

MASTER IN
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Is motherhood one of the causes of the gender pay gap?

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Abstract

Gender wage inequalities continue to exist across Europe, revealing a significant gap where women frequently earn less than their male counterparts. This disparity is even more pronounced when parenthood is taken into account, highlighting how family responsibilities can significantly influence career paths and wages.

This dissertation investigates the impact of motherhood on the gender wage gap in Portugal, comparing its findings with data from several European countries. To achieve this, we utilize anonymized microdata from the European Labor Force Survey covering the years 2009 to 2019, employing an ordered logit model.

Our results indicate a significant “motherhood penalty”, where mothers have a lower likelihood of reaching higher wage deciles compared to men and women without children. Conversely, fatherhood is linked to a “fatherhood premium”, as fathers are more likely to attain higher positions in the wage distribution.

Education enhances wage outcomes for both men and women, but it does not eliminate the gender wage gap. Men still receive greater returns for their human capital, even when women have the same or even higher qualifications. Additionally, the challenges faced by mothers become more pronounced without institutional or family support, highlighting how structural and cultural factors contribute to ongoing wage inequalities.

International comparison further shows that inclusive, gender-neutral policies, particularly those encouraging paternal involvement and ensuring access to childcare, are most effective in reducing the “motherhood penalty”. In Portugal, however, despite recent reforms promoting shared parental leave, low male uptake and insufficient childcare provision continue to limit progress.

Overall, our findings highlight that narrowing the “motherhood penalty” requires not only well-designed public policies, but also cultural change and organizational practices that promote flexible work arrangements, shared caregiving responsibilities, and expanded childcare provision.

Keywords Gender pay gap; Motherhood penalty; Fatherhood premium; Portuguese labor market; European labor market; Labor Economics; Childcare public policies

Resumo

As desigualdades salariais entre os homens e as mulheres continuam a verificar-se na Europa, revelando uma diferença significativa em que as mulheres recebem frequentemente salários inferiores aos dos homens. Esta disparidade torna-se mais acentuada quando se considera a parentalidade, destacando o facto de as responsabilidades familiares influenciarem as trajetórias profissionais e os salários.

Esta dissertação investiga o impacto da maternidade na desigualdade salarial de género em Portugal e compara os resultados com vários países europeus. Para tal, utilizámos microdados anonimizados do *European Union Labour Force Survey*, referentes ao período 2009-2019, e aplicamos um modelo *ordered logit*.

Os nossos resultados confirmam a presença do “*motherhood penalty*”, pois as mães apresentam uma menor probabilidade de alcançar decis salariais superiores em comparação a homens e a mulheres sem filhos. Já a paternidade leva a um prémio salarial (“*fatherhood premium*”), visto que os pais têm uma maior probabilidade de atingir posições superiores na distribuição salarial.

A educação, no geral, melhora os salários, mas não elimina a desigualdade de género. Os homens continuam a obter melhores resultados pelo seu capital humano, mesmo quando as mulheres possuem melhores qualificações. Além disso, as dificuldades enfrentadas pelas mães tornam-se maiores na ausência de apoio institucional ou familiar, o que evidencia a forma como fatores estruturais e culturais contribuem para a persistência das desigualdades salariais.

A comparação internacional mostra que as políticas inclusivas e neutras em termos de género, especialmente as que incentivam a participação dos pais e garantem acesso aos serviços de infância, são mais eficazes na redução do “*motherhood penalty*”. Em Portugal, apesar das reformas recentes, a baixa adesão paterna e a oferta insuficiente de serviços de infância continuam a limitar os progressos.

Em resumo, os nossos resultados demonstram que a mitigação do “*motherhood penalty*” exige não apenas boas políticas públicas, mas também mudanças culturais e práticas organizacionais que promovam regimes de trabalho flexíveis, responsabilidades parentais partilhadas e um maior acesso a serviços de apoio à infância.

Palavras-chave Desigualdade salarial de género; Motherhood penalty; Fatherhood premium; Mercado de trabalho português; Mercado de trabalho europeu; Economia do trabalho; Políticas públicas de apoio à infância

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Chapter 1

Introduction

Persistent gender wage disparities continue to be a significant issue across Europe, and Portugal is no exception. As illustrated in Figure 1.1, between 2009 and 2023, women’s wages were consistently 11% to 21% lower than those of men. National statistics reinforce this, indicating that in 2016, Portuguese women were paid, on average, 15.6% less in monthly wages compared to their male counterparts (CITE, 2018). The wage gap is even more pronounced when considering parenthood. As shown in Figure 1.2, Portuguese mothers experience a sharp decline in wages compared to childless women, particularly in their early 30s, with this “motherhood penalty” persisting throughout much of their working lives. By contrast, fathers tend to earn relatively more than non-fathers in the same age range, reflecting a “fatherhood premium”. Beyond the age of 50, when fertility is no longer a factor, the patterns for men and women converge.

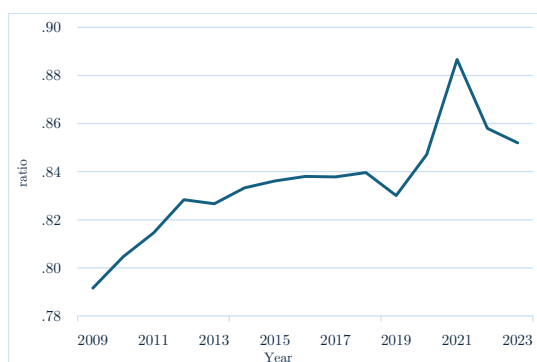


Figure 1.1: Wages ratio between women and men by year (2009-2023).

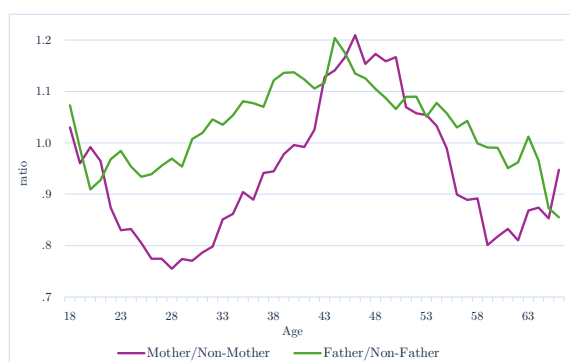


Figure 1.2: Wages ratio between mothers and non-mothers and between fathers and non-fathers by age (2009-2019).

These patterns prompt a crucial question: to what extent can the gender wage gap be attributed to motherhood, and what mechanisms are involved? This dis-

sertation explores this question by analyzing how motherhood influences wages in Portugal and evaluating whether variations in human capital, selection mechanisms, and family support systems contribute to the persistence of these disparities.

The importance of our research question is further supported by international research (Goldin et al., 2024; Kleven et al., 2019; Sigle-Rushton & Waldfogel, 2007) which identifies motherhood as a significant factor contributing to enduring wage inequalities, due to a range of mechanisms, including career interruptions, reduced working hours, and employer discrimination.

Building on this research question, three hypotheses are proposed. H1 posits that motherhood increases the gender wage gap. H2 suggests that differences in human capital, such as education, experience, and tenure, can account for part of the wage gap. H3 considers that the “motherhood penalty” may also result from selection mechanisms and discriminatory practices within the labor market.

To address these hypotheses, we use anonymized microdata from the European Union Labour Force Survey (EU-LFS) covering 2009 to 2019. The sample was constructed to maintain consistency, focusing on working-age individuals aged 18 to 66 who have valid wage information. Observations with inconsistent data, such as implausible household compositions or job tenures exceeding the respondent’s age, were excluded. This resulted in a dataset of over 560,000 individuals from Portugal.

The dependent variable in this analysis is the wage decile, which reflects each individual’s relative position within the national gross monthly wage distribution. Wage deciles divide the income distribution into ten equal groups, with the first decile representing the lowest wages. The independent variables include gender, the number of children in the household, age, job tenure, and education level, as well as a comprehensive set of demographic, professional, and household controls.

Our empirical approach employs an ordered logit model, which is appropriate for ordinal outcomes. A total of six models are estimated iteratively, with each model building upon the previous one. The first model establishes the unconditional gender wage gap. The second model adds demographic, professional, and household controls. The third and fourth models examine the impact of parenthood, both with and without these controls, and include an interaction term with gender to highlight differences between mothers and fathers. The fifth model introduces human capital variables, with a gender-education interaction. Finally, the sixth model combines all the elements into a unified model.

Across all models, men are consistently more likely to occupy higher wage deciles compared to women. At the lower end of the distribution, women are significantly overrepresented; in the first wage decile, there are nearly three women for every man.

But, from the fifth decile onward, men dominate among top earners. Motherhood is associated with a downward shift in the wage distribution, while fatherhood is linked to an upward shift. For example, fathers of four children are more likely to reach the seventh decile or higher than their childless counterparts. In contrast, women’s probabilities remain relatively unchanged regardless of the number of children. Although education boosts wages for both genders, men tend to experience greater returns on their educational investments. Even among individuals with advanced degrees, men have a higher likelihood of attaining top wage deciles. Additionally, when household composition is considered, the negative impact of motherhood becomes more pronounced for women lacking family or institutional support.

To validate the findings, robustness checks were conducted using ordinary least squares (OLS) regressions. Although OLS is not the theoretically optimal method for ordinal data, the results remain consistent with the ordered logit estimates.

Our results reveal that motherhood significantly contributes to gender wage disparities in Portugal. The evidence strongly supports H1, indicating that motherhood exacerbates the gender wage gap. In other words, becoming a mother reduces women’s likelihood of reaching higher wage deciles. The results also confirm H3, which suggests that selection mechanisms and discrimination play a role in the “motherhood penalty”. Even after accounting for differences in family composition and other household characteristics, mothers remain more likely to be concentrated in lower wage deciles. This persistence suggests that structural barriers, such as limited childcare provision, traditional gender norms, or employer bias, play a decisive role in reinforcing the “motherhood penalty”. By contrast, H2 is not validated. Although education, age, and job tenure (human capital factors) are positively associated with wage outcomes, they do not fully explain why women continue to have lower wages than men. In fact, despite Portuguese women achieving higher levels of education than men on average, the gender wage gap remains. This indicates that disparities are not simply the result of differences in qualifications or experience, but rather reflect more profound structural and cultural inequalities.

Finally, the analysis was broadened to include other European countries, each with different institutional frameworks, while still using the same ordered logit model. This international comparison highlights the importance of public policy design: countries that offer inclusive, gender-neutral parental leave and have strong childcare resources experience lower motherhood penalties. In contrast, when policies are specifically aimed at mothers, or when paternal involvement is limited and childcare resources are scarce, the “motherhood penalty” continues to exist, further reinforcing the “fatherhood premium”.

Chapter 2

Related literature

2.1 Gender Pay Gap

According to Blau and Kahn (2017), despite a reduction in the gender pay gap over the past few years, progress has stagnated, and the disparity remains stable. Many authors argue that this phenomenon may be a natural outcome of the human capital theory and discrimination (Altonji & Blank, 1999; Sigle-Rushton & Waldfogel, 2007; Waldfogel, 1998). However, Kleven et al. (2019) indicate that the ongoing wage disparity between genders can largely be linked to the impact of motherhood.

Our analysis of Portuguese data from 2009 to 2023 confirms this persistence. As illustrated in Figure 1.1, the earnings ratio between women and men fluctuates between 79% and 89%, showing that women earn 11%–21% less than men on average.

Sigle-Rushton and Waldfogel (2007) note that human capital theory suggests women generally earn less than men due to their lower levels of human capital, including education, experience, or tenure in the workforce. The 2023 Nobel laureate in Economics, Claudia Goldin, emphasizes that the pay gap between men and women following childbirth is significantly influenced by mothers working fewer hours, which restricts their career advancement opportunities. This decline in full-time work experience aligns with human capital theory, indicating that fewer years of active participation in the workforce lead to reduced future earnings (Goldin et al., 2024). However, our findings suggest that this explanation is insufficient: even women who possess the same educational qualifications and professional traits as men consistently have lower probabilities of attaining the highest wage deciles. This highlights a structural disparity that cannot be fully accounted for by differences in human capital alone.

Recent evidence on wage dynamics in Portugal is presented by Alvarelhão et al. (2024), who explores employment and wage trends in the electricity sector from 2002

to 2020 using the *Quadros de Pessoal* dataset. Their analysis indicates a restructuring of the workforce towards non-routine cognitive occupations, accompanied by slower wage growth in routine tasks. The study also highlights notable gender differences. For men, wages in routine occupations grew at a slower rate compared to non-routine jobs. Moreover, wage growth for women in routine roles lagged behind that of their counterparts in non-routine positions. This evidence reinforces our findings by highlighting that gender wage disparities in Portugal are not only persistent but also shaped by broader structural and technological transformations.

2.2 Motherhood Pay Gap

Some empirical studies have quantified the “motherhood pay gap” and examined its evolution across time and national contexts. Waldfogel (1998) argues that the wage gap between women with children and those without is widening.

Much of the literature suggests that the “motherhood pay gap” is mainly due to mothers generally spending more time out of the labor market while raising children and being more inclined to work part-time or transition into positions that offer more family-friendly policies (Blau & Kahn, 2017; Goldin et al., 2024; Kleven et al., 2019; Sigle-Rushton & Waldfogel, 2007).

An alternative explanation involves selection bias. Sigle-Rushton and Waldfogel (2007) propose that women who experience less success in the labor market may be more likely to have children, have more children overall, and consequently leave the workforce. Conversely, they also point out that according to the rational expectations model, if women foresee significant challenges in managing work alongside childcare, they may opt to invest less in their human capital, ultimately resulting in lower earnings. This perspective aligns with the findings presented by Kleven et al. (2019), Blau and Kahn (2017), and Goldin et al. (2024).

Additionally, Blau and Kahn (2017), Goldin et al. (2024), and Yu and Hara (2021) indicate that the “motherhood pay gap” can partly be attributed to discrimination, as mothers are perceived as less competent and less committed to their jobs, leading to lower starting salaries. A view that aligns with Altonji and Blank (1999) definition of discrimination as a case “in which individuals who provide labor market services and are equally productive in a physical or material sense are treated unequally based on an observable characteristic such as race, ethnicity, or gender”.

In contrast, fathers typically do not face this bias and are often viewed as more dedicated employees (Blau & Kahn, 2017; Waldfogel, 1998). Some studies even report a wage advantage for fathers; for instance, among high-skilled Canadian men,

fathers earn 5% to 7% more than their childless counterparts when working within the same companies (Cooke & Fuller, 2018). Similarly, Yu and Hara (2021) finds a clear “fatherhood premium”, particularly within the same employer, attributing these contrasting effects to employer-based bias, whereby mothers are penalized while fathers are rewarded. Our findings also support the existence of a “motherhood penalty” and a “fatherhood premium” in the Portuguese labor market.

In their 2017 study, Krapf et al. (2017) found insufficient evidence to support the idea that motherhood is linked to diminished research productivity among male and female academic economists. Conversely, Adda et al. (2017) examines the complex relationship between career choices and fertility trends, indicating that women in fields with high wage growth but significant skill decline during career breaks face considerable costs related to motherhood.

Cultural influences are also crucial in understanding these disparities. A study by Kleven et al. (2019) draws two key conclusions. First, societal views on gender roles remain traditional, with the prevailing belief that women should not work full-time while raising children. Second, these attitudes are remarkably consistent across different countries. Additionally, Blau and Kahn (2017) notes that an increase in the hours spent on household chores is associated with lower wages for women.

According to Sigle-Rushton and Waldfogel (2007), women without children tend to earn more, on average, than their counterparts who are mothers. The authors note that in Germany and Netherlands, women who have their first child at age 27 earn, on average, only 63% of what childless women earn by the age of 45. In the United Kingdom (UK), the income disparity is slightly less pronounced; mothers with one child at age 27 earn approximately 67% of the income of childless women, while those with two children, born at ages 25 and 27, earn around 58%. Their findings also indicate that although women’s earnings remain lower than those of men of similar ages and educational backgrounds, the wage gap between childless women and men is smaller than the disparity between mothers and childless women (Sigle-Rushton & Waldfogel, 2007).

In the case of Portugal, a similar pattern emerges. As illustrated in Figure 1.2, the gap between mothers and non-mothers progressively increases until around age 30. At this point, mothers earn approximately 20–25% less than their childless counterparts. Beyond this age, the disparity gradually narrows, and between the ages of 40 and 55, mothers tend to earn more than non-mothers. This likely coincides with a time when children are older and require less intensive care, enabling mothers to re-engage more fully in the labor market. After age 55, however, the wage ratio begins to decline once again. By contrast, fathers display the opposite

trend. Although their ratio relative to non-fathers is close to or slightly below unity in their early 20s, it increases steadily during the fertile years, peaking around the early 40s, before gradually declining towards unity after age 50.

These findings are consistent with the research conducted by Harkness and Waldfogel (1999), who used data from the Luxembourg Income Study to present evidence of a gender pay gap in the UK and Germany. Their analysis uncovered disparities not only in comparisons between mothers and the average male worker, but also between childless women and men, as well as between mothers and non-mothers.

The study by Kleven et al. (2019) demonstrated that when accounting for lifecycle and time trends, the earnings of men and women grow similarly until parenthood. However, once a woman becomes a mother, her gross earnings decline by nearly 30%. In the subsequent years, women’s earnings do not recover to their pre-motherhood levels; even a decade after the birth of their first child, their earnings remain approximately 20% lower than they were before childbirth (Kleven et al., 2019). This conclusion is supported by several other authors, who have observed that women’s earnings significantly decrease upon having their first or second child (Krapf et al., 2017; Sigle-Rushton & Waldfogel, 2007; Waldfogel, 1998; Yu & Hara, 2021).

More recent evidence presented by Cooke et al. (2022) shows that, over time, the extent to which discrimination contributes to the “motherhood penalty” may have decreased in some contexts. Utilizing decomposition methods to isolate the portion of the wage gap that observable characteristics cannot explain, they demonstrate that in countries such as the UK and Finland, the unexplained part, often interpreted as a proxy for discrimination, has decreased in recent years. In contrast, in Germany, this component has remained stable or even increased, indicating a continued or persistent role of discrimination in shaping the motherhood wage penalty.

2.3 Role of Public Policies in Mitigating the Gap

Research consistently shows that motherhood significantly impacts women’s earnings and is a major contributor to the gender pay gap. Therefore, it is essential to understand how public policies can help mitigate these disparities.

In recent decades, work-family reconciliation policies have experienced significant changes, particularly in Europe, aimed at promoting gender equality and supporting parental involvement in caregiving (Thévenon, 2011). In Portugal, family policy reform began in 1976 with Decreto-Lei n.º 112/76, which established the universal right to 90 days of maternity leave. More changes included the Maternity and Paternity Law in 1984, which recognized caregiving as a shared parental responsibility

and introduced paternity leave. A recent reform in 2009 (Decreto-Lei n.º 91/2009) replaced the term “maternity leave” with “initial parental leave” and introduced a 30-day bonus for couples who shared this entitlement (Wall & Leitão, 2016).

Despite these developments, countries across Europe continue to vary widely in how they structure and deliver family policies. As highlighted by Sigle-Rushton and Waldfogel (2007), family-friendly policies can alleviate some of the economic penalties associated with motherhood. For example, paid maternity leave may prevent women from leaving the workforce or losing firm-specific capital, thereby supporting a quicker return to employment and preserving earnings. Generous childcare provisions can also reduce career interruptions and discourage part-time work among mothers. Additionally, policies that promote men’s participation in domestic and caregiving duties, such as non-transferable parental leave for fathers, may further improve mothers’ labor market outcomes.

Blau and Kahn (2017) emphasizes that, before the implementation of mandatory parental leave, motherhood often forced women to sever ties with their employers, resulting in the loss of jobs suited to their qualifications or firm-specific training. Even the anticipation of this outcome could deter women from investing in their human capital and lead employers to avoid such investments. Thus, effective leave policies may help maintain women’s labor market attachment and earnings potential.

Notably, policy design varies considerably across Organisation for Economic Co-operation and Development (OECD) countries, influencing the degree to which the “motherhood penalty” is mitigated. Some countries, like Sweden and Norway, offer a unified parental leave that does not distinguish between maternity and paternity leave. These systems emphasize gender neutrality and shared caregiving roles.

A comparative analysis by Thévenon (2011) reveals large variations in family policies across OECD countries, particularly in terms of structure, generosity, and underlying objectives. Nordic countries offer extensive, well-compensated parental leave, including specific quotas for fathers, alongside universal access to early childhood education and care. In these nations, more than 70% of children under the age of three are enrolled in formal childcare, with public expenditure on services for children under six reaching 1.52% of GDP, nearly double the OECD average.

In contrast, Western European nations focus more on cash benefits and tax relief than on direct services. For instance, France dedicates 2.2% of its GDP to family transfers and tax incentives, and while preschool education is widely accessible, formal childcare options for younger children are relatively scarce.

Southern European countries have seen slower policy development. Nations such as Spain provide shorter paid leave and less extensive childcare coverage. Overall

investment in family support remains below the OECD average, with informal care, often provided by mothers, continuing to play a significant role.

Finally, Anglo-Saxon countries tend to adopt a market-oriented approach, relying on means-tested benefits and providing limited or unpaid leave. Public support for childcare is partial, resulting in higher private expenses and lower participation rates among mothers.

Recent studies highlight that the economic effectiveness of family policies hinges not only on their generosity but also on their institutional design. Olivetti and Petrongolo (2017) demonstrates that short, gender-neutral leave entitlements are more effective in promoting female labor force participation and reducing wage disparities. In contrast, longer or mother-specific leave schemes may reinforce traditional gender roles and exacerbate the “motherhood penalty”, particularly for high-skilled women. Their findings stress the importance of investing in early childhood education and in-work benefits rather than merely extending leave, especially in facilitating the continuous employment of mothers.

Further supporting this perspective, Cooke et al. (2022) analyzes parenthood-related wage gaps in the private sectors of the UK, Germany, and Finland. Their findings challenge the “welfare state paradox”, which posits that generous family policies may unintentionally exacerbate gender inequalities, aligning instead with a mitigation hypothesis: when policies actively promote shared caregiving and gender equality, both the “motherhood penalty” and overall gender wage gaps are reduced. In Finland, for example, the “fatherhood premium” diminishes when controlling for wage trajectories, and the wage gap between mothers and non-mothers narrows. These results indicate that inclusive and balanced policy design, particularly encouraging paternal involvement, plays a crucial role in mitigating gender disparities.

The institutional differences in spending, structure, and inclusiveness help explain the substantial variations in the “motherhood penalty” and gender wage gaps across countries. Ultimately, policies that promote shared caregiving, maintain employment attachment, and alleviate the financial burden of parenthood represent the most effective pathway toward achieving gender equality.

The report by Koslowski et al. (2022), as summarized in Tables A.1 and A.2 in Annex A1, presents a comparative analysis of parental leave duration and structure across various countries, highlighting the distinctions between maternity, paternity, and shared parental leave. Furthermore, it also details national policies related to care leave and flexible working arrangements, emphasizing the varying ways in which different countries support childcare.

Chapter 3

Data

3.1 Data

This study is based on data from the European Union Labour Force Survey (EU-LFS) (Eurostat, [2025b](#)). The dataset corresponds to the LFS release 2024, uploaded on 31 January 2025, and provides quarterly and yearly information (including biennial modules) up to 2023 ([DOI: 10.2907/LFS1983-2023](#)). The responsibility for all conclusions drawn from the data lies entirely with the author.

The anonymized microdata provided by the EU-LFS details individual and household-level information on employment, education, and other socioeconomic variables, allowing for labor market analysis across countries. The EU-LFS targets individuals living in private households, meaning that it does not include those residing in collective housing, such as in pensions, hospitals, or student accommodations. The survey is conducted across multiple European countries by the National Statistical Institutes, and the collected data is subsequently sent to Eurostat, which compiles and analyzes the information at the European level.

The information provided by EU-LFS covers the period from 1983 to 2023 for 31 European countries. However, we restrict our study to the period between 2009 and 2019 in Portugal. First, we disregard the data before 2009 since it does not contain income information. Second, we opt to exclude data collected after 2019 to mitigate the influence of the COVID-19 pandemic on our findings.

The dataset does not permit the identification of individuals across different years, which restricts the construction of a panel dataset. Consequently, each response is treated as a distinct observation, and we construct a pooled cross-sectional dataset. This methodology assumes that samples from each year represent independent cross-sections, allowing for the estimation of average effects over the sample period without tracking individuals over time (Wooldridge, [2013](#)).

3.2 Sample Construction

To ensure a valid statistical analysis, special codes used in the EU-LFS to indicate missing or non-applicable responses were converted into Stata’s missing values, preventing their treatment as valid data.

Given the focus on wage analysis, we restrict the sample to individuals aged between 18 and 66 with valid wage information. In Portugal, the working-age population is defined as those between 16 and 89 years old (Banco de Portugal, 2025), but we set the upper age limit at 66 as it is the legal retirement age, after which fewer people participate in the labor market. We chose the lower age limit of 18 due to the very low number of valid responses under this age, as well as the presence of inconsistent cases, such as 16- and 17-year-olds reporting four or more children, which raised concerns about data reliability. We also exclude observations with more than four children per household, as well as cases where reported job tenure exceeded the respondent’s age (e.g., 18-year-olds with over 10 years of experience). Excluding these outliers helped to create a cleaner and more coherent sample.

Following the application of these restrictions, the final dataset¹ comprises 566,602 observations. Of these individuals, 263,577 are men, and 303,025 are women.

3.3 Definition and Coding of Variables

This study examines the factors that influence individuals’ relative positions within the wage distribution, considering five independent variables: gender, number of children in the household, age, job tenure, and educational attainment level. The observed dependent variable analyzed is the wage decile to which an individual belongs, determined by their average monthly earnings. Also, control variables are included to account for demographic, professional, and household factors.

The variable wage decile, as provided by the EU-LFS dataset, is constructed using the distribution of gross monthly wages within the sample, not the full population. This approach enables an examination of individuals’ relative positions within the wage hierarchy and facilitates comparisons. However, as they are based on survey data, some individuals’ decile placement may differ from that which would result from the full population distribution. Notably, these deciles are recalculated annually by Eurostat, ensuring comparisons across countries and over time.

Table 3.1 provides a detailed overview of each variable, specifying its type and, where relevant, the corresponding coding scheme.

¹The complete Stata code for data import and cleaning is available in Annex A2.

Category	Variable	Type	Description
Main Independent Variables	Wage decile (WAGE)	ordinal	Indicates the individual's position within the national gross monthly wage distribution, divided into ten equally sized groups, from the lowest (Decile 1) to the highest earners (Decile 10).
	MALE	binary	Indicates whether the respondent is male.
	Number of children in the household (NBCHILDREN)	continuous	Indicates the total number of children (aged 0–17) living in the respondent's household. Values range from 0 to 4.
	AGE	continuous	Indicates the respondent's age in completed years.
Demographic Controls	JOBTENURE	continuous	Indicates the number of years the respondent has worked in their current main job, calculated as the difference between the survey year and the year they started that job.
	Educational attainment level (EDUCATION) ⁽¹⁾	categorical	Indicates the highest level of education completed, based on the ISCED classification.
	YEAR	continuous	Indicates the survey year corresponding to the respondent's observation.
	Region of Residence (REGION) ⁽²⁾	categorical	Indicates the NUTS 2 level region in which the respondent resides.
Professional Controls	Degree of urbanization (URBANIZATION)	categorical	Indicates the degree of urbanization of the respondent's area of residence (city, town, or rural area).
	OCCUPATION ⁽³⁾	categorical	Indicates the respondent's main occupation, based on ISCO codes (0 to 9).
	Full-/Part-time job (FTPT)	binary	Indicates whether the respondent considers their main job to be full-time or part-time.
	JOB_PERMANENCY	binary	Indicates whether the respondent's job is permanent or temporary.
	FIRM_SIZE ⁽⁴⁾	categorical	Indicates the number of employees at the respondent's workplace.
	Usual weekly hours worked (WEEKLY_HOURS)	continuous	Indicates the number of hours usually worked per week in the respondent's main job.
	Supervisory responsibilities (SUPERVISOR)	binary	Indicates whether the respondent supervises other workers.
Household Controls	Year since highest qualification (YRS_EDUCATION)	continuous	Indicates the number of years since the respondent completed their highest educational level, calculated as the difference between the survey year and the year in which that level was completed.
	Presence of a spouse/partner (PPARTNER)	binary	Indicates whether the respondent lives with a spouse or cohabiting partner.
	Presence of children in the household (PCHILDREN)	binary	Indicates whether any children are living in the same household.
	Presence of parents in the household (PPARENTS)	categorical	Indicates whether the respondent lives with both parents, only the father, only the mother, or with neither parent.

(1) The classification of educational attainment follows the International Standard Classification of Education (ISCED) and is presented below with the corresponding levels in the Portuguese education system: 0 – Pre-primary education/Educação pré-escolar; 1 – Primary education: 1st and 2nd Cycle/1.º e 2.º Ciclo do ensino básico; 2 – Lower secondary education/3.º Ciclo do ensino básico; 3 – Upper secondary education/Ensino secundário; 4 – Post-Secondary Non-Tertiary/Ensino pós-secundário não superior; 5 – Short-cycle tertiary education/Cursos superiores de curta duração; 6 – Tertiary education – Bachelor level/Ensino Superior – Licenciatura; 7 – Tertiary education – Master's/Ensino Superior – Mestrado; 8 – Tertiary education – PhD/Ensino Superior – Doutoramento.

(2) This study uses NUTS 2 region codes established before the 2021 NUTS revision, which changed the Portuguese regional structure. The following regions are included in the data: Norte; Algarve; Centro; Área Metropolitana de Lisboa (AML); Alentejo; Região Autónoma de Madeira (RAM).

(3) Occupational categories follow the International Standard Classification of Occupations (ISCO), developed by the International Labour Organization (International Labour Organization, 2012): 0 – Armed Forces Occupations; 1 – Managers; 2 – Professionals; 3 – Technicians and Associate Professionals; 4 – Clerical Support Workers; 5 – Service and Sales Workers; 6 – Skilled Agricultural, Forestry, and Fishery Workers; 7 – Craft and Related Trades Workers; 8 – Plant and Machine Operators, and Assemblers; 9 – Elementary Occupations. We harmonized occupational codes into a single variable to ensure comparability over time, using ISCO-88 for 2009–2010 and ISCO-08 for 2011–2019, based on the classification systems outlined by Eurostat (2025a).

(4) The responses have been categorized into four groups: fewer than 10 employees, between 10 and 49 employees, between 50 and 249 employees, and 250 or more employees. Responses such as “Don't know, but fewer than 10” and “Don't know, but more than 10” are included in the first and second groups, respectively.

Table 3.1: Description and classification of variables used in the analysis.

Chapter 4

Descriptive Statistics

This section provides descriptive statistics for Portugal. Beginning with the wage distribution, Figure 4.1 illustrates how men and women are represented across different wage deciles. The purple line represents women, while the green line denotes men, highlighting a gender disparity in wage distribution.



Figure 4.1: Distribution of men and women across wage deciles.

In the lowest wage decile (decile 1), there are 37,662 women and 12,198 men, indicating that women account for approximately 75% of the individuals in this group, which suggests their overrepresentation at the bottom of the income distribution, with nearly three women for every man. The two lines cross at decile 5, where the number of men (24,189) slightly exceeds that of women (23,212). This crossover point marks a shift in the distribution: from this decile onward, men become dominant in higher wage deciles.

In the highest wage decile (decile 10), there are 26,020 men and 20,966 women,

indicating that men are more represented than women among top earners. Although the difference is not as high as in the lowest decile, it still reflects an imbalance of gender representation at the upper end of the wage distribution.

To assess whether gender and wage decile are statistically independent, a Pearson chi-squared test of independence was conducted. The statistically significant result in our case indicates that wage decile and gender are associated ($\chi^2(9) = 21,000$; $p < 0.001$). This test evaluates the null hypothesis that the wage distribution does not vary systematically with gender. As discussed by Agresti (2007), the chi-squared test is a standard method for analyzing contingency tables to determine whether observed frequencies differ significantly from expected values under the assumption of independence.

Turning to family dynamics, Figure 4.2 illustrates the distribution of individuals by gender and household composition. The majority of women and men reside in households without children, with 161,213 women and 146,964 men falling into this category. As the number of children increases, the number of individuals in each subsequent category decreases.

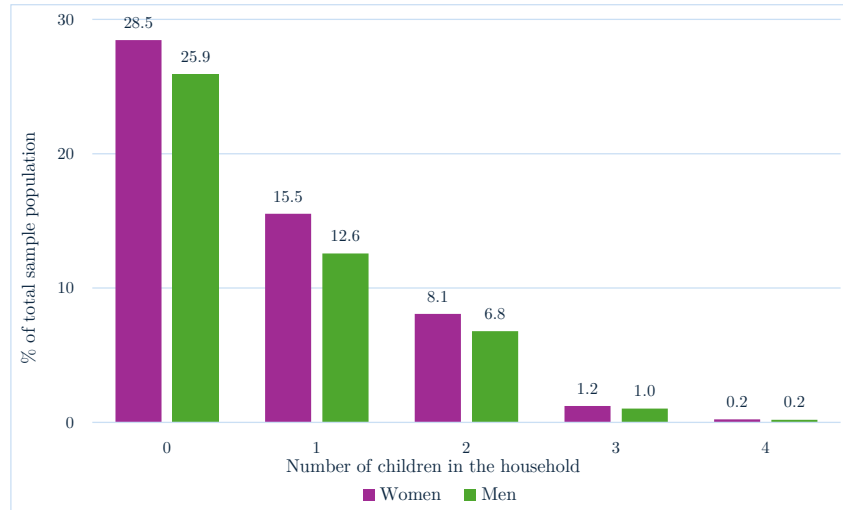


Figure 4.2: Distribution of men and women by number of children in the household.

In addition to household composition, it is also essential to consider the demographic profile of respondents. The age distribution in the sample is illustrated in Figure 4.3. The majority of individuals fall within the 33- to 55-year-old age range, with the distribution peaking at approximately the 43- to 48-year-old age range. Younger individuals (under 25) and older individuals (over 60) are less represented, which is consistent with our emphasis on the active working population (PORDATA, 2025).

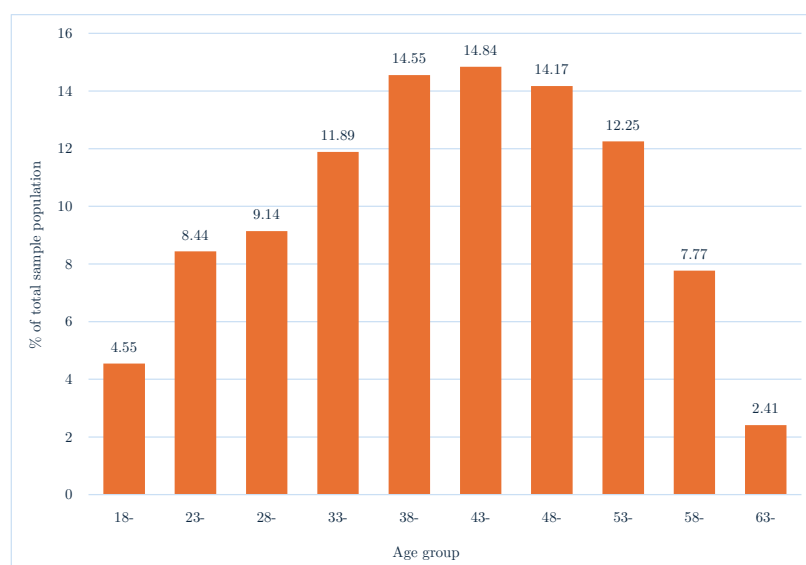


Figure 4.3: Age distribution of the sample population by five-year age groups.

Age is often correlated with labor market experience, so we now turn to job tenure as an additional dimension of labor market experience. Figure 4.4 illustrates the distribution of job tenure, revealing a pronounced right-skewed pattern characterized by a significant concentration of workers with short tenures. The density peaks within the first year and gradually declines as tenure increases. However, a noteworthy number of individuals report tenures extending beyond 20 or even 40 years. The observed spikes at intervals of 5 years may reflect a tendency among respondents to round their job tenure to approximate values.

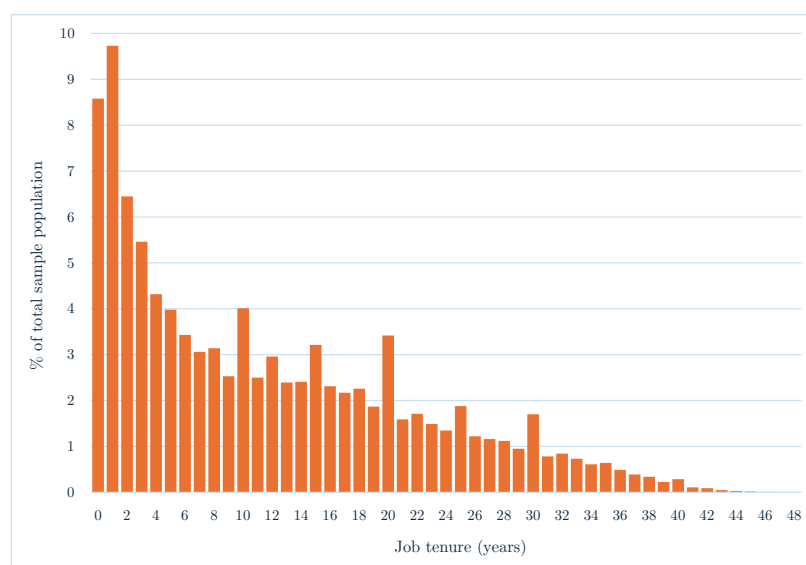


Figure 4.4: Distribution of job tenure in the sample population.

This distribution indicates a labor market marked by a high level of employment turnover, particularly during the initial years of job tenure. Conversely, the long right tail suggests the existence of a more stable segment of the workforce characterized by long-term employment relationships. This duality aligns with labor markets where both temporary and permanent contracts coexist. In this context, Blanchard and Landier (2002) demonstrates that the liberalization of fixed-term contracts in France, intended to reduce youth unemployment, led to higher turnover rates and an increase in the prevalence of short-term contracts. This reform failed to improve transitions into permanent jobs, ultimately reinforcing precarious employment trajectories for young workers. Conversely, the rise in workers with long tenure (20 years or more) in the U.S., as noted by Molloy et al. (2016), is mainly due to population aging and greater stability among women.

In terms of education, Figure 4.5 shows the distribution of individuals by their highest completed level of education, as classified by the International Standard Classification of Education (ISCED)² and disaggregated by gender.

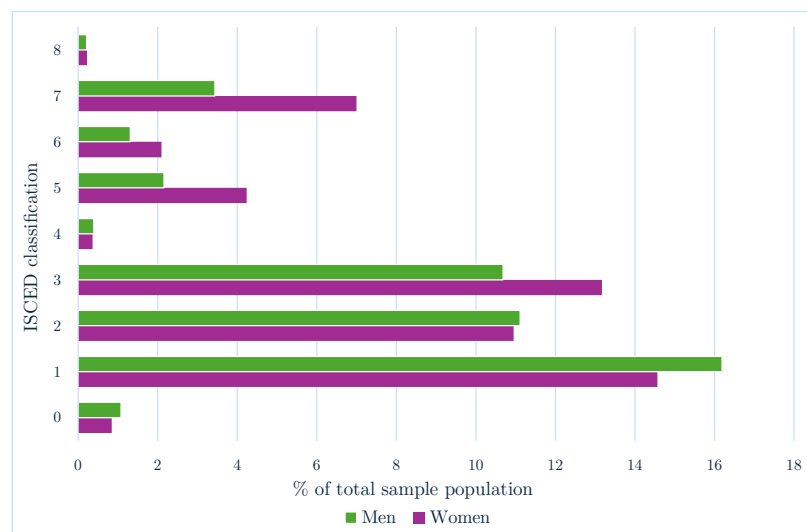


Figure 4.5: Education level by gender, based on the ISCED classification.

In the sample, the most common education levels are ISCED levels 1 and 3, with 90,935 men and 81,806 women at level 1 and 73,973 women compared to 60,008 men at level 3. The data reveal a disparity in educational attainment between men and women. Overall, women tend to be more represented at intermediate and higher levels of education. In comparison, men are more concentrated in the lower levels, particularly ISCED levels 1 and 2, which correspond to basic education. This pattern

²A explanation of the ISCED classification can be found in Table 3.1.

contrasts with the human capital explanation by Sigle-Rushton and Waldfogel (2007) discussed in 2.1, which often attributes the gender pay gap to women’s lower levels of education. Notably, at ISCED level 7 (Master’s level), the percentage of women is approximately twice that of men, highlighting a higher representation of women among individuals with advanced academic qualifications.

Table 4.1 displays the distribution of individuals within the dataset by region and gender. Norte has the highest number of observations, followed closely by Área Metropolitana de Lisboa (AML) and Centro. Although the other regions – Algarve, Alentejo, Madeira (RAM), and Açores (RAA) – yield fewer observations, they enhance the dataset representation of national territory and regional diversity. Overall, the dataset structure largely mirrors the population distribution across various regions of Portugal (Instituto Nacional de Estatística, 2020).

	Norte	AML	Centro	Alentejo	Algarve	RAM	RAA
Women	81,735	55,769	44,279	35,230	31,989	29,459	24,564
Men	73,291	45,855	37,932	31,324	26,353	24,899	23,923
Total	155,026	101,624	82,211	66,554	58,342	54,358	48,487

Table 4.1: Gender distribution by Portuguese NUTS II regions.

To complement the regional composition, Figure 4.6 displays the distribution of workers by skill level in the sample, using the classification adopted by the OECD for international comparability.

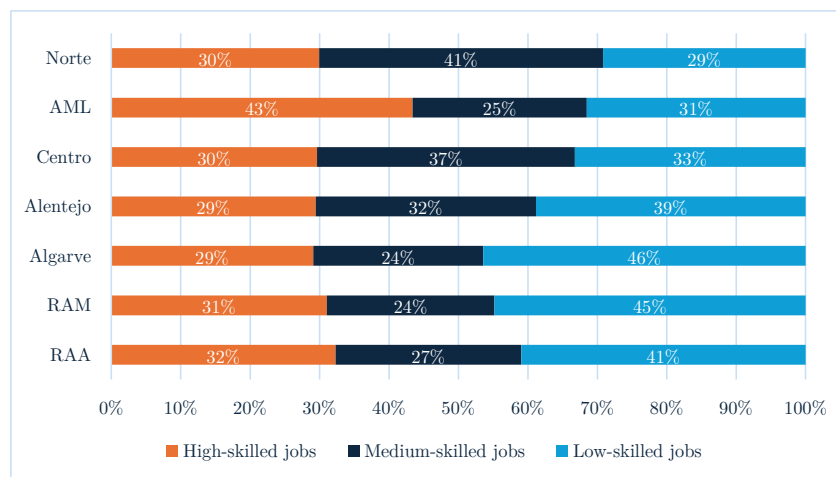


Figure 4.6: Regional distribution of workers by skill level. Skill levels are defined according to ISCO groups: high-skilled jobs include groups 1 to 3, medium-skilled jobs include groups 4, 7, and 8, and low-skilled jobs include groups 5 and 9.

These patterns are broadly consistent with OECD (2024) figures for Portugal,

which are based on the same ISCO skill framework. The alignment between the sample and reference statistics supports the representativeness of the data and reinforces the external validity of the results.

To summarize, this descriptive analysis³ indicates that the sample is broadly representative of the Portuguese working population. The regional distribution aligns with national trends, and the occupational breakdown by skill level adheres to the ISCO classification utilized by the OECD. Additionally, the age and educational profiles in the sample align with anticipated demographic trends. Collectively, these factors ensure the validity of the dataset and of the results presented in the subsequent sections.

³The complete Stata code for descriptive statistics is available in Annex [A3](#).

Chapter 5

Empirical Strategy

This section presents the empirical strategy used to analyze the determinants of the gender wage gap. The goal is to test hypotheses to identify how gender, parenthood, and human capital influence individuals' positions in the wage distribution. By examining these factors, we aim to uncover the mechanisms behind persistent wage disparities and assess the extent to which motherhood contributes to the gender pay gap. The dependent variable in our analysis is the wage decile, an ordinal variable.

We estimate six models, progressively adding independent variables and including demographic, professional, and household controls, as described in Table 3.1.

5.1 Hypothesis

Our primary hypothesis examines whether motherhood contributes to the widening of the gender pay gap. In addition, two further hypotheses drawn from the existing literature explore alternative explanations, including differences in human capital and selection effects. By testing these hypotheses, this research provides valuable insights into the mechanisms that drive the gender pay gap and the extent to which motherhood contributes to this phenomenon.

Therefore, the hypotheses tested in this study are as follows:

- H1. Motherhood increases the gender pay gap.
- H2. Women earn less than men due to lower levels of human capital (Sigle-Rushton & Waldfogel, 2007).
- H3. The “motherhood pay gap” may be influenced by selection biases and discrimination (Blau & Kahn, 2017; Kleven et al., 2019; Sigle-Rushton & Waldfogel, 2007).

5.2 Estimation

5.2.1 Modelling

Wooldridge (2013) explains that using a linear model for ordinal outcomes assumes the distances between categories are significant, which is often not the case. To handle this, we use an ordered logit model, also known as the proportional odds model. As Long and Freese (2014) describes, the ordered logit assumes the existence of an unobserved continuous latent variable, Y^* , which is a linear function of the explanatory variables plus a logistic error term. This latent variable is divided into intervals by a set of threshold parameters (cut-points), and the observed ordinal categories indicate the interval into which Y^* falls (Wooldridge, 2013).

Estimation is based on cumulative logits, where the probability of being in a given category or below is modelled as a function of the covariates. A key feature of the ordered logit is the parallel lines or proportional odds assumption, which states that the relationship between each explanatory variable and the log-odds of being in a higher category is constant across all thresholds (Williams, 2016). When this assumption holds, the coefficients apply uniformly to all cumulative logits, and the odds ratios remain constant regardless of the cut-point chosen. If the assumption is violated, the ordered logit may distort the magnitude or even the direction of effects at certain thresholds.

5.2.2 Model 1: Gender Only

$$\text{WAGE}_i = \beta_0 + \beta_1 \text{MALE}_i + \varepsilon_i$$

The first model only includes the MALE variable as an independent variable. This baseline specification estimates the average difference in wage decile positioning between men and women without controlling for any characteristics. It serves as a reference point for evaluating how much of the observed gender gap persists when additional explanatory variables are included in the extended models.

This model provides an estimate of the unconditional gender pay gap.

5.2.3 Model 2: Gender with Controls

$$\text{WAGE}_i = \beta_0 + \beta_1 \text{MALE}_i + \boldsymbol{\beta} \mathbf{X}_i + \varepsilon_i$$

The second model builds directly upon the first by introducing the complete set of control variables (demographic, professional, and household).

Some continuous control variables are included in both linear and squared forms to account for potential nonlinear relationships between these variables and the outcome (Wooldridge, 2013). Specifically, this applies to the WEEKLY_HOURS and the YRS_EDUCATION variables, allowing the marginal effect of these variables to change across their range. Additionally, the model includes an interaction between MALE and SUPERVISOR variables to explore whether holding a supervisory role has different implications for men and women.

The inclusion of household variables (PPARTNER, PCHILDREN, and PPAR-ENTS) aids in exploring H3, which relates to potential selection mechanisms. Assuming wage differences decreased after considering family structure and household composition, this could suggest that part of the observed gap arises from the circumstances of certain women (e.g., single mothers or those lacking additional household support), who are more likely to face lower earnings or to exit the labor market. This is particularly relevant for women employed in low-skilled ISCO groups, where work schedules often include weekends or irregular hours. In such contexts, the absence of family support to provide childcare can make it difficult, or even impossible, to secure or retain employment, as “flexible or unsocial working hours, especially in the service sector, might not match with the opening hours of childcare institutions and therefore constitute a barrier to paid work for parents” (Hieming et al., 2007).

5.2.4 Model 3: Gender and Parenthood

$$\text{WAGE}_i = \beta_0 + \beta_1 \text{MALE}_i + \beta_2 \text{NBCHILDREN}_i + \beta_3 (\text{MALE}_i \times \text{NBCHILDREN}_i) + \varepsilon_i$$

The third model builds upon Model 1 by incorporating the NBCHILDREN as an independent variable, along with an interaction term between MALE and NBCHILDREN. This allows us to examine whether the presence of children is associated with higher or lower wage outcomes and whether this relationship differs for men and women.

Specifically, a statistically significant negative coefficient on the NBCHILDREN (β_2) may indicate a wage gap associated with parenthood. The interaction term (β_3) reveals whether this gap differs by gender. In this way, the model contributes to testing H1, that motherhood increases the gender pay gap.

5.2.5 Model 4: Gender and Parenthood with Controls

$$\begin{aligned} \text{WAGE}_i = & \beta_0 + \beta_1 \text{MALE}_i + \beta_2 \text{NBCHILDREN}_i + \beta_3 (\text{MALE}_i \times \text{NBCHILDREN}_i) \\ & + \beta \mathbf{X}_i + \varepsilon_i \end{aligned}$$

The fourth model builds upon Model 3 by incorporating the complete set of

control variables introduced in Model 2, offering a more comprehensive assessment of H1 and H3.

While this model still addresses H1, it differs from Model 3 by evaluating whether the “motherhood pay gap” persists after considering changes in job characteristics and household context. The household structure variables are included here to provide a more in-depth assessment of potential discrimination and selection bias related to H3. By incorporating information on family composition, this model allows us to examine whether the observed “motherhood pay gap” is driven by differences in family circumstances, which may lead to selection into specific labor market outcomes.

5.2.6 Model 5: Gender, Parenthood, and Education

$$\begin{aligned} \text{WAGE}_i = & \beta_0 + \beta_1 \text{MALE}_i + \beta_2 \text{NBCHILDREN}_i + \beta_3 (\text{MALE}_i \times \text{NBCHILDREN}_i) \\ & + \beta_4 \text{AGE}_i + \beta_5 \text{AGE}_i^2 + \beta_6 \text{JOBTENURE}_i + \beta_7 \text{JOBTENURE}_i^2 \\ & + \beta_8 \text{EDUCATION}_i + \beta_9 (\text{MALE}_i \times \text{EDUCATION}_i) + \varepsilon_i \end{aligned}$$

The fifth model builds upon Model 3 by including the remaining main independent variables (AGE, JOBTENURE, and EDUCATION) and introducing an interaction term between MALE and EDUCATION. Both AGE and JOBTENURE are included in quadratic form to account for potentially nonlinear relationships.

This model addresses H1, as it investigates whether the “motherhood pay gap” persists after accounting for human capital variables.

By estimating the relationship between wages and individual characteristics, this model examines how the gender wage gap evolves with education, thereby contributing to the assessment of H2. The interaction between MALE and EDUCATION further allows the analysis of how higher education affects the gender pay gap.

It also contributes to understanding H3 as it helps determine whether the observed parenthood effect is partly driven by selection into different levels of education or work experience. In other words, if the “motherhood penalty” decreases once human capital variables are included, this would suggest that part of the gap reflects the labor market profiles of mothers rather than the effect of parenthood itself.

5.2.7 Model 6: Full Specification

$$\begin{aligned} \text{WAGE}_i = & \beta_0 + \beta_1 \text{MALE}_i + \beta_2 \text{NBCHILDREN}_i + \beta_3 (\text{MALE}_i \times \text{NBCHILDREN}_i) \\ & + \beta_4 \text{AGE}_i + \beta_5 \text{AGE}_i^2 + \beta_6 \text{JOBTENURE}_i + \beta_7 \text{JOBTENURE}_i^2 \\ & + \beta_8 \text{EDUCATION}_i + \beta_9 (\text{MALE}_i \times \text{EDUCATION}_i) + \beta \mathbf{X}_i + \varepsilon_i \end{aligned}$$

The sixth model builds upon Model 5 by incorporating the complete set of control variables introduced in Model 2.

This specification enables the assessment of H1 through H3 in a unified framework, as it tests whether the gender wage gap and the “motherhood penalty” persist once all observable individual, professional, and household controls are considered.

Finally, Table 5.1 summarizes the six estimated models⁴, highlighting the systematic incorporation of explanatory and control variables. It serves as a reference for understanding the structure of each model and the overall modeling strategy.

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent Variable	WAGE	✓	✓	✓	✓	✓	✓
Main Independent Variables	MALE	✓	✓	✓	✓	✓	✓
	NBCHILDREN			✓	✓	✓	✓
	AGE					✓	✓
	JOBTENURE					✓	✓
	EDUCATION					✓	✓
Demographic, Professional and Household Controls			✓		✓		✓

Table 5.1: Model specifications across the six regression designs. A check mark (✓) indicates that the variable or group of controls is included in the model. An empty cell indicates that it is not included.

⁴The complete Stata code for model estimation is available in Annex A4.

Chapter 6

Discussion of Results

This section presents the results of the ordered logit regressions, which aim to identify the factors associated with individuals' relative position in the wage distribution.

Table 6.1 presents the results of the six ordered logit models introduced earlier.

WAGE	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
MALE	0.641*** (124.91)	0.981*** (139.89)	0.564*** (84.87)	0.880*** (107.46)	1.548*** (31.53)	1.314*** (111.45)
NBCHILDREN			0.086*** (18.02)	-0.156*** (-30.99)	0.055*** (12.24)	-0.044*** (-8.35)
MALE $\times$ NBCHILDREN			0.119*** (18.63)	0.164*** (24.64)	0.155*** (24.15)	0.163*** (23.93)
AGE					0.187*** (95.02)	0.012*** (4.55)
AGE ²					-0.002*** (-83.80)	0 (0.66)
JOBTENURE					0.077*** (84.33)	0.035*** (31.64)
JOBTENURE ²					0 (-0.95)	0.001*** (20.67)
CONTROLS		✓		✓		✓
EDUCATION					✓	✓
N	468,902	451,443	468,902	451,443	464,492	447,144
Pseudo-R ²	0.007	0.209	0.008	0.210	0.157	0.245

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6.1: Ordered logit results.

6.1 Gender and Parenthood Effects

In all model specifications, the coefficient for the MALE variable is positive and statistically significant (Table 6.1), indicating that men are more likely than women to occupy higher positions in the wage distribution. However, as discussed by Long and Freese (2014), the coefficients from ordered logit models do not represent direct effects on the outcome variable. Instead, they indicate changes in the log-odds of being in a higher versus a lower wage decile, which makes marginal effects (or predicted probabilities⁵) more appropriate for interpretation.

In Models 3 and 5, a positive and statistically significant association is found between the number of children and wage positioning, indicating that individuals with children are more likely to occupy higher wage deciles. One possible explanation for this phenomenon is a selection effect: having children may be more common among individuals with greater income, as they are better equipped to manage the additional costs associated with raising a family. However, when demographic, professional, and, particularly, household characteristics are taken into consideration in Models 4 and 6, the picture changes: the coefficient for the NBCHILDREN becomes negative and is statistically significant. This change suggests that, when controlling for other relevant factors, particularly those related to family support structures (e.g., cohabiting partners, the presence of other adults in the household, or dependent children), having children is associated with a shift in the distribution toward lower wage deciles.

In other words, the initial positive effect observed in Model 3 reflects who can afford to have children in the absence of a support network. However, when we consider household composition, we find that individuals in more complex or dependent-heavy households may face greater economic pressure. This interpretation is consistent with the findings of Sigle-Rushton and Waldfogel (2007), who argue that controlling for family structure exposes selection dynamics and hidden vulnerabilities in household-level economic resilience. This change indicates that the “motherhood penalty” is not merely a consequence of self-selection into varying labor market profiles. Even after controlling for family structure and other relevant characteristics, mothers continue to be more likely to find themselves in lower wage deciles compared to comparable men.

Moreover, the interaction term between MALE and NBCHILDREN is positive and statistically significant in all models where it is included. This suggests that having children results in an upward shift in the wage distribution for men, as we

⁵The complete Stata code for post-estimation commands used to compute predicted probabilities is available in Annex A5.

have already seen. This disparity suggests an unequal impact of parenthood on wage positioning by gender, confirming the existence of a “motherhood penalty” for women and indicating fewer penalties or potential benefits for men, often referred to as the “fatherhood premium”. These results are consistent with findings from Kleven et al. (2019), Sigle-Rushton and Waldfogel (2007), and Cooke et al. (2022).

The persistence of gendered wage disparities, even after considering family context, suggests that structural or discriminatory factors play a crucial role in shaping the unequal impact of parenthood, thereby supporting H3.

To provide a more precise and intuitive understanding of the gender and parenthood effects, we conduct a post-estimation analysis of Model 6, calculating the predicted probabilities of being in each wage decile by gender and number of children. This approach converts the estimated log-odds into meaningful probabilities, facilitating group comparisons (Williams, 2012). Figure 6.1 illustrates the resulting distributions.

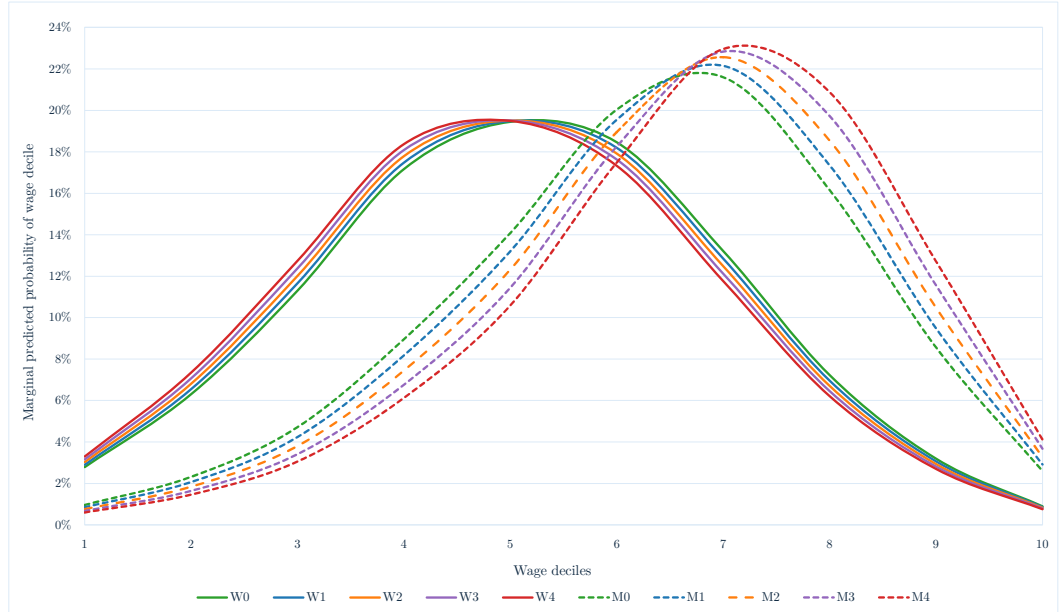


Figure 6.1: Predicted wage decile probabilities by gender and number of children. W0–W4 refer to women with 0 to 4 children; M0–M4 refer to men with 0 to 4 children. Solid lines represent women, dashed lines represent men.

For instance, women without children have a 19.45% chance of falling into the fifth decile, and women with four children show a very similar probability of 19.49%. In the tenth decile, the predicted probabilities for all groups of women are not only remarkably similar, with the curves almost overlapping, but also consistently low.

This suggests that women, regardless of their parental status, have a consistently low likelihood of attaining the highest levels of the wage distribution.

The pattern for men is the opposite of that for women. Their predicted probabilities tend to be concentrated in the sixth and seventh deciles, and these probabilities increase with the number of children. For instance, men without children have a 20.04% chance of being in the sixth decile and a 21.60% chance of being in the seventh. In contrast, fathers of four children have a 17.49% probability of being in the sixth decile and a 22.96% likelihood of being in the seventh decile. In the upper deciles, the probabilities remain distinct, with predicted probabilities rising with the number of children.

These results reveal mirrored trends by gender. Among women, those without children show slightly lower probabilities of being in the lowest wage deciles. However, starting from the fifth decile, childless women gradually become the most likely to occupy higher wage deciles, reversing the order of the groups. In contrast, among men, childless individuals are more likely to be in the lower wage deciles. Nevertheless, from the seventh decile onward, fathers, especially those with more children, have higher probabilities of reaching the top wage deciles. This shift in the ranking between women and men highlights how parenthood negatively affects women's wage prospects while enhancing upward mobility for men.

To better illustrate this point, we compare the expected decile positions, calculated as the weighted mean across all deciles using the predicted probabilities. In Model 6, the expected decile position is approximately 6.30 for men and 5.14 for women without children. In comparison, individuals with one child show an expected decile position of 6.42 for men and 5.09 for women. This suggests that parenthood is associated with a modest increase in the wage position for men, while women experience a slight decrease.

These conclusions offer compelling support for H1, which claims that motherhood contributes to the widening of the gender pay gap.

6.2 Human Capital

In Models 5 and 6, the inclusion of age, job tenure, and educational attainment allows for a more detailed understanding of wage variation. The squared terms for age and job tenure account for nonlinear effects, which aligns with the predictions of human capital theory (Altonji & Blank, 1999), which suggests that wages increase with experience and age, at least up to a certain point. However, in Model 6, the linear coefficient for age is positive, and the quadratic term is not statistically

significant. This indicates a linear and positive relationship between age and wage positioning over the observed age range, with no evidence of a turning point. For job tenure, both the linear and quadratic terms are statistically significant, with the positive quadratic coefficient suggesting a convex relationship. The effect of tenure on wage increases over time, in line with H2, which states that longer tenure is associated with higher wages.

Educational attainment is closely linked to wage levels. All ISCED levels from 2 to 8 are positively and statistically significantly associated with higher wage deciles when compared to ISCED level 0, as shown in Annex A7. However, marginal predictions reveal substantial gender differences in the returns to education. As illustrated in Tables 6.2 and 6.3, men and women with the same level of education do not have the same wage distribution profile. For instance, among individuals with ISCED level 8, women have a 33% probability of being in the top decile, compared to 43% for men. Conversely, men are less likely than women to fall in the bottom deciles at every education level, highlighting persistent gender disparities even among the most educated.

		Wage decile									
		1	2	3	4	5	6	7	8	9	10
ISCED	1	10	18	22	20	13	8	4	2	1	1
	2	4	10	16	20	19	15	9	5	2	1
	3	2	5	10	16	19	20	15	9	4	1
	6	1	2	4	7	12	19	23	18	10	3
	7	0	1	2	5	9	15	23	24	16	6
	8	0	0	0	1	1	3	7	18	37	33

Table 6.2: Predicted wage decile probabilities for women by ISCED level (%).

		Wage decile									
		1	2	3	4	5	6	7	8	9	10
ISCED	1	3	6	11	17	19	19	14	8	3	1
	2	1	3	5	10	15	20	21	15	8	2
	3	1	2	3	7	11	18	23	20	12	4
	6	0	1	2	4	8	14	22	25	18	6
	7	0	1	1	3	5	11	19	27	23	9
	8	0	0	0	0	0	2	5	13	35	43

Table 6.3: Predicted wage decile probabilities for men by ISCED level (%).

Using the expected decile approach, we find a consistent advantage for men across

all educational levels. However, the extent of this gender gap varies significantly, being most pronounced at lower academic levels and gradually narrowing as education increases. For example, among individuals with ISCED level 1, women are positioned at an expected decile of 3.67, while men reach 5.22. A similar pattern appears at ISCED level 2, with women at 3.61 and men at 4.93. In contrast, at ISCED level 8, the gap is much smaller, with women at 8.80 and men at 9.07.

These findings support H2, which suggests that while gender differences in human capital contribute to earnings disparities, human capital alone is insufficient to eliminate these gender-based inequalities. As noted by Sigle-Rushton and Waldfogel (2007), education and experience do not fully bridge the gender gaps. Furthermore, Goldin et al. (2024) highlights that, despite women achieving higher educational attainment than men, earnings gaps persist, particularly after women become mothers.

6.3 Robustness Checks

To evaluate the robustness of our results, we re-estimate the model using ordinary least squares (OLS), as detailed in Annex A8. Despite the differences in methodology, the main qualitative results remain consistent with those of the ordered logit model.

In the OLS regression of Model 6, being male is associated with a significant and substantial increase in wage decile position ($\beta = 1.343$, $p < 0.001$). Conversely, the number of children has a statistically significant adverse effect ($\beta = -0.053$, $p < 0.001$). The interaction between the MALE and the NBCHILDREN variables is positive and statistically significant ($\beta = 0.157$, $p < 0.001$). These findings suggest that motherhood has a negative impact on women’s wage positions, while fatherhood is associated with an upward shift in men’s wage positions.

Also, we have a gradual increase in the pseudo- R^2 across the models, in the ordered logit model, rising from 0.007 in the baseline to 0.245 in the final specification, which highlights the enhanced explanatory power of the variables added throughout the analysis.

These results further stress the robustness of our findings.

6.4 Limitations of the Empirical Analysis

While the empirical findings in this section offer valuable insights into how parenthood influences wage positioning across different genders, several limitations must be acknowledged to contextualize the results and inform future research directions.

The analysis uses cross-sectional data from the EU-LFS, which restricts temporal inference. This framework does not allow tracking of individual wage trajectories over time or the identification of long-term effects of parenthood, such as wage penalties that may accumulate or diminish as children grow older.

While it would have been valuable to complement this analysis with the Portuguese administrative dataset *Quadros de Pessoal*, it was not possible due to lack of information. Unlike the EU-LFS, this dataset would have allowed us to track individuals' wages over their working life, providing a longitudinal perspective.

Moreover, while OLS regression is frequently employed in studies related to income, it is theoretically unsuitable for modeling ordinal dependent variables, such as wage deciles. OLS presumes a continuous outcome with equal spacing between categories, a condition that is not met with ordered but discrete data. As highlighted by Wooldridge (2013), applying OLS to ordinal outcomes can lead to biased estimates and misleading interpretations, as it overlooks the rank-based structure of the dependent variable. Nonetheless, the OLS results, presented in Annex A8, estimated patterns that were broadly consistent with those derived from the ordered logit model. This empirical similarity supports the robustness of the findings, even though the ordered logit framework is the most methodologically appropriate model.

The validity of the ordered logit model depends on the proportional odds assumption, which requires that the relationship between the predictors and the log odds of being in a higher income category remains constant across thresholds. We tested this assumption using the Brant test (Brant, 1990), which yielded a statistically significant result ($\chi^2 = 65,682.04$, $p < 0.001$), indicating that the assumption is violated in this dataset. According to Williams (2016), when this happens, the standard ordered logit model may produce biased or inconsistent estimates. So, more flexible alternatives, like the generalized ordered logit model, should be considered. This result likely reflects the model's high dimensionality, with numerous binary and categorical variables that generate a substantial partitioning of the data.

Our attempt to implement a generalized ordered logit specification failed because of the complexity and high dimensionality of the model which, due to numerous interaction terms and categorical variables, made estimation infeasible. Despite this technical limitation, our results remain meaningful for qualitative purposes.

Although these limitations exist, our empirical analysis offers strong descriptive evidence on how gender and parenthood intersect to shape income distributions. These findings highlight essential patterns that should be further explored with more granular data, such as longitudinal studies.

Chapter 7

International Comparison

In this section, we broaden our analysis beyond the Portuguese context by applying the complete ordered logit specification⁶ (Model 6) to a selection of European countries. We aim to compare how the relationship between gender, parenthood, and wage positioning varies across different institutional settings. By comparing these findings with cross-country differences in parental leave entitlements and work-family reconciliation policies, we seek to evaluate the extent to which public policies can either mitigate or exacerbate the gender wage gap.

In this international comparison we use EU-LFS microdata from Austria (AU), France (FR), Germany (DE), Greece (GE), Italy (IT), Netherlands (NE), Poland (PO), Spain (ES), and the United Kingdom (UK). We previously examined these countries in Chapter 2.3, through Tables A.1 and A.2, which outline parental leave entitlements and work-family reconciliation measures.

Table 7.1 presents the results of an ordered logit regression for each country, based on Model 6. To provide further context for the regression results, we also compiled Tables 7.2 and 7.3 using data from the OECD (2023) Family Database. These tables present cross-country figures on public expenditure in childcare, early childhood education, and family benefits, as well as the duration and generosity of parental leave entitlements for mothers and fathers, measured in full-rate equivalent (FTE) weeks. Together, these indicators capture the scale of financial and institutional support available to families and help to contextualize differences in labor market outcomes across countries.

The results in Table 7.1 indicate that the coefficient for the MALE variable is positive and statistically significant across all countries analyzed, suggesting that men benefit from a relative advantage in wage positioning. However, the impact of parenthood varies significantly across countries.

⁶The complete Stata code used for the cross-country estimations is available in Annex A6.

WAGE	AU	FR	DE	GE	IT	NE	PO	ES	UK
MALE	0.628*** (9.62)	0.826*** (21.99)	0.765*** (10.06)	0.835*** (45.67)	1.110*** (62.11)	0.436*** (12.26)	1.2*** (12.38)	0.728*** (24.92)	0.649* (2.5)
NBCHILDREN	-0.066*** (-15.24)	0.02** (2.59)	0.09*** (20.15)	0.051*** (9.51)	0.029*** (9.7)	-0.12*** (-22.63)	-0.077*** (-18.89)	0.026*** (3.85)	-0.043*** (-5.52)
MALE × NBCHILDREN	0.147*** (29.15)	0.05*** (6.01)	0.327*** (68.1)	0.046*** (7.78)	0.161*** (47.58)	0.188*** (29.21)	0.131*** (25.64)	0.053*** (6.73)	0.093*** (10.46)
AGE	0.136*** (52.17)	0.037*** (6.59)	0.084*** (44.15)	0.033*** (8.67)	0.026*** (15.81)	—	-0.037*** (-13.25)	0.036*** (9.62)	0.108*** (30.66)
AGE ²	-0.001*** (-35.49)	-0.001 (-1.31)	-0.001*** (-30.96)	0.001*** (3.7)	0.001*** (-5.1)	—	0.001*** (17.11)	-0.001*** (-5.09)	-0.001*** (-28.32)
JOBTENURE	0.074*** (94.38)	0.039*** (24.7)	0.027*** (43.91)	0.103*** (88.49)	0.039*** (73.49)	0.084*** (75.67)	0.029*** (30.53)	0.088*** (70.73)	0.042*** (27.14)
JOBTENURE ²	0.001*** (-10.92)	0.001*** (7.39)	0.001*** (13.99)	-0.001*** (-25.69)	0.001 (-0.2)	-0.001*** (-46.16)	0.001*** (-6.66)	-0.001*** (-18.14)	-0.000*** (-9.32)
CONTROLS	✓	✓	✓	✓	✓	✓	✓	✓	✓
EDUCATION	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	726,326	209,159	1,093,856	458,161	1,652,237	313,856	613,375	303,539	198,652
Pseudo-R ²	0.287	0.26	0.233	0.205	0.216	0.312	0.178	0.261	0.27

t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7.1: Ordered logit regression results by country.

In Western European countries such as Austria, Germany, France⁷, and Netherlands⁸, parental leave systems are generous but still reflect gender disparities. In Austria and Netherlands, there is a negative and statistically significant coefficient for NBCHILDREN, combined with a positive and statistically significant coefficient for the interaction between MALE and NBCHILDREN, which indicates a “motherhood penalty” and a “fatherhood premium”. Despite formal leave entitlements, low levels of paternal participation combined with prevailing traditional norms continue to assign the majority of caregiving responsibilities to women. In contrast, Germany and France exhibit a positive and statistically significant coefficient for NBCHILDREN, with the interaction term with MALE also positive and statistically significant, suggesting that motherhood is less penalizing in these contexts, thanks to policy frameworks that support maternal labor force participation through earnings-related benefits and parental leave schemes. The German *ElterngeldPlus* system and France’s comprehensive family transfer network illustrate how institutional design can alleviate adverse labor market effects. This aligns with Sigle-Rushton and Waldfogel (2007), who argue that policies promoting shared responsibility can help mitigate the “motherhood penalty”. As shown in Table 7.3, Germany and France rank among the highest in public spending on childcare, early childhood education, and family benefits, well above the OECD average, further supporting these outcomes.

⁷In France, over 4 million observations were missing valid data on the variable NBCHILDREN.

⁸In Netherlands, none of the observations contained information on AGE.

	Maternity leave	Paternity leave	Parental & home care leave for mothers	Parental & home care leave for fathers	Total paid leave for mothers	Total paid leave for fathers
AU	16	2	35	7	51	9
FR	16	4	4	4	20	8
DE	14	0	29	6	43	6
GE	34	3	19	4	53	7
IT	17	2	8	4	25	6
NE	16	5	6	6	22	11
PO	20	5	20	9	40	14
PT	6	5	16	9	22	14
ES	16	16	0	0	16	16
UK	12	0	0	0	12	0

Table 7.2: Leave entitlements for mothers and fathers, measured in full-rate equivalent (FTE) weeks. FTE weeks are calculated as the product of leave duration (weeks) and the average payment rate. Data refer to 2024. *Source:* OECD (2023) Family Database.

In Southern Europe, which encompasses Portugal, Italy, Greece, and Spain, parental leave entitlements tend to be shorter, formal childcare coverage is limited, and paternal involvement remains restricted. Based on this institutional context, one might expect to observe a “motherhood penalty” across all four countries. However, the results reveal a different pattern: Portugal is the only country in this group with a negative and statistically significant NBCHILDREN coefficient, combined with a positive and statistically significant interaction for MALE and NBCHILDREN (see Table 6.1), indicating a “motherhood penalty” alongside a “fatherhood premium”. Despite recent reforms aimed at introducing shared parental leave and bonuses to promote dual participation, empirical evidence suggests that low cultural uptake and inadequate infrastructure continue to undermine their effectiveness. In contrast, Italy, Greece, and Spain display positive and statistically significant coefficients for NBCHILDREN, yet also show a positive and statistically significant interaction for MALE and NBCHILDREN, confirming the persistence of a “fatherhood premium”. As indicated in Table 7.3, all four countries allocate a smaller percentage of GDP to childcare and early childhood education and care compared to the OECD average. Their overall public spending on family benefits also falls below the OECD average, which may help clarify the limited advancements in achieving gender-equal labor market outcomes, despite the lack of a measurable “motherhood penalty” in three of these countries.

Family benefits for a single-parent, single-earner household two-child family, as a % of average full-time earnings, 2023	Mean average household size, 2024	Public expenditure on childcare and pre-primary education and total public expenditure on early childhood education and care, as a % of GDP, 2019	Total public expenditure on family benefits as a % of GDP, 2019	% of children enrolled in early childhood education and care services, 0–2 years, 2019	Total public expenditure on early childhood education and care per child aged 0–5, USD PPP, 2019	Public expenditure on maternity, paternity, parental and home care leaves per live birth, USD PPP, 2019
AU	9.6	2.2	2.96	19.6	5400	8250
FR	16.0	2.1	3.43	60.4	9200	8871
DE	25.7	2.0	3.18	38.5	7400	14593
GE	7.0	2.6	1.56	35.3	-	8769
IT	13.8	2.2	1.86	27.8	5300	14567
NE	16.3	2.0	1.83	65.5	7200	1306
PO	20.8	2.3	3.32	11.6	3300	17431
PT	9.3	2.4	1.68	53.4	2500	14582
ES	4.6	2.5	1.64	39.6	3700	12134
UK	4.3	2.3	2.51	41.3	3600	5991
OECD	11.9	2.39	2.33	35.9	5800	17248

Table 7.3: Public expenditure on childcare, family benefits, parental leave, and household characteristics in selected OECD countries. *Source:* OECD (2023) Family Database.

Poland exemplifies a Central and Eastern European model that combines moderately long parental leaves paid as a proportion of previous earnings, together with a cultural emphasis on maternal caregiving. The regression results reveal a negative and statistically significant relationship for NBCHILDREN, paired with a positive and statistically significant interaction for MALE and NBCHILDREN. This indicates the presence of a “motherhood penalty” and a “fatherhood premium”. Such patterns align with policy designs that, while providing adequate income replacement, lack robust incentives for fathers to engage in caregiving responsibilities, thereby perpetuating unequal labor market outcomes. Notably, Poland records the lowest enrolment rate of children aged 0–2 in early childhood education and care services among the countries analyzed, and its public expenditure per child aged 0–5 in these services remains well below the OECD average (see Table 7.3).

The United Kingdom exemplifies the Anglo-Saxon or liberal model, characterized by short paternity leaves, long but poorly compensated maternity leaves (see Table 7.2), and a market-driven childcare system. The regression analysis reveals a negative and statistically significant coefficient for NBCHILDREN, alongside a positive and statistically significant coefficient for the interaction between MALE and NBCHILDREN. This pattern confirms the persistence of the “motherhood penalty” and the existence of a “fatherhood premium”. These findings resonate with the conclusions of Cooke et al. (2022), who emphasize that in liberal systems, parenthood often exacerbates gender disparities unless policies actively promote equitable caregiving and fathers utilize the available entitlements.

Table 7.4 provides a comparative overview of the regression results across the European countries. It summarizes the presence of a gender wage gap, the existence of a “motherhood penalty” and of a “fatherhood premium”.

Country	Gender wage gap	Motherhood penalty	Fatherhood premium	Region
AU	✓	✓	✓	Western
FR	✓	✗	✓	Western
DE	✓	✗	✓	Western
NE	✓	✓	✓	Western
GE	✓	✗	✓	Southern
IT	✓	✗	✓	Southern
PT	✓	✓	✓	Southern
ES	✓	✗	✓	Southern
PO	✓	✓	✓	Central and Eastern
UK	✓	✓	✓	Anglo-Saxon

Table 7.4: Summary of gender wage gap, motherhood penalty, and fatherhood premium across selected European countries. A check mark (✓) indicates the presence of the effect, while a cross (✗) indicates its absence.

This international comparison yields three key insights. First, while the “motherhood penalty” and the “fatherhood premium” are nearly universal phenomena (Yu & Hara, 2021), the extent of their impact varies significantly based on the design and implementation of policies.

Second, policies that promote shared and gender-neutral caregiving, such as those in Germany and France, are more effective in mitigating the “motherhood penalty”. In contrast, extended maternity leave or underutilized benefits, as observed in Austria, Netherlands, and in some Southern European countries, tend to reinforce gender inequalities. The evidence presented in Table 7.2 also shows that leave duration alone does not determine outcomes. For example, both Austria and Greece have some of the most generous total leave entitlements for mothers; however, only Austria experiences a “motherhood penalty”. As noted by Olivetti and Petrongolo (2017), highly educated women incur greater opportunity costs when they interrupt their careers. In Austria, women’s educational attainment is slightly higher than in Greece (Eurostat, 2025c), which makes Austrian women particularly vulnerable to the negative effects of lengthy and maternity-specific leave policies. When policies reinforce traditional gender roles rather than encouraging shared caregiving, they may unintentionally amplify these penalties, especially among women with greater educational investment. Also, Spain offers the most extended leave for fathers and shows no “motherhood penalty”, while Germany, Italy, and Greece, despite providing relatively shorter paternal leave, don’t report such a penalty.

Third, the cultural and institutional embrace of these policies is as crucial as the legal framework itself; even generous or progressive policies are unlikely to alleviate the “motherhood penalty” if fathers do not actively participate in leave-taking or if childcare infrastructure remains inadequate.

These observations align with the findings of Sigle-Rushton and Waldfogel (2007), which indicate that while family policies can lessen the “motherhood penalty”, they seldom completely remove it. They also echo Olivetti and Petrongolo (2017) conclusion that excessively long or mother-exclusive leaves can exacerbate labor market disparities. Ultimately, this supports Cooke et al. (2022) in their mitigation hypothesis, which asserts that meaningful reductions in gender disparities require not just legal entitlements, but also practical implementation, cultural transformation, and equal engagement from fathers.

Chapter 8

Conclusion

This dissertation investigates whether motherhood contributes to the gender pay gap in Portugal by testing three core hypotheses using microdata from the EU-LFS and an ordered logit estimation framework.

The first hypothesis proposes that motherhood increases the gender pay gap. Our empirical results strongly support this hypothesis. Women with children are consistently less likely to occupy higher wage deciles compared to both men and childless women. In contrast, fatherhood is positively associated with higher wage positions, a pattern that aligns with the concept of the “fatherhood premium”. In practical terms, parenthood benefits men and disadvantages women, confirming the persistence of the “motherhood penalty” in the Portuguese labor market.

The second hypothesis suggests that women earn less than men because they have lower levels of human capital, such as education, experience, or job tenure. The results show that, although wages do rise with age, tenure, and education, these factors do not fully explain the gender pay gap. Even among men and women with the same qualifications, men are consistently more likely to reach the top wage deciles. Moreover, in Portugal, women are better educated, on average, which means that lower human capital is not the primary reason for their lower earnings.

The third hypothesis explores whether selection mechanisms influence the “motherhood pay gap”, considering that some women might invest less in their careers if they expect difficulties in balancing work and family. The results provide partial support for this idea. Once household characteristics are considered, the data show that mothers face additional disadvantages, especially if they lack strong family or institutional support. This suggests that structural and cultural factors reinforce the “motherhood penalty”, but the evidence for voluntary self-selection alone is limited.

The international comparison reveals that nations with more inclusive and gender-neutral family policies, especially those promoting shared caregiving between par-

ents, experience weaker motherhood penalties.

Portugal has made progress by introducing shared parental leave and bonuses for joint participation. However, cultural barriers, low rates of paternal leave uptake, and insufficient childcare facilities limit the impact of these reforms. Additionally, recent political discussions have raised concerns about possible setbacks in this area, as noted by ECO (2025), with proposals that could restrict breastfeeding breaks to the first two years of a child’s life, alter the framework for gestational bereavement leave, and potentially limit flexible working rights for parents of young children. These developments highlight the precarious nature of policy advancements and the urgent need to protect measures that foster gender equality in the labor market, which this work shows that contributes to reducing inequality.

From a practical perspective, companies can play a central role in narrowing the “motherhood penalty”. Implementing human resource policies that promote flexible schedules, remote or hybrid work options, and gradual return-to-work programs following parental leave can assist mothers in maintaining their career progression. It is equally crucial to encourage fathers to take parental leave and to normalize equal caregiving within the workplace to challenge traditional role divisions. Additionally, providing on-site childcare or facilitating access to external childcare services can minimize career interruptions for women. By actively cultivating a culture of shared responsibility and endorsing family-friendly practices, employers can make a significant contribution to reducing the gender pay gap.

In summary, this study reinforces the notion that motherhood significantly contributes to gender-based wage disparities in Portugal. Addressing these inequalities necessitates a collaborative approach that includes effective public policies, cultural shifts, and corporate strategies aimed at genuinely supporting both women and men in achieving a balance between work and family life.

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Annexes

A1 Childcare public policies

Country	Maternity leave	Paternity leave	Parental leave
Austria (AU)	Mothers are entitled to 16 weeks of leave (8 weeks before and 8 weeks after birth). Leave is mandatory and paid at 100% of average net income.	Fathers are entitled to one month of job-protected leave shortly after birth. During this period, they can receive a specific benefit. Some collective agreements provide additional paid days immediately after childbirth.	Parents are entitled to take unpaid leave until the child turns 2. A parental benefit is available under 2 schemes: a flat-rate option or an income-related benefit that covers up to 80% of the prior income. Only one parent may take leave at a time, and a participation bonus is granted if both parents share the benefit.
France (FR)	Mothers are entitled to 16 weeks of fully paid leave. At least 2 weeks must be taken before birth, and all weeks are mandatory.	Fathers are entitled to 25 working days of fully paid leave. Leave must be taken within 6 months after the birth.	Parents are entitled to unpaid leave until the child turns 3. They can take leave simultaneously. An allowance (PreParE) is available, with the amount and duration depending on the number of children, income, and working status.
Germany (DE)	Mothers are entitled to 14 weeks of fully paid leave, consisting of 6 weeks before and 8 weeks after birth, with the latter being mandatory.	No statutory entitlement.	Parents are entitled to up to 3 years of unpaid, job-protected leave, with 24 months available until the child turns 8. During this period, they may receive benefits such as Basiselterngeld (up to 12 months at 65% of net earnings, plus 2 bonus months if both parents participate) or ElterngeldPlus (up to 24 months at about 32.5% of net income, plus a 4-month bonus if both parents work part-time).
Greece (GE)	Mothers are entitled to 17 weeks of leave in the private sector (8 weeks before and 9 weeks after birth), paid at 100% of earnings, and to 5 months of fully paid leave in the public sector. An additional 6-month special leave is available, paid at a fixed minimum wage level.	Fathers are entitled to 2 working days of paid leave at the time of childbirth. This leave is paid at 100% of earnings and is job-protected.	Parents are entitled to 4 months of unpaid leave each. Leave is available until the child turns 6.
Italy (IT)	Mothers are entitled to 5 months of mandatory leave. Leave may begin before or after childbirth and is paid at 80% of previous earnings, with full pension rights maintained. Public sector employees and many collective agreements provide top-ups of up to 100%.	Fathers are entitled to 10 days of compulsory leave, plus one optional day that can be transferred from the mother. Leave is paid at 100% of earnings and must be taken within 5 months of childbirth.	Parents are entitled to 6 months each, with a family limit of 10 (or 11 if the father takes at least 3). Leave is paid at 30% of earnings until the child turns 6 and is unpaid between ages 6 and 12. Public sector workers may receive 100% for the first 30 days.

Table A.1: Overview of government policies on maternity, paternity and parental leave in selected European countries. *Source:* Adapted from Koslowski et al. (2022).

Country	Maternity leave	Paternity leave	Parental leave
Netherlands (NE)	Mothers are entitled to 16 weeks of fully paid leave. At least 4 weeks before and 6 weeks after birth are mandatory.	Fathers are entitled to birth leave equivalent to one working week, paid at 100%. In addition, they may take up to 5 weeks of supplemental leave, paid at 100% up to 70% of the daily wage.	Parents are entitled to 26 times their weekly working hours in parental leave, which can be taken until the child turns 8. The leave is unpaid.
Poland (PO)	Mothers are entitled to 20 weeks of leave, with at least 14 weeks taken post-birth. Leave is paid at 100% or 80% of average earnings. If the mother selects 100%, subsequent Parental leave is paid at 100% for 6 weeks, then 60% for up to 26 weeks. If she chooses the 80% option, all Parental leave is paid at 80%.	Fathers are entitled to 2 weeks of leave, to be used within 24 months of birth. Leave is paid at 100% of average earnings and may be split into two parts.	Parents are entitled to 32 weeks of parental leave per family, which may be shared. The payment depends on the payment option chosen by the mother taking Maternity leave.
Portugal (PT)	Mothers are entitled to 4 months at 100% or 5 months at 80% pay, starting with 6 weeks of mandatory leave after childbirth. The remaining leave can be shared between parents, and if it is shared, they receive an additional 30 days.	Fathers are entitled to 35 days of parental leave, of which 28 are mandatory. Payment is at 100% of their gross salary.	Parents are entitled to 3 months of additional parental leave each, paid at 30% of average earnings. If both parents take the full leave, the benefit increases to 40%.
Spain (ES)	Mothers are entitled to 16 weeks of fully paid leave. Six weeks are mandatory and must be taken after the birth.	Fathers are entitled to 16 weeks of parental leave, paid at 100% of their average earnings. Six weeks are mandatory and must be taken immediately after the birth.	Parents are entitled to parental leave until the child turns 3. The first year guarantees a return to the same job; after that, only to a similar position. The leave is unpaid.
United Kingdom (UK)	Mothers are entitled to 52 weeks of leave. Two weeks are mandatory and must be taken after the birth. The first 6 weeks are paid at 90% of average earnings, followed by 33 weeks at either a flat rate or 90% of gross weekly earnings, whichever is lower. The final weeks are unpaid.	Fathers are entitled to 1 or 2 weeks, depending on their typical work schedule. The father receives a flat-rate payment per week, or 90% of average weekly earnings if that is less.	Parents are entitled to 18 weeks of leave, but they cannot take it all at once. Each year, they can take up to 4 weeks. The leave is unpaid.

Table A.1. (cont)

Country	Leave to care for sick dependents	Reduced breastfeeding hours	Right to request flexible work
PT	** 30 days per year per family if child <12 years; 15 days if child >12 years.	*** 2 hours per day to 12 months; father or mother can use the right.	Yes: entitlement to work flexible hours until the child is 12 years.
AU	*** 2 weeks per employee per year or * 9 months for a seriously ill child.	*** 90-minute break per day.	x
FR	* 3 days per year or ** up to 3 years for serious disability or illness, with up to 310 days paid.	x	x
DE	*** Up to a maximum of 25 days per year per parent.	*** 60- to 90-minute break per day.	x
GE	* 6 to 14 days per year per parent for sickness, plus 30 days for hospitalisation in the public sector.	*** Flexible leave can be condensed to 3.6 months of paid leave in the public sector.	x
IT	* unlimited to 3 years; 5 days per year for children aged 3 to 8.	*** 1 to 2 hours per day until the child is 12 months.	Yes: until child is 6 years old or, if a child has disabilities, until 18.
NE	*** 2 x working hours/week per year or 6 x working hours/week taken part-time per year, where long-term care is needed.	*** Up to 25% of working hours until the child is 9 months old.	Yes: flexible hours and the option to work from home are available to all employees if the employer has 10 or more employees.
PO	*** 14 days per year per worker.	*** Two 30-minute breaks per day while breastfeeding continues.	Yes: in certain circumstances, e.g., a disabled or seriously ill child.
ES	*** 2 to 4 days per illness per parent; 3 days public sector or unlimited for seriously ill child in hospital or needing treatment at home.	*** 1 hour per day for 9 or 12 months (public sector); individual, nontransferable right of both parents (reduced hours until child is nine to 12 months of age may be consolidated as two to four weeks of full-time leave).	x
UK	* "Reasonable time"	x	Yes: all employees.

Note: * Statutory entitlement without pay; ** Statutory entitlement, paid but either at low flat-rate (less than €1,000/month) or earnings related at less than 66% of earnings or not universal; *** Statutory entitlement, paid for all or part of duration to all parents at an earnings-related level of 66% of earnings or more; x No statutory entitlement.

Table A.2: Leave entitlements and working time adjustments for family care responsibilities in selected European countries. *Source:* Reproduced from Koslowski et al. (2022)

A2 Stata Code — Data Import and Cleaning

```
1  forvalues year = 2009/2019 {
2  import delimited PT'year'_y.csv
3  save PT'year'_y
4  clear
5  }
6
7  use PT2009_y
8
9  forvalues year = 2010/2019 {
10 append using PT'year'_y, force
11 }
12
13 save PT_full_y
14
15 use PT_full_y
16
17 keep year region_2d degurba sex age isco08_1d isco88_1d ftpt temp supervisor sizefirm
    hatlevel hwusual incdecil register hhnbchild hhpartnr hhchildr hhparent
    hatyear ystartwk
18
19 mvdecode ystartwk, mv(9999)
20 mvdecode hatyear, mv(9999)
21 gen qualtime = year - hatyear
22 gen jobtenure = year - ystartwk
23 gen diff = age - jobtenure
24 drop hatyear
25 drop ystartwk
26
27 gen sizefirm2 = .
28 replace sizefirm2 = 1 if sizefirm == "1-9"
29 replace sizefirm2 = 2 if sizefirm == "10"
30 replace sizefirm2 = 3 if sizefirm == "11"
31 replace sizefirm2 = 4 if sizefirm == "23"
32 replace sizefirm2 = 1 if sizefirm == "24"
33 replace sizefirm2 = 2 if sizefirm == "25"
34 drop sizefirm
35 rename sizefirm2 sizefirm
36
37 rename region_2d region
38
39 gen isco = .
40 replace isco = isco88_1d if year == 2009
41 replace isco = isco88_1d if year == 2010
42 replace isco = isco08_1d if year == 2011
43 replace isco = isco08_1d if year == 2012
44 replace isco = isco08_1d if year == 2013
45 replace isco = isco08_1d if year == 2014
46 replace isco = isco08_1d if year == 2015
47 replace isco = isco08_1d if year == 2016
48 replace isco = isco08_1d if year == 2017
49 replace isco = isco08_1d if year == 2018
50 replace isco = isco08_1d if year == 2019
```

```

51 drop isco08_1d
52 drop isco88_1d
53
54 save PT_final
55
56 clear
57
58 use PT_final
59
60 drop if age < 18
61 drop if age > 66
62 drop if hhnbcchild > 4
63 drop if missing(incdecil)
64 drop if incdecil > 98 & register == 3
65 drop if incdecil > 98 & register == 4
66 drop register
67 drop if incdecil > 98 & ftpt == 1
68 drop if incdecil > 98 & ftpt == 2
69 replace sex = 0 if sex==2
70 replace supervisor = 0 if supervisor == 2
71 replace hhpartnr = 0 if hhpartnr == 2
72 replace hhchildr = 0 if hhchildr == 2
73 replace hhparent = 0 if hhparent == 4
74 replace hatlevel = 1 if hatlevel == 100
75 replace hatlevel = 2 if hatlevel == 200
76 replace hatlevel = 3 if hatlevel>299 & hatlevel<400
77 replace hatlevel = 4 if hatlevel>399 & hatlevel<500
78 replace hatlevel = 5 if hatlevel>499 & hatlevel<600
79 replace hatlevel = 6 if hatlevel == 600
80 replace hatlevel = 7 if hatlevel == 700
81 replace hatlevel = 8 if hatlevel == 800
82 mvdecode hatlevel, mv(900)
83 mvdecode hatlevel, mv(999)
84 mvdecode ftpt, mv(9)
85 mvdecode temp, mv(9)
86 mvdecode supervisor, mv(9)
87 mvdecode sizefirm, mv(9)
88 mvdecode hwusual, mv(99)
89 mvdecode incdecil, mv(99)
90 mvdecode isco, mv(99)
91 gen lf = .
92 replace lf = 1 if incdecil > 0
93 replace lf = 0 if missing(incdecil)
94 drop if diff < 18
95
96 save PT_final_clean
97
98 clear

```

The procedure for the remaining countries was similar while considering specific details in each case (for example, regarding the coding of regions). For simplicity, we omit the repeated code, but it is available to be shared upon request to the author.

A3 Stata Code — Descriptive Statistics

```
1 use PT_final_clean
2
3 tabulate incdecil sex, chi2
4 tabulate incdecil hhnbchild, chi2
5
6 tab hhnbchild sex
7 tab region sex
8
9 egen age_group = cut(age), at(18(5)100) label
10 histogram age_group, width(1)
11 graph export "age.pdf"
12
13 histogram age_group if sex == 0, width(1)
14 graph export "age_Women.pdf"
15
16 histogram age_group if sex == 1, width(1)
17 graph export "age_Men.pdf"
18
19 tab hatlevel sex
20 tab incdecil sex
21 tab incdecil hhnbchild
22
23 graph bar, over(incdecil)
24 graph export "incdecil.pdf"
25
26 graph bar if sex == 0, over(incdecil)
27 graph export "incdecil_Women.pdf"
28
29 graph bar if sex == 1, over(incdecil)
30 graph export "incdecil_Men.pdf"
31
32 graph bar if hhnbchild == 0, over(incdecil)
33 graph export "incdecil_0child.pdf"
34
35 graph bar if hhnbchild == 1, over(incdecil)
36 graph export "incdecil_1child.pdf"
37
38 graph bar if hhnbchild == 2, over(incdecil)
39 graph export "incdecil_2child.pdf"
40
41 graph bar if hhnbchild == 3, over(incdecil)
42 graph export "incdecil_3child.pdf"
43
44 graph bar if hhnbchild == 4, over(incdecil)
45 graph export "incdecil_4child.pdf"
46
47 table ftpt sex hhnbchild
48
49 clear
50 use PT_final_clean
51
52 collapse incdecil, by(year sex)
```

```

53 gen inc_w = incdecil if sex == 0
54 gen inc_m = incdecil if sex == 1
55 by year, sort: gen total_inc_w = sum(inc_w)
56 by year, sort: gen total_inc_m = sum(inc_m)
57 gen ratio = total_inc_w / total_inc_m
58 collapse (max) ratio, by(year)
59 twoway (line ratio year, sort)
60 graph export "ratio_Women_Men.pdf"
61
62 clear
63 use PT_final_clean
64
65 gen parent = 0
66 replace parent = 1 if hhnchild > 0
67 collapse incdecil if sex == 0, by(age parent)
68 gen inc_np = incdecil if parent == 0
69 gen inc_p = incdecil if parent == 1
70 by age, sort: gen total_inc_np = sum(inc_np)
71 by age, sort: gen total_inc_p = sum(inc_p)
72 gen ratio = total_inc_p / total_inc_np
73 collapse (max) ratio, by(age)
74 twoway (line ratio age, sort)
75 graph export "ratio_Mother_NonMother_age.pdf"
76
77 clear
78 use PT_final_clean
79
80 gen parent = 0
81 replace parent = 1 if hhnchild > 0
82 collapse incdecil if sex == 1, by(age parent)
83 gen inc_np = incdecil if parent == 0
84 gen inc_p = incdecil if parent == 1
85 by age, sort: gen total_inc_np = sum(inc_np)
86 by age, sort: gen total_inc_p = sum(inc_p)
87 gen ratio = total_inc_p / total_inc_np
88 collapse (max) ratio, by(age)
89 twoway (line ratio age, sort)
90 graph export "ratio_Father_NonFather_age.pdf"

```

A4 Stata Code — Model Estimation

```
1 use PT_final_clean
2
3 eststo: regress incdecil i.sex, allbaselevels robust
4 eststo: regress incdecil i.sex c.year i.region i.degurba i.isco i.ftpt i.temp i.
    sizefirm c.hwusual##c.hwusual c.qualtime##c.qualtime i.supvisor i.sex#i.
    supervisor i.hhpartnr i.hhchildr i.hhparent, allbaselevels robust
5
6 eststo: regress incdecil i.sex c.hhnbchild i.sex#c.hhnbchild, allbaselevels robust
7 eststo: regress incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.year i.region i.
    degurba i.isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.qualtime##c.
    qualtime i.supvisor i.sex#i.supvisor i.hhpartnr i.hhchildr i.hhparent,
    allbaselevels robust
8
9 eststo: regress incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
    jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel, allbaselevels robust
10 eststo: regress incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
    jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
    isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.qualtime##c.qualtime i.
    supervisor i.sex#i.supvisor i.hhpartnr i.hhchildr i.hhparent, allbaselevels
    robust
11
12 esttab, se r2
13 esttab using ols.csv
14 esttab using ols.tex
15 eststo clear
16
17 eststo: ologit incdecil i.sex, allbaselevels robust
18 eststo: ologit incdecil i.sex c.year i.region i.degurba i.isco i.ftpt i.temp i.
    sizefirm c.hwusual##c.hwusual c.qualtime##c.qualtime i.supvisor i.sex#i.
    supervisor i.hhpartnr i.hhchildr i.hhparent, allbaselevels robust
19
20 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild, allbaselevels robust
21 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.year i.region i.
    degurba i.isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.qualtime##c.
    qualtime i.supvisor i.sex#i.supvisor i.hhpartnr i.hhchildr i.hhparent,
    allbaselevels robust
22
23 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
    jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel, allbaselevels robust
24 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
    jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
    isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.qualtime##c.qualtime i.
    supervisor i.sex#i.supvisor i.hhpartnr i.hhchildr i.hhparent, allbaselevels
    robust
25
26 esttab, se scalars(r2_p p)
27 esttab using ologit.csv
28 esttab using ologit.tex
29 eststo clear
```

A5 Stata Code — Post-estimation

```
1 use PT_final_clean
2
3 ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.jobtenure##c.
   jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.isco i.ftpt i
   .temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.supvisor i.sex#i
   .supvisor i.hhpartnr i.hhchildr i.hhparent, allbaselevels robust
4
5 margins, predict() atmeans
6 marginsplot
7 graph export "ologit_margins.pdf"
8
9 margins, predict() at(sex == 0 hhnbchild == 0) atmeans
10 marginsplot
11 graph export "ologit_margins_w_0child.pdf"
12
13 margins, predict() at(sex == 0 hhnbchild == 1) atmeans
14 marginsplot
15 graph export "ologit_margins_w_1child.pdf"
16
17 margins, predict() at(sex == 0 hhnbchild == 2) atmeans
18 marginsplot
19 graph export "ologit_margins_w_2child.pdf"
20
21 margins, predict() at(sex == 0 hhnbchild == 3) atmeans
22 marginsplot
23 graph export "ologit_margins_w_3child.pdf"
24
25 margins, predict() at(sex == 0 hhnbchild == 4) atmeans
26 marginsplot
27 graph export "ologit_margins_w_4child.pdf"
28
29 margins, predict() at(sex == 1 hhnbchild == 0) atmeans
30 marginsplot
31 graph export "ologit_margins_m_0child.pdf"
32
33 margins, predict() at(sex == 1 hhnbchild == 1) atmeans
34 marginsplot
35 graph export "ologit_margins_m_1child.pdf"
36
37 margins, predict() at(sex == 1 hhnbchild == 2) atmeans
38 marginsplot
39 graph export "ologit_margins_m_2child.pdf"
40
41 margins, predict() at(sex == 1 hhnbchild == 3) atmeans
42 marginsplot
43 graph export "ologit_margins_m_3child.pdf"
44
45 margins, predict() at(sex == 1 hhnbchild == 4) atmeans
46 marginsplot
47 graph export "ologit_margins_m_4child.pdf"
```

A6 Stata Code — International Comparison

```
1 use AU_final_clean
2
3 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
   jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
   isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
   supervisor i.sex#i.supervisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
   robust
4
5 clear
6
7 use FR_final_clean
8
9 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
   jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
   isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
   supervisor i.sex#i.supervisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
   robust
10
11 clear
12
13 use DE_final_clean
14
15 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
   jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
   isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
   supervisor i.sex#i.supervisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
   robust
16
17 clear
18
19 use GE_final_clean
20
21 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
   jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
   isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
   supervisor i.sex#i.supervisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
   robust
22
23 clear
24
25 use IT_final_clean
26
27 eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
   jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
   isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
   supervisor i.sex#i.supervisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
   robust
28
29 clear
30
31 use NE_final_clean
32
```

```

33  eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.jobtenure##c.
    jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.isco i.ftpt i.
    .temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.supvisor i.sex#i
    .supvisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels robust
34
35  clear
36
37  use PO_final_clean
38
39  eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
    jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
    isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
    supvisor i.sex#i.supvisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
    robust
40
41  clear
42
43  use ES_final_clean
44
45  eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
    jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
    isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
    supvisor i.sex#i.supvisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
    robust
46
47  clear
48
49  use UK_final_clean
50
51  eststo: ologit incdecil i.sex c.hhnbchild i.sex#c.hhnbchild c.age##c.age c.
    jobtenure##c.jobtenure i.hatlevel i.sex#i.hatlevel c.year i.region i.degurba i.
    isco i.ftpt i.temp i.sizefirm c.hwusual##c.hwusual c.ualtime##c.ualtime i.
    supvisor i.sex#i.supvisor i.hhpartnr i.hhchildr i.hhpature, allbaselevels
    robust
52
53  esttab, se scalars(r2_p p)
54  esttab using internacional.csv
55  esttab using internacional.tex
56  eststo clear

```

A7 Complete Ordered Logit Regression Results

	(1) WAGE	(2) WAGE	(3) WAGE	(4) WAGE	(5) WAGE	(6) WAGE
WAGE	0	0	0	0	0	0
0.MALE	(.)	(.)	(.)	(.)	(.)	(.)
1.MALE	0.649*** (129.09)	1.005*** (146.90)	0.572*** (87.83)	0.905*** (113.23)	1.571*** (32.42)	1.350*** (118.33)
YEAR		-0.0805*** (-88.09)		-0.0810*** (-88.51)		-0.110*** (-107.75)
11.REGION		0 (.)		0 (.)		0 (.)
15.REGION		0.719*** (72.04)		0.722*** (72.29)		0.628*** (61.64)
16.REGION		0.293*** (32.94)		0.292*** (32.88)		0.190*** (21.22)
17.REGION		0.748*** (82.85)		0.752*** (83.30)		0.782*** (85.97)
18.REGION		0.733*** (72.23)		0.732*** (72.17)		0.646*** (62.65)
20.REGION		0.562*** (50.73)		0.569*** (51.30)		0.687*** (62.03)
30.REGION		0.542*** (54.78)		0.548*** (55.37)		0.596*** (59.91)
1.URBANIZATION		0 (.)		0 (.)		0 (.)
2.URBANIZATION		-0.180*** (-24.96)		-0.177*** (-24.53)		-0.104*** (-14.40)
3.URBANIZATION		-0.210*** (-25.04)		-0.207*** (-24.64)		-0.121*** (-14.31)
0.ISCO		0 (.)		0 (.)		0 (.)
10.ISCO		1.428*** (37.62)		1.432*** (37.86)		0.915*** (26.01)
20.ISCO		2.046*** (61.88)		2.049*** (62.33)		0.859*** (27.85)
30.ISCO		0.168*** (5.06)		0.162*** (4.90)		-0.0199 (-0.68)
40.ISCO		-0.741*** (-22.19)		-0.745*** (-22.42)		-0.749*** (-25.21)
50.ISCO		-1.726*** (-52.18)		-1.730*** (-52.62)		-1.270*** (-43.19)
60.ISCO		-2.601*** (-68.06)		-2.600*** (-68.31)		-1.967*** (-54.57)
70.ISCO		-1.880*** (-56.58)		-1.884*** (-57.01)		-1.260*** (-42.34)
80.ISCO		-1.874*** (-55.94)		-1.876*** (-56.33)		-1.216*** (-40.42)
90.ISCO		-2.550*** (-76.41)		-2.555*** (-77.00)		-1.840*** (-61.55)
1.FTPT		0 (.)		0 (.)		0 (.)
2.FTPT		-2.895*** (-81.89)		-2.893*** (-81.73)		-2.537*** (-70.95)
1.TEMP		0 (.)		0 (.)		0 (.)
2.TEMP		-0.696*** (-92.96)		-0.690*** (-92.19)		-0.279*** (-31.08)
1.FIRM_SIZE		0 (.)		0 (.)		0 (.)
2.FIRM_SIZE		0.490*** (63.92)		0.489*** (63.76)		0.445*** (57.12)
3.FIRM_SIZE		0.504*** (56.78)		0.502*** (56.55)		0.444*** (49.61)

4.FIRM_SIZE	0.819*** (113.27)	0.817*** (112.85)	0.622*** (83.95)
WEEKLY_HOURS	0.0864*** (27.80)	0.0870*** (27.98)	0.145*** (43.28)
c.WEEKLY_HOURSc.WEEKLY_HOURS	-0.000630*** (-19.02)	-0.000637*** (-19.24)	-0.00111*** (-31.01)
QUALTIME	0.0450*** (60.08)	0.0465*** (61.80)	0.0714*** (76.14)
c.QUALTIMEc.QUALTIME	-0.000789*** (-53.01)	-0.000845*** (-55.86)	-0.00121*** (-58.50)
0.SUPERVISOR	0 (.)	0 (.)	0 (.)
1.SUPERVISOR	0.660*** (74.71)	0.665*** (75.38)	0.502*** (56.71)
0.MALE0.SUPERVISOR	0 (.)	0 (.)	0 (.)
0.MALE1.SUPERVISOR	0 (.)	0 (.)	0 (.)
1.MALE0.SUPERVISOR	0 (.)	0 (.)	0 (.)
1.MALE1.SUPERVISOR	-0.0237 (-1.85)	-0.0380** (-2.98)	0.166*** (12.76)
0.PPARTNER	0 (.)	0 (.)	0 (.)
1.PPARTNER	0.0394*** (5.17)	0.0449*** (5.89)	0.0339*** (4.39)
0.PCHILDREN	0 (.)	0 (.)	0 (.)
1.PCHILDREN	0.0615*** (9.26)	0.141*** (18.54)	0.118*** (14.83)
0.PPARENTS	0 (.)	0 (.)	0 (.)
1.PPARENTS	-0.704*** (-65.96)	-0.694*** (-65.01)	-0.505*** (-44.55)
2.PPARENTS	-0.469*** (-17.45)	-0.468*** (-17.46)	-0.323*** (-11.91)
3.PPARENTS	-0.473*** (-38.71)	-0.469*** (-38.46)	-0.380*** (-31.03)
NBCHILDREN	0.0792*** (16.77)	-0.161*** (-32.39)	0.0548*** (12.44)
0.MALEc.NBCHILDREN	0 (.)	0 (.)	0 (.)
1.MALEc.NBCHILDREN	0.118*** (18.85)	0.162*** (24.89)	0.151*** (24.17)
age			0.166*** (88.33)
c.agec.age			-0.00165*** (-73.83)
JOBTENURE			0.0894*** (104.71)
c.JOBTENUREc.JOBTENURE			-0.000721*** (-29.76)
0.EDUCATION			0 (.)
1.EDUCATION			1.010*** (25.61)
2.EDUCATION			2.129*** (53.52)
3.EDUCATION			2.993*** (75.12)
4.EDUCATION			3.441*** (59.51)
5.EDUCATION			5.996*** (143.88)

6.EDUCATION					4.486*** (102.94)	2.770*** (121.37)
7.EDUCATION					5.486*** (135.35)	3.314*** (174.27)
8.EDUCATION					7.245*** (92.36)	5.416*** (68.68)
0.MALE0.EDUCATION					0 (.)	
0.MALE1.EDUCATION					0 (.)	0 (.)
0.MALE2.EDUCATION					0 (.)	0 (.)
0.MALE3.EDUCATION					0 (.)	0 (.)
0.MALE4.EDUCATION					0 (.)	0 (.)
0.MALE5.EDUCATION					0 (.)	0 (.)
0.MALE6.EDUCATION					0 (.)	0 (.)
0.MALE7.EDUCATION					0 (.)	0 (.)
0.MALE8.EDUCATION					0 (.)	0 (.)
1.MALE0.EDUCATION					0 (.)	
1.MALE1.EDUCATION					0.0296 (0.60)	0 (.)
1.MALE2.EDUCATION					-0.133** (-2.69)	-0.0730*** (-4.85)
1.MALE3.EDUCATION					-0.355*** (-7.17)	-0.265*** (-17.60)
1.MALE4.EDUCATION					-0.546*** (-7.12)	-0.580*** (-9.45)
1.MALE5.EDUCATION					-1.068*** (-20.05)	-1.078*** (-42.01)
1.MALE6.EDUCATION					-0.747*** (-13.05)	-0.791*** (-24.44)
1.MALE7.EDUCATION					-0.924*** (-18.04)	-0.929*** (-45.27)
1.MALE8.EDUCATION					-0.899*** (-7.85)	-1.056*** (-9.08)
cut1	-1.856*** (-355.89)	-162.8*** (-88.38)	-1.807*** (-297.32)	-163.7*** (-88.84)	5.106*** (97.24)	-217.8*** (-106.15)
cut2	-1.114*** (-256.63)	-161.6*** (-87.73)	-1.064*** (-199.00)	-162.5*** (-88.19)	6.002*** (114.09)	-216.5*** (-105.55)
cut3	-0.541*** (-134.30)	-160.7*** (-87.26)	-0.491*** (-96.05)	-161.6*** (-87.72)	6.753*** (128.04)	-215.6*** (-105.10)
cut4	-0.0501*** (-12.65)	-159.9*** (-86.84)	0.00186 (0.37)	-160.9*** (-87.30)	7.454*** (140.92)	-214.7*** (-104.69)
cut5	0.374*** (92.82)	-159.2*** (-86.46)	0.427*** (83.32)	-160.1*** (-86.91)	8.099*** (152.72)	-214.0*** (-104.31)
cut6	0.795*** (190.21)	-158.5*** (-86.05)	0.851*** (161.65)	-159.4*** (-86.51)	8.778*** (165.03)	-213.1*** (-103.91)
cut7	1.239*** (279.04)	-157.6*** (-85.60)	1.297*** (236.56)	-158.6*** (-86.06)	9.532*** (178.52)	-212.2*** (-103.47)
cut8	1.757*** (363.00)	-156.7*** (-85.09)	1.817*** (311.58)	-157.6*** (-85.55)	10.42*** (194.25)	-211.1*** (-102.95)
cut9	2.581*** (445.69)	-155.3*** (-84.37)	2.643*** (392.48)	-156.2*** (-84.83)	11.71*** (216.79)	-209.6*** (-102.21)
N	490160	471830	490160	471830	485708	467491

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A8 Complete OLS Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	WAGE	WAGE	WAGE	WAGE	WAGE	WAGE
0.MALE	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
1.MALE	1.048*** (130.83)	1.066*** (151.51)	0.911*** (87.80)	0.964*** (118.00)	1.459*** (33.11)	1.343*** (124.21)
YEAR		-0.0772*** (-84.43)		-0.0775*** (-84.82)		-0.0976*** (-102.09)
11.REGION		0 (.)		0 (.)		0 (.)
15.REGION		0.728*** (72.08)		0.730*** (72.33)		0.600*** (62.94)
16.REGION		0.301*** (33.26)		0.301*** (33.20)		0.193*** (22.67)
17.REGION		0.735*** (84.06)		0.739*** (84.48)		0.703*** (85.74)
18.REGION		0.736*** (70.51)		0.735*** (70.51)		0.605*** (61.74)
20.REGION		0.546*** (50.21)		0.552*** (50.82)		0.589*** (58.57)
30.REGION		0.551*** (55.09)		0.556*** (55.58)		0.545*** (58.43)
1.URBANIZATION		0 (.)		0 (.)		0 (.)
2.URBANIZATION		-0.166*** (-23.00)		-0.164*** (-22.70)		-0.0951*** (-14.16)
3.URBANIZATION		-0.207*** (-24.46)		-0.205*** (-24.19)		-0.117*** (-14.81)
0.ISCO		0 (.)		0 (.)		0 (.)
10.ISCO		1.046*** (28.49)		1.048*** (28.65)		0.584*** (18.80)
20.ISCO		1.874*** (55.64)		1.872*** (55.87)		0.783*** (27.23)
30.ISCO		0.261*** (7.66)		0.256*** (7.54)		0.135*** (4.82)
40.ISCO		-0.737*** (-21.32)		-0.739*** (-21.48)		-0.613*** (-21.52)
50.ISCO		-1.846*** (-54.19)		-1.847*** (-54.51)		-1.239*** (-44.07)
60.ISCO		-2.756*** (-70.72)		-2.750*** (-70.84)		-1.940*** (-57.00)
70.ISCO		-1.953*** (-56.89)		-1.954*** (-57.19)		-1.203*** (-42.04)
80.ISCO		-1.929*** (-55.59)		-1.928*** (-55.84)		-1.140*** (-39.30)
90.ISCO		-2.653*** (-77.47)		-2.654*** (-77.89)		-1.726*** (-60.41)
1.FTPT		0 (.)		0 (.)		0 (.)
2.FTPT		-1.865*** (-93.27)		-1.862*** (-93.19)		-1.561*** (-79.97)
1.temp		0 (.)		0 (.)		0 (.)
2.temp		-0.724*** (-96.94)		-0.718*** (-96.22)		-0.293*** (-35.37)
1.FIRM_SIZE		0 (.)		0 (.)		0 (.)

2.FIRM_SIZE	0.484*** (61.68)	0.483*** (61.60)	0.403*** (54.39)		
3.FIRM_SIZE	0.515*** (56.00)	0.513*** (55.85)	0.417*** (48.63)		
4.FIRM_SIZE	0.822*** (111.11)	0.820*** (110.85)	0.583*** (82.79)		
WEEKLY_HOURS	0.0118*** (6.37)	0.0121*** (6.56)	0.0244*** (13.35)		
c.WEEKLY_HOURSc.WEEKLY_HOURS	0.0000892*** (4.24)	0.0000839*** (3.99)	0.0000285 (1.37)		
QUALTIME	0.0420*** (55.66)	0.0433*** (57.17)	0.0487*** (57.58)		
c.QUALTIMEc.QUALTIME	-0.000758*** (-50.25)	-0.000805*** (-52.73)	-0.000707*** (-38.55)		
0.SUPERVISOR	0 (.)	0 (.)	0 (.)		
1.SUPERVISOR	0.742*** (83.51)	0.748*** (84.19)	0.516*** (62.31)		
0.MALE0.SUPERVISOR	0 (.)	0 (.)	0 (.)		
0.MALE1.SUPERVISOR	0 (.)	0 (.)	0 (.)		
1.MALE0.SUPERVISOR	0 (.)	0 (.)	0 (.)		
1.MALE1.SUPERVISOR	-0.135*** (-10.87)	-0.150*** (-12.09)	0.1000*** (8.31)		
0.PPARTNER	0 (.)	0 (.)	0 (.)		
1.PPARTNER	0.0446*** (5.95)	0.0478*** (6.36)	0.0324*** (4.61)		
0.PCHILDREN	0 (.)	0 (.)	0 (.)		
1.PCHILDREN	0.0748*** (11.29)	0.140*** (18.54)	0.0971*** (13.36)		
0.PPARENTS	0 (.)	0 (.)	0 (.)		
1.PPARENTS	-0.760*** (-70.38)	-0.751*** (-69.58)	-0.547*** (-50.37)		
2.PPARENTS	-0.507*** (-18.98)	-0.505*** (-18.95)	-0.347*** (-13.76)		
3.PPARENTS	-0.523*** (-42.65)	-0.519*** (-42.46)	-0.410*** (-35.65)		
NBCHILDREN		0.119*** (16.68)	-0.147*** (-30.61)	0.0548*** (11.26)	-0.0530*** (-11.54)
0.MALEc.NBCHILDREN		0 (.)	0 (.)	0 (.)	0 (.)
1.MALEc.NBCHILDREN		0.205*** (20.78)	0.163*** (25.24)	0.170*** (24.24)	0.157*** (25.72)
AGE				0.208*** (100.89)	0.0378*** (16.43)
c.AGEc.AGE				-0.00213*** (-86.60)	-0.000325*** (-11.79)
JOBTENURE				0.108*** (112.62)	0.0472*** (51.14)
c.JOBTENUREc.JOBTENURE				-0.00103*** (-38.66)	-0.000180*** (-7.39)
0.EDUCATION				0 (.)	

1.EDUCATION					0.801*** (26.26)	0 (.)
2.EDUCATION					2.096*** (66.98)	0.850*** (77.73)
3.EDUCATION					3.135*** (100.18)	1.511*** (130.41)
4.EDUCATION					3.644*** (60.75)	1.812*** (42.64)
5.EDUCATION					6.267*** (190.88)	3.116*** (176.97)
6.EDUCATION					4.875*** (130.35)	2.572*** (118.68)
7.EDUCATION					5.883*** (186.28)	3.041*** (179.93)
8.EDUCATION					6.926*** (135.06)	4.049*** (97.90)
0.MALE0.EDUCATION					0 (.)	
0.MALE1.EDUCATION					0 (.)	0 (.)
0.MALE2.EDUCATION					0 (.)	0 (.)
0.MALE3.EDUCATION					0 (.)	0 (.)
0.MALE4.EDUCATION					0 (.)	0 (.)
0.MALE5.EDUCATION					0 (.)	0 (.)
0.MALE6.EDUCATION					0 (.)	0 (.)
0.MALE7.EDUCATION					0 (.)	0 (.)
0.MALE8.EDUCATION					0 (.)	0 (.)
1.MALE0.EDUCATION					0 (.)	
1.MALE1.EDUCATION					0.495*** (10.98)	0 (.)
1.MALE2.EDUCATION					0.303*** (6.64)	-0.00954 (-0.66)
1.MALE3.EDUCATION					-0.0214 (-0.47)	-0.258*** (-17.91)
1.MALE4.EDUCATION					-0.212* (-2.52)	-0.527*** (-8.69)
1.MALE5.EDUCATION					-1.090*** (-22.35)	-1.244*** (-61.62)
1.MALE6.EDUCATION					-0.621*** (-11.06)	-0.850*** (-27.94)
1.MALE7.EDUCATION					-0.968*** (-20.72)	-1.128*** (-66.15)
1.MALE8.EDUCATION					-1.354*** (-19.53)	-1.554*** (-30.72)
_cons	4.949*** (858.97)	159.7*** (86.75)	4.869*** (651.32)	160.4*** (87.17)	-3.949*** (-80.38)	197.3*** (102.47)
N	490160	471830	490160	471830	485708	467491

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

FACULDADE DE ECONOMIA

