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Dorsoduro 3246
30123 Venezia

Analyzing the gender pay gap in Paraguay

Supervisor
Ch. Prof. Danilo Cavapozzi

Graduand
Luz Marcela Pineda Mariuci
Matriculation Number 864859

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Introduction

This thesis aims to analyze the gender pay gap in the Paraguayan labor market. Paraguay is a country with a low level of female labor force participation, which has been increasing in the last twenty years but still remains far behind men's participation rate. For example, in 2015 men's participation rate among the population aged 25-65 reached 93.5% while female LFP reached only 66.7%. In this context, it becomes relevant to look at the wage differential between men and women. Holding everything else constant, if women are offered lower wages than men, they might be more likely to stay out of the labor market and dedicate to household activities such as home production and care of children and co-residing older adults.

If women expect to earn lower wages than men, they might have less incentives to invest in human capital or choose time demanding occupations. What's more, family responsibilities also affect women's work life in the form of a shorter and discontinuous permanence in the labor market. Therefore, if the relative return offered by the market is lower than that of housework activities, women's rational decision would be to prioritize the family needs at the expense of their working careers.

This thesis will analyze the gender pay gap in order to determine whether it could be a rational explanation for the persistent gender gap in labor force participation in Paraguay. To do this, multivariate OLS and quantile regressions will be estimated allowing controls for an extensive set of socioeconomic, demographic and job-related characteristics. The focus will be on the gender pay gap at the average as well as its variation across the wage distribution. In addition, the analysis will verify the existence of glass ceiling and sticky floors.

In a first stage, OLS and quantile regressions are run by pooling men and women together and restricting the explanatory variables to have a gender-invariant role in wage determination. In a second stage, this assumption will be removed and the wage equations will be estimated separately by gender in order to allow the individual and job characteristics to be rewarded differently across genders.

In both cases, all estimations are carried out both in the overall sample as well as in subgroups defined according to socioeconomic variables of interest such as age, education, partner and number of children in order to assess to what extent the magnitude of the gender pay gap varies with individual characteristics.

The thesis is organized as follows. Chapter I states the motivations for the analysis of the gender pay gap and provides a review of the gender wage gap literature. Chapter II presents the dataset as well as the descriptive statistics of the control variables to be included in the wage regressions and the gender wage gap. Chapter III goes into the econometric models used for the estimation of the gender pay gap and provides the results of OLS and quantile regressions. Finally, the last section includes concluding remarks on the estimation results and their possible economic implications.

Chapter I: Motivations and Literature Review

1.1 Gender gap in Labor Force Participation in Paraguay

Paraguay is a South-American country with a historical low rate of female Labor Force Participation (LFP). The labor force is composed of those individuals who are currently working or actively searching for a job. To obtain LFP rates, the total labor force is divided by the total working-age population. The latter can adopt various definitions according to the age restriction considered (10+, 15+, 15-64, 25-64, etc.).

In a study focused on Paraguayan women, Serafini (2005) analyzes census data and finds that female LFP remained consistently under 26% until 1992. In accordance to the regional trend observed for Latin American countries (see for example Busso and Fonseca, 2015), Paraguayan women increased significantly their participation in the labor market during the 90s and the beginnings of the 21st century.

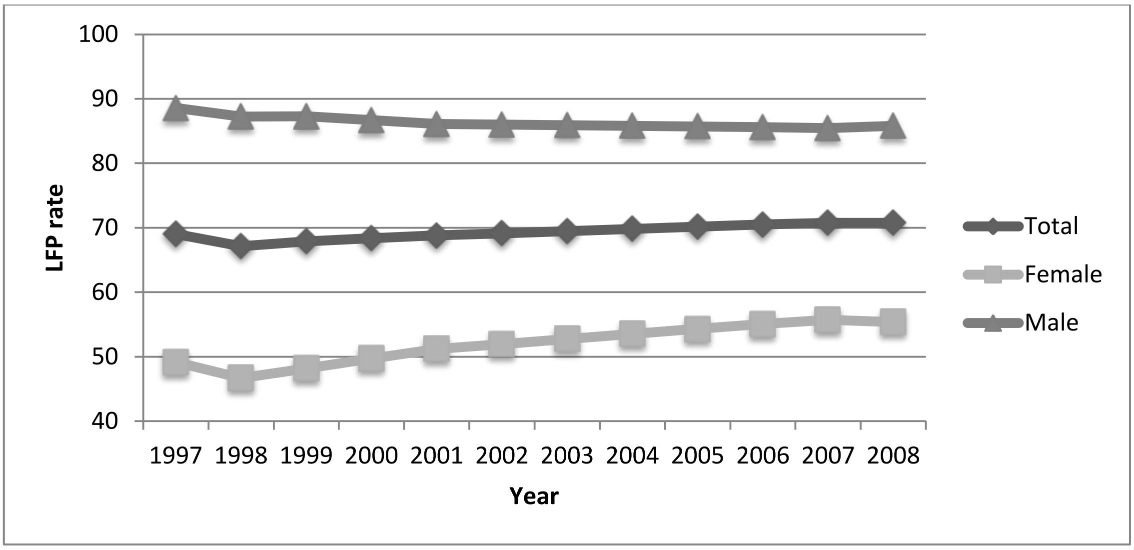

Figure 1. Labor Force Participation in Paraguay, age 15+, 1997-2008. Adapted from http://databank.worldbank.org/data/reports.aspx?source=2&country=PRY#. The World Bank, 2017.

Figure 1 shows LFP rates (retrieved from the World Bank Database) for the period 1997-2008 for Paraguayans aged 15 or older. It is observed that female LFP in Paraguay overall went up by about 6% during this period. However, male LFP remained at a much higher level in spite of showing a decreasing trend (it went down by about 3%). Male LFP reached 85.8% in 2008 while female LFP reached only 55.4%. Nevertheless, it is important to remark that the gender gap in LFP showed an important decrease during this period; it went down from 39.4% in 1997 to 30.4% in 2008.

Several studies concerned with analyzing the conditions of the Paraguayan labor market with a gender perspective have stressed the importance of socioeconomic variables such as age, education, marital status and number of children as possible explanations for the gender gap in LFP. What's more, the area of residence also plays a crucial role when making sense of women's decision to enter the labor force.

Cortés et al. (2003) look at the role of education and age in explaining the gender gap in LFP. Education is a measure of the human capital accumulated by individuals. It has been showed in the economic literature that the participation in the labor market is positively related to bigger investments in education and training. To determine whether this is true in the case of Paraguayan women, the authors use data from the 1997/1998 household survey to compare the level of education between women that are part of the economically active population and women that declare to be out of the labor market. Their results show that women that participate in the labor market are more educated, namely, 12.2% of women that are part of this group have attended college compared to only 2.1% of inactive women. Similarly, 33.4% of active women have a secondary education compared to only 23.8% of women outside the labor force.

Age is also an important factor to consider given that women in their reproductive years might interrupt their work life in order to dedicate to childrearing activities. Cortés et al. (2003) look at LFP rates across different age groups and find that Paraguayan women in their reproductive years present the highest rates of participation. According to household survey results from 1997/1998 and 2000/2001, women in age groups 25-34 and 35-44 residing in urban areas are the ones who participate the most (LFP rates are 71.8% and 66.2% respectively in 2000/2001). According to the authors, this can be explained by the decreasing fertility rates and improvements in access to education observed in the years previous to the period of analysis.

On the other hand, Serafini (2005) analyzes the role of family responsibilities in determining women's decisions to enter the labor market. More specifically, whether having a partner and/or children is negatively related to the labor market participation of women. When comparing data for 1992 and 2002, she finds that women with a partner increased considerably their participation during this period; LFP of married women increased from 20.6% in 1992 to 36.2% in 2002. Nevertheless, women without a partner still present higher rates of participation, particularly separated and divorced women (58.5% and 72.5% respectively in 2002).

Serafini (2005) also looks at female LFP related to the number of children. Her results show that women with one or two children present the highest rates of participation, even surpassing single women. In 2002, single women's LFP reached 35.7% while women with one or two children reached 42.6% and 50.8% for children under and of school age respectively. The author points out that single women might participate less than those with one or two children due to a longer permanence in the education system (LFP rates are calculated here for individuals aged 15 or older). In contrast, the situation of women with three or more children is quite different since they present the lowest rates of participation. A possible explanation is that the cost of entering the labor market in this last case is much higher if women are to be in charge of both work and family responsibilities.

In this sense, it is crucial to consider the effect of cultural perceptions on women's decision to work given that home production and childcare are still widely regarded as a responsibility of women. Echauri and Serafini (2011) argue that even women that enter the labor market are expected to be in charge of the housework. It is noteworthy that Paraguay doesn't count with a daycare system, which could lighten women's workload. Therefore, the wage offered by the market is determinant in their decision to work outside the house.

Moreover, the fact that women are still held responsible for household activities also influences their choice of occupation. Heikel and Piras (2014) point out that even though women have increased their participation in the last two decades, their inclusion into the labor market is still reduced to lower paid positions and occupations than men. This is because women tend to choose occupations that offer more time flexibility in order to be able to balance their work activities with their responsibilities at home.

Borda et al. (2011) study LFP in Paraguay for the period 1997-2008 and focus on the area of residence as a meaningful aspect to consider when analyzing the gender gap in

LFP. Cultural perceptions might change with the area of residence. For instance, social norms in rural areas might be more conservative and see family responsibilities and housework as the main tasks for women.

Their findings show that, although women residing in urban areas participate more, rural women had been increasing their participation more quickly. Rural women's LFP went up almost 13% from 1997 to 2008, while urban women LFP increased by about 1.4% during the same period. The authors search for explanations of this large increase by looking at education. They find, however, that rural women with a primary level of education are the ones for which LFP rates rose the most. In light of this result, they conclude that the main reason for the large rise in rural women LFP lies in the economic cycle, i.e. the economic crises that affected the country during this period may have encouraged women to have their own earnings and contribute to the family income.

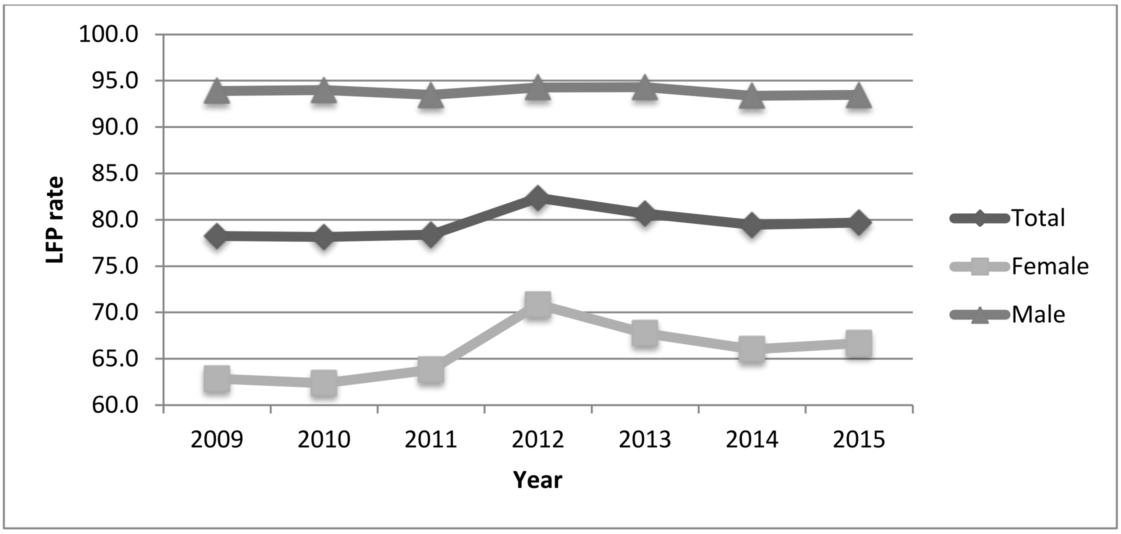

Figure 2. Evolution of Labor Force Participation in Paraguay from 2009 to 2015. Adapted from http://www.dgeec.gov.py/microdatos/index.php. Dirección General de Encuestas, Estadísticas y Censos. Encuesta Permanente de Hogares from 2009-2015.

For the period comprised between 2009 and 2015, LFP rates are estimated using data from the Household Survey (Encuesta Permanente de Hogares) conducted by the National Directorate of Statistics (Dirección General de Estadísticas, Encuestas y Censos - DGEEC). Considering a sample of individuals aged between 25 and 65 years of age, it is possible to discern that female LFP continued to increase until 2012, reaching a peak of 70.8% and then decreased by about 4% in the next three years. On the other hand, men's participation present less sizable changes while still remaining above women's participation rates. Nonetheless, the gender gap in LFP continued to decrease (by 4.3%), although less than in the 1997-2008 period.

In light of the previous findings related to the effects of individual characteristics on LFP, data from the Paraguayan Household Survey is used to calculate LFP rates on subsamples divided by age, education, partner and number of children. The goal is to assess how these socioeconomic variables affect women and men separately.

To take measure of the relation between LFP and age, the sample is divided in 3 age groups: 25-35, 36-49 and 50-65. As seen in Table 1, the younger age groups (25-35 and 36-49) present the highest rates of participation for both women and men with no large differences among them for most of the period.

Table 1. Labor Force Participation by age groups, 2009-2015.

Age group	**25-35**			**36-49**			**50-65**		
Year	*Female LFP*	*Male LFP*	*Gender Gap*	*Female LFP*	*Male LFP*	*Gender Gap*	*Female LFP*	*Male LFP*	*Gender Gap*
2009	66.7	95.6	28.9	65.7	96.6	30.9	54.7	88.3	33.6
2010	66.7	96.8	30.1	66.5	96.4	29.9	51.3	87.8	36.5
2011	67.9	96.3	28.4	67.9	96.5	28.6	53.9	86.9	33.0
2012	72.7	96.1	23.4	75.5	96.7	21.2	63.2	89.2	26.0
2013	72.5	96.7	24.2	72.5	97.2	24.7	55.7	87.9	32.1
2014	69.6	95.3	25.7	71.5	96.9	25.4	55.9	87.4	31.5
2015	68.7	95.0	26.3	72.5	96.1	23.6	57.8	88.8	31.0

Adapted from http://www.dgeec.gov.py/microdatos/index.php. Dirección General de Encuestas, Estadísticas y Censos. Encuesta Permanente de Hogares from 2009-2015.

In contrast, a drop is observed in the participation of the oldest group. Women between the ages of 50 and 65 participate between 10% and 15% less than their younger peers. In the case of men, LFP rates also went down by about 8%. A possible explanation for this could be related to the retirement scheme, which is possible from the age of 55 provided that the person has 30 years of service. However, it is noteworthy that in the public sector retirement is only mandatory when reaching 65 years of age. Moreover, the social security system has a very low coverage in Paraguay.

According to the Statistical Report on Social Security issued by the Ministry of Labor (Ministerio de Trabajo, Empleo y Seguridad Social - MTESS) in 2015, only 22% of the employed population was contributing to the Pension system in 2014.

In the particular case of women, another possible reason for the drop in their participation rate after reaching 50 years of age can be related to family responsibilities. In other words, women in this age group might decide to stop working to dedicate to household activities which might include, for example, taking care of their grandchildren.

Male LFP rates are found to be higher than female's for all age groups. The gender gap in LFP oscillates between 20% and 30% during the whole period and it is larger for the group of individuals between 50 and 65 years of age.

To measure the variation of LFP with respect to education, three groups are defined:

- Low education: this group comprises illiterates as well as those who attended Primary and/or Middle School.
- Middle education : this group includes those who finished High School and those who received a Technical Training after finishing High School (for example, police officers, school teachers, etc.).
- High education: this group comprises those who attended college.

Table 2. Labor Force Participation by education groups, 2009-2015.

Education groups	**Low Education**			**Middle Education**			**High Education**		
Year	*Female LFP*	*Male LFP*	*Gender Gap*	*Female LFP*	*Male LFP*	*Gender Gap*	*Female LFP*	*Male LFP*	*Gender Gap*
2009	56.8	93.8	37.0	68.0	95.0	27.0	82.6	94.7	12.1
2010	55.7	94.3	38.6	67.3	94.4	27.1	84.9	95.9	10.9
2011	56.8	93.1	36.3	67.5	94.7	27.2	86.8	94.2	7.3
2012	65.7	93.8	28.1	73.6	96.5	22.9	86.2	93.4	7.2
2013	59.9	94.0	34.1	71.1	95.4	24.3	85.4	94.6	9.2
2014	59.2	93.0	33.8	66.5	94.5	27.9	86.9	93.7	6.8
2015	59.3	93.3	34.0	68.9	94.7	25.8	85.1	94.8	9.7

Adapted from http://www.dgeec.gov.py/microdatos/index.php. Dirección General de Encuestas, Estadísticas y Censos. Encuesta Permanente de Hogares from 2009-2015.

As seen in Table 2, in the case of women there is a positive relation between the level of education and the participation in the labor market, namely, women with a college education are more likely to enter the labor market than women with only a high school diploma and the latter are, in turn, more likely to participate than those who only attended Primary or Middle School.

In the case of men, participation rates are higher for all education groups with respect to women. However, men do not present large differences in LFP among education groups. The gender gap in LFP is found to be larger for the low education group (34% in 2015). On the contrary, the high education group presents a noticeably smaller gender gap (9.7% in 2015).

To assess the relation of LFP of men and women with the presence of a co-habiting partner, the sample is divided in two groups according to the reported marital status. It is observed that women are more likely to enter the labor force when they do not have a co-habiting partner (see Table 3).

The opposite is found in the case of men, who are more likely to participate in the labor market when they have a partner. As usual, men's participation rates are always higher than women's for both groups considered.

In accordance with the trends described before, the gender gap in LFP is considerably larger for the group of individuals with a co-habiting partner, 32.4% in 2015 compared to 13.5% for the group without a partner in the same year.

Table 3. Labor Force Participation by partner, 2009-2015.

Partner Groups	**With a partner**			**No partner**		
Year	*Female LFP*	*Male LFP*	*Gender Gap*	*Female LFP*	*Male LFP*	*Gender Gap*
2009	60.1	95.5	35.4	70.2	89.3	19.1
2010	58.4	95.5	37.1	73.4	89.5	16.2
2011	59.8	95.0	35.2	73.6	89.2	15.6
2012	68.3	96.2	27.9	77.6	88.9	11.2
2013	64.0	95.6	31.6	76.7	90.8	14.2
2014	61.7	95.0	33.3	76.2	89.3	13.1
2015	63.3	95.7	32.4	74.2	87.7	13.5

Adapted from http://www.dgeec.gov.py/microdatos/index.php. Dirección General de Encuestas, Estadísticas y Censos. Encuesta Permanente de Hogares from 2009-2015.

The last characteristic to be examined is the presence of children. The sample is divided in three groups: individuals with no children, with one child and with two or more children. As seen in Table 4, female LFP does not present remarkable differences between women without children and women with one children. Nevertheless, it is observed that women with two or more children are less likely to enter the labor force.

On the other hand, the number of children seems to be positively related to male LFP. Men with one child participate more than men without children. Similarly, men with two or more children present higher rates of participation than men with only one child.

As a consequence, the gender gap in LFP is negatively related to the number of children. It is larger for individuals with two or more children (31.6% in 2015) and lower for individuals without children (22.2% in 2015).

Table 4. Labor Force Participation by number of children, 2009-2015.

Children groups	**No Children**			**One Child**			**Two or more Children**		
Year	*Female LFP*	*Male LFP*	*Gender Gap*	*Female LFP*	*Male LFP*	*Gender Gap*	*Female LFP*	*Male LFP*	*Gender Gap*
2009	65.8	90.5	24.7	66.7	95.8	29.1	59.9	94.8	34.9
2010	64.8	90.6	25.8	64.4	94.2	29.8	60.3	95.7	35.4
2011	65.1	89.2	24.0	65.3	94.1	28.8	62.5	95.9	33.4
2012	73.0	91.0	18.0	74.8	94.7	19.9	67.7	96.0	28.3
2013	69.0	90.9	21.9	68.8	95.3	26.5	66.4	96.0	29.6
2014	68.8	89.7	20.9	67.8	94.1	26.3	63.5	95.7	32.3
2015	67.5	89.7	22.2	69.5	94.4	24.9	64.3	95.9	31.6

Adapted from http://www.dgeec.gov.py/microdatos/index.php. Dirección General de Encuestas, Estadísticas y Censos. Encuesta Permanente de Hogares from 2009-2015.

In summary, female LFP is found to be always lower than male LFP regardless of the socioeconomic variable considered. Age and education have similar effects across genders. Specifically, younger individuals with a higher level of education have higher rates of participation. On the contrary, the number of children and the presence of a co-habiting partner have opposites effects by gender. That is, having a partner and children has a positive effect on male LFP and a negative effect on female LFP.

1.2 Gender pay gap as an explanation of the gender gap in LFP

The study of the gender wage gap in Paraguay becomes relevant considering the evidence presented of a significant gender gap in LFP which is persistent over time. Women's decision to enter the labor market is deeply related to the prospect of earnings they will receive. Holding everything else constant, if women are offered lower wages than men, they might decide to dedicate to household activities such as, home production and care of children and co-residing older adults. This is a rational choice which can be explained by economic models proposed in the literature.

According to the standard labor supply model derived from Hicks (1946) and described by Pencavel (1986), each individual is endowed with a fixed amount of time which she can decide to sell to the market or use for leisure and other non-labor related activities. The individual receives a wage for each hour worked in the market which can later be used to buy consumption goods. Each individual is supposed to maximize her utility given preferences on consumption of goods and hours of leisure, subject to a budget constraint that equalizes the total value of consumption to the total income of the individual (wages received plus additional non-labor related income). By solving this optimization problem, we can find the individual's reservation wage, that is, the minimum wage at which the individual will be willing to work. If the wage offered by the market is higher than the individual's reservation wage, the rational decision is to participate in the labor market. On the other hand, if the wage offered is lower than the individual's reservation wage, the individual is better off by staying out of the labor market and dedicating her hours to household activities or leisure.

In an empirical study of the determinants of female LFP in Latin America, Busso and Fonseca (2015) remark that decisions on whether to enter the labor market and the amount of time to dedicate to labor rely upon the comparison between the relative returns earned in the labor market and the returns to household activities and/or leisure. Therefore, if women are met with a higher relative return from home production due to for example, the presence of children or older adults who depend on them for care giving, they might be more likely to opt out of the labor market.

It is important to consider that decisions of labor supply can be made not only individually but also in the context of a household unit. This approach is particularly pertinent when analyzing labor supply of women and its relation to the gender wage gap.

A model of time allocation was proposed by Becker in 1965, which incorporates the cost of non-working time into the utility maximization problem of households. In this model, each household has a production function where goods and units of time are combined to produce commodities. The level of welfare is then maximized given preferences on these commodities (or activities) subject to a budget constraint that equalizes expenditure and available resources.

One application of the time allocation model is related to the division of labor among the members of a household. Becker (1965, p. 512) indicates that "instead of simply allocating time efficiently among commodities, multi-person households also allocate the time of different members". Therefore, to achieve efficiency in time allocation, members of a household that are more efficient at market activities spend more time in labor than in other activities. In other words, members who earn higher returns from their time spent in the labor market are expected to dedicate more time to work than the others members, even when assuming all members have identical attitudes towards leisure or home production. In this context, if men receive higher returns from labor (i.e. higher wages than women), they might be more likely to enter the labor market.

Killingsworth and Heckman (1986) used a simplified version of the time allocation model, with a two-person family composed of a husband and a wife and a utility function that depends on a single commodity, to formally show that, provided that the husband has a higher wage than his wife and is "less productive" in housework activities, the labor supply of the wife will be lower than that of his husband but with a higher elasticity. We can conclude from this finding that the labor supply of women is more sensible to an increase in wages. This is coherent with the idea that the existence of a gender wage gap can help explain why women participate less than men in the labor market.

Having discussed how the gender pay gap can be a way to rationalize the gender gap in LFP, it is time to introduce an overview of the main findings in the gender wage gap literature. The fact that women receive lower wages than men has long been a topic of interest for economists and there is a quite an extensive literature that intends to provide an explanation from a theoretical point of view as well as empirical research documenting its extent and evolution over time.

One of the first theoretical models proposed to explain the existence of a gender wage gap in the labor market is the Human Capital Model. Decisions about how much to invest in education as well as the quality and type of education to invest in are usually made before starting the work life and have been showed to be greatly influenced by the future prospect of earnings. At the same time, further investment after starting the work life such as on-the-job training only makes sense for those who expect to be working for a long time and without interruptions.

Mincer and Polachek (1974) developed the human capital earnings function in an effort to relate the earning power with the human capital stock accumulated by individuals. They focus on the fact that women tend to have a very different work trajectory than men, with more interruptions due to family responsibilities. Using data for the United States from the 1967 National Longitudinal Survey of Work Experience (NLS), they analyze the relation between women's earnings and their family and work histories. They estimate earnings functions (i.e. regressions with log wages as the dependent variable) controlling for personal characteristics such as years of education, work experience, periods of work interruption, marital status and number of children. They find that women invest less in human capital, particularly if they anticipate interruptions in the work life due to marriage and presence of children.

According to the Human Capital Model, if lifetime work expectations become more similar for men and women, the latter will have more incentives to increase their investment in human capital which would, in turn, result into a higher female LFP and higher wages.

Another theoretical approach to rationalize the existence of a gender pay gap is based on labor market discrimination, that is, members of a minority group are treated in a less favorable manner despite having the same production capabilities as the rest of the population. Two models are of special interest: taste-based discrimination and statistical discrimination.

The model of taste-based discrimination proposed by Becker in 1957 relies on the assumption that employers have a "taste" for discrimination preferring either not to hire members of the minority group or offering them lower wages. The "taste" for discrimination not only applies to employers, employees may also dislike to work alongside members of the minority group and might require higher wages in order to do so. Finally, consumers can also discriminate against the minority group by refusing to buy their products unless they are offered at a lower price.

The second model, proposed by Phelps (1972) and Arrow (1973), assumes that employers have imperfect information about their employees (their skills or their behavior) and make hiring decisions based on a observable characteristic such as gender or race. This can be influenced by prior information they have on a certain group (for example, stereotypes) or by different levels of accuracy in the information they have for different groups.

More recent theoretical research include contributions of Psychology and Behavioral Economics in the explanation of why labor outcomes differ by gender. Bertrand (2011) takes account of these new developments and groups them into two main currents. The first one sees the gender wage gap as a result of gender differences in psychological attributes such as risk aversion, social preferences and attitudes towards negotiation. Laboratory results show that women tend to be more risk averse, have less of a taste for negotiation and competition, and are more socially oriented.

The second current considers gender identity as the source of the gender wage gap. There exist social norms that dictate the appropriate behavior for women and have a large influence in their economic decisions, namely, decisions regarding labor force participation and choice of occupation. As long as the expected behavior of women is related to household and family responsibilities, women will be more likely to consider family as a priority and will adjust their work trajectories in accordance to the family needs. This is related to a lower investment in human capital, a shorter permanence in the labor market and the choice of occupations that offer more time flexibility, all of which ultimately lead to a lower level of wages.

With respect to the empirical research, the classical literature focused mainly on studying the average gender wage gap by means of OLS regressions. The usual analysis consists in regressing the natural logarithm of wages on a gender dummy and set of control variables that include individual and job characteristics such as education, age, experience, marital status, number of children, occupation, industry, etc. In this approach, the estimation of the average gender wage gap is given by the coefficient of the gender dummy multiplied by 100, holding everything else constant. The reason behind the need to control for other characteristics apart from gender is given by the fact that men and women may have different distributions of these characteristics and these gender differences may account for part of the gender wage gap. For example, men and women may have different levels of educational attainment or work experience that affect their level of wages. If this heterogeneity was not taken into consideration, the difference in wages would be attributed entirely to gender, neglecting the role of education and experience.

One important limitation of the traditional approach is that it restricts the coefficients on the control variables to be gender-invariant. In other words, the relation between wages and covariates is assumed to be the same for both men and women. However, this claim is questionable considering that characteristics such as marital status and number of children have been showed in the economic literature to have markedly different effects by gender. For example, Hill (1979) uses data for the United States from the ninth wave of the Panel Study of Income Dynamics to analyze the effect of marriage and children on the earnings of working households heads and wives aged between 18 and 64 years of age. Wage regressions are estimated controlling for age, education, potential experience, work hours, health, marital status, number of children as well measures of work experience and labor force attachment. Her results show that marriage has a positive effect on men's wages and no noticeable effects on women's wages. On the other hand, the number of children is found to have opposite effects by gender, i.e. it affects women's wages negatively and wages of men positively.

Therefore, assuming equal labor market returns to characteristics for men and women may produce biased results. Even when comparing individuals with identical characteristics, differences in wages may arise due to the different returns provided by the market.

To overcome this limitation, OLS regressions of wages on a set of covariates are run separately by gender. In this way, the coefficients on the control variables are allowed to be different for men and women. The results of these separate regressions are used to implement the Blinder-Oaxaca decomposition analysis, which is generally used when researching the determinants of wage inequality. The aim is to decompose the observed average gender wage gap into a part that is due to gender differences in labor market characteristics and a part that is due to differences in the way these characteristics are rewarded by the market.

For example, O'Neill (2003) analyzes the average gender wage gap in the United States for the period 1979-2001 using data from the CPS (Current Population Survey) and the NLSY (National Longitudinal Survey of Youth). The sample comprises full-time and part-time wage and salary workers aged between 20 and 60 years old. Cross-sectional regressions are conducted separately by sex. The log wage is regressed on potential experience, schooling, part-time status and demographic controls. A further specification also controls for occupational characteristics. Blinder-Oaxaca type decompositions are estimated to discern the effect of gender differences in characteristics on the gender wage gap. The results show that very little of the wage gap is explained when controlling only for education. However, when additional controls are added for work experience and occupational characteristics, the unexplained part of the gender wage gap is significantly reduced. In other words, the reasons behind the reduction of the gender wage gap in the United States during this period are related to women's higher levels of education and longer permanence in the labor market. Nevertheless, women are still found to be more likely to work part-time and in different occupations than men due to childcare and home responsibilities.

Inequality in the wage structure has also been considered as a factor explaining the gender wage gap. Blau and Kahn (1996) undertake the analysis of the average gender wage gap in ten industrialized countries including the United States, considering a sample comprised of individuals aged between 18 and 65 years old. The authors adapt the decomposition method developed by Juhn, Murphy and Pierce (which is an extension of the Oaxaca decomposition) in order to be able to determine the extent to which the international gender pay gap is due to gender differences in characteristics and to differences in the wage structure. Log wages are regressed on human capital variables (education, potential experience, union status, industry, occupation), a part-time dummy and interaction terms of work hours and part-time and full-time status. The main finding is that the larger wage gap in the United States compared to other industrialized countries can be explained by the inequality in the overall wage structure. American women are found to fare favorably in terms of human capital, however, the U.S labor market seems to penalize more those working in low-wage sectors and those with lower levels of skills due to the existence of more decentralized wage-setting institutions.

While looking at the average gender wage gap is useful to determine whether women are being paid less than men, the approach is quite restricted given that individuals in different points of the wage distribution may present dissimilar characteristics (for example, different levels of skill, ambition, education, etc). Because of this, concentrating only on the average is not sufficient and there is a need to look at the variation of the gender wage gap across the entire wage distribution. In this way, it is possible to discern whether women exercising highly-paid positions face a gender wage gap, and at the same time, measure how does this wage gap differs from the one faced by women at low-paid positions. The standard approach to analyze the way in which the gender pay gap varies across the wage distribution is to run quantile regressions of wages on a gender dummy and a set of control variables. This allows the coefficients on the gender dummy to vary across different quantiles and gives an estimate of the gender wage gap at different points of the wage distribution.

For example, Machado and Mata (2002) consider the role of heterogeneity of the workforce when analyzing the conditional wage distribution for Portugal during the period 1982-1994. Data used is from Quadros de Pessoal (an administrative source) and the sample considered is comprised of full-time wage earners employed by firms in mainland Portugal. Quantile regressions of wages on covariates such as gender, human capital (education, experience and tenure), firm attributes (size and ownership) and industry indicators are estimated in order to document the impact of covariates in the distribution of wages. Their main finding is that the dependent variables considered present different returns across the wage distribution, which indicates that workers are heterogeneous at different points of the wage distribution. For instance, education is found to be more valued at the top of the wage distribution, particularly college education. With respect to the size and ownership of firms, larger and private firms are found to have a positive relation with wages at the top of the distribution while public firms have a positive relation with wages at the bottom of the distribution.

Two patterns are of special interest when looking at the variation of the gender wage gap across the wage distribution: glass ceilings and sticky floors. When the wage gap is found to be wider at the top of the distribution, we are in presence of glass ceilings. In this case, women face a limit in their market outcomes and are unable to reach the highest paid positions. On the other hand, when the wage gap is found to be wider at the bottom of the distribution, we are in presence of sticky floors. In this case, women at the bottom of the wage distribution receive lower wages than men and are penalized harder for exercising lower paid occupations or positions.

Nevertheless, it is crucial to note that this approach has the same limitation as the one focusing on the average gender wage gap, i.e. the coefficients on the control variables are constrained to be gender-invariant, implying that labor market returns to characteristics are the same for men and women. As it was mentioned before, even when comparing identical individuals at the same point of the wage distribution, wage differentials may appear due to cross-gender differences in the way labor market characteristics are rewarded.

In order to deal with this issue, separate quantile regressions are run by gender with wages as the dependent variable and controls for a set of personal and job characteristics. These separate regressions are then used in a decomposition analysis adapted to quantile regressions. The Machado and Mata decomposition consists in generating counterfactual densities (for example, one with women retaining their own characteristics but being paid like men and another with women adopting men's characteristics while still being paid like women) in order to determine how much of the observed gender pay gap at a certain quantile is due to gender differences in observable characteristics and how much is due to gender differences in the returns to these characteristics.

Albrecht et al. (2003) were one of the first to consider this approach. Using 1998 micro data for Sweden, they analyze the gender wage gap across the distribution of wages. The analysis is carried out on a sample comprised of full-time employed individuals, excluding self-employed. Quantile regressions are estimated first on a pooled sample where the effect of individual differences in labor market characteristics such as age, education, immigrant status, sector, industry and occupation is controlled for. Additionally, separate quantile regressions are estimated for men and women in order to allow the returns to characteristics to differ by gender. In this last case, marital status and number of children are also included as explanatory variables. The main finding is that the gender wage gap in Sweden presents an increasing pattern throughout the wage distribution, with an acceleration in the upper tail of the distribution. This is defined by the authors as a glass ceiling effect, implying that women have limited prospects in the labor market. A Machado and Mata type decomposition analysis allowed them to determine that the primary reason for the presence of glass ceilings can be attributed to gender differences in rewards to labor market characteristics.

Following Albrecht et al. (2003), Arulampalam et al. (2007) analyzed the gender pay gap across the wage distribution in eleven European countries for the period 1995-2001. Data used is from the ECHP (European Community Household Panel). The sample considered comprises full-time and part-time public and private sector employees aged between 24 and 55 years old working at least 15 hours a week. Quantile regressions are estimated with the log of the average hourly wage as the dependent variable and individual and job characteristics as explanatory variables (age, education, tenure, marital status, type of contract, sector, part-time status, occupation and industry). The Machado and Mata decomposition is used to calculate the effect of different returns for men and women both on a pooled sample and on separate estimations by sector of employment (public and private). The results show that the gender pay gap varies across countries and sectors, with the presence not only of glass ceilings but also of sticky floors for some countries. A sticky floor is defined by the authors as a situation in which the gender wage gap widens at the bottom of the wage distribution. Patterns of sticky floors are found for Italy and Spain when considering a pooled sample and for Germany only for the private sector. On the other hand, patterns of glass ceilings are found for Austria, Belgium, Britain, Denmark, Finland, France, Germany, Italy and the Netherlands when considering a pooled sample and for both the public and private sector. The main finding coincides with the previous paper in the sense that, even if women and men had the same characteristics, the gender wage gap would not disappear given that the labor market rewards men and women differently.

Both the traditional and the quantile regression approach have been used to analyze the gender wage gap in the case of Latin American countries. For example, Ñopo (2012) estimates a non-parametric earnings gap decomposition with a pooled dataset of 18 countries comprising labor income earners between the ages of 18 and 65. The goal is to determine the effect of demographic and job characteristics on the gender pay gap. Covariates include age, education, presence of children, area, type of employment, part-time work, formality status, economic sector, occupation and size of the firm. The results show that in 2007 Latin American women were earning on average ten percent less than men at all ages, at every level of education and in all types of firms and employment.

On the other hand, Monsueto et al. (2006) study gender and race wage differentials in Brazil using Household Survey data from years 1987, 1995 and 2001. Their sample comprises employed individuals aged between 18 and 65 years old living in urban areas. Quantile regressions are estimated with the log of hourly wages as the dependent variable and with a set of control variables including age, a dummy for head of household, education, region and job position. The regressions are estimated separately for the 3 years and for 4 different groups: white men, white women, black men and black women. The decomposition analysis developed by Juhn, Murphy and Pierce is used to evaluate how much of the wage gap is due to differences in observable and unobservable characteristics. Their results show that the wage differentials between white and black men as well as between white and black women in the lowest quantiles (up to the 25th) went down during this period due to a more equal distribution of observable characteristics (particularly education).

Farfán and Ruíz Díaz (2007) study gender wage discrimination in Argentina and evaluate the presence of glass ceilings and sticky floors among education groups. Household Survey data from year 2006 is used considering a sample comprised of employed individuals living in urban areas. Separate wage regressions are estimated by gender and education groups (low and high education) using both OLS and quantile regressions. The dependent variable is the log hourly wages from the respondent's main job. Control variables include potential experience, level of education, an interaction term between experience and presence of children under 18, marital status, a full-time dummy, sector of employment, size of the firm, occupation, industry and region. Their results show that 60% to 65% of Argentinean women suffer from wage discrimination. No sufficient evidence is found to confirm the existence of glass ceilings or sticky floors in the two education groups.

Badel and Peña (2010) estimate quantile regressions with Colombian household survey data from 2006. They consider a sample composed by individuals aged between 25 and 55, working full-time and residing in one of the seven main Colombian cities. Log wages are regressed on socioeconomic variables such as education, age and its square, marital status and a dummy for head of household. Their results show that the gender wage gap in Colombia is U-shaped, so there exists evidence of both glass ceiling and sticky floor effects. By applying the Machado and Mata decomposition technique, the authors are able to determine that gender differences in labor market returns explain most of the gender pay gap. Additionally, the authors take into account the effect of sample selection for women and conclude that it is positive, significant and mostly due to unobservable characteristics.

In the same line, Borraz and Robano (2010) analyze the gender wage gap in Uruguay using household survey data from 2007. The sample includes employed individuals between the ages of 18 and 55 living in Montevideo. Log hourly wages are defined as the dependent variable while explanatory variables include age, education, partner, sector of employment, size of establishment and presence of children under 14. Quantile regressions are estimated on both a pooled sample and subsamples divided by gender. Their results indicate the existence of glass ceilings, mainly due to differences in how the labor market rewards individual characteristics (this is found with the Machado and Mata decomposition technique). The authors also take into account the effect of sample selection and find similar results to Badel and Peña (2010), namely, that the effect is positive and significant for Uruguay and only a third of this effect can be explained by observable characteristics.

In the case of Paraguay, there is no previous study focused specifically on the gender wage gap. Nevertheless, there exists a study on wage inequality which gives some indication of whether men and women are paid differently. González (2008) analyzes the determinants of wage inequality in Paraguay by comparing household survey data from 1999 and 2006. The sample comprises employed individuals from the age of 17 and older. Estimations of Mincerian equations across the wage distribution reveal that the variable gender (dummy with value 1 if male and 0 otherwise) is not only positive all along the distribution but had also increased over time. The same result is found when adding controls for qualifications and occupation. These results point out the existence of a gender wage gap in the Paraguayan labor market.

In light of the theoretical and empirical findings discussed before, this thesis has two main objectives: the first one is to analyze the gender wage gap in Paraguay in order to determine whether this could be a rational explanation for the persistent gender gap in LFP, and the second is to look at the variation of the gender wage gap across the wage distribution to verify if patterns of glass ceilings or sticky floors are to be found. In order to accomplish this, OLS and quantile regressions will be estimated, at first assuming that the control variables have the same returns for both genders and then removing this assumption to predict the gender pay gap between a representative man and a representative woman.

It is not the objective of this thesis to decompose the gender wage gap into a part that is due to gender differences in observable characteristics and a part that is due to gender differences in the way these characteristics are rewarded by the market. Instead, the aim is to the predict the gender pay gap using alternative specifications to assess whether it could be a reason motivating the low LFP of women in Paraguay.

Chapter II : Data and Descriptive Statistics

2. 1 Description of data

This thesis uses data from the Paraguayan Household Survey (Encuesta Permanente de Hogares) conducted by the National Directorate of Statistics (Dirección General de Estadísticas, Encuestas y Censos - DGEEC) under the supervision of the Technical Planning Secretariat (Secretaría Técnica de Planificación). The survey is carried out annually and has national coverage, including the capital and 15 out of the 17 departments in which the country is divided. The information collected comprises demographic variables for all members of private households as well as labor-market variables for the population aged 10 or older. It is noteworthy that the survey is not longitudinal, so the composition of individuals may vary from year to year.

Cross-sectional data from seven waves are considered comprising the period from year 2009 to year 2015. In 2009, a total of 18,421 individuals and 6,000 households were interviewed. The scope of the survey has increased over the years, reaching a total of 30,898 individuals and 8,229 households in 2015. The Paraguayan population went up in approximately 500,000 people during this period while the proportion of men and women remains to be almost equally divided.

The analysis is focused on a sample comprised of employed individuals working full-time, that is, a total of more than 30 hours per week. An age restriction of 25-65 is imposed to avoid coincidences with educational enrollments and to comply with the standard definition of working age population and old-age retirement age requirements set in Paraguay. Self-employed, unpaid family workers as well as individuals working in agriculture and the military are excluded from the analysis. Domestic workers are included in the sample provided that they do not reside in the same house as their employers. Finally, all individuals taking part of the sample have valid observations for the socioeconomic variables included in the wage equations.

The total sample to be analyzed consists of 20,524 observations distributed along the years as seen in Table 5. Men have a higher representation, accounting for 58% of the observations.

Table 5. Number of Observations per year.

Observations/Year	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	**Total**
Men	1,163	1,549	1,647	1,731	1,680	1,714	2,384	11,868
Women	786	1,032	1,117	1,207	1,345	1,244	1,925	8,656
								20,524

This thesis focuses on the gender gap in hourly wages and in particular looks at the log of hourly wages since their differences can be interpreted in percentage terms. The log of hourly wages is derived from monthly wages and weekly work hours available in the data. Information on wages is obtained in the survey with a series of questions regarding the last payment received and the number of hours worked during the week prior to the interview. Only wages from the respondent's main job including payment for overtime hours are considered for the analysis.

Table 6 shows the mean and standard deviation of the log hourly wages and weekly work hours in the sample. Men are found to earn on average higher wages and work more hours than women.

Table 6. Mean and standard deviation of wages and work hours[1].

Variable	Men	Women
Log hourly wage	9.13	9.09
	(0.69)	(0.75)
Weekly work hours	51.41	42.48
	(15.20)	(14.63)

This thesis will assess the gender gap in hourly wages controlling for an extensive set of socioeconomic and job-related characteristics. The variables included in the wage regressions are: age and its square, level of educational attainment, marital status, number of children under 18 years of age, presence of a co-habiting older adult (aged older than 65 and out of the labor market), area of residence, occupation, industry, size of establishment, type of contract, sector of employment and years of tenure.

Table 7 describes the distribution of demographic characteristics such as age, education, marital status, number of children, presence of an older adult and area of residence among the individuals considered for the analysis. No difference is found on

[1] Wages are expressed at prices of 2007 in Guaraníes (Paraguayan currency). Deflators used are given by the Consumer Price Index calculated by the Central Bank of Paraguay.

the distribution of age between men and women. It is noteworthy that the majority of the employed individuals included in the sample are aged between 25 and 35 years of age (47%). In comparison, individuals between 50 and 65 years of age represent around 17% of the sample.

With respect to education, most of the individuals have attended high school or received a technical training. Nevertheless, it is observed that there is higher proportion of employed women with a college education compared to men (31% against 20%). Similar results have been found in previous studies. For example, Cortés et al. (2003) look at household survey data from 1997/1998 and find that among the economically active population, there is a higher proportion of women having attended college compared to men (12.2% against 7.5%).

Table 7. Distribution of demographic variables[2].

Variables	**Men**	**Women**
Age	38.58	38.13
Education		
Low education	0.31	0.26
Middle education	0.48	0.43
High education	0.20	0.31
Co-habiting Partner		
No partner	0.26	0.41
With a partner	0.74	0.59
Children		
No children	0.26	0.24
One child	0.28	0.31
Two or more children	0.45	0.45
Older Adult in the house		
Yes	0.10	0.13
No	0.90	0.87
Area of residence		
Urban	0.81	0.85
Rural	0.19	0.15

Regarding the presence of a co-habiting partner, the majority of individuals included in the subsample declare to live with a partner. However, the proportion of working women without a partner is found to be higher than that of working men.

[2] Sample means are reported. Low education= Illiterates, Primary and Middle school. Middle education= High School and Technical training. High education= University

The distribution of characteristics such as the area of residence, presence of children under 18 years of age and presence of co-residing older adults (defined as older than 65 years old and out of the labor market) do not present large differences by gender. Specifically, both men and women reside mostly in urban areas, have two or more children and do not cohabite with an older adult.

Table 8 describes the distribution of job related characteristics such as occupation, industry, size of the firm, type of contract, sector of employment and years of tenure. All categories for these characteristics are based on the questionnaire design. With respect to the choice of occupation, women seem to be divided between two extremes: they either dedicate to high skilled occupations, which include managers, professional and technical occupations, or they work in low skilled occupations such as blue collar and unskilled workers. In contrast, men are found to work mostly in blue collar jobs.

Table 8. Distribution of job-related characteristics[3].

Variable	**Men**	**Women**
Occupation		
Managers	0.25	0.39
White Collar	0.24	0.26
Blue Collar	0.52	0.35
Industry		
Secondary sector	0.36	0.08
Tertiary sector	0.64	0.92
Size of establishment		
Up to 5 people	0.34	0.42
6-20 people	0.32	0.26
21 people or more	0.34	0.31
Type of contract		
Permanent	0.34	0.40
Fixed-term	0.25	0.20
Verbal	0.41	0.40
Sector of employment		
Private	0.67	0.67
Public	0.33	0.33
Tenure	7.69	7.21

[3] Sample means are reported. Secondary sector= Manufacturing, electricity and construction. Tertiary sector= Retail, communications, finance and social services.

The tertiary sector is found to be the main source of labor for the individuals of the sample regardless of gender. In contrast, manufacturing, electricity and construction related activities employ a smaller proportion of the sample which is composed almost entirely by men (only 8% of women work in the secondary sector).

Concerning the size of establishment for which individuals work for, men are almost equally distributed between small, medium and large enterprises. Women, on the other hand, are found to work mostly for small firms or as domestic workers.

With respect to the type of contract, the verbal contract is the most common for both genders. A verbal contract consists in a verbal agreement between an employer and an employee regarding the conditions of their work relationship. This kind of contract is recognized by the Paraguayan Labor Code. The permanent contract is the second most common with a higher proportion of women (40% against 34% of men).

Regarding the sector of employment, the private sector employs the majority of individuals overall. The category of private workers also include domestic workers which present a large difference in distribution across genders, only 1.5% of men dedicate to domestic service while the proportion of women reaches 26%.

Finally, with respect to the years of tenure, no noticeable difference is found between men and women.

2.2 Raw gender wage gap in Paraguay

In this section, the raw gender wage gap is presented considering the average as well as its variation across the wage distribution. The importance of looking at the raw wage gap along the wage distribution resides in the fact that individuals at different points of the wage distribution may differ in a number of characteristics such as skills, ambition, taste for work, etc. Therefore, we cannot assume that individuals working in high-paid jobs at the top of the wage distribution face the same gender gap that individuals working in low-paid positions. The raw wage gap is presented here for the overall sample as well as for subsamples divided by age, education, partner and number of children.

Table 9 shows the raw gender wage gap estimated for the period 2009-2015. The average gender gap is significant and reaches 4%. When looking at its variation across the wage distribution, the gender gap is found to be significant and negative only at the 10th and 25th percentile. This indicates that women earn lower wages than men when occupying low-paid positions but seem to be better off when occupying positions with wages starting from the median of the wage distribution. The evidence suggests the presence of sticky floors given that the gender gap is found to be wider at the bottom of the distribution.

Table 9. Raw gender wage gap for period 2009-2015.

	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Raw gender wage gap	-0.040***	-0.220***	-0.097***	0.019*	0.075***	-0.025
	(0.009)	(0.016)	(0.013)	(0.011)	(0.011)	(0.019)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Next, the raw wage gap is presented in subsamples divided by age groups. Age is an important factor to consider when analyzing the gender pay gap in Paraguay taking into account that the Paraguayan pension system allows retirement from the age of 55 and that women are more likely to have interruptions in their work life due to family responsibilities (home production and childcare). Therefore, women after age 55 that are still part of the labor force might be more likely to have had periods out of work which may have affected their human capital accumulation. Cross-gender differences in current wages could be explained by cross-gender differences in the composition of the employed population.

Looking at the variation of the raw gender wage gap between age groups, the wage gap is always higher and significant at the bottom of the distribution (Table 10). This indicates the presence of sticky floors for all age groups. Moreover, a positive relation can be observed between the age and the wage gap, namely, older individuals experience larger differences in the way women and men are rewarded by the market when exercising low-paid positions.

For the youngest age group, the average raw wage gap is not significant. Looking at its variation across the distribution, the level of wages is found to be favorable to women starting from the median, indicating that women between 25 and 35 years old earn higher wages than men unless they exercise low-paid positions.

However, for the group of individuals aged between 36 and 49 years of age, the average raw wage gap is found to be significant and reaches 7.4%. In this case, the wage gap is not significant for the median and the 75th percentile and men earn higher wages at the top of the distribution.

Table 10. Raw gender wage gap by age groups for period 2009-2015.

Age groups	OLS	10th	25th	50th	75th	90th
25-35	-0.006	-0.204***	-0.058***	0.028**	0.105***	0.044*
	(0.013)	(0.022)	(0.019)	(0.014)	(0.017)	(0.025)
36-49	-0.074***	-0.217***	-0.130***	0.007	0.006	-0.095***
	(0.016)	(0.028)	(0.022)	(0.020)	(0.018)	(0.032)
50-65	-0.070**	-0.271***	-0.158***	-0.011	0.121***	-0.067
	(0.027)	(0.045)	(0.039)	(0.030)	(0.034)	(0.057)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

For the oldest age group, the average raw gender wage gap is also significant and reaches 7%. Looking at its variation across the wage distribution, the gender gap is found to be either not significant or favorable to women starting from the median.

Education is another relevant factor to consider when analyzing the gender pay gap. In the previous section, gender differences in educational attainment were documented for the individuals that are part of the sample. Different levels of education are usually associated with different levels of wages, for instance, higher levels of education might be accompanied by higher levels of abilities, motivation, etc. The raw gender wage gap presented before for the overall sample might be explained then by differences in education. Therefore, analyzing the gender pay gap in education subgroups will allow to compares wages of men and women with similar education levels.

Starting with the case of individuals with a low level of education, the wage gap reaches here its highest values and is found to be significant across the entire wage distribution (see Table 11). The gender gap presents a decreasing trend along the wage distribution with evidence for the presence of sticky floors, indicating that low-educated women at the bottom of the distribution encounter the biggest difference in wages with respect to men.

For individuals having attended high school and/or with a technical training afterwards, the average raw wage gap is significant and much lower than for the previous group (4.8% against 25.6%). It is higher at the bottom of the distribution, indicating the presence of sticky floors and significant everywhere except at the median.

Finally, for individuals having attended college, the average raw gender wage gap is significant and higher than for the previous group (9.6%). Looking at its variation across the wage distribution, it is found to be significant only from the median presenting an increasing trend which point outs the presence of glass ceilings. In this group, women in high-paid positions encounter the biggest difference in wages with respect to men.

Table 11. Raw gender wage gap by education groups for period 2009-2015.

Education Groups	OLS	10th	25th	50th	75th	90th
Low	-0.256***	-0.363***	-0.292***	-0.259***	-0.182***	-0.176***
education	(0.015)	(0.032)	(0.022)	(0.017)	(0.017)	(0.026)
Middle	-0.048***	-0.196***	-0.059***	0.009	0.051***	-0.040**
education	(0.012)	(0.023)	(0.018)	(0.014)	(0.014)	(0.017)
High	-0.096***	-0.025	-0.028	-0.058***	-0.125***	-0.223***
education	(0.018)	(0.028)	(0.022)	(0.021)	(0.026)	(0.039)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Next, the raw wage gap will be presented for subsamples divided by presence of a partner and number of children. The relevance of these criteria relies on the fact that women are still held responsible for most of the housework and childcare responsibilities. Therefore, women might be more likely to accept low-paid jobs that allow them to combine work and home responsibilities. What's more, women with children might also interrupt their working careers until, for example, their children reach the school age.

When considering subsamples divided by the presence of a co-habiting partner, the average raw gender wage gap is found to be significant only for the group with a co-habiting partner (see Table 12). Looking at the variation across the wage distribution, the bigger differences in wages are found at the bottom of the distribution suggesting the presence of sticky floors.

Evidence of sticky floors is also found for individuals without a co-habiting partner. However, starting from the median the raw wage gap is either positive or not significant.

Table 12. Raw gender wage gap by partner groups for period 2009-2015.

Partner groups	OLS	10th	25th	50th	75th	90th
With a partner	-0.024**	-0.205***	-0.087***	0.059***	0.087***	-0.036
	(0.011)	(0.022)	(0.016)	(0.014)	(0.014)	(0.024)
No partner	-0.008	-0.174***	-0.065***	0.015	0.116***	0.044
	(0.017)	(0.030)	(0.024)	(0.017)	(0.025)	(0.035)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

When considering subsamples divided by the presence of children under 18 years of age, the average raw gender wage gap is found to be significant only for women with two or more children (see Table 13). Looking at the variation across the wage distribution, the higher differences in wages for the three subgroups are found at the bottom of the distribution. There exists a positive relation between the number of children and the wage gap, i.e., women with two or more children experience larger differences in wages with respect to men when exercising low-paid jobs than women with one or with no children. The evidence suggests the presence of sticky floors for the groups of women with children.

Table 13. Raw gender wage gap by children groups for period 2009-2015.

Children groups	OLS	10th	25th	50th	75th	90th
No children	0.010	-0.134***	-0.008	0.056***	0.099***	-0.013
	(0.020)	(0.035)	(0.028)	(0.021)	(0.024)	(0.039)
One child	-0.016	-0.181***	-0.055**	0.031	0.092***	0.002
	(0.017)	(0.031)	(0.023)	(0.019)	(0.021)	(0.036)
Two or more	-0.083***	-0.277***	-0.165***	-0.015	0.059***	-0.056**
Children	(0.014)	(0.025)	(0.019)	(0.017)	(0.017)	(0.028)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The tables presented in this descriptive analysis show how the gender gap varies with individual characteristics one at a time. The next step consists in using multivariate regressions to control for the conjoint role of these characteristics.

Chapter III: Econometric Model and Empirical Results

To analyze the gender wage gap in the Paraguayan labor market both at the average and along the wage distribution, multivariate OLS and quantile regressions are estimated allowing for an extensive set of explanatory variables such as age and its square, education, presence of a partner, children, presence of at least one older adult out of the labor force in the household, area of residence, occupation, industry, size of the firm, type of contract, sector of employment and years of tenure.

Focusing on the average of the gender pay gap is informative but cannot be used to describe the variation of the gender gap along the wage distribution. This is due to the heterogeneity of workers at different points of the wage distribution, i.e. individuals may differ on a number of characteristics which include level of skills, labor market attachment, etc.

In a first stage, following the gender wage gap literature, it is assumed that the control variables affect wages of men and women in the same way. Here, the goal is to measure the extent on which the gender gap can be explained by gender differences in observable characteristics. In a second stage, the assumption of equal returns is dropped and the control variables are allowed to have different returns by gender.

The estimation of the gender wage gap in these two stages is made in the overall sample as well as in subsamples divided by age, education, partner and number of children. In all the cases, standard errors are clustered at the household level to account for the non-independence of observations referring to individuals living in the same household.

3.1 Pooled regressions

In order to measure the effect of individual characteristics in the level of wages, OLS and quantile regressions are estimated on a pooled sample of men and women restricting the control variables to have equal returns by gender. The coefficients on the gender dummy provide an estimation of the gender pay gap once the effect of labor market characteristics has been controlled for. In other words, it represents the part of the gender gap that cannot be explained by cross-gender heterogeneity in observable characteristics.

Table 14 provides the full list of variables included in the wage regressions, their definitions and the baseline groups to which they are compared.

Table 14. Names and definition of control variables[4].

Characteristic	Variables names	Definition	Baseline group
Gender	Dum_Gender	= 1 if female	Male
Wave	Dum_2010 Dum_2011 Dum_2012 Dum_2013 Dum_2014 Dum_2015	= 1 if the interview was in 2010 = 1 if the interview was in 2011 = 1 if the interview was in 2012 = 1 if the interview was in 2013 = 1 if the interview was in 2014 = 1 if the interview was in 2015	Year 2009
Age	Age	Years of age	
Age squared	Agesq		
Education	Dum_IllPriMdS Dum_HighSTech	=1 if the individual has at most a middle school diploma (low education) =1 if the individual has a high school diploma or a technical training (middle education)	High education (college)
Co-habiting partner	Dum_Partner	=1 if the individual has a co-habiting partner	No partner
Presence of children	Dum_1child Dum_Children	=1 if the individual has one child =1 if the individual has two or more children	No children
Presence of an older adult	Dum_OlderAdult	=1 if the individual lives with an older adult	Not living with an older adult
Area of residence	Dum_Urban	=1 if the individual lives in an urban area	Rural area
Industry	Dum_RCFSS	=1 if the industry corresponds to the tertiary sector (retail, finance, etc.)	Secondary sector (manufacturing)
Occupation	Dum_WhiteC, Dum_BlueCUnsk	=1 if the individual works as a white collar =1 if the individual works as a blue collar	Managers
Size of the firm	Dum_Size5dw Dum_Size620	=1 if the firm has at most 5 employees =1 if the firm has 6 to 20 employees	21 or more employees
Contract	Dum_Fixedcontr Dum_Verbalcontr	=1 if the contract is fixed-term =1 if the contract is verbal	Permanent contract
Sector	Dum_Public	=1 if the individual works in the public sector	Private workers
Tenure	Totaltenure	Years of tenure	

[4] Descriptive Statistics for these variables are found in Chapter II.

To estimate the gender pay gap in the overall sample, two econometric models will be presented. The first one includes controls for socioeconomic and demographic characteristics such as age, education, presence of a partner, children, presence of older adults in the household and area of residence. The second one adds controls for job-related characteristics including occupation, industry, size of the firm, type of contract, sector of employment and years of tenure. The aim here is to determine how does the estimated gender wage gap varies when adding more control variables to the specification of the model. The analysis focuses both on the average as well as the gender gap variation across the wage distribution. Standard errors are clustered at the household level.

Table 15 presents the results of OLS and quantile regressions for the first model. In this specification, the average gender wage gap is found to be significant and reaches 10.6%. Moreover, the wage gap is also significant along the wage distribution and presents an U-shaped pattern, i.e. it is larger at the 10th percentile, then decreases until the 75th percentile and increases again at the 90th percentile.

With respect to age (which is used as a proxy for experience), the coefficients are found to be positive and consistent across the entire wage distribution. Considering the level of education, the results show that individuals with a low and middle level of education earn lower wages than those with a college education, particularly at the top of the distribution. Individuals with a primary or middle school education are found to have the lowest wages. On the other hand, having a partner has a positive relation with wages across the entire wage distribution.

The coefficients on the dummy for individuals with one child are found to be not significant, indicating that they do not present differences in wages with respect to individuals without children. In the case of individuals with two or more children, there exists a negative relation with wages that is significant only at the 10th percentile. With respect to the presence of an older adult (aged older than 65 and out of the labor market), the relation with wages is found to be negative and significant starting from the median.

Table 15. Estimation of the gender wage gap controlling for socioeconomic characteristics.

VARIABLES	(1) OLS	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Dum_Gender	-0.106***	-0.167***	-0.112***	-0.074***	-0.065***	-0.110***
	(0.008)	(0.017)	(0.011)	(0.009)	(0.011)	(0.014)
Dum2010	0.083***	0.096***	0.103***	0.068***	0.036*	0.047
	(0.019)	(0.033)	(0.023)	(0.021)	(0.022)	(0.030)
Dum2011	0.139***	0.124***	0.191***	0.138***	0.106***	0.137***
	(0.019)	(0.033)	(0.022)	(0.020)	(0.021)	(0.033)
Dum2012	0.256***	0.268***	0.272***	0.238***	0.216***	0.240***
	(0.018)	(0.031)	(0.022)	(0.020)	(0.023)	(0.028)
Dum2013	0.292***	0.270***	0.281***	0.273***	0.283***	0.302***
	(0.019)	(0.033)	(0.021)	(0.022)	(0.023)	(0.030)
Dum2014	0.359***	0.318***	0.365***	0.338***	0.337***	0.364***
	(0.018)	(0.035)	(0.022)	(0.021)	(0.022)	(0.031)
Dum2015	0.377***	0.332***	0.382***	0.373***	0.369***	0.383***
	(0.017)	(0.030)	(0.020)	(0.020)	(0.021)	(0.028)
Age	0.048***	0.047***	0.045***	0.048***	0.048***	0.042***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.005)	(0.007)
Agesq	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dum_IllPriMdS	-1.006***	-0.902***	-0.899***	-0.948***	-1.050***	-1.181***
	(0.013)	(0.024)	(0.018)	(0.014)	(0.016)	(0.023)
Dum_HighSTech	-0.580***	-0.520***	-0.511***	-0.535***	-0.602***	-0.723***
	(0.012)	(0.020)	(0.016)	(0.012)	(0.015)	(0.021)
Dum_Partner	0.152***	0.156***	0.149***	0.139***	0.139***	0.115***
	(0.010)	(0.019)	(0.014)	(0.011)	(0.013)	(0.017)
Dum_1child	-0.014	-0.023	0.002	-0.009	-0.012	-0.018
	(0.013)	(0.023)	(0.016)	(0.014)	(0.015)	(0.022)
Dum_Children	-0.020	-0.054**	-0.015	-0.017	0.001	0.001
	(0.012)	(0.022)	(0.015)	(0.013)	(0.015)	(0.020)
Dum_OlderAdult	-0.042***	-0.008	-0.028	-0.056***	-0.036*	-0.047*
	(0.014)	(0.024)	(0.018)	(0.015)	(0.019)	(0.025)
Dum_Urban	0.078***	0.097***	0.074***	0.068***	0.040***	0.062***
	(0.012)	(0.020)	(0.015)	(0.013)	(0.013)	(0.018)
Constant	8.221***	7.625***	7.903***	8.212***	8.604***	9.115***
	(0.072)	(0.135)	(0.091)	(0.076)	(0.093)	(0.124)
Observations	20,524	20,524	20,524	20,524	20,524	20,524
R-squared	0.314	0.305	0.312	0.314	0.312	0.310

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Both results could be related to the fact that women hold most of the burden regarding family responsibilities, which include taking care of children and older adults. Therefore, women who live with either two or more children or an older adult are more likely to be in charge of taking care of them, which might in turn motivate them to look for low-paid jobs that gives them more time flexibility to balance their work and family responsibilities.

Finally, individuals residing in urban areas fare better than those living in rural areas regardless of which point of the wage distribution is considered. The variation on wages is positive and significant across the entire wage distribution.

When comparing the estimated raw wage gap with the results of this specification, it is possible to discern that the estimated gender wage gap increases when adding controls for socioeconomic and demographic characteristics, the estimated raw average gender gap is 4% (see Chapter II, Table 9) and with this specification it reaches 10.6% . This could be related to the fact that women in the sample are more educated than men and therefore, gender differences in education cannot fully explain the existence of a gender wage gap. Regarding demographic characteristics such as area of residence, presence of a partner, children and presence of older adults in the household, the distribution in the sample does not present variations across genders and therefore cross-gender differences in these variables are also unable to account for the existence of a gender pay gap.

Table 16 shows the results of OLS and quantile regressions for the second model in which controls for job-characteristics are added. The average gender wage gap increases by about 0.5% compared to the previous model (see Table 15). Looking at the variation along the wage distribution, the gender wage gap is always significant and presents an increasing pattern.

Regarding industry, individuals working in activities related to retail, communications, finance and social services fare worse than those working for the secondary sector. The variation on wages is found to be negative and significant across the entire wage distribution.

Concerning the choice of occupation, white collar, blue collar and unskilled workers earn lower wages than individuals working in high-skilled occupations such as managers and professionals. This wage differential is statistically significant across the whole wage distribution and is largest for blue collars and unskilled workers.

Table 16. Estimation of the gender wage gap when adding job-characteristics.

VARIABLES	(1) OLS	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Dum_Gender	-0.111***	-0.068***	-0.076***	-0.089***	-0.119***	-0.151***
	(0.008)	(0.014)	(0.010)	(0.008)	(0.010)	(0.014)
Dum2010	0.082***	0.067**	0.070***	0.090***	0.075***	0.091***
	(0.017)	(0.029)	(0.019)	(0.016)	(0.022)	(0.032)
Dum2011	0.134***	0.087***	0.119***	0.153***	0.145***	0.146***
	(0.017)	(0.030)	(0.020)	(0.017)	(0.019)	(0.029)
Dum2012	0.255***	0.257***	0.242***	0.261***	0.253***	0.254***
	(0.016)	(0.026)	(0.019)	(0.016)	(0.019)	(0.028)
Dum2013	0.271***	0.239***	0.253***	0.281***	0.275***	0.296***
	(0.016)	(0.028)	(0.020)	(0.016)	(0.019)	(0.030)
Dum2014	0.350***	0.332***	0.341***	0.354***	0.345***	0.358***
	(0.016)	(0.028)	(0.019)	(0.015)	(0.019)	(0.030)
Dum2015	0.354***	0.325***	0.331***	0.363***	0.355***	0.386***
	(0.015)	(0.024)	(0.019)	(0.014)	(0.018)	(0.028)
Age	0.020***	0.013**	0.021***	0.019***	0.023***	0.015***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Agesq	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dum_IllPriMdS	-0.431***	-0.367***	-0.370***	-0.387***	-0.495***	-0.584***
	(0.014)	(0.021)	(0.018)	(0.015)	(0.019)	(0.027)
Dum_HighSTech	-0.292***	-0.191***	-0.216***	-0.253***	-0.373***	-0.461***
	(0.011)	(0.016)	(0.013)	(0.011)	(0.016)	(0.022)
Dum_Partner	0.090***	0.083***	0.089***	0.073***	0.078***	0.096***
	(0.009)	(0.015)	(0.011)	(0.009)	(0.011)	(0.016)
Dum_1child	-0.010	-0.017	-0.002	-0.007	-0.009	-0.020
	(0.011)	(0.020)	(0.013)	(0.011)	(0.014)	(0.019)
Dum_Children	-0.006	-0.008	-0.009	-0.009	-0.007	-0.001
	(0.011)	(0.018)	(0.012)	(0.011)	(0.013)	(0.019)
Dum_OlderAdult	-0.052***	0.007	-0.026**	-0.053***	-0.079***	-0.087***
	(0.012)	(0.020)	(0.013)	(0.012)	(0.015)	(0.022)
Dum_Urban	0.086***	0.056***	0.066***	0.091***	0.097***	0.086***
	(0.010)	(0.020)	(0.012)	(0.011)	(0.012)	(0.018)
Dum_RCFSS	-0.049***	-0.051***	-0.043***	-0.048***	-0.038***	-0.052**
	(0.011)	(0.017)	(0.013)	(0.011)	(0.013)	(0.020)
Dum_WhiteC	-0.353***	-0.319***	-0.335***	-0.335***	-0.335***	-0.381***
	(0.011)	(0.016)	(0.014)	(0.012)	(0.015)	(0.021)
Dum_BlueCUnsk	-0.408***	-0.338***	-0.356***	-0.383***	-0.408***	-0.495***
	(0.013)	(0.018)	(0.015)	(0.013)	(0.017)	(0.024)
Dum_Size5dw	-0.170***	-0.222***	-0.159***	-0.146***	-0.141***	-0.167***
	(0.011)	(0.018)	(0.013)	(0.011)	(0.014)	(0.020)
Dum_Size620	-0.057***	-0.045***	-0.023**	-0.052***	-0.074***	-0.108***
	(0.009)	(0.014)	(0.011)	(0.009)	(0.013)	(0.018)
Dum_Fixedcontr	-0.164***	-0.218***	-0.179***	-0.152***	-0.129***	-0.103***
	(0.011)	(0.016)	(0.012)	(0.012)	(0.015)	(0.021)

Dum_Verbalcontr	-0.347***	-0.461***	-0.379***	-0.321***	-0.275***	-0.248***
	(0.013)	(0.018)	(0.015)	(0.012)	(0.016)	(0.023)
Dum_Public	0.029***	0.049***	0.044***	0.044***	0.030***	0.006
	(0.009)	(0.015)	(0.012)	(0.009)	(0.011)	(0.016)
Totaltenure	0.006***	0.005***	0.007***	0.006***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	9.124***	8.700***	8.759***	9.063***	9.356***	9.920***
	(0.066)	(0.104)	(0.086)	(0.072)	(0.082)	(0.104)
Observations	20,524	20,524	20,524	20,524	20,524	20,524
R-squared	0.466	0.454	0.462	0.465	0.461	0.454

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

With respect to the size of the firm, individuals working for companies with less than 21 employees earn lower wages compared to those working for bigger firms. Working for a company with at most 5 employees is associated with the largest reduction in wages, particularly at the bottom of the distribution (22.2% at the 10th percentile).

Regarding the type of contract, individuals with a verbal contract fare the worst compared to those with a permanent contract. The earnings difference is found to be negative and significant for all quantiles considered and it is larger at the bottom of the distribution (46.1% at the 10th percentile). Moreover, workers with fixed-term contracts earn lower wages, but this differential decreases across the wage distribution, indicating that individuals in the lower half of the distribution are penalized harder for not having a permanent contract. This could be related to the heterogeneity of jobs across the wage distribution, i.e. less qualified jobs are found at the bottom of the distribution while in the upper part we can find high-skilled jobs such as professionalized technicians and managers.

Working for the public sector is associated with higher wages. This difference is always significant except at the top of the distribution (90th percentile). On the other hand, years of tenure have a small positive coefficient that is consistent for all quantiles considered (0.05% to 0.07%).

When comparing results of the first and second model, we can see that adding job-related characteristics to the specification is related to a decrease of the gender pay gap at the bottom of the distribution. However, the opposite happens from the median to the upper part of the distribution, here the gender gap goes up and presents an increasing trend. Therefore, job-related characteristics are able to explain part of the difference in wages between men and women in low-paid jobs but cross-gender differences in these variables cannot account for the wage differential found at the top of the distribution.

In conclusion, looking at the results of these specifications we can state that a gender wage gap exists in the Paraguayan labor market even after controlling for cross-gender differences in a extensive set of individuals characteristics. Therefore, it is possible to say that Paraguayan women in the overall sample are being paid less than men all along the wage distribution and this qualifies as a possible explanation for the gender gap in labor force participation.

3.2 Pooled regressions by socioeconomic groups

Estimations of the gender wage gap are also conducted on subsamples divided by socioeconomic characteristics. The aim is to allow the gender pay gap to vary across socioeconomic groups given that the specifications estimated in the previous section control for individual characteristics but restrict the gender pay gap to be invariant.

In Chapter I the gender gap in labor force participation was disaggregated in subgroups divided by age, education, partner and children. The same is done here for the gender pay gap in order to determine whether it can be a reason for the gap in labor force participation across genders that was documented before.

Table 17. Subsamples.

Subsamples	**Number of observations**
Age	
25-35	9,681
36-49	7,389
50-65	3,454
Education	
Low education	5,999
Middle education	9,427
High education	5,098
Co-habiting Partner	
With a partner	13,932
No partner	6,592
Children	
No children	5,234
One child	6,019
Two or more children	9,271

Table 17 shows the groups that compose each subsample with the number of observations for each one of them.

The estimations by socioeconomic groups use the full specification of the econometric model, i.e. log hourly wages are regressed on a constant, a gender dummy and the full set of control variables, which include: age and its square, education, presence of a partner, children, presence of at least one older adult out of the labor force in the household, area of residence, occupation, industry, size of the firm, type of the contract, sector of employment and years of tenure. Standard errors are clustered at the household level.

Age is an important factor to consider when analyzing the gender pay gap. One of the reasons is that women are more likely to interrupt their work life due to family responsibilities. Age is then an imperfect proxy for experience in the case of women. Dividing the sample by age, it is possible to determine whether the gender pay gap is only an issue at the entry of the labor market or if it remains so during the course of women's working careers.

Another aspect to consider is that the Paraguayan pension system allows retirement of men and women from the age of 55. This availability of the retirement option can alter the composition of the sample of workers. For instance, some women might prefer to retire earlier in order to dedicate to housework responsibilities. Therefore, the women who remain at work might have a higher attachment to the labor market and potentially higher skills and motivations. This new sample composition might alter the gender pay gap.

The sample is divided in three age groups: 25-35, 36-49 and 50-65. Table 18 shows the results of OLS and quantile regressions for the estimation of the gender pay gap for the three age groups. Starting with the age group composed by individuals aged between 25 and 35, the average gender wage gap is significant and reaches 11.2%. Looking at the variation across the wage distribution, the gender gap presents an increasing pattern from the 25th percentile reaching its highest values at the top of the distribution, women in this group earn between 10.6% to 14.8% less than men when exercising high-paid positions.

With respect to the age group composed of individuals between 36 and 49 years of age, the gender wage gap is also found to increase across the wage distribution, with higher values compared to the previous group for most of the quantiles.

Table 18. Estimation of gender wage gap by age groups.

Age groups	OLS	10th	25th	50th	75th	90th
25-35	-0.112***	-0.090***	-0.076***	-0.090***	-0.106***	-0.148***
	(0.011)	(0.017)	(0.014)	(0.012)	(0.014)	(0.020)
36-49	-0.121***	-0.068***	-0.095***	-0.101***	-0.138***	-0.169***
	(0.013)	(0.022)	(0.016)	(0.014)	(0.018)	(0.024)
50-65	-0.056**	-0.008	-0.020	-0.050**	-0.082***	-0.090**
	(0.023)	(0.033)	(0.032)	(0.024)	(0.029)	(0.038)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Regarding the oldest age group, the estimated average gender gap is the lowest. Controlling for all covariates, the results show that a wage gap exists starting from the median of the distribution and it presents an increasing trend, although with smaller variations than for the younger age groups. This could be related to the early retirement of some women due to family responsibilities, leaving only those more attached to the labor market and with higher abilities and motivations. Therefore, a smaller gender gap is found since women that are still at work in this age group are those usually earning the higher wages.

The highest estimates of the gender wage gap are found for the younger age groups, particularly for individuals between the ages of 36 and 49 years old.

The analysis of the gender pay gap by education groups is motivated by the fact that different levels of educational attainment are usually accompanied by different levels of wages. A larger investment in human capital is positively related to higher paid-positions and wages.

The sample is divided in three education groups: low education, which comprises illiterates and individuals having attended primary or middle school; middle education, which includes those with a high school diploma or with a technical training and high education, which includes those with a college education.

For the estimation by education groups all the explanatory variables are included with the exception of the education dummies.

Table 19 shows the results of the gender wage gap estimation by education groups. Starting with the low education group, the wage gap is always significant and presents a decreasing trend across the wage distribution. Low-educated women are penalized harder than men for exercising low-paid jobs.

On the other hand, the gender gap in wages for the middle education group is always significant and increases across the wage distribution. Women in this group earn between 10.7% and 17.1% less than their male counterparts when exercising high-paid positions.

For the high education group, the estimated gender wage gap is also found to be increasing across the wage distribution. When controlling for all individual characteristics, women at the top of the distribution are found to earn between 13.9% and 19.1% less than men.

Comparing the estimated gender wage gap across education groups, we can see that higher levels of education do not go in hand with wage equality for Paraguayan women. High-educated women exercising high-paid positions face similar levels of wage differentials with respect to men than low-educated women in low-paid positions (19.1% and 19.7% respectively).

Table 19. Estimation of gender wage gap by education groups.

Education groups	OLS	10th	25th	50th	75th	90th
Low education	-0.132***	-0.197***	-0.136***	-0.102***	-0.100***	-0.076***
	(0.018)	(0.036)	(0.024)	(0.020)	(0.021)	(0.026)
Middle education	-0.097***	-0.045***	-0.060***	-0.078***	-0.107***	-0.171***
	(0.011)	(0.017)	(0.014)	(0.011)	(0.014)	(0.020)
High education	-0.106***	-0.044*	-0.066***	-0.106***	-0.139***	-0.191***
	(0.016)	(0.025)	(0.018)	(0.018)	(0.024)	(0.030)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The division of the sample in groups by presence of a co-habiting partner is motivated by the fact that having a partner may have a negative effect on women's wages. The reason behind this is that women are still held responsible for home production and care giving of other family members. This may influence their choice of occupation due to the necessity to balance work and family responsibilities.

The sample is divided in two groups: one including those living with a partner and the other one with those who do not live with a partner (single, separated, divorced or widowed individuals).

For this estimation all the explanatory variables are included in the wage regressions with the exception of the partner dummy.

Table 20 shows the results of the gender wage gap estimation for subsamples divided by marital status. For the group of individuals who declare to live with a partner, the gender wage gap is always significant and presents an increasing trend.

For the group of individuals without a partner, the gender gap is significant for all quantiles considered and presents a similar trend to the other group, i.e. it increases across the wage distribution and reaches its highest value at the 90th percentile.

Therefore, the gender wage gap behaves in a similar way for both groups considered. Women are found to earn less than men whether they live with a partner or not, although the difference in wages at the top of the distribution is a little higher (by about 2%) for those with a co-habiting partner.

Table 20. Estimation of gender wage gap for subsamples divided by marital status.

Partner groups	OLS	10th	25th	50th	75th	90th
With a partner	-0.119***	-0.073***	-0.080***	-0.091***	-0.125***	-0.164***
	(0.010)	(0.017)	(0.011)	(0.010)	(0.013)	(0.016)
No partner	-0.102***	-0.081***	-0.074***	-0.091***	-0.110***	-0.146***
	(0.015)	(0.022)	(0.018)	(0.015)	(0.019)	(0.026)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

This division of the sample by presence of children under 18 years of age is motivated by similar reasons than for marital status, namely, women are still held accountable for family responsibilities, which include taking care of children. This influences their choice of occupation and jobs and may lead to a lower level of wages. What's more, women might be more likely to interrupt their work life in order to attend to these responsibilities.

The sample is divided in three groups: one for individuals without children, another for individuals with one child and a third one for those with two or more children.

For the estimation of the gender pay gap for groups divided by the number of children all the explanatory variables are included in the wage regressions with the exception of the children dummies.

Table 21 presents the results of the gender wage gap estimation when considering subsamples divided by the number of children. Starting with the group composed by individuals without children, the gender wage gap is significant starting from the 25th percentile and presents an increasing pattern across the wage distribution.

A similar result is found on the case of individuals with one child. When controlling for the full set of covariates, the gender wage gap is always significant and increases across the wage distribution.

Again, when considering individuals with two or more children, a similar pattern is found. Once the effect of individual characteristics is controlled for, the wage gap is always significant and presents an increasing pattern reaching its highest values at the top of the wage distribution.

Table 21. Estimation of gender wage gap for subsamples divided by number of children.

Children groups	OLS	10th	25th	50th	75th	90th
No children	-0.121***	-0.045	-0.078***	-0.113***	-0.146***	-0.176***
	(0.017)	(0.028)	(0.019)	(0.018)	(0.020)	(0.029)
One child	-0.090***	-0.051**	-0.048**	-0.057***	-0.088***	-0.136***
	(0.015)	(0.023)	(0.020)	(0.014)	(0.019)	(0.027)
Two or more children	-0.119***	-0.098***	-0.092***	-0.090***	-0.117***	-0.145***
	(0.012)	(0.022)	(0.015)	(0.012)	(0.015)	(0.024)

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Therefore, women at the top of the distribution encounter the bigger differences in wages in all of the groups. It is noteworthy that women without children exercising high-paid positions face the larger differences in wages with respect to men (17.6% against 13.6% for women with one child and 14.5% for women with two or more children). One possible reason could be related to unobserved characteristics such as ambition and labor market attachment; women who remain at work even after having children might be more attached to the labor market and more willing to invest in their human capital (education or training), which leads to a reduction of the gender pay gap.

In conclusion, a sizable and significant gender wage gap is found for all socioeconomic groups considered. These results qualify the gender pay gap as a possible rational explanation for the gender gap in labor participation found in Chapter I for the same groups.

A summary of the results of quantile regressions is presented at Table 22. Following Arulampalam et al. (2007), glass ceilings and sticky floors are defined to exist when the extreme quantiles exceed the reference gaps by at least 2 points. The 90th percentile is compared to the 75th and the 50th percentile while the 10th percentile is compared to the 25th and the 50th percentile.

For the overall sample, evidence of glass ceilings is found. At the 90th percentile the estimated gender pay gap is 15.1%, clearly higher than the estimates for the 75th and 50th percentiles, 11.9% and 8.9% respectively (see table 16).

Table 22. Summary of Quantile Regressions Results.

	Glass Ceilings measured by			**Sticky Floors measured by**	
	90th-all gaps	*90th-75th difference*	*90th-50th difference*	*10th-50th difference*	*10-25th difference*
Overall sample		X	X		
Age					
25-35	X	X	X		
36-49	X	X	X		
50-65			X		
Education					
Low education				X	X
Middle education	X	X	X		
High education	X	X	X		
Partner					
With a partner	X	X	X		
No partner	X	X	X		
Children					
No child		X	X		
One child	X	X	X		
Two or more	X	X	X		

For the subgroups divided by age, there is evidence of glass ceilings in all of the cases. For the youngest age groups, the 90th percentile is at least 2 points higher with respect to all the other quantiles (see table 18). Here, the wage gap at the top of the distribution reaches the highest values (14.8% for the 25-35 group and 16.9% for the 36-49 group). In the case of individuals aged between 50 and 65 years old, the 90th percentile is found to be more than 2 points higher only compared to the median (9% against 5%).

When comparing groups divided by education, evidence of sticky of floors is found for women with low education while women with higher levels of education face the presence of glass ceilings. Specifically, for low educated women the estimate at the 10th percentile is more than 2 points higher when compared to both the 25th percentile and the median (see table 19). In the case of women with a high school diploma and women with a college education, the estimate at the 90th percentile is the highest compared to all the other estimates along the wage distribution (17.1% and 19.1% respectively).

Looking at the estimates of the gender pay gap for the groups divided by the presence of a co-habiting partner, evidence of glass ceilings is found in both cases. The estimate at the 90th percentile is found to be at least 2 points higher than all the other quantiles (see Table 20).

A similar result is found when dividing the sample by number of children, there is also evidence of glass ceilings for all groups of interest. The estimated gender pay gap at the 90th percentile for the groups of individuals with children is more than 2 points higher than the estimates for all the other quantiles (see Table 21).

3.3 Regressions by gender

In the previous section, the gender wage gap was estimated under the assumption that the relation between wages and control variables is gender-invariant. The economic literature has emphasized the limitations of this approach given that observable characteristics such as age, education, marital status and presence of children have been showed to have different effects on the wages of men and women. For instance, women are more likely to interrupt their working careers due to family responsibilities which affects their human capital development and therefore also their level of wages. Due to these interruptions, age is only a good proxy for experience in the case of men.

In order to overcome this issue, it is necessary to allow the wage variation associated with each control variable to be gender specific. To do this, OLS and quantile regressions are estimated separately by gender allowing for the full set of explanatory variables (excluding the gender dummy).

Looking at the results of the separate regressions (see Tables 23 & 24), it is possible to discern that there is a gender difference in labor market returns for some characteristics, namely, education, area of residence, industry, occupation, type of contract, sector of employment and years of tenure.

With respect to education, the coefficients for men with a low or middle education level are always negative and for the most part larger than the corresponding coefficients for women. Men without a college education are penalized harder than women without a college degree, particularly in the upper half of distribution (e.g. low educated men at the 75th percentile earn 53.9% less compared to highly educated men while the difference for women at the same point of the wage distribution is 44.5%).

With respect to the area of residence, living in urban areas has a positive relation with wages that is always significant in the case of women. On the other hand, the coefficients for men are found to be either not significant or lower than the corresponding coefficients for women.

Table 23. OLS and quantile regressions for women in the overall sample.

VARIABLES	(1) OLS	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Dum2010	0.066***	0.033	0.047	0.071***	0.065*	0.080
	(0.025)	(0.047)	(0.030)	(0.024)	(0.034)	(0.054)
Dum2011	0.093***	0.051	0.070**	0.116***	0.121***	0.085*
	(0.024)	(0.045)	(0.032)	(0.024)	(0.028)	(0.052)
Dum2012	0.237***	0.218***	0.242***	0.241***	0.242***	0.233***
	(0.024)	(0.047)	(0.030)	(0.022)	(0.028)	(0.049)
Dum2013	0.248***	0.202***	0.231***	0.261***	0.272***	0.278***
	(0.023)	(0.042)	(0.030)	(0.022)	(0.028)	(0.048)
Dum2014	0.338***	0.305***	0.348***	0.353***	0.341***	0.324***
	(0.023)	(0.042)	(0.030)	(0.023)	(0.028)	(0.052)
Dum2015	0.324***	0.301***	0.320***	0.337***	0.345***	0.334***
	(0.022)	(0.042)	(0.028)	(0.023)	(0.027)	(0.049)
Age	0.016***	0.010	0.018**	0.014**	0.011*	0.006
	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Agesq	-0.000**	-0.000	-0.000**	-0.000*	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dum_IllPriMdS	-0.393***	-0.351***	-0.316***	-0.340***	-0.445***	-0.527***
	(0.021)	(0.035)	(0.025)	(0.023)	(0.028)	(0.037)
Dum_HighSTech	-0.265***	-0.158***	-0.171***	-0.220***	-0.339***	-0.455***
	(0.014)	(0.023)	(0.017)	(0.015)	(0.019)	(0.028)
Dum_Partner	0.082***	0.087***	0.081***	0.074***	0.080***	0.071***
	(0.012)	(0.020)	(0.015)	(0.012)	(0.015)	(0.021)
Dum_1child	0.005	-0.009	0.015	0.013	0.015	-0.017
	(0.016)	(0.031)	(0.019)	(0.016)	(0.020)	(0.027)
Dum_Children	0.011	0.012	0.013	0.009	0.018	0.023
	(0.015)	(0.030)	(0.019)	(0.016)	(0.019)	(0.029)
Dum_OlderAdult	-0.034**	-0.018	-0.023	-0.040**	-0.053**	-0.072**
	(0.017)	(0.034)	(0.021)	(0.018)	(0.022)	(0.033)
Dum_Urban	0.112***	0.106***	0.089***	0.085***	0.107***	0.148***
	(0.016)	(0.028)	(0.021)	(0.016)	(0.019)	(0.026)
Dum_RCFSS	0.002	0.096***	0.024	0.009	-0.058*	-0.130***
	(0.025)	(0.034)	(0.037)	(0.028)	(0.034)	(0.043)
Dum_WhiteC	-0.311***	-0.238***	-0.315***	-0.297***	-0.297***	-0.338***
	(0.015)	(0.023)	(0.018)	(0.016)	(0.021)	(0.030)
Dum_BlueCUnsk	-0.423***	-0.318***	-0.410***	-0.408***	-0.422***	-0.494***
	(0.020)	(0.033)	(0.026)	(0.023)	(0.025)	(0.038)
Dum_Size5dw	-0.167***	-0.213***	-0.141***	-0.148***	-0.133***	-0.169***
	(0.018)	(0.034)	(0.022)	(0.020)	(0.022)	(0.035)
Dum_Size620	-0.056***	-0.064***	-0.020	-0.050***	-0.075***	-0.113***
	(0.014)	(0.023)	(0.017)	(0.014)	(0.019)	(0.027)
Dum_Fixedcontr	-0.192***	-0.273***	-0.202***	-0.174***	-0.128***	-0.139***
	(0.017)	(0.028)	(0.019)	(0.018)	(0.022)	(0.033)
Dum_Verbalcontr	-0.433***	-0.620***	-0.514***	-0.419***	-0.330***	-0.273***
	(0.021)	(0.038)	(0.025)	(0.024)	(0.025)	(0.038)

Dum_Public	-0.003	0.026	0.004	0.005	0.002	-0.022
	(0.014)	(0.023)	(0.016)	(0.016)	(0.017)	(0.025)
Totaltenure	0.005***	0.005***	0.007***	0.005***	0.005***	0.004**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	9.055***	8.518***	8.665***	9.029***	9.452***	9.994***
	(0.101)	(0.138)	(0.141)	(0.114)	(0.122)	(0.160)
Observations	8,656	8,656	8,656	8,656	8,656	8,656
R-squared	0.534	0.522	0.530	0.534	0.529	0.512

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Women working in the tertiary sector are found to earn lower wages than those working in the secondary sector at the top of the distribution (-13% at the 90th percentile). The coefficient at the 10th percentile, however is positive and reaches 9.6%. In the case of men, the relation with wages is negative and significant only at the 10th and 75th percentile (-3.5% and -2.7% respectively).

Regarding the choice of occupation, white and blue collars workers are found to earn lower wages than managers and the coefficients are always negative. In the case of men, coefficients for white collar are larger than those for women across the entire wage distribution. White collar men earn on average 38% less than managers while white collar women earn 31.1% less. The coefficients for blue collar are similar for men and women at the top and the bottom of the distribution and higher for women at the rest of the quantiles (25th, 50th and 75th).

With respect to the type of contract, women with either a verbal or a fixed contract earn significantly lower than those with a permanent contract. The coefficients are also always larger than the corresponding coefficients for men (e.g. women with a verbal contract earn on average 43.3% less than women with a permanent contract while the difference is 30.3% in the case of men).

Working for the public sector has a positive and significant relation with wages for most of the wage distribution (except the 90th percentile) in the case of men. For women, however, the coefficients are never significant.

Finally, years of tenure have small positive coefficients for both men and women that are significant all along the wage distribution. The coefficients are found to be slightly higher for men at the top of the distribution (0.9% against 0.4%).

Table 24. OLS and quantile regressions for men in the overall sample.

VARIABLES	(1) OLS	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Dum2010	0.093***	0.095***	0.099***	0.094***	0.082***	0.084**
	(0.021)	(0.030)	(0.023)	(0.022)	(0.028)	(0.035)
Dum2011	0.160***	0.135***	0.166***	0.175***	0.174***	0.173***
	(0.022)	(0.034)	(0.024)	(0.022)	(0.026)	(0.034)
Dum2012	0.268***	0.294***	0.262***	0.269***	0.262***	0.260***
	(0.020)	(0.032)	(0.023)	(0.022)	(0.027)	(0.031)
Dum2013	0.288***	0.265***	0.282***	0.285***	0.282***	0.295***
	(0.021)	(0.032)	(0.023)	(0.021)	(0.026)	(0.036)
Dum2014	0.360***	0.355***	0.363***	0.351***	0.354***	0.374***
	(0.021)	(0.032)	(0.023)	(0.020)	(0.028)	(0.033)
Dum2015	0.371***	0.362***	0.342***	0.369***	0.355***	0.395***
	(0.020)	(0.030)	(0.024)	(0.020)	(0.025)	(0.037)
Age	0.023***	0.012*	0.020***	0.020***	0.026***	0.025***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.005)	(0.007)
Agesq	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dum_IllPriMdS	-0.458***	-0.334***	-0.381***	-0.432***	-0.539***	-0.614***
	(0.019)	(0.029)	(0.021)	(0.021)	(0.026)	(0.040)
Dum_HighSTech	-0.316***	-0.187***	-0.234***	-0.289***	-0.410***	-0.460***
	(0.015)	(0.024)	(0.017)	(0.017)	(0.023)	(0.035)
Dum_Partner	0.105***	0.076***	0.096***	0.086***	0.092***	0.121***
	(0.013)	(0.020)	(0.015)	(0.014)	(0.018)	(0.023)
Dum_1child	-0.022	-0.002	-0.017	-0.021	-0.025	-0.027
	(0.015)	(0.024)	(0.016)	(0.014)	(0.019)	(0.027)
Dum_Children	-0.019	0.013	-0.011	-0.025*	-0.020	-0.019
	(0.014)	(0.023)	(0.016)	(0.014)	(0.018)	(0.023)
Dum_OlderAdult	-0.071***	0.006	-0.034*	-0.063***	-0.100***	-0.101***
	(0.016)	(0.025)	(0.018)	(0.017)	(0.020)	(0.030)
Dum_Urban	0.071***	0.029	0.063***	0.082***	0.089***	0.039
	(0.013)	(0.021)	(0.015)	(0.013)	(0.016)	(0.024)
Dum_RCFSS	-0.039***	-0.035*	-0.014	-0.018	-0.027*	-0.038
	(0.013)	(0.019)	(0.014)	(0.013)	(0.015)	(0.024)
Dum_WhiteC	-0.380***	-0.360***	-0.366***	-0.363***	-0.372***	-0.430***
	(0.016)	(0.024)	(0.018)	(0.017)	(0.022)	(0.035)
Dum_BlueCUnsk	-0.392***	-0.315***	-0.322***	-0.344***	-0.405***	-0.505***
	(0.017)	(0.023)	(0.018)	(0.016)	(0.023)	(0.037)
Dum_Size5dw	-0.167***	-0.190***	-0.139***	-0.128***	-0.143***	-0.180***
	(0.014)	(0.022)	(0.015)	(0.014)	(0.018)	(0.026)
Dum_Size620	-0.065***	-0.041**	-0.034**	-0.056***	-0.082***	-0.105***
	(0.012)	(0.018)	(0.015)	(0.013)	(0.017)	(0.024)
Dum_Fixedcontr	-0.151***	-0.194***	-0.169***	-0.150***	-0.124***	-0.091***
	(0.014)	(0.019)	(0.015)	(0.015)	(0.020)	(0.030)
Dum_Verbalcontr	-0.303***	-0.415***	-0.312***	-0.279***	-0.237***	-0.235***
	(0.016)	(0.023)	(0.017)	(0.015)	(0.020)	(0.031)

Dum_Public	0.038***	0.046**	0.062***	0.053***	0.043***	0.019
	(0.013)	(0.021)	(0.017)	(0.013)	(0.016)	(0.026)
Totaltenure	0.006***	0.003***	0.006***	0.006***	0.007***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	9.077***	8.700***	8.726***	9.034***	9.324***	9.753***
	(0.086)	(0.134)	(0.099)	(0.091)	(0.110)	(0.150)
Observations	11,868	11,868	11,868	11,868	11,868	11,868
R-squared	0.412	0.394	0.408	0.410	0.407	0.404

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Estimating separate regressions by gender is equivalent to add a full set of interaction terms between gender and the other explanatory variables to the specification of the model and estimate it on a pooled sample of men and women (see Appendix, Table 1). The advantage of this last approach is that it allows to test the joint significance of the interaction terms to assess whether the role of the control variables varies with gender. If the null hypothesis that all of these interaction terms are jointly equal to zero is rejected, the role of these variables can be said to be gender-specific. What's more, in this pooled specification of the model, the gender gap varies with the explanatory variables by construction since the gender dummy interacts with all of them.

Table 25 shows the results of the test of equality of coefficients across genders for both OLS and quantile regressions. In all the cases, the null hypothesis that all the interaction terms are jointly equal to zero is rejected. Therefore, it is possible to say that the role of the control variables included in the wage equations varies across genders.

Table 25. Result of the test of equality of coefficients[5].

	OLS	10th	25th	50th	75th	90th
P-value	0.000	0.000	0.000	0.000	0.000	0.001

Next, the coefficient estimates produced by the separate regressions are used in a prediction exercise of the gender wage gap. The goal is to calculate the gender wage gap between a man and a woman sharing the same characteristics and allowing these

[5]The p-value is associated with the test of joint significance of the coefficients on the interaction terms in the pooled specification of the model.

characteristics to be rewarded differently. The profile of common observable characteristics to be shared by the representative man and woman are defined by looking at the median values of all control variables in the overall sample pooling men and women together.

Table 26 describes the profile of representative workers in the overall sample. The representative individual is aged 37 years old, has a middle education level, lives with a partner, has two or more children, does not live with an older adult, resides in an urban area, works in a blue collar job for a small private firm in the tertiary sector, has a verbal contract and has been working in the same job for 5 years.

Table 26. Profile of the representative worker in the overall sample.

Control variables	**Sample median**
Year	2015
Age	37
Age squared	1,369
Education	Middle education
Partner	With a partner
Number of children	Two or more
Presence of older adults	No
Area	Urban
Occupation	Blue Collar
Industry	Tertiary sector
Size of establishment	Up to 5 people
Type of contract	Verbal
Sector	Private
Tenure	5

Wages of men and women are fit based on the gender specific specifications by setting the explanatory variables according to this profile of characteristics defined by the median values in the sample. Their difference gives the estimation of the gender pay gap and a statistical test is carried out to assess its significance. This approach is used both for OLS and quantile regressions.

Table 27 presents the estimated gender wage gap between a representative man and woman in the overall sample. The predicted average gender wage gap is significant and reaches 21%, almost a double of the estimated average gender wage gap when assuming a gender-invariant role of covariates in wage determination, which reaches 11.1% (see Table 16). Looking at the variation across the wage distribution, all estimates are found to be significant but do not present a clear pattern. Additionally, all estimates are higher than in the previous estimation where the gender gap was found to have an increasing pattern across the wage distribution. Based on this result, we can say that allowing for gender differences in observable characteristics and in their returns in the labor market is not sufficient to explain the existence of a gender pay gap in the overall sample.

Table 27. Predicted gender wage gap for the overall sample[6].

	OLS	10th	25th	50th	75th	90th
Gender Wage Gap	-0.21	-0.187	-0.229	-0.232	-0.186	-0.210
Standard Error	0.03	0.054	0.034	0.030	0.034	0.052
P-Value	0.00	0.001	0.000	0.000	0.000	0.000

3.4 Regressions by gender and socioeconomic groups.

The same procedure described in the previous section is now replicated both in terms of the estimation and for the definition of the profile of the representative worker by splitting the sample in groups defined by age, education, partner and number of children. Gender-specific OLS and quantile regressions are estimated for each group of interest and the profile of the representative worker is group-specific.

Next, the profile of representative workers for each group will be presented as well as the results obtained when calculating the predicted gender pay gap.

First, the sample was split by age groups. Table 28 shows the distribution of covariates among the three different groups defined: 25-35, 36-49 and 50-65. The profile of the representative workers coincides in the year of interview, presence of a partner and older adults, occupation, industry, size of the firm, sector of employment and area of residence. In all the cases, the individuals were interviewed in 2015, live with a partner in urban areas and work in blue collar jobs in small private firms dedicated to retail, communications and social services.

Differences are found in the level of education, with the older worker being less educated than his or her younger peers. With respect to the number of children, the oldest worker does not live with children under 18 years of age. The younger workers,

[6] Standard errors and p-values are associated with the significance test of the gender pay gap based on the pooled specification with interaction terms.

however, have two or more children. Regarding the type of contract, it is permanent for the age group 36-49 while the older and younger group have a verbal contract.

Table 28. Profile of representative workers for subsamples divided by age groups.

Control variables	**25-35**	**36-49**	**50-65**
Year	2015	2015	2015
Age	30	42	54
Age squared	900	1,764	2,916
Education	Middle education	Middle education	Low education
Partner	With a partner	With a partner	With a partner
Number of children	Two or more	Two or more	No children
Presence of older adults	No	No	No
Area	Urban	Urban	Urban
Occupation	Blue Collar	Blue Collar	Blue Collar
Industry	Tertiary sector	Tertiary sector	Tertiary sector
Size of establishment	Up to 5 people	Up to 5 people	Up to 5 people
Type of contract	Verbal	Permanent	Verbal
Sector	Private	Private	Private
Tenure	3	7	10

Table 29 presents the results obtained when predicting the gender pay gap in subsamples divided by age groups. Starting with the group of individuals aged between 25 and 35 years old, the estimated average gender wage gap is significant and reaches 18.9%, around 8 points higher that when equal returns to covariates is assumed (see Table 18). Looking at the variation across the wage distribution, the gender gap is always significant and higher than in the previous estimation. The pattern also changes, here the gender gap presents a decreasing pattern until the 75th percentile while before it was increasing from the 25th percentile to the top of the distribution.

For the age group comprised of individuals between 36 and 49 years old, the estimated gender wage gap is found to be significant only at the top of the distribution. This result differs from the one encountered before where the gender wage gap was always significant and increasing along the wage distribution (see Table 18). Nevertheless, the predicted gender wage gap at the 90th percentile is considerably higher than one estimated before (26.6% against 16.9%).

Table 29. Predicted gender pay gap by age groups[7].

	OLS	10th	25th	50th	75th	90th
25-35						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.189	-0.227	-0.198	-0.168	-0.123	-0.146
Standard Error	0.041	0.078	0.050	0.048	0.049	0.078
P-Value	0.000	0.004	0.000	0.001	0.012	0.063
36-49						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.089	0.038	-0.021	-0.078	-0.091	-0.266
Standard Error	0.057	0.126	0.065	0.062	0.077	0.115
P-Value	0.120	0.760	0.746	0.206	0.240	0.021
50-65						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.187	-0.236	-0.251	-0.277	-0.199	-0.048
Standard Error	0.071	0.138	0.094	0.080	0.086	0.114
P-Value	0.008	0.088	0.008	0.001	0.021	0.675

On the other hand, for the oldest age group, the gender wage gap is found to be significant until the 75th percentile, contrary to the previous estimation assuming equal returns to characteristics where it was significant starting from the median. Additionally, the average gender gap is much higher than before (18.7% against 5.6%). The same applies when comparing results across the wage distribution.

Next, education groups are considered. Table 30 describes the profile of representative workers for each education group. Coincidences are found in the year of interview, presence of a partner and older adult, number of children, area of residence, sector of employment and industry. In all the cases, the individuals were interviewed in 2015, live in urban areas with a partner, have two or more children and work for private firms in the tertiary sector.

Considering the median of age among education groups, it is possible to discern that the workers with higher levels of education are younger. With respect to the occupation and size of the firm, the low and middle educated individuals work in small firms as blue collar or unskilled workers while the high educated individuals work in high-skilled jobs in firms with 21 or more employees. Regarding the type of contract and years of tenure, no differences are found between the middle and the high

[7]The standard error and p-value are associated with the significance test of the gender pay gap in the pooled specification with interaction terms estimated for each group.

educated workers. On the other hand, the low educated individual has less years of tenure and has a verbal contract instead of a permanent one.

Table 30. Profile of representative workers for subsamples divided by education groups.

Control variables	**Low education**	**Middle education**	**High education**
Year	2015	2015	2015
Age	41	36	33
Age squared	1681	1,296	1,089
Partner	With a partner	With a partner	With a partner
Number of children	Two or more	Two or more	Two or more
Presence of older adults	No	No	No
Area	Urban	Urban	Urban
Occupation	Blue Collar	Blue Collar	Managers
Industry	Tertiary sector	Tertiary sector	Tertiary sector
Size of establishment	Up to 5 people	Up to 5 people	21 or more
Type of contract	Verbal	Permanent	Permanent
Sector	Private	Private	Private
Tenure	3	5	5

Table 31 presents the estimated gender wage gap for OLS and quantile regressions as well as the results of the significance test in subsamples divided by education. Starting with the low education group, the average gender wage gap is found to be significant and higher than the estimate obtained when assuming equal returns to covariates (20.7% against 13.2%, see Table 19) . Looking at the variation across the wage distribution, the gender wage gap is found to be significant everywhere except at the top of the distribution (90th percentile) and the estimates are higher than for the previous estimation.

For the second education group, the average gender wage gap is found to be significant and higher than the previous estimation by about 3% (9.7% against 12.7%, see Table 19). Nevertheless, when looking at the expected outcomes across the wage distribution, the gender wage gap is found to be significant starting from the median. In contrast, when assuming equal returns to covariates the gender gap was always significant. Based on this comparison, it is possible to say that gender differences in labor market returns might be able explain the gender wage gap at the bottom of the distribution for individuals in the 36-49 group.

Table 31. Predicted gender pay gap in subsamples divided by education.[8]

Low education						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.207	-0.298	-0.240	-0.205	-0.208	-0.207
Standard Error	0.057	0.124	0.079	0.067	0.053	0.132
P-Value	0.000	0.017	0.002	0.002	0.000	0.117
Middle education						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.127	-0.010	-0.012	-0.136	-0.099	-0.221
Standard Error	0.044	0.090	0.059	0.049	0.056	0.082
P-Value	0.004	0.909	0.833	0.006	0.080	0.007
High education						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.056	0.064	-0.049	-0.060	-0.110	-0.093
Standard Error	0.051	0.083	0.068	0.059	0.085	0.114
P-Value	0.269	0.436	0.474	0.312	0.195	0.416

In the case of individuals with a college education, the estimated gender wage gap between a representative man and woman is found to be not significant both for OLS and quantile regressions. In contrast, when returns to covariates were restricted to be gender-invariant, the gender wage gap was always significant (see Table 19). This indicates that for highly educated individuals, there is no evidence that differences in labor market rewards for men and women generate wage differentials.

Next, the sample was split in groups considering the presence of a co-habiting partner. Table 32 describes the profile of representative workers for subsamples divided by marital status. Coincidences are found in the year of interview, level of education, presence of older adults, area of residence occupation, industry, size of the firm, type of contract and sector of employment. Representative individuals were interviewed in 2015, they do not cohabite with an older adult, they reside in urban areas and work as blue collar in small private firms belonging to the tertiary sector. With respect to age and tenure, the median values are lower for the group without a partner. The representative worker with a partner has two or more children. On the contrary, the representative individual without a partner does not have children.

[8] The standard error and p-value are associated with the significance test of the gender pay gap in the pooled specification with interaction terms estimated for each group.

Table 32. Profile of representative workers for subsamples divided by presence of a partner.

Control variables	**With a partner**	**No partner**
Year	2015	2015
Age	38	33
Age squared	1,444	1,089
Education	Middle education	Middle education
Number of children	Two or more	No children
Presence of older adults	No	No
Area	Urban	Urban
Occupation	Blue Collar	Blue Collar
Industry	Tertiary sector	Tertiary sector
Size of establishment	Up to 5 people	Up to 5 people
Type of contract	Verbal	Verbal
Sector	Private	Private
Tenure	5	3

Table 33 presents the results obtained when predicting the gender pay gap in subsamples divided by marital status. For the group of individuals with a co-habiting partner, the average gender gap is found to be significant and higher than the previous estimation when assuming equal returns to covariates (20% against 11.9%, see Table 20). Looking at the variation across the wage distribution, the gender gap is found to be increasing (except at the 75th percentile) and the estimates are higher compared to the previous estimation.

Table 33. Predicted gender pay gap in subsamples divided by marital status[9].

With a partner						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.200	-0.196	-0.213	-0.224	-0.191	-0.230
Standard Error	0.034	0.058	0.042	0.038	0.041	0.067
P-Value	0.000	0.001	0.000	0.000	0.000	0.001
No partner						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.244	-0.208	-0.298	-0.247	-0.216	-0.181
Standard Error	0.051	0.098	0.067	0.054	0.059	0.086
P-Value	0.000	0.034	0.000	0.000	0.000	0.036

[9] The standard error and p-value are associated with the significance test of the gender pay gap in the pooled specification with interaction terms estimated for each group.

For the group without a co-habiting partner, the average gender gap is significant and higher than for the previous group. When looking at the wage distribution, the gender gap presents a decreasing a pattern from the 25th percentile. This pattern is the opposite to the one found with the estimation assuming a gender-invariant role of covariates where the gender gap was increasing along the wage distribution and the estimates were lower, e.g. 14.6% at the 90th percentile (see Table 20) compared to 18.1.% (see Table 31).

Finally, the sample was split in groups considering the presence of children under 18 years of age in the household. Table 34 describes the profile of representative workers for the subsamples divided considering the number of children. No noticeable differences are found when looking at age and tenure. In all the cases, individuals were interviewed in 2015, they have a middle education level, they do not live with an older adult, they reside in urban areas and work as blue collar workers in small private companies that dedicate to the tertiary sector.

With respect to the presence of a partner, the representative worker with no children does not live with a partner. The opposite can be said for workers with children. Regarding the type of contract, the representative worker with one child has a permanent contract while the workers with more and no children have a verbal contract.

Table 34. Profile of representative workers for subsamples divided by number of children.

Control variables	**No children**	**One child**	**Two or more**
Year	2015	2015	2015
Age	37	35	37
Age squared	1,369	1,225	1,369
Education	Middle education	Middle education	Middle education
Partner	No partner	With a partner	With a partner
Presence of older adults	No	No	No
Area	Urban	Urban	Urban
Occupation	Blue Collar	Blue Collar	Blue Collar
Industry	Tertiary sector	Tertiary sector	Tertiary sector
Size of establishment	Up to 5 people	Up to 5 people	Up to 5 people
Type of contract	Verbal	Permanent	Verbal
Sector	Private	Private	Private
Tenure	5	5	5

Table 35 presents the predicted gender wage gap for the subsamples divided by number of children. Starting with the group of individuals without children, the gender wage gap is found to be always significant and reaches a peak at the median of the wage distribution. The estimates are found to be always higher than in the previous estimation where equal returns to characteristics was assumed, e.g. the average gender gap reaches 21.2% compared to 12.1% for the previous estimation (see Table 21). The variation across the wage distribution also changes, now instead of a constant increase, the gender gap increases until the median and then decreases.

For the group of individuals with one child, the predicted gender wage gap is found to be significant only at the median and higher by about 8% compared to the previous estimation (see Table 21). In contrast, the gender gap was significant across the entire wage distribution when the control variables were assumed to have a gender-invariant role in wage determination.

Table 35. Predicted gender pay gap in subsamples divided by number of children[10].

No children						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.212	-0.204	-0.198	-0.281	-0.243	-0.221
Standard Error	0.061	0.109	0.083	0.069	0.068	0.105
P-Value	0.001	0.060	0.017	0.000	0.000	0.035
One child						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.078	-0.048	-0.035	-0.134	-0.078	0.034
Standard Error	0.061	0.143	0.074	0.066	0.069	0.105
P-Value	0.204	0.739	0.633	0.042	0.260	0.749
Two or more children						
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Gender Wage Gap	-0.212	-0.157	-0.206	-0.203	-0.139	-0.222
Standard Error	0.038	0.060	0.052	0.044	0.046	0.067
P-Value	0.000	0.008	0.000	0.000	0.003	0.001

On the other hand, for the group with two or more children, the predicted wage gap is found to be always significant and presents higher values than the results obtained when assuming equal returns to covariates for both men and women. Nevertheless, the pattern of variation across the wage distribution differs among the two

[10] The standard error and p-value are associated with the significance test of the gender pay gap in the pooled specification with interaction terms estimated for each group.

estimations, namely, before the gender gap was found to be increasing while here the pattern of variation is less consistent.

A summary of the results of quantile regressions is presented at Table 36. Following Arulampalam et al. (2007), glass ceilings and sticky floors are defined to exist when the extreme quantiles exceed the reference gaps by at least 2 points. The 90th percentile is compared to the 75th percentile and the median and the 10th percentile is compared to the 25th percentile and the median.

Evidence of glass ceilings is found for the overall sample only when comparing the 75th and the 90th percentiles (18.6% and 21% respectively, see Table 27). Regarding the subsamples divided by age, there is evidence of sticky floors for the youngest age group measured by the difference between the 10th and both the 25th and 50th percentile (see Table 29). No clear pattern is found for the other two age groups.

Table 36. Summary of results for predicted gender wage gaps.

	Glass Ceilings measured by			Sticky Floors measured by	
	90th- all gaps	*90th-75th difference*	*90th-50th difference*	*10th-50th difference*	*10-25th difference*
Overall sample		*X*			
Age					
25-35				X	X
36-49					
50-65					
Education					
Low education				X	X
Middle education			X		
High education					
Partner					
With a partner		X			
No partner					
Children					
No child					
One child					
Two or more		X			

With respect to the education groups, sticky floors are found for individuals with low education for both definitions considered. On the other hand, for individuals with middle education there is evidence of glass ceilings only when comparing the gender gap estimates for the 50th and 90th percentiles (13.6% and 22.1% respectively, see Table 31).

Finally, for the subsamples divided by partner and number of children, there is evidence of glass ceilings only for women with a partner and women with two or more children (see Tables 33 & 35). In both cases, the definition only applies when considering the difference between the 90th and 75th percentile.

In conclusion, when predicting the gender pay gap for a man and woman sharing the same characteristics and allowing these characteristics to be rewarded differently by gender, there is still evidence of a wage differential across genders. It is noteworthy that the estimates for the predicted gender pay gap are usually higher than the ones obtained when assuming equal returns to covariates.

For the overall sample, the gender wage gap is found to be significant across the entire wage distribution. On the other hand, when splitting the sample in socioeconomic groups, the gender gap is still found to be significant for most of the groups with three exceptions: the age group 36-49, the high education group and the group of individuals with one child.

Conclusion

In this thesis, the gender pay gap in Paraguay was analyzed in order to determine whether it could be a way to rationalize the existence of a persistent gender gap in labor force participation. Women's decision to enter the labor force is based on a comparison between the returns offered by the labor market and the returns they can get from household activities (i.e. home production and childcare). Everything else constant, if women are offered lower wages than men, they might be more likely to stay out of the labor market and dedicate to home responsibilities. Multivariate OLS and quantile regressions were estimated allowing controls for an extensive set of observable characteristics. Additionally, the variation of the gender gap across the wage distribution was examined to look for patterns of glass ceilings and sticky floors.

First, the estimations were run in a pooled sample of men and women restricting the control variables to have a gender-invariant role in wage determination. The results show that a gender pay gap exists in Paraguay and it presents an increasing pattern across the wage distribution. The estimated gender pay gap reaches 6.8% at the bottom of the distribution and then goes up reaching its highest value at the top of the distribution (15.1%). Following Arulampalam et al. (2007), the evidence suggests the presence of glass ceilings. Therefore, cross-gender differences in socioeconomic, demographic and job-related characteristics are unable to account for the gender pay gap, which is found to be statistically significant along the entire wage distribution.

The same approach was replicated by splitting the sample in socioeconomic subgroups divided by age, education, partner and number of children. The results point out the existence of a gender pay gap for all the subgroups. Glass ceilings patterns are found for the subgroups divided by age, partner and children. In the case of education, sticky floors are found for low-educated women and glass ceilings for high-educated women.

Next, the assumption of equal returns to covariates was removed and wage regressions were estimated separately by gender. The results show that men and women are rewarded differently by the labor market for most of the individual characteristics considered. A prediction exercise of the gender pay gap was carried out based on a profile of representative workers defined considering the median values of characteristics in the sample. The predicted gender gap in the overall sample was found to be significant and higher compared to the previous estimation assuming equal returns.

The same approach was again replicated for the subsamples divided by age, education, partner and children. The gender pay gap was still found to be significant except for the group of individuals aged between 36 and 49 years old, the highly-educated individuals and the group with one child. Allowing observable characteristics to be rewarded differently produced in most of the cases higher estimates and changes in the pattern of the gender gap across the wage distribution.

Using alternative specifications, the gender gap in the overall sample was found to be sizeable and statistically significant along the whole wage distribution. Based on this result, we can say that the gender pay gap is an issue in the Paraguayan labor market and it qualifies as one of the possible explanations of the gender gap in labor force participation. The estimates obtained show that everything else constant, women receive lower wages than men. It is noteworthy that in Paraguay there are not extensive public policies to support family responsibilities, which are typically managed by women. If women decide to enter the labor force, these services should be bought in the market. Therefore, everything else constant, the gender wage gap increases the probability of women to decide to stay out of the labor market.

The use of quantile regressions is motivated by the fact that there might be unobserved heterogeneity in individual characteristics such as abilities, ambition and labor market attachment along the wage distribution. As a consequence, analyzing the gender gap in different parts of the wage distribution is a way to allow it to vary along the distribution of these unobserved determinants of wages.

The existence of glass ceilings in the overall sample points out that there is limit for women's prospect in the labor market, since they are not able to access the higher positions. Patterns of sticky floors for low-educated individuals suggest that women in low-paid jobs are penalized harder than men. In this sense, sticky floors can be especially relevant to explain decisions of opting out of the labor market. Women at the bottom of the wage distribution are likely to have low levels of human capital investment and labor market attachment. This group of women is at the margin. In other words, lower wages might induce them to stay out of the labor market.

A gender gap in wages and labor force participation might have negative consequences for the human capital accumulation of the country and affect its possibilities of economic growth. If women receive equal wages compared to men, they will have more incentives to invest in education, work more hours and choose high-skilled occupations. What's more, higher levels of education of women are usually associated with better education and health of children, all of which contribute to the economic development of a country.

Economic growth requires equal opportunities across genders in terms of education, access and labor market opportunities but also a legislation preventing gender discrimination. In this sense, the Paraguayan Labor Code establishes some basic rights for working women: the right to receive an equal pay for equal work and some rights related to maternity, namely, periods of parental leave (12 weeks for women and 2 days for men during the period 2009-2015), protection of their work stability during and after the pregnancy and the obligation for firms with 50 or more employees to provide a daycare service for children under 2 years old. Nevertheless, there is still a need for further inclusion of gender equality considerations in the Paraguayan legislation in order to guarantee an equal treatment of men and women in the labor market.

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Appendix

Table 1. OLS and quantile regressions with interaction terms in the overall sample.

VARIABLES	(1) OLS	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Dum_Gender	-0.023	-0.182	-0.061	-0.005	0.128	0.240
	(0.130)	(0.202)	(0.176)	(0.143)	(0.167)	(0.211)
Dum2010	0.093***	0.095***	0.099***	0.094***	0.082***	0.084**
	(0.021)	(0.029)	(0.023)	(0.022)	(0.028)	(0.034)
Dum2011	0.160***	0.135***	0.166***	0.175***	0.174***	0.173***
	(0.022)	(0.033)	(0.025)	(0.022)	(0.025)	(0.034)
Dum2012	0.268***	0.294***	0.262***	0.269***	0.262***	0.260***
	(0.020)	(0.030)	(0.023)	(0.023)	(0.027)	(0.030)
Dum2013	0.288***	0.265***	0.282***	0.285***	0.282***	0.295***
	(0.021)	(0.030)	(0.024)	(0.022)	(0.026)	(0.037)
Dum2014	0.360***	0.355***	0.363***	0.351***	0.354***	0.374***
	(0.021)	(0.032)	(0.024)	(0.021)	(0.027)	(0.032)
Dum2015	0.371***	0.362***	0.342***	0.369***	0.355***	0.395***
	(0.020)	(0.028)	(0.024)	(0.020)	(0.025)	(0.039)
Age	0.023***	0.012*	0.020***	0.020***	0.026***	0.025***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.007)
Agesq	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dum_IllPriMdS	-0.458***	-0.334***	-0.381***	-0.432***	-0.539***	-0.614***
	(0.019)	(0.030)	(0.021)	(0.021)	(0.026)	(0.043)
Dum_HighSTech	-0.316***	-0.187***	-0.234***	-0.289***	-0.410***	-0.460***
	(0.015)	(0.024)	(0.017)	(0.017)	(0.023)	(0.040)
Dum_Partner	0.105***	0.076***	0.096***	0.086***	0.092***	0.121***
	(0.013)	(0.019)	(0.016)	(0.014)	(0.017)	(0.024)
Dum_1child	-0.022	-0.002	-0.017	-0.021	-0.025	-0.027
	(0.015)	(0.024)	(0.017)	(0.014)	(0.019)	(0.029)
Dum_Children	-0.019	0.013	-0.011	-0.025*	-0.020	-0.019
	(0.014)	(0.022)	(0.016)	(0.014)	(0.018)	(0.024)
Dum_OlderAdult	-0.071***	0.006	-0.034*	-0.063***	-0.100***	-0.101***
	(0.016)	(0.024)	(0.019)	(0.017)	(0.020)	(0.030)
Dum_Urban	0.071***	0.029	0.063***	0.082***	0.089***	0.039
	(0.013)	(0.021)	(0.015)	(0.014)	(0.016)	(0.024)
Dum_RCFSS	-0.039***	-0.035*	-0.014	-0.018	-0.027*	-0.038
	(0.013)	(0.019)	(0.014)	(0.013)	(0.015)	(0.025)
Dum_WhiteC	-0.380***	-0.360***	-0.366***	-0.363***	-0.372***	-0.430***
	(0.016)	(0.024)	(0.017)	(0.017)	(0.021)	(0.037)
Dum_BlueCUnsk	-0.392***	-0.315***	-0.322***	-0.344***	-0.405***	-0.505***
	(0.017)	(0.024)	(0.017)	(0.017)	(0.023)	(0.037)
Dum_Size5dw	-0.167***	-0.190***	-0.139***	-0.128***	-0.143***	-0.180***
	(0.014)	(0.022)	(0.015)	(0.014)	(0.018)	(0.025)
Dum_Size620	-0.065***	-0.041**	-0.034**	-0.056***	-0.082***	-0.105***
	(0.012)	(0.017)	(0.014)	(0.013)	(0.017)	(0.024)
Dum_Fixedcontr	-0.151***	-0.194***	-0.169***	-0.150***	-0.124***	-0.091***
	(0.014)	(0.019)	(0.015)	(0.014)	(0.020)	(0.031)
Dum_Verbalcontr	-0.303***	-0.415***	-0.312***	-0.279***	-0.237***	-0.235***

	(0.016)	(0.023)	(0.017)	(0.015)	(0.020)	(0.031)
Dum_Public	0.038***	0.046**	0.062***	0.053***	0.043***	0.019
	(0.013)	(0.021)	(0.017)	(0.013)	(0.016)	(0.030)
Totaltenure	0.006***	0.003***	0.006***	0.006***	0.007***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dum_Gender_Dum2010	-0.027	-0.062	-0.052	-0.024	-0.016	-0.004
	(0.031)	(0.057)	(0.037)	(0.030)	(0.043)	(0.056)
Dum_Gender_Dum2011	-0.067**	-0.083	-0.096**	-0.059*	-0.053	-0.088
	(0.031)	(0.059)	(0.040)	(0.031)	(0.036)	(0.055)
Dum_Gender_Dum2012	-0.031	-0.076	-0.021	-0.027	-0.020	-0.027
	(0.030)	(0.059)	(0.037)	(0.030)	(0.038)	(0.050)
Dum_Gender_Dum2013	-0.040	-0.062	-0.050	-0.024	-0.010	-0.017
	(0.030)	(0.055)	(0.036)	(0.029)	(0.037)	(0.053)
Dum_Gender_Dum2014	-0.021	-0.050	-0.015	0.002	-0.013	-0.050
	(0.030)	(0.054)	(0.037)	(0.030)	(0.038)	(0.054)
Dum_Gender_Dum2015	-0.047	-0.061	-0.021	-0.033	-0.010	-0.062
	(0.029)	(0.052)	(0.034)	(0.029)	(0.036)	(0.056)
Dum_Gender_Age	-0.007	-0.002	-0.002	-0.006	-0.015*	-0.019*
	(0.006)	(0.011)	(0.009)	(0.007)	(0.008)	(0.010)
Dum_Gender_Agesq	0.000	0.000	0.000	0.000	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dum_Gender_Dum_IllPriMdS	0.065**	-0.017	0.065**	0.092***	0.094**	0.087
	(0.028)	(0.049)	(0.033)	(0.031)	(0.038)	(0.055)
Dum_Gender_Dum_HighSTech	0.050**	0.030	0.063***	0.069***	0.071**	0.005
	(0.020)	(0.035)	(0.023)	(0.022)	(0.029)	(0.047)
Dum_Gender_Dum_Partner	-0.023	0.012	-0.016	-0.011	-0.012	-0.050
	(0.017)	(0.029)	(0.022)	(0.018)	(0.022)	(0.031)
Dum_Gender_Dum_1child	0.028	-0.007	0.032	0.034	0.040	0.010
	(0.021)	(0.041)	(0.024)	(0.021)	(0.027)	(0.038)
Dum_Gender_Dum_Children	0.031	-0.001	0.024	0.034	0.037	0.042
	(0.020)	(0.039)	(0.024)	(0.021)	(0.025)	(0.035)
Dum_Gender_Dum_OlderAdult	0.037	-0.025	0.011	0.023	0.047	0.029
	(0.023)	(0.044)	(0.028)	(0.025)	(0.029)	(0.040)
Dum_Gender_Dum_Urban	0.041**	0.077**	0.026	0.003	0.018	0.110***
	(0.020)	(0.034)	(0.026)	(0.020)	(0.024)	(0.033)
Dum_Gender_Dum_RCFSS	0.041	0.131***	0.038	0.028	-0.030	-0.092*

	(0.027)	(0.043)	(0.039)	(0.029)	(0.035)	(0.048)
Dum_Gender_Dum_WhiteC	0.070***	0.122***	0.051**	0.066***	0.075**	0.092**
	(0.022)	(0.034)	(0.025)	(0.023)	(0.031)	(0.046)
Dum_Gender_Dum_BlueCUnsk	-0.031	-0.003	-0.088***	-0.064**	-0.017	0.011
	(0.026)	(0.043)	(0.031)	(0.027)	(0.034)	(0.051)
Dum_Gender_Dum_Size5dw	0.001	-0.023	-0.002	-0.020	0.009	0.010
	(0.022)	(0.043)	(0.026)	(0.023)	(0.027)	(0.040)
Dum_Gender_Dum_Size620	0.009	-0.023	0.014	0.006	0.007	-0.008
	(0.018)	(0.030)	(0.022)	(0.018)	(0.024)	(0.034)
Dum_Gender_Dum_Fixedcontr	-0.042*	-0.079**	-0.034	-0.025	-0.005	-0.048
	(0.021)	(0.035)	(0.023)	(0.022)	(0.029)	(0.043)
Dum_Gender_Dum_Verbalcontr	-0.130***	-0.205***	-0.201***	-0.140***	-0.093***	-0.039
	(0.026)	(0.048)	(0.031)	(0.027)	(0.032)	(0.046)
Dum_Gender_Dum_Public	-0.041**	-0.020	-0.058**	-0.047**	-0.041*	-0.041
	(0.018)	(0.034)	(0.023)	(0.019)	(0.024)	(0.037)
Dum_Gender_Totaltenure	-0.001	0.002	0.001	-0.000	-0.002	-0.004**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	9.077***	8.700***	8.726***	9.034***	9.324***	9.753***
	(0.086)	(0.127)	(0.099)	(0.090)	(0.107)	(0.150)
Observations	20,524	20,524	20,524	20,524	20,524	20,524
R-squared	0.468	0.452	0.462	0.467	0.462	0.452