The Impact of Cash Conditional Transfers on Education and Youth Work in Argentina

Alvarez Camps, Inaki

Master Thesis Capstone: Policy evaluation and explaining human behaviour using microdata
Institute of Public Administration, Leiden University
Master Public Administration: Economics and Governance
A.Y. 2020-2021
Title: The Impact of Cash Conditional Transfers on Education and Youth Work in Argentina
Author: Iñaki Álvarez Camps
Leiden University
04/06/2021
Instructor: Max van Lent

The Impact of Cash Conditional Transfers on Education and Youth Work in Argentina

Table of Contents

Figures and Tables:

Abstract:

Cash conditional transfer programs have become a popular policy option in developing and middle-income countries to both decrease poverty and increase human capital. Through the use of a difference in difference quantitative analysis, this article analyzes how the *Asignación Universal por Hijo* (a CCT program implemented in Argentina in 2009) has affected both school enrolment rates and youth work since its implementation. The main argument of this research is that, due to the increase in income for eligible families and the conditions of the program, there should have been an increase to school enrolment and a decrease to youth work. The findings of the article suggest that work and school are fully substitutable for one another as the results show that the program resulted in an increase in school enrolment that was matched by a similar decrease in youth work. Specifically, the program seems to have been particularly effective in reducing work and increasing school enrolment of teenage males.

I. Introduction

Beginning in the mid-nineties, cash conditional transfer (CCT) programs became a popular policy option in developing countries. The first of these programs to be introduced in Latin America began in Mexico and Brazil in 1994 and have since then spread throughout the region with now there being around 30 different CCT programs across 19 different countries (Cecchini & Atuesta, 2017). The aim of these programs is twofold. Firstly, through the direct transfer of funds to the less wealthy parts of the population, CCT programs aim to address poverty in the short run. Secondly, through the conditions present in the programs, they aim to improve human capital in the long run by breaking intergenerational poverty traps (Cecchini & Atuesta, 2017; Bardasi & Garica, 2014; Brearly, 2016). The conditions of these programs tend to be based on poor families investing in their children's health, and education.

One program of this kind is Argentina's *Asignación Universal por Hijo* (Universal Child Allowance), also known by its Spanish acronym, AUH. The program was implemented in 2009 replacing and extending the previous CCT program that was in place, the *Plan Jefes y Jefas de Hogares Desocupados*. The program provides cash transfers to families with children under the age of 18 whose parents are not working in the formal sector. This includes families where parents are unemployed, informal workers, inactive or earn below the minimum wage. However, the programs cash transfers are conditional on children having an updated vaccination schedule, passing their health checkups, and being enrolled in school.

The focus of this research will be on the effect of the AUH program on school enrolment and youth work on children between the age of 5 and 18. Although the conditionalities of the program are health related for children under the age of 5, the data source used in this research does not include health related measures. Therefore, the main question addressed is the following: "What has been the impact of the UAH program in Argentina on i) the school enrolment rate of children, and ii) youth work since its implementation in 2009?" Although the program does not require that children do not work, it can be expected that due to the increased earnings of families and the schooling of children, the policy will have an impact on youth work. Youth work and school are seen as intertwined decisions and youth work is related to physical and mental health problems, higher school dropout and lower school performance, therefore, lowering the long term earning capability of children (Prifti et al., 2021; Bandara, Dehejia & Lavie-Rouse, 2015). Therefore, the paper will also engage with literature that has focused on the substitutability between work and school in the time allocation of children in households.

The importance of reducing child work in poor families has often been ignored in the literature evaluating CCT programs. However, youth work is often cited as one of the main reasons for which poor families are forced to keep children out of school to increase the family income in the present and limiting their ability to earn higher wages in adulthood, which can in turn perpetuate poverty to future generations (Bardasi & Garcia, 2014; Basu & Van, 1999). Despite, a number of Latin American countries becoming middle income countries in the last three decades, youth work has, in many countries, remained at the world average (Gunnarsson, Orazem, & Sánchez, 2006). Around the continent, many countries have raised the minimum working age of children (which is 16 in Argentina) but these type of policies are only as effective as the enforcement mechanisms that complement them (Gunnarson et al., 2006; Edo, Marchonni & Garganta, 2017). Therefore, CCT programs may provide an indirect tool to address the issue. By analyzing the impact of the program on both schooling and youth work, the aim of the article is to disentangle the less obvious effects of CCT programs on children's time allocation.

A quasi experimental analysis will be conducted comparing the development of school enrolment and youth work in a control and treatment group, before and after the policy was implemented through a difference in difference approach. The analysis is conducted using the *Encuesta Permanente de Hogares* (Household Permanent Survey), also known by its Spanish acronym, EPH, created by the National Argentine Institute of Statistics and Census (INDEC is its

acronym in Spanish). The main empirical findings of the analysis were that the program has had a significant impact on increasing the school enrollment of boys aged between 15 and 17, and a smaller, yet important, impact on increasing school enrollment of girls aged between 15 and 17. Furthermore, the increase in school enrolment of these groups has been matched by a similar decrease in youth work.

The structure of the paper will be as follows. In the next section, a more in-depth description of the AUH program will be provided. This will be followed by a literature review on previous work done on the impact of CCT programs in other Latin American countries, the relation between schooling and youth work, and the role that the gender of children can play in the decision making process of parents leading to the hypotheses of the research. The subsequent section will offer an in-depth description of the methodology and data used in the analysis, before moving on to the results of the impact of UAH on school enrolment and youth work. The empirical results will be further discussed in the subsequent section before concluding the paper and depicting its implications for theory and the design of CCT programs.

II. Description of the AUH Program

As mentioned above, the AUH program was implemented in 2009 by the Cristina Kirchner government replacing and extending the previous CCT program that was in place. The previous CCT program was only available to families with children where both parents were unemployed. Therefore, the AUH, was a serious expansion as benefits were extended to several other groups. These eligible families are those with children under the age of 18 whose parents are in one of the following situations:

a) Independent workers over the age of 18 earning less than minimum wage;
b) Are inactive from the labor market and are not receiving any benefits from unemployment insurance or pension schemes;
c) Are unemployed, informal workers or household workers earning less than minimum wage.

In households where children live with both parents (parents are still together), both parents must meet these criteria. If one of the parents was working in the formal sector, the family would no longer be eligible to the program. In the case that the parents of the children do not live together but both are eligible to the program, the cash transfer is only given to one of the parents and the mother is often prioritized. Finally, to access the program the families must have Argentinian citizenship or be legal residents having lived in the country for more than three years.

Eligible families who sign up to the program are given a monthly transfer to one of the parents, or caretakers. The monetary sum of the transfer is based on the number of children up to a maximum of 5 children (Table 1A of the Appendix). Interestingly, only 80% of the total cash transfers are made on a monthly basis, the remaining 20% is put in a savings account and can only be taken out by the family if they have met all conditions of the program at the end of the calendar year. Therefore, if families fail to meet conditions, they not only face the prospect of being expelled from the program, but they would also not receive the money in the savings account. For children 5 years old or younger, these conditions require that parents provide proof that children are completing their medical checkups and that their vaccination schedule is up to date. For those children that are over the age of 5, parents must provide proof that children are enrolled in school.

Historically, Argentina have had one of the highest primary school enrolment rates in Latin America, this being similar or higher than that of developed countries (Marchionni & Alejo, 2015). Table 3.1 shows the school enrolment rate of the sample used in this research by different age and gender groups. Even before the policy was implemented the enrolment rate of both girls and boys in primary is near perfect, so the program has little room to improve the enrolment rates of this age group. The lowest enrolment rate before the policy was implemented was that of older children in secondary school. Specifically, males in this age group have the lowest enrolment rate in the sample. Therefore, the AUH program has the most room to improve the school enrolment rate of children in this age group.

Table 3.1: Net School Enrolment Rate per Age Group Before 2010

Age	Treatment		Control	
Gender	Girls	Boys	Girls	Boys
6-11	98.92%	98.66%	98.96%	98.86%
12-14	97.07%	95.44%	98.28%	97.25%
15-17	78.12%	71.58%	86.39%	82.56%

Source: own estimation based on *Encuesta Permanente de Hogares* (EPH)

Note: Sample from EPH of all children in the bottom 4 decile income groups. *Treatment*: children with no parents working in the formal sector. *Control:* children without least one parent in the formal sector.

Overall, the aim of the program is to protect and improve the quality of life of vulnerable children and families, and the program is similar to other CCT programs in Latin America that target vulnerable children. As of 2019, it was estimated that around 3.9 million children were receiving benefits from the AUH program and the policy represented around 0.6% of GDP (UNICEF, 2019). The program implies a substantial change to the model of social protection in Argentina by creating a permanent program, not linked to a national emergency, which to an extent, guarantees a minimum income to families in vulnerable positions (Jimenez & Jimenez, 2015).

III. Literature Review

III.I Theoretical model of the Time allocation of Children

Much of the work on the time allocation tradeoff between school attendance and youth work has been based on the theoretical model set out by Becker (1965) and its application to household behavior. Based on this model, households make certain decisions on how to allocate the time of their children around schooling, market labor, household labor and leisure. The model implies that decision making in households is primarily made by the parents or caretakers of the household who are faced with a tradeoff between current consumption versus future consumption (Ravallion & Wodon, 2000; Nielsen, 1999). On the one hand, by children working, present consumption increases as there is extra income coming into the household. On the other hand, by continuing the children's schooling, it should make parents better off in the future, through transfers from their grown children presumably with a higher wage than would have otherwise been the case (Ravallion & Wodon, 2000; Amarente, Ferrando & Vigorito, 2011).

The decision on whether to send children to school or to work is based on the cost of present versus future consumption and the discount rate the family attaches to earnings (Nielsen, 1999). Poorer households will have higher discount rates because an increase in income in the present is worth more to them than an increase in future earnings, whereas for wealthier families the opposite is true (Nielsen, 1999). The decision also depends on the costs of future versus present consumption. That is to say, if the costs of education are low and the return of a child working is low, the relative cost of future consumption decreases whereas if the return of human capital accumulation decreases, the cost of future consumption will increase (the opposite would be true for the cost of current consumption) (Amarante et al., 2011). Therefore, human capital theory offers two reasons for which parents may choose to take their children out of school and into the labor market. Firstly, if the indirect or direct costs of schooling are high or the quality of schooling low relative to the cost, the cost of future consumption increases, and parents may decide to take their children out of school. Secondly, there may be capital market imperfection which prevents investment and returns on human capital, again increasing the costs of future consumption (Khanam, 2008).

Importantly, the model is based on the assumptions that work and school are near perfect substitutes, which will be discussed later in the paper, and that the decision to allocate time to

one or the other are influenced by the same factors (Amarante et al., 2011). Although time at work and school must to some extent be substitutes for one another, because people only have limited time available and more time spent at work or school must take time away from another activity, it may be the case that more time spent at school does not necessarily take time away from work but from other activities such as leisure (Ravallion & Wodon, 2001). For example, it may be the case that if a CCT program increases school enrolment the extra time spent at school does not lead to a decrease in youth work but to a decrease in children's leisure time. If it was the case that work and school where perfect substitutes for one another we can expect three possible outcomes: i) the child attends school, ii) the child drops out of school and works, and iii) a combination of the two in which the child works part time while attending school.

Based on this literature, it may be expected that work and school are only partial substitutes as children's time is also taken up by a number of other activities such as household chores and leisure time (Ravallion &Wodon, 2001). Therefore, an increase in school enrolment may also lead to a decrease in time spent on such other activities rather than a direct and equal decrease in youth work. The aim of this paper is to analyze if CCT programs, specifically the AUH program, may have an influence on factors in this decision-making model leading to changes in school attendance and youth work.

III.II CCT Programs and School Enrolment

Using the model set out in the previous section we can expect that cash transfer may influence household decision-making through an income and a substitution effect. This is particularly true in the case of CCT programs as the transfers are often linked to the schooling of children. Firstly, the cash transfer will lead to an income effect leading to an increase of demand for all goods including education (Ravallion & Wodon, 2000). Secondly, the transfer also leads to a substitution effect that will increase the demand of goods that are a complement to schooling but this will be met with a decrease in demand for goods that are substitutes for schooling (Skoufias et al., 2001; Amarante et al., 2011). Therefore, if work and school are substitutes for one another the CCT program should lead to a decrease in youth work and an increase in school attendance. However, if the two were not substitutes, an increase in schooling may result from a decrease in children's leisure time rather than work. This is not only dependent on the substitutability between the schooling and work but also on the size of the cash transfers themselves. For the

programs to be effective the transfer should not only cover the direct and indirect fees of schooling but also the opportunity cost of the children not working anymore (Amarante et al., 2011).

One of the most extensive branches of literature on this topic has been the effect of CCT programs on school attendance. This is due to the importance of education in breaking intergenerational poverty traps (Barhman et al., 1995; Tilak, 2002). Most empirical studies have found that CCT programs have a positive impact on the school attendance of children (Brow & Hodinot, 2011; Cardoso & Souza, 2001; Edo & Marchionni, 2019). However, the size of the effect of these programs tends to vary between countries and demographic groups. For example, in Ecuador, the *Bono de Desarrollo Humano* has increased school attendance for children between the age of 5 and 17 by around 10 percentage points (Schady & Araujo, 2008). However, studies in Colombia find that the *Familias en Acción* program has mostly had an impact on secondary school attendance of children of between 5 and 8 percentage points, but a smaller effect on primary school children, this being of between 1 and 4 percentage points (Nuñez & Cuesta, 2006).

Much of the literature seems to find similar results to the Colombian example where the increase in the school attendance of children by CCT programs tend to concentrate on secondary school enrollment (Nuñez & Cuesta, 2006; Edo & Marchionni, 2019; Cardoso & Sauza, 2001). These findings are likely to suggest that primary school enrolment is already quite high in most countries, as is the case in Argentina, and so CCT programs have a limited impact in increasing primary school enrollment. Relating this back to time allocation of households, it is likely that in middle income countries the opportunity costs of primary school children going to school rather than work is much lower than that of teenagers because of the limited amount of jobs they are able to do. However, as children grow the opportunity costs of going to school increase because teenagers can do more jobs than young children. Therefore, families may choose to take them out of school to work and contribute to household incomes.

A small amount of the literature has specifically focused on the effect of the AUH program on school attendance. Most importantly, the work by Edo et al., (2017) found that the increase of the school attendance of children in Argentina was due to the UAH program and not the 2006 law that made secondary school education compulsory. The authors found that because the 2006 law had no enforcement mechanism, and the UAH program provided an income effect

associated with the money transfer, the AUH program was behind the increase in school attendance. More specifically, their results indicated that the program increased secondary school enrollment by around 3.9 percentage points for children in secondary school and by less than 1 percentage point for children in primary school. Although, the Edo et al. (2017) paper offers a thorough analysis of the impact of the AUH program on the oldest age group, similar to the one in this research, the paper does not analyze the impact of the program on youth work and, therefore, does not offer an explanation of how the program affects the time allocation of children in Argentina. The Edo et al. (2017) study also does not offer explanations for some of their findings. Most importantly, the authors find that the AUH program had its largest impact in increasing school enrolment of boys in secondary school but do not address why the program has a difference effect size on boys and girls. Therefore, this research will expand on the work of Edo et al. (2017) by analyzing the effect of the program on both school enrolment and youth work, as well as by providing a more in-depth analysis of the effect of the program on boys and girls.

Overall, previous results in the literature suggest that CCT programs provide enough incentives for children not to drop out of school and for dropouts to get back into the education system (Edo et al., 2017). This results in the following hypothesis for this paper:

H1: The AUH has caused a significant increase in school attendance of secondary school children.

However, this literature does not address whether the increased school attendance rate is matched by a decrease in youth employment. This is an important area of study because the substitutability between work and school is not clear as an increase in school attendance may lead to a reduction in children's leisure time instead of work in a scenario where children both work and go to school. Therefore, just because there has been an increase in school attendance this effect may not be matched by an equal or similar decrease to youth work. The importance of knowing if a possible increase in school enrolment leads to a reduction in youth work or the leisure time of children is twofold. Firstly, previous research has found that long hours of work can have a negative effect on education attainment as it limits children’s time to study, complete homework or attend tutorials (Ravallion & Wodon, 2000; Bandara et al., 2015). Therefore, if

CCT programs are not successful in decreasing youth work, human capital may not increase in the long run even if school enrolment is increased as children's school performance may be limited. Secondly, the leisure time of children is not only important for their own wellbeing but also for the accumulation of human capital. This is because through hobbies such as arts and sports, children are able to acquire a number of social and technical skills helping their physical and cognitive development (Yuen, Pedlar & Mannel, 2005). Overall, in the long run, it is more beneficial for children's increase in schooling to come out of time spent in the labor market, as youth work can slow down human capital accumulation and limit the possible impact of CCT programs.

III.III CCT Programs and Youth Work

Previous literature analyzing the effect of CCT programs on youth work have come to differing and sometimes contradicting conclusions. The influential work by Skoufias and Parker (2001) on the PROGRESA program in Mexico found that the program had both a positive impact in increasing school attendance and decreasing youth work. Interestingly, the authors found significant demographic differences as an increase in schooling of secondary school boys was matched by a similar decrease in market labor, but an increase in schooling of girls in secondary school was not matched by a reduction in work but rather a decrease in leisure time. The work of these authors suggests that work and school attendance are substitutable.

However, other literature finds much more modest results. Attanassio et al. (2010) and Ravallion and Wodon (2000) found that CCT programs in Colombia and Bangladesh, respectively, had limited impact on reducing youth work. Both of these papers come to the conclusion that work participation and school attendance are not directly substitutable. Although both programs did lead to a reduction in work participation of children, the decrease of youth work only accounted for a limited amount of the increase in school enrolment. This suggests that increased school attendance came at the cost of children's leisure time and children's school success might be limited due to children's inability to attend tutorial or complete their homework because of their work.

Finally, other papers have found that some CCT programs have had a positive effect on school attendance but no significant effect on labor participation or that CCT programs actually lead to an increase in youth work (Cardoso & Sauza, 2001; Peruffo & Ferreira, 2017). For

example, Peruffo and Ferreira (2017) conducted a simulation of a CCT program in Brazil and found that in the short run, the program increased youth work by 1 percentage point because the transfers where not large enough to cover the costs of schooling. Therefore, children had to work in order to pay for the costs of schooling, while remaining eligible to the program. Overall, the literature offers a number of different results with no clear relationship between CCT programs, youth work and schooling.

The difference between the results of some of these papers and those by Skoufias and Parker (2001) may be partially explained by the difference in the conceptualization and operationalization of youth work. Skoufias and Parker (2001) use a broader definition of youth work which includes market labor, household domestic work, and farm labor. On the other hand, other literature tends to focus on the domestic and market labor of children or just the market labor of children. This might explain why Skoufias and Parker (2001) find a larger effect of the program on the labor of children as they use a broader conceptualization of youth labor that takes into account a larger amount of activities. In this paper, the operationalization and conceptualization of work are only limited to market labor due to the limitations in the database that is being used, which has no information on household labor or leisure time of children. Therefore, we can expect that the effect of the program on youth work will be smaller as the number of activities taken into account as youth work are limited. It is also important to mention that in the literature youth work and youth labor are often used as interchangeable concepts. However, a difference can be drawn between the two. Youth labor is often used to refer to cases where the children working are overworked either by working for too long, being underpaid or working in hazardous conditions. Youth work, on the other hand, are cases where children work in legitimate conditions (Levison, Moe & Knaul, 2001). Again, in this paper the database used does not allow for a distinction between the two. Therefore, the term ‘youth work’ is used to refer to both concepts.

Another reason that may explain why different scholars have come to different conclusions regarding youth work, apart from the broadness of the conceptualization used, is that the papers analyze different CCT programs in different countries, which suggests that different features of these CCT programs may influence the impact that these programs have on the target population. A possible reason for this is the generosity of the programs themselves. If the cash transfers are not large enough to compensate the loss of income that may come from children not

working anymore, it is very unlikely that the program would have any effect as families would have to decrease their present consumption and, for poorer families, this might not be possible. The differences between CCT programs means that the results of this research may not be generalizable to other countries as different features of the program may lead to different effects. However, the results of the paper can give an insight into possible ways in which CCT programs may be improved and the relationship between schooling and youth work.

Despite the range of conclusions regarding the sustainability of labor participation and school attendance, most of the literature tends to suggest that the two are substitutable to an extent. This would mean that, in the analysis of this paper, it could be expected that if the program has had a positive impact in increasing school attendance, it would also lead to a significant effect on reducing child labor market participation. This leads to the following hypothesis:

H2: The AUH has caused a decrease in youth market work.

Two previous studies have been conducted analyzing the effect of the AUH on youth work. Firstly, the work by Salvia, Tuñón, and Piñeiro (2015) estimated the impact of the AUH program on a number of different outcome variables including, food security, economic wellbeing of children, youth work and education. Overall, the authors found that the program had a negative effect decreasing school desertion by 6 percentage points and smaller but significant effect on reducing child work by around 2.6 percentage points. However, the authors use a propensity score matching analysis using data from the *Encuesta de la Deuda Social Argentina* (Survey of the Argentinian Social Debt) made by the Argentinian Catholic University. Although this survey allows the authors to identify the exact recipients of the UAH program by including a specific question, the survey was only carried out after the implementation of the AUH program, from 2010 to 2012, so the number of observations is much more limited (around 3000).

Although this in itself is not a problem, the propensity score matching statistical model used by the authors has been criticized in recent years. One the most important critics of this method is that of King and Nielsen (2019), who in their work claim and show that, while other matching methods try to approximate a fully blocked randomized experiment, propensity score

matching attempts to approximate a fully randomized experiment which makes it more susceptible to imbalances even relative to the original data. Other authors have also claimed that propensity score matching tends to underperform when compared with other matching techniques in terms of statistical preciseness (Abadie & Imbens, 2016, De los Angeles Resa & Zubizarreta, 2016). More generally, matching techniques as a whole are sometimes criticized for dropping relevant observations, reducing the precision and variance of results (Moriarity & Schuren, 2001). For example, the work by Salvia et al. (2015) drops around 1,500 observations from their analysis.

The second study was conducted by Jimenez and Jimenez (2015) who analyzed the effects of the AUH on the levels of school attendance and adolescents at work. Similarly to the previously mentioned literature, the authors find that the program had a negative and slightly larger effect of 8 percentage points on school dissertation and decreased youth work by between 4 and 6 percentage points. However, like the work by Salvia et al. (2015) the authors use a propensity matching score method using data from the 2012/2013 ENGHO database. This means the work has the same weaknesses and these problems are in fact exacerbated, as data is based on observation from a single year and some demographic groups have as little observations as 240. Therefore, this paper should offer an alternative method to previous analysis on the impact of AUH on schooling and youth work by using a difference in difference analysis and comparing these results to the previously mentioned literature that used propensity score matching techniques.

III.IV. CCT Programs and Gender

The Latin American region is a particularly interesting region regarding educational differences between genders because it is the first in the developing world to have a reverse gender gap in education as girls tend to have a higher school enrolment rate and are more likely to graduate from high school than boys (Duryea et al., 2007; Marshall & Calderon, 2006). The literature mentioned in the previous sections often comes to different conclusions regarding not only the effect of CCT programs on youth work but also the differing effects that programs have on different genders. As previously mentioned, Skoufias and Parker (2001) found the PROGRESA program had a larger impact on increasing girls school enrolment than boys school enrolment but a larger impact on reducing boys youth work than that of girls, which suggests that the increase

in girls school enrolment came out of their leisure time whereas the increase in boys school enrolment resulted in less time spent at work. Other studies that have only analyzed the effect of CCT programs on school enrolment have found that these programs tend to have a larger effect on girls than boys (Skoufias & Mcflearty, 2001; Rawlings & Rubio, 2003). However, as previously mentioned, the research done on the Argentinian case have found that the program has had a larger impact in increasing the school enrolment of boys rather than girls (Edo et al., 2017).

There are two main mechanisms that can explain why CCT programs may have differing effects on boys and girls based on Becker's (1965) time allocation model. On the one hand, it may be the case that boys have a higher current opportunity cost of going to school due to a perception that boys have more job opportunities than girls at a young age. Therefore, parents may be more hesitant to take boys out of work and into the education system than girls, as they are able to bring more money into the household (Sosa, Escudero & Marchioni, 1999). If this were the case, the CCT program would be expected to have a larger effect on females due to them having a lower opportunity cost of going to school such that the CCT program transfer is large enough to cover the opportunity cost. On the other hand, it is also possible that parents try to maximize future earnings by investing in the future of the children who they think will have higher lifetime earnings, leading parents to invest in boys education more due to the perception that they have more opportunities in both education and the labor market (Sosa et al., 1999; Kazeem, Jensen & Stokes, 2010). If this is the case, then it would be expected that parents would be more willing to let their male children go to school and so the CCT program would have a larger effect on increasing boys school enrolment.

Finally, the pre-treatment school enrolment rates difference between boys and girls may also plays a role in the results. Table 3.1 shows that the school enrolment of boys aged between 15 to 17 is around 7 percentage points lower than that of girls in the same age group. This means that boys have a larger room for improvement in relation to school enrolment, but both boys and girls school enrolment for that age group is below 80%. Although both mechanisms may play a role in this case study, previous case studies of Argentina and the lower school enrolment of boys in the pretreatment period leads to the following hypothesis:

H3: the AUH program has had a larger effect on increasing school enrolment and decreasing the youth work of boys.

Overall, this paper should contribute to three specific branches of literature. Firstly, by comparing the effects that the program had on schooling and youth work, it should contribute to literature focused on the substitutability between school and work in the time allocation of children. Secondly, it adds and corroborates to growing literature of the effect of CCT programs on schooling and education in Latin America by using evidence from the AUH program. This helps to explore the heterogeneity of CCT programs across Latin America giving an insight into the policy design of new CCT programs or adjustment to those which are currently in place. Lastly, it corroborates and adds to previous literature on the AUH program by analyzing data from the EPH survey using a difference in difference approach, which has previously not been used in regard to youth work in Argentina. More specifically, a difference a difference approach is able to control for factors that are constant in a group over time, through the first difference, while also controlling for time varying factors in the first difference by subtracting the second difference, facilitating causal inference when compared to other statistical methods (Wing, Simon & Bello-Gomez, 2018).

IV. Data and Methodology

IV.I. Data

Analyzing the effect of the AUH program is a difficult task for a number of reasons. Importantly, the program was not randomly assigned, which makes it difficult to define a control group. Secondly, there is no database that measured information regarding beneficiaries before the policy was introduced. However, both of these issues will be addressed using the *Encuesta Permanente de Hogares* (Permanent Household Survey), also known by its Spanish acronym EPH. This is a household survey administered by the Argentinian National Institute of Statistics and Census (INDEC). The microdata database consists of cross-sectional data on labor market variables, quarterly, from the last quarter of 2003 to the second quarter of 2015 (after this, the survey question underwent a number of changes). Aside from the main labor market variables, the dataset contains demographic, physical household characteristics (number of rooms in the household, etc.) and income variables. The survey only covers the 31 largest urban areas in Argentina and, therefore, only represents the urban population of Argentina (which is around 60% of the total population) but not of the those living in rural areas (Edo et al., 2017; Maurizio & Vasquez, 2014).

Although the database contains information before and after the program was implemented, it does not directly identify AUH beneficiaries. However, it remains possible to identify those individuals that are eligible to the program. Therefore, the analysis will be an intention-to-treat analysis. In order for an intention-to-treat analysis to be representative of the population, it is key that there is a reasonably high take up rate of the program. However, this should not be a problem as according to the National Administration of Social Security (ANSES) in Argentina around 80% of eligible households were receiving benefits as of 2010 and this had increased to a reported 87% by 2019 (Roca, 2011; UNICEF, 2019).

IV.II. Methodology:

To measure the impact of the program it is necessary to determine whether the program changed the outcome of participants when compared to what would have been the outcome if they had not participated in the program. Therefore, the problem in determining the effect of the program is that it is impossible to simultaneously observe those eligible to the program as both participants

and non-participants in the program. When fully randomized experiments are not possible to implement, quasi-experiments can be designed to create control groups by means other than randomization. However, these methods are often based on strict assumptions that are hard to verify and are more susceptible to be affected by unobserved characteristics (Burtless, 1995).

In this paper, the method used to analyze the data will be a quasi-experimental, intention-to-treat, difference-in-difference analysis. This analysis consists of comparing the differences in the results of the treatment and control group before and after the policy is implemented (Card, 1990; Card & Kruger, 2000). This methodology is particularly useful for both its simplicity in estimating the impact of the program, but also for its potential to avoid endogeneity problems that may arise when comparing heterogenous individuals (Bertrand, Duflo & Mullainathan, 2004).

The analysis will entail comparing a treatment group, made up of children between the age of 5 and 17 whose parents do not work in the formal sector (those eligible to the program), with a control group made up of children between the age of 5 and 17 who have at least one parent/caretaker working in the formal sector (those not eligible to the program), before and after 2009. These groups will be based on the 4 bottom income deciles as the program is aimed at children who are living in poverty[1]. The EPH survey defines household income by asking respondents about the total income (both labor and non-labor related) that each individual in the household received the previous month and adding each value for the total household income. Again, it is important to reiterate that the survey does not offer a question that directly identifies the recipients of the AUH program. Therefore, the treatment groups represent those individuals which could *potentially* be in the program, independently of whether they are actually receiving the benefit (intention-to treat). Overall, the total number of observations is around 100,000.

Table 4.1 shows some descriptive variables means and t-test results of those individuals in the treatment and control group before and after the implementation of the program. The table shows that there are some clear differences between the two groups, particularly, regarding the head of household variables. Since most of the descriptive and outcomes variables are binary with values of one and zero, the coefficients can be interpreted as percentages by multiplying the coefficients by 100. For example, those in the treatment group are around 20 percentage points

[1] In the appendix Tables 2A and 3A take into account all deciles and Tables A4 and A5 take into account the bottom 6 income deciles

Table 4.1: Sample Descriptive Using an Independent Sample t-test for Equality of Means. All children 5-17.

	Before 2010			After 2010		
	Treatment	Control	t-test	Treatment	Control	t-test
Age	11.45	11.30	-4.90***	11.57	11.40	-4.76***
	(0.0160)	(0.0269)		(0.0212)	(0.294)	
Female	0.4920	0.4968	-1.04	48.35%	49.66%	2.50*
	(0.0023)	(0.0039)				
School enrolment	0.9328	0.9600	12.62***	0.9472	0.9643	7.80***
	(0.0012)	(0.0015)		(0.0014)	(0.0016)	
Youth Work	0.0894	0.0568	-13.17***	0.0688	0.0459	-9.22***
	(0.0013)	(0.0018)		(0.0015)	(0.0018)	
Head of household controls						
Female	0.4003	0.2042	-46.00***	0.4644	0.2778	-37.19***
	(0.0023)	(0.0031)		(0.0030)	(0.0038)	
Single parents	0.1717	0.0645	-33.94***	0.2045	0.0885	-30.36***
	(0.0018)	(0.0019)		(0.0025)	(0.0024)	
Below tertiary education	0.9626	0.9285	-18.11***	0.9530	0.9285	-10.28***
	(0.0009)	(0.0020)		(0.0013)	(0.0022)	
Household controls						
Number of people in the household	5.51	5.22	-14.46***	5.07	4.74	-16.60***
	(0.0105)	(0.0159)		(0.0122)	(0.0141)	
Income per per capita (In Argentine Pesos)	130.94	193.91	59.66***	683.37	888.86	40.86***
	(0.5020)	(1.065)		(2.769)	(4.501)	

Source: Own estimations based on EPH

Note: Independent Sample t-test. *Before*: observation between 2003-2009. *After*: observation between 2010-2015. *Treatment:* children's with no parents working in the formal sector. *Control:* children without least one parent in the formal sector. *Single parent*s 1 if single parent household and 0 if not; *female head of household* 1 if head of household is female and 0 if not; Head of household education 1 if head of household education is above secondary education and 0 if its below; *Number of people in the household* and *per capita income* (Argentine currency). Means of sample group above clustered robust standard errors that are in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

more likely to have a female head of household and around 10 percentage points more likely to be in a single parent household. Both of the t-test results for these variables are large and, statistically significant at the 0.001 level which suggest that the difference in means of these variables between the two groups is different from 0. Even though these variables seem to follow a common trend it remains important to control for these characteristics when estimating the impact of the program. In terms of the two dependent variables, school enrolment and work, there was a statistically significant difference between the means of both group as the control group had a larger school enrolment rate and a smaller number of children in the workforce than the treatment group before the policy was implemented. Although the difference in means of the dependent variables are small, this is likely to be due to the high enrolment rate and low youth work rate in the youngest cohort. Therefore, these results will be further explored in the next section by dividing the groups by gender and age.

Importantly, before a difference in difference analysis can be carried out, two assumptions must be met. Firstly, there must not be a contemporaneous policy implementation at the time of the inception of the UAH program that could have also caused a difference in the effect on the treatment and control groups. This does not seem to be a problem as there was no major policy implementation that could have affected youth work and education at the time. Secondly, in absence of the reform, both the control group and treatment group should have evolved parallel in regard to school attendance and youth work involvement. Although it is not possible to test this assumption, by performing a placebo test it gives an indication of the trends of the treatment and control group before the policy was implemented (the results of these placebo test are given in the next section of the paper).

The following equation gives the linear structure of the difference in difference model:

$$Y_{dt} = \alpha + \beta\ Treat_d + \gamma time_t\ + \delta\ (Treat_d * Time_t\ ) + \pi X_i + \varepsilon_d$$

In this equation, Y represents the two outcome variables. Firstly, one of the models will be focused on the effect of the program on school enrollment. The EPH survey provides a question that asks respondents: “Are you assisting any educational institutions?”. Originally this binary variable was coded to equal 1 if the respondent did assist any educational institutions and 2 if they did not. However, this variable was re-coded into the “education” variable so that a

value of 0 means that the respondent does not attend any educational institutions and a value of 1 has the same meaning as before. Therefore, this variable contains information on whether an individual is enrolled in school or not but not how much time the individual spends in school. For the second model the dependent variable is youthwork. The EPH survey asks respondents to classify their labor status. The variable was originally coded so that 1 = "working", 2 = "not working", 3 = "inactive" but has been recorded into a dummy variable where a value of 1 means that the respondent is working and 0 means that the respondent is not working or inactive. Again, this variable only has information regarding whether an individual is involved in the labor market or not, but not the amount of time spent at work. Therefore, the outcome variables in this analysis do not contain information on how much time is spent in school or at work as the EPH survey does not include questions regarding the amount of time that individuals spend in each activity. Nonetheless, the variables do provide information on whether a child is going to school or working at all, which gives an indication on whether the AUH program has had an impact on school enrollment and youth work overall.

On the right hand side of the equation, i) *Treat* is a variable identifying the treatment group where individuals in the treatment group have a value of 1 and the control groups have a value of 0, ii) *Time* is a dummy variable where years after the implementation (from 2010 and onwards) are valued at 1 and years before the implementation (before 2009) are 0, and iii) $Treat_d$*Time is the interaction between the two variables and is the main independent variable in the analysis.

Finally, the equation also includes X which will control for other variables. A number of variables will be included in the difference-in-difference regression that are similar to those used in previous studies analyzing the effect of CCT programs (Edo et al., 2017; Salvia et al., 2015; Skoufias & Parker, 2001; Ravallion & Wodon; 2000). These include individual level controls, such as the age and gender of the children, head of household level controls, such as gender, single parents, education level and employment statues, and household level controls including number of people in the household, and income per capita. Finally, the regression will also include control for fixed regional and time trends. Therefore, assuming that assumptions are met and there are no confounding factors it is expected that parameter δ should give the overall effect of the program on school enrolment and youth work.

V. Results and Analysis

In this section the main results of the empirical analysis will be discussed. Firstly, the analysis will focus on the effect of the AUH program on school enrollment. As previously stated, the hypothesis based on previous literature is that the AUH program has had a positive effect on increasing school enrollment. The first model will be focused on analyzing the effect of the program on different demographics groups split into gender and age groups. After this, several controls will be added to analyze the robustness of the results. The second model will analyze the effect of the AUH program on youth work. In this model, the hypothesis is that the program would lead to a reduction in youth work due to the increase in income for families involved and the obligation of children to go to school. Again, at first the focus will be on the effect of the program on different demographic groups and several controls will be added after this initial difference in difference regression. A further robustness checks will be carried out on both models, reducing the number of years in the pre- and post-treatment bias in order to test whether the results suffer from long term bias. Finally, an analysis is carried out to measure the effect on school enrolment and youth work when the eligibility status of an individual changes.

V.I. AUH and school enrolment

Table 5.1 shows the main results of the impact of the program on school enrollment splitting the regressions into gender and age groups. As expected, the table shows that there was no significant effect of younger children in the increase of school enrolment[2]. Columns 1 to 4 show that the effects of the program on boys and girls between the age of 6 and 14 is very small and not statistically significant. This is very likely to be due to the fact that the enrollment of young children was already at a high level for both the control and treatment group before the program was implemented and, therefore, the program had no significant effects on increasing the school attendance of these children.

However, the program had a significant effect on older children in secondary school. In models 5 and 6, the coefficient of the explanatory variable for older girls and boys is statistically significant. In model 5, the interaction term is positive and statistically significant at the 0.05

[2] Although Tables A2 and A4 of the Appendix show that when more income deciles are taken into account the program also increase school enrolment for the youngest age group, the effect is very small (around 0.05 percentage points)

level. The coefficient has a value of 0.0265 which suggests that the program had an effect of around 2.65% in increasing school enrollment in the treatment group. However, the effect of the group was larger and more significant for males aged between 15 and 17. In model 6, the effect of the program is positive and statistically significant at the 0.01 level. The coefficient has a value of 0.0458 which suggests that the program increased school enrolment of children in the treatment group by around 4.58%.

The overall results are similar to those of previous studies and support the hypothesis that the program was particularly effective in increasing the school enrollment of older children. However, it had a limited impact on the school enrolment of younger children most likely due to the already high enrolment rate of this demographic group (Check Table 3.1).

Table 5.1: Effect of AUH program on School enrolment

Age	6-11		12-14		15-17	
Education	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girls	Boys	Girls	Boys	Girls	Boys
Time*Treatment	0.0038	0.0013	-0.0004	0.0000	0.0265*	0.0458**
	(0.0028)	(0.0029)	(0.0042)	(0.0048)	(0.0120)	(0.0136)
Time	-0.0005	0.0029	0.0024	0.0067	0.0189*	0.157
	(0.0024)	(0.0023)	(0.0032)	(0.0037)	(0.0094)	(0.0100)
Treatment	-0.0001	-0.0021	-0.0098***	-0,0139***	-0.0782***	-0.0967***
	(0.0020)	(0.0021)	(0.0030)	(0.0035)	(0.0088)	(0.0100)
Observations	23,418	24,362	18,589	19,393	12,790	14,035

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * p < 0.05, ** p <0.01, *** p < 0.001.

In Tables 5.2 and 5.3, these results are tested further through different robustness checks. Firstly, Table 5.2 shows the results of a difference in difference regression where both the pre-treatment and post-treatment periods are reduced. In model 1, the general model that has been used for previous tables is used with the time periods between 2003 and 2015 and children

between the age of 15 and 17. In model 2, the pre-treatment period is decreased from beginning in 2004 to beginning in 2006 and in model 3, the shortened pre-treatment period is used with post-treatment period between 2010 and 2013.

This is done to ensure that the results are not influenced by having too long a pre- or post-treatment period where the chance of contamination of the sample increases. The results in Table 5.2 are mixed. On the one hand, even in model 3 when the period of analysis is the smallest, the program had an effect on increasing school enrollment of boys although the significance of the results is reduced to the 0.05 level. On the other hand, when the shorter time period is used, the results obtained for the girls group lose their significance, even if the coefficient remains at around 2 percentage points.

Table 5.2: Effect of AUH on School Enrolment using Shortened Time Periods

Education	Original model		2006-2009, 2010-2015		2006-2009, 2010-2013	
Gender	Girls	Boys	Girls	Boys	Girls	Boys
Time*Treatment	0.0265*	0.0458***	0.0186	0.0439**	0.0221	0.0396*
	(0.0120)	(0.0136)	(0.0135)	(0.0155)	(0.0144)	(0.0166)
Time	0.0189*	0.0157	-0.0161	-0.0201	0.0145	0.0183
	(0.0026)	(00.26)	(0.0105)	(0.0123)	(0.0112)	(0.0132)
Treatment	-0.0782***	-0.0782***	-0.0704***	-0.0948***	-0.0704***	-0.0948***
	(0.0088)	(0.0100)	(0.0107)	(0.0124)	(0.0107)	(0.0124)
Observations	23,418	24,362	11,059	11,367	9,343	9,520

Source: Own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* is defined differently in each model (model 1 uses the same period as previous tables, model 2 equal 1 between 2010 and 2015 and 0 between 2007 and 2009 and model 3 equals 1 between 2010 and 2013 and 0 between 2007 and 2009). Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

As a further robustness check, Table 5.3 is the same model as used in Table 5.1 (only for the oldest age group), but several head of household and household level controls are included. This table shows that the results of the unconditional difference in difference model are robust. For both the girls and boys, none of the control variables make the results insignificant or significantly decrease the effect of the program on school enrolment. In fact, adding the control in some cases increases the coefficient and significance. Most significantly, when controls for the amount of people in a household or income per capita are included, the coefficient for girls increases by almost 0.01 or one percentage point and becomes significant at the 0.001 level. This is also true for the boys as adding either of the controls, the coefficient increases and becomes significant at the 0.001 level. In the appendix, Tables A8 and A10 shows the results of adding the controls to the other age groups and, again, the results do not show much of a difference compared to the unconditional model, that is to say, the coefficients remain insignificant. Therefore, once controls are added, the main results of the unconditional model remain robust, showing evidence that the program has been able to increase school enrolment of children between the age of 15 and 17 and has had a larger impact for boys in this age group.

In Table 5.4 a number of placebo tests are carried out in order to gain some evidence that the identification assumption is met. As previously mentioned, the identification assumption underlying the difference in difference method is that the trend of the treatment and control groups regarding school enrollment would have developed similarly if the AUH program was not implemented. The placebo experiments test this assumption by pretending that the program was implemented in any year before 2009, the year the program was actually implemented. Table 5.4 shows the results of a fake implementation of the program in all the years before 2009 that there is data for. Since none of the interaction terms are significant, this suggests that it was only after 2009 that something caused a change on the treatment groups school enrolment. A further falsification test is carried out in the Appendix using only the pretreatment period and again, none of the coefficients are statistically significant (refer to Table A12).

Table 5.3: Effect of AUH on School Enrolment of Children 15-17 with Controls

Education	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Gender	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Time*treatment	0.0262*	0.0459***	0.0258*	0.0457***	0.0272*	0.0451***	0.0315**	0.0474***	0.0340***	0.0524***	0.0322**	0.0493***
	(0.132)	(0.0147)	(0.0132)	(0.0147)	(0.0132)	(0.0147)	(0.0130)	(0.0147)	(0.0132)	(0.0148)	(0.0119)	(0.0136)
Single parent household	-0.0133	-0.0105									-0.0310**	-0.0224*
	(0.0080)	(0.0080)									(0.0091)	(0.0099)
Female head of household			-0.0098	-0.0144*							-0.0215**	-0.0221**
			(0.0062)	(0.0068)							(0.0089)	(0.0076)
Head of household education					-0.0894***	-0.0854***					-0.0649***	-0.0684***
					(0.131)	(0.0149)					(0.0089)	(0.0117)
Number of people in the Household							-0.0234***	-0.0178***			-0.0235***	-0.0178***
							(0.0014)	(0.0015)			(0.0018)	(0.0019)
Per capita income (in Argentine Pesos)									0.000***	0.0000**	0.0000*	0.0000
									(0.000)	(0.0000)	(0.0000)	(0.0000)
Observation	14,003	14,503	14,003	14,503	14,003	14,503	14,004	14,509	14,004	14,509	14,003	14,503

Source: Own estimations based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Controls: refer to Table 4.1 for a description of the control variables. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.4: Placebo Tests on School Enrolment

Education Year	Model 1 2004	Model 2 2005	Model 3 2006	Model 4 2007	Model 5 2008
Time*Treatment	0.0103	0.0142	0.0231	0.0189	0.0044
	(0.0165)	(0.0141)	(0.0133)	(0.0136)	(0.0163)
Time	0.0006	-0.0037	-0.0039	-0.0057	0.0121
	(0.0136)	(0.0115)	(0.0108)	(0.0109)	(0.0128)
Treatment	-0.0959***	-0.0970***	-0.0753***	-0.0950***	-0.0881***
	(0.0022)	(0.0114)	(0.0095)	(0.0086)	(0.0075)
Observations	27,825	27,825	27825	27825	27825

Source: Own estimations based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* is defined depending on the year (for example in model 4, it equals 0 from 2003 to 2007 and 1 for 2008 and 2009). Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Finally, Table 5.5 shows the results of analysis which take into account a change in the employment status of parents, that is to say, it evaluates the effect of parents becoming formally employed on the school enrolment of children. To carry out this analysis a new treatment and control are created using the same sample as used in the previous analyses. The treatment group is made up of children whose parents either made the transition from informal employment or unemployment to formal employment. Therefore, the group is based on children who were at one point eligible to the program but then became ineligible once their parents became formal workers. The control group is made up of those who remained eligible to the AUH program throughout the period of interest. The EPH survey allows for the recognition of a change in employment status through its rotational scheme. This scheme entails that each respondent is surveyed four times. First in two successive quarters and then, after a year has passed, they are surveyed again in two successive quarters. Therefore, the treatment group would be made up of the children of parents who during one of their first two appearances in the survey were unemployed or informal workers and in one of the second appearances were formally employed. In this model a different outcome variable is used than in previous models. The variable is a binary variable with a value of 1 for children who dropped out of school; in other words, those

who were in school in the first appearance on the survey but where not in school in the next appearance in the survey, and a value of 0 for those who stayed in school. The results for all age groups were small and statistically insignificant. It could have been expected that, for those families that become formal workers and lost access to the extra income provided by the AUH program, children would drop out of school either due to no longer having conditionalities or to bring extra income into the household. However, the results suggest that once eligible children are in school, they do not drop out of school even if parents become formally employed and they lose out on the extra income provided by the program.

Table 5.5: Effect of a Change in Eligibility Status on School Dropout Rate

Age	6-11		12-14		15-17	
School Dropout	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girl	Boy	Girls	Boys	Girls	Boys
Time*Treatment	-0.0018	0.0173	0.0011	-0.0153	0.0083	0.0047
	(0.0128)	(0.0134)	(0.0221)	(0.0198)	(0.0223)	(0.0246)
Time	-0.0296***	-0.0343***	-0.0429***	-0.0350***	-0.0484***	-0.0631***
	(0.0036)	(0.0035)	(0.0058)	(0.0057)	(0.0066)	(0.0069)
Treatment	0.0350***	0.0344***	0.0527***	0.0525***	0.0360*	0.0743***
	(0.0090)	(0.0089)	(0.0154)	(0.0138)	(0.0155)	(0.0177)
Observations	23,418	24,362	18,589	19,393	12,790	14,035

Source: Own estimations based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *School Dropout*, 1 if a child drops out of school and 0 if not; *treatment* 0 for children who remained eligible for the program throughout the period surveyed and 1 for children who became ineligible during the period they were surveyed; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

V.II AUH and Youth Work:

Table 5.6 shows the results of the difference in difference analysis of the effect of the AUH program on youth work. Surprisingly, the results of the analysis are very similar to the corresponding results from the analysis on school attendance. Again, the results show that the

policy had a limited impact on the youth work of those under the age of 14[3]. Although most models show the correct sign (negative indicating a decrease in youth work), the size of the effect is very small and not statistically significant, apart from model 4, which shows a positive coefficient. As explained before, this may be caused by a few factors. On the one hand, the fact that school enrolment is high for these children may mean that these groups do not have time to work in the market. One reason for this is that, these groups of children may not be able to bring in a lot of money from the labor market, due to the limited skills and jobs they are able to perform, so it is an easier decision for parents to let them go to school. It may also be the case that because these children are not able to contribute to household income, they are more likely to be involved in household chores and labor, but due to the limitations of the survey, it is not possible to test whether the program has had any impact on the time spent on chores in households. However, Table 5.6 shows that like in the case for school enrolment, the program has had a significant impact on older children between the age 15 and 17. Model 5 shows that the interaction term is negative and statistically significant at the 0.05 level. The coefficient of 0.0275 is very similar to that obtained in the corresponding model of Table 5.1 and suggests that the program has led to a decrease of 2.75% of labor participation of women between 15 and 17. The results of model 6 are also negative, significant and very similar to the corresponding results on Table 5.1. The coefficient of 0.0418 suggests that the program led to a decrease of 4.18% decrease in youth work.

Overall, the results suggest that the program had no effect on younger children but had a significant effect on reducing youth work of older children. Compared to the previous studies, which had conducted propensity score matching methods to estimate the impact of the program, it seems that these studies had slightly overestimated their results when compared to this analysis (Salvia et al. 2015; Jimenez & Jimenez, 2015). More importantly, the results also find evidence for hypothesis 2. The program did lead to reduction in youth work and since both the outcome variables are binary with values of 1 and 0, the coefficient suggests that the increase in school enrolment was similar to the decrease in youth work.

[3] Interestingly, when all deciles are included in Table A3 of the Appendix the results indicate that the program also decreased the youth work of girls in the youngest age group by 0.66 percentage points.

Table 5.6: Effect of AUH program on Youth Work

Age	6-11		12-14		15-17	
Youth Work	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girls	Boys	Girls	Boys	Girls	Boys
Time*Treatment	-0.0027	-0.0020	-0.0038	0.0009	-0.0274*	-0.0418**
	(0.0031)	(0.0032)	(0.0052)	(0.0062)	(0.0133)	(0.0152)
Time	0.0004	0.0017	-0.0033	-0.0160**	-0.0354***	-0.0443***
	(0.0026)	(00.26)	(0.0040)	(0.0046)	(0.0107)	(0.0124)
Treatment	0.0014	0.0033	0.0183***	0.0206***	0.0823***	0.1054***
	(0.0022)	(0.0023)	(0.0037)	(0.0046)	(0.0010)	(0.0152)
Observations	23,418	24,362	18,589	19,393	12,790	14,035

Source: Own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The same robustness checks as in Table 5.2 are carried out by reducing the pre-treatment and post-treatment periods using the youth work variable as the independent variable in Table 5.7. Again, the results between the two tables are very similar. In this case, there are mixed results of the impact of the program on youth work once the post-treatment and pre-treatment periods are reduced. In both models 2 and 3, the coefficient of the effect of the program on youth work is no longer statistically significant for the girls, but the coefficient for the boys remains large and significant. This means that, at least for the boys between 15 and 17, the program already had a noticeable impact soon after being implemented, whereas for the girls, the robustness check suggests that the effect of the program on that group may not be as strong.

Table 5.8 shows that these results are robust to a number of controls being added. In all of the models reported in the table, the interaction term coefficient remains statistically significant and relatively large. Again, some of the coefficients increase when the controls are added but the significance of these results does not increase like is case for the conditional difference in difference model of school enrolment in Table 5.3. When the controls are added to

the other age groups, the results remain similar to that of the unconditional model and none of the coefficients become insignificant[4]. Therefore, the results of the unconditional model remain robust to household and head of household controls being added to the model. The results provide evidence that the AUH program has had an impact in reducing the youth labor market work of those children aged between 15 and 17 and more specifically boys in this age range.

Table 5.7: Effect of AUH model on School Enrolment using Shortened Time Periods

Time Periods	Original model		2007-2009, 2010-2015		2007-2009, 2010-2013	
Gender	Girls	Boys	Girls	Boys	Girls	Boys
Time*Treatment	-0.0274*	-0.0418**	-0.0204	-0.0414**	-0.0218	-0.0353*
	(0.0133)	(0.0152)	(0.0151)	(0.0170)	(0.0161)	(0.01182)
Time	-0.0354***	-0.0443***	-0.0316**	-0.0401**	-0.0306*	-0.0377**
	(0.0107)	(0.0124)	(0.0105)	(0.0123)	(0.0128)	(0.0132)
Treatment	0.0823***	0.1054***	0.0753***	0.105***	-0.0753***	0.1051***
	(0.0010)	(0.0152)	(0.0121)	(0.0137)	(0.0121)	(0.0137)
Observations	12,790	14,035***	11,059	11,367	9,343	9,520

Source: Own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* is defined differently in each model (model 1 uses the same period as previous tables, model 2 equal 1 between 2010 and 2015 and 0 between 2007 and 2009 and model 3 equals 1 between 2010 and 2013 and 0 between 2007 and 2009). Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.9 conducts the placebo effects which were carried out in Table 5.4 but in this case the dependent variable is now youth work. Again, in every model for every year before the program was implemented, the interaction term is not statistically significant. This suggests that it was only in 2009 once the AUH program was implemented that there was a decrease in the youth work unemployment of the treatment groups.[5]

[4] Tables A9 and A11

[5] A further falsification test is carried out in the Appendix using only pretreatment period and again, none of the coefficients are statistically significant (refer to Table A13).

Table 5.8: Effect of AUH on Youth Work with Controls

Youth Work	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Gender	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Time*treatment	-0.0262*	-0.0422**	-0.0257*	-0.0417**	-0.0281**	-0.0410**	-0.0325*	-0.0435**	-0.0354***	-0.0494***	-0.0323*	-0.0463***
	(0.132)	(0.0152)	(0.0134)	(0.0151)	(0.0134)	(0.0151)	(0.0132)	(0.0147)	(0.0134)	(0.0152)	(0.0132)	(0.0151)
Single parent household	0.0211**	0.0290**									0.0486***	0.0391**
	(0.0090)	(0.0080)									(0.0112)	(0.0122)
Female head of household			0.0253***	0.0337***							0.0218*	0.0357***
			(0.0068)	(0.0075)							(0.0089)	(0.0099)
Head of household education					0.0914***	0.1062***					0.0677***	0.0887***
					(0.109)	(0.0149)					(0.0110)	(0.0132)
Number of people in the Household							0.0238***	-0.0178***			0.0256***	0.0197***
							(0.0017)	(0.0015)			(0.0019)	(0.0020)
Per capita income (In Argentine Pesos)									0.0000***	0.0000**	0.0000	0.0000
									(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observation	14,003	14,503	14,003	14,503	14,003	14,503	14,004	14,509	14,004	14,509	14,003	14,503

Source: Own estimations based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. For description of control variables, refer to Table 4.1. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.9: Placebo Tests on Youth Work

Youth Work Year	Model 1 2004	Model 2 2005	Model 3 2006	Model 4 2007	Model 5 2008
Time*Treatment	0.0014	-0.0094	-0.0196	-0.0225	-0.0062
	(0.0183)	(0.0032)	(0.0151)	(0.0153)	(0.0181)
Time	-0.0182	-0.0106	-0.0098	-0.0060	-0.0308*
	(0.0160)	(0.0134)	(0.0125)	(0.0125)	(0.0143)
Treatment	0.0930***	0.0999***	0.1025***	0.102***	0.0942***
	(0.0022)	(0.0131)	(0.0109)	(0.0098)	(0.0085)
Observations	27825	27825	27825	27825	27825

Source: Own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* defined depending on the year (refer to Table 5.4).

Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Finally, Table 5.10 shows the results of carrying a similar statistical model as the one used in Table 5.5, by using the same treatment and control group. However, in Table 5.10 a different outcome variable is used. The variable is a binary variable with a value of 1 for children who were not working the first time they were surveyed but were working in any following survey and a value of 0 for those who did not work at any point they were surveyed. As previously explained, it may be expected that the children of parents who became ineligible to the program are more likely to begin work to make up for the loss of income from the AUH program. However, similarly to the results in Table 5.5, none of the coefficients are significant. This suggests that children who become ineligible for the program are not more likely than eligible children to pick up work. Therefore, the results of both Table 5.5 and 5.10 provide evidence that once children become ineligible to cash transfers, they are not likely to drop out of school or join the workforce.

Table 5.10: Effect of a Change in Eligibility Status on Youth Work

Age	6-11		12-14		15-17	
Change in Work Status	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girl	Boy	Girls	Boys	Girls	Boys
Time*Treatment	-0.0018	0.0173	0.0011	-0.0153	0.0083	0.0047
	(0.0128)	(0.0134)	(0.0221)	(0.0198)	(0.0223)	(0.0246)
Time	-0.0296***	-0.0343***	-0.0429***	-0.0350***	-0.0484***	-0.0631***
	(0.0036)	(0.0035)	(0.0058)	(0.0057)	(0.0066)	(0.0069)
Treatment	0.0350***	0.0344***	0.0527***	0.0525***	0.0360*	0.0743***
	(0.0090)	(0.0089)	(0.0154)	(0.0138)	(0.0155)	(0.0177)
Observations	23,418	24,362	18,589	19,393	12,790	14,035

Source: Own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Change in Work Status*, 1 if a child was not working and being to work and 0 if a child does not work at all; *treatment* 0 for children who remained eligible for the program throughout the period surveyed and 1 for children who became ineligible during the period they were surveyed; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

VI. Discussion

The results in the previous section suggest that the AUH program was successful in increasing the school enrollment and decreasing youth market labor of boys aged between 15 and 17 and to, a smaller extent, of girls aged between 15 and 17. In this section, the results will be related back to the theory set out earlier in the paper focusing on the heterogenous effect the program had on different groups and the substitutability between youth work and schooling.

As mentioned in the literature review, most scholars have found that schooling is only partially substitutable to work and, therefore, most CCT programs tend to have a larger impact on schooling rather than work as the conditionality of these programs is based on school enrolment. However, the results of this study are more in line with those found by Skoufias and Parker (2001), as the findings suggest that work and schooling are close to fully substitutable for one another. The main coefficients in regard to the effect of the program on youth work and school enrollment are both very similar; around 4 percentage points for boys and 2.5 percentage points for girls. This suggests that those people who rejoined school or decided not to drop out also stopped any participation in the labor market. This provides evidence to the hypothesis that work and school are competing activities and, therefore, allocating more time to one implies, at least in part, a reduction of the other.

If this were true, then CCT programs could proof a useful tool to increase school enrollment as the monetary transfers provided by these programs can be enough to replace the income brought in by children's work so that, through the conditionalities, parents decide to take their children out of work and into school, increasing the human capital of the country in the long term. In the case of the AUH, the positive impact of the program on both increasing school enrolment and decreasing youth work suggests that the monetary transfers of the program have been large enough to provide an incentive for school enrolment. It is important to mention that, because the survey does not have measures for leisure time of children and household work, it may be the case that the program has also had an effect on these factors of children's time. For example, school enrolment may have meant that children can no longer work in the labor market due to school taking up most of their time, but it might be the case that children are made to do more household chores as parents work more hours due to the decrease in income. Therefore, this paper is limited in that respect.

Interestingly, the results suggest that parents becoming ineligible to the program after being previously eligible has no effect on the school enrolment or youth work of children (refer to Table 5.5 and 5.10). It could be expected that once parents lose access to the transfers provided by the program, they may have less incentives to keep their children in school as they would no longer be subject to conditionalities and would lose a source of income. However, the results imply that becoming ineligible does not lead to children dropping out of school or beginning to work. These results could be explained by two mechanisms or a combination of the two. On the one hand, it is likely that, once parents become employed or formally employed, household income will increase as parents will bring more money into the household, and so, it would not be necessary that children drop out of school and begin to work. However, it is also possible that the AUH cash transfers are large enough to not only cover the opportunity cost of children going to school but also to have long lasting effects on the income of the family so that it may not be necessary for children to drop out of school even if parents loose eligibility to the program. Although this study does not analyze the long-term effect of the AUH program on household income, early research on the program showed that those eligible to the AUH program reduced their presence in the bottom two income deciles of the population by 36% since the beginning of the program, suggesting a combined effect of an increase in both the labor market income and Government transfers of the eligible families (Bustos & Villafane, 2011).

Another important result of the analysis is the heterogeneity found between the effect that the program had on different groups. The program seems to have had the biggest effect on older secondary school boys, with a somewhat smaller effect on secondary school girls and no real effect on children younger than 14. These results are again very similar to those by Skoufias and Parker (2001) who found that the PROGRESA had its biggest impact on older secondary school boys and around half of the effect on secondary school girls. These findings are somewhat expected due to the high enrolment rate of primary school children so that the program had little room for improvement[6]. In the theory two types of mechanism are often used to explain the heterogeneity in school attendance of different age groups, an inertia effect and the increasing opportunity cost effect. The inertia effect reflects on the fact that older children have been in school longer and are closer to finishing their schooling. Therefore, this children are likely to choose to remain in school and so it would be expected that the program would have the largest

[6] Refer to Table 3.1

effect on children who are just beginning high school as they are more likely to drop out because they have not invested as much time to school as older high school students.. However, the findings in this research suggest that older children are most affected by the policy providing evidence for the opportunity cost effect (Dankmeyer, 1996). Young children in middle income countries have limited opportunities to work in the labor market. Therefore, parents are less likely to be able to find a job for younger children or, if they are able to find a job, the income they would earn would not be high enough to take them out of school. It is much less likely that young children would not be in school unless the direct or indirect costs of schooling are high. However, the opportunity cost of older children is larger as they are more likely to find a job. This could explain why the transfer provided by the program incentivize older children to remain in school without having a real impact on the time allocation of young children.

A second important heterogeneity of the results is that between the effect of the program on boys and girls, as the effect of the program on girls is around half of that for the boys in both work and schooling. Again, this might be partially explained by the fact that the school enrolment figures of girls were already higher than that of boys and so there was less room for improvement when it came to increasing school attendance[7]. However, the school enrolment of both groups was low enough so that there was considerable room for improvement. This suggest there is likely to be another reason why the program had a particularly large effect on boys. As mentioned in the literature review, some authors have theorized that the time allocation of girls may be more inelastic than that of boys, as findings from other studies show that income increases in households leads to an increase in boys school attendance but not that of girls (Sosa et al., 1999). Two main theoretical explanations for the difference between the inelasticity of boys and girls could help explain these results. On the one hand, Sosa et al, (1999) argue that the inelasticity of girls' time allocation may be due to cultural factors. On the other hand, the expected lifetime earnings may be lower for girls than boys due to discrimination and shorter working life. In order to distribute scarce resources efficiently parents may decide to invest in their sons' education as they are more likely to get a job and to get paid more in the labor market. Therefore, parents may decide that the long-term benefits of girls going to school are small and may take them out of school to help in the household or in the labor market (Bardasi & Garcia,

[7] Table 3.1 shows that the school enrolment of boys in the oldest age group of the treatment group before 2009 was around 71% and that of the equivalent group of girls was 78%

2014). Both mechanisms can help explain why the AUH program had a larger impact on boys than girls.

VII. Conclusion

Since its implementation, the AUH program has become one of the largest benefit schemes in Argentina and the program that implied a large step towards providing vulnerable families with a minimum income. The aim of CCT programs, such as the AUH, is not only to provide an income to vulnerable families, but also to make these transfers conditional on school attendance and health of children in order to increase human capital in the long run. In this study, the effect of the program on both schooling and work has been tested in order to see whether the program has led to an increase in school enrolment and reduction in youth work. The results of the difference in difference analysis suggest that the program has been successful in increasing school enrolment and decreasing youth work of older children in secondary school. Furthermore, the results suggest some heterogeneity between the impact of the program on girls and boys, having a larger impact on boys than girls. In this respect, the results are largely similar to those that have analyzed the impact of the AUH program on schooling using a propensity score matching technique (Jimenez & Jimenez, 2015; Salvia et al., 2015).

The results in regard to the relationship between work and school largely coincide with the work by Skoufias and Parker (2001) who find that the two are largely substitutable for one another. This has important implications for the development of CCT programs as it suggests that in order for a CCT program to be effective, the monetary transfers should be large enough that it may offset the loss of income by children no longer working. Otherwise, families will not take their children out of work. Therefore, it seems that the monetary transfers of the AUH program have been large enough to make a significant impact. However, it is important to mention that the analysis does not take domestic work into account or how this may affect the relationship between different variables. It may be the case that an increase in schooling and decrease in labor market work leads to an increase in domestic work as parents are forced to work more hours to make up for the loss in income.

The heterogeneity of the results also has implications for the possible improvement of CCT programs. Due to the high enrolment of young children, it may be more cost effective to either decrease the transfer sums to families with younger children or to offer larger sums to families with children in secondary school. These seem to be the most vulnerable group of dropping out of school due to the larger opportunity cost of going to school and not working.

Furthermore, it may also be wise to increase the transfer of payments to families with girls in secondary school as these groups are more vulnerable, due to cultural reasons, to be taken out of school. A limited number of CCT programs that target specific groups by gender or age have been introduced in Jamaica, Grenada and the Democratic Republic of Congo (Bardasi & Garcia, 2014). However, research on the effect of these programs is still scarce. This offers a possible research opportunity in relation to the effect of targeted CCT program, the cost effectiveness of CCT programs, in general, and the possibility of using targeted CCT programs as a more cost-effective tool for increasing school enrollment.

Another area of further research of CCT programs that this study does not address is the possible negative effect that programs may have on adult labor market behavior. The eligibility criteria of the program may incentivize adults to become informal workers in order to qualify for the benefit or, in the case of informal and unemployed workers, may decrease the incentives to find a job or to move into the formal sector. Although a full assessment of these claims is beyond the scope of this paper, the literature has generally found that the program provided incentives for informal workers to remain in the sector but not enough incentives for formal workers to move into the informal sector (Maurizio & Vasquez, 2014). Furthermore, the result of the more general effect on labor is more mixed as some authors have found the program to have no effect on decreasing incentives to work overall, while others have found that it has had a negative impact on the female labor force (Garganta, 2011; Garganta, Gasparini & Marchioni, 2011). Overall, further studies would be needed to analyze the overall impact of the program on the labor force.

Finally, further work needs to be done in regards to the exact mechanisms that are responsible for the AUH increasing school enrolment and decreasing youth work. In this paper, an income and substitution have been identified as possible mechanism that could lead to the AUH increasing youth enrolment of decreasing youth work. However, it is not clear if the results in this paper are caused by the conditionalities attached to the program, the increase in income that the program provides or a combined effect of both mechanisms. Overall, in order to fully understand exactly how CCT programs can aid vulnerable families and increase human capital, a more thorough study of these mechanisms is needed.

Reference list:

Abadie, A., & Imbens, G. W. (2016). Matching on the estimated propensity score. *Econometrica*, *84*(2), 781-807.

Amarante, V., Ferrando, M., & Vigorito, A. (2011, December). School Attendance, Child Labor and Cash Transfers. An Impact Evaluation of PANES. In *Conferencia de la Red de Investigación de Política Económica y Pobreza, Siem Riap, Camboya*.

de los Angeles Resa, M., & Zubizarreta, J. R. (2016). Evaluation of subset matching methods and forms of covariate balance. *Statistics in medicine*, *35*(27), 4961-4979.

Attanasio, O., Fitzsimons, E., Gomez, A., Gutierrez, M. I., Meghir, C., & Mesnard, A. (2010). Children's schooling and work in the presence of a conditional cash transfer program in rural Colombia. *Economic development and cultural change*, *58*(2), 181-210.

Bandara, A., Dehejia, R., & Lavie-Rouse, S. (2015). The impact of income and non-income shocks on child labor: Evidence from a panel survey of Tanzania. *World development*, *67*, 218-237.

Basu, K., & Van, P. H. (1999). The economics of child labor: Reply. *American Economic Review*, *89*(5), 1386-1388.

Bardasi, E., & Garcia, G. (2014). Social safety nets and gender: learning from impact evaluations and World Bank projects.

Barham, V., Boadway, R., Marchand, M., & Pestieau, P. (1995). Education and the poverty trap. *European Economic Review*, *39*(7), 1257-1275.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The economic journal*, *75*(299), 493-517.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?. *The Quarterly journal of economics*, *119*(1), 249-275.

Brearley, E. J. (2016). A history of social protection in Latin America: From conquest to conditional cash transfers. *Revue Interventions économiques. Papers in Political Economy*, (56).

Burtless, G. (1995). The case for randomized field trials in economic and policy research. *Journal of economic perspectives*, *9*(2), 63-84.

Bustos, J. M., & Villafañe, S. (2011). Asignación Universal por Hijo. Evaluación del impacto en los ingresos de los hogares y el mercado de trabajo. *Serie Estudios*, *10*, 2002-2015.

Card, D. (1990). The impact of the Mariel boatlift on the Miami labor market. *ILR Review*, *43*(2), 245-257.

Card, D., & Krueger, A. B. (2000). Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania: reply. *American Economic Review*, *90*(5), 1397-1420

Cardoso, E., & Souza, A. P. (2004). The impact of cash transfers on child labor and school attendance in Brazil.

Cecchini, S., & Atuesta, B. (2017). Conditional cash transfer programmes in Latin America and the Caribbean: Coverage and investment trends. *Available at SSRN 3037640*.

Dankmeyer, B. (1996). Long run opportunity-costs of children according to education of the mother in the Netherlands. *Journal of Population Economics*, *9*(3), 349-361.

Deb, P., & Rosati, F. C. (2002). Determinants of child labour and school attendance: the role of household unobservables. *Understanding Children's Work (UCW) Working Paper*.

Di Santi, M. (2015, December 22). La evaluacion de la AUH desde que se implemento. *Chequeado.* Retrieved from https://chequeado.com/el-explicador/la-evolucion-de-la-auh-desde-que-se-implemento/

Duryea, S., Galiani, S., Ñopo, H., & Piras, C. C. (2007). The educational gender gap in Latin America and the Caribbean.

Edo, M., & Marchionni, M. (2019). The impact of a conditional cash transfer programme on education outcomes beyond school attendance in Argentina. *Journal of Development Effectiveness*, *11*(3), 230-252

Edo, M., Marchionni, M., & Garganta, S. (2017). Compulsory Education Laws or Incentives from Conditional Cash Transfer Programs? Explaining the Rise in Secondary School Attendance Rate in Argentina. *Education Policy Analysis Archives*, *25*(76), n76.

Garganta, S. (2011). *Asignación Universal por Hijo: Impacto sobre la formalidad laboral* (Doctoral dissertation, Universidad Nacional de La Plata).

Garganta, S., Gasparini, L., & Marchionni, M. (2017). Cash transfers and female labor force participation: the case of AUH in Argentina. *IZA Journal of Labor Policy*, *6*(1), 1-22.

Gunnarsson, V., Orazem, P. F., & Sánchez, M. A. (2006). Child labor and school achievement in Latin America. *The World Bank Economic Review*, *20*(1), 31-54

Jiménez, M., & Jiménez, M. (2015). *Asistencia escolar y participación laboral de los adolescentes en Argentina: el impacto de la Asignación Universal por Hijo*. ILO.

Kazeem, A., Jensen, L., & Stokes, C. S. (2010). School attendance in Nigeria: Understanding the impact and intersection of gender, urban-rural residence, and socioeconomic status. *Comparative education review*, *54*(2), 295-319.

Khanam, R. (2008). Child labour and school attendance: Evidence from Bangladesh. *International Journal of Social Economics*, *35*(1/2), 77-98.

King, G., & Nielsen, R. A. (2019). Why propensity scores should not be used for matching.
de los Angeles Resa, M., & Zubizarreta, J. R. (2016). Evaluation of subset matching methods and forms of covariate balance. *Statistics in medicine*, *35*(27), 4961-4979.

Levison, D., Moe, K. S., & Knaul, F. M. (2001). Youth education and work in Mexico. *World Development*, *29*(1), 167-188.

Marchionni, M., & Alejo, J. (2015). Funding basic education throughout the demographic transition in Argentina.

Marshall, J. H., & Calderón-Mejía, V. (2006). *Social exclusion in Education in Latin America and the Caribbean*. Inter-American Development Bank, Sustainable Development Department, Education Unit.

Maurizio, R., & Vázquez, G. (2014). Argentina: Impacts of the child allowance programme on the labour-market behaviour of adults. *Cepal Review*.

Moriarity, C., & Scheuren, F. (2001). Statistical matching: a paradigm for assessing the uncertainty in the procedure. *Journal of Official Statistics*, *17*(3), 407.

Nielsen, H. S. (1998). Child labor and school attendance: Two joint decisions. *University of Aarhus CLS Working Paper*, (98-015).

Núñez, J., & Cuesta, L. (2006). Colombia: Programa Familias en Acción. *Transferencias con Corresponsabilidad: Una Mirada Latinoamericana*, 227-78.

Peruffo, M., & Ferreira, P. C. (2017). The long- term effects of conditional cash transfers on child labor and school enrollment. *Economic Inquiry*, *55*(4), 2008-2030.

Prifti, E., Daidone, S., Campora, G., & Pace, N. (2021). Government Transfers and Time Allocation Decisions: The Case of Child Labour in Ethiopia. *Journal of International Development*, *33*(1), 16-40.

Ravallion, M., & Wodon, Q. (2000). Does child labour displace schooling? Evidence on behavioural responses to an enrollment subsidy. *The economic journal*, *110*(462), 158-175.

Rawlings, L. B., & Rubio, G. M. (2003). *Evaluación del impacto de los programas de transferencias condicionadas en efectivo*. Secretaría de Desarrollo Social.

Roca, E. E. (2011). Extension of the universal family allowance: The universal child allowance. *Innovative*, 25

Salvia, A., Tuñón, I., & Piñeiro, S. P. (2015). Asignación Universal por Hijo para la Protección Social: impacto sobre el bienestar económico y el desarrollo humano de la infancia. *Población & sociedad*, *22*(2), 1.

Schady, N., Araujo, M. C., Peña, X., & López-Calva, L. F. (2008). Cash Transfers, Conditions, and School Enrollment in Ecuador [with Comments]. *Economía*, *8*(2), 43-77.

Skoufias, E., & McClafferty, B. (2001). *Is PROGRESA Working? Summary of the Results of an Evaluation by IFPRI* (No. 583-2016-39672).

Skoufias, E., Parker, S. W., Behrman, J. R., & Pessino, C. (2001). Conditional cash transfers and their impact on child work and schooling: Evidence from the progresa program in mexico [with comments]. *Economia*, *2*(1), 45-96.

Sosa Escudero, W., & Marchionni, M. (2000). Household structure, gender and the economic determinants of school attendance in Argentina.

Tilak, J. B. (2002). Education and poverty. *Journal of human development*, *3*(2), 191-207.

UNICEF. (2019). Universal Child Benefit Case Studies: The Experience of Argentina. Retrieved from https://www.unicef.org/media/70446/file/ARG-case-study-2020.pdf

Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing difference in difference studies: best practices for public health policy research. *Annual review of public health*, *39*.

Yuen, F. C., Pedlar, A., & Mannell, R. C. (2005). Building community and social capital through children's leisure in the context of an international camp. *Journal of Leisure Research*, *37*(4), 494-518.

Appendix

Table A1: Benefits per child in Argentina Pesos (for years analysed in the study)

Year	Per child under 18 (nominal)	Per child under 18 (real)	Families with more than 5 children (nominal)	Families with more than 5 children (real)
2009	180	180	900	900
2010	220	179	1100	895
2011	270	178	1350	890
2012	340	181	1700	905
2013	460	186	2300	930
2014	644	201	3220	1005
2015	836	207	4180	1035

Source: Di Santi, 2015

Table A2: Effect of AUH on school enrolment when all income deciles are included

Age	6-11		12-14		15-17	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girl	Boy	Girls	Boys	Girls	Boys
Time*Treatment	0.0055***	0.0031*	-0.0013	0.0059	0.0114	0.0385***
	(0.0015)	(0.0016)	(0.0033)	(0.0037)	(0.0071)	(0.0078)
Time	-0.0013	-0.0005	0.0004	0.0006	0.0083*	0.0087**
	(0.0010)	(0.0001)	(0.0017)	(0.0018)	(0.0038)	(0.0043)
Treatment	-0.0029**	-0.0027**	-0.0144***	-0.0264***	-0.0849***	-0.1192***
	(0.0001)	(0.0001)	(0.0020)	(0.0023)	(0.0045)	(0.0050)
Observations	63,920	67,254	33,458	34,986	34,200	35,422

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3: Effect of AUH on youth work when all income deciles are included

Age	6-11		12-14		15-17	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girl	Boy	Girls	Boys	Girls	Boys
Time*Treatment	-0.0063*** (0.0018)	-0.0022 (0.0019)	0.0016 (0.0041)	-0.0128** (0.0046)	-0.0074 (0.0079)	-0.0475*** (0.0087)
Time	0.0026* (0.0011)	0.0013 (0.0012)	-0.0020 (0.0022)	-0.0058* (0.0023)	-0.0240*** (0.0044)	-0.0208*** (0.0050)
Treatment	0.0051*** (0.0011)	0.0047*** (0.0012)	0.0211*** (0.0025)	0.0402*** (0.0030)	0.0933*** (0.0051)	0.1436*** (0.0056)
Observations	63,920	67,254	33,458	34,986	34,200	35,422

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4: Effect of AUH on school enrolment when bottom 6 income deciles are included

Age	6-11		12-14		15-17	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girl	Boy	Girls	Boys	Girls	Boys
Time*Treatment	0.0043*	0.0050*	-0.0015	0.0059	0.0254**	0.0400***
	(0.0018)	(0.0020)	(0.0040)	(0.0047)	(0.0092)	(0.0102)
Time	-0.0004	-0.0010	0.0031	0.0021	0.0094	0.0172*
	(0.0011)	(0.0015)	(0.0025)	(0.0029)	(0.0061)	(0.0071)
Treatment	-0.0032**	-0.0031*	-0.0141***	-0.0246***	-0.0821***	-0.1010***
	(0.0012)	(0.0013)	(0.0025)	(0.0030)	(0.0059)	(0.0066)
Observations	40,679	42,781	21,064	21,883	20,779	21,329

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5: Effect of AUH on youth work when the bottom 6 income deciles are included

Age	6-11		12-14		15-17	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girl	Boy	Girls	Boys	Girls	Boys
Time*Treatment	-0.0037	-0.0042	-0.0010	-0.0122*	-0.0232*	-0.0426***
	(0.0022)	(0.0025)	(0.0051)	(0.0058)	(0.0103)	(0.0113)
Time	0.0003	0.0016	-0.0029	-0.0093*	-0.0300**	-0.0383***
	(0.0015)	(0.0018)	(0.0032)	(0.0036)	(0.0070)	(0.0080)
Treatment	0.0049***	0.0047**	0.0210***	0.0377***	0.0850***	0.1217***
	(0.0014)	(0.0015)	(0.0032)	(0.0038)	(0.0067)	(0.0074)
Observations	40,679	42,781	21,064	21,883	20,779	21,329

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Clustered robust standard errors in parentheses; * p < 0.05, ** p <0.01, *** p < 0.001.

Table A6: Effect of AUH on school enrolment controlling for regional and time fixed effects (bottom 4 income deciles)

Age	6-11		12-14		15-17	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girls	Boys	Girls	Boys	Girls	Boys
Time*Treatment	0.0042	0.0010	-0.0022	-0.0005	0.0248*	0.0426**
	(0.0026)	(0.0026)	(0.0051)	(0.0060)	(0.0120)	(0.0102)
Treatment	-0.0045	-0.0017	-0.0119***	-0.0173***	-0.0766***	-0.0966***
	(0.0018)	(0.0019)	(0.0037)	(0.0045)	(0.0088)	(0.0100)
Year and regional controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,003	29,246	14,004	14,506	13,790	14,035

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. *Year and regional controls*, region fixed effects for the 6 regions in the EPH survey and yearly time fixed effects. Clustered robust standard errors in parentheses; * p < 0.05, ** p <0.01, *** p < 0.001.

Table A7: Effect of AUH on youth work controlling for regional and time fixed effects (bottom 4 income deciles)

Age	6-11		12-14		15-17	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gender	Girl	Boy	Girls	Boys	Girls	Boys
Time*Treatment	-0.0030	-0.0013	-0.0029	0.0023	-0.0257	-0.0361**
	(0.0029)	(0.0031)	(0.0064)	(0.0076)	(0.0134)	(0.0151)
Treatment	0.0026	0.0038	0.0203***	0.0233***	0.0805***	0.1018***
	(0.0020)	(0.0022)	(0.0046)	(0.0058)	(0.0099)	(0.0113)
Year and regional controls	yes	Yes	yes	yes	yes	yes
Observations	28,003	29,246	14,004	14,506	13,790	14,035

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. Tear and regional controls (refer to Table A6). Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

.

Table A8: Effect of AUH School enrolment (Children between 12 and 15)

Education	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Gender	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Time*treatment	-0.0023	-0.0000	-0.0024	-0.0002	-0.0026	-0.0000	-0.0023	0.0002	-0.0005	0.0013	-0.0015	0.0003
	(0.0050)	(0.0060)	(0.0050)	(0.0060)	(0.0050)	(0.0060)	(0.0050)	(0.0060)	(0.0051)	(0.0060)	(0.0051)	(0.0060)
Single parent	-0.0043	-0.0076									-0.0091*	-0.0079
	(0.0039)	(0.0049)									(0.0044)	(0.0055)
Female head of household			0.0018	-0.0061							0.0005	-0.0079*
			(0.0028)	(0.0033)							(0.0031)	(0.0038)
Head of household education					-0.0099*	-0.0234***					-0.0047	-0.0187***
					(0.0045)	(0.0041)					(0.0045)	(0.0041)
Number of people in the Household							-0.0049***	-0.0053***			-0.0048***	-0.0055***
							(0.0008)	(0.0009)			(0.0009)	(0.0010)
Per capita income (in Argentina Pesos)									0.000***	0.0000**	0.0000	0.0000
									(0.000)	(0.0000)	(0.0000)	(0.0000)
Observation	14,003	14,503	14,003	14,503	14,003	14,503	14,004	14,509	14,004	14,509	14,003	14,503

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. For description of control variables, refer to Table 4.1. Clustered robust standard errors in parentheses; * p < 0.05, ** p <0.01, *** p < 0.001.

Table A9: Effect of AUH on youth work (children aged between 12 and 15)

Youth work	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Gender	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Time*treatment	-0.0041	0.0010	-0.0038	0.0012	-0.0037	0.0010	-0.0041	0.0007	-0.0053	-0.0006	-0.0041	0.0004
	(0.0064)	(0.0076)	(0.0050)	(0.0076)	(0.0064)	(0.0076)	(0.0063)	(0.0076)	(0.0064)	(0.0076)	(0.0051)	(0.0076)
Single parent	0.0078	0.0118*									0.0094	0.0107
	(0.0050)	(0.0060)									(0.0054)	(0.0012)
Female head of household			0.0046	0.0098*							0.0059	0.0110*
			(0.0035)	(0.0041)							(0.0039)	(0.0047)
Head of household education					0.0087	0.0259***					0.0040	0.0205**
					(0.0064)	(0.0065)					(0.0065)	(0.0066)
Number of people in the Household							0.0047***	0.0053***			0.0051***	0.0055***
							(0.0010)	(0.0011)			(0.0010)	(0.0012)
Per capita income									-0.000*	-0.0000*	0.0000	-0.0000
									(0.000)	(0.0000)	(0.0000)	(0.0000)
Observation	14,003	14,503	14,003	14,503	14,003	14,503	14,004	14,509	14,004	14,509	14,003	14,503

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. For description of control variables, refer to Table 4.1. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A10: Effect of AUH on School enrolment (children aged between 6 and 11)

Education	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Gender	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Time*treatment	0.0042 (0.0026)	0.0012 (0.0026)	0.0042 (0.0026)	0.0012 (0.0026)	0.0043 (0.0026)	0.0012 (0.0026)	0.0042 (0.0026)	0.0013 (0.0027)	0.0047 (0.0027)	0.0012 (0.0027)	0.0047 (0.0027)	0.0009 (0.0027)
Single parent	-0.0028 (0.0019)	-0.0019 (0.0019)									-0.0030 (0.0020)	-0.0012 (0.0023)
Female head of household			-0.0012 (0.0013)	-0.0028* (0.0014)							-0.0007 (0.0015)	-0.0033* (0.0016)
Head of household education					0.0046 (0.0032)	-0.0018 (0.0026)					0.0054 (0.0033)	-0.0009 (0.0026)
Number of people in the Household							-0.0006 (0.0004)	-0.0014*** (0.0004)			-0.0006 (0.0004)	-0.0016*** (0.0004)
Per capita income									0.000*** (0.000)	-0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Observation	28,002	29,242	28,002	29,242	28,002	29,242	28,002	29,242	28,002	29,242	28,002	29,242

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if attending school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. For description of control variables, refer to Table 4.1. Clustered robust standard errors in parentheses; * p < 0.05, ** p <0.01, *** p < 0.001.

Table A11: Effect of AUH on Youth Work (children aged between 6 and 11)

Youth work	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Gender	Girl	Boy	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Time*treatment	-0.0029	-0.0016	-0.0029	-0.0016	-0.0029	-0.0016	-0.0029	-0.0016	0.0047	0.0012	-0.0033	-0.0010
	(0.0030)	(0.0031)	(0.0029)	(0.0031)	(0.0029)	(0.0030)	(0.0026)	(0.0031)	(0.0027)	(0.0027)	(0.0030)	(0.0031)
Single parent	0.0027	0.0047									0.0032	0.0039
	(0.0021)	(0.0024)									(0.0023)	(0.0027)
Female head of household			0.0008	0.0040*							0.0002	0.0039*
			(0.0015)	(0.0014)							(0.0017)	(0.0027)
Head of household education					-0.0034	0.0039					-0.0042	0.029***
					(0.0034)	(0.0029)					(0.0035)	(0.0029)
Number of people in the Household							0.0027	0.0047*			0.0007***	0.0021***
							(0.0021)	(0.0024)			(0.0004)	(0.0005)
Per capita income (In Argentina Pesos)									0.000***	-0.0000	0.0000	0.0000
									(0.000)	(0.0000)	(0.0000)	(0.0000)
Observation	28,002	29,242	28,002	29,242	28,002	29,242	28,002	29,242	28,002	29,242	28,002	29,242

Source: own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* 0 before 2009 and 1 after. For description of control variables, refer to Table 4.1. Clustered robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A12: Placebo Tests on Education using only Pretreatment Period

Education Periods	Model 1 2003-2005, 2006-2009	Model 2 2003-2007, 2008-2009
Time*Treatment	0.0142	0.0189
	(0.0141)	(0.0136)
Time	-0.0037	-0.0057
	(0.0115)	(0.0109)
Treatment	-0.0970***	-0.0950***
	(0.0114)	(0.0086)
Observations	14,815	14,815

Source: Own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Education*, 1 if enrolled in school 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* defined depending on the model (Model 1 equal 0 for years before 2006 and 1for years between 2006 and 2009, Model 2 equal 0 for years before 2008 and 1 for years between 2008 and 2009). Clustered robust standard errors in parentheses; * p < 0.05, ** p <0.01, *** p < 0.001.

Table A13: Placebo Tests on Youth Work using only Pretreatment Period

Youth work Year	Model 1 2005	Model 2 2007
Time*Treatment	-0.0094	-0.0225
	(0.0160)	(0.0153)
Time	-0.0106	-0.0060
	(0.0134)	(0.0125)
Treatment	0.0999***	0.1020***
	(0.0131)	(0.0153)
Observations	14,815	14,815

Source: Own estimation based on EPH

Note: Difference in difference regression. OLS estimates. Dependent variable: *Work*, 1 if working 0 if not; *treatment* 0 for ineligible children and 1 for eligible children; *time* defined depending on the year (Model 1 equal 0 for years before 2006 and 1for years between 2006 and 2009, Model 2 equal 0 for years before 2008 and 1 for years between 2008 and 2009). Clustered robust standard errors in parentheses; * p < 0.05, ** p <0.01, *** p < 0.001.