cash Transfer is more efficient. For now, let’s first analyse what economic theory suggests on CCT impacts on the work supply.

3.2. Theoretical considerations

Impacts of welfare programs on labour supply has long been a subject of interest for economists. Undeniably, researchers and policy makers are interested in possible indirect, unintended effects of these transfers. The discussion of the CCT impacts on labour supply should consider the standard model of labour supply, the conditions of the cash transfer¹⁴ and the model of the household.

¹⁴ Here, conditions are health and education requisites. Hence, there are no conditions imposed with regard to labour effort of beneficiaries.

In the standard neoclassical model of labour-leisure choice, where the economic agent chooses the combination of goods and leisure that maximizes his/her utility (with a budget constraint composed of wage, initial wealth and monetary or in-kind transfers), an increase of nonlabour income (holding wages constant) leads to a rise of both expenditures on consumption goods and number of leisure hours consumed. This because consumption and leisure are both considered as normal goods¹⁵. As a result, a decrease in employment and number of working hours¹⁶. This impact is called the “**income effect**” (Borjas. 2012, pp 21-83).

The conditions linked to the program could change numerous aspects of family dynamics and adults’ behaviours. Firstly, a certain number of hours are going to be needed for the respect of the conditions. Because it is the women who are the one receiving the allocation and are responsible for the respect of the conditions, one can assume that they are the ones allocating hours on the task (Perova, E. & Vakis, R. (2012). Undeniably, going to the health check-ups and bringing the children to school can take some hours per week. This could lead to a reallocation¹⁷ of women’s number of hours from so called “conventional labour”¹⁸ to “domestic labour” because this last one becomes more productive thanks to the transfer (Faug Jean-pierre. 1980). Let’s call this the “conventional – domestic **reallocation effect**”. Secondly, if school attendance of children for beneficiary households increases, then hours dedicated to childcare could decrease and parents could augment their labour participation (Fernandez, F. & Saldarriaga, V. 2014). Although, it could also lead to children helping less for Laboral work¹⁹ increasing the number of working hours necessary for parents and changing households’ budget constraint.

If the CCT incites children to substitute the time spent on labour (domestic production, working in the familial firm, paid work and other)²⁰ into their education, literature would assume that the adult will increase his/her domestic production or labour supply (in the familial firm or for paid work) to compensate the decrease of the children’s supply. This argument combined with the income effect could lead to a net effect of the CCT on labour supply not significantly differ to zero. This would mean that the standard model of work supply is not questioned by the empirical results above. Therefore, it

¹⁵ When there is an increase of purchasing power, demand for normal goods will increase while demand for inferior goods will decrease.

¹⁶ Extensive margins correspond to the employment rates (working or not) and intensive margins correspond to number of working hours or earnings conditional on working.

¹⁷ We consider here that the domestic work is a perfect substitute to the conventional work (Blundell, R. & Macurdy, T. 1999, pp 1657-71)

¹⁸ By conventional work here, I mean the work for formal (where everything is declared) or informal sector, other than domestic tasks performed for their own household.

¹⁹ Here by labour work, I mean the fact of helping parents in the field.

²⁰ Note that before receiving the Conditional Cash Transfer, if the children were helping with the domestic tasks or were working on paid work has different impacts on parents. The first one may lead to an increase of parent’s domestic production while de second situation would lead to an increase the parents paid work.

is important to also analyse the “pure income effects”. This can be done by selecting the families for which there is no impact on children’s education.

Uncertainties remain for who in the family reduces his/her working effort. This depends on how the transfer is distributed among family members. If the unitary model²¹ for the household is assumed (*Samuelson 1956*), it means that the transfer is shared among the family members²². It would mean here that both man and woman should have an income effect. On the other hand, if there are intra-family bargaining processes²³, there might be different results across family members where, as for “Juntos”, money is transferred to the mother (*Fernandez, F. & Saldarriaga, V. 2014*).

Lastly, the CCT might create spill-over effects on labour markets and cause external effects on non-beneficiaries. E.g. If beneficiaries decrease their labour supply, this might create more facilities for non-beneficiaries to find work. Also, there might exist anticipation of the program, for people slightly over the eligibility conditions, who would change their labour supply behaviours in order to become eligible. This to change their usual habits as soon as the transfer is received. It could lead to biased results and this needs to be taken into consideration.

Altogether, regarding possible impacts of the Conditional Cash Transfer “Juntos” on labour supply, theory may advance an income effect for man and women, depending on the household model. But there is possible compensation of labour supply of parents because of children spending more time for education. Finally, there might be a reallocation effect for women, with an increase in domestic work. Altogether, the sign (can be negative or positive) of the net effect cannot be clearly estimated. The objective of the paper here is to analyse whether there are “pure income effects” and compare results between families where there are only “income effects” and families where there are also “reallocation effects”. This also enables the analysis of the difference between having Conditional Cash Transfers and Unconditional Cash Transfers in terms of labour supply reaction.

3.3. Impact evaluation of “Juntos”

This Conditional Cash Transfer program has already been evaluated in many ways. *Jones, N. Vargas, R. & Villar, E. (2006)* investigate the impacts of the program on poverty via its multidimensionality. All this based on a **qualitative** analysis for two communities in the region of Ayacucho, the first region in which the pilot phase of the program was implemented. This analysis can establish **correlation links** but no

²¹ In the unitary model there is a pooling of all incomes of the household and the utility becomes the household’s utility and not the aggregated individual utility of each member of the household.

²² The unitary model can be opposed to the dominant family member of Becker (1981).

²³ The transfer is not equally distributed among the family.

causality links. Their results suggest higher school attendance in (there is no specification for which age groups) districts where “Juntos” has been implemented, with a decrease of children’s agricultural and domestic chores leading to an increase in going to school. Although they still carry out work activities after school, on weekends and holidays to support the family. Their research suggests that much of this work has been taken on by women, thereby increasing their workload. They also suggest a higher involvement of some fathers in domestic tasks, childcare and their children’s education partly because of greater financial support and less pressure to work as daily laborers or to migrate outside the community for work. The second-dimension tackles healthcare and suggests that “Juntos” leads to higher health-seeking behaviour helping to overcome malnutrition, this thanks to the health conditionalities of the program. Also, because having a National Identity Document is a prerequisite of “Juntos”, it helped identify part of the population. “Juntos” also improved the bargaining power of women, reducing their economic dependence and familial violence (this because women receive the transfer). Moreover, it improves household livelihood thanks to increase of purchasing power. “Juntos” also promotes joint responsibility between citizens and state for education and health. It has community dynamics in which households receiving the transfer could suffer exclusion.

Díaz, R. Vargas, R. & al. (2009) use the beneficiaries’ regions of Huancavelica, Apurímac and Huánuco and included three non-beneficiary regions to have a comparative view. Their results are based on **qualitative data** and should be seen as **correlation links** but not as established causality links. The paper first pointed out that while the program increased health and education demands, it was not introduced with the supply improvement of these services, lacking mostly in the most poor and isolated zones.

Another result reveals that “Juntos” has an impact on consumption habits (more eggs, fruits and vegetables). The evolution of prices of these goods was not analysed nor taken in account here. They find that women’s empowerment in the community and household improved and that there are higher concerns for children’s education and future in the beneficiary’s households.

Escobal, J. & Benites, S. (2012) wrote a technical report based on **quantitative** data from “niños del milenio” for all children who were born between 1994 and 2002. This report establishes **causality links**. They find that beneficiaries households change their consumption habits and that they have more probabilities of buying eggs, fruits and vegetables (same as *Díaz, Ramón & al.*). The paper also finds some evidence that the time children spend for paid work increases but the number of non-paid work hours decreases (this result is not banal because “Juntos” aims to decrease child labour and here it increases). In absolute, the time children spend on education and recreation does not change. There is no evidence of impacts on cognition and nutrition of children, but they find negative impacts of the program on women’s and children’s happiness.

Perova, E. & Vakis, R. (2012) use quantitative data (2006 to 2009) and establish causality links. This using for methodology an Instrumental Variable²⁴ and differential effects. The impacts of the welfare program of “Juntos” are the following:

- (i) the transfer constitutes approximately 15 percent of average household spending among beneficiaries;
- (ii) there is significant increase in consumption and income;
- (iii) there is a significant decrease in national poverty numbers;
- (iv) there is an increasing utilization of health services among children under the age of 6 and women of child bearing age (12 to 49 years old);
- (v) there is a significant increase of school attendance and registration for children aged 6 to 14 linked to lower post school registration and attendance of beneficiaries compared to non-beneficiaries.

Fernandez, F. & Saldarriaga, V. (2014) use **quantitative data** and establish **causality links** of the welfare program. The paper finds that there are short-term term effects of the Conditional Cash Transfer on the working effort of adults. Women’s (but not men’s) weekly hours of work are reduced mostly for married women with children aged 5 or less. There were no results for labour force participation. Here the empirical evidence is reconciling with the theory of the standard model of labour supply.

Alcázar Valdivia, L. & Espinoza Iglesias, K. (2014) use the **quantitative data** of ENDES and establish **causality links**. They discover an increase for women empowerment, this via higher negotiation power regarding family matters, for education and health decisions. Also, via higher economic empowerment thanks to the transfer²⁵. There is no change regarding participation to the labour force. This because of their unchanged educational level (most of the women only know Quechua²⁶), and unchanged geographical situation. Finally, negotiation regarding domestic work depends on the households but in many cases, women still think they are made for the house work and men for the Laboral work. The conclusion of this paper is that the program helps for the empowerment of women and that the higher limits are mostly conditional to the rural context and poverty. Women who have higher probability to

²⁴ Here, the Instrumental Variable is an interaction between a dummy equal to one if a respondent is eligible based on his/her proxy means score (based on the formula of “Juntos” administration), and the number of months over which the district had been receiving “Juntos”.

²⁵ This is heterogenous among families and is correlated to the women’s education level.

²⁶ *Quechua* is the main surviving indigenous language of the Andes and is one of the official languages in Peru, it is used for everyday communication in informal contexts. Because most native speakers of Quechua are illiterate in their native language, it remains largely an oral language. In formal contexts, such as government, administration, commerce, education, and the media, Spanish is the language used in Peru.

gain empowerment are those who had better education, that live in a context in which they have easier access to work, those who are younger, have less children and have better self-esteem.

Sanchez, A., Melendez, G. & Behrman, J. (2016) use quantitative data and establish **casualty links**. They find that exposure to “Juntos” during the three first years of life reduces the probability of being severely malnourished at age 7-9 by 13.4 percentage points. There is no effect for those exposed between age 5 and 7. There is no evidence on cognitive developments for children. One of the reasons might be that school enrolment in primary level in Peru is already close to universal (98 percent of children aged 6 to 12 are attending school full-time) which reduces possible impacts of “Juntos” to this matter. This result is opposed to a previous paper where there was a significative impact on school enrolment and attendance. It could be explained by the fact that here, heterogeneity between rural parts of Peru and urban parts in percentage of school attendance is not considered and the difference of the treated period (2006-2009 to 2009-2013). This is important because “Juntos” is a program mostly targeting rural areas. The aspect of conditionality might lead to a later impact on educational achievement given that pre-school attendance is still relatively low in Peru.

Lastly the MEF impact analysis of “Juntos” in 2017 shows that this program achieved to reduce extreme poverty by 18.9%. They also found that “Juntos” lead to an increase in secondary school attendance by 8.2% and reduced dropouts by 8.8%.²⁷

Many papers analysed the Impacts of the Conditional Cash Transfer in Peru, this with many different focuses and some heterogeneous results. This could be linked to the used methodology, the available data and to the chosen period. For all papers mentioned above however, there are impacts related to children’s development (health, nutrition and education). For education there does not seem to be a lot of impacts on primary level because of the already high level of school attendance in Peru, however, there are changes in consumption habits of the households. The transfer has a positive impact on the position of women in the community and her family thanks to the increase in bargaining power. But on the other hand, this results in more time needed for the conditions respect. There seems to be little impact on men’s behaviours besides having some more concerns for children’s education and changing their labour supply. The results concerning labour supply²⁸ suggest that women are working less for Laboral work and spending more time in domestic work. Men seem not to have a change in the number of hours they work but they feel less pressure to work as daily laborers or to migrate outside the community for work.

²⁷ <http://www.juntos.gob.pe>

²⁸ Jones, N., Vargas, R. & Villar, E. (2006); Escobal, J. & Benites, S. (2012); Fernandez, F. & Saldarriaga, V. (2014); Alcázar Valdivia, L. & Espinoza Iglesias, K. (2014).

3.4. Empirical evidence from Latin America

Many economists are interested by the different impacts of cash transfers on labour supply. I am going to focus on the different papers focused on Latin America. This because it allows, to some extent, to imagine possible results of “Juntos” in Peru. But also, because CCT’s have been implemented intensively in many Latin American countries such as Colombia, Mexico, Brazil, Ecuador, Argentina, etc. Of course, every program has its own specificities, in the way the population was targeted, and the different conditions linked to the transfer.

Vargas Juliana Mesén (2018) analysed the causality impacts of the Conditional Cash Transfer in Mexico PROGRESA (now known as oportunidades), where the CCT was given randomly targeting poor households. In the scientific paper, there is a focus on a subsample of the population (exogenously defined) of adults for whom, the conditionalities were not binding.²⁹ This allows to put attention only on the so called “income effect”. Results show a positive effect of an Unconditional Cash Transfer on the number of working hours. This is explained as follows, *“The lack of savings, the limited possibilities to get indebted, together with the extreme poverty, may explain that people prefer to use the money provided by PROGRESA to face urgent expenditures or to make investments instead of working less”*. *Gertler et al. (2012) find that PROGRESA beneficiaries invested part of the transfers in productive assets, which allowed them to increase agricultural income by almost”... “The better food intake can translate in better health outcomes (Gertler, 2000) which in turn may increase productivity and availability to work”*³⁰. *Parker and Skoufias (2000)* Also estimate the causality effect of the CCT PROGRESA on the participation rate for men and women. But they focus not only on a subsample as Juliana but on a representative longitudinal sample of approximately 24,000 households from 506 communities located in the first states receiving PROGRESA benefits. They find a positive effect for men and a negative effect for women participation rates. Nevertheless, most of the results are not statistically significant and may contain income effects but also reallocation effects. This means there is no impacts of PROGRESA on the intensive margins of labour supply.

Attanasio, Orazio et al (2010) Focused on Colombia with the CCT “Familias en Acción” given in rural areas. This CCT is not randomly given. They focus on causal outcomes for and for children of 8 to 13 and 14 to 16 years old and find that because of the educational condition of the CCT, there is an increased enrolment in school for both ages. The effects are larger in urban areas than in rural areas. Also, children’s participation in domestic work decreases. There is no effect on their participation in

²⁹ The subsample is composed of households with children in primary school because their school enrolment is not affected by the transfer PROGRESA (the level of enrolment is already close to 100 percent).

³⁰ Vargas Juliana Mesén. (2018). Conclusion.

income-generating work which leads to the conclusion that the increased time at school may be drawn from children's leisure time. This means that parents use the transfer for other uses than to fully replace the earnings from the work of their children.

Miguel Nathan Foguel & Ricardo Paes De Barros (2010) estimate the causal effects of the CCT programs in Brazil on the labour supply (participation rate and average number of hours worked) for both men and women. This thanks to a time-series-cross-section sample. Results show *(i)* no significant effect for all women participation rate. *(ii)* Negative effect on the number of working hours for the women's who are situated above the median income. *(iii)* No effect on the number of women below the average wage. *(iv)* Positive impact on the participation rate for all men (small in magnitude). *(v)* No impact on number of working hours for all men.

Ferro & Nicollela (2007) Find no causal effects of the CCT in Brazil for both men and women on the participation rate in urban and rural areas. For the number of hours worked, they discover a negative effect for men in rural areas, a positive effect for urban women and a negative for women living in rural areas. *Medeiros & al (2007)* find no effects of the CCT on participation rate in the labour market.

To sum everything up, most of the empirical evidence suggests effects of a CCT on labour supply (but for most, little effect), both along the intensive and extensive margins. When there are causal effects, they are for most positive but sometimes negative for women. But it always depends on the sample used for the analysis, the specificities of the welfare program and the cultural, geographical and economical context in which it is implemented.

4. Data

4.1. Data collection

My aim was to collect individual data (linked to household data) over a period where the rules governing "Juntos" were stable. The task turned out to be more difficult than expected.

The Dataset is based on household surveys on national level in Peru. The survey is named ENAHO³¹ and is available on the website of the national institute of statistics and informatics of Peru *INEI*³². ENAHO is a continuous annual survey with data on a household's employment situation, their income, their consumption behaviours, education, health, and includes information about "Juntos" program since 2009. The questionnaire can be found in *Appendix 1*. The datasets are divided on five different themes.

³¹ Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza.

³² Instituto Nacional de Estadística e Informática. <https://www.inei.gob.pe/>

Three datasets are at an individual level: for education, health and expenditures and earnings. Two are at household level: for the characteristics of the housing and the expenditures and earnings' summary. To have in the same dataset information about the labour supply of the parents and their children's educational level, a merge of the two individual datasets, (i) education and (ii) expenditures and earnings have been made. Finally, the dataset gathers yearly information from 2011 to 2015. The creation of a coherent data set at the individual level but with household information as well turned out to be a difficult task, some data sets did not contain an individual (household) identifier. Other panels were available however, like the one that was first chosen for 2013 to 2017. This to have as many years as possible in which the eligibility requirements and the conditions did not change. This panel³³ has been abandoned however, after some unsuccessful attempts in merging the two datasets as said before. This because of a missing individual and household identifier. The same problem occurred for the data panel available for 2012 to 2016. This last one has identification variables, but with different values for both datasets of interest.

When downloading the dataset, a technical sheet and a variable dictionary is also downloaded. They are useful to identify important information and understand better how specificities of the different datasets work. All documents are provided in Spanish and the dataset itself is also in Spanish. For a better understanding, after the selection of variables of interests, the merge and the reshape of the dataset from wide to long, I translated the names and labels of the variables to English.

How the information is gathered is explained in details on the website of [INEI](#). The interviewers gather the information on the field. They insert observations directly via mobile equipment (introduced since 2011). They gather the information for all household members via questions preestablished by the survey to the informers. Informers are the household's head, the partner and people older than 12 years old. This means that some information regarding younger kids are given by an informer. Supervisors are those controlling the advancement of interviewers. The role of the interviewer is clear, and hr/she has specific rules to follow while interviewing. E.g. the interviewer cannot have conversations other than asking the stipulated questions of the survey and cannot give his/her opinion. All these guidelines are to avoid any kind of bias linked to the way information is gathered. Interviewers also need to highlight the anonymous nature of the survey and are obliged to go back to the household as many times as needed to have complete information. Possible biases could occur because of the presence of other household members while one is interviewed. Some of the informers may not want to participate to the survey because of lack of time. Then the interviewer needs to find another time to do the survey. It can occur that some informers do not want to participate in the interview. When this happens,

³³ A Panel data set has observations for same individuals over a certain amount of years (minimum two years).

interviewers try to convince them and report the situation to their supervisor. All information is finally verified at local, departmental and then national level. This with corrections on extreme and missing observations.

The Survey itself has been created in collaboration with many other Peruvian ministries (ministry of education, health, economics and finance, women and vulnerable population, ...). It is also verified every year by the “*Comité Asesorinterinstitucional de medición de le Pobreza*”. This comity is sponsored by the World bank.

The way the sample is gathered is randomized, which means that all members of a population have same probabilities of being selected. It is organized by geographical proportions and stratified, which means there is a weight given to some groups or socioeconomic levels. All this to make the sample more representative. Lastly, it has a multi-stage process (first it's the population centre, then the conglomerate and then the household).

To conclude, the dataset is based on household surveys on national level in Peru (ENAH0). It gathers yearly information from 2011 to 2015. It assembles information over the education and the expenditures and earnings on an individual basis and has identifiers on individual and household level. This for whole regions of Peru and all ages.

4.2. Summary of statistics

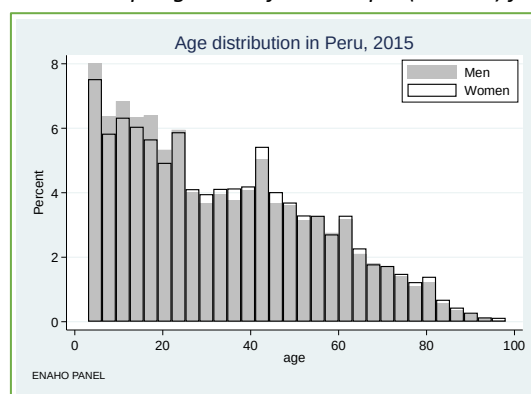
The first part of this section aims to verify that the sample is representative of the population of Peru and to make sure that there are no aberrant observations. Children younger than two years old are not represented in the sample. As said before, information about children younger than 14 years old observations are given by household informers. *Table 1* shows that the sample is constituted of 1 567 719 observations and that there is no aberrant observation related to the age of the respondents. Both pieces of information are good news for having unbiased results later.

Table 1: Summary of the variable age for the years 2011 to 2015 for the sample (ENAH0)

Variable	Obs	Mean	Std. Dev.	Min	Max
age	1,567,719	33.68275	21.43841	2	102

Comparing *graph 1 and 2* also makes it possible to assume that the sample is representative of the population of Peru. This because both follow similar trends. In *Appendix 0* one can find the age distribution per gender of the sample for the years 2013 and 2014.

Graph 1: age distribution per gender of the sample (ENAH0) for the year 2015



Graph 2: age distribution per gender in Peru for the year 2015 ³⁴

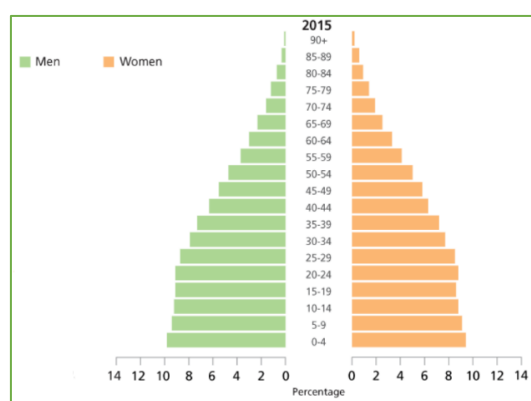


Table 2 shows some educational characteristics of the sample. It can be pointed out that there is still a consequent percentage of the population with no educational level. Most of the population has a primary school level, not much of the population has a diploma higher than secondary school. Table 3 shows that Quechua and Spanish are the two most spoken languages in Peru. Quechua and Aymara are mostly spoken in rural areas and by people who have a lower educational level.

Table 2 : Educational level for men and women for the years 2011 to 2015 for the sample (ENAH0)

gender	RECODE of EDUC (educative level)					Total
	no level	kindergar	primary c	secondary	higher ed	
Man	13,977	67,226	74,897	71,989	28,584	256,673
	5.45	26.19	29.18	28.05	11.14	100.00
	31.42	47.50	51.73	54.46	48.80	49.21
Woman	30,508	74,300	69,897	60,210	29,994	264,909
	11.52	28.05	26.39	22.73	11.32	100.00
	68.58	52.50	48.27	45.54	51.20	50.79
Total	44,485	141,526	144,794	132,199	58,578	521,582
	8.53	27.13	27.76	25.35	11.23	100.00
	100.00	100.00	100.00	100.00	100.00	100.00

³⁴ <https://www.paho.org/salud-en-las-americanas-2017/?p=3232> ; **Source:** Pan American Health Organization, based on data from the UN Department of Economic and Social Affairs. Population Division. 2015 Revision. New York; 2015.

Table 3: Mother tongue for individuals in the sample (ENAH0) for the years 2011 to 2015

mothertongue	level of education					Total
	no level	kindergar	primary c	secondary	higher ed	
Quechua	15,686	29,381	26,184	12,998	3,636	87,885
Aymara	1,354	2,698	3,380	2,368	652	10,452
other native language	1,750	4,153	2,785	801	154	9,643
Spanish	25,060	104,949	112,210	115,767	53,994	411,980
English	7	36	75	43	40	201
Portuguese	18	79	72	98	22	289
other foreign language	13	30	29	69	62	203
sign language	597	193	54	23	14	881
Total	44,485	141,519	144,789	132,167	58,574	521,534

Table 4 shows the statistical summary of the variable representing the relationship with the head of the households. There is no strange observation. This says a lot about family trends of Peru. Many families live together with their grandparents, uncles and aunts, cousins. But also, there is sometimes a “household worker” living in the house. Someone hired to do all kinds of domestic work.

Table 4: Summary of the variable “Relationship with head of the household” for the sample (ENAH0 2011-2015)

relationship to head of hh	Freq.	Percent	Cum.
household head	143,383	27.47	27.47
partner	95,625	18.32	45.79
children	218,764	41.91	87.70
son-in-law	9,882	1.89	89.59
grandchild	28,283	5.42	95.01
parents-in-law	7,901	1.51	96.52
other relatives	11,686	2.24	98.76
household worker	650	0.12	98.88
pensioner	12	0.00	98.89
other - no relatives	5,811	1.11	100.00
Total	521,997	100.00	

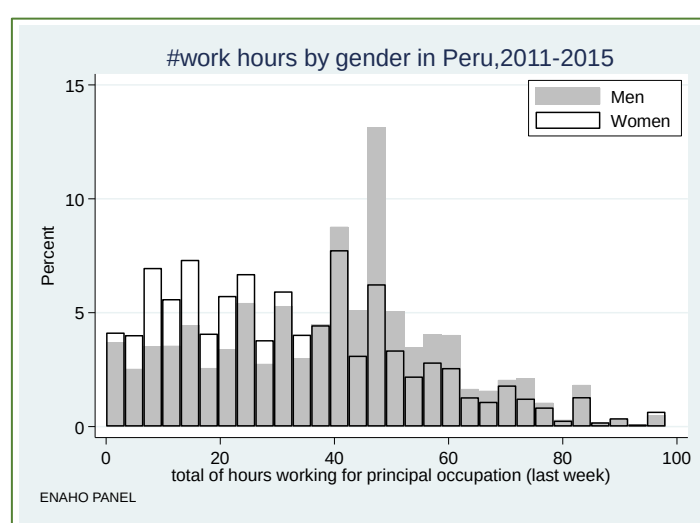
Table 5 show that there are many observations for the variable “workp” which is the number of hours worked in their principal work the week before answering the survey. The variable “worklw” is a binary variable with value 1 when the individual worked the week before answering the survey and two if not. The two other variables are not represented well enough. Therefore, the computation in the next section does not analyse the impacts of “Juntos” on these two variables. “Works” is the number of hours worked for the secondary or complementary work. There might be less observations because not everyone has a complementary job. “WorkU” is the answer to the question “which is the usual/average number of hours worked in total per week?”.

Table 5: Summary of the variables related to labour supply for the sample (ENAH0) for the years 2011 to 2015

Variable	Obs	Mean	Std. Dev.	Min	Max
workU	44,680	40.21626	18.6038	0	98
workp	311,041	35.9156	21.03471	0	98
works	75,230	16.22695	13.61175	1	98
worklw	409,777	1.317992	.4656971	1	2

The nature of the observations for the variable “workU” seem accurate. It is indeed a binary (with value one and two) variable as mentioned above. For “workp”, observations are also accurate. The minimum numbers of hours worked is zero (also takes in account the individuals that do not work) and the maximum is 98 hours. The maximum number of hours worked is equivalent to working fourteen hours every single day of the week. The distribution is represented in graph 3 and shows that there is a small percentage of workers working more than 80 hours. There is a great part of workers working between 40 and 50 hours per week. Younger women seem to work more than man. The trend changes in opposite direction for population older than 40 years old.

Graph 3: number of working hours for the principal job for the years 2011 to 2015 for the sample (ENAH0)



As we can see in table 6, women are mostly independent workers and domestic workers. It must be highlighted that working on domestic tasks is not considered as “work”. This needs to be kept into account when understanding the results. The “domestic worker” refers to women working in other households on domestic tasks to make money. Employed means someone working somewhere as an employee and labourer means working on the fields.

The measures include a formal and informal sector. The number of working hours is in accordance to people working in the informal sector because part of the observations is way higher than the standard numbers of work hours in the formal sector which is 48 hours a week.³⁵

Table 6: nature of the principal work for the years 2011 to 2015 for the sample (ENAH0)

kind of work (principal work)	gender		Total
	Man	Woman	
employer or boss	10,783	3,872	14,655
independent worker	63,697	49,421	113,118
employed	28,442	27,968	56,410
labourer	43,379	12,368	55,747
non-paid family worke	18,247	45,148	63,395
domestic worker	262	5,466	5,728
other	764	1,007	1,771
Total	165,574	145,250	310,824

The definition of work that is going to be used in this paper must be clear. The two dependent variables of interest are, the participation rate and the number of hours worked for the principal job. There is some data about the secondary job but there are too many missing variables. There could be different reactions on the principal and secondary/complementary work. For this it is possible to also use an aggregate measure, adding principal and secondary number of worked hours. But keeping in account that people having a secondary job might be linked to their compositional characteristics. In the paper, the analysis is focused only on the observations for the principal work and there is no use of an aggregate value of the principal and secondary number of worked hours.

Concerning the *participation rate*, the definition of work does not consider domestic work, meaning time spent by a member of the family on domestic tasks for free. The definition of work here refers to the formal and informal sector. This can be seen in *Appendix 5*. People working in the agricultural sector in their fields are considered as independent workers and the survey allows working with a non-registered firm, not receiving any wage and not having any contract. These activities are consequently not taxed and are not included in the GDP and GNP of the country. Having the informal sector taken in account in the results is important because there is still a high amount of informal economy in Peru.³⁶

The number of hours worked for the *principal job* gathers information about formal and informal sector (as for the participation rate). It also takes into account non-paid work for the family. This must not be confused with domestic work. This non-paid work for the family refers to young women working in a family, helping with domestic tasks and taking care of kids, in exchange for living in the family and having

³⁵ <https://www.nationmaster.com/country-info/stats/Labor/Hours-worked/Standard-workweek>

³⁶ <https://perureports.com/perus-informal-economy-persist-decades-report/3901/>

access to their resources.³⁷ It is not clear whether this mother spending hours into domestic work is taken into account in the section. To have more certainty on the matter, more information would have been welcome. These are not available on the web and the different attempts to gather more information via contacts working for “Juntos” were unaccomplished.

There are two available variables with some measures of *domestic work*. The first one is the available answer to the question “what were you doing last week?” – domestic work. The second is the answer to the question “Why weren’t you looking for a job?” with as available answer – the domestic work did not allow me to find other work.

Table 7: Summary of the variable “Juntos” for the years 2011 to 2015 for the sample (ENAH0)

juntos? Binary (yes or no)	gender		Total
	Man	Woman	
si	617	15,122	15,739
no	199,420	194,618	394,038
Total	200,037	209,740	409,777

In table 7, “Juntos” is equal to one if the individual received the transfer and equal to zero when not. A first important observation shows that that the CCT is given to women (except for reasons like a deceased mother, ...). 15,122 women receive the transfer. Only 617 men receive the transfer. This is normal because the transfer is usually given to the mother. In total 15,739 households receive the transfer. This need to be considered when looking at the impacts of “Juntos” on labour supply for men. A new variable needs to be created, equal to one for every member of the household when the mother receives the transfer.

Table 8: Pearson correlation between “Junto”s, labour supply for the sample (ENAH0)

	Juntos	workp	worklw
Juntos	1.0000		
workp	-0.1412*	1.0000	
worklw	-0.0759*	-0.3079*	1.0000

³⁸

In table 8, the Pearson correlation shows a negative correlation between the fact that someone in the household receives the transfer and the number of hours worked. There is an opposite correlation

³⁷ <https://www.perutelegraph.com/peru-information/legal-stuff/domestic-workers-in-peru>

³⁸ Pearson correlation. It is a measure of the strength and direction of association that exist between two variables. The value can range between -1 (perfect negative linear correlation) and + 1 (perfect positive linear correlation). Here there is also information on whether the results are statistically significant at one percent level (P. value. < 0.01)

regarding the participation rate because the variable “worklw” is equal to one when worked and two when not. We cannot conclude any type of causality effect here because correlation does not mean causality. Working less for example could influence probabilities of receiving the transfer because it is only given to poor households. There is also a negative correlation between number of hours of work and the participation rate. This because the variable “worklw” is equal to one when the individual works and 2 if not. In this case it means that working more hours is correlated to participation in labour market. Later on, this variable is recoded to zero when the individual does not work and one when the individual works.

5. Methodology

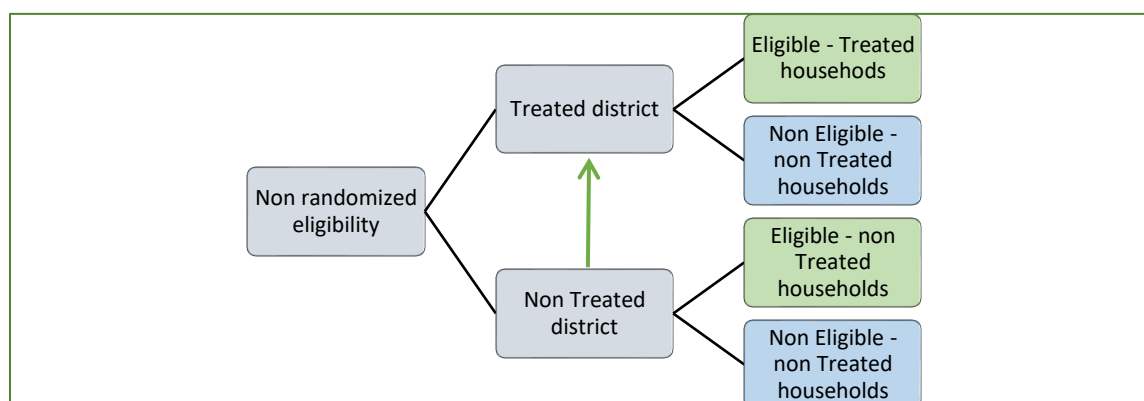
5.1. Primary pieces of information

It would be ideal to implement the empirical strategy with the control and treatment group being randomly assigned. Unfortunately, as most of the CCT programs, “Juntos” was implemented with a specific targeting of population. The objective now is to produce a control group that resembles the most to the treatment group. Because the available dataset is a panel, the first methodology I chose was the First Differences model. The second chosen methodology is the Propensity Score Matching. For both methods, the pros and cons are going to be explained.

Computation can only be done starting from the observations of 2013 because then, eligibility conditions remain stable. Therefore here, the focus is on the years 2013 to 2015. There are new districts and new household eligible to the program during this period. Here, it is assumed to be exogenous. Which means that it is not linked to any compositional characteristics of these districts but instead thanks to financial expansion. But as explained before in section 2.1, it could be that some districts adjust in order to become eligible. This could lead to biased results linked to anticipation effects. It would mean that the entry of the districts is exogenous. A second possible bias could be linked to political bargaining. These two possible biases are taken into consideration in later conclusions.

As said before, “Juntos” is a non-randomized Conditional Cash Transfer. Here follows a tree diagram to have a better understanding of the situation.

Graph 4: eligibility diagram of the welfare program “Juntos” in Peru³⁹



It is not because a district is not treated in a specific year that it won't be treated after. Between 2013 and 2015 there were some districts that were not included in the program and from one year to another, became included.⁴⁰ In *Appendix 6* you can see the late inclusion of districts located in the regions of San Martin (2014), Arequipa (2015), Lambayeque (2015), Ucayali (2015), Lima (2016), Madre De Dios (2017) and Tacna (2017).

Inside each region, the districts can be introduced in the program in different periods. For example, in Ucayali, only the district of Atalaya has access to the program in 2015 while the districts Padre Abad and Coronel Portillo have access in 2016 and Purus only in 2017.

Each individual is categorized as part of the treatment group as soon as he/she is part of a household in which someone receives the CCT. All the others, those who never receive the transfer, are the control group. This can be done via the variable named “Juntos” for which the value is equal to zero if the individual is part of the control group and one if the individual is part of the treated group. The specificities of the treatment group and the control group are explained for each methodology (First Differences and Propensity Score Matching).

When treated, if the household already receives the transfer for 4 years or if the conditions are not followed, the households stop receiving the transfer. This means that treated households can become non-treated. Firstly, it could be linked to exogenous reasons. Secondly, it could also be linked to the compositional characteristics of the household which could also lead to some biases. As already mentioned in section 2.3. more information would be welcomed on whether there is a monitoring of the households that stop receiving the transfer and on whether there is change of behaviours

³⁹ In section 2.1 – Eligibility one can find clear explanation on the administrative division of Peru for better understanding.

⁴⁰ <http://www2.juntos.gob.pe/infojuntos/indexe.html>

(anticipation effects) of the households that are close to the eligibility requirements in order to receive the transfer. Unfortunately, as already explained before, non-have been found. Therefore, there is no other solution that continuing the analysis taking into account all possible biases.

Because there is a focus on effects on labour supply, the chosen age of the population is those older than eighteen years old because it is the legal age to work in Peru. In reality, people between 16 and 18 years old can work but need the authorization of their legal supervisor.⁴¹

The rest of this section will be constituted of the different used methodologies, their advantages but also their limitations. All estimations are going to be on two-year period because it enables to have a bigger sample. This for the First difference method but also for the Propensity score matching.

5.2. Subsample and the “pure income effect”

As already explained in section 3.2. it is important to analyse the pure income effect via a selection of the families for which there is no substitution effect (children spending more time in school could lead to parents increasing the number of working hours to compensate the loss). Therefore, for both methods (DID and PSM), the regression is also made only keeping the households that only have children in primary school. So, children from six to twelve years old. Taking this section of the population allows us to make estimations for the transfer if it was unconditional.

It allows to estimate results for an Unconditional Cash Transfer thanks to the pre-existing high level of enrolment and attendance in primary school in Peru. The study made by the MEF show that there is already high percentage of attendance to primary school in Peru.

Secondly because most of the health check-ups are for children younger than 5 years old and for pregnant woman. Let's assume here that when all children are already older than 5, there is lesser chance for a woman to be pregnant. The best solution would have been to drop all households where the woman is pregnant. Assuming being pregnant as a random, exogenous event. The assumption can be wrong and depends of the culture of the country. In many countries, it can be proven that having children is anticipated for most women.

The problem here is that I do not have information on that matter with the two merged datasets. One solution is to delete the households where there is a pregnant woman, but it could make the sample

⁴¹ <https://loentiendo.com/edad-minima-y-maxima-para-trabajar/>

too small. Because of this limit, I chose to assume that the probability of being pregnant, when all children are already older than 5, is lower.

It is not possible to keep households with children in secondary school because as mentioned in the empirical evidence, there are impacts of the transfer on secondary level enrolment and attendance.

Because the assumption of non-separated revenues has been made before, with the Unitary model, the transfer received by the woman is shared with the household. Therefore, it is important to estimate the effects on both woman and man. One big advantage of the data is that there is enough information over women's labour supply.

Finally, after the estimations of this subsample I also analyse the same subsample but only keeping labour supply for men. This because of the simplified assumption made for pregnant woman and to make sure that the results show the effects of an Unconditional Cash Transfer in Peru.

Estimating the results for an Unconditional Cash Transfer has the advantage that the reallocation of work to the task of following the conditions is eliminated. Thanks to this, results can focus on the "pure income effects" of the transfer.

5.3. First Differences (FD)⁴²

There are two possible cases in which the method can be used. This is important because each case imposes different identification conditions. Firstly, when the available data is composed of repeated cross-section observations. Then it is the Difference-in-Difference (DD) estimator that can be used. This is via the estimation of a regression on a period time larger than two. This first option is exposed to the risk of change of the cohort's composition.

The second case is when the available data is a panel. The First Differences (FD) estimator can be used. With this situation the risk of change of the cohort's composition is eliminated thanks to the fact that the sample (cylindric panel, without attrition) is the same for all the periods. It eliminates possible biases linked to non-observed individual fixed effects. In this paper, the data set is a panel. Therefore, the methodology used in this second case is the First Differences.

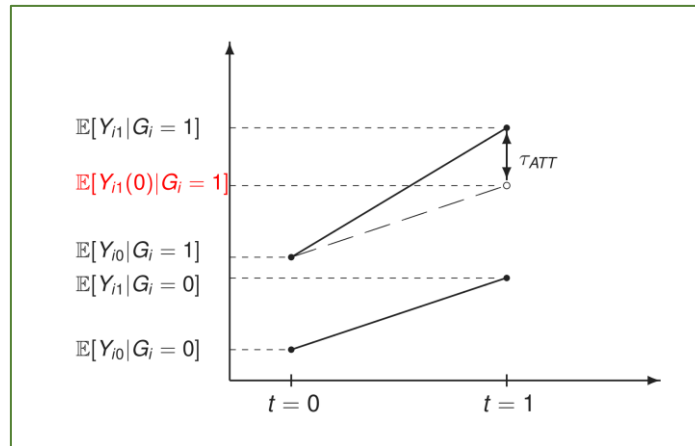
The method consists of taking account for the systematic differences of labour supply of the treatment group and control group. There are two main conditions for this model:

⁴² *Jeffrey M. Wooldridge (2016)*

Assumptions

- Parallel trend assumption. If no transfer, the treatment and control group should follow the same trends of evolution regarding the dependent variable. This means that there should be no effect of time. Their evolution in time must remain parallel if there is no program implementation.

Graph 5: Parallel trend assumption ⁴³



In graph 5, $E[Y_{i0}|G_i = 0]$ is the expected value of the control group ⁴⁴ ($G_i = 0$) in period zero (Y_{i0}). $E[Y_{i1}|G_i = 0]$ is the expected value for the control group ($G_i = 0$) in period one (Y_{i1}). $E[Y_{i0}|G_i = 1]$ is the expected value for the treated group ($G_i = 1$) in period zero (Y_{i0}). $E[Y_{i1}|G_i = 1]$ is the expected value for the treated group ($G_i = 1$) in period one (Y_{i1}). Finally, $E[Y_{i1}(0)|G_i = 1]$ is the estimation of the treated group ($G_i = 1$) in period one (Y_{i1}) if this group was not treated. This last one is not observable but can be estimated.

In the graph 5 one can see how the treatment group would have evolved in the same direction and intensity from period zero to period one if it would not have been treated, as the control group evolved from period zero to period one.

This assumption also implies that before the implementation of the program, there should be no anticipation leading to change of behaviour from probable beneficiaries.

- The second necessary condition is that the program does not affect the control group. Here meaning all those who did not receive the transfer from “Juntos”.

For example, there could be some spill out effects that would make that this condition is not followed. If the treatment group changes their labour supply behaviour because of the program, this could lead to externalities on the control group.

⁴³ Twppwi Yamamoto (2016) ; ATT. For the average treatment effect on treated.

⁴⁴ The control group is the group that do not receive the treatment.

Estimation

The first differences model, for a two years panel data, looks like this:

$$Y_{it} = \beta_0 + \delta_0 d_t + \beta_1 Juntos_{it} + \alpha_i + \mu_{it}, t = 1, 2$$

Individuals are represented by “i” and time is represented by “t”. d_t is equal to one for the t1 (here for the year 2013) and equal to two for t2 (here for the year 2014). α_i are the non-observed and constant factors in time. This is named the fixed effect or individual effect. μ_{it} are the non-observed factors that vary in time. It is named the idiosyncratic effect. Here “Juntos” is a variable equal to one when the individual is part of a household that receives the transfer (this is the treatment group) and “Juntos” is equal to zero when not (this is the control group).

The first difference method allows to delete the individual effect:

$$\begin{aligned} Y_{i1} &= \beta_0 + \beta_1 Juntos_{i1} + \alpha_i + \mu_{i1} \\ Y_{i2} &= \beta_0 + \delta_0 + \beta_1 Juntos_{i2} + \alpha_i + \mu_{i2} \\ \Delta Y_i (Y_{i2} - Y_{i1}) &= \delta_0 + \beta_1 \Delta Juntos_i + \Delta \mu_i \end{aligned}$$

This is how the FD regression would look like:

$$\Delta Y_{work} = \delta_0 + \beta_1 \Delta Juntos_i + \Delta \mu_i$$

The variation of “Juntos” looks like this:

- if the individual was in the control group and becomes eligible (treatment group), then the coefficient β_1 is equal to one;
- if the individual was in the control group and stays in the control group, the coefficient β_1 is equal to zero;
- if the individual was in the treated group (receive the transfer) and stays in the treated group, the coefficient β_1 is equal to zero;
- if the individual was in the treated group (receive the transfer) and stop receiving the transfer, the coefficient β_1 is equal to one.

Here, the impact evaluation is not necessarily done on the effects of receiving the transfer but more generally, the effects of a variation (start receiving the transfer or stop receiving it). After some estimations I concluded that when the population that stop receiving the transfer is not taken into account the results do not change. This is most probably linked to the fact that there are few observations for the households that stop receiving the transfer. Some estimations taking out the

population that stop receiving the transfer are available in Appendix 24. If compared to the results in the following sub-sections, one can see that there is no variation in the conclusions.

Control variables

Control variables need to be introduced to minimize biases linked to omitted variables. Variables that are constant in time cannot be included. These (gender, race, etc.) are part of α_i . Age and Education are the first important control variables. This because the age and the level of education can influence both, the work supply of an agent and the fact of receiving the transfer from “Juntos” (directly or indirectly).

The variable Education is scaled from one being no education to five being higher education (table 2). Adding the control variable “agesquare”, is important because without it, there could be an assumption that there is a linear effect of all ages on the dependent variable. It might be better to also introduce a variable “age-square” into the model to estimate accurately the effect of age, which may have a non-linear relationship with the dependent variable.

The Civil Status is the next control variable here. (1) Having a partner, (2) being married, (3) being a widow/widower, (4) being divorced, (5) separated or (6) being single, can affect the work supply of the agent and the fact of receiving the transfer from “Juntos” (directly or indirectly). Therefore, it is needed to take in account this variable. The values of the variable go from one to six following the order used just before. The relationship with the head of the household can also affect the work supply of an agent and the fact of receiving the transfer. Here the values of this variable are going from one to ten following the order in table 4 (can be found in section 4.2.). The type of work is also included (can also influence the labour supply of an agent and the fact of receiving the transfer). In table 9 one can find the different values of this variable. The values go from one to seven following the order in the table.

Table 9: characteristics of the variable “type of work”

kind of work (principal work)	Freq.	Percent	Cum.
employer or boss	1,582	5.24	5.24
independent worker	12,412	41.13	46.37
employed	5,562	18.43	64.80
labourer	5,188	17.19	81.99
non-paid family worker	4,860	16.10	98.09
domestic worker	464	1.54	99.63
other	112	0.37	100.00
Total	30,180	100.00	

It is interesting to add an interaction variable between Juntos's and the gender to estimate the different impacts of men and women. This because women were given an important role, they receive the transfer. Therefore, there might be some collateral effects of the program on women empowerment. For this we can use partial effects. Note that the variable gender is equal to one if the person is a man and zero if the person is a woman. The estimations can also be done separately for man and woman.

Clusters

Finally, to have a better measure of standard errors, clusters should be implemented. The transfer of "Juntos" was given to a certain type of households, that have similar characteristics. This creates an error linked to the group effect. Therefore, it is needed to control these effects. The clustering is done on the household level and allows the control over all compositional characteristics of households. But the transfer is also given only to the households living in eligible districts. Therefore, the clustering could also be done on the district level. But I have chosen to make the clustering on the highest level possible. It is indeed recommended to use the highest level of clustering. This only fails if there are few clusters at the highest level and the intra-cluster correlation of the predictor is high.

Because we only have control over the household level, there still needs to be a maximum amount of control variables for the individual level.

Here follows the estimation with the number of hours worked per week as dependent variable. This also takes into account the people that do not work (for whom the numbers of hours worked is equal to zero).

$$(1) \Delta Y_{\#hours\ work} = \delta_0 + \beta_1 \Delta Juntos_i + \gamma_2 Juntos * Gender + \beta_3 \Delta Age + \beta_4 \Delta Agesquare + \beta_4 \Delta Education + \beta_5 \Delta Civil\ Status + \beta_6 \Delta Relation\ to\ Head + \beta_7 \Delta Type\ of\ Work + \Delta \mu_i, cluster\ (household)$$

Here follows the estimation for the participation rate in labour market for each agent (extensive margin). The value of ΔY_{work} is equal to zero when the respondent did not work last week and equal to one when he/she did work last week. The used method is the Probit and Logit method because the dependent variable is a binary variable.

$$(2) \Delta Y_{work} = \delta_0 + \beta_1 \Delta Juntos_i + \gamma_2 Juntos * Gender + \beta_3 \Delta Age + \beta_4 \Delta Agesquare + \beta_4 \Delta Education + \beta_5 \Delta Civil\ Status + \beta_6 \Delta Relation\ to\ Head + \beta_7 \Delta Type\ of\ Work + \Delta \mu_i, cluster\ (household)$$

Number of hours of work

Table 10 shows the results for the first equation (1) explained above. It shows the results for all agents in the sample being older than 18 years old. This for the years 2013 to 2014. Let's remember here that the results are for the number of hours of work and includes individuals that do not work.

This regression estimates that there are no significative effects of receiving "Juntos" transfer on the number of hours of work.

The age and type of work have effects at 1% of statistical significative level. Because age-square is significative, it means that the relationship between age and number of hours of work is a decreasing marginal function. For the activity type, interpretation is complicated because of the nature of the variable. The only thing we could say is that the nature of work influences the number of hours worked per week.

The Fisher probability is smaller than 0.01. Fisher tests the null hypothesis "all coefficients of the independent variables are equal to zero". This hypothesis is rejected with more than 99 percent of probability. This means that the model has explicative power of 1% statistical significative level.

Table 10: estimation of number of hours of work for 2013-2014 for all agents older than 18 years old

<pre>. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation > D.activityp, vce(cluster hhid)</pre>						
Linear regression			Number of obs		=	13,648
			F(8, 7417)		=	2.52
			Prob > F		=	0.0098
			R-squared		=	0.0020
			Root MSE		=	21.134
(Std. Err. adjusted for 7,418 clusters in hhid)						
Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.76663	1.32904	0.58	0.564	-1.838666	3.371926
DJUNTOS_fem	.4411419	1.771531	0.25	0.803	-3.031561	3.913845
age						
D1.	1.422534	.54999	2.59	0.010	.344397	2.50067
agesquare						
D1.	-.0137933	.0049606	-2.78	0.005	-.0235175	-.0040691
educ						
D1.	.2988547	.4619389	0.65	0.518	-.6066766	1.204386
Dciv	-.1535405	.306695	-0.50	0.617	-.7547497	.4476688
hhrelation						
D1.	.2714387	.351762	0.77	0.440	-.4181147	.9609921
activityp						
D1.	.6508496	.1935453	3.36	0.001	.2714459	1.030253
cons	-.213604	.2692181	-0.79	0.428	-.7413479	.3141399

There might be a problem linked to not enough variation for some variables. For example, people do not change that easily the nature of their work from one year to another, this because of a certain level of specialization linked to their activity. The small variation leads to a small standard error, if the variation is too small, it makes it impossible to estimate the effect with precision.

The same problem could exist for the estimation of the effects of “Juntos” on the number of hours of work of individuals. In the Appendix 25, one can find tables where the variation of these variables is displayed. As expected, the variation for the education, the kind of work, the civil status and the relationship to the household are low. Regarding the variation of the variable “Juntos”, in Appendix 25 one can see that there is enough variation.

To remain precautionary, it may be better to not make any precipitated conclusions yet. The same estimation has been done for the years 2013 to 2015 and for 2014 to 2015. The results are available in [Appendix 7](#). The results for these years stay the same regarding “Juntos”, differ for age but not for activity type, which always remain statistically significant. This is bad news for the robustness of the estimation and could be linked to the lack of variation as specified before.

To not make any mistakes linked to too highly correlated explicative variables in the next estimations, collinearity is checked in table 11.

Table 11: Collinearity check

. vif		
Variable	VIF	1/VIF
agesquare		
D1.	9.01	0.110932
age		
D1.	9.01	0.110936
DJUNTOS	2.08	0.481731
DJUNTOS_fem	2.08	0.481752
Dciv	1.00	0.997047
activityp		
D1.	1.00	0.998391
educ		
D1.	1.00	0.998811
hhrelation		
D1.	1.00	0.998896
Mean VIF	3.27	

The variance inflator factor (VIF)⁴⁵ is a widely-used diagnostic for multicollinearity. VIF is $\frac{1}{1-R^2}$ and estimates how much the variance of a coefficient is “inflated” because of linear dependence with other

⁴⁵ *Paul Allison (2012)*; * *Help Stata – VIF: “Uncentered requests that the computation of the uncentered variance inflation factors. This option is often used to detect the collinearity of the regressors with the constant. estat vif, uncentered may be used after regression models fit without the constant term.*

predictors. The higher the VIF, the bigger the coefficient would be if the predictor would be completely uncorrelated with all other predictors. VIF has a lower bound of 1 and no upper bound. Scholars have different opinions on when the VIF starts to constitute a problem. For this paper, I decided to set it to 2.5 (as Paul Allison did in 2012), this corresponds to an R^2 of 0.60 with the other variables.

There is high collinearity for the variables “age” and “age-square”. This is not something to be concerned about as *Paul Allison (2012)* explains, because the high VIFs here are caused by inclusion of powers of other variables and the p-values are not affected by it. This is the case for the variables “age” and “age-square”, “Juntos” and “Juntos_fem”. “Juntos_fem” is the interaction variable “Juntos*Gender”.

In conclusion, even though results might suggest that the transfer has no effect on labour supply, to remain precautionary, it may be better to not make any precipitated conclusion yet. It is better to first have a look on other results found with another methodology. Next sub-session uses the same regression but with a logged labour supply (number of hours of work).

Intensive margins

Now the same estimation can be found in table 12 but with the dependent variable changed to a logarithmic variable. This to decrease the impact of extreme observations. Equation (3) is the estimation.

$$(3) \Delta \log Y_{\#hours\ work} = \delta_0 + \beta_1 \Delta Juntos_i + \gamma_2 Juntos * Gender + \beta_3 \Delta Age + \beta_4 \Delta Agesquare + \beta_4 \Delta Education + \beta_5 \Delta Civil\ Status + \beta_6 \Delta Relation\ to\ Head + \beta_7 \Delta Type\ of\ Work + \Delta \mu_i, cluster\ (household)$$

In the section on summary statistics, it was shown that there is a high upper bound of number of hours worked for some observations. These extremes could drive some results. One important fact that needs to be highlighted is that transforming the dependent variable in a logarithmic variable eliminates the observations for which the value is zero. We are only focusing on the population that is participating in the labour market. Results can only be interpreted for this population and can be called now the intensive margins of labour supply. Also, the interpretation of the results differs because of the use of logged independent variables.

Interpretation of table 12 follows the following logic: If the explicative variable X increases 1 unit, the variation on the dependent variable Y is approximatively equal to (100*Coefficient of X) %. But only if the p-value and the t-stat of the coefficient shows that there is a statistical significative effect.

Results of table 12 do not differ from the previous estimation (table 10). There is statistical significance on the average impacts of age and activity on the number of hours of work per week. The Fisher probability is smaller than 0.01. This means that the model has an explicative power of 1% statistical significance level. The Results for the years 2013 to 2015 and for 2014 to 2015 are available in **Appendix 8**. The results for these years differ only for education, which is not significant here but significant for the two other estimations. This is already better than the estimation made before. Estimations linked to the transfer remain the same. It seems that receiving the transfer has no impact on the number of hours worked per week for the principal work. Remember that only the population that is participating in labour market are represented. The conclusion remains the same: to remain precautionary, it may be better to not make any precipitated conclusion yet. Next sub-section is an estimation for the dichotomic dependent variable, the participation rate.

Table 12: estimation of logged intensive margins for 2013-2014 for all agents older than 18 years old

<pre>. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelati > on D.activityp, vce(cluster hhid)</pre>						
Linear regression			Number of obs		=	13,089
			F(8, 7256)		=	6.67
			Prob > F		=	0.0000
			R-squared		=	0.0065
			Root MSE		=	.77115
(Std. Err. adjusted for 7,257 clusters in hhid)						
Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.0251856	.053248	0.47	0.636	-.0791959	.1295672
DJUNTOS_fem	.0550391	.0722432	0.76	0.446	-.0865786	.1966568
age D1.	.0649783	.0206903	3.14	0.002	.0244192	.1055374
agesquare D1.	-.0006374	.0001927	-3.31	0.001	-.0010152	-.0002595
educ D1.	.0126353	.0158068	0.80	0.424	-.0183507	.0436213
Dciv	-.0114302	.010589	-1.08	0.280	-.0321877	.0093273
hhrelation D1.	-.0090559	.0125633	-0.72	0.471	-.0336835	.0155718
activityp D1.	.0492763	.0079242	6.22	0.000	.0337426	.0648101
cons	.0020932	.009564	0.22	0.827	-.016655	.0208414

Extensive margins

For now, it looks like the model has no impacts on the number of hours of work per week. Same for the intensive margins of labour supply. Now it is also important to check if there are no impacts on the

extensive margins. Meaning, analyse whether there are impacts of the governmental transfer “Juntos” on the participation rate of agents in the labour market. The estimation is the equation (2) mentioned above.

One can see on table 13 that available variable for participation rate is the answer to the question “did you work last week?”. The answer can only be yes or no for this is a dichotomic variable. I recoded the values so that if the answer was “no”, its linked value would be zero and when the answer is “yes”, it would be one.

Table 13: possible values for the variable “worklw” representing participation rate in the labour market

RECODE of lwwork (last week has a job?)	Freq.	Percent	Cum.
no	10,194	27.06	27.06
yes	27,475	72.94	100.00
Total	37,669	100.00	

This type of dependent variable needs a probit and logit model to estimate correctly the different effects of the independent variables. Given modern computers and available computer software (here I used Stata), the most difficult aspect of probit and logit model is presenting and interpreting the results. The coefficients give the sign of the partial effect of each explicative variable on the response probability. The statistical significance of each explicative variable, as for other models, is determined by whether we can reject the null hypothesis (coefficient of explicative variable equal to 0) at enough small significative level. This via the t-stat and the p-value. The average partial effects (APE) is the average variation of the conditional probability (z-score) of the dependent variable changes when the explicative variable changes, Ceteris Paribus. For the probit and logit model, the APE is not equal to the estimated coefficient via the regression. It depends of the values of the other estimated coefficients. In Stata, the command margins used after the regression provides for the average partial effects. Stata uses default choices of the coefficients.

Nevertheless, the average partial effect is small. The position in the household (hhrelation) also is statistically significant but small.

This estimation is also made with the logit model to compare results. This can be found in [Appendix 9](#). Results are similar, which is a good sign for the robustness. The model is also estimated for the years 2013 to 2015 and 2014 to 2015 in [Appendix 10](#). Results do not differ in a preoccupant way. The

The chi-two Wald probability is high. This test is a test of joint significance and would mean that the model is has no explicative power. This is logical because there are few significative coefficients.

Table 14: PROBIT estimation of extensive margins for 2013-2014 for all agents older than 18 years old

```
. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activitytyp,
> vce(cluster hhid)

Iteration 0:    log pseudolikelihood = -4737.0137
Iteration 1:    log pseudolikelihood = -4731.5103
Iteration 2:    log pseudolikelihood = -4731.4961
Iteration 3:    log pseudolikelihood = -4731.4961

Probit regression                               Number of obs   =       13,648
                                                Wald chi2(8)      =        11.62
                                                Prob > chi2       =         0.1688
Log pseudolikelihood = -4731.4961              Pseudo R2        =         0.0012

                                     (Std. Err. adjusted for 7,418 clusters in hhid)

+-----+-----+-----+-----+-----+-----+-----+
| Dworklw |          Robust          | z | P>|z| | [95% Conf. Interval] |
|          | Coef.   Std. Err.      |   |      |          |
+-----+-----+-----+-----+-----+-----+
| DJUNTOS | .1567838 | .1047367 | 1.50 | 0.134 | -.0484963 | .3620639 |
| DJUNTOS_fem | -.3531175 | .1495425 | -2.36 | 0.018 | -.6462153 | -.0600196 |
|          |          |          |      |      |          |          |
| age     |          |          |      |      |          |          |
| D1.     | -.0224016 | .0376091 | -0.60 | 0.551 | -.0961141 | .0513111 |
| agesquare |          |          |      |      |          |          |
| D1.     | .0002999 | .0003502 | 0.86 | 0.392 | -.0003865 | .0009862 |
| educ    |          |          |      |      |          |          |
| D1.     | .0402524 | .0361622 | 1.11 | 0.266 | -.0306242 | .1111129 |
| Dciv    | .0145434 | .0228938 | 0.64 | 0.525 | -.0303277 | .0594144 |
| hhrelation |          |          |      |      |          |          |
| D1.     | .0385729 | .0226811 | 1.70 | 0.089 | -.0058813 | .0830271 |
| activitytyp |          |          |      |      |          |          |
| D1.     | -.0069121 | .0148677 | -0.46 | 0.642 | -.0360523 | .0222281 |
| cons    | -1.229429 | .0196498 | -62.57 | 0.000 | -1.267942 | -1.190916 |
```

Table 15: *PROBIT estimation of extensive margins (2013-2014). Individuals > 18 years old. Average partial effects*

. margins, dydx(*)						
Average marginal effects			Number of obs		= 13,648	
Model VCE : Robust						
Expression : Pr(Dworklw), predict()						
dy/dx w.r.t. : DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activitytp						
	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.0295001	.0197116	1.50	0.135	-.0091339	.0681342
DJUNTOS_fem	-.0664419	.0281576	-2.36	0.018	-.1216298	-.011254
age						
D1.	-.004215	.0070746	-0.60	0.551	-.0180809	.0096509
agesquare						
D1.	.0000564	.0000659	0.86	0.392	-.0000727	.0001855
educ						
D1.	.0075738	.0068035	1.11	0.266	-.0057607	.0209083
Dciv	.0027364	.0043079	0.64	0.525	-.0057069	.0111798
hhrelation						
D1.	.0072578	.0042683	1.70	0.089	-.0011078	.0156234
activitytp						
D1.	-.0013006	.0027971	-0.46	0.642	-.0067827	.0041816

One can see in table 14 and 15 that the results of the estimation are statistically significant. Negative effects of receiving “Juntos” on men (the variable gender is equal to 0 for women and 1 for men).

All estimations made until now were for all adults in the household. Therefore, the impacts of the transfer on older children still living in the household are also taken into account in the estimations. In [Appendix 11](#), one can find estimations made only for the head of the household and his/her partner. These results do not differ from most results estimated above. Only the estimation via the probit and logit differ in one important aspect: the interaction variable “Juntos_fem”. Between 2013 to 2014 the interactive variable is still statistically significant but only on a 10% level. Between 2013 to 2015 it is significant on 5% level. The estimation from 2014 to 2015 finds no significant result.

To conclude: until now results show a similar trend, which is that the governmental transfer “Juntos” might have a small, but significant negative impact on participation rate. There seems to be no result regarding the number of hours of work and for the intensive margins of labour supply. For now, it is better to remain cautious and not make any precipitated conclusions yet. We can keep these results in mind to check whether next estimations follow the same trends. But then again, without the robustness checks, these results cannot be considered as non-biased estimation and existent causal effects.

Estimations for the Subsample

As explained above in the section for all used models, I estimated the results in a subsample. This subsample is constituted of the households for whom all children are in primary school, aged between six and twelve years old. As stipulated before, this enables to compare the pre-existing results to the estimations of the subsample, which represents the part of the population for whom there are no conditionalities. Therefore, estimations of the subsample allow to analyse whether there is an “income effect” or not. All following results are for the head of the household and his/her partner. Firstly, the model with as dependent variable the number of hours of work (equation (1)).

In table 16, just like in previous results, the estimation shows no impacts of “Juntos” on the numbers of hours of work. This when “Juntos” can be considered unconditional for these households. [Appendix 12](#) estimates the same model for subsamples of the years 2013 to 2015 and 2014 to 2015. The results are similar, for there is no statistically significant effect of the transfer on labour supply. The Fisher probability is smaller than 0.01 which means that the model has explicative power on 1% statistical significant level. In [Appendix 13](#), the estimation is made only for men. The results do not differ. All results of this estimation suggest that there is no “income effect” linked to the transfer.

Table 16: estimation od number of hours of work for 2013-2014 for all agents in the subsample older than 18 years old

<pre>. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D > .activityp, vce(cluster hhid)</pre>						
Linear regression			Number of obs	=	3,392	
			F(8, 2085)	=	2.92	
			Prob > F	=	0.0030	
			R-squared	=	0.0085	
			Root MSE	=	21.592	
(Std. Err. adjusted for 2,086 clusters in hhid)						
Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.5945765	2.426645	0.25	0.806	-4.164322	5.353475
DJUNTOS_fem	-.5971688	3.393259	-0.18	0.860	-7.251697	6.05736
age D1.	2.426213	1.382831	1.75	0.079	-.2856591	5.138086
agesquare D1.	-.0240705	.0139398	-1.73	0.084	-.0514078	.0032669
educ D1.	1.712118	1.069251	1.60	0.109	-.3847931	3.809029
Dciv	-.017981	.9743565	-0.02	0.985	-1.928794	1.892832
hhrelation D1.	.1552969	3.652182	0.04	0.966	-7.007005	7.317599
activityp D1.	1.666127	.3777057	4.41	0.000	.9254079	2.406847
_cons	-.4371656	.6144649	-0.71	0.477	-1.642194	.767863

In table 17 one can find the estimation for the same subsample with a logged dependent variable as already done previously (equation (3)). This estimation has the same results as the estimation of table 16 regarding the impacts of “Juntos” on labour supply. [Appendix 14](#) estimates the same model for the years 2013 to 2015 and 2014 to 2015. Both results are stable. This also suggests that there is no income effect. The Fisher probability is smaller than 0.05 which means that the model has an explicative power of 5% statistical significative level. One important fact here that needs to be highlighted is that the results for the logged depended variable for the whole population had overall similar results. [Appendix 15](#) shows the results only for man. These estimations also show no significative impact of the transfer “Juntos” on the number of hours of work per week. Again, all this suggests that there is no income effect of the transfer.

Table 17: estimation of intensive margins (2013-2014) - agents in the subsample older than 18 years old

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelatio
> n D.activityp, vce(cluster hhid)
```

Linear regression	Number of obs	=	3,255
	F(8, 2042)	=	4.46
	Prob > F	=	0.0000
	R-squared	=	0.0154
	Root MSE	=	.80006

(Std. Err. adjusted for 2,043 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.047879	.0926139	0.52	0.605	-.1337484	.2295065
DJUNTOS_fem	-.0136606	.1428035	-0.10	0.924	-.2937164	.2663952
age						
D1.	.0746898	.0514848	1.45	0.147	-.0262783	.1756579
agesquare						
D1.	-.0007639	.0005323	-1.44	0.151	-.0018078	.00028
educ						
D1.	.055615	.037572	1.48	0.139	-.0180684	.1292984
Dciv	.0266082	.031402	0.85	0.397	-.0349751	.0881916
hhrelation						
D1.	.0483226	.1421364	0.34	0.734	-.2304248	.32707
activityp						
D1.	.0878938	.0157504	5.58	0.000	.0570052	.1187824
_cons	-.0023746	.0229176	-0.10	0.917	-.0473189	.0425696

Finally, in table 18 and 19, the estimation on the participation rate (equation (3)). The estimation shows no statistically significant impact of “Juntos” on the participation rate, nor for women nor for man. In [Appendix 16](#), one can find the same estimates for the years 2013 to 2015 and 2014 to 2015. The chi-two Wald probability is high. This test is a test of joint significance and would mean that the model is has no explicative power. This is logical because there is no significative coefficient.

Results are following a similar trend for all estimations. This is important because the results here differ from the results made via the estimation for the whole sample. This would mean that the negative impacts of “Juntos” on the average working hours per week for men is most probably not linked to income effects.

Table 18: *PROBIT estimation of extensive margins for 2013-2014 - agents in the subsample older than 18 years old*

```
. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(c
> luster hhid)
```

Iteration 0: log pseudolikelihood = -1097.8396
Iteration 1: log pseudolikelihood = -1093.879
Iteration 2: log pseudolikelihood = -1093.8705
Iteration 3: log pseudolikelihood = -1093.8705

Probit regression

Number of obs = 3,392
Wald chi2(8) = 8.84
Prob > chi2 = 0.3563
Pseudo R2 = 0.0036

Log pseudolikelihood = -1093.8705

(Std. Err. adjusted for 2,086 clusters in hhid)

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.2370905	.1801703	1.32	0.188	-.1160368	.5902178
DJUNTOS_fem	-.1698326	.2717626	-0.62	0.532	-.7024774	.3628122
age						
Dl.	.1234582	.0976605	1.26	0.206	-.0679529	.3148693
agesquare						
Dl.	-.0012285	.0010025	-1.23	0.220	-.0031934	.0007364
educ						
Dl.	.0600826	.0815992	0.74	0.462	-.0998489	.2200142
Dciv	.1345509	.0689874	1.95	0.051	-.0006619	.2697637
hhrelation						
Dl.	.2358651	.2244979	1.05	0.293	-.2041426	.6758729
activityp						
Dl.	-.0245813	.0319936	-0.77	0.442	-.0872877	.0381251
_cons	-1.316762	.0379326	-34.71	0.000	-1.391108	-1.242415

Table 19: *PROBIT estimation of extensive margins for 2013-2014 for all agents in the subsample older than 18 years old. Average partial effects*

```
. margins, dydx(*)
```

Average marginal effects

Model VCE : Robust

Number of obs = 3,392

Expression : Pr(Dworklw), predict()

dy/dx w.r.t. : DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.041269	.0313369	1.32	0.188	-.0201502	.1026882
DJUNTOS_fem	-.0295618	.0473087	-0.62	0.532	-.1222851	.0631616
age						
Dl.	.0214897	.0170069	1.26	0.206	-.0118433	.0548226
agesquare						
Dl.	-.0002138	.0001746	-1.22	0.221	-.000556	.0001283
educ						
Dl.	.0104582	.0142103	0.74	0.462	-.0173934	.0383098
Dciv	.0234205	.0120077	1.95	0.051	-.0001142	.0469552
hhrelation						
Dl.	.0410557	.0390907	1.05	0.294	-.0355607	.117672
activityp						
Dl.	-.0042787	.0055677	-0.77	0.442	-.0151913	.0066338

In *Appendix 17*, one can find the logit estimation. Results via this model are really close to those found with the probit model. This is good news for the robustness. *Appendix 18* show the results for man only. Two out of the three estimations follow the same trend just as above. Nevertheless, for the years 2013-2014 there is a positive, statistically significant impact of the transfer on men's participation rates. This result might however be biased because of the small number of observations.

5.4. Propensity Score Matching

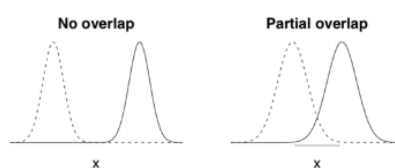
Because the assignment of the transfer depends on individual characteristics, the selection bias disappears if X is correctly controlled. To control it, both matching and propensity score matching can be used. The fundamental principle of these methods is to match every treated observation to a non-treated observation, with similar characteristics.

These two methods rely on two main assumptions: the conditional-independence assumption and the overlap assumption.

Assumptions

- The conditional-independence stipulates that after controlling the characteristics X , there is no heterogeneity bias anymore. The common variables that affect both the treatment assignment and the treatments' specific outcomes are controlled thanks to observed variables. The unobserved variables can only become problematic if they are correlated to the outcomes and to the characteristics X . The big difficulty linked to this assumption is that we need enough available control variables. It also created an issue linked to the dimensionality (how close are the observations to each other, which distance?). The solution is to use a propensity score matching (PSM) that adjusts the differences between the two populations based on their propensity score (conditional probability to be treated).
- The overlap assumption requires that both the treated and the control group, must have minimum similarities. They need to overlap for some of their characteristics.

Graph 6: Overlap assumption ⁴⁶



⁴⁶ <https://statmodeling.stat.columbia.edu/2018/11/10/matching-discarding-non-matches-deal-lack-complete-overlap-regression-adjust-imbalance-treatment-control-groups/>

Estimation

In practice, the propensity score matching is implemented with as a first step, the estimation of the Average Treatment effect (ATE). The ATE is done via the matching distance h . While it allows to decrease the selection bias, the comparison with experimental methods shows that for most cases, a bias subsists.

The Kernel Matching could be used, it gives more weight to closer observations. $K(Z)$ is the variable that is equal to 0 when Z (the distance) is too high, $Z > 1$. If not, $K(Z)$ equals to 1. P is the propensity score.

$$Z = \frac{p_i - p_j}{h}$$

After this, we estimate the MCO with a ponderation of the found weights for each pairing. If $K(Z)$ is high, these individuals have a higher weight in the estimation. A trade-off needs to be done between having less bias but having not enough variation.

The main difficulty is to compute the optimal h . To test the robustness the h can be changed a bit and if the results vary a lot It means that the results are not robust. If this happens, the X , variables of control, need to be changed. This because of the conditional-independence assumption.

Control variables

The equation (4) is the model of the estimation. To choose the control variables, I used the same logic as for the control variables introduced in equation (1) for the First Differences estimation. The difference here is that constant variables can be added. Therefore, the control variable mother tongue is added here. The paper of *Dearden, Emmerson, Frayne and Maghir (2009)* was also a useful example. This paper analyses a Conditional Cash Transfer and uses as Matching variables income of the household, education of parents and children, health issues, childcare used, mobility, ...

The results of this estimation via the propensity score matching method are displayed in table 20. The estimation finds a significative negative impact of the program on the average number of hours worked for men. And a positive one for women.

This result does not match with the result found before via the first difference model. The significance of the result here is at 1 percent statistical level. The same estimation for 2013 to 2015 and for 2014 to 2015 are available in *Appendix 19*. These estimations all have similar results. This is good news for the internal validity of the model.

The chi-two Wald probability is smaller than 0.01. This test is a test of joint significance and would mean that the model is has explicative power on statistical level of 1 percent. This is logical because there are few significative coefficients. In [Appendix 20](#) the same estimation is made but the value of h is changed. This to test the internal validity of the model. Estimations are stable with this change which is good news.

Number of hours of work

$$(4) \Delta Y_{\#hours\ work} = \delta_0 + \beta_1 Juntos_i + \gamma_2 Juntos * Gender + \beta_3 Gender + \beta_4 Age + \beta_5 Agesquare + \beta_6 Education + \beta_7 Mothertongue + \beta_8 Civil\ Status + \beta_9 Relation\ to\ Head + \beta_{10} Type\ of\ Work + \beta_{11} geographic\ ubication + \Delta\mu_i$$

Table 20: PSM estimation of number of hours of work for 2013-2014 for all agents older than 18 years old.

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)</pre>						
Probit regression			Number of obs		=	30,174
			LR chi2(11)		=	359.11
			Prob > chi2		=	0.0000
Log likelihood = -3131.8482			Pseudo R2		=	0.0542
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.1761527	.103972	1.69	0.090	-.0276287	.3799342
Juntgen	-.3777927	.1185445	-3.19	0.001	-.6101357	-.1454498
gender	.0436605	.0363743	1.20	0.230	-.0276318	.1149528
age	-.0267388	.0067955	-3.93	0.000	-.0400576	-.0134199
agesquare	.0001841	.0000683	2.70	0.007	.0000503	.0003179
educ	-.2656636	.0186177	-14.27	0.000	-.3021537	-.2291736
mothertongue	.0406623	.0143465	2.83	0.005	.0125437	.0687809
CIV	.0089598	.0103828	0.86	0.388	-.0113901	.0293096
hhrelation	.0449893	.0174225	2.58	0.010	.0108418	.0791367
activitytype	.0628651	.0155665	4.04	0.000	.0323553	.0933749
estrato	-.0174502	.0080255	-2.17	0.030	-.0331799	-.0017205
_cons	3.371705	.2114996	15.94	0.000	2.957174	3.786237
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.128712871	.106321839	-.001884775	.000093297	-20.20
	ATT	.128712871	.11881105	.009901821	.035653058	0.28

In [Appendix 21](#), the same estimation is made except for keeping the head of the household and his/her partner. This to eliminate the possible variation of results linked to the children that are old enough to work but are still living in the household. The trend of the results is also stable in these results, but the coefficient for the interactive variable “Juntgen” is bigger. “Juntos” has even more negative effects on the number of hours of work for the head of household and his/her partner.

Estimations for the subsample

Table 21 shows the results for the subsample, constituted by the households with children between 6 and 12 years old and in primary school. This allows to focus on the possible income effects linked to the transfer. The following estimation is for the years 2013 to 2014.

The estimation still finds an average negative impact of “Juntos” on the number of hours of work for men at a 5% of statistical significative level. Also, the coefficient of the interactive variable “Juntgen” is here lower than for the estimation for the whole population. Note that in the subsample only the head of the family and the partner are taken into account.

Table 21: PSM estimation of number of hours of work for 2013-2014 for all agents of the subsample older than 18 years old.

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)</pre>						
Probit regression			Number of obs		=	8,579
			LR chi2(11)		=	82.00
			Prob > chi2		=	0.0000
Log likelihood = -878.35279			Pseudo R2		=	0.0446
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.0641204	.1437466	0.45	0.656	-.2176178	.3458586
Juntgen	-.3160583	.1614988	-1.96	0.050	-.6325902	.0004735
gender	-.0052361	.1244464	-0.04	0.966	-.2491466	.2386743
age	-.0530263	.0224222	-2.36	0.018	-.0969729	-.0090796
agesquare	.0005333	.0002351	2.27	0.023	.0000725	.0009941
educ	-.1857614	.0351841	-5.28	0.000	-.2547209	-.1168019
mothertongue	.0582182	.0249636	2.33	0.020	.0092904	.1071461
CIV	-.0430799	.0362475	-1.19	0.235	-.1141237	.0279638
hhrelation	.157533	.1266435	1.24	0.214	-.0906837	.4057498
activityp	.0379247	.0296084	1.28	0.200	-.0201068	.0959562
estrato	.0084555	.0157585	0.54	0.592	-.0224306	.0393415
_cons	3.452944	.6022839	5.73	0.000	2.272489	4.633399
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.194444444	.255208333	-.003506072	.000221464	-15.83
	ATT	.194444444	.249942346	-.055497902	.074145733	-0.75

In [Appendix 22](#), one can find the results for other years and with other values for h. The results remain stable. In [Appendix 23](#), the estimations are made for men and the results follow the same trend.

In conclusion, via the propensity score matching model, it seems that there are negative impacts on the intensive labour margins, for men.

5.5. Robustness check

Internal validity

The internal validity consists of minimizing all biases that can appear via the chosen methodology. Firstly, to have greater internal validity, all estimations were made for the three different periods (2013 to

2014; 2014 to 2015; 2013 to 2015). For most estimations, results for these three periods follow the same trends. This is already good news.

Secondly, to ensure the internal validity of an estimation, the assumptions made by the used methodology need to be verified. For the First Differences method, it is both the common trend assessment and the treatment group not affecting the control group that need to be verified. For the Propensity Score Matching method, it is the conditional-independence and the overlap assumption that need to be verified.

First Differences

The common trend assessment is a necessary condition for the use of the First Difference methodology. To verify the common trend assessment, the evolution of the control group and the treatment group are analysed before the treatment group receives the treatment. Here, this can be done via the outcomes for the population that started receiving the transfer “Juntos” in 2014 before for the years before they received it (2011 to 2013) with the population that never receives the transfer from “Juntos”. If for the variable of interest (labour supply), both populations follow similar trends, it means that the estimation should be robust at this point.

For this, some tables are available in the [Appendix 25](#). In these tables one can see that the control group and treatment group before being treated do not necessarily follow the same trends. This would mean that the results obtained via the First Difference method can not be interpreted and that the method should not have been used in the first place. But as one can see in the tables there is no big amount of observations available for the treated for one year and neither for the rest. This could lead to a biased information over the common trend assessment.

There are different possible explanations for this why an estimation does not follow the common trend assessment. One of the reasons could be, for example, that poor react in a different way to economic shocks than the rest of the population because they have less security money (savings).

The conclusion here, regarding the common trend assessment, is that one should test this assumption before even starting the estimations. I consider that as one of my biggest mistakes. This is something I will certainly keep in mind when working on other projects like this one.

The second necessary condition for the utilization of the First Differences method is that the program does not affect the control group. In order to control the “spill out” effects of the transfer “Juntos”, one should study the impacts on the whole district. For this test there is a need of random variations. The robustness check is not possible here because the whole program is based on a specific targeting of the population.

The conclusion regarding the two conditions of the First Difference method is that the results cannot be generalized nor trusted. Moreover, as said in section 5.3, there is also a problem in the estimations linked to not enough variation for some variables (Appendix 25). The small variation leads to a small standard error, if the variation is too small, it makes it impossible to estimate the effect with precision.

To remain precautionary for any kind of mistaken results, I prefer to say that the estimations made via the First Difference method are most probably biased. However, this should not be considered as a failure. Trying out and using the method thought me a lot. It thought me how to use it in the software STATA, how to interpret the results and how to test for its robustness.

Now follows the robustness check for the second methodology used, the Propensity Score Matching.

Propensity Score Matching

The first assessment that needs to be controlled is the conditional-independence assumption which relies on the chosen control variables. In the estimation (4), all possible and available control variables were used. This condition is unfortunately untestable. Estimating the model numerous times for different years and changing the value of “h” can provide an idea of the accuracy of the estimations. However, if the results remain stable, it is good news for the internal validity of the estimations. For these results, this is exactly the case, which is positive.

In order to test the quality of the match (balancing of the variables after the matching), one can use the “pstest”⁴⁷ in the software STATA after the estimation. In table 22, one can find the “pstest” for the estimation of table 20. The balance is checked considering the next three points:

- the t-tests for the equality of means in the treated and non-treated groups, both before and after the matching: for good balancing, these should be non significant after matching. Unfortunately, in table 22, all t-test are significant;
- the standardized bias before and after the matching (formulae from Rosenbaum and Rubin, 1985): this should be less than 5 percent after matching. In table 22 the variables “CIV”, “hhrelation” and “estrato” have biases that are higher than 5 percent which is bad news;
- the summary option outputs some diagnostics of covariate balancing before and after matching. The average percentage of the absolute bias before matching was 20.6 percent. After the matching it became 16.7 percent. This means that the matching reduces the bias starting unbalancing but not good enough because it should be smaller than 5 percent.

⁴⁷ Leonardo Grill and Carla Rampichini (2011)

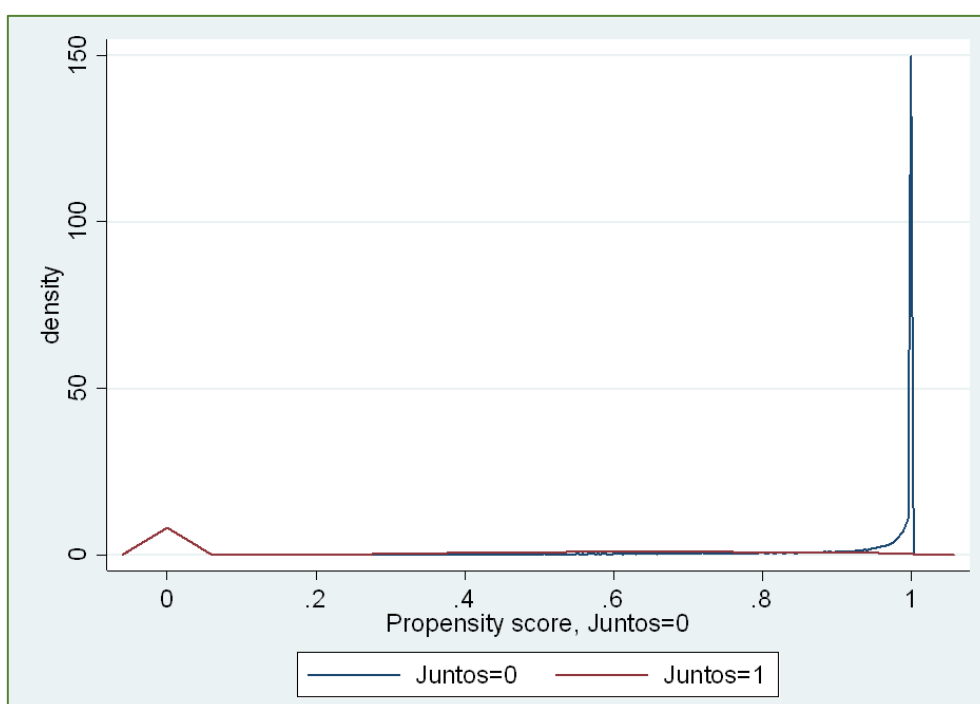
Table 22: “pptest” of PSM estimation in table 20 for all agents older than 18 years old.

. pptest gender age agesquare educ mothertongue CIV hhrelation activityyp estrato, both								
Variable	Unmatched Matched	Mean Treated Control		%bias	%reduct bias	t-test t p> t		V(T) / V(C)
gender	U	.43564	.58621	-30.4		33.01	0.000	.
	M	.43564	.59858	-32.9	-8.2	124.28	0.000	.
age	U	44.941	47.379	-16.2		-12.63	0.000	1.42
	M	44.941	46.509	-10.4	35.7	-68.77	0.000	1.27
agesquare	U	2283.9	2432.8	-9.9		-16.19	0.000	1.32
	M	2283.9	2371.4	-5.8	41.3	-88.33	0.000	1.17
educ	U	3.2376	3.8491	-54.0		25.25	0.000	0.78
	M	3.2376	3.6427	-35.8	33.8	141.67	0.000	0.77
mothertongue	U	3.297	3.273	1.9		8.74	0.000	0.96
	M	3.297	3.2524	3.6	-85.6	90.54	0.000	0.93
CIV	U	2.901	2.6624	13.3		-1.42	0.155	1.24
	M	2.901	2.7036	11.0	17.3	-37.59	0.000	1.18
hhrelation	U	1.9109	1.6796	18.3		-4.58	0.000	1.44
	M	1.9109	1.7336	14.0	23.4	-24.02	0.000	1.27
activityyp	U	2.4851	2.7141	-21.5		-11.29	0.000	2.54*
	M	2.4851	2.6935	-19.5	9.0	-123.76	0.000	2.26*
estrato	U	4.7525	4.3075	19.6		-38.45	0.000	0.93
	M	4.7525	4.3639	17.1	12.7	-248.39	0.000	0.88
* if variance ratio outside [0.67; 1.48] for U and [0.67; 1.48] for M								
Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.052	346.21	0.000	20.6	18.3	68.1*	0.94	13
Matched	0.010	20.51	0.015	16.7	14.0	31.8*	1.32	13
* if B>25%, R outside [0.5; 2]								

In conclusion here, the matching helps to reduce biases but could have been better. The solutions to this would have been to change the matching method (here the method used is the Kernel matching) in which all treated units find a better match. Another possibility is to change the propensity score matching (choose other control variables for example) and redo the estimation. Here again, I should have tested this beforehand in order to test the different solutions.

Finally, to test the overlap assumption, the best method is to make a histogram with the treated and control group with the control variables that are used in the estimation. If the histogram shows an overlap between both groups' characteristics, it means that the estimations should be robust at this point. Graph 7 shows that there is enough overlap between the control and the treatment group.

Graph 7: overlap between the control group and the treatment group.



Other possible biases

As already explained, throughout the document, there are missing pieces of information about certain important aspects of the “Juntos” program. The following pieces of information were incomplete (not available on the web or via contacts working for “Juntos”).

- Since 2013 more districts were gradually becoming eligible. All gathered information would lead to assume that this expansion is due to the increasing financial capacity of “Juntos”. More information on how the districts were chosen would have been welcome.
- The eligible districts must fulfil all characteristics, this via pre-determined thresholds. It could be that some districts, for whom almost all conditions are fulfilled, try to adjust in order to become eligible. More information on how the program avoids these kinds of responses would have been needed.
- There could be political bargaining from the districts to become eligible. This should have been proven wrong.
- More information would have been welcome on whether there is monitoring of the households that stop receiving the transfer. Also, there should be information on whether the program takes in account the fact that some households, close to the fulfilment of the eligibility conditions, might change their behaviours in order to become eligible.
- Finally, it is not clear whether mother spending hours doing domestic work is taken into account.

External validity

The external validity refers to the possible generalization of the results. Firstly, if the internal validity is not present then it is impossible to extrapolate the results. Secondly, even if there is good internal validity, results can be specific to the environment, meaning the economical, the cultural, the geographical and epigraphical context in which the program exists. For example, here, since the transfer is only given to poor, it is not precatious to extrapolate the results to all the population.

In conclusion, the results found in this paper cannot be used to explain, predict or assume impacts of a similar program in another context. Still, it is interesting to analyse the impacts of this program in this specific context. If by luck, all other existing literature for similar programs in different contexts find similar results, then maybe a generalization could be done.

In conclusion for this section, the results found via the First Differences method should not be interpreted because the estimation is too much biased. The results found via the Propensity Score Matching can be interpreted in a certain measure but can not be extrapolated to all similar programs. One should remain precatious about these results because even though the overlap condition is followed, the matching is not perfect. Moreover, the biases linked to missing information should also be taken into account.

5.6. Further research and self-improvement

Further research could be done by testing other methodologies. The most interesting one could be to use an instrumental variable for the variable “Juntos”. Meaning, a variable that is correlated to the fact of receiving the transfer “Juntos” but not correlated to the labour supply of the individuals. This is interesting because it could help to avoid biases linked to the endogeneity. The endogeneity would come from the fact that the variable “Juntos” (the fact of receiving the transfer) could also be correlated or the fact of working or not (reversed causality). One Instrument I already thought of is using the districts that became eligible between 2013 and 2017 together with the fact of being poor or not. The problem is that my dataset did not gather enough information to use this method. Therefore, if the data allows it, I would recommend trying this method for further analysis.

Also, if the data allows it, I would recommend trying the Propensity Score Matching method with more variables in order to check whether the results remain equal.

All along the way of this document, I learned many things, improved my English and my Spanish and I used many of the courses that I followed during these 5 years of University. Now, looking back, I regret not knowing some pieces of information before I started the thesis. Here follow some of the things I would have done differently:

- Concerning the Dataset, I would have focused not only on the information it gathers but also on the capacity I need to open the dataset on the available software and if there are clear identifiers. I would also try to avoid merging different datasets and find one that gathers directly all the information I need. This is of course not necessarily possible but, in the future, I am going to keep in mind all difficulties that one can have because of the dataset.
- Concerning the missing information, even though I sent many mails and messages already starting two months ago, I should have started earlier, and I should have been more persistent.
- Concerning the Robustness checks, some of them should have been done before even starting the estimations. This mostly for the common trend assessment in the First Differences method and the “pstest” for the Propensity Score Matching. One can find more information on these subjects in section 5.5.

To conclude this section, working on this paper thought me a lot. It thought me how to use it in the software STATA, how to interpret the results and how to test for its robustness. It also thought me good reflexes for further work in my upcoming career such as making sure all necessary assessments are followed before making any kind of estimation.

6. Results review

The results found via the First Differences methodology firstly suggest that there are no impacts of the transfer on extensive margins (for both estimations made on the whole sample and estimations made on the subsample). Secondly for the number of hours of work, when the estimation is done for all agents, it suggests a small, negative impact for men. But when the estimation is only done for the subsample, this effect disappears. All these results should not be taken into account as already explained in section 5.5.

The result found via the Propensity Score Matching methodology is that for both estimations (made on the whole sample and estimations made on the subsample) there seems to be a negative impact of the transfer on the number of hours of work for men. Women however, increase the number of hours of work for the first estimation made on the whole sample but they have no variation of their number of hours of work when the estimation is only done on the subsample. These results can be considered but one still needs to remain precautionary. In the next section, these results are interpreted and discussed.

7. Discussion

First, it is important to point out that there can be no conclusions made without having robustness check-ups. All possible biases need to be verified and stipulated. Here, the results that can be

interpreted are the fact that men work a smaller number of hours because of the transfer received from “Juntos”. This would imply that the Conditional Cash Transfer has perverse effects on men’s labour supply (in this case meaning the number of hours of work). The result for the subsample reflects the pure income effect of the transfer. The result matches with the theory (section 3.4): when an individual receives a cash transfer with no conditions, this individual decreases the number of hours of work.

One important result is that for the women there is a positive variation of the number of hours of work for the whole sample but no variation for the subsample. This could mean that women have no pure income effect, but that they increase their number of hours of work because of reallocation effects explained in section 3.2. This could be the mother working more hours to counterbalance the kids working less because they go to school. Since we’ve already seen some empirical literature on “Juntos” proving that there are positive effects on kids’ enrolment and attendance to school, this explanation is conceivable. It might be that women increase also the number of tasks performed for the household (domestic labour) if the children were helping more before going more to school. Concerning the “pure income effect”, the results for women does not match with the theory.

All these results and assumptions could imply political implications. This is why every economist needs to remain precautionary in the interpretation of econometrical results. For this reason, I would like to recall that the results in this paper are not completely unbiased and might need to be revised before making any kind of conclusions. All interpretations and discussion about the results in this section should remain plausible but should not be seen as explaining the whole reality. Moreover, I focused on the impacts on labour supply, but the transfer has many other implications such as improving education and health, but also having less intergenerational poverty traps and even improving women empowerment. However, the results of this paper regarding labour supply imply no difference between Conditional and Unconditional Cash Transfer for men but imply a difference between Conditional and Unconditional Cash Transfer for women. The outcomes on labour supply for women when the transfer comes with the conditions are an increase of their number of hours of work while when no conditions, there is no impact on their labour supply.

One important question is the role of the government, in society (already discussed in section 3.1). Undeniably, one of the biggest criticisms that could be made to this Conditional Cash Transfer “Juntos”, as for all CCT, is its paternalistic approach. In other words, is it the role of the government to say to poor how they should spend the money they receive? To this question, most of the answers are linked to ideological thoughts embellished with objectivised arguments.

I prefer not to give my opinion on the matter, but these questions interest me, and I would love to work on these subjects in the future. I have learned thanks to the courses I had of development economics that there are many mistaken stereotypes given to the behaviour of poor individuals. But whether it means Unconditional Cash Transfers should be preferred to Conditional Cash Transfers is not for me to say. I think it mostly depends on the environment and conditions in which the transfer is implemented.

8. Conclusion

In this paper, results show that the transfer given by “Juntos” decreases the number of hours of work for men and increases the number of hours of work for women, but not for those who only have children in primary school. The results for men are in accordance with the theoretical considerations and can prove that there is a “pure income effect” of the transfer on men. The results for women could be explained by the “reallocation effect” (section 3.2). However, the results for women does not match with the theory concerning the “pure income effect”.

If these results are brought to light regarding literature over Unconditional and Conditional Cash Transfers, it could be said the sign of the outcome for men does not differ between the two times of transfer. However, the outcomes on labour supply for women when the transfer comes with the conditions are an increase of their number of hours of work while when no conditions, there is no impact on their labour supply.

These results are not completely unbiased and might need to be revised. All interpretations and discussion about the results must remain plausible but should not explain the reality with a certainty of a hundred percent. One should highlight the policy implications that all econometrical interpretations can have. But one must also realize that generalizing one result is wrong because responses to a certain policy can differ completely from one context to another. The country where it is implemented, the cultural context, the economic situation, the geographical and demographical circumstances, the intra-household way of working, ... So many circumstances that have influence over the impacts of just one policy. Therefore, Conditional Cash Transfer should not always be preferred to Unconditional Cash Transfer and vice-versa. In order to choose between the two, one must firstly analyse all possible reactions to the two possibilities. But also stipulate wanted impacts of the policy and finally, chose the most adapted policy to the context and objectives. Concerning the best option for Peru, I prefer not to give my opinion on the matter. Firstly, because the results of this paper are not perfectly unbiased. Secondly because the analysis in this paper is focused on the impacts on labour supply, but the transfer has many other implications such as improving education and health, but also having less

intergenerational poverty traps and even improving women empowerment. If one wants to build a structured opinion, all these different dimensions should be taken into account.

Finally, I recommend that further research should be made via other methods or with an improvement of the methodologies used in this paper.

Abbreviations

CCT. Conditional Cash Transfer

ENAH. Encuesta Nacional de Hogares (Peruvian National Household Survey)

FD. First Difference

DD. Difference-in-Differences

FE. Fixed Effects

INEI. Instituto Nacional de Estadística (Peruvian National Institute of Statistics)

IV. Instrumental Variable

“Juntos”. Conditional Cash Transfer in Peru

MDGs. Millennium Sustainable Goals

PROGRESA. Conditional Cash Transfer in Mexico

UCT. Unconditional Cash Transfer

PSM. Propensity Score Matching

ATE. Average Treatment Effect

ATT. Average Treatment Effect on the Treated

VIF. Variance Inflator Factor

Intensive margins. number of working hours or earnings conditional on working

Extensive margins. employment rates (working or not)

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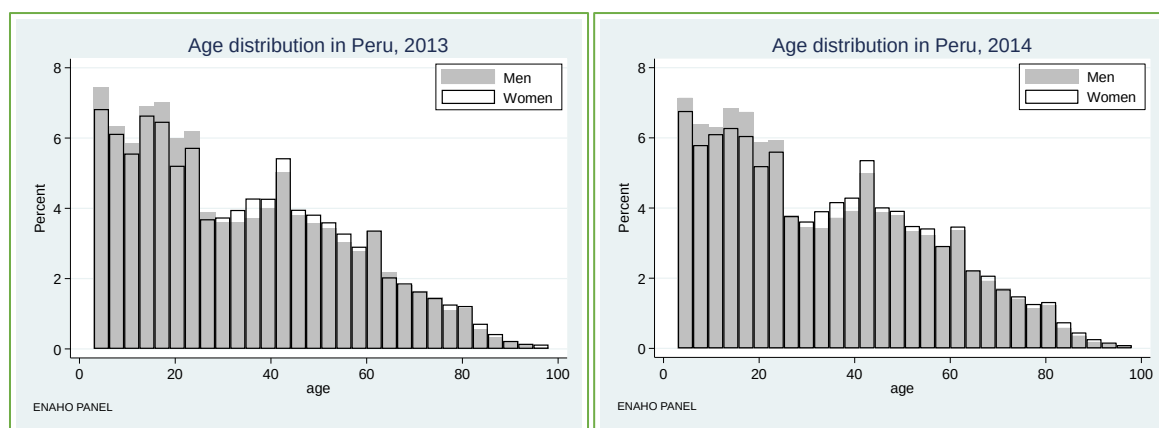
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Appendix

Appendix 0. Age distribution of the sample for 2013 and 2014.



Appendix 1. ENAHO survey for different types of transfers. Answer to the question “Did you receive any transfers in the last 6 months from...?”

556. EN LOS ÚLTIMOS 6 MESES, DE..... A..... ¿RECIBIÓ UD. INGRESOS POR CONCEPTO DE:

SI	NO	MONTO POR VEZ (S/.)				DEL EXTERIOR	
		FRE- CUEN- CIA	DEL PAÍS?	FRE- CUEN- CIA	DEL EX- TRAN- JERO?	INSTIT. DONDE COBRA	DES- TINO DEL ENVIÓ
1	2						
1	2						
1	2						
1	2						
1	2						
1	2						
1	2						
1	2						
1	2						
(Especifique)							
1	2						
(Especifique)							
TOTAL							

FRECUENCIA:
 Diario.....1 Bimestral.....5
 Semanal.....2 Trimestral.....6
 Quincenal.....3 Semestral.....7
 Mensual.....4 Anual.....8

COBRA UD. EN:
 Empresa de Transf. de Fondo(ETF).....1
 Bancos.....2
 Asoc. y Coop. de Japón.....3
 Servicio postal, agencia de viajes.....4
 Familiares, amigos o personas que viajan.....5
 Otro (especifique).....6

DESTINO
 Vivienda.....1
 Ahorros.....2
 Gastos del hogar (alimento, vestido, etc.) 3
 Educación.....4
 Otro (especifique).....6

Appendix 2. ENAHO survey on labour supply. Answer to the question “Last week, did you work?” without taking account for domestic work.

CONDICIÓN DE ACTIVIDAD

501. LA SEMANA PASADA, DEL..... AL..... ¿TUVO UD. ALGÚN TRABAJO?
 (Sin contar los quehaceres del hogar)

Si.....1 → **PASE A 505**

No.....2

Appendix 3. ENAHO survey on labour supply. Answer to the question “You worked for your principal job as...?”

507. UD. SE DESEMPEÑÓ EN SU OCUPACIÓN PRINCIPAL O NEGOCIO COMO:	
¿Empleador o patrono?	1
¿Trabajador independiente?	2
¿Empleado?	3
¿Obrero?	4
} PASE A 510	
¿Trabajador familiar no remunerado?	5
→ PASE A 510A1	
¿Trabajador del hogar?	6
→ PASE A 511	
¿Otro?	7
(Especifique) → PASE A 510	

Appendix 4. ENAHO survey on labour supply. Answer to the question “what were you doing last week?” Answer 5 for domestic work. And answer to the question “Why did not look for a job?” Answer 6 for too much domestic work.

546. ¿QUÉ ESTUVO HACIENDO LA SEMANA PASADA:	549. ¿POR QUÉ NO BUSCÓ TRABAJO?
Hizo trámites, buscó local, gestionó préstamos para establecer su propio negocio?	No hay trabajo
1	1
Reparando sus activos (local, máquina, equipo)?	Se cansó de buscar
2	2
} PASE A 551	
Esperando el inicio de un trabajo dependiente (como obrero, empleado o trabajador del hogar)?	Por su edad
3	3
Estudiando?	Falta de experiencia
4	4
Quehaceres del hogar?	Sus estudios no le permiten
5	5
Vivía de su pensión o jubilación u otras rentas?	Los quehaceres del hogar no le permiten
6	6
Enfermo o incapacitado?	Razones de salud
7	7
Otro?	Falta de capital
(Especifique) 8	8
	Otro
	(Especifique) 9
	Ya encontró trabajo
	10
	Si buscó trabajo
	11
	→ PASE A 552
	→ PASE A 551

Appendix 5. ENAHO survey on labour supply

511A. BAJO QUÉ TIPO DE CONTRATO	510A1. EL NEGOCIO O EMPRESA DONDE TRABAJA, ¿SE ENCUENTRA REGISTRADO EN LA SUNAT, COMO:	507. UD. SE DESEMPEÑÓ EN SU OCUPACIÓN PRINCIPAL O NEGOCIO COMO:	
¿Contrato indefinido, nombrado, permanente?	Persona Jurídica (Sociedad Anónima; SRL; Sociedad Civil; EIRL; Fundación ó Asociación, etc.)?	¿Empleador o patrono?	
1	1	1	
¿Contrato a plazo fijo (sujeto a modalidad)?	Persona Natural (con R.U.C., RUS, RER, u otro régimen)?	¿Trabajador independiente?	
2	2	2	
¿Está en período de prueba?	NO ESTA REGISTRADO (no tiene RUC)?	¿Empleado?	
3	3	3	
¿Convenios de Formación Laboral Juvenil / Prácticas Pre-Profesionales?		¿Obrero?	
4		4	
¿Contrato por locación de servicios (Honorarios Profesionales, R.U.C.), SNP?		} PASE A 510	
5		¿Trabajador familiar no remunerado?	→ PASE A 510A1
¿Régimen Especial de Contratación Administrativa (CAS)?		¿Trabajador del hogar?	→ PASE A 511
6		¿Otro?	→ PASE A 510
¿Sin Contrato?		(Especifique)	
7			
¿Otro?			
(Especifique) 8			

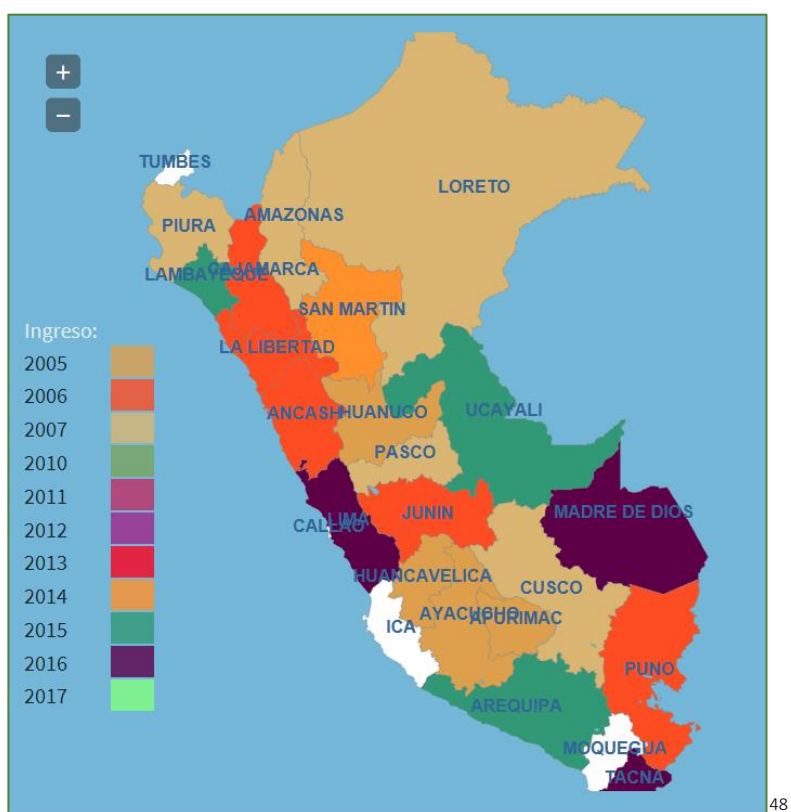
511. ¿EL TIPO DE PAGO O INGRESO QUE UD. RECIBE EN SU OCUPACIÓN PRINCIPAL ES: (Acepte una o más alternativas)
Sueldo?
1
Salario?
2
Comisión?
3
Destajo?
4
Subvención?
5
Honorarios profesionales (con R.U.C.)?
6
Ingreso (ganancia) por negocio o servicio?
7
Ingreso como productor agropecuario?
8
Propina?
9
En especie?
10
Otro?
11
(Especifique)
NO RECIBE
12

Appendix 6. Departments included in the “Juntos” program in Peru, by year, 2005 to 2017.

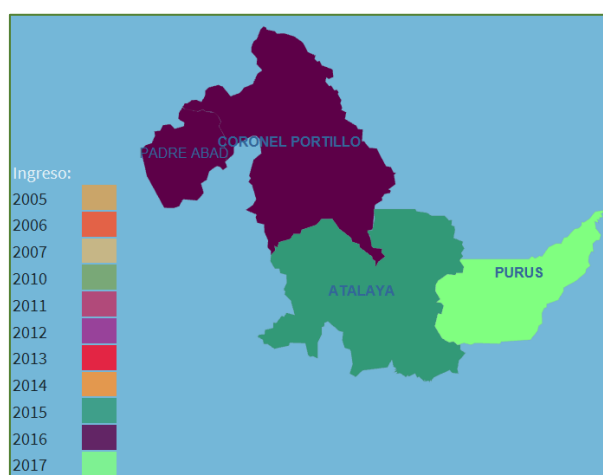
<http://www2.juntos.gob.pe/infojuntos/indexe.html>

Departamento	Hogares abonados 2005	Hogares abonados 2006	Hogares abonados 2007	Hogares abonados 2008	Hogares abonados 2009	Hogares abonados 2010	Hogares abonados 2011	Hogares abonados 2012	Hogares abonados 2013	Hogares abonados 2014	Hogares abonados 2015	Hogares abonados 2016	Hogares abonados 2017
AMAZONAS	0	0	3,383	7,722	7,720	9,781	9,521	16,426	26,393	32,148	33,104	29,131	32,192
ANCASH	0	6,638	20,621	26,793	26,023	30,075	29,008	38,700	38,672	41,285	40,743	34,808	35,313
APURIMAC	3,030	20,956	29,924	30,376	29,811	32,753	36,926	37,712	35,528	41,320	41,570	35,571	34,422
AREQUIPA	0	0	0	0	0	0	0	0	0	0	720	811	2,031
AVACUCHO	9,258	27,074	31,221	35,053	32,462	39,056	47,874	45,582	40,734	44,513	44,316	38,537	35,380
CAJAMARCA	0	13,630	59,581	78,056	77,204	88,214	85,874	115,481	108,894	111,445	111,841	97,666	108,584
CUSCO	0	0	28,203	34,122	34,294	36,892	37,841	54,242	55,446	63,720	63,371	52,717	52,247
HUANCAYELICA	7,809	30,797	38,932	38,890	36,785	40,839	44,460	42,499	38,140	40,888	40,822	35,019	34,727
HUANUCO	2,453	33,709	49,534	49,881	48,661	54,506	48,934	54,857	53,132	56,199	55,701	46,342	45,094
JUNIN	0	4,854	9,400	14,746	13,537	17,395	16,911	24,334	23,848	28,042	28,641	23,426	22,638
LA LIBERTAD	0	13,678	33,693	39,766	38,471	45,159	42,156	52,136	59,676	65,297	67,492	58,576	56,272
LAMBAEQUE	0	0	0	0	0	0	0	0	0	0	818	1,822	4,915
LIMA	0	0	0	0	0	0	0	0	0	0	0	223	598
LORETO	0	0	2,730	8,217	8,720	10,877	10,692	43,764	44,884	58,272	58,211	52,587	53,505
MADRE DE DIOS	0	0	0	0	0	0	0	0	0	0	0	0	479
PASCO	0	0	1,828	3,157	3,080	3,346	3,061	7,170	8,373	10,899	11,837	10,000	9,650
PIURA	0	0	18,929	26,709	26,998	33,231	32,158	53,122	68,891	80,488	81,506	71,564	80,528
PUNO	0	7,888	25,088	27,003	25,844	29,387	28,648	33,698	46,123	56,266	59,439	52,097	52,999
SAN MARTIN	0	0	0	0	0	0	0	0	0	24,774	28,796	26,414	28,196
TACNA	0	0	0	0	0	0	0	0	0	0	0	469	749
UCAVALI	0	0	0	0	0	0	0	0	0	0	230	250	2,985
Total	22,550	159,224	353,067	420,491	409,610	471,511	474,064	619,723	648,734	755,556	769,158	668,030	693,504

Map visualization.



Department of Ucayali.



⁴⁸ <http://www2.juntos.gob.pe/infojuntos/>

Appendix 7. Estimation via First Difference. Number of hours of work

First Differences regression for 2013 to 2015. Number of hours of work

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(cluster hhid)
> er hhid)
```

Linear regression

Number of obs = 23,461
F(8, 6749) = 3.02
Prob > F = 0.0022
R-squared = 0.0018
Root MSE = 20.782

(Std. Err. adjusted for 6,750 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.1484379	.9042333	0.16	0.870	-1.624145 1.92102
DJUNTOS_fem	.1947706	1.291313	0.15	0.880	-2.336611 2.726152
age D1.	.4499604	.3348286	1.34	0.179	-.2064094 1.10633
agesquare D1.	-.005275	.0032864	-1.61	0.109	-.0117173 .0011673
educ D1.	.5270871	.3928245	1.34	0.180	-.242973 1.297147
Dciv	.072158	.2565532	0.28	0.779	-.4307672 .5750833
hhrelation D1.	-.1637149	.3197332	-0.51	0.609	-.790493 .4630632
activityp D1.	.7543612	.1664497	4.53	0.000	.4280674 1.080655
_cons	.3838167	.1974018	1.94	0.052	-.0031532 .7707865

First Differences regression for 2014 to 2015. Number of hours of work

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(cluster hhid)
> er hhid)
```

Linear regression

Number of obs = 13,960
F(8, 7689) = 4.13
Prob > F = 0.0001
R-squared = 0.0031
Root MSE = 20.577

(Std. Err. adjusted for 7,690 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.3668582	1.212585	0.30	0.762	-2.01014 2.743856
DJUNTOS_fem	-1.493765	1.725957	-0.87	0.387	-4.877111 1.889582
age D1.	-.0618898	.4629707	-0.13	0.894	-.9694385 .8456588
agesquare D1.	.0010631	.0044188	0.24	0.810	-.0075989 .0097251
educ D1.	1.286037	.4561073	2.82	0.005	.3919423 2.180132
Dciv	.2887676	.3159845	0.91	0.361	-.3306482 .9081833
hhrelation D1.	-.0889128	.3984457	-0.22	0.823	-.8699749 .6921493
activityp D1.	.9290846	.1873475	4.96	0.000	.5618325 1.296337
_cons	.5627715	.260713	2.16	0.031	.051703 1.07384

Appendix 8. Estimation via First Difference. Intensive margins.

First Differences regression for 2013 to 2015. Intensive margins.

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(c1
> uster hhid)
```

Linear regression

Number of obs	=	22,546
F(8, 6664)	=	8.71
Prob > F	=	0.0000
R-squared	=	0.0060
Root MSE	=	.75125

(Std. Err. adjusted for 6,665 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.0309867	.0376914	0.82	0.411	-.0429004 .1048739
DJUNTOS_fem	-.0039325	.0533128	-0.07	0.941	-.1084428 .1005777
age D1.	.0372926	.0132999	2.80	0.005	.0112205 .0633647
agesquare D1.	-.0004065	.0001264	-3.22	0.001	-.0006543 -.0001588
educ D1.	.0271803	.0133472	2.04	0.042	.0010155 .0533451
Dciv	.0004169	.0078268	0.05	0.958	-.0149261 .0157599
hhrelation D1.	-.0124925	.0108351	-1.15	0.249	-.0337328 .0087478
activityp D1.	.0500012	.0067022	7.46	0.000	.0368628 .0631396
_cons	.0206215	.0067329	3.06	0.002	.0074229 .0338202

First Differences regression for 2014 to 2015. Intensive margins.

```
. *log DID
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(c1
> uster hhid)
```

Linear regression

Number of obs	=	13,443
F(8, 7531)	=	8.14
Prob > F	=	0.0000
R-squared	=	0.0075
Root MSE	=	.73333

(Std. Err. adjusted for 7,532 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.070127	.0523783	1.34	0.181	-.0325491 .172803
DJUNTOS_fem	-.1096254	.0708144	-1.55	0.122	-.2484414 .0291907
age D1.	.0345396	.0169222	2.04	0.041	.0013674 .0677118
agesquare D1.	-.0003243	.0001593	-2.04	0.042	-.0006365 -.0000121
educ D1.	.0504315	.015808	3.19	0.001	.0194435 .0814195
Dciv	.0019544	.0095561	0.20	0.838	-.0167782 .020687
hhrelation D1.	.0018976	.0135723	0.14	0.889	-.024708 .0285031
activityp D1.	.0535378	.0074431	7.19	0.000	.0389473 .0681283
_cons	.0257366	.0091611	2.81	0.005	.0077782 .0436949

Appendix 9. Estimation via First Difference. Dichotomic dependent variable. Logit

```
. logit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp,
> vce(cluster hhid)
```

Iteration 0: log pseudolikelihood = -4737.0137
Iteration 1: log pseudolikelihood = -4731.5819
Iteration 2: log pseudolikelihood = -4731.5262
Iteration 3: log pseudolikelihood = -4731.5262

Logistic regression

Number of obs = 13,648
Wald chi2(8) = 11.48
Prob > chi2 = 0.1762
Pseudo R2 = 0.0012

Log pseudolikelihood = -4731.5262

(Std. Err. adjusted for 7,418 clusters in hhid)

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.2942725	.193267	1.52	0.128	-.084524 .6730689
DJUNTOS_fem	-.6779515	.290789	-2.33	0.020	-1.247888 -.1080155
age					
D1.	-.0442164	.072564	-0.61	0.542	-.1864393 .0980065
agesquare					
D1.	.0005905	.0006839	0.86	0.388	-.00075 .001931
educ					
D1.	.0770283	.069927	1.10	0.271	-.060026 .2140827
Dciv	.0287922	.0456026	0.63	0.528	-.0605872 .1181716
hhrelation					
D1.	.068826	.0412485	1.67	0.095	-.0120196 .1496716
activityp					
D1.	-.0150242	.0329875	-0.46	0.649	-.0796785 .04963
cons	-2.096864	.0373367	-56.16	0.000	-2.170043 -2.023686

```
. margins, dydx(*)
```

Average marginal effects

Model VCE : Robust

Number of obs = 13,648

Expression : Pr(Dworklw), predict()
dy/dx w.r.t. : DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.0288487	.0189547	1.52	0.128	-.0083019 .0659993
DJUNTOS_fem	-.0664623	.0285413	-2.33	0.020	-.1224021 -.0105224
age					
D1.	-.0043347	.0071115	-0.61	0.542	-.018273 .0096035
agesquare					
D1.	.0000579	.000067	0.86	0.388	-.0000735 .0001892
educ					
D1.	.0075514	.0068547	1.10	0.271	-.0058837 .0209864
Dciv	.0028226	.004471	0.63	0.528	-.0059403 .0115856
hhrelation					
D1.	.0067473	.0040447	1.67	0.095	-.0011803 .0146748
activityp					
D1.	-.0014729	.0032333	-0.46	0.649	-.0078101 .0048643

Appendix 10. Estimation via First Difference. Dichotomic dependent variable.

Estimation via First Difference. Dichotomic dependent variable. 2013 to 2015. Probit

Iteration 0: log pseudolikelihood = -7777.0459						
Iteration 1: log pseudolikelihood = -7770.5543						
Iteration 2: log pseudolikelihood = -7770.5267						
Iteration 3: log pseudolikelihood = -7770.5267						
Probit regression						
			Number of obs	=	23,461	
			Wald chi2(8)	=	12.64	
			Prob > chi2	=	0.1248	
Log pseudolikelihood = -7770.5267			Pseudo R2	=	0.0008	
(Std. Err. adjusted for 6,750 clusters in hhid)						
Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.1165107	.0767088	1.52	0.129	-.0338358	.2668572
DJUNTOS_fem	-.341229	.1194909	-2.86	0.004	-.5754269	-.107031
age						
D1.	.0138284	.031386	0.44	0.660	-.047687	.0753437
agesquare						
D1.	-.0001156	.0003058	-0.38	0.705	-.0007149	.0004837
educ						
D1.	.034868	.0249344	1.40	0.162	-.0140025	.0837385
Dciv	-.0149673	.0178281	-0.84	0.401	-.0499098	.0199752
hhrelation						
D1.	.0180713	.0223698	0.81	0.419	-.0257726	.0619153
activityp						
D1.	-.0070948	.010471	-0.68	0.498	-.0276175	.013428
cons	-1.266726	.0166896	-75.90	0.000	-1.299437	-1.234015

Estimation via First Difference. Dichotomic dependent variable. 2013 to 2015. Logit

Iteration 0: log pseudolikelihood = -7777.0459						
Iteration 1: log pseudolikelihood = -7770.5748						
Iteration 2: log pseudolikelihood = -7770.4792						
Iteration 3: log pseudolikelihood = -7770.4792						
Logistic regression						
			Number of obs	=	23,461	
			Wald chi2(8)	=	12.32	
			Prob > chi2	=	0.1374	
Log pseudolikelihood = -7770.4792			Pseudo R2	=	0.0008	
(Std. Err. adjusted for 6,750 clusters in hhid)						
Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.2228031	.1443386	1.54	0.123	-.0600952	.5057015
DJUNTOS_fem	-.6711458	.2379463	-2.82	0.005	-1.137512	-.2047796
age						
D1.	.0264887	.0596908	0.44	0.657	-.0905031	.1434804
agesquare						
D1.	-.0002242	.0005962	-0.38	0.707	-.0013927	.0009443
educ						
D1.	.0678623	.0484807	1.40	0.162	-.027158	.1628827
Dciv	-.0299661	.0354336	-0.85	0.398	-.0994148	.0394826
hhrelation						
D1.	.0333206	.0404472	0.82	0.410	-.0459545	.1125957
activitytp						
D1.	-.0164172	.0235981	-0.70	0.487	-.0626686	.0298341
_cons	-2.16827	.0318709	-68.03	0.000	-2.230735	-2.105804

Estimation via First Difference. Dichotomic dependent variable. 2014 to 2015. Probit

Iteration 0: log pseudolikelihood = -4442.935						
Iteration 1: log pseudolikelihood = -4434.1246						
Iteration 2: log pseudolikelihood = -4434.0939						
Iteration 3: log pseudolikelihood = -4434.0939						
Probit regression						
			Number of obs	=	13,960	
			Wald chi2(8)	=	17.33	
			Prob > chi2	=	0.0269	
Log pseudolikelihood = -4434.0939			Pseudo R2	=	0.0020	
(Std. Err. adjusted for 7,690 clusters in hhid)						
Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.0587814	.1079119	0.54	0.586	-.152722	.2702847
DJUNTOS_fem	-.3200937	.1652024	-1.94	0.053	-.6438844	.003697
age						
D1.	.0513187	.0388325	1.32	0.186	-.0247916	.127429
agesquare						
D1.	-.0006242	.0003632	-1.72	0.086	-.001336	.0000877
educ						
D1.	.0258826	.0362735	0.71	0.476	-.0452122	.0969774
Dciv	-.0501484	.0216039	-2.32	0.020	-.0924914	-.0078055
hhrelation						
D1.	-.0078284	.0339788	-0.23	0.818	-.0744257	.0587688
activityp						
D1.	-.0214028	.015945	-1.34	0.180	-.0526544	.0098487
cons	-1.29188	.0194236	-66.51	0.000	-1.329949	-1.25381

Estimation via First Difference. Dichotomic dependent variable. 2014 to 2015. Logit

Iteration 0:	log pseudolikelihood =	-4442.935				
Iteration 1:	log pseudolikelihood =	-4434.0459				
Iteration 2:	log pseudolikelihood =	-4433.9401				
Iteration 3:	log pseudolikelihood =	-4433.94				
Logistic regression			Number of obs	=	13,960	
			Wald chi2(8)	=	17.16	
			Prob > chi2	=	0.0285	
Log pseudolikelihood = -4433.94			Pseudo R2	=	0.0020	
(Std. Err. adjusted for 7,690 clusters in hhid)						
Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.1151403	.2075992	0.55	0.579	-.2917465	.5220272
DJUNTOS_fem	-.6475723	.3356943	-1.93	0.054	-1.305521	.0103765
age						
D1.	.1010264	.0756525	1.34	0.182	-.0472498	.2493026
agesquare						
D1.	-.0012013	.0007063	-1.70	0.089	-.0025857	.000183
educ						
D1.	.0516265	.0707645	0.73	0.466	-.0870694	.1903223
Dciv	-.0963296	.0412601	-2.33	0.020	-.177198	-.0154612
hhrelation						
D1.	-.0131347	.0689636	-0.19	0.849	-.1483009	.1220316
activityp						
D1.	-.0482431	.0357146	-1.35	0.177	-.1182425	.0217563
cons	-2.220678	.0370969	-59.86	0.000	-2.293386	-2.147969

Appendix 11. Estimations via First Differences. Household's head and partner

First Differences regression for 2013 to 2014. Household's head and partner. Number of hours of work.

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp,
> vce(cluster hhid)
```

Linear regression

Number of obs	=	10,126
F(8, 6801)	=	2.81
Prob > F	=	0.0042
R-squared	=	0.0029
Root MSE	=	21.182

(Std. Err. adjusted for 6,802 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	1.086421	1.331796	0.82	0.415	-1.524316 3.697158
DJUNTOS_fem	-.4850007	1.897873	-0.26	0.798	-4.205425 3.235424
age D1.	1.370932	.6468539	2.12	0.034	.1028962 2.638968
agesquare D1.	-.0107469	.0058509	-1.84	0.066	-.0222165 .0007228
educ D1.	.0577014	.5485056	0.11	0.916	-1.017541 1.132944
Dciv	-.1151099	.4260692	-0.27	0.787	-.9503389 .7201192
hhrelation D1.	-.9107252	1.968433	-0.46	0.644	-4.769471 2.94802
activityp D1.	.9525258	.2269033	4.20	0.000	.5077243 1.397327
_cons	-.6459668	.322129	-2.01	0.045	-1.27744 -.0144932

First Differences regression for 2013 to 2015. Household's head and partner. Number of hours of work.

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression

Number of obs	=	18,059
F(8, 6324)	=	3.81
Prob > F	=	0.0002
R-squared	=	0.0028
Root MSE	=	20.764

(Std. Err. adjusted for 6,325 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.1301646	.9709051	0.13	0.893	-1.773139 2.033468
DJUNTOS_fem	-.0833246	1.438935	-0.06	0.954	-2.904124 2.737475
age D1.	.6924078	.4480387	1.55	0.122	-.1859 1.570716
agesquare D1.	-.0051422	.0042349	-1.21	0.225	-.0134441 .0031596
educ D1.	.2534893	.4548908	0.56	0.577	-.6382509 1.145229
Dciv	.0664041	.3336356	0.20	0.842	-.5876348 .720443
hhrelation D1.	-1.796804	1.639762	-1.10	0.273	-5.011295 1.417687
activityp D1.	.9939879	.1904206	5.22	0.000	.620699 1.367277
_cons	.0240348	.254797	0.09	0.925	-.4754538 .5235234

First Differences regression for 2014 to 2015. Household's head and partner. Number of hours of work.

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression

Number of obs	=	10,489
F(8, 7084)	=	3.90
Prob > F	=	0.0001
R-squared	=	0.0040
Root MSE	=	20.49

(Std. Err. adjusted for 7,085 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.3483655	1.382446	0.25	0.801	-2.361642 3.058373
DJUNTOS_fem	-.9734368	2.087404	-0.47	0.641	-5.065373 3.118499
age D1.	-.3471105	.608346	-0.57	0.568	-1.539651 .8454295
agesquare D1.	.0052901	.0057603	0.92	0.358	-.0060019 .0165821
educ D1.	1.061891	.535482	1.98	0.047	.0121861 2.111596
Dciv	.0750685	.4027101	0.19	0.852	-.7143637 .8645007
hhrelation D1.	-1.634398	2.0656	-0.79	0.429	-5.683591 2.414796
activityp D1.	1.09979	.219381	5.01	0.000	.6697376 1.529842
_cons	.325647	.2899998	1.12	0.262	-.2428393 .8941332

First Differences regression for 2013 to 2014. Intensive margins. Household's head and partner

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression

Number of obs	=	9,678
F(8, 6600)	=	5.85
Prob > F	=	0.0000
R-squared	=	0.0075
Root MSE	=	.77077

(Std. Err. adjusted for 6,601 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.0519329	.0584167	0.89	0.374	-.0625826 .1664485
DJUNTOS_fem	-.0031718	.0811755	-0.04	0.969	-.1623021 .1559584
age D1.	.0551526	.0251522	2.19	0.028	.0058462 .1044589
agesquare D1.	-.0004766	.0002406	-1.98	0.048	-.0009483 -4.94e-06
educ D1.	.0002665	.018789	0.01	0.989	-.0365661 .037099
Dciv	-.006844	.0138091	-0.50	0.620	-.0339143 .0202262
hhrelation D1.	-.0128505	.0823782	-0.16	0.876	-.1743384 .1486375
activityp D1.	.0582675	.0091848	6.34	0.000	.0402622 .0762727
_cons	-.010466	.0117574	-0.89	0.373	-.0335142 .0125822

First Differences regression for 2013 to 2015. Intensive margins. Household's head and partner

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(c1
> uster hhid)
```

Linear regression

Number of obs	=	17,320
F(8, 6228)	=	8.03
Prob > F	=	0.0000
R-squared	=	0.0074
Root MSE	=	.74988

(Std. Err. adjusted for 6,229 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.0376211	.0405631	0.93	0.354	-.0418966 .1171387
DJUNTOS_fem	-.0117728	.0586883	-0.20	0.841	-.1268221 .1032764
age					
D1.	.0480464	.0173198	2.77	0.006	.0140937 .0819991
agesquare					
D1.	-.0004339	.0001624	-2.67	0.008	-.0007523 -.0001155
educ					
D1.	.0119657	.0152083	0.79	0.431	-.0178478 .0417793
Dciv	.004044	.0109638	0.37	0.712	-.0174489 .0255369
hhrelation					
D1.	-.0320081	.0620069	-0.52	0.606	-.153563 .0895467
activityp					
D1.	.0577974	.0077108	7.50	0.000	.0426816 .0729131
_cons	.0081357	.0082371	0.99	0.323	-.0080118 .0242832

First Differences regression for 2014 to 2015. Intensive margins. Household's head and partner

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(c1
> uster hhid)
```

Linear regression

Number of obs	=	10,076
F(8, 6900)	=	6.76
Prob > F	=	0.0000
R-squared	=	0.0088
Root MSE	=	.72695

(Std. Err. adjusted for 6,901 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
DJUNTOS	.0598739	.0549142	1.09	0.276	-.0477748 .1675226
DJUNTOS_fem	-.0655684	.0803819	-0.82	0.415	-.2231417 .0920049
age					
D1.	.0314342	.0211644	1.49	0.138	-.0100546 .072923
agesquare					
D1.	-.0002521	.0001978	-1.27	0.203	-.0006397 .0001356
educ					
D1.	.0371882	.0184111	2.02	0.043	.0010968 .0732797
Dciv	.0026463	.013665	0.19	0.846	-.0241412 .0294339
hhrelation					
D1.	-.024628	.0729526	-0.34	0.736	-.1676375 .1183815
activityp					
D1.	.0603831	.0087595	6.89	0.000	.0432118 .0775545
_cons	.0186609	.0095824	1.95	0.052	-.0001236 .0374453

First Differences regression for 2013 to2014. Dichotomic dependent variable. Probit. Head and partner

```
. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp,
> vce(cluster hhid)
```

Iteration 0: log pseudolikelihood = -3401.1567
Iteration 1: log pseudolikelihood = -3393.6903
Iteration 2: log pseudolikelihood = -3393.6832
Iteration 3: log pseudolikelihood = -3393.6832

Probit regression

Number of obs = 10,126
Wald chi2(8) = 14.85
Prob > chi2 = 0.0622
Pseudo R2 = 0.0022

Log pseudolikelihood = -3393.6832

(Std. Err. adjusted for 6,802 clusters in hhid)

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.1208467	.1132784	1.07	0.286	-.1011749 .3428683
DJUNTOS_fem	-.2787254	.1687918	-1.65	0.099	-.6095512 .0521004
age D1.	-.1133898	.0507238	-2.24	0.025	-.2128067 -.0139728
agesquare D1.	.0012316	.0004468	2.76	0.006	.000356 .0021073
educ D1.	.0350134	.0421051	0.83	0.406	-.0475111 .1175379
Dciv	.0242907	.0334736	0.73	0.468	-.0413164 .0898978
hhrelation D1.	-.0288865	.1600377	-0.18	0.857	-.3425548 .2847817
activityp D1.	.0182699	.0180132	1.01	0.310	-.0170353 .0535751
_cons	-1.264809	.0227151	-55.68	0.000	-1.309329 -1.220288

```
. margins, dydx(*)
```

Average marginal effects

Number of obs = 10,126

Model VCE : Robust

Expression : Pr(Dworklw), predict()
dy/dx w.r.t. : DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.0219251	.0205532	1.07	0.286	-.0183585 .0622087
DJUNTOS_fem	-.0505689	.0306261	-1.65	0.099	-.110595 .0094572
age D1.	-.0205722	.0092075	-2.23	0.025	-.0386185 -.0025259
agesquare D1.	.0002235	.0000811	2.76	0.006	.0000645 .0003824
educ D1.	.0063524	.0076401	0.83	0.406	-.0086218 .0213267
Dciv	.004407	.0060727	0.73	0.468	-.0074953 .0163093
hhrelation D1.	-.0052409	.0290356	-0.18	0.857	-.0621495 .0516678
activityp D1.	.0033147	.0032673	1.01	0.310	-.0030892 .0097185

First Differences regression for 2013 to 2014. Dichotomic dependent variable. Logit. Head and partner

```
. logit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(c1
> uster hhid)
```

Iteration 0: log pseudolikelihood = -3401.1567
Iteration 1: log pseudolikelihood = -3393.6726
Iteration 2: log pseudolikelihood = -3393.5491
Iteration 3: log pseudolikelihood = -3393.5491

Logistic regression

Number of obs = 10,126
Wald chi2(8) = 15.77
Prob > chi2 = 0.0458
Pseudo R2 = 0.0022

Log pseudolikelihood = -3393.5491

(Std. Err. adjusted for 6,802 clusters in hhid)

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.2272573	.2130083	1.07	0.286	-.1902313	.6447459
DJUNTOS_fem	-.545031	.3309276	-1.65	0.100	-1.193637	.1035751
age D1.	-.2139961	.094496	-2.26	0.024	-.399205	-.0287873
agesquare D1.	.0023036	.0008271	2.79	0.005	.0006825	.0039247
educ D1.	.0655827	.0821874	0.80	0.425	-.0955016	.226667
Dciv	.0490551	.0673848	0.73	0.467	-.0830166	.1811269
hhrelation D1.	-.0566339	.3212317	-0.18	0.860	-.6862364	.5729685
activityp D1.	.0420552	.0406503	1.03	0.301	-.0376179	.1217283
_cons	-2.162902	.0420142	-51.48	0.000	-2.245248	-2.080555

```
. margins, dydx(*)
```

Average marginal effects

Number of obs = 10,126

Model VCE : Robust

Expression : Pr(Dworklw), predict()
dy/dx w.r.t. : DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.0213168	.0199838	1.07	0.286	-.0178508	.0604844
DJUNTOS_fem	-.051124	.0310514	-1.65	0.100	-.1119837	.0097357
age D1.	-.0200729	.0088729	-2.26	0.024	-.0374635	-.0026823
agesquare D1.	.0002161	.0000777	2.78	0.005	.0000638	.0003683
educ D1.	.0061517	.0077109	0.80	0.425	-.0089614	.0212648
Dciv	.0046014	.0063205	0.73	0.467	-.0077866	.0169893
hhrelation D1.	-.0053123	.0301318	-0.18	0.860	-.0643696	.053745
activityp D1.	.0039448	.0038118	1.03	0.301	-.0035262	.0114158

First Differences regression for 2013 to 2015. Dichotomic dependent variable. Probit. Head and partner

. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)						
Iteration 0: log pseudolikelihood = -5857.6991						
Iteration 1: log pseudolikelihood = -5852.2288						
Iteration 2: log pseudolikelihood = -5852.2131						
Iteration 3: log pseudolikelihood = -5852.2131						
Probit regression			Number of obs	=	18,059	
			Wald chi2(8)	=	10.69	
			Prob > chi2	=	0.2197	
Log pseudolikelihood = -5852.2131			Pseudo R2	=	0.0009	
(Std. Err. adjusted for 6,325 clusters in hhid)						
Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	.0825066	.0855333	0.96	0.335	-.0851356	.2501488
DJUNTOS_fem	-.2906076	.1322055	-2.20	0.028	-.5497257	-.0314896
age						
D1.	-.0705467	.0407924	-1.73	0.084	-.1504983	.0094048
agesquare						
D1.	.0006418	.0003786	1.70	0.090	-.0001003	.0013838
educ						
D1.	.0354554	.0284479	1.25	0.213	-.0203013	.0912122
Dciv	-.0043135	.0238439	-0.18	0.856	-.0510468	.0424197
hhrelation						
D1.	-.0825567	.1114765	-0.74	0.459	-.3010467	.1359332
activityp						
D1.	.0088204	.0121753	0.72	0.469	-.0150428	.0326836
_cons	-1.276278	.020059	-63.63	0.000	-1.315593	-1.236963

First Differences regression for 2014 to 2015. Dichotomic dependent variable. Probit. Head and partner

```
. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)
```

```
Iteration 0:  log pseudolikelihood = -3253.5685
Iteration 1:  log pseudolikelihood = -3250.0941
Iteration 2:  log pseudolikelihood = -3250.0742
Iteration 3:  log pseudolikelihood = -3250.0742
```

```
Probit regression
```

```
Number of obs      =    10,489
Wald chi2(8)       =      7.30
Prob > chi2        =    0.5043
Pseudo R2         =    0.0011
```

```
Log pseudolikelihood = -3250.0742
```

```
(Std. Err. adjusted for 7,085 clusters in hhid)
```

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	-.0138084	.1261432	-0.11	0.913	-.2610445	.2334278
DJUNTOS_fem	-.2455662	.1946322	-1.26	0.207	-.6270384	.1359059
age						
D1.	.0039779	.0488374	0.08	0.935	-.0917417	.0996974
agesquare						
D1.	-.000145	.0004523	-0.32	0.749	-.0010314	.0007415
educ						
D1.	.0093896	.0428753	0.22	0.827	-.0746444	.0934236
Dciv	-.0442375	.0278846	-1.59	0.113	-.0988903	.0104153
hhrelation						
D1.	.0290155	.1565509	0.19	0.853	-.2778186	.3358495
activityp						
D1.	-.0114201	.0185764	-0.61	0.539	-.0478291	.0249889
cons	-1.304694	.0218022	-59.84	0.000	-1.347426	-1.261963

Appendix 12. Estimation via First Difference. Subsample

First Differences regression for 2013 to 2015. Subsample. Number of hours of work.

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression

Number of obs	=	6,014
F(8, 2138)	=	5.31
Prob > F	=	0.0000
R-squared	=	0.0096
Root MSE	=	21.202

(Std. Err. adjusted for 2,139 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	1.113603	1.744847	0.64	0.523	-2.308173	4.535378
DJUNTOS_fem	-1.286865	2.5171	-0.51	0.609	-6.223084	3.649354
age D1.	1.354017	.9238876	1.47	0.143	-.4577953	3.165829
agesquare D1.	-.0162366	.0087046	-1.87	0.062	-.0333069	.0008337
educ D1.	1.493751	.8840371	1.69	0.091	-.2399118	3.227413
Dciv	-.2551825	.6808813	-0.37	0.708	-1.590441	1.080076
hhrelation D1.	-3.811269	3.180162	-1.20	0.231	-10.0478	2.425266
activityp D1.	1.796289	.2984487	6.02	0.000	1.211009	2.381569
_cons	.1991214	.4272798	0.47	0.641	-.6388059	1.037049

First Differences regression for 2014 to 2015. Subsample. Number of hours of work.

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression

Number of obs	=	3,454
F(8, 2135)	=	4.41
Prob > F	=	0.0000
R-squared	=	0.0120
Root MSE	=	20.782

(Std. Err. adjusted for 2,136 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	2.90551	2.262063	1.28	0.199	-1.530567	7.341587
DJUNTOS_fem	-3.42085	3.399052	-1.01	0.314	-10.08665	3.244949
age D1.	-.6691245	1.379608	-0.49	0.628	-3.374641	2.036392
agesquare D1.	.0046494	.0125249	0.37	0.711	-.0199129	.0292116
educ D1.	1.194755	.9923147	1.20	0.229	-.7512497	3.140759
Dciv	-.498859	.7568898	-0.66	0.510	-1.983177	.9854592
hhrelation D1.	-7.473334	3.960479	-1.89	0.059	-15.24013	.2934655
activityp D1.	1.861229	.3514355	5.30	0.000	1.172038	2.550421
_cons	.2969415	.5227315	0.57	0.570	-.7281747	1.322058

Appendix 13. Estimation via First Difference. Number of hours of work. Subsample. Men

First Differences regression for 2013 to 2014. Subsample. Only men. Number of hours of work.

(Std. Err. adjusted for 1,823 clusters in hhid)						
Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.264707	2.508679	0.11	0.916	-4.655481	5.184896
DJUNTOS_fem	0	(omitted)				
age						
D1.	2.608969	1.932638	1.35	0.177	-1.181449	6.399388
agesquare						
D1.	-.0210392	.0195099	-1.08	0.281	-.0593032	.0172249
educ						
D1.	1.166438	1.377824	0.85	0.397	-1.535843	3.868718
Dciv						
D1.	-1.96156	1.748831	-1.12	0.262	-5.391486	1.468365
hhrelation						
D1.	-6.628812	8.445461	-0.78	0.433	-23.19261	9.93499
activitytp						
D1.	2.369226	.6111054	3.88	0.000	1.170685	3.567767
_cons	-1.350253	.7741828	-1.74	0.081	-2.868632	.1681264

First Differences regression for 2013 to 2015. Subsample. Only men. Number of hours of work.

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activitytp, vce(cluster hhid)
> er hhid)
note: DJUNTOS_fem omitted because of collinearity
```

Linear regression

Number of obs

=

3,173

F(7, 1826)

=

6.19

Prob > F

=

0.0000

R-squared

=

0.0190

Root MSE

=

21.564

(Std. Err. adjusted for 1,827 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.1904898	1.772429	0.11	0.914	-3.285711	3.666691
DJUNTOS_fem	0	(omitted)				
age						
D1.	1.915278	1.312148	1.46	0.145	-.6581905	4.488746
agesquare						
D1.	-.01879	.012324	-1.52	0.128	-.0429606	.0053806
educ						
D1.	1.189055	1.118952	1.06	0.288	-1.005505	3.383615
Dciv						
D1.	-1.407559	1.316603	-1.07	0.285	-3.989766	1.174647
hhrelation						
D1.	-11.17543	9.550669	-1.17	0.242	-29.90681	7.555956
activitytp						
D1.	2.955092	.4778367	6.18	0.000	2.017928	3.892256
_cons						
	-.6199395	.5294654	-1.17	0.242	-1.658361	.4184819

First Differences regression for 2014 to 2015. Subsample. Only men. Number of hours of work.

```
. regress Dworkp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(cluster hhid)
> er hhid)
note: DJUNTOS_fem omitted because of collinearity
```

Linear regression	Number of obs	=	1,818
	F(7, 1817)	=	4.26
	Prob > F	=	0.0001
	R-squared	=	0.0218
	Root MSE	=	21.248

(Std. Err. adjusted for 1,818 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.1132259	2.287809	0.05	0.961	-4.373786	4.600238
DJUNTOS_fem	0	(omitted)				
age D1.	.5788699	1.86164	0.31	0.756	-3.072309	4.230049
agesquare D1.	-.0079311	.0177079	-0.45	0.654	-.042661	.0267988
educ D1.	1.383873	1.278789	1.08	0.279	-1.124178	3.891924
Dciv	-1.085188	1.448935	-0.75	0.454	-3.926943	1.756566
hhrelation D1.	-13.93356	12.30486	-1.13	0.258	-38.06672	10.1996
activityp D1.	3.066158	.5819425	5.27	0.000	1.924812	4.207505
_cons	-.4516348	.6904409	-0.65	0.513	-1.805776	.9025064

Appendix 14. Estimation via First Difference. Intensive margins. Subsample

First Differences regression for 2013 to 2015. Intensive margins. Subsample.

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(cluster hhid)
> uster hhid)
```

Linear regression	Number of obs	=	5,784
	F(8, 2112)	=	6.16
	Prob > F	=	0.0000
	R-squared	=	0.0147
	Root MSE	=	.77647

(Std. Err. adjusted for 2,113 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.0460255	.0672849	0.68	0.494	-.0859262	.1779771
DJUNTOS_fem	-.0277971	.1041402	-0.27	0.790	-.2320253	.176431
age D1.	.0474788	.0340592	1.39	0.163	-.0193142	.1142719
agesquare D1.	-.0005556	.0003296	-1.69	0.092	-.0012019	.0000908
educ D1.	.0332743	.0298415	1.12	0.265	-.0252474	.0917961
Dciv	-.0024279	.0205584	-0.12	0.906	-.0427447	.0378888
hhrelation D1.	-.0638624	.1157236	-0.55	0.581	-.2908066	.1630818
activityp D1.	.0850976	.0127587	6.67	0.000	.0600767	.1101186
_cons	.0228035	.015784	1.44	0.149	-.0081504	.0537573

First Differences regression for 2014 to 2015. Intensive margins. Subsample.

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression		Number of obs	=	3,328
		F(8, 2099)	=	4.55
		Prob > F	=	0.0000
		R-squared	=	0.0159
		Root MSE	=	.741
(Std. Err. adjusted for 2,100 clusters in hhid)				

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.1028673	.0945975	1.09	0.277	-.0826473	.2883819
DJUNTOS_fem	-.1072731	.1362278	-0.79	0.431	-.3744287	.1598826
age D1.	-.0065276	.0419307	-0.16	0.876	-.0887576	.0757025
agesquare D1.	.0000335	.000399	0.08	0.933	-.000749	.000816
educ D1.	.0028862	.0353186	0.08	0.935	-.066377	.0721494
Dciv	-.0241942	.0246672	-0.98	0.327	-.0725689	.0241806
hhrelation D1.	-.1353213	.1347833	-1.00	0.315	-.3996442	.1290016
activityp D1.	.0822494	.0143717	5.72	0.000	.0540651	.1104337
_cons	.0345681	.0162441	2.13	0.033	.002712	.0664243

Appendix 15. Estimation via First Difference. Intensive margins. Subsample. Only men

First Differences regression for 2013 to 2014. Intensive margins. Subsample. Only men.

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityp, vce(cluster hhid)
```

```
> yp, vce(cluster hhid)
```

note: DJUNTOS_fem omitted because of collinearity

Linear regression		Number of obs	=	1,729
		F(7, 1728)	=	3.35
		Prob > F	=	0.0015
		R-squared	=	0.0170
		Root MSE	=	.77678
(Std. Err. adjusted for 1,729 clusters in hhid)				

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.0437317	.1033053	0.42	0.672	-.158885	.2463483
DJUNTOS_fem	0	(omitted)				
age D1.	.0941981	.0703231	1.34	0.181	-.0437292	.2321254
agesquare D1.	-.0008043	.0007504	-1.07	0.284	-.0022762	.0006676
educ D1.	.0239387	.0469006	0.51	0.610	-.0680492	.1159266
Dciv	-.0657106	.0696503	-0.94	0.346	-.2023184	.0708971
hhrelation D1.	-.1906189	.2647033	-0.72	0.472	-.7097915	.3285538
activityp D1.	.1011506	.023237	4.35	0.000	.0555751	.1467261
cons	-.0337106	.0275169	-1.23	0.221	-.0876805	.0202593

First Differences regression for 2013 to 2015. Intensive margins. Subsample. Only men.

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityyp, vce(c1
> uster hhid)
note: DJUNTOS_fem omitted because of collinearity
```

Linear regression			Number of obs	=	3,011	
			F(7, 1761)	=	6.97	
			Prob > F	=	0.0000	
			R-squared	=	0.0252	
			Root MSE	=	.7511	
(Std. Err. adjusted for 1,762 clusters in hhid)						
Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.0275296	.0748755	0.37	0.713	-.1193246	.1743839
DJUNTOS_fem	0	(omitted)				
age						
D1.	.0777715	.0463277	1.68	0.093	-.0130916	.1686346
agesquare						
D1.	-.0007572	.0004585	-1.65	0.099	-.0016565	.0001421
educ						
D1.	-.00582	.0372628	-0.16	0.876	-.078904	.067264
Dciv	-.0426766	.0387142	-1.10	0.270	-.1186072	.033254
hhrelation						
D1.	-.3089004	.3132677	-0.99	0.324	-.9233162	.3055154
activityyp						
D1.	.1222762	.0182084	6.72	0.000	.0865639	.1579885
_cons	-.0030575	.0187387	-0.16	0.870	-.0398098	.0336949

First Differences regression for 2014 to 2015. Intensive margins. Subsample. Only men.

```
. regress Dln_workp DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ D.civ D.hhrelation D.activityyp, vce(c1
> uster hhid)
note: DJUNTOS_fem omitted because of collinearity
```

Linear regression			Number of obs	=	1,726	
			F(7, 1725)	=	5.06	
			Prob > F	=	0.0000	
			R-squared	=	0.0299	
			Root MSE	=	.7148	
(Std. Err. adjusted for 1,726 clusters in hhid)						
Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
DJUNTOS	.0100019	.0906138	0.11	0.912	-.1677225	.1877264
DJUNTOS_fem	0	(omitted)				
age						
D1.	.0318857	.0542713	0.59	0.557	-.0745587	.1383302
agesquare						
D1.	-.0003296	.0005484	-0.60	0.548	-.0014052	.0007461
educ						
D1.	-.0295896	.0473006	-0.63	0.532	-.1223622	.0631831
Dciv	-.0466497	.0408778	-1.14	0.254	-.1268251	.0335256
hhrelation						
D1.	-.3497836	.3782403	-0.92	0.355	-1.091641	.3920741
activityyp						
D1.	.1232144	.0217165	5.67	0.000	.0806209	.1658079
_cons	.0148107	.0213774	0.69	0.489	-.0271177	.0567391

First Differences regression for 2013 to 2015. Dichotomic dependent variable. Probit. Subsample.

First Differences regression for 2014 to 2015. Dichotomic dependent variable. Probit. Subsample

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Appendix 17. Estimation via First Difference. Dichotomic dependent variable. Subsample. Logit estimation for 2013 to 2014.

```
. logit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(c1
> uster hhid)
```

Iteration 0: log pseudolikelihood = -1097.8396
Iteration 1: log pseudolikelihood = -1093.8946
Iteration 2: log pseudolikelihood = -1093.8468
Iteration 3: log pseudolikelihood = -1093.8468

Logistic regression

Number of obs	=	3,392
Wald chi2(8)	=	9.04
Prob > chi2	=	0.3387
Pseudo R2	=	0.0036

Log pseudolikelihood = -1093.8468

(Std. Err. adjusted for 2,086 clusters in hhid)

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.4469827	.3329474	1.34	0.179	-.2055823 1.099548
DJUNTOS_fem	-.3068165	.5135077	-0.60	0.550	-1.313273 .6996402
age D1.	.2326944	.1758483	1.32	0.186	-.111962 .5773508
agesquare D1.	-.0023222	.001805	-1.29	0.198	-.00586 .0012156
educ D1.	.122523	.1638542	0.75	0.455	-.1986254 .4436714
Dciv	.251529	.1270571	1.98	0.048	.0025017 .5005563
hhrelation D1.	.4304856	.4223477	1.02	0.308	-.3973007 1.258272
activityp D1.	-.0558429	.0700732	-0.80	0.425	-.1931838 .0814979
_cons	-2.265836	.0719236	-31.50	0.000	-2.406804 -2.124869

```
. margins, dydx(*)
```

Average marginal effects

Number of obs	=	3,392
---------------	---	-------

Model VCE : Robust

Expression : Pr(Dworklw), predict()
dy/dx w.r.t. : DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp

	Delta-method dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.0398967	.0297015	1.34	0.179	-.0183171 .0981105
DJUNTOS_fem	-.0273858	.0458453	-0.60	0.550	-.1172408 .0624693
age D1.	.0207698	.0157105	1.32	0.186	-.0100222 .0515619
agesquare D1.	-.0002073	.0001612	-1.29	0.199	-.0005233 .0001088
educ D1.	.0109361	.0146356	0.75	0.455	-.017749 .0396213
Dciv	.0224509	.0113502	1.98	0.048	.0002049 .044697
hhrelation D1.	.0384242	.0377188	1.02	0.308	-.0355033 .1123517
activityp D1.	-.0049844	.0062528	-0.80	0.425	-.0172397 .0072709

Appendix 18. Estimation via First Difference. Dicho. dependent variable. Subsample. Men

First Differences regression for 2013 to 2014. Dichotomic dependent variable. Probit. Subsample. Only for men

```
. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activitytp,
> vce(cluster hhid)
```

note: DJUNTOS_fem omitted because of collinearity
Iteration 0: log pseudolikelihood = -420.93768
Iteration 1: log pseudolikelihood = -418.5862
Iteration 2: log pseudolikelihood = -418.56093
Iteration 3: log pseudolikelihood = -418.56092

Probit regression

Number of obs	=	1,823
Wald chi2(7)	=	6.64
Prob > chi2	=	0.4678
Pseudo R2	=	0.0056

Log pseudolikelihood = -418.56092

(Std. Err. adjusted for 1,823 clusters in hhid)

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.323264	.1908744	1.69	0.090	-.0508431 .697371
DJUNTOS_fem	0 (omitted)				
age					
DL.	.039621	.1372695	0.29	0.773	-.2294224 .3086643
agesquare					
DL.	-.0005393	.0013945	-0.39	0.699	-.0032725 .0021939
educ					
DL.	.0145062	.1299021	0.11	0.911	-.2400973 .2691096
Dciv					
DL.	.1503401	.1419934	1.06	0.290	-.1279619 .4286422
hhrelation					
DL.	.254014	.1842342	1.38	0.168	-.1070783 .6151064
activitytp					
DL.	.0391675	.0589651	0.66	0.507	-.0764019 .1547369
_cons	-1.557641	.0555836	-28.02	0.000	-1.666583 -1.448699

First Differences regression for 2013 to 2015. Dichotomic dependent variable. Probit. Subsample. Only for men

```
. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activitytp, vce(clust
> er hhid)
```

note: DJUNTOS_fem omitted because of collinearity
Iteration 0: log pseudolikelihood = -716.3655
Iteration 1: log pseudolikelihood = -714.79299
Iteration 2: log pseudolikelihood = -714.79007
Iteration 3: log pseudolikelihood = -714.79007

Probit regression

Number of obs	=	3,173
Wald chi2(7)	=	6.50
Prob > chi2	=	0.4827
Pseudo R2	=	0.0022

Log pseudolikelihood = -714.79007

(Std. Err. adjusted for 1,827 clusters in hhid)

Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
DJUNTOS	.1318526	.1588985	0.83	0.407	-.1795828 .4432881
DJUNTOS_fem	0 (omitted)				
age					
DL.	.0682057	.1241083	0.55	0.583	-.1750421 .3114534
agesquare					
DL.	-.0006182	.0012498	-0.49	0.621	-.0030677 .0018314
educ					
DL.	-.0524908	.0770818	-0.68	0.496	-.2035684 .0985867
Dciv					
DL.	-.0417299	.0803223	-0.52	0.603	-.1991588 .115699
hhrelation					
DL.	.2399816	.1351207	1.78	0.076	-.0248502 .5048133
activitytp					
DL.	.044028	.0374841	1.17	0.240	-.0294395 .1174954
cons	-1.579804	.0459395	-34.39	0.000	-1.669844 -1.489764

First Differences regression for 2014 to 2015. Dichotomic dependent variable. Probit. Subsample. Only for men

<pre>. probit Dworklw DJUNTOS DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(clust > er hhid)</pre>						
<pre>note: DJUNTOS_fem omitted because of collinearity Iteration 0: log pseudolikelihood = -415.15425 Iteration 1: log pseudolikelihood = -412.47725 Iteration 2: log pseudolikelihood = -412.44304 Iteration 3: log pseudolikelihood = -412.44303</pre>						
<pre>Probit regression Number of obs = 1,818 Wald chi2(7) = 5.80 Prob > chi2 = 0.5629 Log pseudolikelihood = -412.44303 Pseudo R2 = 0.0065</pre>						
(Std. Err. adjusted for 1,818 clusters in hhid)						
Dworklw	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
DJUNTOS	-.0946163	.2417749	-0.39	0.696	-.5684863	.3792537
DJUNTOS_fem	0	(omitted)				
age						
D1.	.1594582	.1616332	0.99	0.324	-.157337	.4762535
agesquare						
D1.	-.0013807	.0015684	-0.88	0.379	-.0044547	.0016933
educ						
D1.	.0419115	.1277377	0.33	0.743	-.2084499	.2922728
Dciv	-.2127069	.155293	-1.37	0.171	-.5170755	.0916617
hhrelation						
D1.	.3221799	.2387611	1.35	0.177	-.1457832	.790143
activityp						
D1.	.0556089	.0553104	1.01	0.315	-.0527974	.1640152
_cons	-1.593305	.063689	-25.02	0.000	-1.718133	-1.468476

Appendix 19. Propensity Score Matching.

Propensity Score Matching estimation for 2013 to 2015.

```
. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ
> ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)
```

Probit regression

Number of obs = 38,804
 LR chi2(11) = 456.61
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0554

Log likelihood = -3890.5571

workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Juntos	.180272	.0910509	1.98	0.048	.0018155 .3587286
Juntgen	-.4626458	.1022029	-4.53	0.000	-.6629599 -.2623317
gender	.0129663	.0330503	0.39	0.695	-.0518111 .0777436
age	-.0299711	.0062636	-4.78	0.000	-.0422474 -.0176947
agesquare	.0002176	.0000626	3.48	0.001	.0000095 .0003402
educ	-.2695641	.0166823	-16.16	0.000	-.3022609 -.2368673
mothertongue	.0333638	.0128699	2.59	0.010	.0081393 .0585884
CIV	.0108438	.0094859	1.14	0.253	-.0077481 .0294357
hhrelation	.0262922	.0156963	1.68	0.094	-.004472 .0570564
activitytyp	.0533182	.0139828	3.81	0.000	.0259124 .080724
estrato	-.0163168	.0072517	-2.25	0.024	-.0305297 -.0021038
_cons	3.579173	.1948369	18.37	0.000	3.1973 3.961047

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.117647059	.130536131	-.002001775	.000086808	-23.06
	ATT	.117647059	.139084115	-.021437056	.032013979	-0.67

Propensity Score Matching estimation for 2014 to 2015.

```
. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ
> ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)
```

Probit regression

Number of obs = 31,059
 LR chi2(11) = 381.82
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0603

Log likelihood = -2973.2626

workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Juntos	.2488583	.1099687	2.26	0.024	.0333236 .4643931
Juntgen	-.5075342	.1219526	-4.16	0.000	-.746557 -.2685115
gender	-.0309452	.0375044	-0.83	0.409	-.1044525 .042562
age	-.0350994	.0071447	-4.91	0.000	-.0491027 -.0210961
agesquare	.0002607	.0000718	3.63	0.000	.000012 .0004014
educ	-.2864633	.0193386	-14.81	0.000	-.3243663 -.2485603
mothertongue	.0212209	.0150323	1.41	0.158	-.0082418 .0506836
CIV	.0205273	.0106637	1.92	0.054	-.0003732 .0414278
hhrelation	.0065252	.0159584	0.41	0.683	-.0247527 .0378031
activitytyp	.032669	.0158985	2.05	0.040	.0015085 .0638295
estrato	-.0309598	.008298	-3.73	0.000	-.0472237 -.014696
_cons	3.996513	.2223925	17.97	0.000	3.560632 4.432395

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.123595506	.128834356	-.002142139	.00009901	-21.64
	ATT	.123595506	.142879854	-.019284349	.037809281	-0.51

Appendix 20. Propensity Score Matching. Different value for h.

Propensity Score Matching estimation for 2013 to 2014. With $h=0.01$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.01) out(Juntos)</pre>						
Probit regression			Number of obs		=	30,174
			LR chi2(11)		=	359.11
			Prob > chi2		=	0.0000
Log likelihood = -3131.8482			Pseudo R2		=	0.0542
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.1761527	.103972	1.69	0.090	-.0276287	.3799342
Juntgen	-.3777927	.1185445	-3.19	0.001	-.6101357	-.1454498
gender	.0436605	.0363743	1.20	0.230	-.0276318	.1149528
age	-.0267388	.0067955	-3.93	0.000	-.0400576	-.0134199
agesquare	.0001841	.0000683	2.70	0.007	.0000503	.0003179
educ	-.2656636	.0186177	-14.27	0.000	-.3021537	-.2291736
mothertongue	.0406623	.0143465	2.83	0.005	.0125437	.0687809
CIV	.0089598	.0103828	0.86	0.388	-.0113901	.0293096
hhrelation	.0449893	.0174225	2.58	0.010	.0108418	.0791367
activitytyp	.0628651	.0155665	4.04	0.000	.0323553	.0933749
estrato	-.0174502	.0080255	-2.17	0.030	-.0331799	-.0017205
_cons	3.371705	.2114996	15.94	0.000	2.957174	3.786237
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.128712871	.106321839	-.001884775	.000093297	-20.20
	ATT	.128712871	.126380573	.002332299	.036298856	0.06

Propensity Score Matching estimation for 2013 to 2014. With $h=0.07$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.07) out(Juntos)</pre>						
Probit regression			Number of obs		=	30,174
			LR chi2(11)		=	359.11
			Prob > chi2		=	0.0000
Log likelihood = -3131.8482			Pseudo R2		=	0.0542
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.1761527	.103972	1.69	0.090	-.0276287	.3799342
Juntgen	-.3777927	.1185445	-3.19	0.001	-.6101357	-.1454498
gender	.0436605	.0363743	1.20	0.230	-.0276318	.1149528
age	-.0267388	.0067955	-3.93	0.000	-.0400576	-.0134199
agesquare	.0001841	.0000683	2.70	0.007	.0000503	.0003179
educ	-.2656636	.0186177	-14.27	0.000	-.3021537	-.2291736
mothertongue	.0406623	.0143465	2.83	0.005	.0125437	.0687809
CIV	.0089598	.0103828	0.86	0.388	-.0113901	.0293096
hhrelation	.0449893	.0174225	2.58	0.010	.0108418	.0791367
activitytyp	.0628651	.0155665	4.04	0.000	.0323553	.0933749
estrato	-.0174502	.0080255	-2.17	0.030	-.0331799	-.0017205
_cons	3.371705	.2114996	15.94	0.000	2.957174	3.786237
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.128712871	.106321839	-.001884775	.000093297	-20.20
	ATT	.128712871	.112327711	.01638516	.0355324	0.46

Propensity Score Matching estimation for 2013 to 2014. With $h=0.03$

. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.03) out(Juntos)						
Probit regression			Number of obs		=	30,174
			LR chi2(11)		=	359.11
			Prob > chi2		=	0.0000
Log likelihood = -3131.8482			Pseudo R2		=	0.0542
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.1761527	.103972	1.69	0.090	-.0276287	.3799342
Juntgen	-.3777927	.1185445	-3.19	0.001	-.6101357	-.1454498
gender	.0436605	.0363743	1.20	0.230	-.0276318	.1149528
age	-.0267388	.0067955	-3.93	0.000	-.0400576	-.0134199
agesquare	.0001841	.0000683	2.70	0.007	.0000503	.0003179
educ	-.2656636	.0186177	-14.27	0.000	-.3021537	-.2291736
mothertongue	.0406623	.0143465	2.83	0.005	.0125437	.0687809
CIV	.0089598	.0103828	0.86	0.388	-.0113901	.0293096
hhrelation	.0449893	.0174225	2.58	0.010	.0108418	.0791367
activitytyp	.0628651	.0155665	4.04	0.000	.0323553	.0933749
estrato	-.0174502	.0080255	-2.17	0.030	-.0331799	-.0017205
_cons	3.371705	.2114996	15.94	0.000	2.957174	3.786237
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.128712871	.106321839	-.001884775	.000093297	-20.20
	ATT	.128712871	.125192805	.003520066	.035852433	0.10

Propensity Score Matching estimation for 2013 to 2015. With $h=0.01$

. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.01) out(Juntos)						
Probit regression			Number of obs		=	38,804
			LR chi2(11)		=	456.61
			Prob > chi2		=	0.0000
Log likelihood = -3890.5571			Pseudo R2		=	0.0554
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.180272	.0910509	1.98	0.048	.0018155	.3587286
Juntgen	-.4626458	.1022029	-4.53	0.000	-.6629599	-.2623317
gender	.0129663	.0330503	0.39	0.695	-.0518111	.0777436
age	-.0299711	.0062636	-4.78	0.000	-.0422474	-.0176947
agesquare	.0002176	.0000626	3.48	0.001	.0000095	.0003402
educ	-.2695641	.0166823	-16.16	0.000	-.3022609	-.2368673
mothertongue	.0333638	.0128699	2.59	0.010	.0081393	.0585884
CIV	.0108438	.0094859	1.14	0.253	-.0077481	.0294357
hhrelation	.0262922	.0156963	1.68	0.094	-.004472	.0570564
activitytyp	.0533182	.0139828	3.81	0.000	.0259124	.080724
estrato	-.0163168	.0072517	-2.25	0.024	-.0305297	-.0021038
_cons	3.579173	.1948369	18.37	0.000	3.1973	3.961047
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.117647059	.130536131	-.002001775	.000086808	-23.06
	ATT	.117647059	.135945191	-.018298132	.032735359	-0.56

Propensity Score Matching estimation for 2014 to 2015. With $h=0.01$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.01) out(Juntos)</pre>						
Probit regression			Number of obs		=	31,059
			LR chi2(11)		=	381.82
			Prob > chi2		=	0.0000
Log likelihood = -2973.2626			Pseudo R2		=	0.0603
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.2488583	.1099687	2.26	0.024	.0333236	.4643931
Juntgen	-.5075342	.1219526	-4.16	0.000	-.746557	-.2685115
gender	-.0309452	.0375044	-0.83	0.409	-.1044525	.042562
age	-.0350994	.0071447	-4.91	0.000	-.0491027	-.0210961
agesquare	.0002607	.0000718	3.63	0.000	.00012	.0004014
educ	-.2864633	.0193386	-14.81	0.000	-.3243663	-.2485603
mothertongue	.0212209	.0150323	1.41	0.158	-.0082418	.0506836
CIV	.0205273	.0106637	1.92	0.054	-.0003732	.0414278
hhrelation	.0065252	.0159584	0.41	0.683	-.0247527	.0378031
activitytyp	.032669	.0158985	2.05	0.040	.0015085	.0638295
estrato	-.0309598	.0082298	-3.73	0.000	-.0472237	-.014696
_cons	3.996513	.2223925	17.97	0.000	3.560632	4.432395
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.123595506	.128834356	-.002142139	.00009901	-21.64
	ATT	.123595506	.13701631	-.013420805	.038976896	-0.34

Appendix 21. Propensity Score Matching. Only head of household and partner

Propensity Score Matching estimation for 2013 to 2014. Only head of household and partner. With $h=0.05$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)</pre>						
Probit regression			Number of obs		=	21,977
			LR chi2(11)		=	267.57
			Prob > chi2		=	0.0000
Log likelihood = -2477.7584			Pseudo R2		=	0.0512
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.2190919	.1190828	1.84	0.066	-.014306	.4524899
Juntgen	-.4054037	.1335741	-3.04	0.002	-.6672042	-.1436032
gender	.1660212	.0606185	2.74	0.006	.0472113	.2848312
age	-.0172291	.0089912	-1.92	0.055	-.0348515	.0003933
agesquare	.0001002	.0000854	1.17	0.241	-.0000671	.0002675
educ	-.2655394	.0204376	-12.99	0.000	-.3055963	-.2254825
mothertongue	.0493475	.015129	3.26	0.001	.0196951	.0789998
CIV	.0360234	.0173241	2.08	0.038	.0020688	.069978
hhrelation	.2784647	.0675745	4.12	0.000	.1460212	.4109083
activitytyp	.0451269	.0175864	2.57	0.010	.0106582	.0795956
estrato	-.021515	.0091733	-2.35	0.019	-.0394943	-.0035357
_cons	2.732192	.2831546	9.65	0.000	2.177219	3.287164
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.153846154	.117647059	-.001969809	.000113768	-17.31
	ATT	.153846154	.129274395	.024571759	.043509802	0.56

Propensity Score Matching estimation for 2013 to 2015. Only head of household and partner. With $h=0.05$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)</pre>						
Probit regression			Number of obs		=	29,267
			LR chi2(11)		=	359.41
			Prob > chi2		=	0.0000
Log likelihood = -3095.3313			Pseudo R2		=	0.0549
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.2184833	.1037461	2.11	0.035	.0151447	.4218219
Juntgen	-.4929888	.1147412	-4.30	0.000	-.7178774	-.2681002
gender	.1548615	.0554122	2.79	0.005	.0462555	.2634674
age	-.0197098	.0083932	-2.35	0.019	-.0361602	-.0032594
agesquare	.0001284	.0000792	1.62	0.105	-.0000268	.0002836
educ	-.2695886	.0182887	-14.74	0.000	-.3054338	-.2337433
mothertongue	.0416572	.0135048	3.08	0.002	.0151882	.0681262
CIV	.0309303	.0155404	1.99	0.047	.0004716	.0613889
hhrelation	.2882811	.0619768	4.65	0.000	.1668088	.4097534
activitytyp	.0362308	.0158047	2.29	0.022	.0052542	.0672074
estrato	-.0230153	.0082853	-2.78	0.005	-.0392543	-.0067763
_cons	2.898835	.2635763	11.00	0.000	2.382235	3.415435
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.144444444	.147398844	-.002001734	.000103819	-19.28
	ATT	.144444444	.150773351	-.006328907	.03983297	-0.16

Propensity Score Matching estimation for 2014 to 2015. Only head of household and partner. With $h=0.05$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)</pre>						
Probit regression			Number of obs		=	22,823
			LR chi2(11)		=	299.54
			Prob > chi2		=	0.0000
Log likelihood = -2323.2229			Pseudo R2		=	0.0606
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.3758095	.1350047	2.78	0.005	.1112051	.6404139
Juntgen	-.6383832	.1462743	-4.36	0.000	-.9250755	-.3516909
gender	.1271563	.0635472	2.00	0.045	.0026061	.2517065
age	-.0191442	.0096097	-1.99	0.046	-.0379789	-.0003095
agesquare	.0001219	.0000911	1.34	0.181	-.0000567	.0003004
educ	-.2929843	.0213649	-13.71	0.000	-.3348588	-.2511098
mothertongue	.0324061	.0158694	2.04	0.041	.0013027	.0635095
CIV	.0322032	.0178228	1.81	0.071	-.0027289	.0671354
hhrelation	.2534243	.0710482	3.57	0.000	.1141725	.3926762
activitytyp	.0111253	.0181037	0.61	0.539	-.0243573	.0466079
estrato	-.0393279	.0096187	-4.09	0.000	-.0581801	-.0204756
_cons	3.219451	.3026605	10.64	0.000	2.626248	3.812655
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.147540984	.142857143	-.002102112	.000119527	-17.59
	ATT	.147540984	.151079667	-.003538683	.048660012	-0.07

Appendix 22. Propensity Score Matching. Subsample

Propensity Score Matching estimation for 2013 to 2014. With $h=0.01$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.01) out(Juntos)</pre>						
Probit regression			Number of obs		=	8,579
			LR chi2(11)		=	82.00
			Prob > chi2		=	0.0000
Log likelihood = -878.35279			Pseudo R2		=	0.0446
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.0641204	.1437466	0.45	0.656	-.2176178	.3458586
Juntgen	-.3160583	.1614988	-1.96	0.050	-.6325902	.0004735
gender	-.0052361	.1244464	-0.04	0.966	-.2491466	.2386743
age	-.0530263	.0224222	-2.36	0.018	-.0969729	-.0090796
agesquare	.0005333	.0002351	2.27	0.023	.0000725	.0009941
educ	-.1857614	.0351841	-5.28	0.000	-.2547209	-.1168019
mothertongue	.0582182	.0249636	2.33	0.020	.0092904	.1071461
CIV	-.0430799	.0362475	-1.19	0.235	-.1141237	.0279638
hhrelation	.157533	.1266435	1.24	0.214	-.0906837	.4057498
activitytyp	.0379247	.0296084	1.28	0.200	-.0201068	.0959562
estrato	.0084555	.0157585	0.54	0.592	-.0224306	.0393415
_cons	3.452944	.6022839	5.73	0.000	2.272489	4.633399
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.194444444	.255208333	-.003506072	.000221464	-15.83
	ATT	.194444444	.258083792	-.063639348	.078079312	-0.82

Propensity Score Matching estimation for 2013 to 2015. With $h=0.05$

<pre>. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)</pre>						
Probit regression			Number of obs		=	11,447
			LR chi2(11)		=	132.89
			Prob > chi2		=	0.0000
Log likelihood = -1140.6095			Pseudo R2		=	0.0550
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.1533249	.134285	1.14	0.254	-.1098688	.4165187
Juntgen	-.5191708	.1465928	-3.54	0.000	-.8064874	-.2318542
gender	-.0339283	.1158417	-0.29	0.770	-.2609738	.1931172
age	-.0444477	.0195348	-2.28	0.023	-.0827352	-.0061602
agesquare	.0004561	.0002042	2.23	0.026	.0000559	.0008562
educ	-.2042576	.0312519	-6.54	0.000	-.2655102	-.143005
mothertongue	.0561816	.0218151	2.58	0.010	.0134248	.0989384
CIV	-.0278931	.0331615	-0.84	0.400	-.0928885	.0371023
hhrelation	.1624172	.1178022	1.38	0.168	-.0684709	.3933052
activitytyp	.0207187	.0263144	0.79	0.431	-.0308565	.072294
estrato	.0064903	.0141066	0.46	0.645	-.0211582	.0341388
_cons	3.375173	.5331808	6.33	0.000	2.330158	4.420188
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.179487179	.302788845	-.003696879	.000200475	-18.44
	ATT	.179487179	.274446716	-.094959536	.069048685	-1.38

Propensity Score Matching estimation for 2014 to 2015. With $h=0.05$

. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)						
Probit regression			Number of obs		=	9,012
			LR chi2(11)		=	115.16
			Prob > chi2		=	0.0000
Log likelihood = -821.11987			Pseudo R2		=	0.0655
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	.407724	.1841343	2.21	0.027	.0468274	.7686207
Juntgen	-.748537	.1969317	-3.80	0.000	-1.134516	-.362558
gender	-.1387917	.1381166	-1.00	0.315	-.4094953	.1319119
age	-.0486568	.0238531	-2.04	0.041	-.0954081	-.0019055
agesquare	.0005191	.0002523	2.06	0.040	.0000246	.0010137
educ	-.2288016	.0370938	-6.17	0.000	-.301504	-.1560991
mothertongue	.0580328	.0259431	2.24	0.025	.0071853	.1088802
CIV	-.0546509	.0395482	-1.38	0.167	-.132164	.0228621
hhrelation	.0490536	.1400192	0.35	0.726	-.225379	.3234862
activitytyp	-.0030176	.0309681	-0.10	0.922	-.0637141	.0576788
estrato	-.0245232	.0165633	-1.48	0.139	-.0569867	.0079404
_cons	4.022373	.6492268	6.20	0.000	2.749911	5.294834
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.2	.30726257	-.003933903	.000230245	-17.09
	ATT	.2	.263541043	-.063541043	.098758233	-0.64

Appendix 23. Propensity Score Matching. Subsample. Only for man

Propensity Score Matching estimation for 2013 to 2014. Only for man. With h=0.05

. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ > ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)						
note: Juntgen omitted because of collinearity						
note: gender omitted because of collinearity						
Probit regression			Number of obs		=	4,409
			LR chi2(9)		=	22.37
			Prob > chi2		=	0.0078
Log likelihood = -564.46441			Pseudo R2		=	0.0194
workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Juntos	-.188465	.1039697	-1.81	0.070	-.3922419	.0153119
Juntgen	0	(omitted)				
gender	0	(omitted)				
age	-.0380898	.0268271	-1.42	0.156	-.0906699	.0144903
agesquare	.0003791	.0002733	1.39	0.165	-.0001566	.0009148
educ	-.1233133	.0460539	-2.68	0.007	-.2135772	-.0330493
mothertongue	.0594261	.0302261	1.97	0.049	.000184	.1186683
CIV	-.079139	.0513188	-1.54	0.123	-.1797221	.021444
hhrelation	-.1145007	.2097066	-0.55	0.585	-.525518	.2965167
activitytyp	-.0774166	.0419379	-1.85	0.065	-.1596135	.0047803
estrato	-.0199063	.0205201	-0.97	0.332	-.0601249	.0203123
_cons	3.648436	.7372867	4.95	0.000	2.20338	5.093491
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.352941176	.307086614	-.00434618	.000315513	-13.77
	ATT	.352941176	.305633564	.047307613	.126424303	0.37

Propensity Score Matching estimation for 2013 to 2015. Only for man. With h=0.05

```
. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ
> ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)
note: Juntgen omitted because of collinearity
note: gender omitted because of collinearity
```

Probit regression

Number of obs	=	5,817
LR chi2(9)	=	39.05
Prob > chi2	=	0.0000
Pseudo R2	=	0.0246

Log likelihood = -772.90618

workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Juntos	-.3231789	.0880206	-3.67	0.000	-.4956961 -.1506617
Juntgen	0	(omitted)			
gender	0	(omitted)			
age	-.0214684	.022397	-0.96	0.338	-.0653656 .0224288
agesquare	.0002221	.0002278	0.97	0.330	-.0002244 .0006686
educ	-.1547743	.0401804	-3.85	0.000	-.2335264 -.0760221
mothertongue	.0604528	.0258759	2.34	0.019	.009737 .1111686
CIV	-.0503078	.0460487	-1.09	0.275	-.1405616 .0399461
hhrelation	-.0363537	.2048323	-0.18	0.859	-.4378176 .3651103
activitytyp	-.0820362	.0361776	-2.27	0.023	-.1529431 -.0111294
estrato	-.0116264	.0179087	-0.65	0.516	-.0467268 .0234739
_cons	3.207608	.6275039	5.11	0.000	1.977723 4.437493

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.294117647	.372881356	-.00481965	.000286689	-16.81
	ATT	.294117647	.353329838	-.059212191	.119745733	-0.49

Propensity Score Matching estimation for 2014 to 2015. Only for man. With h=0.05

```
. psmatch2 workp Juntos Juntgen gender age agesquare educ mothertongue CIV hhrelation activ
> ityp estrato, kernel k(epan) bwidth (0.05) out(Juntos)
note: Juntgen omitted because of collinearity
note: gender omitted because of collinearity
```

Probit regression

Number of obs	=	4,573
LR chi2(9)	=	38.46
Prob > chi2	=	0.0000
Pseudo R2	=	0.0325

Log likelihood = -571.75475

workp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Juntos	-.2671238	.0992837	-2.69	0.007	-.4617163 -.0725313
Juntgen	0	(omitted)			
gender	0	(omitted)			
age	-.033851	.0275596	-1.23	0.219	-.0878669 .0201648
agesquare	.0003635	.0002847	1.28	0.202	-.0001944 .0009215
educ	-.1750585	.0465029	-3.76	0.000	-.2662026 -.0839144
mothertongue	.0764178	.0301132	2.54	0.011	.017397 .1354385
CIV	-.0552649	.0537886	-1.03	0.304	-.1606886 .0501588
hhrelation	.1122971	.2445231	0.46	0.646	-.3669593 .5915536
activitytyp	-.0796151	.041964	-1.90	0.058	-.1618631 .0026328
estrato	-.0414676	.02088	-1.99	0.047	-.0823916 -.0005436
_cons	3.506601	.7590402	4.62	0.000	2.018909 4.994292

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Juntos	Unmatched	.285714286	.392307692	-.005074476	.000328913	-15.43
	ATT	.285714286	.365886683	-.080172397	.189619782	-0.42

Appendix 24. Estimations via First Differences for 2013 to 2014. Without taking into account the individuals that stop receiving “Juntos”.

Fist Differneces estimation for 2013 to 2014. Number of hours of work.

```
. regress Dworkp Djuntos DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression

Number of obs	=	13,418
F(8, 7298)	=	2.25
Prob > F	=	0.0214
R-squared	=	0.0019
Root MSE	=	21.152

(Std. Err. adjusted for 7,299 clusters in hhid)

Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
Djuntos	.4684572	1.789007	0.26	0.793	-3.038515 3.975429
DJUNTOS_fem	.0160247	2.326556	0.01	0.995	-4.544698 4.576748
age					
D1.	1.397845	.5546835	2.52	0.012	.3105046 2.485185
agesquare					
D1.	-.0134933	.0050081	-2.69	0.007	-.0233106 -.0036759
educ					
D1.	.2450732	.4650773	0.53	0.598	-.6666128 1.156759
Dciv	-.1838395	.3088628	-0.60	0.552	-.7892998 .4216209
hhrelation					
D1.	.2544811	.3550737	0.72	0.474	-.4415659 .9505281
activityp					
D1.	.6355732	.1955155	3.25	0.001	.2523062 1.01884
_cons	-.2110564	.2699557	-0.78	0.434	-.7402476 .3181349

Fist Differneces estimation for 2013 to 2014. Intensive margins of labour supply.

```
. regress Dln_workp Djuntos DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)
```

Linear regression

Number of obs	=	12,869
F(8, 7139)	=	6.21
Prob > F	=	0.0000
R-squared	=	0.0063
Root MSE	=	.77118

(Std. Err. adjusted for 7,140 clusters in hhid)

Dln_workp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
Djuntos	.0129361	.0712956	0.18	0.856	-.1268244 .1526965
DJUNTOS_fem	.0256502	.0963997	0.27	0.790	-.1633217 .2146221
age					
D1.	.0641035	.0208516	3.07	0.002	.0232281 .1049789
agesquare					
D1.	-.0006279	.0001945	-3.23	0.001	-.0010091 -.0002467
educ					
D1.	.0106051	.0158478	0.67	0.503	-.0204613 .0416714
Dciv	-.013584	.0105889	-1.28	0.200	-.0343415 .0071734
hhrelation					
D1.	-.0096167	.0126991	-0.76	0.449	-.0345106 .0152773
activityp					
D1.	.0491187	.0080247	6.12	0.000	.0333879 .0648494
_cons	.0024876	.0095918	0.26	0.795	-.0163152 .0212904

Fist Differneces estimation for 2013 to 2014. Extensive margins of labour supply.

. regress Dworkp Djuntos DJUNTOS_fem D.age D.agesquare D.educ Dciv D.hhrelation D.activityp, vce(cluster hhid)						
Linear regression		Number of obs	=	3,557		
		F(8, 2195)	=	3.06		
		Prob > F	=	0.0020		
		R-squared	=	0.0087		
		Root MSE	=	21.637		
(Std. Err. adjusted for 2,196 clusters in hhid)						
Dworkp	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
Djuntos	-1.181476	2.939291	-0.40	0.688	-6.945559	4.582608
DJUNTOS_fem	1.72874	4.045609	0.43	0.669	-6.204883	9.662362
age						
Dl.	2.188651	1.366798	1.60	0.109	-.4917007	4.869004
agesquare						
Dl.	-.0192556	.0139672	-1.38	0.168	-.0466459	.0081347
educ						
Dl.	2.003356	1.038696	1.93	0.054	-.0335748	4.040287
Dciv	.5319598	.9812756	0.54	0.588	-1.392366	2.456286
hhrelation						
Dl.	1.563178	3.462307	0.45	0.652	-5.226563	8.352918
activityp						
Dl.	1.652613	.3768672	4.39	0.000	.9135596	2.391667
_cons	-.6540714	.5703702	-1.15	0.252	-1.772593	.4644505

Appendix 25. Tabulation of the variation of control variables between 2013 and 2014. First Differences method

Variable “Juntos”.

. tab Djuntos				. tab DJUNTOS			
Djuntos	Freq.	Percent	Cum.	DJUNTOS	Freq.	Percent	Cum.
-1	274	0.73	0.73				
0	35,573	94.35	95.08	0	35,573	94.35	94.35
1	1,855	4.92	100.00	1	2,129	5.65	100.00
Total	37,702	100.00		Total	37,702	100.00	

Variable “Dciv” representing the civil status and variable “DEDUC” representing the level of education.

. tab Dciv				. tab DEDUC			
Dciv	Freq.	Percent	Cum.	DEDUC	Freq.	Percent	Cum.
-5	142	0.47	0.47				
-4	115	0.38	0.86	-3	6	0.02	0.02
-3	58	0.19	1.05	-2	87	0.24	0.25
-2	70	0.23	1.28	-1	1,820	4.97	5.23
-1	535	1.79	3.07	0	30,686	83.82	89.05
0	28,017	93.48	96.55	1	3,934	10.75	99.79
1	674	2.25	98.80	2	72	0.20	99.99
2	86	0.29	99.09	3	4	0.01	100.00
3	104	0.35	99.43				
4	143	0.48	99.91				
5	27	0.09	100.00				
Total	29,971	100.00		Total	36,609	100.00	

Variable “DHHRELTION” representing the relationship to the household and variable “DACTIVITY” representing the type of principal work.

Total	36,609	100.00					
. tab DHHRELATION							
DHHRELATION	Freq.	Percent	Cum.	DACTIVITY	Freq.	Percent	Cum.
-9	8	0.02	0.02	-6	1	0.00	0.00
-8	2	0.01	0.03	-5	19	0.09	0.10
-7	15	0.04	0.07	-4	101	0.48	0.58
-6	33	0.09	0.16	-3	731	3.48	4.06
-5	52	0.14	0.30	-2	828	3.95	8.01
-4	63	0.17	0.47	-1	1,419	6.76	14.77
-3	47	0.13	0.60	0	14,935	71.20	85.97
-2	289	0.79	1.39	1	1,396	6.66	92.63
-1	213	0.58	1.97	2	767	3.66	96.29
0	35,505	96.92	98.89	3	654	3.12	99.40
1	117	0.32	99.21	4	101	0.48	99.89
2	90	0.25	99.45	5	19	0.09	99.98
3	51	0.14	99.59	6	5	0.02	100.00
4	72	0.20	99.79				
5	52	0.14	99.93				
6	15	0.04	99.97				
7	5	0.01	99.98				
8	4	0.01	99.99				
9	2	0.01	100.00				
Total	36,635	100.00		Total	20,976	100.00	

Appendix 26. Common trend assessment

Common trend assessment tested via the available data of the district of San Martin (2011 to 2014)..

. by year, sort : sum worklw if Juntos == 0						
-> year = 2011						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	103	.8349515	.3730396	0	1	
-> year = 2012						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	103	.8349515	.3730396	0	1	
-> year = 2013						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	104	.8076923	.396022	0	1	
-> year = 2014						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	86	.8139535	.3914266	0	1	
. by year, sort : sum worklw if junt == 1						
-> year = 2011						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	16	.8125	.4031129	0	1	
-> year = 2012						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	17	.8823529	.3321056	0	1	
-> year = 2013						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	17	.7647059	.4372373	0	1	
-> year = 2014						
Variable	Obs	Mean	Std. Dev.	Min	Max	
worklw	17	.7647059	.4372373	0	1	

Common trend assessment tested via the available data of the district of Ucayali (2013 to 2015).

. do "C:\Users\astri\AppData\Local\Temp\STD47b0_000000.tmp"					
. by year, sort : sum worklw if Juntos == 0					
-> year = 2013					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	369	.804878	.3968326	0	1
-> year = 2014					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	364	.7967033	.4030054	0	1
-> year = 2015					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	356	.755618	.430325	0	1
. by year, sort : sum worklw if junt == 1					
-> year = 2013					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	124	.7903226	.4087298	0	1
-> year = 2014					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	126	.8253968	.3811428	0	1
-> year = 2015					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	128	.8203125	.3854355	0	1

Common trend assessment tested via the available data of the district of Ucayali (2012 to 2015).

. by year, sort : sum worklw if Juntos == 0					
-> year = 2012					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	172	.7093023	.4554101	0	1
-> year = 2013					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	133	.8045113	.3980758	0	1
-> year = 2014					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	127	.7716535	.4214295	0	1
-> year = 2015					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	129	.7131783	.4540409	0	1
. by year, sort : sum worklw if junt == 1					
-> year = 2012					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	51	.7254902	.4507075	0	1
-> year = 2013					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	51	.8627451	.3475404	0	1
-> year = 2014					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	52	.8653846	.3446423	0	1
-> year = 2015					
Variable	Obs	Mean	Std. Dev.	Min	Max
worklw	52	.8269231	.3820047	0	1