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Female selection into employment along the earnings distribution.

María Eugenia Echeberría*

Resumen

En Uruguay, las tasas de empleo de las mujeres han aumentado en las últimas décadas, guiado principalmente por el aumento de la oferta laboral de las mujeres en pareja. Sin embargo, persiste una brecha de género significativa en el empleo, lo que señala la necesidad de corregir la selección muestral en estudios empíricos que abordan las brechas salariales. La literatura reciente que estudia las brechas salariales de género ha destacado la importancia de corregir la selección en el empleo a lo largo de la distribución de ingresos.

En este trabajo, estimo la brecha de género en ingresos a lo largo de la distribución, corrigiendo la selección en el empleo y observando su evolución con el tiempo. Basándome en la Encuesta Continua de Hogares para el período 2009-2019, aplico el modelo de corrección de sesgo de selección cuantílico propuesto por Arellano y Bonhomme (2017), para estimar las distribuciones de ingresos por hora corregidas por selección. Utilizo una medida de ingresos potenciales fuera del trabajo condicional a que el individuo no esté empleado como instrumento para corregir la selección en el empleo. Los resultados muestran que los patrones de selección varían según el estado civil. Las brechas potenciales en ingresos laborales son mayores que las brechas sin corregir en toda la distribución de ingresos para las personas que están en pareja, aunque mantienen la tendencia decreciente durante el período estudiado. La diferencia entre ambas distribuciones de ingresos es mayor para los cuantiles de menores ingresos, lo que sugiere la existencia de "suelos pegajosos". Por último, al considerar a las personas casadas y en unión libre por separado, encuentro que la selección de las mujeres en el empleo obedece a la selección de las mujeres casadas.

Palabras clave: brecha salarial de género, selección muestral, regresiones cuantílicas, techos de cristal, suelos pegajosos

Códigos JEL: C21, J16, J31

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Abstract

In Uruguay, women's employment rates have increased over recent decades, mostly driven by the increase of labour supply of women in couples. However, a significant gender employment gap remains, which reflects the need of correcting for sample selection in empirical wage gap studies. Recent literature studying gender wage gaps have highlighted the importance of correcting for selection into employment along the earnings distribution.

In this study, I estimate the evolution of the gender gap in earnings along the earnings distribution, correcting for selection into employment. Based on the Uruguayan household surveys, Encuesta Continua de Hogares, for the period 2009-2019, I apply the three-step quantile selection model proposed by Arellano and Bonhomme (2017)

to estimate the selection-corrected hourly earnings distributions. I use a measure of potential out-of-work income as an instrument to correct for selection into employment. Results show that selection patterns vary across marital statuses. Potential earnings gaps are greater than the uncorrected (raw) earnings gap for individuals in couples in all earnings quantiles, albeit maintaining a decreasing trend over the studied period. The difference between both earning distributions is larger for lower earnings quantiles, suggesting the existence of 'sticky floors'. Lastly, when considering married and cohabiting individuals separately, I find that women's selection into employment is driven by the selection of married women.

Keywords: gender wage gaps, sample selection, quantile regressions, glass ceiling, sticky floors

JEL Classification: C21, J16, J31

1 Introduction

Over recent decades, women's participation in the labour market has shown an increasing trend in western economies, which is related to multiple factors, including the feminist movement, scientific advancements in contraceptive methods, increasing levels of education, divorce rates, and the average age at which women marry. The increasing participation is also related to long-term career prospects for women, decisions regarding motherhood, and household decisions regarding the division of unpaid work, among other aspects. Simultaneously, women's improved prospects in the labour market enhanced their integration and, consequently, their wages, creating a virtuous circle (Goldin, 2006, 2021). However, the conditions and intensity of this participation vary between and within countries[1], with socioeconomic factors playing an important role.

Gender differences in wages can be partially explained by differences in labour market participation. While the majority of adult men work full-time, women's participation is strongly influenced by gender roles that traditionally assign them a greater share of unpaid tasks in the household. Factors such as educational level, motherhood, or marital status play a central role in explaining this gender difference in participation. This leads to women working on average less than men in both the extensive and the intensive margin.

Uruguay is not an exception to the changes observed in the Western economies. Between 1986 and 2010, Uruguay witnessed a significant increase in women's labour force participation rate, which was mainly guided by women in couples, who until then were mostly seen as secondary workers (Espino et al., 2014, 2009). In 2019, 81.4% of women aged 25 to 59 were participating in the labour market, while the participation of men was 93.3%, according to data from the National Institute of Statistics (INE). Regarding the gender pay gap, previous studies, such as Colacce et al. (2020), document a declining trend of the gender labour earnings gap. Nevertheless, in 2018, female workers in the private sector earned on average 29% less per month than their male counterparts, reflecting the persistence of the problem.

When comparing observed wages between men and women we are dealing with a case of selection bias. This happens because we observe wages only for employed individuals and, given the existent gender employment gaps, that leads to a comparison between a selected sample of women against a more representative sample of men. Two concepts of major relevance for this study can be distinguished, the potential and the observed wage gap. The potential gap is a hypothetical measure of the wage gap if

[1] As shown in Marchionni et al. (2019) for Latin America, the average participation rate of women aged 25 to 54 in 2015 was 65%, while this number was 50% in Guatemala, and 80% in the case of Uruguay.

everyone were employed, while the observed wage gap is conditional on employment. In particular, in full-time participation, women with high educational levels and unmarried status are over-represented (Bertrand, 2011; Blau and Kahn, 2007), which may lead to an underestimation of the wage gap compared to the potential gap.

Gender wage gaps show significant differences along the wage distribution (Albrecht et al., 2003; Blau and Kahn, 2017). At the extremes of the distribution, these differences are referred to as 'glass ceilings' and 'sticky floors'. Glass ceilings refer to the presence of explicit or invisible barriers, in this case for women, to access higher-ranking positions, and sticky floors denote the greater difficulty women experience in surpassing lower-paid jobs or positions, often due to limitations in their labour supply related to a heavy burden of unpaid work. This bias varies along the wage distribution, as does the participation gap (Ferber, 1982), and it is expected to vary over time, given that female and male employment rates have shown different trends in recent decades (Granados et al., 2020). Besides selection bias being a problem for empirical studies, correcting for selection into employment is important as observed wage gaps could be hiding larger inequalities. Also, when studying the evolution of the gender wage gap across time, it is crucial to account for selection, especially if there have been changes in the workforce composition.

In this study, I estimate the gender gap in earnings along the distribution, correcting for selection into employment and observing its evolution over time. I use the Uruguayan household surveys, Encuesta Continua de Hogares for the years 2009, 2014 and 2019.[2] I use the term 'earnings' along this study to refer to all labour income, as I include non-dependent, self-employed workers and employers in the analysis. Prior research for Uruguay estimating gender wage gaps along the distribution while correcting for selection into employment, are from the past decade (Borraz and Robano, 2010; Bucheli and Sanromán, 2004). This motivates estimations for more recent years and applying another, more recent, quantile selection model which have not yet been used in the study of the Uruguayan case.

To estimate the selection-corrected hourly earnings distribution, I apply the three-step quantile selection model proposed by Arellano and Bonhomme (2017). First, I estimate the probability of being employed through a Probit model. At least one instrumental variable is included in this equation, a variable that helps explain employment, without directly affecting potential earnings. I use a measure of potential out-of-work income, conditional on unemployment. Second, through a Copula function, the dependence between the error term from the employment and earnings equation is estimated. Third, the

[2]Since I include two non-contributory cash transfers in the instrumental variable implemented in 2006 and 2008, I chose 2009 as the first year of study to have a comparable instrumental variable along the studied period. On the other hand, the last year taken into account is 2019, since the COVID-19 pandemic affected the Uruguayan labour market in 2020. Further information about the studied period and the instrumental variable is available in Sections 3.2 and 4.3

quantile coefficients from the earnings estimation are shifted as a function of the amount of selection in each part of the distribution (measured through the copula function in step 2). Given differences found in previous literature for women's labour supply between different marital statuses, I carry out marital status-specific estimations (Binstock et al., 2016; Espino et al., 2009).

I find that female selection into employment is statistically significant, contrary to what happens to men. Potential earnings gaps are greater than the uncorrected (raw) earnings gap for individuals in couples for all earnings quantiles, especially in 2009. Furthermore, the difference between both earning distributions is larger on the left side of the distribution, indicating the existence of 'sticky floors'. The parameter of selection decreases between 2009 and 2014 as women's participation in the labour market increases and stays stable between 2014 and 2019. When considering married and cohabiting individuals separately, I find that women's selection into employment is explained by the selection of married women. This is new to the Uruguayan literature on gender pay gaps, as these groups are usually studied as a whole. This leaves an open question about what explains the difference between both groups. Beliefs regarding sexual division of labour, characteristics of women who choose marriage and women who choose cohabitation, anticipating behaviours regarding probabilities of dissolution of the union, are among the factors that may help to understand the different behaviour of married women.

The contribution of this study lies, on one hand, in the comparison of the potential and observed gender earnings gap, which offers further information on gender inequalities in the Uruguayan labour market. If working individuals are systematically different from non-working individuals, not correcting for selection leads to biased results. Additionally, estimating selection-corrected gaps along the earnings distribution shows whether inequalities are accentuated in particular earnings groups. Likewise, the comparison of the observed gap with the potential gap shows whether the selection bias is heterogeneous along the earnings distribution. Finally, I estimate gender gaps through the novel methodology proposed by Arellano and Bonhomme (2017). This approach has the challenge of finding an excluded instrument for participation. Unlike previous studies for Uruguay, which look at marital status, husband's income, or children in the household, I calculate an out-of-work potential income conditional on unemployment to be used as the excluded instrument, and estimate the corrected gap along the distribution for three points in time (2009, 2014, 2019).[3] This approach provides information in three dimensions: the comparison between the observed and corrected gaps, the evolution of the gap over time, and differences in selection along earnings distribution. Although this method has been applied in developed economies (Elass, 2022; Maasoumi and Wang, 2019) this is, up to my knowledge, the first application for a developing

[3]The robustness of the instrument is assessed by comparing the main results at the median with estimations applying the selection correction method proposed by Olivetti and Petrongolo (2008), which does not require an instrumental variable.

country, where female participation rates, institutional factors and labour market structures differ greatly.

2 Mechanisms that explain gender wage gaps

The existing literature studying the mechanisms behind gender wage gaps is extensive and dates back to the mid-20th century (Goldin and Rouse, 2000; Becker, 1971; Oaxaca, 1973). Ponthieux and Meurs (2015) identify four interrelated main mechanisms that explain gender wage gaps: gender discrimination, occupational segregation, psychological factors, and maternity penalty.

Gender discrimination refers to a lower remuneration of women compared to men, for the same tasks, because the employer has the idea that they are, on average, less productive than men (statistical discrimination). Additionally, as explained in Becker (1971), individuals may have a taste for discrimination, meaning that they are willing to pay extra for not working with people based on certain characteristics such as gender or ethnicity. Regulations have been implemented over time to prohibit such situations, although gender discrimination can still be observed in women's reduced access to traditionally male-dominated jobs or lesser opportunities for advancement to higher positions of power, among other aspects.

The term **occupational segregation** is the result of vertical and horizontal segregation. Vertical segregation refers to women being underrepresented in high-hierarchy positions. This can be related to simple discrimination, or to the demand for full-time workers that can not be fulfilled by women who are are often constrained by the load of non-paid work in the domestic sphere. Horizontal segregation refers to the phenomenon where women and men tend to work in different sectors of the economy. There are multiple reasons why this may occur. Gender differences in the chosen fields of study -resulting from preferences, stereotypes, or other factors- may explain horizontal segregation (Blackburn et al., 2001). Ponthieux and Meurs (2015) present multiple studies using experiments that demonstrate the presence of gender discrimination in the labour market, indicating that it explains part of the existing segregation. Disparities in career choices have a direct consequence on occupation and pay. Women are over-represented in careers and jobs related to care and the social sphere, which are not highly valued, reflecting a low average pay. Alternatively, the decision about the company or field in which to work is strongly linked to unpaid work and motherhood (Goldin, 2021). Women, on average, dedicate more time than men to household tasks and care activities, including raising their children. This may lead them to seek jobs with more flexible hours, part-time opportunities, or lower costs of interrupting their activity. The role that a career plays in women's lives is expanding, and their participation in traditionally male-dominated professions is also increasing (Goldin, 2021). Studies such as Espino (2013) and Amarante and Espino (2004) address segregation for the Uruguayan case, finding that occupational segregation plays an important role in explaining gender wage gaps in Uruguay given that women concentrate in feminized and low-paid occupations associated with education, health and care.

Some argue that part of the existing wage gap is due to gender differences in **psychological factors** such as a preference for competition, negotiation or risk aversion (Bertrand, 2011). Gender difference in the preference for negotiation have been found to be highly related to the context. When negotiating for themselves, women tend to perform worst than men, but this difference attenuates when they are negotiating for someone else (Bowles et al., 2005). Multiple studies, such as Niederle and Vesterlund (2011) find, through laboratory experiments, that women are more risk-averse than men. Risk aversion influences the election between a more stable job or a job with higher remuneration. Additionally, these studies find that women have less preference for competition, which may also revert in lower remuneration, as sectors with high competition tend to have higher pay. Among the various explanations given for this difference in willingness to compete, there are cultural factors, gender norms, and biological factors. However, this studies have been widely questioned, as it is unclear to what extent these differences are attributed to biological differences rather than social and cultural influences (nature vs nurture) (Bertrand, 2011).

Finally, the term **motherhood penalty** refers to the decline in women's income when becoming mothers compared to fathers or women who do not have children (Kleven et al., 2019). Multiple factors may explain this penalty, most of them are related to the mechanisms mentioned above. Firstly, many mothers exit the labour market due to a significant increase in childcare hours during early childhood. During this period, they may lose experience that is later reflected in remuneration upon re-entering the workforce, or they may switch to jobs with tasks or schedules more compatible with parenting. Additionally, companies may anticipate this potential work interruption and offer lower salaries or inferior positions to equally qualified women compared to their male counterparts, which is known as 'statistical discrimination' (Tilcsik, 2021; Blau and Kahn, 2017). Querejeta and Bucheli (2023) find a significant motherhood penalty in formal employment studying the Uruguayan case. In particular, the authors find a 23% reduction in formal employment rates one year after the childbirth, that increases with time, and a decrease of 8% on monthly wages. They find that evolution of monthly earnings is explained mainly by changes in employment.

2.1 Gender wage inequalities along the wage distribution

The aforementioned mechanisms may operate differently along the distribution. The concepts of glass ceilings and sticky floors reflect this differential effects.

The **glass ceiling** concept reflects inequalities in access to high-ranking positions, where women typically encounter greater barriers. There is a direct relationship between these barriers, whether implicit or explicit, and the mechanisms mentioned earlier. Women have limited access to certain positions, partly due to gender discrimination, partly due to their different attitude towards competition, partly because they are underrepresented in certain economic sectors, resulting in fewer women available for these positions, and partly due to the burden of unpaid work that is incompatible with highly demanding jobs. Glass ceilings imply a larger gender pay gap in higher-income segments (Albrecht et al., 2003). Certain studies find evidence that supports the existence of a glass ceiling for working women in Uruguay such as Carrillo et al. (2014) and Bucheli and Sanromán (2004).

Similarly, the term **sticky floors** focuses on lower segments of the income distribution. Women face greater difficulty in mobility between and within firms, either due to poorer market offers or a less favourable response from companies towards women. Additionally, in cases where women and men face similar promotion rates, women tend to receive smaller wage increases than men (Booth et al., 2003). Within low-qualified jobs, those in which women are over-represented (services and care) tend to have lower pay (Espino, 2013). The existence of sticky floors implies a larger gender pay gap at lower earnings quantiles.

2.2 The role of marital status on labour market participation

The relation between marital status and women's labour supply has been extensively documented. Blundell and MaCurdy (1999) suggest that women's labour supply and its multiple dimensions are better understood in a family supply framework. Because of gender roles, married women have historically taken upon the role of added workers.[4] This results in a high elasticity of their participation to their husband's income. On the other side, single and cohabitant women have a more similar labour market behaviour than men. They have higher market labour attachment which gives them greater economic independence in anticipation of a possible dissolution of the union (Blau and Kahn, 2007).

The large increase in women's participation observed in the last decades was mainly driven by changes in married women. Blau and Kahn (2007) find that women's labour supply elasticity to their

[4] The term added worker refers to individuals, historically married women, entering the labour market temporarily as a response to their partner becoming unemployed (Lundberg, 1985).

husband's income decreased during 1980-2000 in the USA. Additionally, married women's labour supply increased, although it remains smaller than single women's labour supply. Espino et al. (2009) study changes in women's labour supply in Uruguay for the period 1981-2006 finding an increase in married and cohabiting women's labour supply during their period of study. They suggest that this may have been related to the decrease in the gender wage gap, because of the increase in their wage and the relative decrease of their partner's wage.

An aspect that must be addressed when studying women's selection into employment over time is the changes in the way unions are conceived. There has been a tendency over the last decades to postpone union formation, as well as childbearing. This has been accompanied by an increase in cohabitation together with a decline in marriage (CEPAL, 2017). There are different theories of what the reasons behind this tendency are. Some argue that it is a cultural change, a turn towards individualism. Individuals are more focused on themselves and their own needs and seek types of relationships or family arrangements that are more flexible, such as cohabitation (Lesthaeghe et al., 1995). Others see marriage as an exchange between two parties that complement each other and benefit from it. With women's educational attainment increasing over the last decades, specialisation decreases and marriage loses value (Becker, 1987). Another theory establishes that different forms of unions are strictly related to the partner's future economic uncertainty. This way, marriage can be a long-term agreement that does not adapt well to increasing economic uncertainty (Oppenheimer, 1988).

These changes in marriage and cohabiting trends are relevant to this study because of the differences in attitudes towards labour market participation between women in different types of unions. Marriage tends to be a more traditional union, in which the gender division of roles is stronger and therefore, women participate less. Cohabitation unions appear to be more egalitarian in terms of labour market participation (Binstock et al., 2016). As further explained in Lafortune and Low (2023), marriage can be thought of as a type of insurance against the risk that specialisation implies on women. This way, married couples can specialise, which could be the optimal solution to maximise their benefits. Contrary to other unions, in the context of Lafortune and Low (2023)'s study, in the case the marriage dissolves, the division of assets provides women with some economic support. This commitment is particularly strong among wealthy couples. The authors find, in their study for the USA, that marriage rates are higher for people with higher wealth. Accordingly, they find that marriage rates do not fall among wealthy couples (whom they proxy by looking at homeowners), following an opposite trend than the rest of society. In this line, Binstock et al. (2016) state that different types of unions most certainly have different meanings for different social groups.

3 Background

3.1 Wage differences: previous studies

Differences in labour income between men and women and their potential determinants have been extensively studied within the field of economics. In the last decades, multiple studies have addressed the importance of sample selection when estimating gender wage gaps, as only wages for those who are working are observed. Most of these studies are for advanced economies.

Arellano and Bonhomme (2017) applies their semi-parametric quantile model to compare selection-corrected wage distributions of men and women in the UK in the period 1978-2000. The authors find that both men and women have a positive selection into employment, which means that non-employed individuals have, on average, worse labour market characteristics than those who are working. However, this selection is larger in the case of men, especially men in the lower part of the wage distribution. This pattern is associated with a decrease in male participation during the studied period. Selection into employment is not statistically significant for single women. As a result, once selection is accounted for, gender wage gaps decrease, especially at the bottom of the distribution.

Dolado et al. (2020) examine how changes in employment patterns due to the Great Recession affect measures of the gender wage gap in European Union countries during the period 2007-2012. In particular, they analyse whether the crisis (and its recovery phase) changes the non-random selection into employment. To do so, potential gaps are estimated at the median following the imputation method proposed in Olivetti and Petrongolo (2008). As a robustness check, they also estimate selection-corrected wage gaps following Arellano and Bonhomme (2017). They find positive male selection in southern European Union countries, and a changing direction of female selection throughout the studied period. In the same line, Elass (2022) estimates gender wage gaps along the income distribution for the period 2007-2018 in three countries; UK, France, and Finland. One of the main questions this paper addresses is whether the Great Recession affected the gender wage gap differently along the wage distribution, correcting for male and female selection into employment. The author uses the methodology developed by Arellano and Bonhomme (2017) and finds that selection patterns vary across countries, and France and UK present sizeable male selection into employment. As in this paper, the exclusion restriction used by the author is a measure of potential out-of-work welfare.

Lastly, Maasoumi and Wang (2019) also estimate gender wage gaps accounting for selection into employment following Arellano and Bonhomme (2017), for the period 1976-2013 in the United States. By correcting selection of male and female employment, they find that selection-corrected gaps show a slower reduction than observed gaps. Changes in trends for specific segments of the wage distribution reaffirm the importance of studying gender differences in the labour market beyond the mean or the median.

As reported by Marchionni et al. (2019), considering individuals aged 25 to 54 from urban areas of 18 Latin American countries, women earn 89% of men's wages. This gap is very heterogeneous between countries. Gender wage gaps result smaller between younger and single individuals, in comparison to older and married. Also for Latin America, Atal et al. (2009) find that, when conditioning on observable characteristics, the hourly gender wage gap changes from 9,5% to more than 20%. This result has a large variation across countries (from 4% in Guatemala to almost 35% in Brazil).

Colacce et al. (2020) examines the evolution of the gender labour income gap in Uruguay for the period 1990-2018. The authors estimate the gender gap in labour income under different definitions, specifying the implications of each estimation. In each of the calculated gaps, the decreasing trend persists. This trend is not constant, with a stagnation in the decline observed between 2000 and 2009. While the study acknowledges the issue of selection bias and presents a descriptive evolution of the gap along the distribution, it does not incorporate the selection correction in its estimation.

The gender wage gap along the distribution has been previously studied in Uruguay by Carrillo et al. (2014), Borraz and Robano (2010) and Bucheli and Sanromán (2004). Bucheli and Sanromán (2004) explores the existence of a glass ceiling for Uruguayan working women. They estimate gender wage gaps along the income distribution in 2002. The authors carry out estimations with and without correcting for selection into employment. To correct for selection, they follow Buchinsky (1998), which is based on Heckman (1979) two-step model, but corrects for selection along the distribution.[5] Additionally, they use the decomposition methodology proposed in Oaxaca (1973), which allows the identification of which part of the gap is explained by differences in characteristics of men and women, and which part is explained by different returns to those characteristics. The authors estimate two different models (one which only includes individuals' characteristics, and another one that adds characteristics of the firm in which they are employed), for women and men separately and with and without controlling for sample selection. The results show that after controlling for selection, the returns to education and experience increase for women and only the returns to experience increase for men in the first model. In the second model changes are smaller. They find that the gender wage gap is larger at the top of the wage distribution, which suggests the existence of a glass ceiling for Uruguayan working women.

[5]The independent variables included in the selection equation are; age and years of education, both linear and squared, a variable indicating currently studying, a variable indicating Government cash transfers, marital status, type of household, presence of children, region, per-capita household income, unemployment in the household and household size.

Borraz and Robano (2010) estimate the gender wage gap along the wage distribution in 2007, in Montevideo. They apply Machado and Mata (2005), correcting for non-random selection into employment on a previous stage following Buchinsky (1998).[6] The authors find that Uruguayan women were positively selected into employment in 2007. In general, working women have more years of education and experience than non-working women, but the difference in observable characteristics explains one-third of the difference between both groups. Selection is not constant along the wage distribution, it decreases at the top. Their findings support the existence of a glass ceiling as well, explained by both, characteristics and their returns.

Prior research for Uruguay estimating gender wage gaps along the distribution while correcting for selection into employment, are from the past decade (Borraz and Robano, 2010; Bucheli and Sanromán, 2004). This motivates estimations for more recent years and applying another, more recent, quantile selection model which have not yet been used in the study of the Uruguayan case.

The primary contribution of this study lies in considering the aforementioned points: selection bias, the gender earnings gap along the distribution, and its evolution over time. Unlike previous studies for Uruguay, which look at marital status, husband's income, or children in the household, I calculate an out-of-work potential income conditional on unemployment to be used as the excluded instrument, and estimate the corrected gap along the distribution for three points in time, 2009, 2014 and 2019. As further explained in Section 4.3, the main reason to choose 2009 as the starting year of the studied period is the availability of a comparable instrumental variable, and I chose 2019 as the last year as COVID-19 pandemic affected Uruguay's labour market in 2020. Uruguay's labour market context during this period in given in Section 3.2. Lastly, this study is conducted for a non-developed country with a dual labour market, thus contributing to the international literature on selection-corrected gaps, which has predominantly focused on developed countries until now. This allows for a more nuanced discussion of the role of institutions characteristics of our region along the earnings distribution.

3.2 An insight on Uruguayan Labour Market

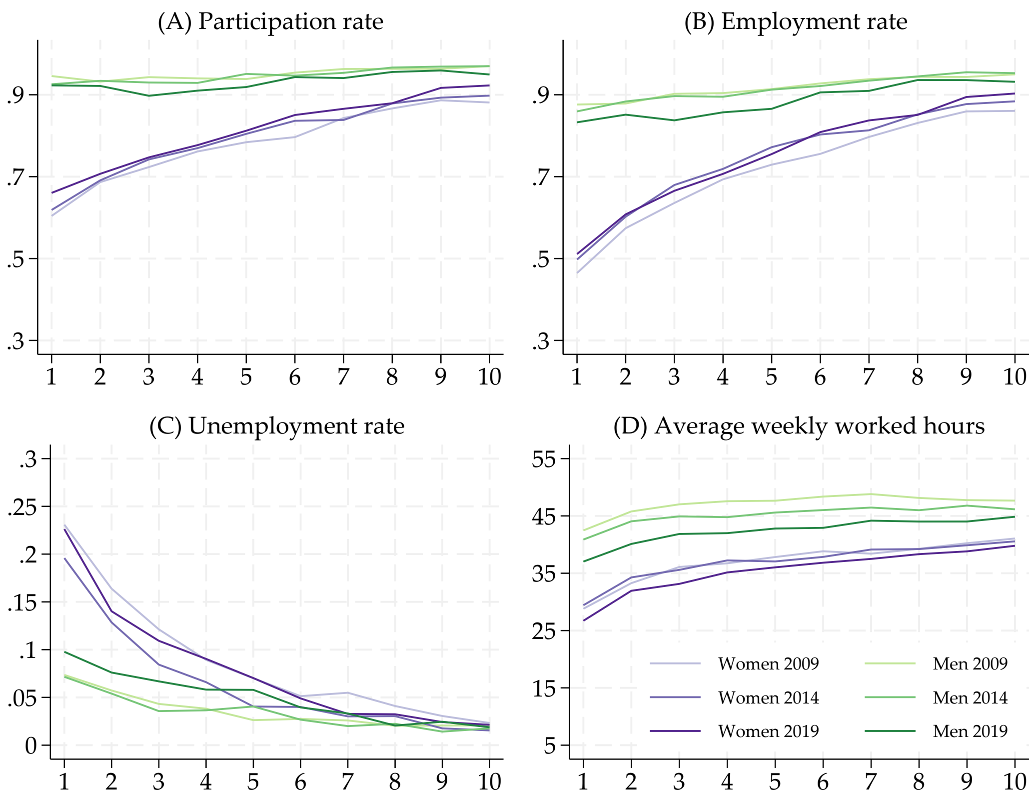
Evolution. The Uruguayan labour market has experienced several changes in the past decades. In terms of participation, men's participation has remained stable throughout the studied period. Meanwhile, women's participation increased in the first half and remained stable between 2014 and 2019. In terms of the number of hours worked, both women and men exhibit a decrease, which could reflect changes in

[6] The selection equation includes as independent variables age and years of education, both linear and squared, dummy indicating in a couple (married or cohabiting), dummy indicating working in the public sector, dummies indicating the size of the firm, and dummies indicating the presence of children under 6 o between 6 and 14 years old.

the way individuals conceive the workday. Men and women worked on average 47 and 37 hours a week in 2009, respectively. In 2019 this number decreased to 42 and 35 hours, according to household survey data. Even though both men and women now dedicate fewer hours to the labour market, the decline in hours worked is proportionally larger in the case of men, leading to a convergence between men and women. These changes, in turn, influence gender earnings gaps, as shown in Table A1 for the years of interest.

As shown in Figure 1, these changes were not homogeneous along the income distribution. Regarding participation, while men's participation has a stable behaviour between different household per-capita income deciles, women's participation appears to be positively related to income. Gender employment rates have an analogous behaviour. In both cases, there is a clear tendency towards convergence over the years between the rates of women and men, despite remaining differences.

Figure 1: Labour market statistics along the household per-capita income distribution



Source: Own elaboration based on ECH data. **Note:** This figure presents labour market statistics along the distribution. Deciles are constructed using household per-capita income. Individuals aged 25 to 59 are included.

Women's unemployment rate decreases significantly as household income increases, and it does not have a constant evolution throughout the studied period. Women belonging to the right tail of the distribution have unemployment rates close to men. On the other hand, the gender difference in average weekly hours worked is important for every decile and for the whole period. Both women and men tend to decrease their number of hours worked, but the average for men remains larger along the income distribution and for the whole period.

Differences between marital status The labour market statistics shown in Figure 1 differ greatly between marital statuses, as shown in Figure 2.

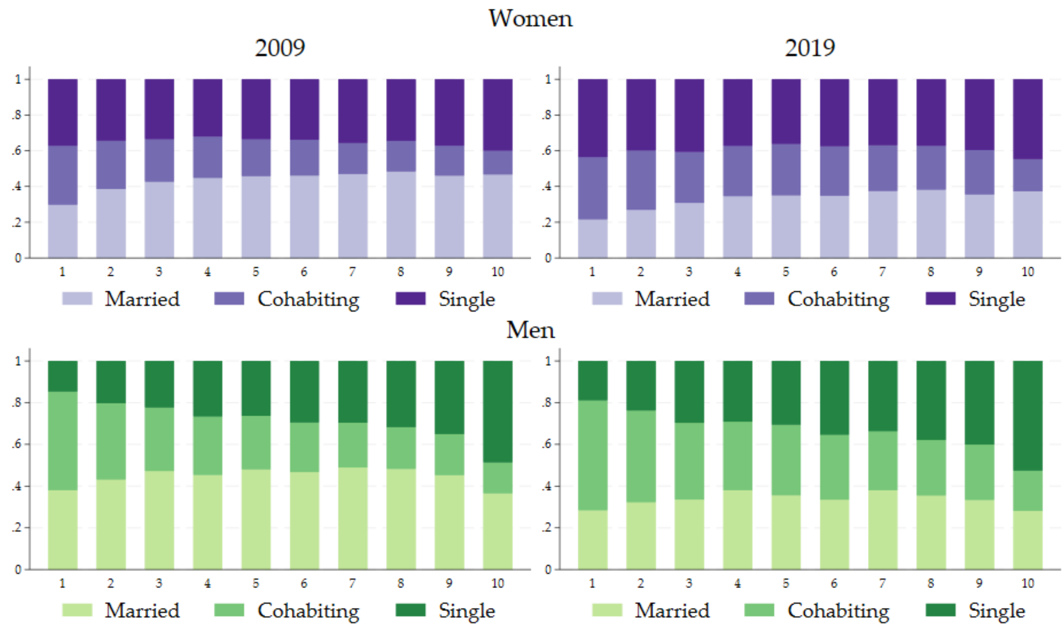
Figure 2: Marital status-specific labour market statistics along the household per-capita income distribution

Source: Own elaboration based on ECH data. **Note:** This figure presents labour market statistics along the distribution. Solid lines correspond to Married, dashed lines to Cohabitants, and dashed-dot lines to Single individuals. Individuals aged 25 to 59 are included. Deciles are constructed using household per-capita income.

Married women have lower participation rates than women who are cohabiting or single, although increasing during the studied period. Female participation is positively related to the household's per-capita income, independent of the marital status. This is very different for men, married and cohabiting men have very high participation rates, constant along the household's per-capita income distribution, while single men's participation rate is lower, specially for lower income deciles. Regarding employment, single women have higher employment rates than cohabitant and married women. Cohabitants and married women have similar employment rates at the lower income deciles, while cohabitant's employment rates converge with single women's at higher income deciles. Men's employment rates behave very similar to men's participation rates. Women who are cohabiting and men who are single have the largest unemployment rates within each gender, and the difference between marital statuses decreases with income in both cases. Lastly, single women work on average more hours weekly than cohabitants and married women. In the case of men, cohabitants and married men work a similar amount of weekly hours, and single men work less, although this difference decreases for higher income deciles.

Espino et al. (2009) observe an increase in women's labour market participation during the period 1981-2006 in Uruguay, which was mostly guided by changes in married and cohabitant women's participation rates. The authors estimate women's labour supply elasticities to their own and their partner's wages in Uruguay during the period. Higher wages increase women's labour supply, while higher partner's wage decreases it. When looking at the average elasticities in periods of three years, both elasticities (to their own and their partner's wage) decrease, although the elasticity to their own wage does not present a constant tendency throughout the period. This is relevant to this study given the changes in marital status composition along the studied period.

Figure 3: Marital status along the household per-capita income distribution



Source: Own elaboration based on ECH data. **Note:** This figure shows the distribution of marital status within sex and household per-capita income deciles in 2009 and 2019. Deciles are constructed using household per-capita income. Individuals aged 25 to 59 years old are included.

The proportion of married and cohabitant women evolves inversely in the studied period, and singles increase. As shown in Figure 3, the proportion of women in marriage decreases between 2009 and 2019, and this decrease is not constant along the household's per-capita income distribution. Simultaneously, cohabitants increase, and the difference across deciles decreases. This shows that in this period not only did the proportion of women in each marital status change, but also there were changes in the characteristics of each group. The proportion of single women is similar along the distribution and increases over the period. The magnitude of the increase is slightly more pronounced in the higher-income groups. Regarding men, the proportions change in the same way, marriage decreases while cohabitants and singles increase, but the distribution across income quantiles is more pronounced than for women. Men who are cohabitants are mostly on the left side of the distribution, while single men are more present at high-income deciles.

Regulation. The Uruguayan labour market has gone through some important institutional changes which are potentially related to female labour force participation and the gender wage gaps. Firstly, between 1993 and 2004, the previous centralised bargaining scheme involving the Government, employers' federations and workers' unions was suspended, moving to a decentralised bargaining scheme, where firms and employees participated in establishing wages. In 2005 collective bargaining agreements were reestablished and bargaining went back to being tripartite (Blanchard et al., 2021). Minimum wages and central bargaining affect gender wage gaps, especially when looking at young or less educated groups of people. If women are over-represented in the lower part of the wage distribution, one can expect that setting a minimum wage affects them more than men, mainly because women would be the majority among workers for whom minimum wage is binding (Majchrowska and Strawiński, 2018; Dex et al., 2000). Cabrera et al. (2013) find that between 2007 and 2011, the percentage of non-compliance of the minimum wages by sector established through collective bargaining presents a statistically significant decrease. Uruguay's per-capita labour earnings inequality decreased during this period, Amarante et al. (2016) show a change in the Gini Index from 0.40 to 0.35 in the period 2009-2013. Changes in labour market institutions such as national minimum wage explained part of the decrease (Blanchard et al., 2021; Amarante et al., 2016).

Other policies potentially related to women's participation in the labour market are the modifications to parental rights proposed in 2013 (Law Nº 19.161). These changes included larger maternity leaves (going from 12 to 14 weeks), the inclusion of non-dependent workers as beneficiaries, a gradual extension of paternity leave (from 3 to 10 days from 2013 to 2016), and the creation of a parental subsidy to be used by either parent, among other policies (Galván et al., 2021). Alongside, the National Integrated Care System was established in 2015 (Law No. 19.353), recognising care as both a human right and a social responsibility. The primary objective of this system is to ensure that children and dependent individuals receive the assistance they need to accomplish daily tasks and fulfil their basic needs. This initiative aims to alleviate, partially, the costs of care responsibilities, which are disproportionately carried out by women.

4 Empirical Strategy

In this study, I estimate marital status-specific gender earnings gaps along the earnings distribution, correcting for selection into employment during the decade 2009-2019 in Uruguay. I use the term 'earnings' to refer to all labour income, as I include non-dependent, self-employed workers and employers. The estimation of selection-corrected gaps is complementary to the observed gaps, as they offer different information. Observed gender earnings gaps offer an approximation of gender earnings inequality, within working individuals. If, for various reasons, certain groups of individuals stay systematically out of employment, they are not taken into account even if their employment status could result from these inequalities.

4.1 Quantile Regressions

Observed earnings are also estimated, in order to compare two estimated distributions when observing the difference between uncorrected and selection-corrected earnings distributions. Hourly earnings distributions are obtained using quantile regressions (QR). QR, developed by Koenker and Bassett (1978), estimates conditional quantiles of the dependent variable, admitting quantile-specific coefficients. Based on gender and marital status specific earnings estimations, I recover the corresponding distributions by multiplying the percentile-specific coefficients by individuals' characteristics. Much of the previous literature has focused on gender gaps at the mean or median, but this measures may hide heterogeneous differences along the distribution. Estimating gender gaps along the entire earnings distribution allows to contrast the existence of glass ceilings and sticky floors. As mentioned in Koenker (2005), quantile regressions results provide a more comprehensive and targeted perspective than examining only conditional mean models. The predicted earnings resulting from QR estimations are conditional on employment, these estimations do not correct for sample selection.

The QR model developed in Koenker and Bassett (1978) assumes linearity of the conditional quantile of y in the regressors x, so $q_\tau = x\beta(\tau)$. QR is defined for $0 < \tau < 1$, and the vector of coefficients $\beta(\tau)$ is estimated as the solution to the following problem:

$$min_{b \in R^K}[\sum_{t \in t: y_t \geq x_t b} \tau |y_t - x_t b| + \sum_{t \in t: y_t < x_t b} (1-\tau)|y_t - x_t b|] \tag{1}$$

The coefficients $\beta(\tau)$ represent the marginal effect of the covariates at different points of the distribution. Log hourly earnings are estimated for individuals in couples (married and cohabiting) and single separately to obtain marital status-specific earnings distributions.[7]

4.2 Selection Correction

Selection bias is one of the primary challenges in estimating earning gaps, as earnings are a latent variable observed only when individuals decide to accept the job offer, leading to a non-randomly selected sample. There are different methodological approaches aiming to correct selection bias in employment. The different selection-correction models aforementioned are summarised in Table A8.

Arellano and Bonhomme (2017)'s model

This study follows the quantile selection model proposed in Arellano and Bonhomme (2017). The main reason for this choice is the possibility of estimating selection-corrected gender earnings gaps along the distribution. This is a semi-parametric approach that estimates the joint distribution of potential earnings by quantiles.

Selection is modelled via a bivariate cumulative function (copula function), of the errors in the outcome (earnings, in this case) and the selection equation (employment).

$$Y^* = q(U,X), \tag{2}$$
$$D = 1V \leq p(Z), \tag{3}$$
$$Y = Y^* ifD = 1 \tag{4}$$

Y^* is the outcome, logarithm of the market earnings, and X is the vector of observable characteristics. D is the labour market participation indicator. U and V are the corresponding error terms. $Z = (B,X)$ contains X and the excluded covariates, B, included only in the participation equation.

The model's main assumption is the **exclusion restriction**, which implies that (U,V) is jointly statistically independent of Z given X. The presence of dependence between U and V is the source of sample selection bias. Following recent literature (Arellano and Bonhomme, 2017; Elass, 2022), I use a measure of potential out-of-work income as my main instrumental variable, further explained in Section 4.3. The remaining three assumptions are; **unobservables**: (U,V) follow a cumulative distribution function (c.d.f) denoted $C_x(u,v)$, **continuous outcomes**: the c.d.f. and it's inverse are strictly increasing and $C_x(u,v)$ is increasing with u, and **propensity score**: $p(Z) \equiv Pr(D = 1|Z) > 0$ with probability 1, describes the selection probability.

[7] Figures A1 and A2 show that estimated and observed hourly earnings for women and men, respectively, are practically identical.

In the presence of sample selection, with $\tau \in (0,1)$, we have:

$$Pr[Y^* \leq g(\tau,x)|D=1, Z=z] = Pr[U \leq \tau|V \leq p(z), Z=z] = G_x(\tau, p(Z)) \neq \tau \quad (5)$$

Where $G_x(\tau, p(Z)) = C_x(\tau, p)/p$ is the conditional copula. Equation 5 maps latent to observed ranks by shifting the percentile ranks as a function of the amount of selection, which allows to recover the quantile function.

The estimation consists of three steps. First, the probability of participation in the labour market is estimated through a Probit model, where the main exclusion restriction, the potential out-of-work income, is aided by a dummy variable indicating the presence of children under six years old in the household. Second, the copula parameter ρ is obtained. In this step, I adopt the choice of a Frank Copula,[8] which is used in previous studies (Arellano and Bonhomme, 2017; Elass, 2022; Maasoumi and Wang, 2019). One of the main advantages of this type of copulas is the simple interpretation of the single parameter, ρ. This parameter represents the dependence structure between the error term from the participation and earnings equation. Frank copulas admit a positive and negative relation between both variables, and the parameter indicates the intensity of the dependence ($\rho = 0$ means independence). The sign of the parameter is opposite to the sign of the selection. A negative ρ indicates positive selection into employment, and vice-versa. In the last step, the selection corrected coefficients are obtained, by shifting the percentile-specific coefficients as a function of the amount of selection as:

$$\hat{\beta}_\tau(c) \equiv argmin_{b \in \beta} \sum_{i=1}^{N} D_i[\hat{G}_{\tau i}(Y_i - X_i'b)^+ + (1-\hat{G}_{\tau i})(Y_i - X_i'b)^-] \qquad \forall \tau \in (0,1) \quad (6)$$

In Section 6, I present results obtained using the selection correction models from Heckman (1979) and Olivetti and Petrongolo (2008) for the mean and median of the earnings distribution, respectively in order to show robustness of my results.

4.3 Data and variables

This study is based on data from the Uruguayan Encuesta Continua de Hogares (ECH) conducted by the Instituto Nacional de Estadística for 2009, 2014 and 2019. These surveys, representative at the national level, provide information on labour market participation, employment, income and a wide set of individual characteristics.

Consistent with part of the existing literature on gender wage gaps in Uruguay, only individuals aged

[8] In section 6, I estimate the main model with a Gaussian Copula to assess the robustness of my results.

25 to 59 in urban localities (more than 5,000 inhabitants) are considered.[9] This age range predominantly captures individuals who have completed their education and are under the retirement age. All workers are included, private and public sector, employees, self-employed and employers, part-time and full-time workers. This allows to correct for selection into employment, and not into employment with certain characteristics. This choice results in smaller gender earnings gap than if I kept only the private sector, or only full-time workers, given that women are over-represented in the public sector, and in part-time jobs (where there is a wage premium (Atal et al., 2009)), where the hourly earnings gap is smaller.[10] Same-sex couples, people with missing information regarding their marital status, and domestic service workers who live in their employer's house are dropped from the sample.[11] Employment rates for the mentioned age group are available in Table A2.

For earnings estimations, the dependent variable is the logarithm of labour hourly earnings. The choice of earnings and not wages derives from the inclusion of all working individuals and not only employees. The estimation is based on hourly earnings as I include part-time and full-time workers. The control variables included are age (linear and quadratic), four groups of educational level, and whether the person lives in the capital city, Montevideo. The selection equation dependent variable is a dummy that indicates whether the person is employed.[12] The control variables are the same as in the earnings equation, plus a dummy variable that indicates if there are children under age 6 years old in the household and the out-of-work potential income, which is the main instrumental variable for identification, explained in detail below.

Each estimation is gender and marital status-specific. This follows previous literature that finds different participation and employment patterns between women who are single or in couples (Blau and Kahn, 2007; Blundell and MaCurdy, 1999; Espino et al., 2009). Table A2 shows the composition of marital status, participation and employment rates, as well as descriptive statistics of the main variables for individuals in couples (which includes married and cohabiting) and single, for both men and women and the three selected years. The proportion of individuals in couples decrease over the studied period. The same descriptive statistics are shown in Table A3 for married and cohabitants separately, as well as mean-comparison tests. The proportion of cohabitants increase between 2009 and 2019. Within the couples group, there are large differences between married and cohabitants. Married individuals are on average older than cohabitants and singles for the three years. Cohabitants have on average more

[9] This allows to compare the results with previous studies for Uruguay.

[10] See Table A1

[11] This accounts for a 0%, 0% and 0.1% of the 2009 sample, respectively, 0.2%, 0% and 0% of the 2014 sample, and 0%, 0% and 0.7% of the 2019 sample.

[12] The dependent variable is employment and not participation, as earnings for the unemployed are not observed.

children, and the proportion of individuals who are currently studying is larger for singles.

Instrumental Variable

Following Arellano and Bonhomme (2017)'s model, I first estimate the probability of being employed through a Probit model. The excluded variable from the selection equation should explain the probability of participating in the labour market while being independent from the individual's earnings. Two variables have been traditionally used as exclusion restrictions to instrument women's participation in the labour market: the presence of young children and the household's income (husband's or capital income) (Heckman, 1979; Mulligan and Rubinstein, 2008)). However, these assumptions often do not hold for these variables (Huber and Mellace, 2014). On one hand, individuals tend to form relationships with people who share similar characteristics such as educational level (Becker, 1973). Therefore, the partner's income might be correlated with one's wage. On the other hand, some studies find a direct relation between motherhood and perceived earnings. Women may look for more flexible jobs, with lower pay, which fits their non-paid care work. Additionally, mothers spend more time out of work to raise their children compared to women who are not mothers or men. This results in a potential loss of experience, which may impact their earnings (Gough and Noonan, 2013).

In this study, I use a measure of potential out-of-work income as the excluded variable, which represents the individual's reservation wage. The variable includes two main income sources. First, household per-capita capital income (returns of investments and income from rent).[13] Second, I impute two government cash transfers, AFAM-PE and TUS. AFAM-PE is targeted to poor households with children under 18 years old and pregnant women. To be eligible for this transfer, households must not exceed a certain earnings threshold. To check this condition, I construct a fictitious household per-capita income that does not include the individuals' labour income, it represents the household per-capita income if the person was unemployed. In addition, households have to be identified as poor in terms of a vulnerability index that I reconstruct in the data. In the case of TUS, eligibility is defined only by the vulnerability index, and the threshold to access is more strict. Based on the fictitious household per-capita income and the household's vulnerability index, if the household is eligible for Government cash transfers, I impute the corresponding amount. Regarding AFAM-PE, Law Nº 18.227 establishes that in case there is more than one adult responsible of the children in the household, the woman receives the transfer. In this exercise, when the household is eligible for AFAM-PE, the entire transfer amount is imputed in the women's out-of-work income. If the household is eligible for TUS, I impute the per-capita amount.[14]

[13] Capital income is usually not entirely captured through household surveys, and Uruguay is no exception (De Rosa and Vilá, 2023)

[14] A description of both cash transfers included is available in Appendix A.2.

TUS and AFAM-PE transfers were implemented in the years 2006 and 2008, respectively. This explains the choice 2009 as the first year of study.[15] On the other side, 2019 is the last year taken into account for this study due to the COVID-19 pandemic that affected Uruguay's labour market in 2020.

The primary assumption underlying this analysis is that potential out-of-work income is exogenous to an individual's potential earnings. Capital income is highly concentrated in the top 0.5% or top 1% of the income distribution in Uruguay (Burdín et al., 2022), so its potential relation with individual's earnings is not a big concern for exogeneity of the instrumental variable. However, transfers raise bigger concerns as some studies have shown that they could be related to earnings. Bérgolo and Vilá (2019) shows that individuals from whom the AFAM-PE is removed due to no longer meeting the income condition, learn from this threshold and under-report their income in the future. Bergolo and Cruces (2021) further finds that AFAM-PE has an effect on formal employment rates. This could potentially impact on individual's earnings, as individuals in the informal sector normally earn less. Additionally, government cash transfers may partially reflect the household's composition (especially AFAM-PE), although this is not as direct as including number of children as the instrumental variable. Despite its limitations, this measure of potential out-of-work income remains a more reliable excluded variable than alternative traditional options.

5 Results

5.1 Main model

Selection equation

The first step of the selection correction model proposed by Arellano and Bonhomme (2017), is the estimation of the probability of being employed in the labour market. To do so, I estimate a Probit model that includes as explanatory variables; age (linear and quadratic), four groups of education attainment dummies (6 years or less, 7 to 9 years, 10 to 12, 13 years of education or more, the first dummy is the omitted one) and binary variables to indicate if the person lives in the capital city and if she lives in a household with at least one child under 6 years old. The main exclusion restriction of the model is the potential out-of-work income, also included as independent variable. Table A4 shows the results of the Probit model estimations for men and women. Men and women's probability of being employed are explained by different factors. Results for women are as expected and follow previous studies (Elass,

[15] There were other non-contributory transfers before 2009 (Tarjeta Alimentaria, for example), but the coverage was considerably smaller. I opted to focus on years where the instrumental variable has the same components, aiming to provide clearer insights into the results. Nevertheless, the instrument remains applicable to earlier years, although with less explanatory power on the employment rate. I check the results for 2005 in the next section.

2022). The potential out-of-work income has a statistically significant negative effect on women's employment across the studied period. This effect has a similar magnitude between in couples and single women. Age and education have a significant positive effect for all women across the period. The region does not explain female employment in most cases. The presence of children under six years old has a significant negative effect, and this is larger for women in couples than for single women. On the other hand, the potential out-of-work income does not have a statistically significant effect on men's probability of being employed, as shown in Table A4. This can either be because the amount is smaller given they receive less transfers,[16] or because men's labour supply is inelastic to out-of-work income. Nevertheless, identification is further aided by the copula function (Maasoumi and Wang, 2019). Regarding the other variables, age and education have a positive effect on men's probability of being employed, while the region and the presence of children under 6 years old don't seem to explain it.

Selection parameter

The results from step one are used to obtain the selection parameter, ρ and selection-corrected coefficients that result from shifting quantile coefficients as a function of the selection in each part of the distribution. Table 1 shows the selection parameter obtained for each group and year. The parameter is statistically significant in for all women in 2009, and single women in 2014. Women in couples tend to self-select positively into the labour market (indicated by ρ having a negative sign), while single women select negatively in the first two years, and positively in 2019.

This means that employed women in couples have higher earnings than the potential earnings of non-employed women in couples. This is consistent with women carrying out a greater share of unpaid household tasks, compared to their male partners.[17] The cost of entering the labour market is greater, leading to only those who have good enough offers participating. When selection is positive, the selection-corrected earnings distribution is expected to decrease in comparison to the uncorrected distribution. In addition, the evolution of selection is not constant over the studied period. It decreases in the first half but increases slightly again in 2019. This aligns with the evolution of women's employment rates across the period, as there is an increase between 2009 and 2014 and remains constant between 2014 and 2019.

Single women, on the other hand, are negatively selected. As seen in Table A2, single women have on average fewer children, and a larger proportion are currently studying, compared to married women. The negative selection into employment could be related, on one side, to single women choosing not to

[16] This is explained by AFAM-PE transfer being assigned to women only. Monthly average out-of-work income by sex and marital status is available in Table A2, and the monthly amounts along the earnings distribution are shown in Figure A3 for the three years.

[17] As Batthyány et al. (2015) shows, using time use surveys from 2013, 69.9% of non paid work is carried out by women.

work to continue studying. In this case, women with potentially good wages are out of the labour market. On the other side, single women who are mothers may be willing to work for a smaller pay than mothers who are in couples, given they don't have a partner's income. When selection is negative, the selection-corrected earnings distribution is expected to increase in comparison to the distribution conditional on employment.

Regarding men, the selection parameter is not statistically significant in any year except for married men in 2019, as shown in Table A5. This differs from previous findings for European countries (Elass, 2022; Dolado et al., 2020). However, these studies focus on selection into employment during economic crises, where male employment rates suffer large changes. That is not the case of men in Uruguayan labour market during 2009-2019, where male participation rates are stable and high (see Table A2).

Table 1: Female selection parameter

	In couple	Single
2009		
ρ	-1.7297	1.7389
95% CI	[-2.601;-0.858]	[0.106; 3.371]
N° Observations	17,077	9,275
2014		
ρ	-0.6937	2.409
95% CI	[-1.675;0.288]	[0.834;3.984]
N° Observations	16,765	9,349
2019		
ρ	-0.7099	-0.427
95% CI	[-1.732;0.312]	[-1.618;0.763]
N ° Observations	12,421	8,075

Source: Own elaboration based on ECH data. **Note:** The table shows the Copula parameter, ρ, for each marital status and year estimation. Estimations include women aged 25 to 59, living in urban areas. Parameters are estimated separately for each marital status. Each column shows the coefficients and 95% confidence intervals in brackets for women in Couples and Single, respectively. A negative sign of the selection parameter, ρ, indicates a positive selection into employment, and vice-versa.

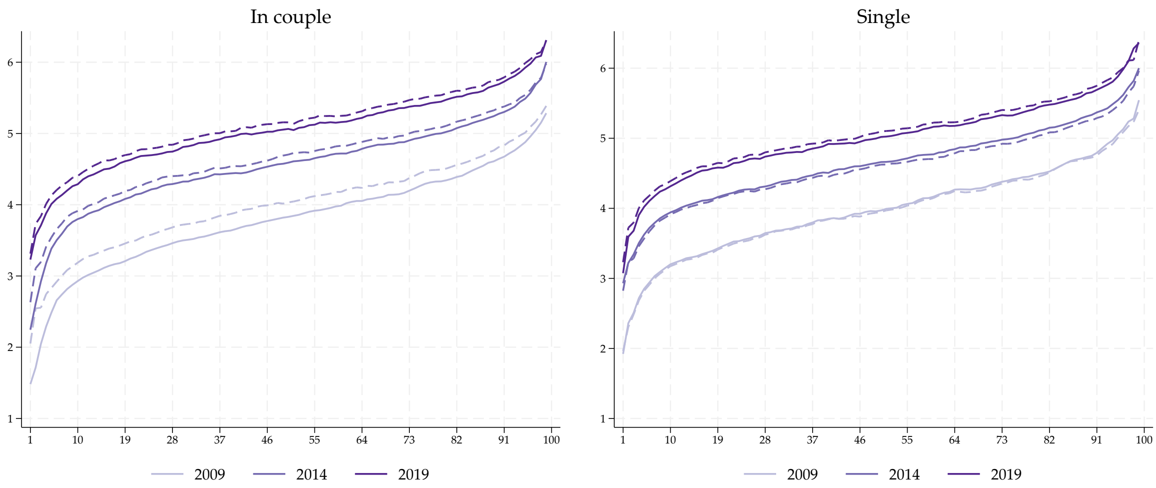
Selection-corrected earnings distributions

Due to the absence of male selection, I will focus on the model with only female selection bias correction. Male hourly earnings are estimated using Quantile Regressions.[18] After obtaining the selection-corrected coefficients for the entire distribution, I proceed to randomly assign positions to women along the earnings distribution as done in Elass (2022) and Arellano and Bonhomme (2017). The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. This process is con-

[18] Male selection-corrected hourly earnings distributions are available in Figure A4, and are identical as the observed distributions.

ducted separately for single women and women who are in couples.

Figure 4: Log of female hourly earnings distribution



Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include women aged 25 to 59, living in urban areas. Solid lines correspond to selection corrected and dashed lines to observed hourly earnings distributions. Percentiles are constructed using hourly earnings from the selection-corrected and observed distributions, respectively.

Figure 4 shows the distribution of female hourly earnings. As expected, once female selection is accounted for, the distribution of hourly earnings decreases for women in couples. This change is not homogeneous along the distribution, especially in 2009, when selection appears to be stronger for women with lower potential earnings. Hourly earnings distributions for single women remain virtually identical after correcting for selection. This is not expected when looking at the selection parameter for single women as it is statistically significant in 2009 and 2014, but it is consistent with the larger employment rate of single women relative to women who are in couples. As their employment rate is high, the hourly earnings distribution does not change much when correcting for selection. When estimating the same model for all women, grouping the different marital statuses, the difference between selection-corrected and non-corrected distributions is considerably smaller, which is expected as the negative selection of single women attenuates the result (See Figure A5).

Given that women in couples and single are different in the proportion who are currently studying and the proportion of mothers, I estimate the same model with two additional samples, one dropping individuals who are currently studying, and the second one dropping non-parents from the sample. The reason for this is to study whether the selection is explained by these characteristics and not marital status. The results are shown in Figures A6 and A7, respectively. The evolution of the selection-corrected distributions remains unchanged, which supports the selection being explained by the marital status.

Table 2: Ratio of women's average hourly earnings p90/p10

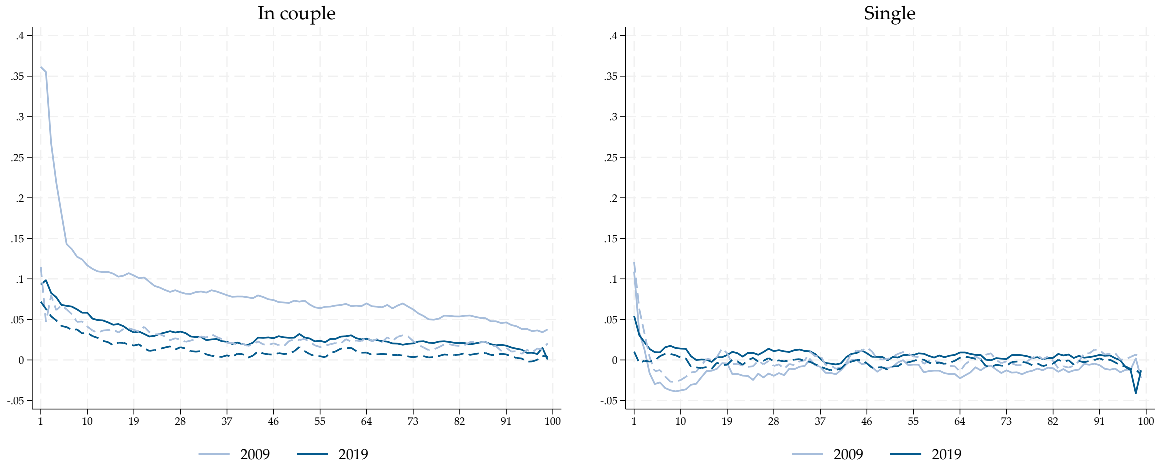
	2009	2014	2019
Couples			
Observed	1.489	1.353	1.320
Selection corrected	1.565	1.369	1.326
Singles			
Observed	1.490	1.338	1.291
Selection corrected	1.488	1.359	1.305

Source: Own elaboration based on ECH data. **Note:** Estimations include women aged 25 to 59, living in urban areas. Each column shows the ratio of log hourly earnings from the 90th percentile to the 10th percentile of women in Couples and Single in 2009, 2014 and 2019, respectively. Observed ratio refers to the ratio of estimated log hourly earnings, conditional on employment.

As selection into employment is not random along the earnings distribution, correcting for selection increases inequality within women's earnings for all marital statuses, except for single women in 2009 (Table 2). For women in couples and single women in 2019, where selection into employment is positive, correcting for selection includes individuals with lower potential earnings. For single women in 2014, the increase in inequality may be explained by higher potential earnings from the unemployed, compared to the employed, as selection is negative in this case. In 2009, women in couples have similar earnings inequality as single women, but both ratios differ when looking at the selection corrected earnings distribution. Earnings inequality is much higher for women in couples than single women once selection is accounted for.

Since the employment rate of women in couples is lower than the employment rate of single women, earnings inequality is expected to change more once corrected for selection. Both women in couples and single women experience a decrease in their earnings inequality between 2009 and 2019 (Amarante et al., 2016). Within women in couples, the earnings inequality difference between observed and selection-corrected earnings decreases between 2009 constantly 2019. For single women, the difference is largest in 2014.

Figure 5: Gender earnings gaps along the earnings distribution



Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected gender earnings gaps along the distribution represented by dashed and solid lines, respectively. The observed gender gaps result from the ratio of average log hourly earnings of women and men, estimated using quantile regressions. Estimations are carried out separately for each gender and marital status, and are conditional on employment. The selection corrected gaps result from the ratio of average log hourly earnings in each percentile of women's selection-corrected distribution and men's quantile regression estimations, for each marital status separately. Estimations include individuals aged 25 to 59, living in urban areas.

Once the hourly earnings distributions are obtained, I proceed to examine the gender earnings gaps. Figure 5 shows the observed and selection corrected gender gaps for 2009 and 2019. When considering couples, once selection is accounted for, the gender gap in hourly earnings increases, especially in 2009, where female selection is the largest. Selection-corrected gender gaps are very similar to the observed gaps for single individuals, which is explained by female earnings distributions practically not changing once selection bias is corrected. For individuals in couples, the gap is not constant along the distribution, it is larger on the left side of the median. This is in line with the existence of sticky floors. Unlike previous literature that studies gender wage gaps in Uruguay, I find no evidence that supports the existence of glass ceilings for women in the Uruguayan labour market (Carrillo et al., 2014; Borraz and Robano, 2010; Bucheli and Sanromán, 2004). Nevertheless, these studies referred to an earlier period (years 2000, 2007 and 2002, respectively), and in the case of Borraz and Robano (2010) and Bucheli and Sanromán (2004), used a different selection correction method as they follow Buchinsky (1998).

The large difference in the gap's performance throughout the studied period may have multiple causes. Firstly, from 2009 until 2014, Uruguay's GDP presented a great growth of 4.75% on average, while the average growth was 1.31% for the second half of the period. The economy's growth in the first half was accompanied by a decrease in wage inequality, a large increase in the national minimum wage and a small increase in the collective negotiation agreement's compliance (Cabrera et al., 2013). The mentioned events are expected to favour female earnings, as women are over-represented in the lower part of the earnings distribution.

5.2 Differences within groups

Given the existing evidence referring to different behaviour patterns across marital statuses discussed in Section 2 and 3 (CEPAL, 2017; Binstock et al., 2016; Espino et al., 2009), and the fact that previous work for Uruguay gender wage gaps along the distribution had not differentiated between married and cohabitants (Carrillo et al., 2014; Bucheli and Sanromán, 2004), I estimate the same model as in the previous section, but for three groups: married, cohabitants, and single.

Results from the first step are shown in Table A4. Potential out-of-work income results statistically significant in explaining women's employment in every year and marital status group. A higher potential out-of-work income decreases the probability of being employed in the labour market, and the coefficient is larger for cohabitant than married women. Cohabitant women are also more sensible than women in marriage to the presence of children in the household.

Table 3: Female marital status specific selection parameter

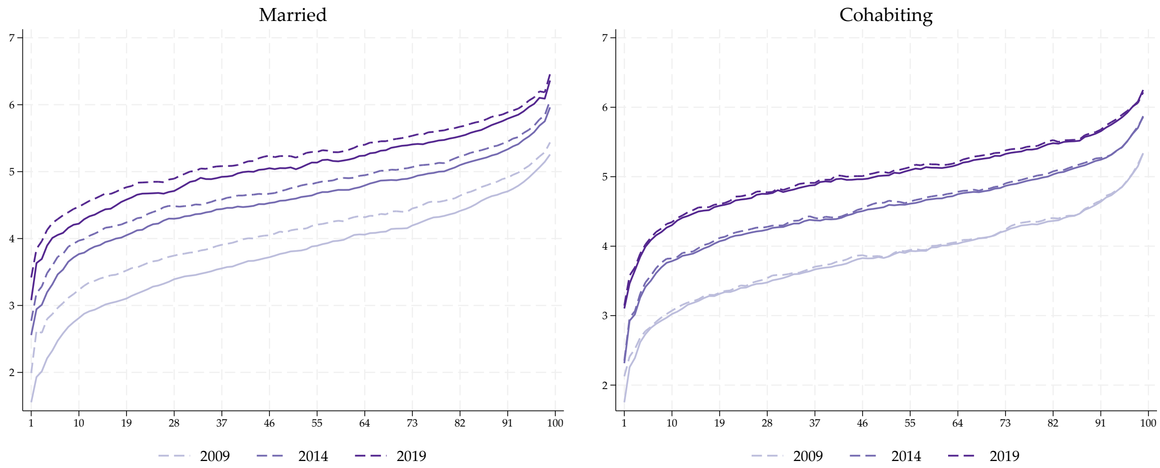
	Married	Cohabitation	Single
2009			
ρ	-3.3473	0.8256	1,7388
95% CI	[-5.337;-1.357]	[-0.606;2.257]	[0.106;3.371]
N° Observations	11,475	5,602	9,275
2014			
ρ	-1.7078	0.2907	2.409
95% CI	[-4.616;1.200]	[-0.818:1.399]	[0.783;4.036]
N° Observations	9,977	6,788	9,349
2019			
ρ	-2.0225	0.4129	-0.4275
95% CI	[-3.539;-0.506]	[-1.135;1.961]	[-1.633;0.778]
N° Observations	6,814	5,607	8,075

Source: Own elaboration based on ECH data. **Note:** The table shows the Copula parameter, ρ, for each marital status and year estimation. Estimations include women aged 25 to 59, living in urban areas. Parameters are estimated separately for each marital status. Each column shows the coefficients and standard errors in brackets for women in Marriage, Cohabitation and Single, respectively. A negative sign of the selection parameter, ρ, indicates a positive selection into employment, and vice-versa.

Table 3 shows the selection parameter for each group. The selection bias observed previously for women in couples seems to be driven by married women, as the selection parameter is not statistically significant for women cohabiting in any year.

Figure 6 reflects the different patterns of selection between married and cohabiting women. Compared with Figure 4, the distance between selection corrected and observed earnings distributions increases for married women respect to in couple. Additionally, the largest gap lies in the lower part of the distribution, which is in line with the smaller participation and employment rates in this part of the distribution. The distribution of hourly earnings for cohabiting women remains unchanged once selection is accounted for, due to no selection. The decrease in selection between 2009 and 2019 for all women, especially in couples, (seen as the decrease in the distance between selection corrected and observed earnings distributions) may potentially be related to the decrease in the proportion of married women and the consequent increase in women who are cohabiting and single seen in Figure 3.

Figure 6: Log of female hourly earnings distribution

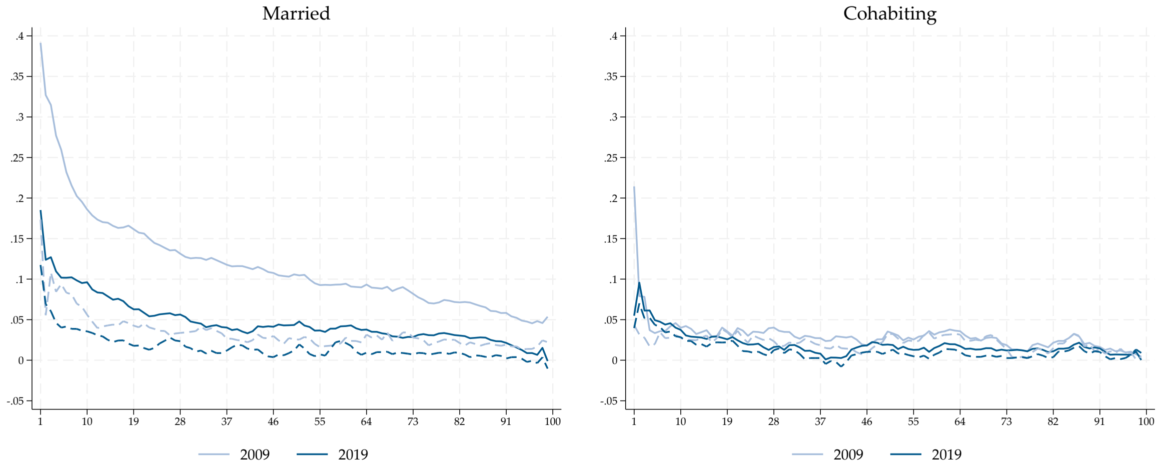


Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include women aged 25 to 59, living in urban areas. Solid lines correspond to selection corrected and dashed lines to observed hourly earnings distributions. Percentiles are constructed using hourly earnings from the selection-corrected and observed distributions, respectively.

The evolution of the hourly earnings gender gap in 2009 and 2019 seen in Figure 7 remains the same for both married and cohabitants after correcting for selection, compared to the evolution seen in Figure 5 for women in couples. When looking at the gender gaps between married individuals, the difference along the distribution increases in both years, compared to individuals in couples in Figure 5. All distributions converge in the highest earnings percentiles, especially in 2019.[19]

[19] Figure A8 shows marital status specific gender earnings gaps for the three estimated years, as 2014 was omitted from Figures 5 and 7 for more clarity.

Figure 7: Gender earnings gaps along the earnings distribution



Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected gender earnings gaps along the distribution represented by dashed and solid lines, respectively. The observed gender gaps result from the ratio of average log hourly earnings of women and men, estimated using quantile regressions. Estimations are carried out separately for each gender and marital status, and are conditional on employment. The selection corrected gaps result from the ratio of average log hourly earnings in each percentile of women's selection-corrected distribution and men's quantile regression estimations, for each marital status separately. Estimations include individuals aged 25 to 59, living in urban areas.

Married and cohabitant women differ in observable characteristics. Table A3 shows that cohabitants are on average younger than married individuals for both, women and men. Additionally, the mean age at which individuals enter their first marriage increased in Uruguay in the early 2000's (Binstock et al., 2016; Cabella, 2009). The average number of children is smaller for married than cohabitant women, and the proportion of cohabitant women that are currently studying almost doubles the figure for married women. Thus, I estimate the main model separating groups by age, instead of marital status, to explore if this is what explains the different selection pattern. Figure A9 shows hourly earnings for all women under 35 and women over 45 years old, separately. If this was the case, one would expect to see a larger selection for older women in the sample. Results support that selection is explained by marital status, and not age.

A possible explanation could be that cohabitants could be less aligned with traditional beliefs regarding sexual division of labour. Van der Lippe et al. (2014) studies agreement and disagreement differences between married and cohabitant couples for 22 European countries, and find that cohabiting couples agree more, on average, than married couples in the division of paid work, in line with having a less traditional belief and more egalitarian unions. Espino et al. (2009) discusses, studying the Uruguayan case, that the potential instability of cohabiting unions may motivate women in these unions to participate more. As a first approximation to studying differences in gender norms or attitudes between married and cohabitant women, I carry out a decomposition of the selection variable, that shows to what extent the difference between married and cohabitant women is explained by characteristics, coefficients (that represent unobservables such as gender norms, culture or attitudes), or the interaction of both. I estimate the mean decomposition following Oaxaca (1973) and Blinder (1973). In line with previous studies, Table A6 shows that the unobservable component favours the larger employment of cohabiting women, supporting the idea of cohabiting women having attitudes and gender norms that favour labour market participation in a larger extent than married women. The unobservable component explains most of the difference in the three years. In particular, in 2019 the difference in endowments is nearly null. The difference in unobservables is attenuated by an opposite difference in characteristics, given that married women are on average older and have higher educational attainments both positively correlated with employment rates.

The variation in employment selection patterns between married and cohabitant women could be object of future research. One possible explanation lies in different characteristics of those who opt for cohabitation versus those who choose marriage (being younger, for example). On the other side, this difference could also respond to differences in cultural or gender norms i.e. cohabitation being a more egalitarian type of union, where both men and women who engage in such relationships exhibit more similar labour market attitudes. Nevertheless, individuals may also choose cohabitation as a type of union previous to marriage. This way, cohabitation groups couples who think of it as a modern type of union and couples who are waiting to get married (Binstock et al., 2016). The changes in selection into employment observed in Table 1 can also be explained by the changes in the proportion of married and cohabitant individuals during the studied period. Lastly, one could try to explain this through a theoretic model in line with what Lafortune and Low (2023) propose. *A priori*, this theory may not appear highly plausible in the context of Uruguay during the studied period, as the legal framework protecting women does not significantly differ based on the type of union they have. However, it cannot be entirely dismissed, especially for older women in the sample.

6 Robustness checks and discussion

In order to assess robustness of my results, I look into my choice of copula function and model specification. Then, I compare my results with others obtained by applying alternative methodologies to study the strength of my instrumental variable.

Following previous works that apply the model developed in Arellano and Bonhomme (2017) (Elass, 2022; Maasoumi and Wang, 2019), I chose a Frank copula to model the relation between the error term from the wage and participation equations. It has the advantage that it has one parameter that indicates the sign and magnitude of the selection, which makes the interpretation and comparison easy. Also, the Frank copula is flexible and can model a wide range of dependency structures, from independence to extreme dependence. However, I asses robustness of my copula choice by estimating the same models using a Gaussian copula, which is also low-dimensional. Both estimations return a comparable parameter, Spearman's Rho which is a measure of the strength of relation between both variables. The parameters obtained with both copula functions are shown in Table 4. The results are stable, except for single women in 2019. However, as Table 3 shows, the selection parameter is not statistically significant for single women in that year.

Table 4: Comparison of different copula choices

	Spearman's Rho			
	In couple		Single	
	Frank	Gaussian	Frank	Gaussian
2009	-0.2774	-0.3128	0.2788	0.3139
2014	-0.1149	-0.1323	0.3736	0.2588
2019	-0.1175	-0.1569	-0.0711	0.2480

Source: Own elaboration based on ECH data. **Note:** Estimations include women aged 25 to 59, living in urban areas. Parameters are estimated separately for each marital status. Each column shows the comparable dependence parameter, Spearman's Rho, corresponding to selection-correction estimations with Frank and Gaussian copulas, for women in couples and single, respectively.

Discussion of the instrumental variable

As mentioned before, in this work I use a measure of potential out-of-work income as the main instrumental variable for the estimations. This type of variable, to my knowledge, has not yet been used to instrument women's employment in Uruguay. Regarding the specification of the main model, I estimated the same model adding another dummy variable in the selection equation indicating the presence of children aged 6 to 11, besides the already used instrumental variables, the out-of-work potential income and the presence of children under 6 years old. The resulting hourly earnings distributions are shown in Panel A of Figure 8. All results mentioned above hold under this model specification.

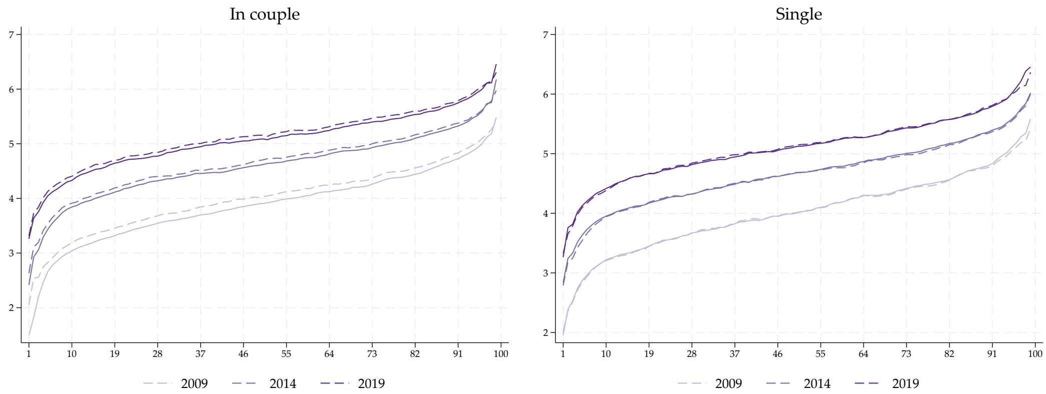
Besides, I estimate the main model using the number of children under 12 years old living in the household as the main instrument, in line with previous literature such as Dolado et al. (2020), Maasoumi and Wang (2019), and González and Rossi (2007) for the Uruguayan case. The number of children does not come as a good instrumental variable in either group. As seen in Panel B of Figure 8, the change is larger for single women compared women in couples, which does not seem plausible given the higher employment rates from the former. In the case of women in couples, the distributions remain practically unchanged, whether selection-corrected distributions increase for single women in the upper part of the distribution.

Additionally, as mentioned in Section 4.3, the instrumental variable works for previous years. I estimate the same model for the year 2005. In this case, the instrumental variable only includes the household's per-capita capital income. Selection parameter and selection corrected distributions for the year 2005 are shown in Panel C of Figure 8. The selection parameter is not statistically significant, which can be explained by the smaller capacity of the out of work potential income to explain women's employment given that without AFAM-PE and TUS cash transfers the amount decreases greatly. However, the selection corrected hourly earnings distribution present the same behaviour as in the studied period. Women in couples' hourly earnings distribution decreases, while single women's distribution remains unchanged.

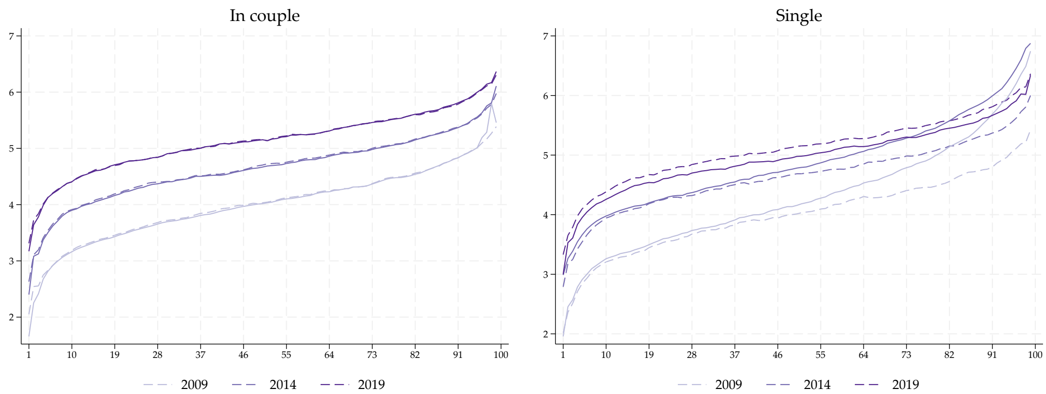
Further, I compare the results obtained following Arellano and Bonhomme (2017) to results obtained following the selection correction methods developed by Heckman (1979) and Olivetti and Petrongolo (2008). Both methods are briefly described in Section A.3. The gender gaps are shown in Figure 9 for couples and singles, in Panels A and B respectively. The mean gap estimated using Heckman (1979) follows the main result very closely in the case of women in couples. It presents larger gaps for the three years which is expected as this measures the gap at the mean and not the median, which are usually larger as women are over-represented in the lower part of the earnings distribution. I then estimate the hourly gender earnings gaps at the median following Olivetti and Petrongolo (2008). As explained in Section 4, this model does not use instrumental variables, so it avoids potential endogeneity problems derived from the instrument. Regarding individuals in couples, although the estimates obtained applying the model proposed by Arellano and Bonhomme (2017) are systematically lower than those obtained with Olivetti and Petrongolo (2008), the evolution of the gaps coincides for the entire studied period. These results provide greater robustness to the choice of the instrument.

Figure 8: Log of hourly earnings distribution

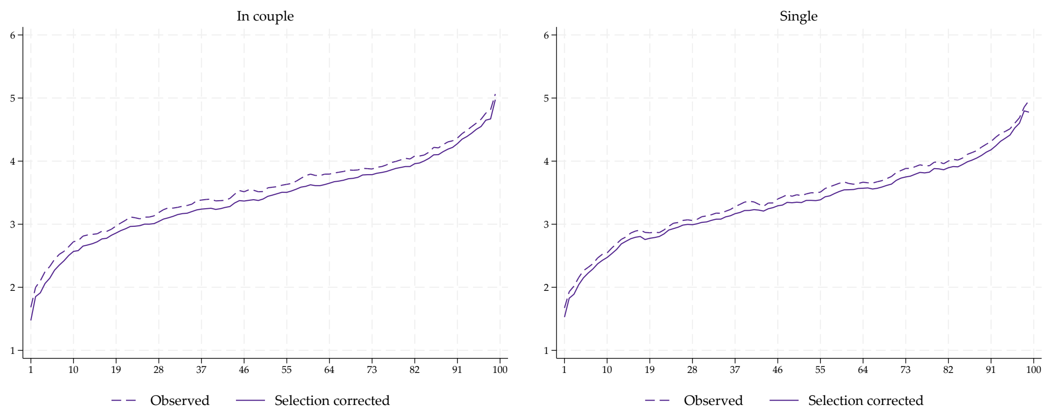
(A) - Adding an indicator of the presence of children aged 6 to 11



(B) - Number of children as IV



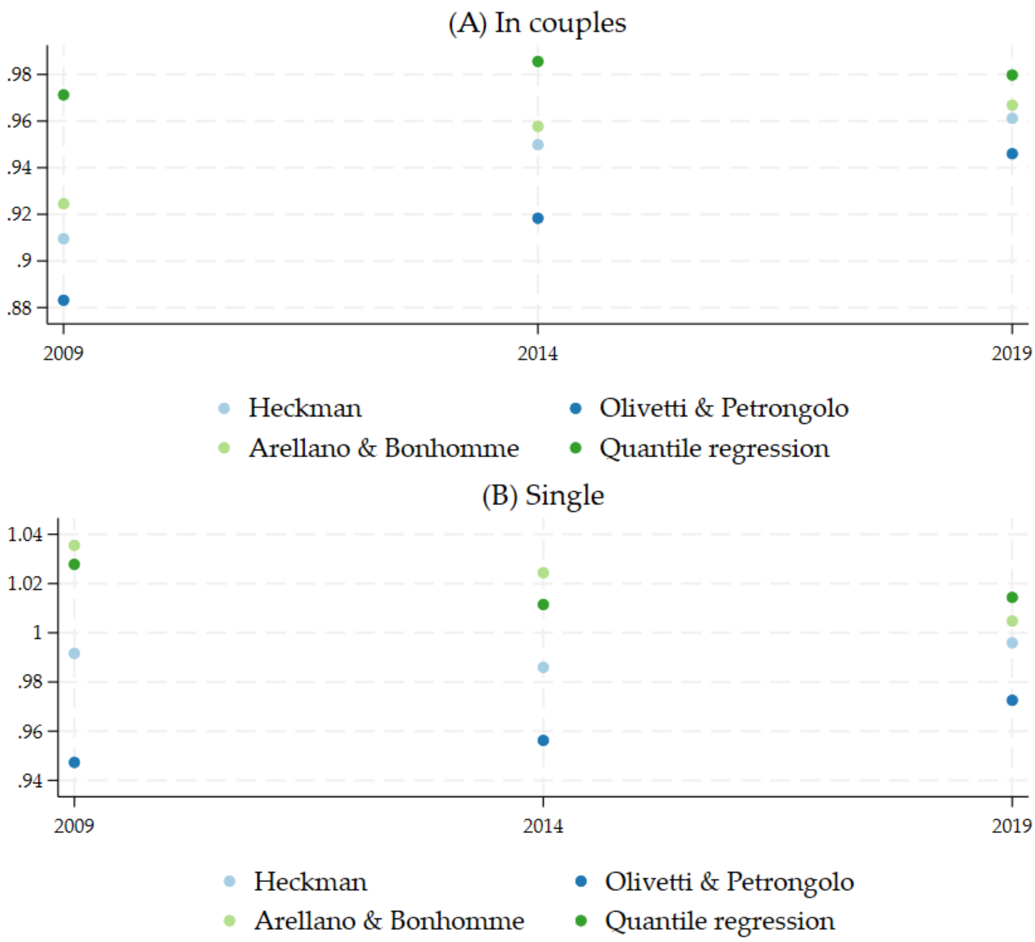
(C) - 2005, Household's per-capita capital income as IV



Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected female hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include women aged 25 to 59, living in urban areas. Solid lines correspond to selection corrected and dashed lines to observed hourly earnings distributions. Percentiles are constructed using hourly earnings from the selection corrected and observed distributions, respectively. In panel C, the estimated parameter, ρ, is -0.034 for women in couples and -0.520 for single women, both not statistically significant.

In the case of the earnings gaps for single individuals, the tendency does not hold for the last year for different estimation methods. In particular, 2019 shows an opposite trend in the main estimation. Thus, we can only find a hint of selection into employment for this group. Nevertheless, this result should be interpreted carefully as the obtained selection parameter for this year and group is not statistically significant.

Figure 9: Gender earnings gaps comparison applying different estimation methods



Source: Own elaboration based on ECH data. **Note:** The figure shows gender earnings gaps for the three years of interest estimated with different methods. Panel A includes individuals in couples, and panel B singles. Estimations include individuals aged 25 to 59, living in urban areas.

7 Final Remarks

In this study, I estimate gender gaps in earnings along the earnings distribution, correcting for selection into employment for the years 2009, 2014 and 2019 by applying the quantile selection model proposed by Arellano and Bonhomme (2017).

Correcting for selection into employment of individuals in couples in Uruguay results in larger potential earnings gaps during the studied period. The difference between uncorrected and selection corrected gaps is explained by positive selection of married women. This finding is new to the Uruguayan literature as married and cohabiting individuals are usually studied as one single group when estimating gender earnings gaps (Carrillo et al., 2014; Borraz and Robano, 2010; Bucheli and Sanromán, 2004). The selection variable decomposition suggests that this difference is explained by both, characteristics and unobservables at the beginning of the period, and mostly explained by unobservables (gender norms, or attitudes) in 2019.

As expected, selection is not homogeneous along the earnings distribution. Non random selection is a larger problem for lower income groups, which reflects the behaviour of the female employment rates in Uruguay. I find no evidence of glass ceilings for women in Uruguay for observed nor selection-corrected distributions. However, I do find evidence that suggests the presence of sticky floors. This results differ from previous studies for the Uruguayan labour market (Borraz and Robano, 2010; Bucheli and Sanromán, 2004), although I study a different group of individuals, period of time, method and instrumental variable.

Positive and statistically significant selection along the entire distribution for married women means that the selection corrected earnings distribution is lower than the observed one. In other words, the selection corrected gender hourly earnings gap is larger than the observed earnings gaps. This difference between both gaps is not constant during the studied period. Selection within married women is the largest in 2009, it decreases in 2014 and slightly increases again in 2019. The gender earnings gap decreases notoriously in the first half of the studied period, and remains stable during the second half.

When estimating the selection corrected earnings gap by applying Heckman (1979) and Olivetti and Petrongolo (2008), the tendencies remain the same for women in couples. The comparison of the main results to the gaps obtained with the methodology proposed by Olivetti and Petrongolo (2008) is desirable, as the latter does not require an exclusion variable. The fact that both earnings gaps have the same behaviour along the studied period brings more confidence to the use of potential out-of-work income to instrument women's employment in the Uruguayan labour market.

In conclusion, this study has brought light to previously overlooked labour market differences between married and cohabiting women in Uruguay. This findings underscore the need for further study to better understand the gaps in selection into employment between women in both groups, particularly regarding changes in cultural factors and gender norms. Gaining a deeper insight into these dynamics will enable the development of more targeted policies aimed at promoting greater gender equality in the labour market.

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A Appendix

A.1 Tables and Figures

Table A1: Gender earnings gaps

	All workers	Dependent workers	Formal sector
Hourly earnings gaps			
2009	0.97	0.94	0.88
2014	0.98	0.95	0.95
2019	0.99	1.00	1.04
Monthly earnings gaps			
2009	0.95	0.96	0.97
2014	0.96	0.96	0.97
2019	0.97	0.97	0.98

Source: Own elaboration based on ECH data. **Note:** This table shows gender log earnings gaps for 2009, 2014 and 2019. Panel A shows the hourly earnings gaps and panel B the monthly earnings gaps. The columns show the gaps for all workers, dependent workers and formal sector (workers that are registered to social security). The earnings gaps are constructed as the ratio of the average labour earnings of women to that of men.

Table A2: Descriptive statistics by gender and marital status

	Women			Men		
	2009	2014	2019	2009	2014	2019
Single						
Age	41.26	41.76	41.79	38.37	38.59	38.88
Years of education	10.02	10.23	10.58	9.20	9.48	9.72
Region	0.54	0.48	0.47	0.52	0.48	0.49
Number of Kids	0.90	0.86	0.77	0.35	0.28	0.26
Currently studying	0.09	0.10	0.11	0.09	0.09	0.10
Out_work_income	547.1	668.1	933.5	502.7	523.4	725.0
Participation rate	0.86	0.86	0.86	0.90	0.90	0.87
Employment rate	0.80	0.81	0.80	0.84	0.83	0.80
Proportion	35.2%	35.8%	39.4%	28.5%	29.8%	33.7%
In couple						
Age	41.49	41.88	42.43	42.27	42.71	43.20
Years of education	9.80	10.19	10.62	9.00	9.27	9.70
Region	0.47	0.41	0.41	0.46	0.41	0.40
Number of Kids	1.28	1.15	1.06	1.32	1.20	1.11
Currently studying	0.05	0.05	0.06	0.03	0.03	0.03
Out_work_income	634.52	711.65	1000.2	286.1	334.1	477.8
Participation rate	0.74	0.78	0.78	0.97	0.96	0.95
Employment rate	0.67	0.71	0.72	0.95	0.95	0.92
Proportion	64.8%	64.2%	60.6%	71.4%	70.1%	66.2%
Difference						
Age	-0.22*	-0.12	-0.64***	-3.89***	-4.12***	-4.32***
Years of education	0.22***	0.04	-0.04	0.19***	0.20***	0.01
Region	0.07***	0.06***	0.06***	0.06***	0.07***	0.08***
Number of Kids	-0.38***	-0.29***	-0.29***	-0.97***	-0.92***	-0.85***
Currently studying	0.04***	0.05***	0.05***	0.06***	0.06***	0.06***
Out_work_income	-87.4***	-43.5**	-66.7*	216.5***	189.3***	247.2***
Participation rate	0.12***	0.07***	0.07***	-0.07***	-0.07***	-0.08***
Employment rate	0.12***	0.09***	0.06***	-0.11***	-0.12***	-0.12***

Source: Own elaboration based on ECH data. **Note:** The first and second panel show the mean for each variable for single and in couple individuals. The third panel shows the difference in mean between single and in couple individuals. Statistics are based on people aged 25 to 59, living in areas of more than 5000 inhabitants, single or in heterosexual couples. The out-of-work potential income is expressed in current monthly amounts. The labour force participation rate is constructed as the ratio of working and unemployed people to the population aged 25 to 59 in that marital status group. Employment rates are calculated as the ratio of working people to the population aged 25 to 59 in that marital status group. ***, ** and * denote statistical significance at levels of 1%, 5% and 10% of means test.

Table A3: Descriptive statistics by gender and marital status

	Women			Men		
	2009	2014	2019	2009	2014	2019
Married						
Age	43.69	44.89	45.75	44.76	45.93	46.68
Years of education	10.10	10.45	10.85	9.35	9.56	10.00
Region	0.46	0.42	0.42	0.46	0.41	0.42
Number of Kids	1.20	1.05	0.98	1.48	1.13	1.06
Currently studying	0.04	0.04	0.04	0.02	0.02	0.02
Out_work_income	604.1	648.7	961.8	325.9	380.7	564.7
Participation rate	0.73	0.74	0.76	0.97	0.97	0.95
Employment rate	0.68	0.70	0.72	0.95	0.95	0.92
Proportion	67.20%	59.51%	54.86%	62.80%	55.15%	50.90%
Cohabitants						
Age	36.97	37.46	38.40	38.09	38.77	39.60
Years of education	9.18	9.82	10.34	8.42	8.92	9.39
Region	0.48	0.41	0.39	0.48	0.41	0.39
Number of Kids	1.44	1.29	1.16	1.41	1.29*	1.18
Currently studying	0.07	0.07	0.08	0.04	0.04	0.05
Out_work_income	696.8	804.1	1046.8	218.7	276.8	387.8
Participation rate	0.76	0.78	0.81	0.98	0.98	0.97
Employment rate	0.67	0.72	0.74	0.96	0.96	0.94
Proportion	32.80%	40.49%	45.14%	37.20%	44.85%	49.10%
Difference						
Age	6.71***	7.43***	7.35***	6.66***	7.15***	7.07***
Years of education	0.92***	0.63***	0.50***	0.92***	0.63***	0.60***
Region	-0.01**	0.008	0.03***	-0.02**	0.00	0.03***
Number of Kids	-0.23***	-0.24***	-0.18***	-0.13***	-0.16***	-0.12***
Currently studying	-0.03***	-0.03***	-0.04***	-0.02***	-0.01***	-0.03***
Out_work_income	-92.7***	-155.4***	-84.9**	107.2***	103.8***	176.8***
Participation rate	-0.03***	-0.04***	-0.04***	-0.016***	-0.014***	-0.02***
Employment rate	0.00	-.02***	-0.02***	-0.006*	-0.006*	-.013***

Source: Own elaboration based on ECH data. **Note:** The first and second panel show the mean for each variable for married and cohabitant individuals. The third panel shows the difference in mean between married and cohabitant individuals. Statistics are based on people aged 25 to 59, living in areas of more than 5000 inhabitants, single or in heterosexual couples. Individuals with no information regarding their marital status, and women who declare to be domestic workers living in their employers house are not included. The out of work potential income is expressed in current monthly amounts. Labour force participation rate is constructed as the ratio of working and unemployed people to the population aged 25 to 59 in that marital status group. Employment rates are calculated as the ratio of working people to the population aged 25 to 59 in that marital status group. ***, ** and * denote statistical significance at levels of 1%, 5% and 10% of means test.

Table A4: Probability of being employed in the labour market

	2009				2014				2019			
	Couple	Married	Cohabitant	Single	Couple	Married	Cohabitant	Single	Couple	Married	Cohabitant	Single
a. Men												
Age	1.299***	1.424***	0.787***	0.579***	1.238***	1.640***	0.681***	0.803***	1.321***	1.106***	1.219***	1.079***
	(0.147)	(0.219)	(0.235)	(0.162)	(0.152)	(0.248)	(0.221)	(0.159)	(0.168)	(0.321)	(0.231)	(0.163)
Age	-1.431***	-1.583***	-0.882***	-0.529***	-1.389***	-1.804***	-0.817***	-0.787***	-1.490***	-1.334***	-1.378***	-1.027***
Squared	(0.142)	(0.204)	(0.239)	(0.166)	(0.147)	(0.230)	(0.223)	(0.163)	(0.163)	(0.291)	(0.233)	(0.168)
7 to 9 years	0.068***	0.046***	0.089***	0.199***	0.067***	0.049***	0.082***	0.192***	0.029***	0.008	0.048*	0.211***
of education	(0.017)	(0.022)	(0.026)	(0.021)	(0.017)	(0.024)	(0.026)	(0.021)	(0.020)	(0.028)	(0.029)	(0.023)
10 to 12 years	0.110***	0.083***	0.146***	0.185***	0.084***	0.068***	0.096***	0.228***	0.109***	0.126***	0.085**	0.240***
of education	(0.018)	(0.023)	(0.031)	(0.022)	(0.018)	(0.025)	(0.027)	(0.022)	(0.021)	(0.029)	(0.030)	(0.023)
Over 12 years	0.118***	0.094***	0.139***	0.214***	0.129***	0.107***	0.143***	0.204***	0.188***	0.180***	0.189***	0.275***
of education	(0.021)	(0.026)	(0.040)	(0.023)	(0.022)	(0.029)	(0.036)	(0.023)	(0.026)	(0.035)	(0.039)	(0.026)
Region	-0.016	-0.009	-0.023	0.025	-0.014	-0.002	-0.027	0.013	-0.049***	-0.034	-0.066**	0.031
	(0.015)	(0.019)	(0.025)	(0.018)	(0.016)	(0.021)	(0.024)	(0.018)	(0.017)	(0.024)	(0.025)	(0.019)
Children	-0.009	-0.004	-0.023	0.014	-0.008	-0.014	0.003	-0.013	-0.021	-0.036	0.005	-0.014
<6 years old	(0.020)	(0.023)	(0.039)	(0.014)	(0.018)	(0.022)	(0.034)	(0.013)	(0.022)	(0.026)	(0.040)	(0.014)
Out of work	0.007	0.025	-0.011	-0.040	0.011	-0.004	0.028	-0.040	0.020	0.001	0.029	0.056
income	(0.015)	(0.022)	(0.023)	(0.029)	(0.016)	(0.024)	(0.021)	(0.033)	(0.017)	(0.028)	(0.023)	(0.036)
Number of observations	16,025	10,063	5,962	6,405	15,663	8,638	7,025	6,653	11,375	5,790	5,585	5,796

	2009				2014				2019			
	Couple	Married	Cohabitant	Single	Couple	Married	Cohabitant	Single	Couple	Married	Cohabitant	Single
a. Women												
Age	0.926***	1.001***	0.785***	1.523***	0.937***	1.100***	0.783***	1.710***	1.088***	1.021***	1.167***	1.512***
	(0.098)	(0.131)	(0.175)	(0.132)	(0.101)	(0.152)	(0.159)	(0.132)	(0.118)	(0.193)	(0.178)	(0.140)
Age	-0.995***	-1.062***	-0.785***	-1.523***	-1.035***	-1.174***	-0.829***	-1.715***	-1.175***	-1.100***	-1.217***	-1.470***
squared	(0.097)	(0.126)	(0.183)	(0.132)	(0.100)	(0.144)	(0.166)	(0.132)	(0.116)	(0.181)	(0.184)	(0.140)
7 to 9 years	0.152***	0.132***	0.199***	0.216***	0.145***	0.155***	0.138***	0.193***	0.180***	0.149***	0.223***	0.245***
of education	(0.012)	(0.015)	(0.020)	(0.018)	(0.012)	(0.017)	(0.019)	(0.018)	(0.016)	(0.022)	(0.023)	(0.020)
10 to 12 years	0.208***	0.179***	0.280***	0.233***	0.161***	0.146***	0.192***	0.212***	0.218***	0.172***	0.284***	0.263***
of education	(0.011)	(0.014)	(0.020)	(0.017)	(0.012)	(0.015)	(0.019)	(0.017)	(0.015)	(0.020)	(0.023)	(0.020)
Over 12 years	0.432***	0.411***	0.500***	0.335***	0.425***	0.429***	0.430***	0.320***	0.455***	0.415***	0.519***	0.401***
of education	(0.012)	(0.015)	(0.025)	(0.018)	(0.013)	(0.016)	(0.022)	(0.018)	(0.016)	(0.022)	(0.026)	(0.021)
Region	0.019*	0.023*	0.008	0.027*	0.009	0.013	0.001	-0.002	0.047***	0.056***	0.036*	-0.004
	(0.010)	(0.012)	(0.018)	(0.015)	(0.010)	(0.0137)	(0.016)	(0.015)	(0.012)	(0.016)	(0.019)	(0.016)
Children	-0.106***	-0.076***	-0.145***	-0.080***	-0.123***	-0.106***	-0.122***	-0.059***	-0.092***	-0.066***	-0.114***	-0.043***
<6 years old	(0.010)	0.014	(0.017)	(0.016)	(0.010)	(0.015)	(0.017)	(0.017)	(0.012)	(0.019)	(0.017)	(0.018)
Out of work	-0.072***	-0.060***	-0.095***	-0.075***	-0.080***	-0.055***	-0.141***	-0.087***	-0.076***	-0.064***	-0.088***	-0.075***
income	(0.011)	(0.013)	(0.022)	(0.013)	(0.011)	(0.013)	(0.015)	(0.013)	(0.013)	(0.017)	(0.021)	(0.013)
Number of observations	17,077	11,475	5,602	9,275	16,765	9,977	6,788	9,349	12,421	6,814	5,607	8,075

Source: Own elaboration based on ECH data. **Note:** Panel a shows the coefficients resulting from the Probit model estimations for men and panel b for women in 2009, 2014 and 2019. Estimations include individuals aged 25 to 59, living in areas of more than 5000 inhabitants, single or in heterosexual couples. Each column shows the coefficients and standard errors in parenthesis for individuals in Couples, Married, Cohabitants and Single, respectively. Couples groups both, married and cohabiting individuals. ***, ** and * denote statistical significance at levels of 1%, 5% and 10%.

Table A5: Male selection parameter

	Married	Cohabitation	Single
2009			
ρ	-0,981	0,132	0,870
95% CI	[-2.429;0.466]	[-1.197;1.463]	[-0.715;2.456]
N° Observations	10,063	5,962	6,405
2014			
ρ	0,913	1,181	-1,642
95% CI	[-0.876;2.702]	[-0.901;3.265]	[-3.504;0.219]
N° Observations	8,638	7,025	6,653
2019			
ρ	2,103	0.839	-1.268
95% CI	[0.355;3.851]	[-0.958;2.638]	[-3.025;0.488]
N° Observations	5,790	5,585	5,796

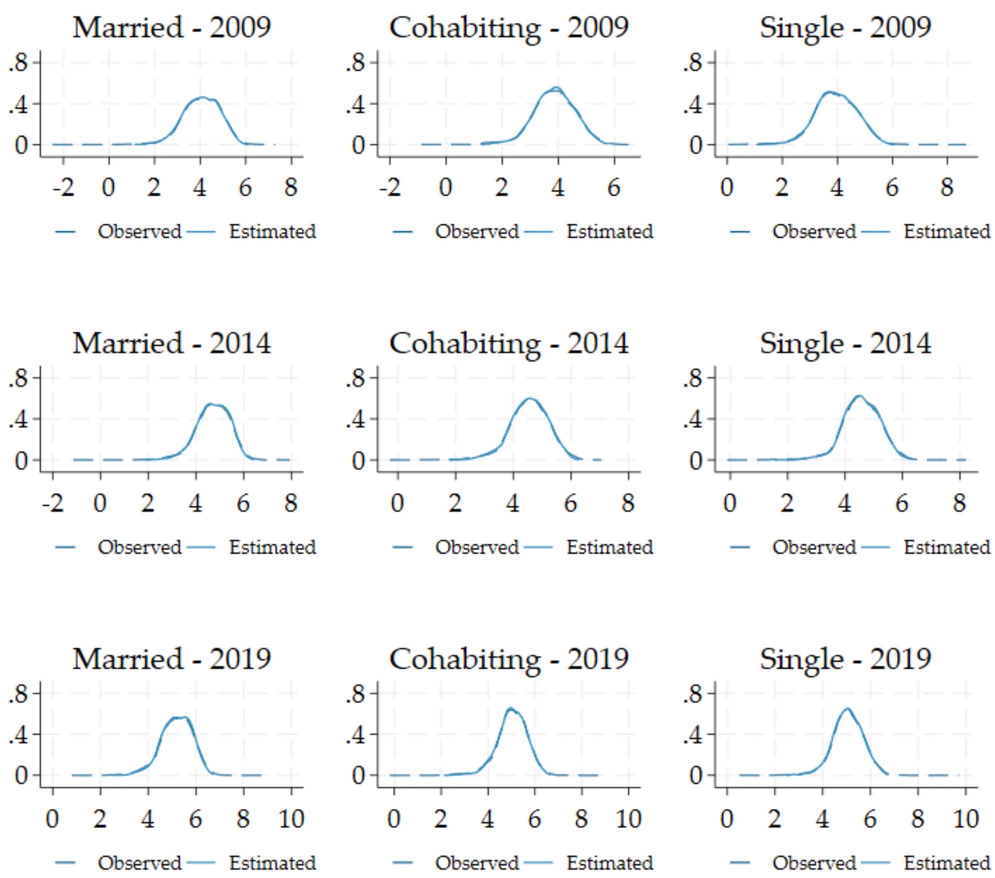
Source: Own elaboration based on ECH data. **Note:** Estimations include men aged 25 to 59, living in urban areas. Parameters are estimated separately for each marital status. Each column shows the coefficients and 95% confidence intervals in brackets for and men in marriage, cohabitation and single, respectively. A negative sign of the selection parameter, ρ, indicates a positive selection into employment, and vice-versa.

Table A6: Married and cohabiting women employment Oaxaca-Blinder decomposition

	2009	2014	2019
Difference	-0.0015	0.0182**	0.0202**
Endowments	-0.0307***	-0.0214***	-0.0064
Coefficients	0.0542***	0.0494***	0.0390***
Interaction	-0.0249***	-0.0096	-0.0123

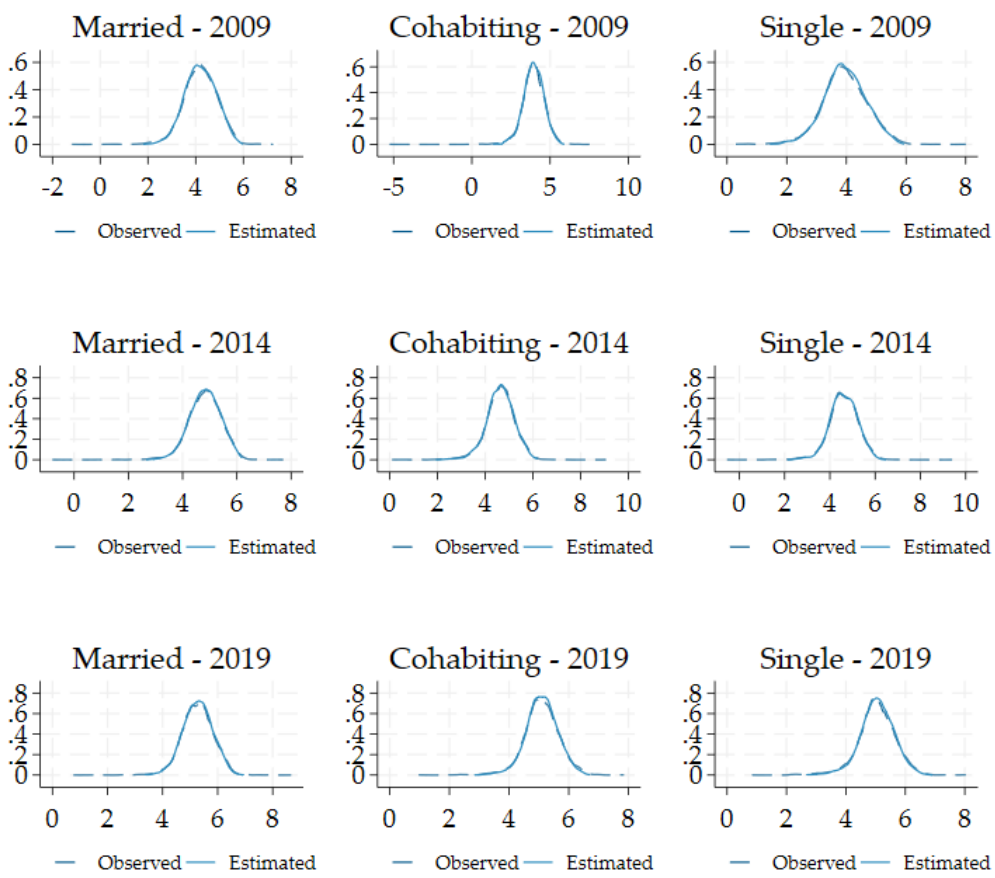
Source: Own elaboration based on ECH data. **Note:** This table shows what part of the difference in being employed is explained by endowments, coefficients and the interaction of both, between married and cohabiting women. Group 0 corresponds to cohabiting and group 1 to married women.

Figure A1: Observed and estimated hourly earnings - Women



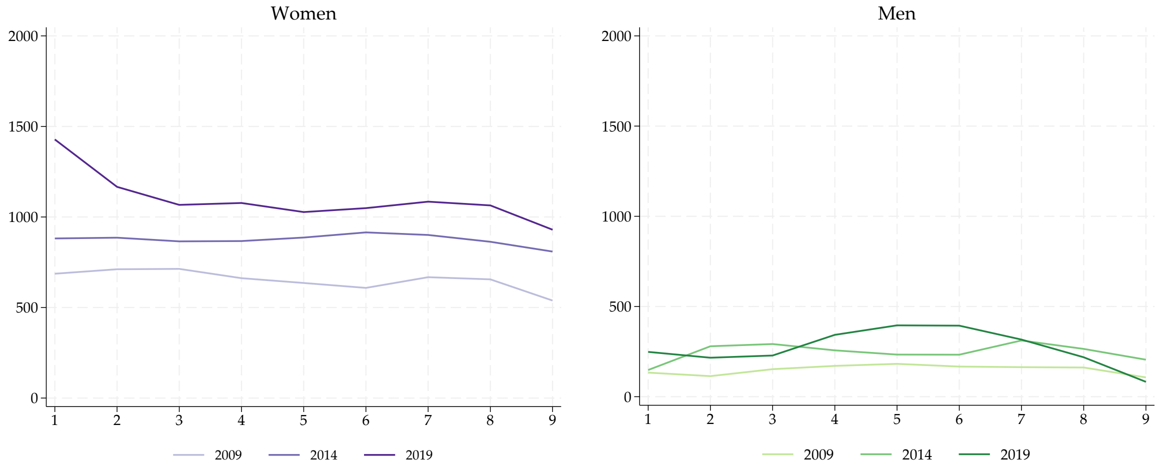
Source: Own elaboration based on ECH data. **Note:** Figure shows kernel estimations of the observed and estimated with Quantile Regressions log hourly earnings for women. Estimations include women aged 25 to 59, living in urban areas. Dashed lines represent observed hourly earnings of working women and solid lines show female estimated hourly earnings using Quantile regressions.

Figure A2: Observed and estimated hourly earnings - Men



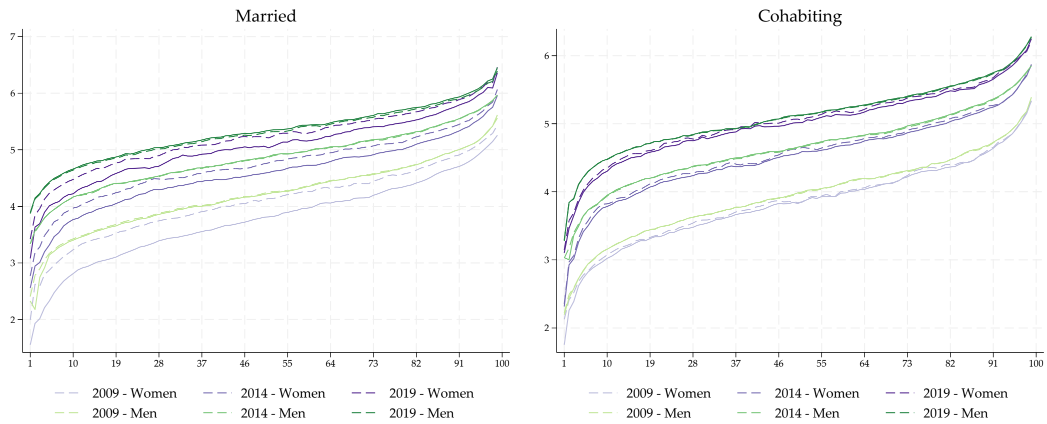
Source: Own elaboration based on ECH data. **Note:** Figure shows kernel estimations of the observed and estimated with Quantile Regressions log hourly earnings for men. Estimations include men aged 25 to 59, living in urban areas. Dashed lines represent observed hourly earnings of working women and solid lines show female estimated hourly earnings using Quantile regressions.

Figure A3: Out of work potential income along the distribution



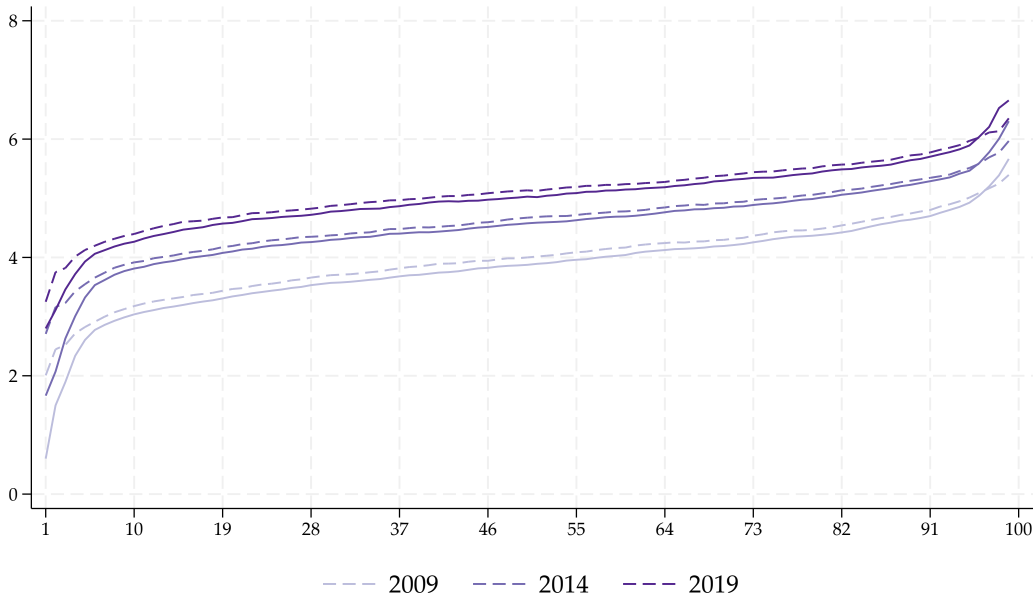
Source: Own elaboration based on ECH data. **Note:** Figure shows the average amount of out of work income along the earnings distribution, by gender and year.

Figure A4: Hourly earnings distribution by marital status and year, correcting for male and female selection into employment



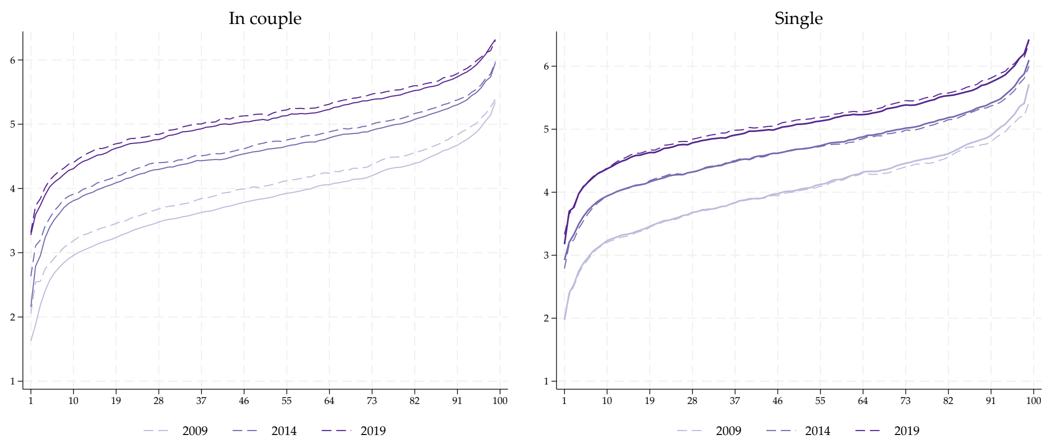
Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include individuals aged 25 to 59, living in urban areas. Dashed lines represent observed and solid lines represent selection-corrected hourly earnings.

Figure A5: Log of hourly earnings distribution - All women



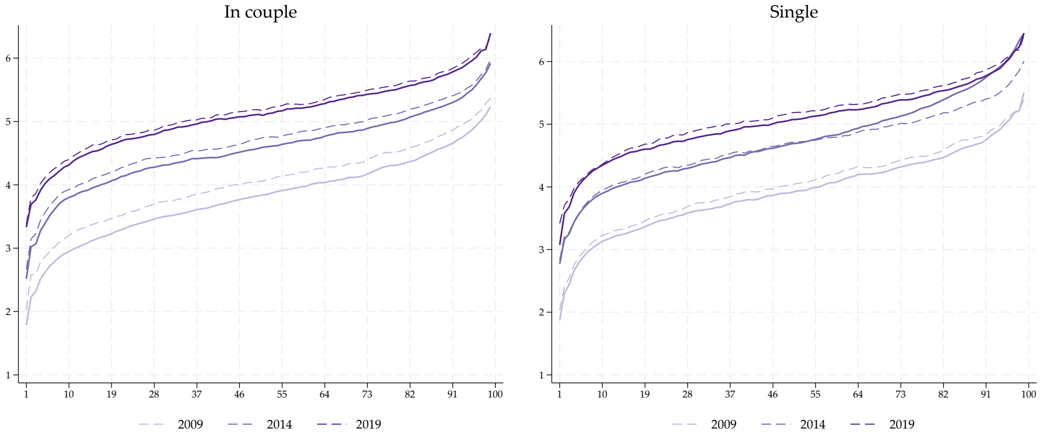
Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include women aged 25 to 59, living in urban areas. Dashed lines correspond to observed and solid lines to selection-corrected hourly earnings distributions. Percentiles are constructed using hourly earnings from the selection corrected and observed distributions, respectively.

Figure A6: Log of hourly earnings distribution dropping studying individuals from the database



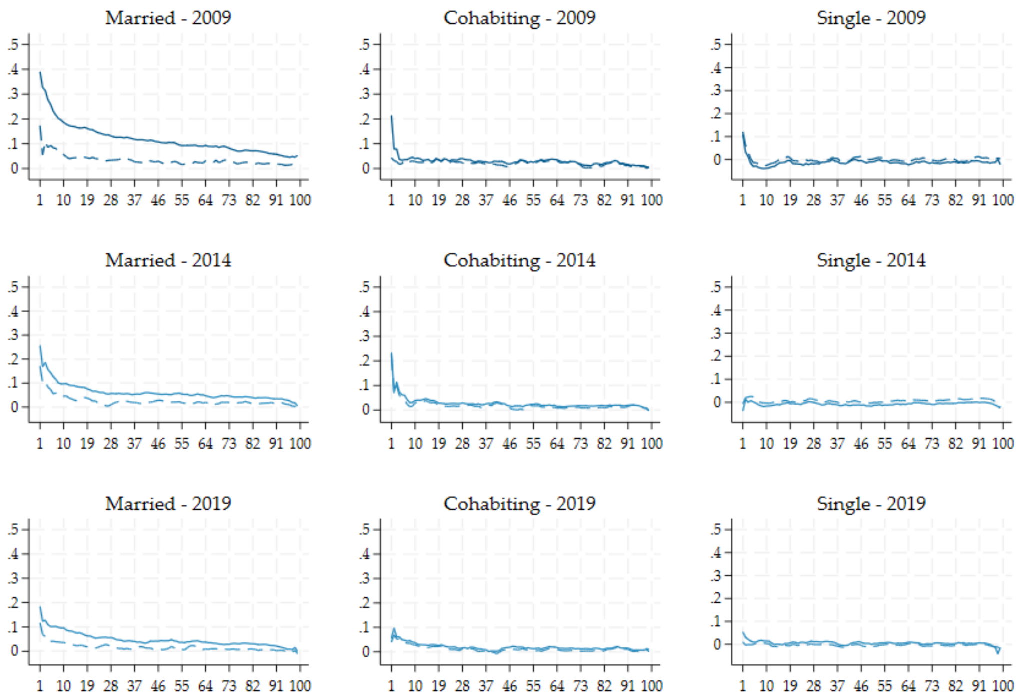
Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include women aged 25 to 59, living in urban areas. Solid lines correspond to selection corrected and dashed lines to observed hourly earnings distributions. Percentiles are constructed using hourly earnings from the selection corrected and observed distributions, respectively.

Figure A7: Log of hourly earnings distribution dropping non parents from the database



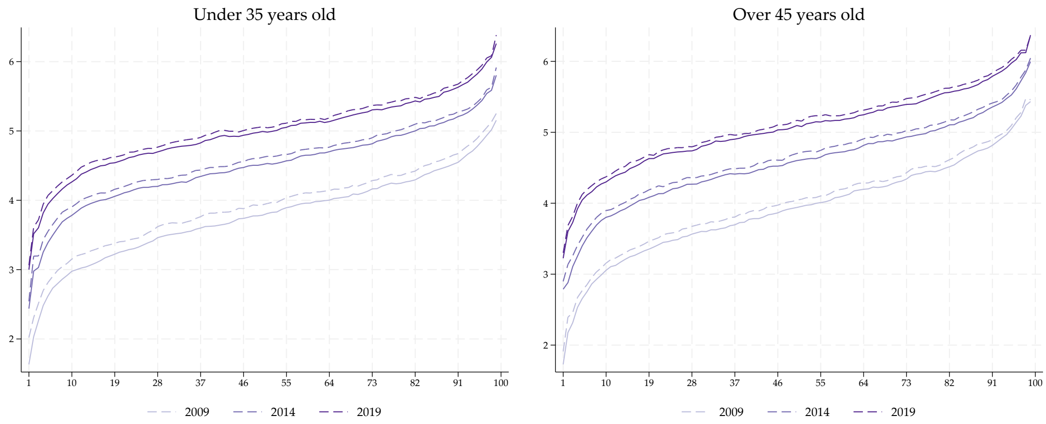
Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include women aged 25 to 59, living in urban areas. Solid lines correspond to selection corrected and dashed lines to observed hourly earnings distributions. Percentiles are constructed using hourly earnings from the selection corrected and observed distributions, respectively.

Figure A8: Estimated and selection corrected gender earnings gaps by marital status and year



Source: Own elaboration based on ECH data. **Note:** The figure shows hourly gender earnings gaps along the earnings distribution. The gap results from the ratio between women and men's average earnings in each percentile. Estimations include individuals aged 25 to 59, living in urban areas. Dashed lines show hourly gender earnings gaps conditional on employment, solid lines show selection-corrected hourly gender earnings gaps.

Figure A9: Log of hourly earnings distribution by age group



Source: Own elaboration based on ECH data. **Note:** The figure shows observed and selection corrected hourly earnings distributions. The selection-corrected earnings distribution is derived by multiplying each individual's observable characteristics by the corresponding quantile coefficients, based on the percentile assigned to each. Estimations include women under 35 and over 45 years old separately, living in urban areas. Solid lines correspond to selection corrected and dashed lines to observed hourly earnings distributions. Percentiles are constructed using hourly earnings from the selection corrected and observed distributions, respectively.

A.2 Government cash transfers

AFAM-PE

One of the main cash transfers available in Uruguay is called Asignaciones Familiares - Plan de Equidad (AFAM-PE) created in 2008. This is a non-contributory transfer aimed at households with children under 18 years old or pregnant women. The monetary benefit is conditional on health check-ups and school attendance. AFAM-PE is currently the largest non-contributory transfer program in coverage and magnitude in Uruguay Bergolo and Cruces (2021). Eligibility is defined by two conditions. First, earnings from registered employment, other Governmental cash transfers, or pensions, can't exceed a certain threshold. Applicants must declare their income, which is then compared with social security records. Second, households have to be identified as poor in terms of a vulnerability proxy index (Índice de carencias críticas, ICC). This index combines socioeconomic variables declared by the applicant households and checked in a visit, to proxy the household's well-being. The household's ICC value must be over a threshold[20]. The amount of the transfer is updated regularly following the Consumer Price Index, and it is not linear on the number of children. The household receives monthly a fix amount per under-age child, and a complement for each child attending secondary school:

$$AFAM-PE = A*(age0\_17)^{0.6} + C*(age0\_17secondary)^{0.6} \tag{7}$$

Table A7: Cash transfer amounts per year

	AFAM		TUS							
			Simple				Double			
	Fixed amount	Complement	1 kid	2 kids	3 kids	4 kids or more	1 kid	2 kids	3 kids	4 kids or more
2009	764.3	327.6	435	660	840	1170	-	-	-	-
2014	1096.4	469.9	736	1117	1420	1980	1472	2234	2840	3960
2019	1615.23	692.25	1061	1610	2048	2853	2122	3220	4096	5706

Source: Own elaboration. **Note:** The table shows the amount of AFAM and TUS per year in current Uruguayan pesos added to eligible households in the out-of-work potential income.

Tarjeta Uruguay Social

The other program taken into account for the construction of potential out-of-work income is Tarjeta Uruguay Social (TUS), created in 2008. This is a non-contributory and unconditional transfer that aims to ensure access to basic necessity products. Most of the households participating in this program have children, but unlike AFAM-PE, it is not a necessary condition. The monthly transfer has four different amounts depending on the quantity of children living in the household. Since 2011, there have been two kinds of transfer; TUS simple, and TUS doble. The latter has double the amount of transfer and is

[20] ICC index ranges from 0 to 1, where values near 1 reflect the most vulnerable households.

for the most vulnerable households. The eligibility system uses the same index as AFAM-PE, ICC, but the thresholds fixed to access TUS are more strict. During the construction of the potential out-of-work income, the per capita amount of TUS transfer is imputed to each member of the household, if eligible.

A.3 Selection correction

One of the first and widely applied selection correction methods is the two-step model developed in Heckman (1979), which models selection bias at the mean through an exclusion restriction. Heckman's two-step method, applied to wage distributions, implies estimating in the first step the propensity of an individual being at work. This requires an exclusion variable that is related to employment but not to the outcome (earnings). As a second step, earnings are estimated for working individuals, including in the equation the inverse Mill's ratio, derived from step one, to adjust the predicted earnings based on the probability of being selected. This two-step parametric estimation assumes a joint normal distribution of the errors of the outcome and selection equation. This model has two main restrictions; it is difficult to find instrumental variables that meet the aforementioned assumption, and it only corrects for selection at the mean. This implies that it is not able to consider different selection patterns along the earnings distribution.

Other selection correction methods are based on imputation, as proposed by Olivetti and Petrongolo (2008), which assign a fictitious earning to those not participating in the labour market, correcting for selection at the median. The authors aim to allocate individuals who are not working to either side of the median in the earnings distribution. For this, they only need to make an accurate guess about which side of the median non-workers would belong to. They propose three different ways to perform earnings imputation. If panel data is available, one approach is to assign to each non-working individual the position (above or below the median) that they had at another point in time. However, this method has limitations; for instance, if employment patterns are relatively constant over the analysed period or the panel is too short, is will not be efficient in correcting the selection, as those not currently working may have never worked throughout the panel. Another approach is to define thresholds above which the individual is on either side of the median based on a few observable variables (such as age and education). For example, if the years of education are high enough, the individual is imputed on the right side of the earnings median. This method can be effective in assigning individuals at the extremes of the distribution but fails when the values in the selected variables hover around the averages. Lastly, one can estimate the probability of being below the earnings median and include them with a low earning and probability p, and a high earning with probability $1 - p$. Gender wage gaps using this selection-correction method are the result of comparing the median of men and women's wage imputed distributions.

Table A8: Different approaches to selection-correction

Model	Description	Position in distribution	Applications
Heckman (1979)	Two-step model. Estimate the probability of being employed including at least one IV. Estimate earnings including the inverse Mill's ratio derived from step 1.	Mean	González and Rossi (2007) - Uruguay
Buschinsky (1998)	Additive control function method. Analogue Heckman (1979)'s , for quantile regressions and does not assume normality and homoscedasticity.	Entire distribution	Bucheli and Sanroman (2004) - Uruguay Borraz and Robano (2010) - Uruguay
Olivetti and Petrongolo (2008)	Imputes non-employed individuals to either side of the median of the earnings distribution. This imputation may be based on observations from other waves in case on panel datasets, based on few observable characteristics, or through estimating the probability of being on one side of the earnings median.	Median	Dolado et al. (2020) - EU countries
Arellano and Bonhomme (2017)	Three step estimation model. Estimate the probability of being employed including at least one IV. Estimate dependence between error terms from the employment and earnings equations through a Copula function. Shift quantile coefficients as a function of the selection in step 2.	Entire distribution	Maasoumi and Wang (2019) - USA Elass (2022) - UK, France and Finland

Source: Own elaboration. **Note:** This table shows a brief description of the selection-correction methods mentioned in this study, if the model corrects selection at the mean, median or the entire distribution, and some applications. When available, I mention previous studies for the Uruguayan case.