LUND UNIVERSITY
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Master in Economic Development and Growth

Determinants of child poverty in Uruguay

The impact of gender inequality

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Abstract: The objective of this thesis is to examine the response of child poverty to wage and educational gender gaps within a household. The analysis combined household level longitudinal data, from Uruguay's Continuous Household Survey carried on in 2012 and 2013, with the survey of Nutrition, Child Development and Health conducted in the country in the same years. We use two different models to estimate these linkages: a Probit model based on the income measurement of poverty, and a Logit model based on a multidimensional measurement of deprivations. Child poverty, both considered as an income constraint or deprivation, responds strongly to changes in wage and educational gender gaps, although the effects are larger in the first case. We find a strong and significant effect of parental education and labour status, especially for females, on child poverty. The study then calls for policy measures in favour of increasing opportunities in the labour market for women, and educational opportunities for adults in general, as an imperative tool to lower child poverty rates in the country.

Key words: Child poverty, gender wage gaps, educational gender gaps.

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List of Acronyms and Abbreviations

ECLAC	Economic Comission for Latin America and the Caribbean
ECH	Continuous Household Survey (Encuesta Continua de Hogares)
ENDIS	Survey of Nutrition, Child Development and Health (Encuesta de Nutrición, Desarrollo Infantil y Salud)
INE	National Statistics Institute (Instituto Nacional de Estadísticas)
HH	Household
MEC	Ministery of Education and Culture (Ministerio de Educación y Cultura)
MIDES	Ministry of Social Development (Ministerio de Desarrollo Social)
MLE	Maximum Likelihood Estimator
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
OPP	Planning and Budget Office (Oficina de Planeamiento y Presupuesto)
UNICEF	United Nations International Children's Emergency Found
UNDP	United Nations Program for Development
WHO	World Health Organization

I. Introduction

Over the past decades, poverty reduction was the main objective of public policies in developing countries. However, not many of these policies consider poverty as a heterogeneous phenomenon. One of the factors that cause this heterogeneity is the age stage of individuals. Along with this, several studies have suggested that children are particularly vulnerable to fall under poverty and to stay in that condition (Huston 1991; Duncan et al. 1994; Brooks-Gunn and Duncan 1997; Machin 1998, Bradbury and Jantti 2001; Gordon et al. 2003; Blanden and Macmillan 2007, Chen and Corak 2008; Blanden et al. 2013). The incorporation of child poverty into the economic development analysis is then crucial, in order to have a deeper understanding of the country's situation and ensure the effectiveness of social security and child protection policies implemented.

I.1 Problem statement

Consistent with the aforementioned, some scholars have suggested that there exists a link between the upgrading of women's opportunities and intergenerational transfer of welfare. In this regard, empirical works have shown that increases in female education cause improvements in child health and schooling (Mensch et al. 1986; Strauss and Thomas 1995; Thomas et al. 1991; King and Hill 1997; World Bank 2001; Schultz 2002; Brown 2006). These effects are expected to be greater than those produced by similar rises in men's education. Another branch of literature claims that something similar occurs when it comes to an increment in the earning power. These studies suggest that women are more likely than men to destine a larger share of their income to the next generation, e.g. greater expenditures on children's education, nutrition and healthcare are expected (Thomas 1990; Engle 1993; Handa 1994; Strauss and Thomas 1995; Hoddinott and Haddad 1995; Lundberg and Pollak 1996; Haddad et al. 1997; Thomas 1997; Buvinic 1998; Quisumbring and Maluccio 2000; Duflo and Udry 2004; Pagés and Piras 2010).

Moreover, the gender gap in education could also affect the participative action of wives. In addition to affecting their earning potential, it could also influence the division of labor and responsibilities in the household (King and Hill 1997). From an economic perspective, there is an opportunity cost between working in the market and devoting time to the household. It is therefore rational that husbands designate more hours to the market if they are better remunerated, and for wives to assign more time to housework. This allocation might have worse consequences for children, as stated before. Kids could benefit from having their mother home but, because of how women diversify their expenses, an increment in the number of hours worked by them could translate more directly into an increase in the welfare of their children. In addition, the existence of educational gender gaps within a couple may also affect their reproductive lives and their income level. Less educated women have fewer opportunities to control over their fertility. Previous research has suggested three main explanations for this phenomenon: knowledge affects woman's ability to adopt birth control methods; their relatively smaller incomes and thus smaller income forgone due to childbearing could lead them to want more children; or the access to health information provided through education may translate into inferior children's survival rates and increase their welling to have more (Kim 2016). This could result in larger families, affecting their wellbeing as those are more likely to be poor (World Bank 1995; King and Hill 1997).

Taking these transmission channels into account, scholars claimed that it is then crucial to understand how resources are distributed within a family; more specifically, the way husbands and wives negotiate the scatter of their income (Sen 1984). If capital allocation is considerably unequal between the household head and his partner, women's power in the decision making is expected to be weaker. This could hinder poverty reduction and future growth as a consequence.

I.2 Aim and scope of the analysis

The main purpose of this research is to analyze the determinants of child poverty in Uruguay. Particularly, what is the relationship between child poverty and the wage and educational gender gaps within a household.

More specifically, the main questions this study address are the following:

- Is child poverty in Uruguay explained by the socio-economic characteristics of parents and household configuration?
- To what extent do wage and educational gender gaps contribute to such situation?
- Do these results change when considering Income Measurements of Poverty or a Multidimensional Measurement?

I.2 Uruguay as a case of study

Despite the decrease of poverty in Uruguay over past decades, this remains one of its main weaknesses. For every thousand children younger than six years old, 206 are under the poverty line. The vulnerability of this group to poverty has persisted in the country over the last decade.

Additionally, the existence of employment and gender wage gaps for every level of education in Uruguay was shown to exist by several studies performed by national and international institutions (Amarante and Espino 2002; Espino 2013; OECD 2014; ECLAC 2014). This is even more true for lower-income households: most women within the first quintile of the income distribution do not work, or spend large part of their time working in the house and taking care of the children (ENDIS survey 2014). Furthermore, there is also evidence of the presence of an educational gender gap in Uruguay (Amarante and Espino 2002). Two mechanisms influencing educational gender gap in the country were proposed by the literature. First one suggest that the educational gender gap might be due to discrimination in the labor market, as it is considered that women need more education to access the same jobs as men. The second hypothesis propose that socio-economic constraints existing in the country might worsen this situation, as poor households achieve inferior levels and higher dropout rates (MEC 2015).

Although previous works have addressed the problematic of child poverty in Uruguay (Kaztman and Filgueira 2001; Nuñez 2014), none of them have included the gender gaps as a possible contributing factor. For this reason, the present document employs some proxies' measurement of wage and educational gender gaps, in order to incorporate them into the analysis.

I.4 Empirical strategy

With the intention of answer the questions, we applied Linear Regression Models estimated by OLS and Logit and Probit models using MLE. This allowed us to approximate how each determinant contributes to the probability of a child to experience poverty. Some scholars suggested that consider households as object of analysis provides more accurate results when studying unequal distributions of resources and responsibilities (Sen 2008). Taking this into consideration, we used data from the National Household Survey (ECH) and the Nutrition, Child Development and Health Surveys (ENDIS), both performed by the National Statistics Institute from Uruguay, for the years 2012 and 2013.

Next, two measurements of poverty were considered, as there is a disagreement on the best measure of poverty. Some authors claim that poverty should be measured as the deprivation of capacities and opportunities, more than just the lack of income or access to goods (Sen 2000). Others argue, however, that although income measurement of poverty has limitations; it is still good for estimating household's vulnerability to changes in the labor market and the economy (Nuñez et al. 2005). As determinants might have different effects depending the type of poverty measurement considered, we included income measurements but also multidimensional measurement of poverty into the analysis.

1.5 Contributions of the research

The results obtained for applying the above mentioned empirical strategy contribute firstly to the empirical evidence on child poverty for Uruguay by applying new methodologies (the multidimensional index) and considering new variables (gender gaps). This are important when taking into account that previous analysis on the subject is not as extended as it is expected to be given the relevance of the subject. Moreover, the results of the investigation also contributed as empirical evidence for the lack of consensus on the relationship of some particular variables and the economic performance of a household (the gender of the household head and the relationship between gender wage gap and educational gender gap on household economic performance). In addition, this study might also be presented as empirical evidence against the traditional household model, that argues that resources are equally distributed within its members, and that they have the same level of participation in decision making. Finally, all the above mentioned and the conclusions obtained can help policymakers to determine accurate social security policies to reduce child poverty rates.

I.6 Outline

The rest of this thesis is organized as follows. Chapter 2 presents a description of some of the fundamental aspects of poverty, education and labor market situation in Uruguay. Chapter 3 discloses the theoretical framework and previous empirical work about the influence of gender inequalities on poverty. Chapter 4 discusses the methodology, presents and describes the key variables used in the model. Section 5 discusses the results and finally, Section 6 concludes and discuss some policy implications.

II. Context

The following subsections aim to describe some of Uruguay's stylized facts. The main purpose of this section is to state why the country represents an interest case of analysis. Firstly, we present a brief framework of its economic and social conditions in order to compare the country with the rest of the region and report changes of recent years. Secondly, the issue of interest, child poverty in the country, is exposed. Finally, the gender gaps existing in the nation are also displayed.

II.1 Economic and social conditions in Uruguay

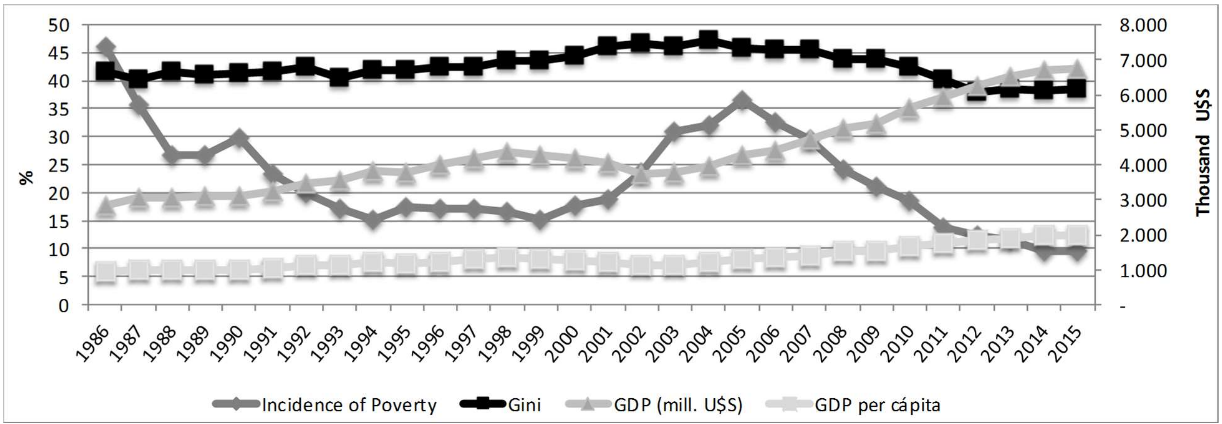
For the last 25 years, Uruguay exhibited the lowest levels of inequality and poverty among the Latin American countries. The country experienced a reduction of the poverty rate from 18.8% in 2005 to 5.7% in 2013 (ECLAC 2014).

Uruguay also had good economic performances in the past decades, increasing its growth from an average of 3.1% annually in the period 2000-2009 to a growth of 5.8% in the period 2009-2013 (World Bank database). However, the country entered in a stagnation phase from 2014, with a de-acceleration of the economic performance of 1.8% over the previous year. The income inequality, measured by the Gini index, also worsened, with an increase of 1.3% from 2014 to 2015. This can be observed in Figure 2.1. As stated, the evolution of income inequality presents a relative growing trend until 2008, declining afterwards and deteriorating in the last two years. Additionally, the historical evolution of poverty measured in terms of incidence of poverty behaves similarly to the performance of Gross Domestic Product (GDP) in the country. This suggests the existence of a pro-poor growth[1] in the country. However, researchers have shown that the growth experienced in Uruguay in the last fifteen years was not favorable for people with low incomes. Evidence suggest that in fact, in the period 1991-2006 incidence of poverty increased, as well

[1] Pro-poor growth is defined by The World Bank as a changing in the distribution of relative incomes through the economic growth process, to favor the poor.

income inequality, while economic growth favored classes with higher incomes (Amarante and Perazzo 2008). Moreover, the income of individuals (calculated as the ratio of GDP at constant prices / total population in the country) displayed an increasing tendency to stagnate in the recent years, as a result of the economic slowdown. A turning point is observed in 2002 - 2003 as a consequence of the macro-financial crisis experienced in the country.

Figure 2.1 Historical evolution of poverty, growth and inequality. Uruguay, 1986-2015.



Source: Data from the National Institute of Statistics and Central Bank of Uruguay.

Notes: (1) Until 2005, no information was available for the whole country, as the Household Survey coverage only locations that had 5,000 or more inhabitants. (2) GDP in constant prices, base 2005.

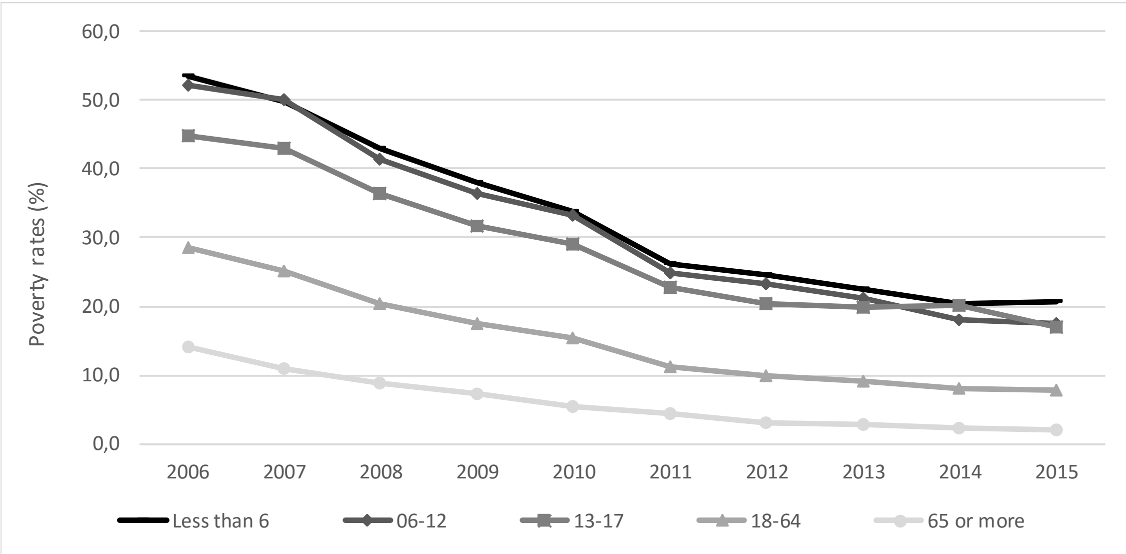
As it can be observed from Figure 2.1, although the country has maintained levels of sustained growth and low inequality in relative terms, the situation started to stagnate from 2014. It is then important to identify who are the most affected by this slowdown and the transmission channels of these effects. Previous studies suggested that children are predominantly vulnerable to fall under poverty and to stay in that condition (Huston 1991; Duncan et al. 1994; Brooks-Gunn and Duncan 1997; Machin 1998, Bradbury and Jantti 2001; Gordon et al. 2003; Blanden and Macmillan 2007, Chen and Corak 2008). Particularly in the case of Uruguay, empirical analyses suggested that children younger than six years old are the most affected by the incidence of poverty (Kaztman and Filgueira 2001; Ferrari 2008; INE 2015). The possible causes of the high likelihood of children under six years old to be under the poverty line in Uruguay are discussed in the next subsection.

II.2 Child poverty in Uruguay

The last census conducted shown that half of the children in the country aged between 0 and 11 years old lived under poverty conditions (INE 2015). Particularly, the kids younger than six years old are the most affected by the incidence of poverty. For every 1,000 children younger than six years old, 206 are poor; while the proportion is 78 for every 1,000 people aged from 18 to 64. In addition, although it is beyond the scope of the analysis, children of this age are also a vulnerable group when referring to indigence: for every 1,000 children under six years old, 7 are indigent. As it can be observed in Figure 2.2, this situation persisted for several years in the country. Despite that poverty reduced to the half for almost every age group, the incidence of poverty remained constant for the last two years.

One possible explanation of this persistence could be the level of education within the members of the household. Previous studies performed in the country have shown the existence of an intergenerational educational correlation from parents to children (Ferrari 2008). This supports theoretical approaches to human capital and skills transmissions. It could also indicate a perpetuation of low levels of schooling among the poor. Following this line, another study suggests that there is a link observed between households with low education levels in the country and the amount of children they have (Kaztman and Filgueira 2001). These authors suggest that the amount of kids might be also creating limitations in the availability of employment for the household head, especially if it is a woman.

Figure 2.2 Evolution of the incidence of poverty by age group. Uruguay, 2006-2015



Source: Data from the National Institute of Statistics and Central Bank of Uruguay.

Is there a relationship between child poverty and gender inequalities in the country? In order to answer that question, it is necessary to describe the condition of gender gaps in the country.

II.3 Presence of gender inequality in Uruguay

When it comes to employment inequalities, both the *activity rate* (measured by the number of individuals aged 14 and more who have at least one occupation) and the *unemployment rate* (defined as individuals who wanted a paid work and were available at the time to start working but did not work during the period of reference) are less favorable for women. As it can be observed in Table 2.1, this is the case in the country since 1990.

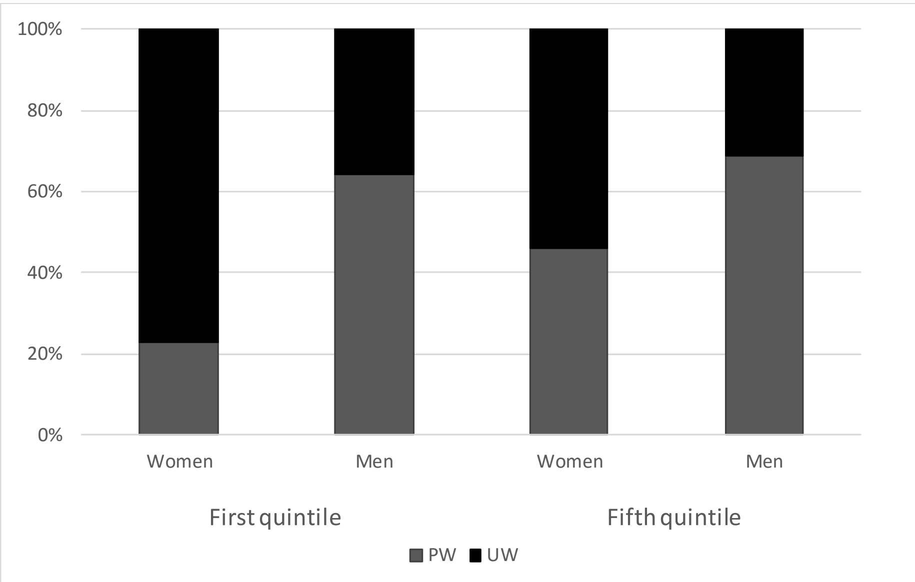
Table 2.1 Activity and unemployment rates by sex. Uruguay, 1990-2014.

	Activity Rate			Unemployment Rate		
Year	Total	Men	Women	Total	Men	Women
1990	57.0	73.2	43.5	8.5	6.9	10.9
1995	59.0	73.8	46.6	10.3	8.0	13.3
2000	59.6	71.9	49.1	13.6	10.9	17.0
2005	58.5	69.3	49.5	12.2	9.5	15.3
2010	62.9	73.1	54.0	7.2	5.3	9.4
2014	64.7	74.3	55.9	6.6	5.1	8.3

Source: Data from the National Household Surveys (ECH).

According to a research performed by Office of Planning and Budget of the country, these inequalities are larger when considering the different levels of household income. As shown in Figure 2.3, the indicator of overall workload can explain these differences: the poorest women spend more hours in unpaid work (housework) (OPP 2015). The study even suggests, regarding data from the ENDIS survey that this is mainly due to young children in the house. Of the survey sample, to the question *"Who takes care of the children?"* the answer was the mother in 99% of the cases, and only in 60% the father.

Figure 2.3 Percentage distribution of the burden of paid work (PW) an unpaid work (UW), by gender and income quintile. Uruguay, 2013.



Source: Prepared by MIDES based on INE data.

Furthermore, although there is no public access information referring to the wages perceived, several researches performed in the country had proven that there is a *"glass ceiling"*[2] in female's wages in Uruguay, that could be indicating the existence of a gender pay gap (Amarante and Espino 2002; Espino 2013). Additionally, the UNDP confirmed that Uruguayan women earn less than men in every educational level, although the gap gets less pronounced as the amount of years of schooling increases (UNDP 2015).

There are socio-economic constraints impacting education, although it is a public service. The level of income is related to the educational level. As a result, low-income households are characterized mostly by individuals who have not reached to overcome primary level. In contrast, the richest households are characterized by the highest proportion of people who attend or have completed tertiary levels. Particularly, the ratios estimated are that one of every two people in the highest quintile access tertiary levels, while six out of ten in the lowest quintile do not reach secondary education. Among the reasons for dropping out the educational system, two are the most recurrent: (1) the conditions at home, particularly, the socio-economic status and mother's educational level; (2) the pursuit of finding alternative routes for insertion into society, such as early childbearing or the accumulation of work experience. (MEC 2015). Finally, information collected from statistical offices of different educational institutions suggests that although there is not a big gender gap until secondary education, there is a very high participation of women in tertiary education. Six out of ten of those enrolled in universities or institutes of tertiary education are women, while three out of four enrolled in tertiary courses are females. Males are overrepresented in the technical and technological education, where six out of ten students are men (Papadópulos and Radakovich 2003). This suggests that in the country, women use higher levels of education to access same employment than men.

Considering the situation of child poverty in the country, and the empirical evidence that suggest the existence of gender inequalities, Uruguay is an interesting case of analysis. One of its main advantages relative to other possible case studies is that, as a small country, surveys that have been carried out in the territory are very representative of the

[2] The concept of "glass ceiling" refers to an unfair system that prevents women or other group to get upper quality jobs.

national reality. This could improve the robustness of the analysis conducted. Another factor that led to opt for the country as object of analysis is the availability of relevant data to conduct our analysis. During 2012-2013, Uruguay developed a survey specifically to analyze the quality of life of children, relative to their health, schooling and shelter conditions, among others. This survey, that was very useful for the construction of the different proxies for the multidimensional measurement of poverty, is not frequently performed by other countries.

However, before analyzing the relationships between gender gaps and child poverty, it is necessary to understand the transmission channels between these variables. Particularly for this purpose, a brief review of the available literature on this subject is presented in the next chapter.

III. Literature Review

Literature relating to gender inequality and child poverty is wide, given the importance that these disparities have on economic and social development. Consequently, this chapter is divided in three subsections. The first subsection focuses on the empirical evidence of the existing relationship between child poverty, educational gender gaps and gender wage gaps. The second subsection pulls together the empirical evidence related to other child poverty determinants, beyond gender gap variables. The third and last one, the theoretical debate on the use of an Income or Multidimensional Measurement of poverty is shown. This subsection is intended to argue why both type of measurements were applied in the study.

III.1 Linkages between gender gaps and child poverty

Several researchers have suggested that children are particularly vulnerable to fall under poverty and to stay in that condition. This perpetuation of disadvantage is due to the constraints in the cognitive and physical development they experience (Huston 1991; Duncan et al. 1994; Brooks-Gunn and Duncan 1997; Machin 1998, Bradbury and Jantti 2001; Gordon et al. 2003; Blanden and Macmillan 2007, Chen and Corak 2008). The literature sustains that the children who were born poor or experienced deprivations under six years old are more likely to remain poor during adulthood, drop out of school, experience teen births or access to worse employment conditions (Ratcliffe and McKernan 2010; Notten and Roelen 2011a, 2011b; UNICEF 2012).

In addition, as children depend on the wealth status of their parents or caregivers, they are particularly susceptible to be affected by economic crisis and by household and parental characteristics. They are also the most vulnerable group to the intra-household distribution of resources (Ravallion 1996). To understand how resources and decision power is distributed within the households is then of primary interest. Particularly, how husbands and wives negotiate their scattering is crucial for a better understanding of the risks children experience (Sen 1984). Children could be living in households that are not-income poor, but were insufficient resources are designated to them. This may engender less likely poverty reduction and future growth as a consequence.

Two of the possible causes of unequal resources and decision power allocation are the **educational gender gap** and the **gender wage gap** between the household head and his/her partner. The following sub-sections will review the available literature referred to each one of them.

III.1.1 Educational gender gap and intra-household allocation

When it comes to men's and women's education, the research carried out has shown they have different intergenerational consequences. Particularly, female education is expected to generate greater positive "externalities" on children, meaning that upgrading women's opportunities have a direct link on intergenerational transfer of welfare. Several empirical works have shown that, even when controlling for household's income, increases in female education causes improvements in child health and schooling. Those improvements were greater than those produced by equal increases in men's education. (Mensch et al. 1986; Thomas et al. 1991; Strauss and Thomas 1995; King and Hill 1997; Glewwe 1999; World Bank 2001; Schultz 2002; Brown 2006). The transmission channels argued by these authors are, among others, that higher educated mothers implement safer health and hygiene practices (Glewwe 1999); are more likely to access to a broader range of information and take better decisions as a consequence (Caldwell 1979; Thomas et al. 1991) and that they have higher probabilities of greater bargaining power within the household and stronger involvement in the investment decision-making (Morrison et al. 2007). Nevertheless, there is a correlation within the educational level of the couples that should be considered in empirical studies: better educated women are generally more likely to marry better educated men. This could be biasing results by an unobserved component of husband's preferences for healthier and better-educated children (Schultz 2002).

Additionally, the gender gap in education might also affect the participative action of wives within a household. This is not only due to restrictions in women's earning potential, but also because of the division of labor that educational gender gaps could generate (King and Hill 1997). From an economic perspective, there is an opportunity cost between working in the market and devoting time to the house. It will then be rational for husbands to designate more hours to the market if they are better remunerated. This allocation might have worse consequences for children, as stated before: although they could benefit from having their mother on the house, increases in the amount of hours work by her will translate more directly into rises in their wellness. Furthermore, the existence of educational gender gaps within a couple may also have an effect in their reproductive lives and economic level. If women are less educated, there are fewer probabilities for them to take all the control over their fertility. Less educated women have more children for several reasons: knowledge affects woman's ability to adopt birth control methods; they tend to marry younger and possess more years for childbearing, their relatively smaller incomes and thus smaller income forgone due to childbearing could lead them to want more children; or the access to health information provided through education may translate into inferior children's survival rates and increase their welling to have more (World Bank 2001; Kim 2016). This might result in larger families as an outcome, affecting their wellbeing as those are more likely to be poor (World Bank 1995; King and Hill 1997).

III.1.2 Gender wage gap and inter-household allocation

The second possible cause considered in this document for unequal distribution of resources within households is the existence of a **gender wage gap**. The **gender pay gap** measures the differences in the labor market between the average wage of a male and the average salary of a woman who have gainful employment (European Commission 2015). A large number of studies concluded that, in general, women receive less than the average wage earned by men.

When it comes to the situation within households, a growing body of empirical evidence states that once they experience an increase in earning power, women are relatively more likely than men to destine a larger share of their income on the next generation. This translates into greater expenditures on children's education, nutrition and healthcare (Thomas 1990; Engle 1993; Handa 1994; Strauss and Thomas 1995; Hoddinott and Haddad 1995; Lundberg and Pollak 1996; Haddad et al. 1997; Thomas 1997; Buvinic

1998; Quisumbring and Maluccio 2000; Duflo and Udry 2004; Pagés and Piras 2010). This evidence works against the Unitary Model assumptions on the conception of a household. According to this model, gender of who control income should not affect the resource allocation. Several studies have proven that in fact it does matter, not only for the intergenerational transfer mentioned before but also for household outcomes (World Bank 2001).

Although it goes beyond the scope of this thesis, it is important to mention that there is a factor that is expected to influence household's decision-making and resources allocation: institutions/sociological framework. In general, this variable is not considered because it is not easy to include in the econometrical analysis. Nonetheless, some authors have suggested that uncertainties in the environment and cost of transactions, as well as the existing rules and norms affect decision making and could generate some paths of predictability (Todaro and Fapohunda 1987; Folbre 1994; Kabeer 2000 and 2003).

III.2 Child poverty determinants

Related to child poverty determinants, the empirical evidence pretends to justify the selection of the household and parental characteristics considered in this document, that are an adaptation of the model suggested by Bárcena et al. 2015.

III.2.1 Household characteristics

With reference to household characteristics, previous work has shown that there is a strong and positive relation between the **number of household members** and poverty (Fofack 2002; Marrugo et al. 2015). As the number of people within the household rises, so do the probabilities of its members of being under the poverty line. This is particularly the case if the increase experienced is in those who are not economically active (like elder people or children).

Following the above-mentioned, the **number of children** has a strong correlation with child poverty (Chen and Corak 2008; TARKI 2010; Bárcena et al. 2015). These authors suggested that the different ages of the children in the household should be taking into account when analyzing their risk of poverty. This is because the different developmental stages are associated with diverse levels of expenditure that child caring requires.

Moreover, the link between the **gender of the household head** and poverty is still an issue of debate. Some empirical studies have shown a negative relationship between female-headed households and its economic performance compared to the male-headed counterparts (Lipton and Ravallion 1995; Barros et al. 1997; Meenakshi and Ray 2002). Others suggested that, in fact, when analyzing cross-sectional datasets, female headship and poverty relationship is strong just for a few cases (Buvinic and Gupta 1997; Fuwa 2000; Quisumbing and Otsuka 2001).

III.2.1 Parental characteristics.

Furthermore, scholars have shown that parental socioeconomic and demographic characteristics have an imperative relation with child poverty (Bradbury and Jantti 2001; Chen and Corak 2008; Gornick and Jantti 2012). It is expected for children with young mothers or fathers to be over-represented among those at risk of poverty (TARKI 2010; Bárcena et al. 2015). This is particularly the case for households under the poverty line in Uruguay (INE 2015). Due to the all this, the **age of the household head and his/her partner** was then considered in the analysis.

Along with parental characteristics, **education attainment of the household head and his/her partner** was also considered in previous analysis. It was suggested by several scholars that this variable has a positive impact on poverty (Milcher 2006; Chen and Corak 2008; Chzhen and Bradshaw 2012; Gornick and Jantti 2012). As the level of education of the parent increases, it is less likely for the children to be poor. This is associated with the link between educational level and the probability to access to better jobs and earnings.

In addition, the **employment status of the household head and his/her partner** was also proven to have a significance relationship with the economic status of the household members (Bradbury and Jantti 2001; Moller and Misra 2005; Whiteford and Adema 2007; Chen and Corak 2008; Munzi and Smeeding 2008; Gornick and Jantti 2012).

In contrast to all the previous variables considered, when it comes to analyzing the effects of education in the household wealth separated by gender, results are contradictory. On one hand, some scholars had stated that there is a negative impact of female education on economic performance, and a positive impact for male education (Barro and Lee 1994; Barro and Sala-i-Martin 1995; Perotti 1996). On the other hand, others claimed that when improving the econometric analysis and the extension of the dataset, the results were just the opposite (Benavot 1989; King and Hill 1997; Caselli et al. 1996; Forbes 2000; Klasen and Lamanna 2009). Finally, there is a third body of researchers that sustain that in fact, when adding other variables into the analysis, there is no significant difference between genders of education on economic performance (Stokey 1994; Birdsall et al. 1997; Dollar and Gatti 1999).

Additionally, several empirical country-case studies have found an adverse impact from gender inequality in education to poverty. In the case of study performed for Pakistan, results after applying a Logit regression suggested that household size and female-male educational enrolment ratio have strong and positive association with the risk of poverty (Chaudhry et al. 2009). In the same line, analysis performed for the case of Nigeria during the period 1980-1996 claimed that female-headed households were more likely to be poor than male-headed, but this probability differences felt with higher levels of education (Okojie 2002). Something similar was suggested for Bangladesh: alleviation of poverty was founded to be possible only by the empowering of women through education (Siddique 1998). Further panel-data studies reached similar conclusions between inequalities in human capital and economic development (Castello and Domanech 2002; Klasen and Lamanna 2009).

When it comes to the analysis of the relationship between gender wage gap and economic performance of a household, the empirical evidence is also not conclusive. In one hand, a study performed for eight Latin American countries suggested that the eradication of gender inequalities would result in a rise in household income and a decline in poverty (Costa et al. 2009). Applying the same technique for European countries, other scholars reached similar conclusions, suggesting that wage discrimination was an important determinant of poverty in the region (Gradín et al. 2006). The latest also pointed out the fundamental role working women have when considering an increasing group of female-headed households. Furthermore, case-specific analyses were not conclusive either. For the case of Colombia and using data from National Household Surveys from 1982 to 2000, it was found that increases in the wage gender gap experienced in the country led to increases in relative poverty (Urinola and Wodon 2003). For the case of Chile, by using data from national household surveys for the years 1990 to 1998 a causality relationship between wage differentials and income distribution was founded (Montenegro 2001). Different from previous case-studies, one performed for Cameroon showed that eradication of discrimination in the formal sector could improve living conditions and reduce the incidence of poverty, but the impact this has on income inequalities is not very clear (Nguetse Tegoum et al. 2010). Possible causes evidenced for the lack of consensus is the problem of defining the head of the household. Some studies just take the definition used by national surveys, others the self-reported headship status by the respondents and others specify the categorization based on the contribution of the individual to the household income. Another reason for the diverse results is the heterogeneity present among female-headed households, such as the number of children or dependent adults, among others (Morrison et al. 2007). Furthermore, the definition of poverty considered might also influence in the results obtained: it could be the case that a variable affect negatively considering some measure, but changes its statistical significance or sign considering another method.

Particularly for this last reason, the following sub-section presents the theoretical debate within using an Income or Multidimensional Measurement of poverty. This subsection is intended to argue why both type of measurements were applied in the study.

III.3 Poverty estimation debate: income or multidimensional measurement?

The method and units that are applied to measure a variable can have consequences on the results of an investigation. Because of this, and to adequately estimate the effect of some variables with reference to poverty, there is a debate in the field about what is the best measure of it.

Predominantly, valuation of poverty is categorized as *welfarist* and *non-welfarist* (Ravallion 1994). The first group is typical for micro-econometrical analysis, where well-being of individuals is measured in terms of the availability of purchase some commodities. Poverty is then perceived by these scholars as those households where resources (expressed in money terms) are insufficient to purchase some goods required for material well-being (Noble and Cluver 2007). The second group claims that there are some basic needs relative to well-being that can be observed and monitored by multidimensional models. In general, these basic needs are linked with the concept of *capabilities* presented by Sen (1992). According to the author, these capabilities do not only cover elementary levels as having a good health, being well nourished or having access to some public services, but also other personal levels as being happy or able to take decisions. The opportunities that an individual has of accessing those capabilities are then a proxy to measure what is his/her wellness level. As a result from this debate, during the past years a shift from more classical measurements to multidimensional conceptualizations was experienced in studies referred to poverty, inequality and well-being. Particularly, one of the most applied methodologies recently is known as deprivation indexes. Deprivations can be defined as states of observable disadvantages to access to some things in several levels (like diet, clothing, housing, education, public services, etc.) with respect to the local community (Gordon et al. 2003).

Both types of approaches present strengths and weaknesses. The welfarist approach (that from now on will be referred to as Income Measurement) has simplicity and the availability of data as advantages, as household incomes or expenditures are in general collected by national surveys. However, as data was not collected specifically for the sake of the investigation, this approach does not always reach unbiased estimations. Conversely, the non-welfarist approach (from now on, referred to as the Multidimensional Measurement) is more accurate and more specific if the aim of the investigation is to generate information for policy-making. Nevertheless, this approach is in general associated to indirect indicators, due to the scarcity of data, which is a weaknesses compared with the other approach. This could derive into vague reflections of the true situation of poverty if the proxies are not well specified. In addition, the sensitivity of both type of approaches to the breaking point below where an individual starts to be considered poor (poverty line or number of deprivations), is also a weakness. In particular, a causality problem could arise in this investigation when considering the gender wage gap using an Income Measurement of poverty. It is possible that poor households experience less or worse employment opportunities for women in the market, and household poverty then explains wage differentials and not the reverse. This problem can be solved when considering Multidimensional Measurements instead (Arim and Vigorito 2007).

The empirical strategy was then separated in two steps, in order to achieve clear and consistent results. In a first stage, models were performed with the intention to quantify the effects of the different determinants considered in the likelihood of a household to be poor, evaluating that probability with income poverty measures. In a second stage, the same models were carried out, but instead of using income, a multidimensional measurement was applied. Having both models allow comparisons and reach firmer conclusions.

The summary of the theoretical framework and some of the available empirical evidence suggest that although there is a vast amount of literature, there is no agreement on the value and significance of the coefficients of the relationship between effects of gender education or gender wage gaps with the probability of its members of being poor. Furthermore, there is also a lack of consensus when it comes to what is the best method to measure poverty. New empirical evidence, both for the relationship between gender gaps and child poverty and also in how the poverty measurements differ could then be an important contribution to the field.

In the following chapter, the empirical strategy followed in order to contribute to these debates is described.

IV. Empirical Strategy

This chapter defines the methodology applied in the document. Firstly, a description of the data sources used for this research is displayed, followed by possible limitations of the use of that dataset. Secondly, an explanation of the model and the econometrical assumptions that were applied are described. Finally, there is a description of the variables included in the model and how they were constructed.

IV.1 Data

The data used for this document comes from multiple sources. In the case of the first model, information at a household and individual level was collected from the Continuous Household Survey (Encuesta Continua de Hogares - ECH) from the years 2012 and 2013. These particular years were considered as a way to merge the data with ENDIS survey in the second stage of the analysis. It is worth mentioning that individuals residing in collective type of housing such as hospitals, hotels, prisons, etc. were excluded from the study. Thus, the first panel was composed by an urban sample of 2,666 households, formed by a total of 12,100 participants who were subsequently taken into account for the analysis.

In the case of the second model, the one with multidimensional measurement of poverty, information was collected from the same sources than the previous model combined with the Nutrition, Child Development and Health Survey (ENDIS). This survey was conducted by the National Institute of Statistics in the years 2012 and 2013. The second panel was also composed by a sum of 2,666 households, formed by a total of 12,100 participants, although the number of observations was 9,666 when monoparental households were excluded for the sake of the analysis.

IV.1.1 Data Sources

ECH is a multipurpose and continuous survey, conducted in Uruguay every year since 1968. Probability samples for this survey are stratified with optimal allocation for per capita income of households and unemployment variables, and are representative of the entire national territory. Some previous analysis has found that Uruguay is one of the countries with lowest incidence of rural poverty in the region (Quijandría et al. 2003). For this reason, the fact that the surveys considered only refer to urban population (that took samples from urban localities of 5,000 inhabitants or more) is not a big concern as it would have been for other countries.

ENDIS is a survey performed for the first time in the country, with the purpose of studying the living conditions of early childhood when it comes to their nutritional status, their health and their development. It is important to note that so far no data representative of all children living in urban areas of the country was available. This panel is composed by 3,077 children and 2,711 adults responsible, corresponding to 2,666 households across the country.

IV.1.2 Limitations of the data

Despite this study could contribute to policy decisions as it is performed taking into account gender gaps variables that were not considered before, there are also limitations. First, there are some restrictions regarding the use of Household Surveys for the analysis. As stated by previous authors, one of the first things researchers should contemplate when working with this data is that in general, surveys were not collected with the purpose the researcher wants do deal with, which can lead to a number of econometric and interpretation problems (Deaton 1995). Moreover, in the type of survey that we considered, there could be a possible endogeneity bias and self-selection problem, as the economic situation and the distribution of tasks within the household are self-reported. In addition to all the possible restrictions stated before, other scholars suggested that the relationship between gender and poverty it is not easy to measure as there is a lack of sex-disaggregated data on expenditures and consumption within a household that could allow researchers to account for the distribution of resources (Moser 2007). According to Moser, the introduction of multi-dimensional poverty measures has a positive impact on the interpretation of the results as it allows more specific comparisons. This arose as another reason to perform Model 2.

It is due to all the aforementioned that the conclusions that emerged from this study should be considered approximations of the real situation. While intended to contribute to the greater understanding of the subject, results were derived from regressions that might have minor disturbances.

IV.2 Empirical model specification

Following the approaches performed by previous works in the field, the estimation strategy corresponds to the following model:

$$Y_i = \alpha_0 + \beta_1 X_i + \gamma_1 Z_i + \delta_1 wagegap_i + \theta_1 educationalgap_i + \varepsilon_i \qquad (1)$$

where Yi is the probability of a child of living in a household under the Poverty Line that takes value equal one if the household is under the line and zero if the event does not happen; *X*i is a vector of household characteristics; *Z*i is a vector of parental characteristics particular for each household; *wagegap* is a variable that measures the existence of differences in the hourly wage perceived by the head of the household and his/her partner; *educationalgap* is an indicator of the difference in the assistance to secondary education measured in number of years between the household head and his/her partner; and ε_i is a residual term. Although all coefficients were of interest, particular attention was paid to δ_1 and θ_1 as they capture the effects that educational and gender wage gaps have on the probability for a household with children of being poor.

The first strategy consisted on estimating equation 1 using a Linear Probability Model by Ordinary Least Squares. However, this specification presents some problems that should be considered in the analysis. Specifically, the residuals that result from Linear Probability Models violate the error's homoscedasticity and normality assumptions of OLS regressions, which could lead to frequently biased and almost always inconsistent estimators (Amemiya 1997; Horrace and Oaxaca 2006).

This leads to second and third strategy: the estimation of equation 1 by using Logit and Probit Models by Maximum Likelihood. Under these methodologies, it was possible to link the estimation of the set of factors considered with their contribution to the probability of realization of the phenomenon under study. As an improvement from the Linear Regression, the outputs from these estimations were not biased as a result of the large samples, and they were also consistent. Moreover, it is noteworthy that although these models can be classified as binomial (when there are two possible alternatives under analysis) or multinomial (when there are more than two alternatives in the result), this research approached binomial type model. A multinomial model would imply that the existence of different levels of poverty status could be in the same level of selection, which is not the case in Uruguay due to the near absence of extreme poverty.

Nonetheless, this type of models could also present some statistical problems if they are misspecified. Several authors have sustained that maximum likelihood estimators are not consistent if the error term is heteroscedastic, there are omitted variables in the model or there is a mistake in the distributional assumption (Davidson and MacKinnon 1984; Wooldridge 2002; Green 2012). Heteroscedasticity will be particularly a different problem for Maximum Likelihood estimators in comparison with OLS. The dependent variable of models like Probit or Logit is a probability that embodies itself a certain percentage of uncertainty which comes from all those variables that were not included in the model. There is an econometrical debate about this point. For some authors, there is nothing that can be done for this problem, and the investigator should limit to express that the dependent variable of interest was defined to be the probability given the control variables in the model. That model will be then give an accurate description of what was found in the data, but will not be accurate to the interpretation of counterfactual situations. Other authors, like the mentioned before, sustain that it is necessary to prove what is the situation of the error term variance in order to sustain the model is well specified. In the case of this study, results of the heteroscedasticity analysis will be presented as a robustness check of the models.

IV.2.2 Variables considered

The total number of individual observations used for this analysis was 9,666, with representation of the 19 municipalities of the country in the years 2012 and 2013. This is because in order to adapt the data to the purpose of the study, only those households that are composed by a couple[3] and at least one children under 14 years old were analyzed.

The final models based on those observations consisted of sixteen variables each, differing only in how the dependent variable was estimated. As it can be observed in Table 4.1, five of those variables correspond to household characteristics, eight to parental characteristics and two to gender gap indicators.

As mentioned above, both models share the explanatory variables but differ greatly in the construction of its dependent variables. Because of this, the construction and description of each variable will be presented below in two sub-sections: dependent variables and explanatory variables.

IV.2.2.1 Dependent variables

None of the methodologies to measure poverty suggested by the theory were proven to be better than the other. For this reason, the dependent variable of each model was created in order to consider both, Income and Multidimensional Poverty Measurements.

For the case of *Model 1* that contemplates the Income measurement of poverty, the variable **childpov** was created. This is a dichotomous nominal scale, that takes value 1 if the household was considered poor (total household income under the poverty line) and zero otherwise. In order to make the results comparable, the poverty line considered for both years was the one calculated for 2006.

In the case of *Model 2*, the Bristol Deprivation Approach for measuring child poverty in developing countries was took into consideration (developed by Gordon et al. 2003; and adjusted for developing countries for UNICEF 2004). The approach considers a set of seven basic needs to which a child should have access, that are transformed in

[3] Monoparental households were not included in the analysis because they generate noises in the analysis of the gaps.

deprivations: nutrition, safe drinking water, sanitation facilities, health care, shelter (or housing), education and information. Considering Gordon et al. 2003 description of the variables, and the data available from the ENDIS survey, proxies of these variables were created for the construction of the index. Those proxies and how they were formulated are available in Annex A.

One challenge with the construction of multidimensional poverty indices is choosing weights for each one of the components. Although the available literature suggests equal weights, frequency-based weights or even multivariate weights, none of the aforementioned was proved to be the best. Moreover, the breaking point in the index under which children start to be considered poor will also influence the model's fit. In this document, CEPAL's adaptation of Bristol's approach for Latin American countries was adopted. In other words, all the levels were considered with the same weight. The index was then a sum of all deprivations, and a child was categorized as poor if he/she present an index valued in two or more. The variable **child_deprivation** is then also a dichotomous nominal scale, that takes value of one for those individuals living in a household where a child experienced two or more deprivations, and zero otherwise.

Table 4.1 Variable Description for both models.

Variable	Description of the variable
Dependent Variable	
Probability of Being Poor (childpov) or Deprivation Index	= 1 if household is poor/ =1 if deprivation index is greater than 2 = 0 if household is non-poor / =0 if deprivation index is smaller than 2
Independent Variables	
Household Characteristics X_I	
Total HH members (size)	Number of household members
HH head sex (hheadsex)	=1 for males = 0 for females
Under two years (lessthan2)	Number of children aged less than two years old living in the household
Between 3 and 5 years (between2and5)	Number of children with more than 2 but less than 5 years old living in the household
Between 6 and 14 years (between 6 and 14)	Number of children with more than 6 but less than 14 years old living in the household
Parental Characteristics Z_i	
Mom's age (youngmom)	= 1 if female HH head or partner is younger than 30 years old = 0 if she is older
Dad's age (youngdad)	= 1 if male HH head or partner is younger than 30 years old = 0 if he is older
Mom's prim. education (momprimedu)	=1 if female HH head or partner completed primary education = 0 if she did not
Dad's prim. education (dadprimedu)	=1 if male HH head or partner completed primary education =0 if he did not
Mom's sec. education (momsecedu)	=1 if female HH head or partner attended at least one year of middle school = 0 if she did not
Dad's sec. education (dadsecedu)	=1 if male HH head or partner attended at least one year of middle school = 0 if he did not
Mom's employment status (momwork)	=1 if female HH head or partner worked at least 20 hours last week = 0 if she did not??
Dad's employment status (dadwork)	=1 if male HH head or partner worked at least 20 hours last week = 0 if he did not
Gap Indicators	
Gender wage gap (wagegap)	$\left(\frac{Hour\ pay\ for\ males - Hour\ pay\ for\ females}{Hour\ pay\ for\ males}\right) x\ 100$
Educational gender Gap (educationalgap)	$\left(\frac{Years\ of\ schooling\ for\ males - Years\ of\ schooling\ for\ females}{Years\ of\ schooling\ for\ males}\right) x\ 1$

IV.2.2.2 Explanatory variables

The selection of the explanatory variables for Model 1 and Model 2 is based on the literature review. Regarding **household characteristics**, the household **size** was proven to have a strong and positive relationship with poverty (Fofack 2002; Marrugo et al. 2015). A continuous variable *[size]* that measured the total number of household members, excluding domestic workers was added in the model. Following the aforementioned, the **number of children** was also proven to have a strong correlation with child poverty (Chen and Corak 2008; TARKI 2010; Bárcena et al. 2015). Quantitative and continuous variables where then included in the model, defining the total number of children present in the household under an age rage considered *[lessthan2]; [between2and5]; [between6and14]*. These ranges are an adaptation of the ones suggested by Bárcena et al. (2015). Age 14 was considered as the upper limit instead of 16 like in other countries, because it is legal to start working in part jobs at this age in Uruguay. Kids from 14 to 17 are minors, but no children for the National Institute of Statistics. Finally, the **gender of the household head** was included as there is no empirical consensus about the relationship of this variable and poverty. A dummy variable that took the value of 1 if the household head was a man was then considered *[hhheadsex]*.

Furthermore, regarding **parental characteristics,** the **age of the household head and his/her partner** was proven to have a positive and strong relationship with the risk of experiencing poverty (TARKI 2010; Bárcena et al. 2015). Due to this, dichotomous variables were considered *[youngmom]; [youngdad]* and took value of one if he/she was younger than 30 years old, and zero otherwise. This classification of young mothers and young fathers was taken from Bárcena et al. (2015). Along with parental characteristics, **education attainment of the household head and his/her partner** was suggested by several scholars to have a positive impact on poverty (Milcher 2006; Chen and Corak 2008; Chzhen and Bradshaw 2012; Gornick and Jantti 2012). As the level of education of the parent increases, it is less likely for the children to be poor. The effects for mothers and fathers are expected to affect differently in child well-being. For this reason, two type of educational variables were considered, both for the mother and the father in the household. First, dummy variables that considered household head or partner assistance to primary education were included in the model. *[momprimedu]; [dadprimedu]*. As school in Uruguay requires six years of education, the variable took value of zero if the individual did not complete that number of years, and one if he/she did. Secondly, dichotomous variables were created for secondary education *[momsecedu]; [dadsecedu]*. Different from the dummy variables for primary education, these took value one if the individual completed at least the Basic Cycle, and zero if he/she did not. Abovementioned specification is due to the very high dropout rate present in the country for this level of education. As the variable needs to be representative of the population analyzed, this adjustment took place. Finally, the **employment status of the household head and his/her partner** was also proven to have a significance relationship with the economic status of the household members (Bradbury and Jantti 2001; Moller and Misra 2005; Whiteford and Adema 2007; Chen and Corak 2008; Munzi and Smeeding 2008; Gornick and Jantti 2012). In these sense, two dummy variables were created *[momworks]; [dadworks]*. Considering that part-time jobs in the country are defined as 20 hours per week, these variables took value of one if the individual worked at least 20 hours the previous week at the moment that the survey took place; zero if he/she worked less hours or did not work at all.

In addition, regarding **gender gap** variables, both wage and educational gender gaps were included into the model as there is a lack of consensus on its effects on child poverty. In one hand, following the equation provided by the United Nations Economic Commission for Europe (ECE), a variable for gender wage gap was created *[wagegap]*. This variable reflected the difference in hourly wage salary existing in the household between the household head and his/her partner. In order to create it, two transformations of the data were performed: (1) a conversion of the amount of hours worked by the individual from hours per week to hours per month[4]; (2) a conversion of the wage perceived, from monthly to per hour, by dividing (monthly wage/amount of monthly hours worked). The transformation took place because hourly paid wages are preferred to monthly or annual salaries, because it measures the wage for a fixed amount of work, that it is not directly affected by the number of hours the person work or the period he/she spent without a

[4] In order to perform this transformation, it was assumed that individual worked approximately the same amount of hours each week. The change performed was then multiplying the amount of hours per week by four, in order to state the amount of hours worked in the month.

payment. This is important if we consider the difference in the number of hours that gender specific employment could generate. On the other hand, a variable for educational gender gap *[educationalgap]* was also included in the model. This variable was created trying to adapt the wage gap equation to the educational gender gap. As primary school attendance in the country approaches almost 100%, only the number of years of secondary education were considered. In order to create this indicator, a variable of total number of secondary schooling was generated, by adding the amount of basic secondary education years approved to the amount of higher years of secondary education approved.

As it can be observed in Table 1.1 of Annex B, the variables included do not present high levels of correlations[5] that should be taken into consideration. The only values that are high are those concerning the number of children between 6 and 14 years old in the household and the size, which is normal. In addition, the age of the parent and the mother is in the limit (0.49), but this could be due that in general, couples have similar ages.

Once all variables were created, the different models were estimated. The results obtained, together with robustness tests performed will be described in the next chapter.

[5] High correlation considered as 0.5 or more.

V. Estimation Results

The results of the different models performed are divided into two subsections. In the first one, the effects of considering the dependent variable as an output of the *Income Poverty measure*, as well as their robustness checks, are presented. In addition, the second subsection refers to the results and robustness checks obtained after considering a *Multidimensional Poverty measure*.

As it will be stated through this chapter, the educational gender gap and the gender wage gap (together with all the household and parental characteristics that were included in the model specification) seem to be strongly related with child poverty. This is the case for both types of poverty measurement considered.

V.1 Income measurement of poverty

As mentioned before, the first empirical strategy for the analysis was the application of a Linear Probability Model using OLS. Afterwards, a Probit and Logit model were also performed. Probit model emerged as the model that best fitted the dataset according to Information Criteria and estimations consistency.

V.1.1 Results of income measurement of poverty

The following table presents the coefficient values and standard errors estimated by Linear Model (1); Logit Model (2) and Probit Model (3). It is important to mention that the models are not comparable in terms of magnitude of the coefficients, but they all have the expected sign and all the variables were statistically significant. At first glance, when the number of members of the household or the number of child it has in its composition increases, so does the probability of them to be poor. Besides, if the household head is a man, or if he/she and his/her partner worked or reached some level of education, it is less probable for the household members to be poor. Finally, the existence of wage or educational gender gaps among the household head and his/her partner increases the probability of the child members of the household to be poor.

Table 5.1 Coefficients of determinants on Child Poverty. Estimation Results for Income Poverty Measurement.

Independent Variables	Dependent Variable: childpov		
	Linear Model (1)	Logit (2)	Probit (3)
size	0.006^{***}	0.083^{***}	0.051^{***}
	(0.003)	(0.026)	(0.015)
hheadsex	-0.032^{***}	-0.257^{***}	-0.139^{***}
	(0.008)	(0.066)	(0.037)
lessthan2	0.099^{***}	0.572^{***}	0.324^{***}
	(0.012)	(0.091)	(0.051)
between2and5	0.096^{***}	0.550^{***}	0.306^{***}
	(0.007)	(0.053)	(0.030)
between6and14	0.083^{***}	0.496^{***}	0.278^{***}
	(0.005)	(0.040)	(0.022)
youngmom	0.090^{***}	0.736^{***}	0.406^{***}
	(0.009)	(0.073)	(0.041)
youngdad	0.072^{***}	0.558^{***}	0.330^{***}
	(0.011)	(0.083)	(0.046)
momwork	-0.138^{***}	-1.299^{***}	-0.707^{***}
	(0.008)	(0.073)	(0.039)
dadwork	-0.115^{***}	-0.768^{***}	-0.449^{***}
	(0.012)	(0.080)	(0.047)
momprimedu	-0.032^{**}	-0.265^{***}	-0.141^{***}
	(0.013)	(0.104)	(0.059)
dadprimedu	-0.117^{***}	-0.635^{***}	-0.383^{***}
	(0.040)	(0.241)	(0.145)
momsecedu	-0.115^{***}	-0.665^{***}	-0.385^{***}
	(0.009)	(0.065)	(0.038)
dadsecedu	-0.128^{***}	-0.887^{***}	-0.505^{***}
	(0.009)	(0.063)	(0.036)
educationalgap	0.013^{***}	0.097^{***}	0.051^{***}
	(0.005)	(0.034)	(0.020)
wagegap	0.036^{***}	0.254^{***}	0.130^{***}
	(0.005)	(0.033)	(0.019)
constant	0.404^{***}	-0.638^{**}	-0.371^{***}
	(0.046)	(0.288)	(0.170)
Number of observations	9,666	9,666	9,666
Pseudo R^2	0.268	0.266	0.266
Wald Test	0.000	0.000	0.000

Note: Robust standard errors are presented in parentheses. *, ** and *** denotes statistical significance of 10%, 5% and 1% respectively. In the case of OLS, Adjusted R^2 is presented. In the case of Logit and Probit models, McFadden pseudo R^2 is shown. Moreover, while Wald Test is presented in the case of Probit and Logit for the significance of all the variables together in the model, F test is displayed for the Model (1). In every case, the presented model is better than an empty one.

Econometric literature suggests that marginal effects provided by Logit and Probit models should be more similar to the coefficients estimated by Linear Probability Models (Amemiya 1977; Wooldridge 2002). As it can be observed in Table 5.2, this is the case for the data available. Although further analysis is performed once the type of model that best fits the data is identified, it should be noted that marginal effects are very useful especially when analyzing dichotomous variables. Due to this, as a first comment it is important to note that the variables that appear to be increasing the likelihood of children to live in a household under the poverty line appear to be the number of minors in the house (that increases as they are younger); youth status of parents (greater in the case of men than for women); and the existence of a gender wage gap rather than an educational gender gap. The latter may be because, in general, the theory holds that couples tend to have similar educational levels. Moreover, the variables that reduce the risk of being under poverty appear to be the employment status of the mother rather than the father, and the education status of both, although higher for men. The latter may be due to the fact that it was found that there are what is known as *"glass ceilings"* in the country for the case of women: among women and men with the same educational level, it is the latter one who receive higher wages, for all educational levels. For more information, see Amarante and Espino 2002, and Espino 2013.

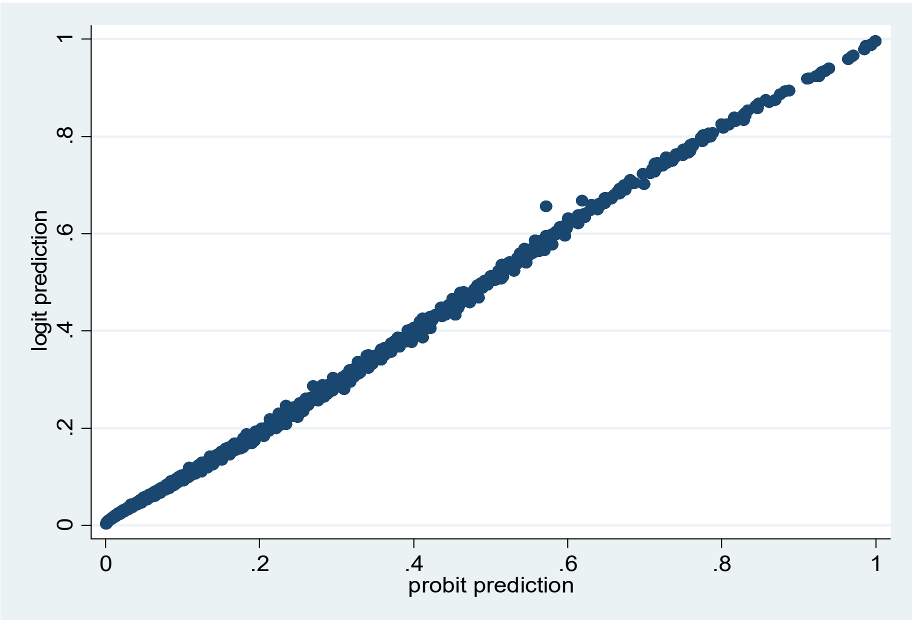
Table 5.2 Marginal Effects of determinants on Child Poverty. Estimation Results for Income Poverty Measurement.

Independent Variables	Dependent Variable: childpov		
	Linear Model (1)	Logit (2)	Probit (3)
size	0.006***	0.011***	0.012***
	(0.003)	(0.003)	(0.003)
hheadsex	-0.032***	-0.035***	-0.035***
	(0.008)	(0.009)	(0.009)
lessthan2	0.099***	0.075***	0.075***
	(0.012)	(0.012)	(0.012)
between2and5	0.096***	0.072***	0.075***
	(0.007)	(0.007)	(0.007)
between6and14	0.083***	0.065***	0.069***
	(0.005)	(0.005)	(0.005)
youngmom	0.090***	0.106***	0.107***
	(0.009)	(0.011)	(0.011)
youngdad	0.072***	0.082***	0.089***
	(0.011)	(0.014)	(0.014)
momwork	-0.138***	-0.159***	-0.163***
	(0.008)	(0.008)	(0.008)
dadwork	-0.115***	-0.101***	-0.111***
	(0.012)	(0.011)	(0.011)
momprimedu	-0.032**	-0.035***	-0.035***
	(0.013)	(0.014)	(0.014)
dadprimedu	-0.117***	-0.102**	-0.111**
	(0.040)	(0.046)	(0.048)
momsecedu	-0.115***	-0.097***	-0.103***
	(0.009)	(0.011)	(0.011)
dadsecedu	-0.128***	-0.128***	-0.134***
	(0.009)	(0.009)	(0.010)
educationalgap	0.013***	0.013***	0.013***
	(0.005)	(0.004)	(0.005)
wagegap	0.036***	0.033***	0.032***
	(0.005)	(0.004)	(0.005)

Note: Robust standard errors are presented in parentheses. *, ** and *** denotes statistical significance of 10%, 5% and 1% respectively.

In order to choose which of the models is the one that better fits the data for the analysis of the coefficients, the Akaike (AIC) and Bayesian Information Criteria (BIC) were performed. Both criteria recommended the use of the Probit model, although the difference is positive but not really strong (regarding Raftery 1995 classification[6]). The table of the criteria can be found in Appendix B. Furthermore, it was discussed before that Linear Regression models are probably inconsistent and biased. Taking all these into consideration, Probit model was chosen as Model 1 for the analysis of Income measurements of poverty. In any case, predictors of the Maximum Likelihood models do not differ in great amount as it can be seen in Figure 5.1.

Figure 5.1 Scatter of Logit and Probit Predictors, Model 1



Results just for the Probit regression are reported in Table 5.3 As it can be observed, all the variables are statistically significant at a 5% level. The Log likelihood of the fitted model indicates that all predictors' regression coefficients are simultaneously different from zero, and the Likelihood Ratio Chi-Square suggest that not even one of the predictor's regression coefficients are equal to zero. The McFadden's pseudo R-squared is not equivalent to the R-squared found for OLS regressions, and because of that we won't give an interpretation. Similar results were found for the Logit model as a Robustness Check, and the information is available in Appendix B.

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[6] Raftery (1995) claimed that for the Bayesian criteria, only a difference bigger than 6 points will be considered a strong difference.

Moreover, the interpretation of the coefficients in a Probit regression is not as straightforward as it could be in a linear or Logit regression. The increase in the probability attributed to one-unit increase in a given variable of analysis depends in great way in the starting value of the predictor. Nevertheless, a positive coefficient will mean that an increase in the predictor variable leads to an increase in the predicted probability, while a negative coefficient will lead to a decrease. (Introduction to SAS, accessed May 10th 2016). Taking this into account, it can be observed that all the predictors have the expected sign: those variables concerning the size of the household and the case of a household with young household head and partner increase the likelihood of a child to be under poverty conditions. It also seems like those household that present wage or educational gender gaps between them, are more likely to present child poverty. Additionally, in those households that the head and his/her partner have some education or access to the labor market, as well as those whose household head is a man, children are less likely to be under poverty. A Wald test performed indicates that none of the parameters is expected to take a zero value. The results for that test are available in Appendix B.

V.1.1 Marginal effects of income measurement of poverty

When it comes to the marginal effects, a problem is presented: they are calculated by the statistical program for the whole sample mean. In order to present the marginal effects for each individual, Table 5.3 presents the *average marginal effects*. The interpretation is then more direct, and the changes in all variables are considered *ceteris paribus* (the rest of explanatory variables remain constant).

A unit change in the total member of the households will increase the probability of each child in that household of being poor in a 1,1%. This is consistent with previous results (Maxwell 1996; Maxwell et al. 1999; Lipton 1999; Fofack 2002; Marrugo et al. 2015).

Furthermore, if the household head was previously a female and is now a man, the probability of being poor will decrease 3% for each child living in the household. Although the sign of this variable is under debate, these results were also suggested by some of the available literature (Lipton and Ravallion 1995; Barros et al. 1997; Meenakshi and Ray 2002).

Moreover, a unit change in the total number of kids under 2 years old, or between 2 and 5, or between 6 to 14, will increase the probability of each child in that household of being poor by 7, 6.7 and 6% respectively. These results are consistent with the empirical evidence (Chen and Corak 2008; TARKI 2010; Bárcena et al. 2015).

When it comes to the interpretation of *youngmom* and *youngdad*, it is important to mention than in this case they do not have a clear counterfactual. It is not possible for a person that was older than 30 years old before to became younger.

Additionally, data suggested that a mother that previously worked less than 20 hours per week or did not work at all and starts working will decrease the probability of their kids of being poor by 15,5%. For the case of a father, the decrease will be of 9,9%. The decreasing sign is consistent with the literature reviewed (Bradbury and Jantti 2001; Moller and Misra 2005; Whiteford and Adema 2007; Chen and Corak 2008; Munzi and Smeeding 2008; Gornick and Jantti 2012). Furthermore, the fact that the effect was larger in the case of the mothers could be evidence in favor of those empirical evidence that claim that an increase in the earning power of a mother will translate in an improvement in the quality of life of their child (Thomas 1990; Engle 1993; Handa 1994; Strauss and Thomas 1995; Hoddinott and Haddad 1995; Lundberg and Pollak 1996; Haddad et al. 1997; Thomas 1997; Buvinic 1998; Quisumbring and Maluccio 2000; Duflo and Udry 2004; Pagés and Piras 2010).

Referring to the education variables, an assumption should be made. As all the variables relative to schooling are dichotomous, the marginal effects reflect a variation. In this case, that change will be a father or a mother that did not completed primary or basic cycle before, but finished their studies now. In that scenario, both primary and secondary education will decrease the probability of their child of being poor further for man that for woman (8% for primary education and 11% for secondary, against 3% and 8,5% respectively). The fact that schooling decrease the probability of experience poverty follows the empirical evidence aforementioned (Milcher 2006; Chen and Corak 2008; Chzhen and Bradshaw 2012; Gornick and Jantti 2012). The fact that the effects are greater for men that for women might reflect two realities in Uruguay. First, it is expected for women to have greater education than men. For that reason, the marginal effect of increasing one year in education may have a stronger effect in men's skill level. Secondly, as there exist *"glass ceilings"* for women in the country, it is expected that the increase in their education does not translate completely in an increase on their incomes, that is at the end what influence the economic condition of a child.

Finally, the educational gender gap is expected to have a smaller effect for each individual in the household when it comes to their probability of being poor than the gender wage gap: an increase in one unit (1%) of the educational gender gap will generate an increase of 1% on the probability of being poor of the kids, while an increase in 1% in the gender wage gap will translate into a 3% increase in the probability of each child to be under the poverty line. The fact that both gender gap variables increases the probabilities of a child of experience poverty is related with part of the available literature (Siddique 1998; Montenegro 2001; Okojie 2002; Castello and Domanech 2002; Urinola and Wodon 2003; Gradín et al. 2006; Klasen and Lamanna 2009). In addition, that the educational gender gap has lower effects than the gender wage gap might be reflecting the transmission channels suggested by previously stated theory that claimed that an unequal distribution of resources within a family might have less likely poverty reduction as a consequence (Sen 2000).

As it can be observed in Appendix B as a Robustness Check, all the marginal effects computed by a Logistic Regression Model have similar results.

Table 5.3 Effect of determinants on Child Poverty. Probit Estimation Results for Income Poverty Measurement.

Independent Variables	Dependent Variable: childpov	
	Coefficients	Average Marginal Effects
size	0.051^{***}	0.011^{***}
	(0.015)	(0.003)
hheadsex	-0.139^{***}	-0.030^{***}
	(0.037)	(0.008)
lessthan2	0.324^{***}	0.071^{***}
	(0.051)	(0.011)
between2and5	0.306^{***}	0.067^{***}
	(0.030)	(0.006)
between6and14	0.278^{***}	0.061^{***}
	(0.022)	(0.004)
youngmom	0.406^{***}	0.089^{***}
	(0.041)	(0.009)
youngdad	0.330^{***}	0.073^{***}
	(0.046)	(0.010)
momwork	-0.707^{***}	-0.155^{***}
	(0.039)	(0.008)
dadwork	-0.449^{***}	-0.099^{***}
	(0.047)	(0.010)
momprimedu	-0.141^{***}	-0.031^{**}
	(0.059)	(0.013)
dadprimedu	-0.383^{***}	-0.084^{**}
	(0.145)	(0.032)
momsecedu	-0.385^{***}	-0.085^{***}
	(0.038)	(0.008)
dadsecedu	-0.505^{***}	-0.111^{***}
	(0.036)	(0.008)
educationalgap	0.051^{***}	0.011^{***}
	(0.020)	(0.004)
wagegap	0.130^{***}	0.030^{***}
	(0.019)	(0.004)

Note: Robust standard errors are presented in parentheses. *, ** and *** denotes statistical significance of 10%, 5% and 1% respectively.

V.1.2 Robustness checks

Several post-estimation tests were performed in order to analyze the model's accuracy. Table 5.4 shows an overall rate of correct classification estimated at 82.98%. Classification is sensitive to the relative sizes of each component group, in favor of the larger one. This singularity is clear here: 94.34% of the normal weight group was correctly classified (*specificity*) while only a 44.69% of the low weight group was correctly classified (*sensitivity*).

Table 5.4 Classification Estimates Output, Model 1

Probit model for childpov

Classified	True D	True -D	Total
+	988	422	1410
-	1223	7033	8256
Total	2211	7455	9666

Classified + if predicted Pr(D) >= .5
True D defined as childpov ! = 0

Sensitivity	Pr (+|D)	44.69%
Specificity	Pr (-|-D)	94.34%
Positive predictive value	Pr (D|+)	70.07%
Negative predictive value	Pr (-D|-)	85.19%
False + rate for true -D	Pr (+|-D)	5.66%
False - rate for true D	Pr (-|D)	55.31%
False + rate for classified ·	Pr (-D|+)	29.93%
False - rate for classified -	Pr (D|-)	14.81%
Correctly classified		82.98%

When considering the Pearsons $\chi2$ goodness-of-fit test for the fitted model, there is also evidence to support a well fit of the model (as the P value is 0.000). Moreover, the number of covariate patterns (2,065) is not very close to the number of observations (9,666), making the applicability of the test less questionable.

Another way of testing the specification of the model is the Link test that checks the dependent variable. This test regresses the explanatory variable on its prediction and the prediction squared. If the model is specified correctly, the prediction squared should not have an explanatory power. As it can be observed in Table 5.5, the link test reveals no problem with the specification.

Table 5.5 **Link Test Output, Model 1**

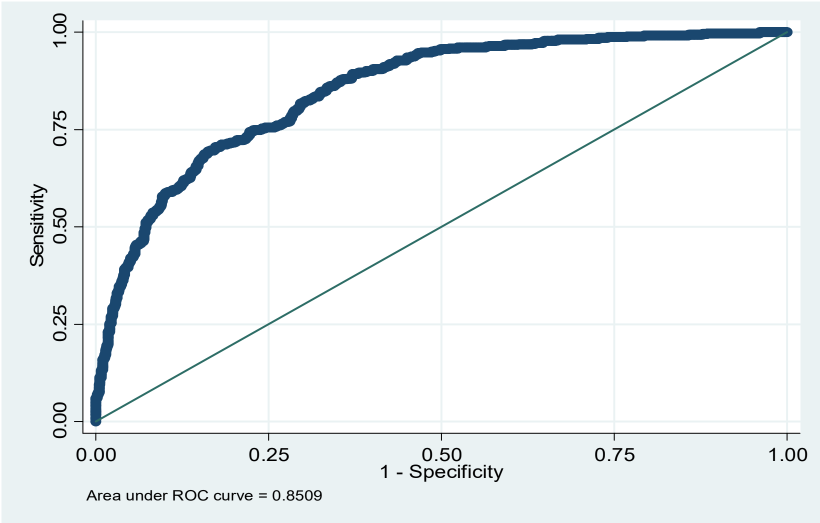
Probit regression				Number of obs	=	9666
				Wald chi2(2)	=	1696.84
				Prob > chi2	=	0.0000
Log pseudolilelihood = -1281.6873				Pseudo R2	=	0.7534

childpov	Coef.	Robust Std. Err.	z	P > |z|	[95% Conf. Interval]	
_hat	.9958124	.0283547	35.12	0.000	.9402381	1.051387
_hatsq	-.017087	.0255163	-0.67	0.503	-.067098	.032924
_const	.0172982	.038499	0.45	0.653	-.0581406	.092737

All the aforementioned tests were also performed for the Logit model as robustness checks, with similar results. They can be consulted in the Appendix B.

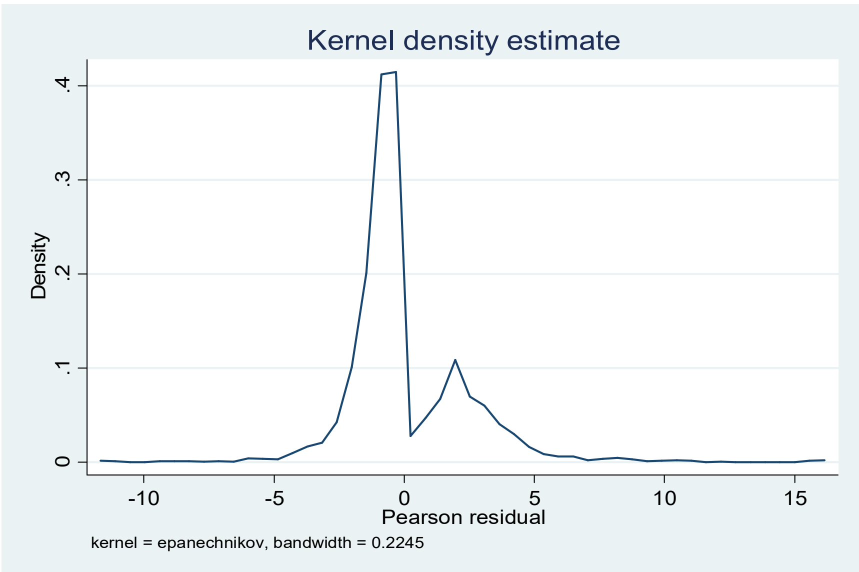
Finally, two graphs were performed in order to validate the assumptions of the model specification. The first one is the graph of the ROC curve: sensitivity versus one minus specificity as the cutoff c is varied. Sensitivity in this case refers to the fraction of observed positive-outcome cases that were correctly classified, while specificity is the fraction of observed false-positive cases that were classified as correct, but were incorrect. The greater the predictive power, the more bowed the curve will be. This is the reason that the area beneath the curve is used usually as a measure of the predictive power (the closer to one, the greater power). As it can be observed in Figure 5.2 the area under the curve of this model is approximately 0.85, indicating an acceptable discrimination.

Figure 5.2 ROC curve, Model 1



The second one pretends to represent the probability density function of the residuals, in the way of the Kernel Density Function. This function is known as a data smoothing mechanism where inferences about the population are made based on a finite sample. As it can be observed in Figure 5.3, the residuals of the estimation seem to be smoothed and to behave in something similar to a Normal distribution, which is one of the necessary assumptions of the model.

Figure 5.3 Kernel Density estimate, Model 1



Besides, when it comes to the assumption of homoscedasticity of the error term, due to the fact that there is not enough information that could suggest which is the variable that might be causing heteroscedasticity, a procedure suggested by Wooldridge (2002) is applied to the dataset. Firstly, the probit model is estimated, and the fitted linear indices (xibhat) are obtained. After that, an augmented model by probit is estimated, including the original variables xi as well as [xibhat*xi] for each independent variable in the first regression. Finally, the significance of each interaction is tested by using the standard Wald test. As it can be observed in the Appendix B, this test suggests that the variables *between2and5*, *momwork* and *educationalgap* could be generating a heteroscedastic variance. Hetprob test is performed in order to analyze if there is a need to adjust the model due to this. At a 1% significance level, the Wald test suggests that the model does not have this problem[7].

Another robustness check performed was the inclusion of a control variable such as the municipality (or department, for the case of Uruguay) that controls where the house is located. This variable could be relevant in the analysis as a proxy of those factors that are inseparable from the house but have a qualitative effect on it, such as access to public assets such as water, electricity or health. Moreover, sometimes the origin of the head of the household is a major factor for understanding the economic status as well. As it can be observed in the output in Appendix B, despite the fact that the adjusted R^2 improved a slight amount, the inclusion of the variable only decreased the significance of the household head sex (that still significant at a 10% level) and from mother's primary education (still significant at a 5% level). In order to estimate if the department variable was an omitted variable, and if it should be included in the original model, a Likelihood Ratio test was performed. As it can be observed in Table 5.6, both the Akaike and the Bayesian Information Criteria support the use of the constraint model (without the inclusion of dpto).

[7] Considering a 5 or 10% level, this assumption is not met. However, for the purpose of the model, it was decided to consider a 1% significance level.

Table 5.6 Likelihood Ratio Test, Model 1

Likelihood-ratio test				LR chi2(1)	=	225.83
(Assumption: unconstrained nested in constrained)				Prob > chi2	=	0.0000

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
unconstrained	9666	-5197.884	-3813.029	16	7658.059	7772.881
constrained	9666	-5197.884	-3700.115	17	7434.23	7556.229

Note: N= Obs used in calculating BIC

Moreover, applying the test for the measures of fit of the models, another Bayesian Information Criteria (BIC') also provides strong support for the model that do not include the control variable (considered the current model). Output of that test can be observed in Appendix B.

V.2 Multidimensional measurement of poverty

The same procedures that were performed for the Income measure of poverty were implemented for the case of the Multidimensional measure. Again, the application of a Linear Probability Model using OLS was performed, and compared with Logit and Probit models. In this case, the Logit model was the one that better fitted the data.

V.2.1 Results on multidimensional measurement of poverty

Following Table 5.7, nearly all the coefficient values are statistically significant, and have the expected sign.[8] The results obtained are almost the same than those found for Income Poverty models. When the number of members of the household or the number of child it has in its composition increases, so does the probability of them to be poor. Furthermore, if the household head is a man, or if he/she and his/her partner worked or reached some level of education, it is less probable for the household members to be poor. Finally, the

[8] This is not the case for the variable *between6and14* for the case of the Linear Regression. This is not a problem because, as it was stated before, it is expected for this type of regressions' estimations to be inconsistent and biased.

existence of wage or educational gender gaps among the household head and his/her partner increases the probability of the child members of the household to be poor.

Table 5.7 Coefficients of determinants on Child Poverty. Estimation Results for Multidimensional Poverty Measurement.

Independent Variables	Dependent Variable: child_deprivation		
	Linear Model	Logit	Probit
	(1)	(2)	(3)
size	0.014***	0.187***	0.099***
	(0.002)	(0.030)	(0.015)
hheadsex	-0.021**	-0.438***	-0.221***
	(0.005)	(0.111)	(0.053)
lessthan2	0.038**	0.531***	0.283***
	(0.015)	(0.198)	(0.100)
between2and5	0.028***	0.345***	0.177***
	(0.006)	(0.087)	(0.043)
between6and14	0.007	0.305**	0.120**
	(0.005)	(0.130)	(0.061)
youngmom	0.017***	0.319**	0.159**
	(0.006)	(0.140)	(0.065)
youngdad	0.057***	1.032***	0.523***
	(0.007)	(0.146)	(0.069)
momwork	-0.028***	-0.954***	-0.405***
	(0.004)	(0.139)	(0.062)
dadwork	-0.029***	-0.376***	-0.225***
	(0.007)	(0.139)	(0.072)
momprimedu	-0.028*	-0.562**	-0.292**
	(0.017)	(0.274)	(0.139)
dadprimedu	-0.142***	-0.996***	-0.548***
	(0.047)	(0.277)	(0.155)
momsecedu	-0.037***	-0.735***	-0.345***
	(0.006)	(0.109)	(0.053)
dadsecedu	-0.038***	-0.919***	-0.416***
	(0.005)	(0.118)	(0.054)
educationalgap	0.011***	0.163***	0.086***
	(0.004)	(0.049)	(0.026)
wagegap	0.019***	0.214***	0.107***
	(0.004)	(0.035)	(0.020)
constant	0.148***	-2.661**	-1.510***
	(0.049)	(0.356)	(0.189)
Number of observations	9,666	9,666	9,666
Pseudo R^2	0.208	0.204	0.202
Wald Test	0.000	0.000	0.000

Note: Robust standard errors are presented in parentheses. *,** and *** denotes statistical significance of 10%, 5% and 1% respectively. In the case of OLS, Adjusted R^2 is presented. In the case of Logit and Probit models, McFadden pseudo R^2 is shown. Moreover, while Wald Test is presented in the case of Probit and Logit for the significance of all the variables together in the model, F test is displayed for the Model (1). In every case, the presented model is better than an empty one.

Marginal effects comparison between Linear Regression, Logit and Probit models was also performed. As it can be observed in Table 5.8, elasticities tend to be similar between the models as suggested by the literature. In the same way as for Income Poverty measures, the variables that appear to be increasing the likelihood of children to live in a household that experience two or more deprivations appear to be the number of minors in the house (that increases as they are younger); youth status of parents (greater in the case of men than for women); and the existence of a gender wage gap rather than an educational gender gap. The latter again might be empirical evidence to support that couples do have in general similar educational levels. Furthermore, the variables that reduce the risk of being under poverty seem to be the employment status of the mother rather than the father, and the education status of both, although higher for men. This is exactly the same results founded with the Income Poverty models, and again, it could be due to the existence of *"glass ceilings"* in the country.

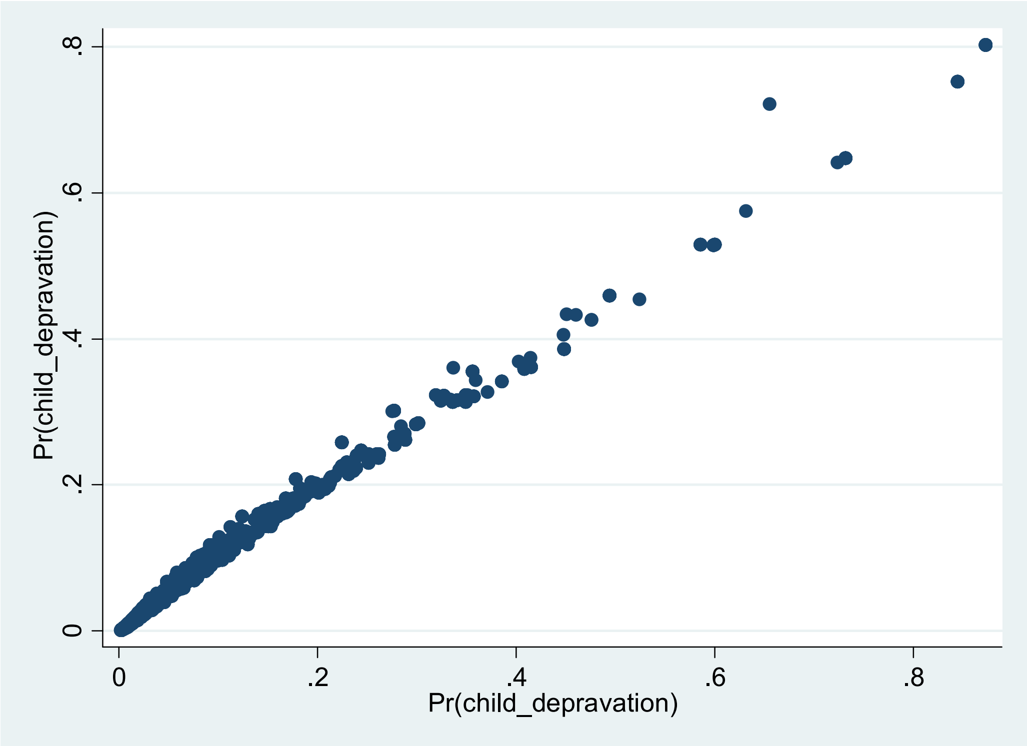
Table 5.8 Marginal Effects of determinants on Child Poverty. Estimation Results for Multidimensional Poverty Measurement.

Independent Variables	Dependent Variable: childpov		
	Linear Model (1)	Logit (2)	Probit (3)
size	0.014^{***}	0.004^{***}	0.005^{***}
	(0.002)	(0.001)	(0.001)
hheadsex	-0.021^{**}	-0.012^{***}	-0.015^{***}
	(0.005)	(0.003)	(0.004)
lessthan2	0.038^{**}	0.013^{***}	0.017^{***}
	(0.015)	(0.005)	(0.006)
between2and5	0.028^{***}	0.008^{***}	0.010^{***}
	(0.006)	(0.002)	(0.003)
between6and14	0.007	0.007^{**}	0.007^{**}
	(0.005)	(0.003)	(0.003)
youngmom	0.017^{***}	0.008^{**}	0.010^{**}
	(0.006)	(0.003)	(0.004)
youngdad	0.057^{***}	0.035^{***}	0.043^{***}
	(0.007)	(0.007)	(0.007)
momwork	-0.028^{***}	-0.022^{***}	-0.022^{***}
	(0.004)	(0.003)	(0.003)
dadwork	-0.029^{***}	-0.009^{***}	-0.013^{**}
	(0.007)	(0.003)	(0.004)
momprimedu	-0.028^{*}	-0.014^{**}	-0.017^{**}
	(0.017)	(0.007)	(0.008)
dadprimedu	-0.142^{***}	-0.039^{**}	-0.054^{**}
	(0.047)	(0.016)	(0.023)
momsecedu	-0.037^{***}	-0.021^{***}	-0.024^{***}
	(0.006)	(0.004)	(0.004)
dadsecedu	-0.038^{***}	-0.026^{***}	-0.029^{***}
	(0.005)	(0.004)	(0.004)
educationalgap	0.011^{***}	0.004^{***}	0.005^{***}
	(0.004)	(0.001)	(0.002)
wagegap	0.019^{***}	0.005^{***}	0.006^{***}
	(0.004)	(0.001)	(0.001)

Note: Robust standard errors are presented in parentheses. *, ** and *** denotes statistical significance of 10%, 5% and 1% respectively.

In order to choose which of the models is the one that better fit the data, same information criteria used before (AIC and BIC) were considered. Despite the fact that both criteria recommend the Linear Regression model, this kind of specification might have statistical problems that were mentioned before (inconsistency and biased estimators). Because of this, Logit model was selected as the *"second best"*. In this case, the difference between Logit and Probit is strong (according to Raftery 1995 criteria). The table of the criteria can be found in Appendix C. Predictors of the Maximum Likelihood models do not differ in great amount as it can be seen in Figure 5.4, and Probit results will be also available as Robustness Checks in Appendix C. [9]

Figure 5.4 Scatter of Logit and Probit Predictors, Model 2



Results just for the Logit regression are reported in Table 5.9. As it can be observed and was commented before, all the variables are statistically significant at a 5% level. The Log likelihood of the fitted model indicates that all predictors' regression coefficients are simultaneously different from zero, and the Likelihood Ratio Chi-Square suggest that not even one of the predictor's regression coefficients are equal to zero. The McFadden's pseudo R-squared is not equivalent to the R-squared found for OLS regressions, and because of that we won't give an interpretation.

Different from what happened before with the Income Poverty models, in this case the best-fitting model is a Logit and because of that, the interpretation of the coefficients is more straightforward. Instead of looking at the coefficients or the marginal effects, the odd ratios will be interpreted. Firstly, at the coefficient interpretation, similar to what happened

[9] Nevertheless, it is important to mention that because the Logit model fits strongly better than Probit model, the predictors are not as similar as it was in the case of Income Poverty models.

with the Income Poverty models, it can be observed that all the predictors have the expected sign. The variables concerning the size of the household, the case of a household with young household head and partner and those household that present wage or educational gender gaps between them, increase the probability of a child living there to experience deprivations. Moreover, in those households where the head and his/her partner have some education or access to the labor market, as well as those who's household head is a man, children are less likely to experience deprivations. A Wald test performed for the significance of all the predictors indicates that none of the parameters is expected to take a zero value. The results for that test are available in Appendix C.

V.2.1 Marginal effects of multidimensional measurement of poverty

When it comes to the odd ratios, the interpretation is as follows. To start, an estimation value greater than one is going to suggest a positive association between the explanation variable and the dependent variable. An estimation value smaller than one, on the contrary, is going to denote a negative association, while a value equal to one implies no association. Taking this into consideration, the available data suggest that the presence of large sizes; a greater number of children (at any age); the youth of the household head and his/her partner and the existence of gender gaps within the household are associated with an increased occurrence of the event "child experience 2 or more deprivations". Different from this, the fact that the household head is a man; the case where the household head and his/her partner work more than 20 hours per week; and the primary and secondary education levels presented by the household head and his/her partner are associated with a lesser occurrence of the event "child experience 2 or more deprivations".

In addition, for continuous variables, a unit increase of Xi is associated with a $(1-\widehat{\beta}) * 100$ increase/decrease (depending on the sign of the coefficient) off the odds of Yi. For discrete variables, the estimated value $\hat{\beta}$ will be showing how many times more likely the odds of finding a Xi in a household/individual in someone with Yi=1 is compared to finding the Xi in someone with Yi=0. As well as for the interpretations of marginal effects on the Probit Model 1, all the increases in the explanatory variables are considered *ceteris* *paribus* (the rest of the variables remain constant). The intercept was not analyzed in this case because there are continuous variables in the model that do not take value of zero.

A unit increase in the size of the household (an extra person, no matter the age) will imply a 20% increase in the odds of a child living in that household to experience some deprivation. This effect is greater than those founded in the case of income measurement of poverty. Moreover, correspondingly for the case of income measurement model, these results go along with the empirical evidence aforementioned (Maxwell 1996; Maxwell et al. 1999; Lipton 1999; Fofack 2002; Marrugo et al. 2015).

Moreover, it is 65% less likely to find kids under deprivation in those households where the head is a man, in comparison with those where the head is a woman. These results go along with the one founded in the case of Model 1, and are also related with some of the available literature (Lipton and Ravallion 1995; Barros et al. 1997; Meenakshi and Ray 2002).

In addition, a unit increase in the number of kids in the household will imply a 70 %, 41 % or 36% increase in the odds of deprivation for the child living in there, if that increase is in kids with less than 2 years, between 2 and 5 or older than 6 respectively. These results are greater than those founded for the case of the Income measurement of poverty. In the same way than those results, are consistent with the empirical evidence (Chen and Corak 2008; TARKI 2010; Bárcena et al. 2015).

In contrast to the Probit model performed before, for the case of the Logit model the variables *youngmom* and *youndad* do have clear interpretations. The odds of finding a father younger than 30 years old in those households that experience two or more deprivations almost triple compared with those households that experience less than two. Besides, it is twice likely to find young mothers in those type of households than in households that present less than two deprivations. This is consistent with previously reviewed literature (TARKI 2010; Bárcena et al. 2015). This was the expected sign for the case of Uruguay, as it is more likely for young people to be under poverty because of how labor is absorbed by the market (INE 2015).

Consistent with the results obtained from the Income measurement model, it is 39% less likely to find a household under deprivations if the mother of that household worked 20 hours or more. For the case of the fathers, it is 69% less likely. Despite the effect is larger than the one suggested for Model 1, the decreasing sign is consistent with the literature reviewed (Bradbury and Jantti 2001; Moller and Misra 2005; Whiteford and Adema 2007; Chen and Corak 2008; Munzi and Smeeding 2008; Gornick and Jantti 2012).

When it comes to education, it is 57 and 37% less likely to find parents who completed primary level in households where child experience deprivation (if who assisted was the mother or the father, respectively). For the case of secondary education, the odds decrease 48 and 40% respectively. Firstly, in accordance with the findings for Model 1, the fact that schooling decrease the probability of experience poverty follows the empirical evidence aforementioned (Milcher 2006; Chen and Corak 2008; Chzhen and Bradshaw 2012; Gornick and Jantti 2012). Additionally, contrary of the effects that were proposed by the income poverty model, the likelihood is smaller for the case of mother's education. These results seem to agree with the arguments presented by the theory: female education is expected to generate greater externalities on children when considering basic needs, such as health or access to information more than just income (Mensch et al. 1986; Thomas et al. 1991; Strauss and Thomas 1995; King and Hill 1997; Glewwe 1999; World Bank 2001; Schultz 2002; Brown 2006).

Finally, a unit change in the educational gender gap is expected to have a smaller effect on the probability of a child of experience more than two deprivations than the gender wage gap (23% for the gender wage gap, 18% for educational gender gaps). These results are consistent with those found for the income measurements of poverty. In the same way that the evidence of Model 1, the fact that both gender gap variables increases the probabilities of a child of experience poverty is related with part of the available literature (Siddique 1998; Montenegro 2001; Okojie 2002; Castello and Domanech 2002; Urinola and Wodon 2003; Gradín et al. 2006; Klasen and Lamanna 2009). In addition, that the educational gender gap has lower effects than the gender wage gap might be reflecting the transmission channels suggested by previously stated theory that claimed that an unequal distribution of resources within a family might have less likely poverty reduction as a consequence (Sen

2000).

Table 5.9 Effect of determinants on Child Poverty. Logit Estimation Results for Multidimensional Poverty Measurement.

Independent Variables	Dependent Variable: child_deprivation	
	Coefficients	Marginal Effects
size	0.187^{***}	1.205^{***}
	(0.030)	(0.036)
hheadsex	-0.438^{***}	0.645^{***}
	(0.111)	(0.071)
lessthan2	0.531^{***}	1.701^{***}
	(0.198)	(0.337)
between2and5	0.345^{***}	1.411^{***}
	(0.087)	(0.113)
between6and14	0.305^{**}	1.357^{**}
	(0.130)	(0.178)
youngmom	0.319^{**}	1.376^{***}
	(0.140)	(0.193)
youngdad	1.032^{***}	1.808^{***}
	(0.146)	(0.409)
momwork	-0.954^{***}	0.385^{***}
	(0.139)	(0.054)
dadwork	-0.376^{***}	0.687^{***}
	(0.139)	(0.095)
momprimedu	-0.562^{**}	0.570^{**}
	(0.274)	(0.156)
dadprimedu	-0.996^{***}	0.369^{***}
	(0.277)	(0.102)
momsecedu	-0.735^{***}	0.479^{***}
	(0.109)	(0.053)
dadsecedu	-0.919^{***}	0.399^{***}
	(0.118)	(0.047)
educationalgap	0.163^{***}	1.177^{***}
	(0.049)	(0.058)
wagegap	0.214^{***}	1.238^{***}
	(0.035)	(0.043)

Note: Robust standard errors are presented in parentheses. *, ** and *** denotes statistical significance of 10%, 5% and 1% respectively.

V.2.2 Robustness checks

Several post-estimation tests were also performed in the case of the Multidimensional Poverty model in order to analyze its accuracy. Table 5.10 shows an overall rate of correct classification estimated in 95.09%. Classification is sensitive to the relative sizes of each component group, in favor of the larger one, which is more than true in the case of the Logit model estimated: 99.77% of the normal weight group was correctly classified (*specificity*) while only a 6.97% of the low weight group was correctly classified (*sensitivity*).

Table 5.10 Classification Estimates Output, Model 2

Probit model for childpov

Classified	True D	True -D	Total
+	34	21	55
-	454	9157	9611
Total	488	9178	9666

Classified + if predicted Pr(D) >= .5
True D defined as childpov ! = 0

Sensitivity	Pr (+|D)	6.97%
Specificity	Pr (-|-D)	99.77%
Positive predictive value	Pr (D|+)	61.82%
Negative predictive value	Pr (-D|-)	95.28%
False + rate for true -D	Pr (+|-D)	0.23%
False - rate for true D	Pr (-|D)	93.03%
False + rate for classified ·	Pr (-D|+)	38.18%
False - rate for classified -	Pr (D|-)	4.72%
Correctly classified		95.09%

When considering the Pearsons χ^2 goodness-of-fit test for the fitted model, there is also evidence to support a well fit of the model (as the P value is 0.000). Moreover, the number of covariate patterns (1,895) is not very close to the number of observations (9,666), making the applicability of the test less questionable.

Furthermore, as it can be observed in Table 5.11 the test of the dependent variable did not reveal any problem with the specification of the deprivation index.

Table 5.11 Link Test Output, Model 2

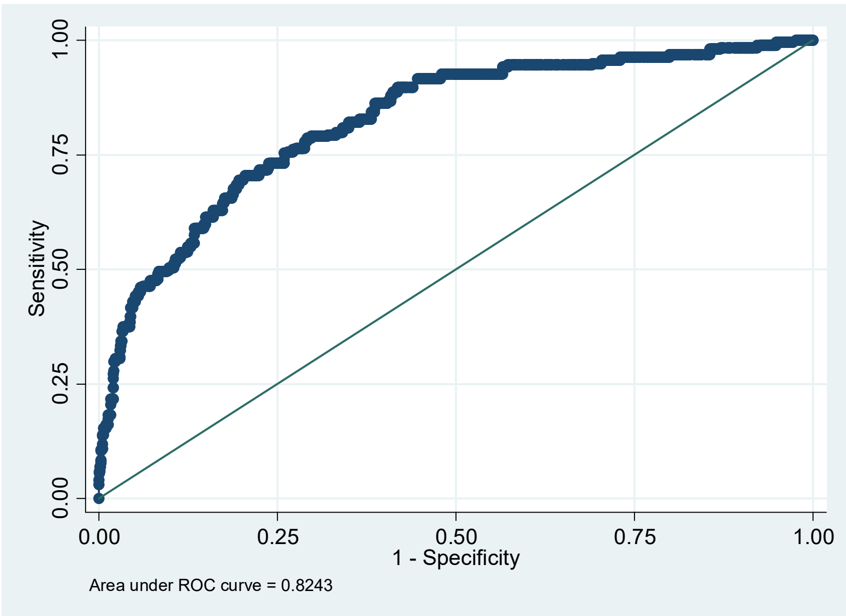
Probit regression				Number of obs	=	9666
				Wald chi2(2)	=	791.83
				Prob > chi2	=	0.0000
Log pseudolilelihood = -1536.7485				Pseudo R2	=	0.2049

child_deprivation	Coef.	Robust Std. Err.	z	P > |z|	[95% Conf. Interval]	
_hat	1.072673	.1079045	9.94	0.000	.8611837	1.284162
_hatsq	.015612	.0212486	0.73	0.463	-.0260345	.0572584
_const	.0605105	.1369267	0.44	0.659	-.2078608	.3288818

All the aforementioned tests were also performed for the Probit model as robustness checks, with similar results. They can be consulted in the Appendix C.

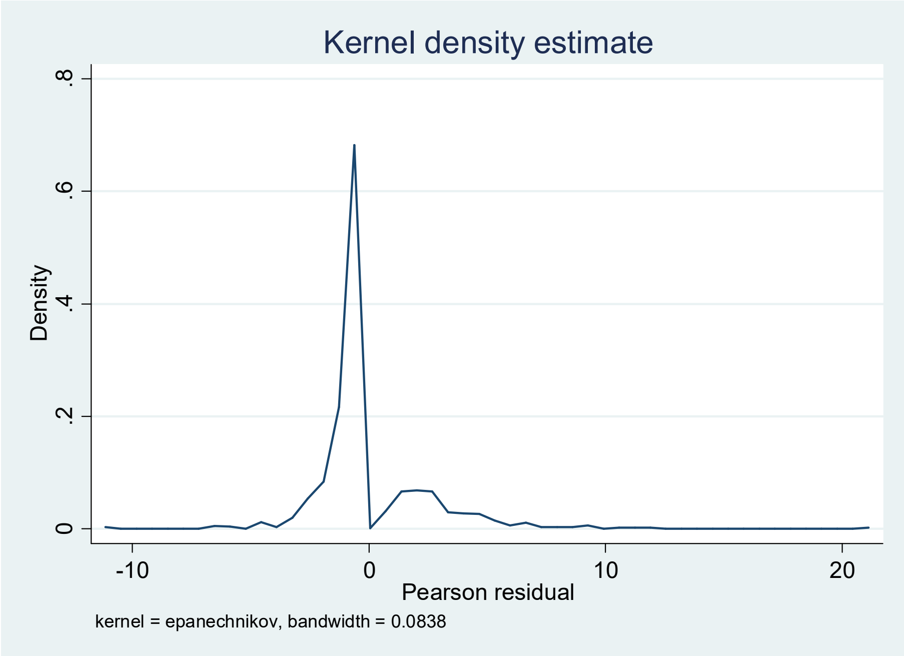
Finally, the ROC curve and Kernel density of the residuals were performed in order to analyze the robustness of the model specification. The ROC curve seems to be indicating and acceptable discrimination, with an area under the curve estimated in 0.82 as it can be observed in Figure 5.5.

Figure 5.5 ROC curve, Model 2



Moreover, the density function of the residuals seems to be smoothed and to behave similar to a Normal distribution, as it can be observed in Figure 5.6.

Figure 5.6 Kernel Density estimate, Model 2



Then again, as we are using a logistic regression to analyze the odd ratios, and this model does not assume a linear relationship between the dependent and independent variable, the problem of the heteroscedasticity assumption is overcome.

The final robustness check performed was again the inclusion of the control variable for the different departments of the country, as a proxy of factors that are intrinsic to the place where the household is situated but were not considered in the model. As it can be observed in the output in Appendix C, the R^2 did not change, neither did the significance of the other variables. In order to estimate if the department variable was an omitted variable, and if it should be included in the original model, a Likelihood Ratio test was performed. As it can be observed in Table 5.11, both the Akaike and the Bayesian Information Criteria support the use of the constraint model (without the inclusion of dpto), as it was the case of the models of income poverty measurement.

Table 5.12 Likelihood Ratio Test, Model 2

Likelihood-ratio test				LR chi2(1)		5.52
(Assumption: unconstrained nested in constrained)				Prob > chi2	=	0.0188

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
unconstrained	9666	-1932.663	-1537.021	16	3106.041	3220.863
constrained	9666	-1932.663	-1534.26	17	3102.521	3224.519

Note: N= Obs used in calculating BIC

The above-mentioned results work as empirical evidence that suggest that household unequal allocation of resources could be affecting the conditions of a child living in that household. Particularly, the effect is greater for wage differentials than for educational gender gaps. This is true when considering both an Income measurement of poverty and a Multidimensional index.

This propose that the traditional perspective of the household (were the researcher assumes that resources are equally distributed within its members, and that they have the same level of participation in decision making) is not true, at least in the case of Uruguay. In addition, these inequalities have a greater effect when considering deprivations more than only income measurements of poverty. Something similar happens for the rest of explanatory variables. As it will be stated in the following chapter, these results might be important for policy implications.

The following chapter has the objective of summarize the above-mentioned results, and derive some policy implications for the country from those outputs.

VI. Conclusions

In this final chapter, the answers found to the research questions, along with possible political implications, contributions and limitations of the results obtained are presented.

VI.1 Research Objectives

The main purpose of this document was to analyze the determinants of child poverty in Uruguay. Particularly, what is the relationship between child poverty and the existence of wage or educational gender gaps within a household. Based on household surveys performed in the country in 2012 and 2013, it seems that the determinants of child poverty and child deprivation for Uruguayans' children are the total number of members of the household; the proportion of children; the age of the household head and his/her partner; their educational level; their employment status; and the differences between the household head and his/her partner at an educational level and in the wages perceived. The first research question of the thesis was:

Is child poverty in Uruguay explained by the socio-economic characteristics of parents and household configuration? A causality relationship between the determinants above-mentioned and the standard of living of a child is suggested by this study. The determinants that increase the likelihood of children to live in a household under the poverty line or to experience some kind of deprivation are: the number of minors in the house (increasing as they are younger); the youth status of the parents (greater in the case of men than for women) and the existence of gender wage gaps rather than educational gender gaps. Besides, the variables that reduce the risk of child poverty or child deprivation are the employment status of the mother rather than the status of the father, and the educational status of both. This last variable was greater for women in the case of the Multidimensional measurement of poverty, in line with what was suggested by the reviewed literature (that female education is expected to generate greater externalities on children when considering basic needs such as health or access to information more than just income). However, these were the results of a model built specifically with these variables, for a particular country and certain time. Future research is recommended in order to support these findings. The second research question was:

To what extent wage and educational gender gaps contribute to such situation? Results from both approaches showed that the educational gender gap has less effect on the likelihood that a child will experience poverty. This could be related with the fact that the gender wage gap is a deeper problem that has perpetuated in the country. Particularly for the income poverty measurement, an increase in 1% of the educational gender gap is expected to generate an increase of 1% on the probability of being poor, while an increase in 1% in the gender wage gap will translate into a 3% probability's increases. Furthermore, for the multidimensional poverty measurement, a unit change in the educational gender gap is expected to increase the odds of a child to experience more than two deprivations in a 18%, while a unit increase on the gender wage gap is expected to increase the odds of a child to experience more than two deprivations 23%. The third question was:

Do these results change when considering Income Measurements of Poverty or a Multidimensional Measurement? Although this is more a methodological question than a research question, it is interesting to analyze how the results changed when different measures were considered. The answer to this question is ambiguous, because it might be the case that the models applied and the dependent variable considered in each one of them are not very comparable. However, it is true that both variables have an impact on child poverty with a positive relationship, in both types of measures considered. In order to suggest which methodology is better, it is necessary to be aware of the aim of the analysis/policy applied.

VI.2 Policy Implications

An important disclosure that is derived from this study is that policymakers should not only consider the income perspective when trying to eradicate child poverty. This might lead to biases in the specificity of the policy applied, while considering poverty as a multidimensional phenomenon could generate a more accurate outcome. For example, mother's education was considered to have a smaller effect than father's education when taking into account poverty measured by income. When the multidimensional measurement of poverty was considered, the results obtained were just the opposite. It will be then necessary firstly to specify which the aim of the policy is in order to analyze which of the measurements fits better.

Additionally, one of the most important lesson drawn from this thesis is that child poverty reduction strategy of the country should focus more on better labor opportunities for women with children, and to reduce the gender wage gap problem. It was suggested throughout the estimations achieved by this investigation that to improve the conditions of mothers, whether they are small with reference to those perceived by fathers, will have positive effects on children. Particularly, the probabilities of a child of experience poverty decreased 15,5% if his/her mother started to work more than 20 hours per week. In the case of deprivation measurement, the decrease of experience deprivations was 39%. These results are evidence in favor of the literature that claim that an increase in the earning power of a mother will translate into an improvement in the quality of life of her children (Thomas 1990; Engle 1993; Handa 1994; Strauss and Thomas 1995; Hoddinott and Haddad 1995; Lundberg and Pollak 1996; Haddad et al. 1997; Thomas 1997; Buvinic 1998; Quisumbring and Maluccio 2000; Duflo and Udry 2004; Pagés and Piras 2010). More and better labor opportunities for women with children arise from this research as an immediate need in the country. Furthermore, when it comes to gender wage gaps, results obtained showed that this variable is more important than the educational gender gaps existing in the household. While it was estimated that a unit increase (1%) of the educational gender gap will generate an increase of 1% on the probability of being poor of the kids, an increase in 1% in the gender wage gap will translate into a 3% increase in the probability of each child to be under the poverty line. For the case of deprivations, the results were similar: a unit change in the educational gender gap is expected to have a smaller effect on the probability of a child of experience more than two deprivations than the gender wage gap (23% for the gender wage gap, 18% for educational gender gaps). In both cases, results might be reflecting that an unequal distribution of resources within a family might have less likely poverty reduction as a consequence (Sen 2000). This should be also taking into account for policy makers, in order to make interventions that have child poverty reduction as a main goal more accurate.

Finally, the role of education was once again proven as a strong determinant. For the case of poverty considered as income limitations, the results showed that probabilities for kids to experience poverty decreased in a more significantly share if the fathers improved their education, they also decreased when the mothers improved it. This difference might just be reflecting that, as is expected for women in the country to have greater education than men, the marginal effect is greater for males as it might have a stronger effect in their skill level. Moreover, as there exist “glass ceilings” in the country, it is expected that the increase in women education does not translate completely in an increase on their incomes. Moreover, the results were just the opposite for the case of multidimensional measurement of poverty: mother’s education was expected to generate greater externalities on children than father’s education when considering basic needs such as health or access to information more than just income. Nevertheless, as both variables showed a negative relationship with child poverty, efforts in the educational aspect should be continued in order to ensure a better future for the country. School programs with flexible schedules or monetary compensations on wages for those who finish high school (for example), could be attractive to parents who want to complete their studies.

VI.3 Contributions and limitations of the analysis

Beyond the possible political implications, it is also relevant to highlight some of the contributions of the analysis performed. First, the application of two type of poverty measurements into a micro-econometrical analysis, in line with the current debate, that showed that both type of measurements are interesting for analysis and should be considered in equal manner for researchers. Secondly, the contribution to the empirical evidence on child poverty for Uruguay, that is not as extended as it could be expected given the relevance of the subject. Moreover, this is the first study that considers variables of gender gaps as determinants of poverty, at least for Uruguay. Thirdly, the analysis contributed as empirical evidence for the lack of consensus on the relationship of some particular variables and the economic performance of a household. Particularly, this investigation suggested that households that have a man as the household head are less likely to be poor or experience deprivations, as suggested by Lipton and Ravallion (1995); Barros et al. (1997) and Meenakshi and Ray (2002). Furthermore, when it comes to the gender gap variables debate, this study stated that for the country those variables are positively related with poverty and deprivation of its members. This was also suggested before by Siddique (1998); Montenegro (2001); Okojie (2002); Castello and Domanech (2002); Urinola and Wodon (2003); Gradín et al. (2006); Klasen and Lamanna (2009); Costa et al. (2009); and Chaudhry et al. (2009). Finally, this study might also be presented as empirical evidence against the traditional household model, that claims that resources are equally distributed within its members, and that they have the same level of participation in decision making.

Despite the aforementioned contributions, this research has some restrictions. On the one hand, there are some constraints related to the variables included in the models. Firstly, the multidimensional measurement was constructed based on the data availability, which is not the best scenario. Secondly, due to time and economic limitations, the dimensions and determinants included in the analysis relied severely on academic evidence. The analysis might be deeper with a more specifically designed survey, or with the inclusion of more precise variables for the country. Another constraint related to the surveys used for analysis emerges. As it was suggested before, the uses of surveys that were not collected precisely for the aim of the investigation might create some biases in the estimations. This should be taken into account when interpreting the results and also, for additional research.

VI.4 Future Research

For enabling a deeper understanding of child poverty and its determinants in Uruguay, more research is needed. To start with, poverty analysis is deeper if it is considered as a dynamic variable rather than a static one. For this reason, if the ENDIS survey continues, it would be interesting to analyze how the indicators of the different dimensions have changed over time. Monitoring why a family with children managed to escape from poverty or fell into it will surely generate recommendations of greater impact.

Limitations of the dataset and methodology applied could also be solved with further research. Although it will take more time, it could be interesting to give a deeper look into children's realities, and incorporate the effect of other type of dimensions that might be also affecting child well-being.

Another research extension that might lead to interest results could be the introduction of fertility into the analysis. How does the relationship between fertility and the different educational and economic level vary in the country? Could this perpetuate child poverty?

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Appendix A: Variables used for the construction of multidimensional index.

The variable *child_depravation* was constructed as the sum of all the following dummy variables. A kid was considered poor if he/she experienced more than two of these deprivations.

Shelter deprivation

According to Gordon et al. (2003), the type of material used for the floor and the roof or the household, as well as the ratio of people and number of rooms are indicators of wealth and health risk. Due to this, the dichotomous variable *shelter_deprivation* was created taking value one if the household had more than four members and less than two rooms, or if the roof of the household was made of straw or waste, or if the floor of the household was stated by the survey as *"underlayment without floor"* or just *"ground"*.

Sanitation deprivation

It is well known that proper sanitation can prevent diseases and reduce illness. Moreover, the sanitation condition of a household can also be a proxy of its income level. In this case, the dummy variable *sanitation_deprivation* took value of one for those households where the toilet had no flush or there was no toilet at all (latrine or composting toilets instead).

Water deprivation

Safe drinking water sources are also well-known as diseases prevention and standard of well-being. The dichotomous variable *water_deprivation* was then created and took the value one if the household water came from a well, a stream, a river or other.

Information deprivation

Access to information is considered as a high value intangible, not only for decision making but also because it can affect health and hygiene. Furthermore, it also works as a household wealth proxy. *Information_depravation* was created and took value of one in those households that did not own a radio or a TV as suggested by Bristol's approach[10].

Food deprivation

Undernutrition is well known to be one of the main reasons of child mortality around the world. For the construction of this variable, three standardized anthropometric indices were constructed: the height forage index (*stuning*) as an indicator of growth retardation or deficits, the weigth for height index (*wasting*) as an indicator of body mass, and the weight for age (*under-weight*) as an indicator of undernutrition. Each of this index was created separately for ages and sex of the children using the ENDIS variables available, and standardized by the international normal and well-fed reference population constructed by the World Health Organization[11.] The *food_depravation* variable took the value of 1 if the children was below the average for children of their age or sex in any of the tree measures explained before (stuning, wasting or under-weight).

Education deprivation

Education is one of the main variables that allow to forecast the future economic condition of a child. In Uruguay, primary education is mandatory for all children in schooling ages, but nevertheless, there are some parents that choose not to send them to school. Considering this, *education_depravation* was created from the ENDIS survey, taking value of one for all those times that a child was not send to school as a decision of their parents or because transport or materials needed could not be covered by the household.

Health deprivation

Health deprivation pretends to measure the lack of access to public health more than the health status of the child per-se. Considering the ENDIS dataset, the dummy variable took

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[10] The inclusion of a computer was considered, but due to the Plan Ceibal implemented in 2005 in the country, all kids in schooling age are now owners of a computer, and the inclusion of computers might bias the results.

[11] Information consulted on May, 12th 2016.
http://www.who.int/childgrowth/publications/technical_report_pub/en/

the value 1 if the child experienced cough, diarrhea or lung infection and was not examined by a doctor.

Appendix B: Model of Income Poverty

Table 1.1 Correlation of the Variables included in Model of Income Poverty

	childpov	size	lessth~2	betwee~5	betwe~14	hheadsex	youngmom	youngdad	momwork	dadwork	mompri~c	dadpri~c	momsec~u	dadsec~u	wagegap	educat~p
childpov	1.0000															
size	0.3346	1.0000														
lessthan2	0.1559	0.3163	1.0000													
between2and5	0.2116	0.3252	0.0489	1.0000												
between6a~14	0.3117	0.7064	0.0691	0.1101	1.0000											
hheadsex	-0.0273	-0.0122	0.0476	-0.0221	-0.0330	1.0000										
youngmom	0.1028	-0.2619	0.0248	0.0644	-0.1326	-0.0007	1.0000									
youngdad	0.0768	-0.1906	0.0567	0.0428	-0.1228	-0.0039	0.4917	1.0000								
momwork	-0.2736	-0.1367	-0.0980	-0.0945	-0.1182	-0.0465	-0.1205	-0.0741	1.0000							
dadwork	-0.1368	-0.1088	-0.0591	-0.0439	0.0023	0.0044	0.0768	0.1040	0.0742	1.0000						
momprimeduc	-0.0101	0.0004	0.0215	0.0269	0.0042	-0.0350	0.0144	-0.0240	0.0228	-0.0220	1.0000					
dadprimeduc	-0.0897	-0.0707	-0.0581	-0.0601	-0.0236	0.0589	-0.0302	0.0016	0.0029	0.0965	-0.0058	1.0000				
momsecedu	-0.2842	-0.3573	-0.0798	-0.0734	-0.2210	-0.0340	0.0366	0.0548	0.2424	0.0901	0.1022	0.0865	1.0000			
dadsecedu	-0.3026	-0.3693	-0.0889	-0.0811	-0.2415	-0.0403	0.0533	0.0707	0.1895	0.1345	0.0249	0.1278	0.3692	1.0000		
wagegap	-0.0104	-0.0641	-0.0450	-0.0497	-0.0632	-0.0563	-0.0929	-0.0578	0.2300	-0.1002	0.0204	-0.0285	0.0776	0.0379	1.0000	
educationa~p	0.0119	0.0135	0.0262	-0.0004	-0.0229	-0.0034	-0.0298	-0.0178	0.0067	0.0245	-0.0312	0.0149	-0.0060	-0.0147	0.0179	1.0000

Table 1.2 Selection of Model of Income Poverty

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
m1	9666	-5330.692	-3814.124	16	7660.247	7775.069
m2	9666	-5197.884	-3816.695	16	7665.389	7780.211
m3	9666	-5197.884	-3813.029	16	7658.059	7772.881

Note: N=Obs used in calculating BIC; see [R] BIC note

Note: M1 represent the Linear Probability Model, m2 represents Logit Model and m3 represent Probit.

Table 1.3 Wald Test for the Probit model variables.

```
( 1)  [childpov]size = 0
( 2)  [childpov]hheadsex = 0
( 3)  [childpov]lessthan2 = 0
( 4)  [childpov]between2and5 = 0
( 5)  [childpov]between6and14 = 0
( 6)  [childpov]youngmom = 0
( 7)  [childpov]youngdad = 0
( 8)  [childpov]momwork = 0
( 9)  [childpov]dadwork = 0
(10)  [childpov]momprimedu = 0
(11)  [childpov]dadprimedu = 0
(12)  [childpov]momsecedu = 0
(13)  [childpov]dadsecedu = 0
(14)  [childpov]educationalgap = 0
(15)  [childpov]wagegap = 0
(16)  [childpov]dpto = 0

          chi2( 16) = 2121.75
        Prob > chi2 =    0.0000
```

Tables 1.4 to 1.6 Logit model Estimates Result as Robustness Check

Logistic regression

Number of obs	=	9666
Wald chi2(15)	=	1722.05
Prob > chi2	=	0.0000
Pseudo R2	=	0.2657

Log pseudolikelihood = -3816.6947

childpov	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
size	.0828473	.0261812	3.16	0.002	.0315332	.1341614
hheadsex	-.2571055	.0662464	-3.88	0.000	-.3869461	-.1272649
lessthan2	.5720392	.0914083	6.26	0.000	.3928821	.7511962
between2and5	.5501459	.0530682	10.37	0.000	.4461341	.6541576
between6and14	.4955535	.0404069	12.26	0.000	.4163574	.5747496
youngmom	.7361582	.073365	10.03	0.000	.5923654	.8799511
youngdad	.558068	.0831128	6.71	0.000	.39517	.7209661
momwork	-1.299932	.0732218	-17.75	0.000	-1.443445	-1.15642
dadwork	-.7676621	.0804697	-9.54	0.000	-.9253798	-.6099443
momprimedu	-.2652883	.1036979	-2.56	0.011	-.4685324	-.0620441
dadprimedu	-.6345809	.241297	-2.63	0.009	-1.107514	-.1616475
momsecedu	-.6647317	.0650951	-10.21	0.000	-.7923157	-.5371477
dadsecedu	-.8865367	.06278	-14.12	0.000	-1.009583	-.7634902
educationalgap	.0966949	.0340667	2.84	0.005	.0299254	.1634644
wagegap	.2542715	.0336822	7.55	0.000	.1882555	.3202874
_cons	-.6375123	.2875031	-2.22	0.027	-1.201008	-.0740167

Marginal effects after logit
y = Pr(childpov) (predict)
= .15132489

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
size	.0128317	.00343	3.74	0.000	.006116	.019547	5.06621
hheadsex*	-.0185042	.00922	-2.01	0.045	-.036581	-.000427	.757811
lesst~n2	.0725686	.01174	6.18	0.000	.049551	.095586	1.11515
betwee~5	.0680734	.007	9.72	0.000	.054344	.081803	.347921
betwe~14	.0654527	.00523	12.50	0.000	.055193	.075712	.830954
youngmom*	.1030419	.01123	9.17	0.000	.081025	.125059	.324953
youngdad*	.0987866	.01444	6.84	0.000	.070481	.127092	.197186
momwork*	-.1591091	.00778	-20.46	0.000	-.174348	-.14387	.396338
dadwork	-.0937564	.0105	-8.93	0.000	-.114331	-.073182	.88713
mompri~u	-.0292501	.01354	-2.16	0.031	-.05579	-.00271	-.384099
dadpri~u*	-.1245552	.05657	-2.20	0.028	-.235437	-.013673	.99131
momsec~u*	-.1054658	.01087	-9.70	0.000	-.12677	-.084161	.731119
dadsec~u*	-.1339999	.00992	-13.51	0.000	-.153439	-.114561	.650735
educat~p	.0115925	.00454	2.55	0.011	.002686	.020498	.143516
wagegap	.0367404	.0042	8.75	0.000	.028515	.044966	-.364617
dpto	-.0095715	.00069	-13.78	0.000	-.010933	-.00821	6.86603

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tables 1.7 to 1.9 Statistical significance of Logit Model

Logistic model for childpov

Classified	True D	True ~D	Total
+	1001	422	1423
-	1210	7033	8243
Total	2211	7455	9666

Classified + if predicted Pr(D) >= .5
True D defined as childpov != 0

Sensitivity	Pr(+| D)	45.27%
Specificity	Pr(-|~D)	94.34%
Positive predictive value	Pr(D| +)	70.34%
Negative predictive value	Pr(~D| -)	85.32%
False + rate for true ~D	Pr(+|~D)	5.66%
False - rate for true D	Pr(-| D)	54.73%
False + rate for classified +	Pr(~D| +)	29.66%
False - rate for classified -	Pr(D| -)	14.68%
Correctly classified		83.12%

Logistic model for childpov, goodness-of-fit test

number of observations =	9666
number of covariate patterns =	2065
Pearson chi2(2048) =	8764.05
Prob > chi2 =	0.0000

Logistic regression

Number of obs =	9666
Wald chi2(2) =	1509.03
Prob > chi2 =	0.0000
Pseudo R2 =	0.7513

Log pseudolikelihood = -1292.6857

childpov	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	.9958066	.027106	36.74	0.000	.94268	1.048933
_hatsq	-.006204	.0076373	-0.81	0.417	-.0211728	.0087648
_cons	.0165432	.0586196	0.28	0.778	-.0983492	.1314355

Table 1.10 Outputs with the control variable "*dpto*"

Probit regression	Number of obs	=	9666
	Wald chi2(16)	=	2121.75
	Prob > chi2	=	0.0000
Log pseudolikelihood = -3700.1152	Pseudo R2	=	0.2881

childpov	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
size	.0639583	.014975	4.27	0.000	.0346078	.0933088
hheadsex	-.0688178	.0383191	-1.80	0.073	-.1439218	.0062863
lessthan2	.3175485	.0520565	6.10	0.000	.2155196	.4195774
between2and5	.2931289	.0309879	9.46	0.000	.2323936	.3538641
between6and14	.285286	.022403	12.73	0.000	.2413769	.329195
youngmom	.4127995	.0411032	10.04	0.000	.3322388	.4933602
youngdad	.3891041	.0470609	8.27	0.000	.2968665	.4813417
momwork	-.7357582	.0399262	-18.43	0.000	-.8140121	-.6575044
dadwork	-.4278121	.0474264	-9.02	0.000	-.5207662	-.334858
momprimedu	-.1213621	.0594212	-2.04	0.041	-.2378255	-.0048988
dadprimedu	-.4372016	.1600859	-2.73	0.006	-.7509643	-.123439
momsecedu	-.4227786	.0384969	-10.98	0.000	-.4982311	-.347326
dadsecedu	-.5364325	.0365246	-14.69	0.000	-.6080195	-.4648456
educationalgap	.0472268	.0206768	2.28	0.022	.006701	.0877526
wagegap	.1500637	.0200097	7.50	0.000	.1108454	.1892821
dpto	-.0424429	.0029867	-14.21	0.000	-.0482968	-.036589
_cons	-.1151904	.1844441	-0.62	0.532	-.4766943	.2463135

Table 1.11 Goodness of fit of the model, including or not variable *dpto*

Measures of Fit for probit of childpov

	Current	Saved	Difference
Model:	probit	probit	
N:	9666	9666	0
Log-Lik Intercept Only	-5197.884	-5197.884	0.000
Log-Lik Full Model	-3700.115	-3813.029	112.914
D	7400.230(9649)	7626.059(9650)	225.828(1)
LR	2995.539(16)	2769.710(15)	225.828(1)
Prob > LR	0.000	0.000	0.000
McFadden's R2	0.288	0.266	0.022
McFadden's Adj R2	0.285	0.263	0.022
ML (Cox-Snell) R2	0.266	0.249	0.017
Cragg-Uhler(Nagelkerke) R2	0.404	0.378	0.026
McKelvey & Zavoina's R2	0.465	0.434	0.031
Efron's R2	0.308	0.288	0.020
Variance of y*	1.868	1.767	0.101
Variance of error	1.000	1.000	0.000
Count R2	0.830	0.825	0.005
Adj Count R2	0.256	0.234	0.022
AIC	0.769	0.792	-0.023
AIC*n	7434.230	7658.059	-223.828
BIC	-81142.562	-80925.910	-216.652
BIC'	-2848.717	-2632.065	-216.652
BIC used by Stata	7556.229	7772.881	-216.652
AIC used by Stata	7434.230	7658.059	-223.828

Difference of 216.652 in BIC' provides very strong support for current model.

Note: p-value for difference in LR is only valid if models are nested.

Note: Saved probit as the model that includes the variable dpto, current probit as the one that left the variable out.

Table 1.12 Heteroscedasticity analysis.

Wald tests

```
. test sizehat, constant

 ( 1)  [childpov]sizehat = 0

           chi2(  1) =    0.44
         Prob > chi2 =    0.5068

. test hheadsexhat, constant

 ( 1)  [childpov]hheadsexhat = 0

           chi2(  1) =    0.34
         Prob > chi2 =    0.5615

. test lessthan2hat, constant

 ( 1)  [childpov]lessthan2hat = 0

           chi2(  1) =    2.38
         Prob > chi2 =    0.1225
```

```
. test betweenw2and5hat,constant

 ( 1)  [childpov]betweenw2and5hat = 0

           chi2(  1) =    3.59
         Prob > chi2 =    0.0580

. test between6and14hat,constant

 ( 1)  [childpov]between6and14hat = 0

           chi2(  1) =    0.86
         Prob > chi2 =    0.3538

. test youngmomhat,constant

 ( 1)  [childpov]youngmomhat = 0

           chi2(  1) =    0.84
         Prob > chi2 =    0.3585

. test youngdadhat, constant

 ( 1)  [childpov]youngdadhat = 0

           chi2(  1) =    2.49
         Prob > chi2 =    0.1144
```

```
. test momworkhat

 ( 1)  [childpov]momworkhat = 0

           chi2(  1) =    9.03
         Prob > chi2 =    0.0027

. test dadworkhat

 ( 1)  [childpov]dadworkhat = 0

           chi2(  1) =    0.67
         Prob > chi2 =    0.4139

. test momprimeduhat

 ( 1)  [childpov]momprimeduhat = 0

           chi2(  1) =    0.01
         Prob > chi2 =    0.9218

. test dadprimeduhat, constant

 ( 1)  [childpov]dadprimeduhat = 0

           chi2(  1) =    1.37
         Prob > chi2 =    0.2424
```

```
. test momseceduhat, constant

 ( 1)  [childpov]momseceduhat = 0

           chi2(  1) =    0.06
         Prob > chi2 =    0.8117

. test dadseceduhat, constant

 ( 1)  [childpov]dadseceduhat = 0

           chi2(  1) =    2.08
         Prob > chi2 =    0.1497

. test educationalgaphat, test

 ( 1)  [childpov]educationalgaphat = 0

           chi2(  1) =    7.03
         Prob > chi2 =    0.0080

. test wagegaphat, constant

 ( 1)  [childpov]wagegaphat = 0

           chi2(  1) =    2.05
         Prob > chi2 =    0.1522
```

Hetprob test

```
Heteroskedastic probit model                      Number of obs     =       9666
                                                  Zero outcomes     =       7455
                                                  Nonzero outcomes  =       2211

                                                  Wald chi2(15)     =     908.65
Log pseudolikelihood =  -3808.44                  Prob > chi2       =     0.0000
```

childpov	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
childpov						
size	.0449114	.0142325	3.16	0.002	.0170162	.0728067
hheadsex	-.1376528	.0348532	-3.95	0.000	-.2059638	-.0693417
lessthan2	.3152766	.0480436	6.56	0.000	.2211128	.4094404
between2and5	.3131519	.0314947	9.94	0.000	.2514234	.3748804
between6and14	.2606219	.0222451	11.72	0.000	.2170224	.3042214
youngmom	.3650978	.0420262	8.69	0.000	.2827279	.4474676
youngdad	.2994195	.0439304	6.82	0.000	.2133174	.3855216
momwork	-.5975786	.0733235	-8.15	0.000	-.74129	-.4538672
dadwork	-.4342116	.0441302	-9.84	0.000	-.5207052	-.3477179
momprimedu	-.1051739	.0572876	-1.84	0.066	-.2174556	.0071078
dadprimedu	-.3326807	.135841	-2.45	0.014	-.5989242	-.0664372
momsecedu	-.3554454	.0376022	-9.45	0.000	-.4291444	-.2817464
dadsecedu	-.4691285	.0370753	-12.65	0.000	-.5417949	-.3964622
educationalgap	.0885387	.0314848	2.81	0.005	.0268297	.1502477
wagegap	.1235388	.0187657	6.58	0.000	.0867587	.1603189
_cons	-.3729561	.15764	-2.37	0.018	-.6819248	-.0639873
lnsigma2						
between2and5	-.0821922	.0416499	-1.97	0.048	-.1638245	-.00056
momwork	-.0789908	.0567907	-1.39	0.164	-.1902985	.0323169
educationalgap	-.08678	.0402185	-2.16	0.031	-.1656068	-.0079533

```
Wald test of lnsigma2=0:             chi2(3) =      8.41   Prob > chi2 = 0.0382
```

Appendix C: Model of Multidimensional Poverty

Table 2.1 Correlation of the Variables included in Model of Multidimensional Poverty

	child_~n	size	hheadsex	lessth~2	betwee~5	betwe~14	youngmom	youngdad	momwork	dadwork	mompri~c	dadpri~c	momsec~u	dadsec~u	educat~p	wagegap
child_depr~n	1.0000															
size	0.2037	1.0000														
hheadsex	-0.0450	-0.0122	1.0000													
lessthan2	0.0953	0.3079	-0.0040	1.0000												
between2and5	0.1396	0.3252	-0.0221	0.0478	1.0000											
between6a~14	0.0966	0.5061	-0.0002	0.0644	0.0224	1.0000										
youngmom	0.0529	-0.2619	-0.0007	-0.0859	0.0644	-0.1225	1.0000									
youngdad	0.0900	-0.1906	-0.0039	-0.0753	0.0428	-0.1291	0.4917	1.0000								
momwork	-0.1192	-0.1367	-0.0465	-0.1275	-0.0945	-0.0934	-0.1205	-0.0741	1.0000							
dadwork	-0.0137	0.0681	0.0112	0.1297	0.0170	-0.0193	-0.0560	-0.0724	-0.0339	1.0000						
momprimeduc	-0.0200	0.0011	-0.0039	-0.0169	-0.0078	-0.0008	0.0006	0.0003	0.0052	-0.0037	1.0000					
dadprimeduc	-0.0955	-0.0707	0.0589	-0.0060	-0.0601	-0.0023	-0.0302	0.0016	0.0029	-0.0394	0.0001	1.0000				
momsecedu	-0.1660	-0.3573	-0.0340	-0.1319	-0.0734	-0.1692	0.0366	0.0548	0.2424	-0.0983	-0.0132	0.0865	1.0000			
dadsecedu	-0.1740	-0.3693	-0.0403	-0.1674	-0.0811	-0.1816	0.0533	0.0707	0.1895	-0.1042	-0.0028	0.1278	0.3692	1.0000		
educationa~p	0.0382	-0.0135	0.0034	0.0598	0.0004	0.0113	0.0298	0.0178	-0.0067	0.0067	-0.0169	-0.0149	0.0060	0.0147	1.0000	
wagegap	0.0221	-0.0641	-0.0563	-0.0599	-0.0497	-0.0646	-0.0929	-0.0578	0.2300	0.0696	0.0034	-0.0285	0.0776	0.0379	-0.0179	1.0000

Table 2.2 Selection of Model of Multidimensional Poverty

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
model1	9666	966.5161	1465.929	16	-2899.858	-2785.036
model2	9666	-1932.663	-1537.021	16	3106.041	3220.863
model3	9666	-1932.663	-1541.809	16	3115.619	3230.441

Note: N=Obs used in calculating BIC; see **[R] BIC note**

Note: Model1 represent the Linear Probability Model, model2 represents Logit Model and model3 represent Probit.

Table 2.3 Wald Test for the Logit model variables.

```
( 1)  [child_depravation]size = 0
( 2)  [child_depravation]hheadsex = 0
( 3)  [child_depravation]lessthan2 = 0
( 4)  [child_depravation]between2and5 = 0
( 5)  [child_depravation]between6and14 = 0
( 6)  [child_depravation]youngmom = 0
( 7)  [child_depravation]youngdad = 0
( 8)  [child_depravation]momwork = 0
( 9)  [child_depravation]dadwork = 0
(10)  [child_depravation]momprimeduc = 0
(11)  [child_depravation]dadprimeduc = 0
(12)  [child_depravation]momsecedu = 0
(13)  [child_depravation]dadsecedu = 0
(14)  [child_depravation]educationalgap = 0
(15)  [child_depravation]wagegap = 0

       chi2( 15) =  610.80
     Prob > chi2 =    0.0000
```

Robustness Check: Probit model.

```
Probit regression                               Number of obs   =       9666
                                                Wald chi2(15)   =     575.22
                                                Prob > chi2     =     0.0000
Log pseudolikelihood = -1541.8095               Pseudo R2       =     0.2022
```

child_depravation	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
size	.0993092	.0151462	6.56	0.000	.0696233	.1289951
hheadsex	-.2213869	.0535043	-4.14	0.000	-.3262535	-.1165204
lessthan2	.2838441	.1004281	2.83	0.005	.0870085	.4806796
between2and5	.17733	.0425857	4.16	0.000	.0938635	.2607965
between6and14	.1202795	.0605266	1.99	0.047	.0016495	.2389095
youngmom	.1589486	.0653644	2.43	0.015	.0308367	.2870605
youngdad	.5253258	.0687739	7.64	0.000	.3905314	.6601201
momwork	-.4046914	.0624295	-6.48	0.000	-.5270509	-.2823319
dadwork	-.2246736	.0718396	-3.13	0.002	-.3654767	-.0838705
momprimeduc	-.2922374	.1391403	-2.10	0.036	-.5649474	-.0195273
dadprimeduc	-.5478385	.1547295	-3.54	0.000	-.8511027	-.2445742
momsecedu	-.3445828	.0532934	-6.47	0.000	-.4490359	-.2401297
dadsecedu	-.4160119	.0538963	-7.72	0.000	-.5216466	-.3103771
educationalgap	.0855048	.025872	3.30	0.001	.0347967	.1362129
wagegap	.1069589	.0200831	5.33	0.000	.0675969	.146321
_cons	-1.51053	.1885782	-8.01	0.000	-1.880137	-1.140924

```
Marginal effects after probit
      y  = Pr(child_depravation) (predict)
         =  .02585757
```

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
size	.0059704	.00097	6.17	0.000	.004074	.007867	5.06621
hheadsex*	-.0149263	.00402	-3.71	0.000	-.022802	-.007051	.757811
lessth~2	.0170646	.00608	2.81	0.005	.005144	.028985	.081575
betwee~5	.010661	.00258	4.13	0.000	.005602	.01572	.347921
betwe~14*	.007244	.00362	2.00	0.045	.000154	.014334	.499586
youngmom*	.010112	.00443	2.28	0.023	.00142	.018804	.324953
youngdad*	.0435576	.00744	5.85	0.000	.028969	.058146	.197186
momwork*	-.0228527	.00311	-7.35	0.000	-.028949	-.016756	.396338
dadwork	-.0135073	.00441	-3.06	0.002	-.022152	-.004863	-.890027
mompri~c	-.0175692	.0084	-2.09	0.036	-.034031	-.001107	-.023691
dadpri~c*	-.0548223	.02305	-2.38	0.017	-.100008	-.009636	.99131
momsec~u*	-.0244064	.00444	-5.50	0.000	-.033103	-.01571	.731119
dadsec~u*	-.0287151	.0041	-7.01	0.000	-.036743	-.020687	.650735
educat~p	.0051405	.00159	3.24	0.001	.002032	.008249	-.143516
wagegap	.0064303	.00122	5.27	0.000	.004039	.008822	-.364617

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tables 2.4 to 2.6 Statistical significance of Probit Model

Probit model for child_depravation

	True		
Classified	D	~D	Total
+	34	20	54
-	454	9158	9612
Total	488	9178	9666

Classified + if predicted Pr(D) >= .5
True D defined as child_depravation != 0

Sensitivity	Pr(+| D)	6.97%
Specificity	Pr(-|~D)	99.78%
Positive predictive value	Pr(D| +)	62.96%
Negative predictive value	Pr(~D| -)	95.28%
False + rate for true ~D	Pr(+|~D)	0.22%
False - rate for true D	Pr(-| D)	93.03%
False + rate for classified +	Pr(~D| +)	37.04%
False - rate for classified -	Pr(D| -)	4.72%
Correctly classified		95.10%

Probit model for child_depravation, goodness-of-fit test

number of observations =	9666
number of covariate patterns =	1895
Pearson chi2(1879) =	9662.33
Prob > chi2 =	0.0000

```
Iteration 0:   log likelihood = -4507.7904
Iteration 1:   log likelihood = -3997.3398
Iteration 2:   log likelihood = -3992.9468
Iteration 3:   log likelihood = -3992.9461
Iteration 4:   log likelihood = -3992.9461
```

Probit regression — Number of obs = 9666; LR chi2(2) = 1029.69; Prob > chi2 = 0.0000; Pseudo R2 = 0.1142

Log likelihood = -3992.9461

childdep3	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	1.128442	.0856467	13.18	0.000	.9605773	1.296306
_hatsq	.0791905	.0483373	1.64	0.101	-.0155488	.1739298
_cons	.033355	.0391691	0.85	0.394	-.0434151	.1101251

Table 2.7 Outputs with the control variable "*dpto*"

```
Logistic regression                               Number of obs   =       9666
                                                  Wald chi2(16)   =     669.97
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -1535.0835                 Pseudo R2       =     0.2057
```

child_depravation	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
size	.1821623	.0299945	6.07	0.000	.1233741	.2409505
hheadsex	-.4422839	.1123285	-3.94	0.000	-.6624438	-.222124
lessthan2	.3968936	.2059422	1.93	0.054	-.0067457	.8005329
between2and5	.4116479	.0860658	4.78	0.000	.242962	.5803339
between6and14	.2926044	.1289223	2.27	0.023	.0399213	.5452874
youngdad	1.028173	.1451997	7.08	0.000	.7435869	1.312759
youngmom	.3084393	.1375994	2.24	0.025	.0387493	.5781292
momworks	-.8786718	.1275315	-6.89	0.000	-1.128629	-.6287147
dadworks	-.4309044	.1597311	-2.70	0.007	-.7439717	-.1178372
momprimedu	-.5917873	.2749175	-2.15	0.031	-1.130616	-.0529589
dadprimeduc	-1.055529	.2750634	-3.84	0.000	-1.594644	-.5164148
momsecedu	-.7303929	.1099605	-6.64	0.000	-.9459115	-.5148744
dadsecedu	-.9280065	.1210934	-7.66	0.000	-1.165345	-.6906679
educationalgap	.1611414	.0503476	3.20	0.001	.0624618	.259821
wagegap	.2723097	.0368612	7.39	0.000	.200063	.3445564
dpto	.021932	.0083727	2.62	0.009	.0055217	.0383422
_cons	-2.713425	.3505253	-7.74	0.000	-3.400442	-2.026408