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THE STROLLER SLOWDOWN

HOW THE MOTHERHOOD PENALTY INFLUENCES WAGE DYNAMICS

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Abstract

Resorting to longitudinal data from Portuguese Social Security and Quadros de Pessoal, we estimate the motherhood penalty and found that it increases as the years after childbirth pass. Moreover, by applying a Gelbach decomposition, we explore the role of workers' and firms' heterogeneity concluding that mothers have time-invariant characteristics that are associated with lower wages, and are more present in firms with less generous wage policies. When analyzing the motherhood penalty across the wage distribution we conclude that mothers amongst high-wage earners suffer higher "child" penalties.

JEL Classification: J13, J16, J22, J31, J71

Keywords: Wage Inequality, Family Gap, Motherhood Penalty, Childbearing

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1 Introduction

At the beginning of the 20th century, most women (especially married women) did not work outside the home. They would dedicate their time to housekeeping and child-rearing. However, as the century went by, a continuing rise in the participation rate of women was observed. Several factors facilitated this increase including a significant rise in wages, the improvement of working conditions making jobs cleaner and safer, greater accessibility to birth control, and the decline in the relative price of goods that can replace household work (such as washing machines and child care services). These improvements were important for the introduction of women into the labor market, especially those who had children as it became possible to conciliate market employment with domestic responsibilities.

Despite all these advancements, a penalty for mothers associated with having children still exists nowadays. The phenomenon by which women's pay decreases once they become mothers, relative to women without children, is commonly denominated the motherhood penalty (or ”child” penalty) or motherhood wage gap. There are several explanations for this penalty such as the depreciation of human capital during career breaks associated with childbirth (Waldfogel 1997); sorting of mothers and non-mothers across more (or less) family-friendly firms and occupations that are associated with lower (or higher) pay, respectively (Felfe 2012); and discrimination of mothers (Correll, Benard, and Paik 2007).

The purpose of this study is to not only quantify the motherhood penalty but also shed some light on the mechanisms behind it, namely the role of worker, firm, and occupation heterogeneity.

Resorting to data from Portuguese Social Security and Quadros de Pessoal, we estimate the raw motherhood penalty (conditional on labor market experience) which amounts to 11.95 log points in the first dataset and 6.01 log points in the second. Moreover, the penalty increases throughout the years after childbirth, which is consistent with the hypothesis that after becoming mothers, women slow down their careers (Blau and Kahn 2017). Controlling for worker and firm fixed effects substantially decreases the estimated motherhood penalty. Moreover, applying a Gelbach (2016) decomposition, we explore the role of worker and firm heterogeneity. We conclude that, among these covariates, worker heterogeneity explains the biggest share of the motherhood penalty.

Finally, we evaluate the role of heterogeneity of the ”child” penalty across the wage distribution, finding that high-wage earners suffer higher motherhood penalties.

This study contributes to the literature on the motherhood penalty in two ways. Firstly, it is the first paper that uses longitudinal data in the quantification of the ”child” penalty in Portugal. Secondly, by applying the Gelbach (2016) it unfolds the role of worker, firm, and occupation fixed effects in explaining the motherhood wage gap.

The paper is structured as follows. In Section 2, we will present an overview of the evolution of parental leave, female labor force participation, and maternal employment, in Portugal. In section 3, an overview of the literature related to the motherhood penalty, its estimation and possible mechanisms, will be presented. Section 4 provides some details about the data used, and Section 5 discusses the empirical framework used. In section 6, we present the main results: estimation of the motherhood penalty, decomposition of the role of firm and worker fixed effects, and evaluation of the heterogeneity across percentiles of the wage distribution. Section 7 presents some additional results. And Section 8 concludes the study.

2 Institutional Background

In Portugal, the first legislation regarding parental leave dates back to 1976, which decreed 90 days of maternity leave.[1] Afterwards several other parental leave policies were implemented namely the introduction of the father’s right to share maternity leave with the mother [2] and of days exclusive to fathers after childbirth [3]. Currently, in 2023, paid and job-protected parental leave can last between 120 to 150 days and includes exclusive leave for the mother and the father. If they decide to share the parental leave 30 days can be added up to the leave period. When parents choose to benefit from 120 days of parental leave they receive a subsidy equivalent to 100% of their

1. Decreto-Lei n.º 112/76, de 7 de fevereiro, *Diário do Governo n.º 32/1976, Série I de 1976-02-07*
2. Lei n.º 17/95, de 9 de junho, *Diário da República n.º 134/1995, Série I-A de 1995-06-09*
3. Lei n.º 142/99, de 31 de agosto, *Diário da República n.º 203/1999, Série I-A de 1999-08-31*

reference remuneration, this value decreases if they decide to extend the period.[4] After the parental leave period, for children up to three years old, parents can resort to childcare mostly provided by childminders or by nurseries which are private both non-profit institutions and for-profit bodies. However, in 2020, the coverage rate of this type of service was only 48.8% (GEP 2021). These services were partly financed by the state under certain circumstances, however, from 2024 on nurseries would be free of charge.[5] For children from three years old to the age of compulsory education (six years), pre-primary education is available and free of charge from the age of four.[6]

In terms of labor market characteristics, Portugal presents a high female labor force participation for women with and without children. In fact, among the OECD countries, it presented the second-highest maternal employment rate after Slovenia, with a 4.4% part-time employment rate and 79.2% full-time employment rate, in 2021. The maternal employment rate is even highest when considering mothers with high education (94.6%). Moreover, for women with children aged 0-2, Portugal presents the highest employment rate around 83.7% (with 68.3% of women not absent and 15.4% absent on maternity leave) (OECD 2023).

3 Literature Review

The motherhood penalty has been estimated in several studies using different methods from controlled OLS regressions to fixed effects specifications. In this section, we start by presenting a summary of the main empirical evidence regarding the estimation motherhood penalty. Afterward, we dive into the empirical evidence regarding the mechanisms behind this penalty.

Beginning with the estimation of the motherhood penalty, Davies and Pierre (2005), resorting to data from the European Community Household Panel Survey (ECHP), found significant motherhood penalties in pay in Germany, the United Kingdom, Ireland, Spain, and Portugal. They compared the results from an OLS regression controlling for human capital and other observable characteristics (age, partnership status, education, potential experience, tenure, and industry), with

4. Decreto-Lei n.º 53/2023, de 5 de julho, *Diário da República n.º 129/2023, Série I de 2023-07-05*
5. Lei n.º 2/2022, de 3 de janeiro, *Diário da República n.º 1/2022, Série I de 2022-01-03*
6. Lei N.º 65/2015, de 3 de julho, *Diário da República n.º 166/2009, Série I de 2009-08-27*

the Heckman (1979) selection model to account for the non-randomness of the sample of working women, and the individual fixed effects specifications to account for constant unobserved individual heterogeneity. They found that, for Portugal, having one child is associated with a 6% reduction in gross hourly earnings and having two children with a 7% reduction.

For the United States, in a cross-section of working women, Anderson, Binder, and Krause (2002) estimated a total motherhood wage gap of around 15 percent per child, however, when including individual fixed effects the wage penalty dropped to 4 percent per child. Simonsen and Skipper (2008) applied propensity score matching and found that mothers receive 7.4 percent lower average wages compared to non-mothers.

More recently, using an event-study approach, the arrival of children was found to lead to an increase of 32 percentage points in the gender income gap and 10 percentage points in the gender wage gap, in Sweden (Angelov, Johansson, and Lindahl 2016). In Denmark, having one child was found to create a long-run gender gap in earnings of around 20 percent (Kleven, Landais, and Søgaard 2019). Moreover, also resorting to Danish data and using an instrumental variable (IV) approach, based on in vitro fertilization, Lundborg, Plug, and Rasmussen 2017 found that fertility has negative, large, and long-lasting effects on women's earnings.

Having shown empirical evidence regarding the quantification of the motherhood penalty, it is important to comprehend the underlying mechanisms that contribute to this phenomenon.

The most common explanations for the differences in pay between mothers and non-mothers are related to human capital theory (Becker 1985). It is argued that the motherhood penalty is mainly explained by the lower level of human capital of women with children.

Mothers often interrupt their careers after childbirth or reduce the hours worked due to child-rearing responsibilities which will lead to a reduction in labor market experience. There is evidence showing that mothers have lower levels of actual experience, which would be translated into a lower level of human capital, due to career interruptions, preferences for shorter work hours, and a higher probability of working part-time as a consequence of child-rearing responsibilities (Davies and Pierre 2005; Costa Dias, Joyce, and Parodi 2021; Waldfogel 1997). In a study about the careers of MBAs in the United States, women with children were found to shift into lower-hours positions and leave the labor force after the first childbirth. It was noticed that a mother is 20 percentage points less likely to work in a given year than the average man, while a woman without children is only 3 percentage points less likely to be employed than the average man. Furthermore, in this MBA sample, choosing a job because of ”flexible hours”, ”opportunity to work remotely” or ”limited travel schedule” is associated with 64 log points, 20 log points, and 7 log points decline in earnings, respectively (Bertrand, Goldin, and Katz 2010).

Moreover, the anticipation of these career breaks could also result in an under-investment in education and on-the-job training as the expected returns on this investment would be reduced, enhancing the differences in human capital. As shown by Bishop (1998), the degree of continuity of employment is likely to influence the level of on-the-job training.

Another explanation of the motherhood penalty has to do with unobserved heterogeneity. It might be the case that mothers have a stronger preference for non-market activities and a more home-centered lifestyle and women without children prefer to invest in their careers. Resorting to data from the 1968-88 National Longitudinal Survey of Young Women, from the United States, Anderson, Binder, and Krause (2003) concluded that 55-57% of the wage gap between mothers and non-mothers was explained by human capital inputs and unobserved heterogeneity.

Furthermore, gender norms would also intensify this phenomenon, as mothers are usually seen as the primary caregivers and the ones responsible for child-rearing within the couple. Kleven, Landais, and Søgaard (2019) found that child penalties are transmitted through generations, women who grew up in traditional families (where the father was the breadwinner and the mother was responsible for home production) were found to experience larger child penalties. This corroborates the idea that female gender identity and preferences formed during her childhood greatly influence the motherhood penalty. Moreover, Andresen and Nix (2022) found that gender norms, preferences, and labor market discrimination against mothers, which will be addressed later, significantly explain child penalties.

It is also argued that mothers have a preference for family-friendly jobs that enhance temporal flexibility and shorter work hours, which makes them compatible with child-rearing responsibilities. However, flexible schedules often come at a high price, especially in the corporate, finance, and legal worlds (Goldin 2014). This would lead to a labor market sorting of individuals between family-friendly and non-family-friendly jobs, and, ultimately, results in a penalty for individuals who have a preference for more flexible schedules. Using data from the German Socio-Economic Panel, Felfe (2012) found that compensating wage differentials might be behind the motherhood penalty because mothers often choose jobs that are more compatible with childcare but pay lower salaries.

Lastly, after controlling for all the factors mentioned above, the remaining motherhood penalty is often attributed to discrimination. Employers might discriminate against mothers as they are seen as more likely to interrupt their careers, present higher levels of absence, and possibly opt out of training investments due to child-rearing responsibilities. In this way, employers would prefer to hire and promote non-mothers and men as they see it as a signal for a long-term commitment. Correll, Benard, and Paik (2007) conducted a laboratory experiment and an audit study to evaluate the role of status-based discrimination in the motherhood penalty. With the laboratory experiment, they were able to conclude that indeed mothers were penalized in what concerns perceived competence and recommended starting salary. The audit study corroborates these results.

4 Data

4.1 Portuguese Social Security Data

To perform the analysis, two databases were used. The first one is a database from the Portuguese Social Security entitled *Microdados do Sistema de Informação da Segurança Social*, which is a 1% representative sample of Social Security contributors containing information about 139 427 individuals.

This database provides demographics about the individuals (such as gender, date of birth, nationality, and district of residence) and their career history namely the start and end of each of their professional qualifications. For each month between January 2005 and March 2012, it contains information on monthly earnings (base wage, regular, and non-regular benefits). This database also has information on maternity benefits more specifically the type of benefit and their starting and ending date. Resorting to maternity benefits, it was possible to identify consecutive periods in which a woman was benefiting from parental leave which afterward allowed the identification of the number of children. Unfortunately, this dataset does not have information on the levels of education and professional characteristics (such as working in the private versus public sector or profession), which would further enrich the analysis.

Furthermore, as mentioned before, information on monthly earnings, including parental benefits, is only available for the period between 2005 and 2012, making it only possible to analyze workers' wages during this period and identify children born after 2005. To minimize the bias that could come from the under-identification of children, the sample of study had to be restricted. Therefore, we only consider women who were at most 25 years old when first entering the dataset. As shown in Table A.1 in the Appendix, according to *Inquérito à Fecundidade 2019*, 95.18% of women between 18 and 25 years old did not have children. Moreover, individuals younger than 16 years old and who died during the period of study were also deleted from the sample. Finally, regarding the number of days worked only observations with the number of days between 25 and 30 (inclusive) were considered to avoid the inconsistencies made when recording the data.

The sample was further restricted to the largest connected set, which is defined when at least one element of a worker and firm combination links the rest of the group (Abowd, Creecy, and Kramarz 2002). The largest connected set corresponded to 61% of the sample.[7]

The restricted sample has 413,399 observations comprising 10,430 women among which 4,533 are mothers and 5,897 did not have any children during the period of study. The descriptive statistics for the sample are reported in Table A.2.

7. The percentage of observations included in the largest connect sets is reduced because this database is a 1% sample of Social Security contributors

4.2 Quadros de Pessoal

The Quadros de Pessoal (QP), a longitudinal matched employer-employee dataset, will serve as the second dataset for conducting the analysis. QP result from an annual mandatory employment survey, managed by the Portuguese Ministry of Employment, and covers all establishments with at least one paid employee. Data from Quadros de Pessoal relates to the month of October of each year. The study covers the period between 2010 and 2021.

Quadros de Pessoal dataset provides detailed information about each establishment, the firm with which it is affiliated, and its workers. Data on workers include gender, age, education, occupation, tenure, hours worked, and earnings (base wages, regular benefits, irregular benefits, and overtime payments). More importantly, it has information on the reason that led to the worker's absence which implied a reduction in the remuneration paid by the employer to the employee in October of each year, among which parental leave is included.

The last variable mentioned allows the partial identification of the number of children each worker has. In each of the years the worker's remuneration was reduced because she was benefiting from parental leave, she was considered to have had a child. However, two limitations should be mentioned. Firstly, there is only information about this variable after 2010, therefore, children born before 2010 cannot be identified. For this reason, to reduce the bias in the estimates we decided to apply the same restriction as in the Social Security dataset: the first time a woman was recorded she had to be at most 25 years old. Secondly, as this variable is recorded in October some children, even if born after 2010, might not be identified. As was presented before, the standard maternity leave in Portugal is four months so if a child is born in January, for example, it is highly likely that the mother will not be benefiting from maternity leave in October. This data limitation will probably bias the magnitude of our results as due to the incomplete identification of mothers some women with children will be included in the "control" group. For this reason, the estimates should be interpreted as a lower bound of the motherhood penalty.

The sample was further restricted to the largest connected set, which corresponded to 92% of the sample. Moreover, only full-time workers who receive more than 80% of the minimum wage are considered.

Therefore, the sample includes 1,809,967 observations among which 217,809 correspond to mothers (women that we were able to identify as having children during the period of study) and 1,592,158 correspond to non-mothers. Encompassing information about 412,633 women, 31,374 mothers and 381,259 non-mothers. The sample descriptive statistics can be checked in Table A.3.

5 Empirical Framework

5.1 Estimation of the motherhood penalty

To estimate the penalties in the pay gap associated with motherhood, the following benchmark model is estimated:

$$lnY_{it} = \beta_0 + \beta_1 X_{1_{it}} + \gamma_t + \sum_{j=1}^{10} \delta_{0j} \cdot \mathbb{1}[j = c] + \epsilon_{it} \quad (1)$$

where lnY_{it} is the outcome of interest, the natural logarithm of the real monthly total wage, which includes base wages, regular benefits, irregular benefits, and overtime payments, for individual i in year t; $X_{1_{it}}$ is a vector of controls for experience [8] and β_1 represents their coefficients; γ_t are calendar year fixed effects included to control for time trends such as wage inflation and business cycles; c=1, ..., 10 denotes the year relative to first childbirth; $\mathbb{1}[\cdot] = 1$ if the expression inside parenthesis is true and 0 otherwise; and, ϵ_{it} is an error term. The parameter of interest δ_{0j}, for j=1, ..., 10, gives us the estimated motherhood (or ”child”) penalty on women’s wages in each year after childbirth.[9]

The raw ”child” penalty, conditional on experience, obtained from model (1) can be divided into three parts: the unexplained child penalty, the child penalty explained by worker heterogeneity between the two groups, and the child penalty explained by the heterogeneous allocation to

8. With the Social Security data, a quadratic term on actual labor market experience will be included. With Quadros de Pessoal, quadratic terms on age and tenure will be used as proxies for labor market experience.

9. Using the Social Security data, it is only possible to estimate the motherhood penalty between the first and the seventh year after childbirth.

firms. Therefore, to estimate the unexplained child penalty after controlling for experience, worker heterogeneity, and firm heterogeneity, we will estimate a full regression of the following form:

$$lnY_{it} = \beta_0 + \beta_1 X_{1_{it}} + \gamma_t + \sum_{j=1}^{10} \delta_{1j} \cdot \mathbb{1}[j = c] + \alpha_i + \lambda_{F(i,t)} + \epsilon_{it} \tag{2}$$

where α_i is an individual fixed effect and $\lambda_{F(i,t)}$ is a firm fixed effect. In this equation, the parameter of interest δ_{1j}, with j=1, ..., 10, will represent the unexplained child penalty.

Enhancing our understanding of the three elements (unexplained child penalty, workers' heterogeneity, and firms' heterogeneity) that constitute the raw penalty, the unexplained child penalty includes factors that we were not able to account for due to data limitations, and discrimination against mothers. Workers' heterogeneity or individual fixed effects comprise all time-invariant characteristics of workers such as education (which is often a permanent characteristic of individuals from the moment they start to work), ability, preferences, and discrimination that do not change over time. Firms' heterogeneity or firm-fixed effects will capture all time-invariant characteristics of each firm. Furthermore, it allows us to control for the heterogeneous allocation of mothers and non-mothers among firms, meaning that we are controlling for the sorting of women between firms with better or worse-paying schemes.

To disentangle the role of worker and firm heterogeneity in explaining the motherhood penalty we will resort to a Gelbach (2016) decomposition as it will be explained in the next subsection.

5.2 Decomposition of the role of workers' and firms' heterogeneity

To better understand the mechanisms behind the motherhood penalty, more specifically the contributions of worker and firm heterogeneity, we will decompose the variation in the coefficients of interest (δ_j). To perform this decomposition, the methodology developed by Gelbach (2016), which uses the omitted variables bias formula, will be applied.

Departing from a base regression model (Eq.(3)), additional controls would be added (namely individual fixed effects and firm fixed effects) arriving at the full regression model (Eq.(4)). The

Gelbach decomposition allows us to disentangle the contribution of each of the covariates to the change in the coefficients of interest (δ_j), which measure the motherhood penalty. As stated by Gelbach (2016), many economists add variables sequentially to a model to understand how these new covariates impact the estimated coefficient of interest and attribute the change in the coefficient to the most recently added set of variables. However, this approach can be problematic because the order in which additional covariates are added can influence the results.

The base regression model in matrix formulation would be as follows:

$$Y = X\eta_0 + D\delta_0 + u_0 \tag{3}$$

where Y is the log of a person's wage, X is a matrix of control variables (experience and year dummies), η_0 is a vector of regression coefficients, D contains the dummies indicating the number of years after the first childbirth, δ_0 is our estimated coefficient of interest which measures the motherhood penalty and u_o is the error term.

Moreover, the full regression model in matrix formulation would be the following:

$$Y = X\eta_1 + D\delta_1 + W\alpha_1 + F\lambda_1 + u_1 \tag{4}$$

where W is a matrix containing worker dummies and α_1 represents their coefficients, and F is a matrix containing firm dummies and λ_1 represents their coefficients. The correct identification of worker and firm fixed effects is assured when using the connect sets (Abowd, Creecy, and Kramarz 2002).

Therefore, using Guimarães and Portugal (2010) iterative procedure, it is possible to obtain the estimated coefficients of the full regression. Observed Y can be expressed as follows:

$$Y = X\hat{\eta_1} + D\hat{\delta_1} + W\hat{\alpha_1} + F\hat{\lambda_1} + \hat{u_1} \tag{5}$$

To find the contribution of each of the covariates (worker fixed effects and firm fixed effects) to the variation in the coefficient of interest ($\hat{\delta_0} - \hat{\delta_1}$), we should regress the estimated fixed effects

($\hat{\alpha_1}$ and $\hat{\lambda_1}$) on the covariates of the base regression as follows:

$$\hat{\alpha_1} = X\eta_w + D\tau_w + u_w \tag{6}$$

$$\hat{\lambda_1} = X\eta_f + D\tau_f + u_f \tag{7}$$

The OLS estimates $\hat{\tau_w}$ and $\hat{\tau_f}$ represent the contribution of worker and firm, respectively, to the variation in ($\hat{\delta_0} - \hat{\delta_1}$). It can be expressed in the following way:

$$\hat{\delta_0} - \hat{\delta_1} = \hat{\tau_w} + \hat{\tau_f} \tag{8}$$

Hence, applying the Gelbach decomposition, we can exactly discern the impact of worker ($\hat{\tau_w}$) and firm ($\hat{\tau_f}$) time-invariant heterogeneity on the change of the coefficient of interest, and at last on the motherhood penalty.

6 Main Results

6.1 Motherhood penalty estimation

Table 1 (and Figure 1) and Table 2 (and Figure 2) present the results from the estimation of the base (Eq. (1)) and full (Eq. (2)) specifications using Social Security data and Quadros de Pessoal data, respectively.[10]

Starting with Social Security data (Table 1), looking at specification 1, conditional on labor market experience, we observe that one year after the first childbirth, mothers' wages were estimated to be, on average, 6.53 log points lower than the wages of women without children. The raw motherhood penalty increases as the years after the first childbirth pass. Seven years after the first childbirth, the gap between mothers and non-mothers increases to 21.31 log points. Quadros de Pessoal (Table 2) estimates present the same trend, with the raw motherhood penalty increasing

10. As explained before, motherhood penalty estimates from Quadros de Pessoal should be regarded as a lower bound due to the incomplete identification of mothers.

with the years after childbirth. However, in terms of magnitude, the estimates are lower, with an estimated raw child penalty equal to 3.39 log points in the first year increasing to 11.95 log points ten years after childbirth. These results are consistent with the hypothesis which states that mothers' career progression slows down after childbirth possibly due to child-rearing responsibilities (Blau and Kahn 2017).

Controlling for worker and firm heterogeneity (results presented in Tables 1 and 2, Column (2)) leads to a significant decrease in the estimated motherhood penalty that becomes more salient as the years after the first childbirth pass. In this way, using Social Security data, one year after the first child is born, the estimated motherhood penalty is, on average, 0.71 log points (compared to 6.53 in the base model). The unexplained penalty increases to 3.65 log points seven years after childbirth, on average. Focusing on specification 2, which aggregates the penalty felt between the first and the seventh year after childbirth, after controlling for experience, worker and firm fixed effects, mothers' wages are, on average, 1.83 log points lower than wages of women without children compared to 9.67 log points in the base model (Column (1)).

Resorting to QP data, in the first year the unexplained motherhood penalty is, on average, 2.90 log points. The highest estimated unexplained penalty, in the full model, is recorded eight years after childbirth (3.53 log points). Similarly, in specification 2, we can observe that the aggregated motherhood penalty (between years one and ten after childbirth) reduces from 5.93 log points to 2.86 log points when controlling for individual and firm fixed effects.

The significant decrease in the estimates associated with motherhood from the base model to the full model indicates that worker and firm heterogeneity between the two groups (mothers and non-mothers) can explain partially the raw motherhood penalty. Therefore, in the following subsection, we will decompose the contribution of each of the covariates to the variation in the estimates between the two models.

Figure 1: Motherhood wage gap using SS data

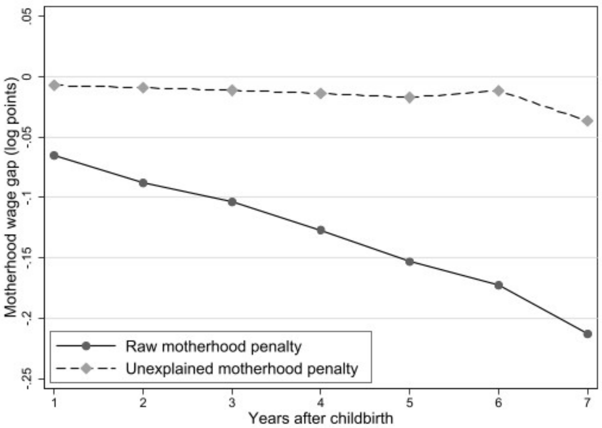
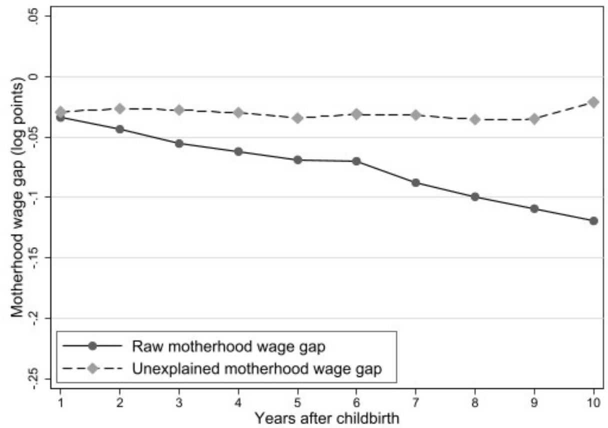


Figure 2: Motherhood wage gap using QP data



6.2 Decomposition of the role of workers' and firms' heterogeneity

Applying the Gelbach (2016) decomposition, which appeals to the omitted variables bias formula, we were able to disentangle the contribution of worker and firm heterogeneity to the variation in the estimated coefficient of the motherhood penalty ($\hat{\delta}_0 - \hat{\delta}_1$). The results are presented in Tables 1 and 2, Columns (3) and (4).

Starting with Table 1, which presents the decomposition resorting to Social Security data, in specification 2, we can notice that the total variation in $\hat{\delta}$ is -7.84 log points ($\hat{\delta}_0 - \hat{\delta}_1$). That is, worker and firm fixed effects explain 7.84 log points of the estimated raw motherhood penalty (which was 9.67 log points). Therefore, combined these two factors explain around 81% of the penalty. Individual fixed effects account for -3.94 log points of the variation in $\hat{\delta}$, explaining around 50% of the variation and 41% of the estimated raw motherhood penalty. Firm fixed effects account for -3.90 log points of the change in $\hat{\delta}$, explaining around the other 50% of the variation and 40% of the estimated motherhood penalty. Looking at the results from the first specification, we can see that as the years after the first childbirth pass, the difference between $\hat{\delta}_0$ and $\hat{\delta}_1$ increases as well as the share of the motherhood penalty explained by worker and firm fixed effects. Moreover, analyzing the decomposition of the motherhood penalty between one and seven years after the first childbirth, we can see that worker-fixed effects are usually the control that explains the biggest share of the variation of $\hat{\delta}$.

Comparable meaning results are obtained using Quadros de Pessoal (Table 2). The total variation in $\hat{\delta}$ from the base to the full model is -3.07 log points (Second Specification). Therefore, worker and firm fixed effects explain 52% of the raw motherhood penalty. Individual permanent heterogeneity accounts for the biggest share of the variation 75% (corresponding to -2.29 log points which explain 30% of the raw motherhood penalty). Contrasting with firm permanent heterogeneity which was found to explain 25% of the variation in $\hat{\delta}$, which resembles -0.79 log points explaining 13% of the raw motherhood penalty. As the years after childbirth pass (First specification), the share of the raw motherhood penalty explained by worker and firm fixed effects increases with individual fixed effects assuming a dominant role.

The results obtained in this subsection give us a better understanding of the mechanisms behind the motherhood penalty. Firstly, focusing on worker permanent heterogeneity (measured by worker fixed effects), we observe that women with children have time-invariant observed and unobserved characteristics that are associated with lower wages. These characteristics can include education, preferences, and permanent discrimination, for example. Starting with education, expecting lower returns due to career breaks could lead to an under-investment in education. Furthermore, mothers might have stronger preferences for non-market activities than non-mothers and invest less in their careers. Both possibilities will culminate in lower levels of human capital for mothers when compared to non-mothers which partially explains the lower salaries and the motherhood penalty. These permanent characteristics contribute to an increasing raw motherhood penalty over time.

Regarding firm fixed effects, we concluded that the allocation of mothers and non-mothers to different types of firms is another important factor accounting for the change in $\hat{\delta}$. This means that mothers are, on average, more present in firms associated with less generous wage policies. A possible explanation behind this result is the hypothesis that mothers self-select into firms that are more family-friendly and allow flexible schedules which could be associated with lower-paying schemes (Goldin 2014).

Table 1: Motherhood Penalty Estimation and Decomposition using Social Security data

			Decomposition	
Variables	Base model (δ_{0j})	Full model (δ_{1j})	Worker FE	Firm FE
	(1)	(2)	(3)	(4)
First specification				
Year after first childbirth				
1	-0.0653***	-0.0071***	-0.0309***	-0.0273***
	(0.0062)	(0.0026)	(0.0053)	(0.0045)
2	-0.0881***	-0.0090**	-0.0441***	-0.0349***
	(0.0070)	(0.0035)	(0.0062)	(0.0052)
3	-0.1038***	-0.0111**	-0.0478***	-0.0449***
	(0.0082)	(0.0045)	(0.0075)	(0.0063)
4	-0.1267***	-0.0137**	-0.0563***	-0.0567***
	(0.0094)	(0.0055)	(0.0090)	(0.0074)
5	-0.1532***	-0.0170**	-0.0736***	-0.0626***
	(0.0107)	(0.0066)	(0.0104)	(0.0090)
6	-0.1728***	-0.0114	-0.0906***	-0.0708***
	(0.0143)	(0.0089)	(0.0149)	(0.0144)
7	-0.2131***	-0.0365*	-0.1542***	-0.0224
	(0.0360)	(0.0194)	(0.0338)	(0.0387)
R-squared	0.0473	0.8967	0.0427	0.0113
Second specification				
After childbirth	-0.0967***	-0.0183***	-0.0394***	-0.0390***
	(0.0062)	(0.0029)	(0.0058)	(0.0048)
R-squared	0.0490	0.8968	0.0377	0.0114
Observations	405,130	405,130	405,130	405,130

Note: The dependent variable is the natural logarithm of real monthly total wages. Controls for actual experience (and its square) and time dummies were included in both models. Column 1 reports the base model regression coefficient estimates. Column 2 reports the full model regression coefficient estimates in which worker and firm fixed effects were included. Columns 3 presents the contribution of the worker fixed effects to the variation in the estimated coefficient from the base to the full model. Column 4 presents the contribution of the firm fixed effects to the variation in the estimated coefficient from the base to the full model. The decomposition was performed according to the method described in section 5. Specification 1 presents the estimates for each year after childbirth. Specification 2 aggregates the seven years after childbirth and presents an estimate for the overall motherhood penalty. Standard errors are clustered at the worker level.
** p<0.01, ** p<0.05, * p<0.1

Table 2: Motherhood Penalty Estimation and Decomposition using Quadros de Pessoal data

Variables	Base model (δ_{0j}) (1)	Full model (δ_{1j}) (2)	Decomposition: Worker FE (3)	Decomposition: Firm FE (4)
First specification				
Year after first childbirth				
1	-0.0339***	-0.0290***	-0.0027	-0.0022*
	(0.0022)	(0.0013)	(0.0017)	(0.0012)
2	-0.0435***	-0.0263***	-0.0121***	-0.0051***
	(0.0025)	(0.0015)	(0.0019)	(0.0013)
3	-0.0554***	-0.0274***	-0.0188***	-0.0093***
	(0.0029)	(0.0017)	(0.0022)	(0.0015)
4	-0.0616***	-0.0297***	-0.0229***	-0.0090***
	(0.0033)	(0.0020)	(0.0025)	(0.0017)
5	-0.0685***	-0.0341***	-0.0256***	-0.0088***
	(0.0039)	(0.0023)	(0.0029)	(0.0020)
6	-0.0698***	-0.0309***	-0.0295***	-0.0094***
	(0.0046)	(0.0028)	(0.0034)	(0.0023)
7	-0.0877***	-0.0317***	-0.0416***	-0.0143***
	(0.0054)	(0.0033)	(0.0040)	(0.0029)
8	-0.0991***	-0.0353***	-0.0448***	-0.0190***
	(0.0066)	(0.0041)	(0.0048)	(0.0036)
9	-0.1090***	-0.0349***	-0.0545***	-0.0196***
	(0.0083)	(0.0052)	(0.0060)	(0.0044)
10	-0.1195***	-0.0210***	-0.0745***	-0.0241***
	(0.0115)	(0.0073)	(0.0081)	(0.0063)
R-squared	0.1338	0.8594	0.3388	0.0078
Second specification				
After childbirth	-0.0593***	-0.0286***	-0.0229***	-0.0079***
	(0.0021)	(0.0012)	(0.0017)	(0.0012)
R-squared	0.1339	0.8594	0.3401	0.0078
Observations	1,773,147	1,773,147	1,773,147	1,773,147

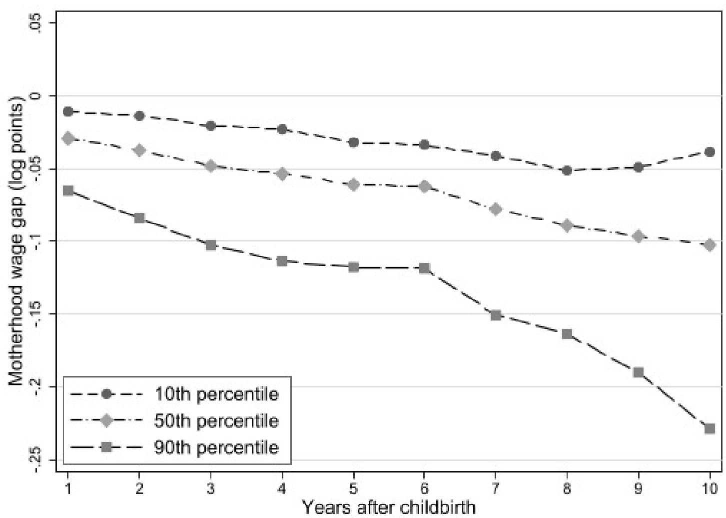
Note: The dependent variable is the natural logarithm of real monthly total wages. Controls for age (and its square), tenure (and its square), and time dummies were included in both models. Column 1 reports the base model regression coefficient estimates. Column 2 reports the full model regression coefficient estimates in which worker and firm fixed effects were included. Columns 3 presents the contribution of the worker fixed effects to the variation in the estimated coefficient from the base to the full model. Column 4 presents the contribution of the firm fixed effects to the variation in the estimated coefficient from the base to the full model. The decomposition was performed according to the method described in section 5. Specification 1 presents the estimates for each year after childbirth. Specification 2 aggregates the ten years after childbirth and presents an estimate for the overall motherhood penalty. Standard errors are clustered at the worker level.

** p<0.01, ** p<0.05, * p<0.1

6.3 Heterogeneity: motherhood penalty across the wage distribution

After estimating the motherhood penalty, we decided to study its variation across the wage distribution. For that purpose, we use a Machado and Santos Silva (2019) method of moments estimator that allows the estimation of regression quantiles in panel data models with high-dimensional fixed effects. For the purpose of this exercise, we decided to focus on the results obtained from Quadros de Pessoal data as it covers all establishments with at least one employee.[11] More than the quantification of the motherhood penalty across percentiles, it is of interest here to understand if there are significant differences between them. The results are presented in Table 3 and Figure 3.[12]

Figure 3: Raw motherhood wage gap using QP data



Beginning by looking at the aggregate measure of the motherhood penalty (Second specification), we observe that the raw motherhood penalty is smaller in the lower tail of the wage distribution (at the 10^{th} percentile), with an estimated penalty of 2.28 log points after childbirth (Column (1)). While in the upper tail (at the 90^{th} percentile), the estimated penalty is around 10.86 log points (Column (3)). This shows that mothers with higher wages suffer higher child penalties than those with lower wages. Moreover, the penalty at the conditional mean that was estimated before (5.93

11. Social Security data only covers a 1% representative sample of Social Security contributors which will pose problems in the correct estimation of the motherhood penalty across percentiles. Nonetheless, the results can be checked in Table A.5.

12. The complete table can be checked in the Appendix (Table A.4)

Table 3: Motherhood penalty across percentiles of wage distribution using Quadros de Pessoal

	Base model			Full Model		
	Percentiles			Percentiles		
Variables	10	50	90	10	50	90
	(1)	(2)	(3)	(4)	(5)	(6)
Second specification						
After childbirth	-0.0228***	-0.0517***	-0.1086***	-0.0334	-0.0289	-0.0235
	(0.0010)	(0.0011)	(0.0026)	(0.0925)	(0.0465)	(0.0618)

Note: The dependent variable is the natural logarithm of real monthly total wages. Controls for age (and its square), tenure (and its square), and time dummies were included in both models. Columns 1-3 report the base model regression coefficient estimates for the 10, 50, and 90 percentile, respectively. In the full model, worker and firm fixed effects were included. Columns 4-6 report the full model regression coefficient estimates for the 10, 50, and 90 percentile, respectively. Specification 2 aggregates the ten years after childbirth and presents an estimate for the overall motherhood penalty. The estimates were obtained using Machado and Santos Silva's (2019) method of moments estimator for quantile regressions.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

log points) is higher than the penalty at the conditional median which is 5.17 log points. When including worker and firm fixed effects (Columns 4-6) the estimated penalty was reduced and became higher in the lower tail. This indicates that worker and firm heterogeneity plays a bigger role in explaining the motherhood penalty for higher-wage earners.

Moving to the first specification, the results previously explained were corroborated. In this way, controlling for age and tenure, mothers who were part of the lowest-wage earners group suffered lower penalties throughout the period between 1 and 10 years after childbirth, starting with a penalty of 1.06 log point in the first year that increased gradually to 3.83 log points ten years after childbirth. Mothers amongst the highest-wage earners group suffered the higher penalties: one year after childbirth the wage gap between mothers and non-mothers in this group was -6.52 log points and widened to -22.89 log points ten years after childbirth. Controlling for worker, firm, and profession fixed effects the estimated motherhood penalty substantially attenuates across all regions of the wage distribution.

The results achieved in this section interestingly shed light on the mechanisms behind the motherhood penalty. By showing that high-wage earners are the ones that suffer the most with parenting we infer that there is possibly a glass ceiling associated with motherhood. As it was explained before, one possible explanation for the motherhood penalty has to do with career breaks that lead to the depreciation of human capital. This depreciation becomes more critical the more specialized a job is, and as we know more specialized jobs are associated with higher wages. Another explanation has to do with the fact that mothers often reduce the hours worked due to child-rearing responsibilities which can slow career progression.

7 Additional results

In this section, we will explore one additional extension which due to lack of information in the Social Security data is only possible to estimate resorting to Quadros de Pessoal data.

7.1 The role of occupational heterogeneity

We will explore the role of occupational heterogeneity in explaining the motherhood penalty, applying the methodology proposed by Gelbach (2016) explained in Section 5.2. The starting point will be the base model previously presented in Equation 3. In the full regression occupation fixed effects would be added as follows:

$$Y = X\eta_1 + D\delta_1 + W\alpha_1 + F\lambda_1 + P\phi_1 + u_1 \tag{9}$$

where P is a matrix containing occupation dummies and ϕ_1 represents their coefficients.[13]

Therefore, the variation in the estimated coefficients of interest $\hat{\delta}$ will now include a third element $\hat{\tau_p}$. It represents the contribution of occupation time-invariant heterogeneity to the change in the $\hat{\delta}$. It can be written in the following way:

$$\hat{\delta_0} - \hat{\delta_1} = \hat{\tau_w} + \hat{\tau_f} + \hat{\tau_p} \tag{10}$$

13. The correct identification of worker, firm, and occupation fixed effects is assured when using the worker-firm-occupation largest connected set, which corresponds to 92% of the sample.

Table 4: Understanding the role of occupational heterogeneity

Variables	Base model δ_{0j} (1)	Full model δ_{1j} (2)	Decomposition Worker FE (3)	Firm FE (4)	Occupation FE (5)
Second specification					
After childbirth	-0.0593***	-0.0277***	-0.0164***	-0.0066***	-0.0086***
	(0.0021)	(0.0012)	(0.0015)	(0.0011)	(0.0004)
R-squared	0.1339	0.8620	0.3729	0.0058	0.0446
Observations	1,773,144	1,773,144	1,773,144	1,773,144	1,773,147

Note: The dependent variable is the natural logarithm of real monthly total wages. Controls for age (and its square), tenure (and its square), and time dummies were included in both models. Column 1 reports the base model regression coefficient estimates. Column 2 reports the full model regression coefficient estimates in which worker, firm, and occupation fixed effects were included. Column 3 presents the contribution of the worker fixed effects to the variation in the estimated coefficient from the base to the full model. Column 4 presents the contribution of the firm fixed effects to the variation in the estimated coefficient from the base to the full model. Column 5 presents the contribution of occupation fixed effects to the variation in the estimated coefficient from the base to the full model. The decomposition was performed according to the method described in section 5. Specification 2 aggregates the ten years after childbirth and presents an estimate for the overall motherhood penalty. Standard errors are clustered at the worker level.
** p<0.01, ** p<0.05, * p<0.1

The results are presented in Table 4 (and Table A.6 in the Appendix). Looking at the estimated unexplained motherhood penalty (Columns (2)), we can see that including the occupation fixed effect further reduced the unexplained penalty. Moreover, performing the Gelbach (2016) decomposition, we observe that the share of the raw motherhood penalty explained by firm fixed effects and, especially, individual fixed effects is reduced. This is the case because some individuals might not change occupation during their careers.

Focusing on the role of occupation heterogeneity, we find that mothers' are more concentrated in professions associated with lower wages. This could be the case because mothers might have a preference for family-friendly jobs that allow temporal flexibility and shorter work hours, making them compatible with parenting (Goldin 2014). This hypothesis follows the compensating wage differentials theory. Thus, mothers typically earn lower wages as they opt for occupations that offer lower pay, on average, but are more compatible with child-rearing.

8 Conclusion

Despite the evolution observed in the last decades, a wage gap between mothers and non-mothers still exists. Resorting to longitudinal data from the Portuguese Social Security and Quadros de Pessoal, we were able to quantify the motherhood penalty and shed some light on the mechanisms behind it.

Firstly, we found that the raw ”child” penalty (conditional on experience) increases as the years after childbirth pass. Using Social Security data we found that one year after childbirth the estimated raw motherhood penalty was, on average, 6.53 log points increasing to 21.31 log points, seven years after. Utilizing Quadros de Pessoal data, the estimates for the raw motherhood penalty were 3.39 and 11.95 log points, for the first and tenth year after childbirth, respectively. Controlling for worker and firm heterogeneity significantly reduces the estimates.

Secondly, applying the Gelbach (2016) decomposition, we were able to obtain the share of worker and firm fixed effects in explaining the raw motherhood penalty. Overall, the workers' heterogeneity played a bigger role, explaining away 41% and 30% of the estimated raw motherhood penalty in the SS and QP samples, respectively. Moreover, it was found that women with children have time-invariant characteristics associated with lower wages such as education and preferences, and there is a certain level of sorting of mothers and non-mothers between firms with less (or more) generous wage policies.

Thirdly, analyzing the penalty across the wage distribution, we concluded that high-wage earners suffer higher penalties, starting with a raw penalty of 6.52 log points, one year after childbirth, which increases to 22.89 log points, ten years after childbirth. The estimates contrast with the ones for the lowest-wage earners, with an initial raw penalty of 1.06 log points which increases to 3.83 log points ten years after childbirth.

Additionally, we explored the role of occupational heterogeneity and concluded that there is some level of sorting of mothers and non-mothers across professional occupations with mothers typically opting for occupations that pay less probably because they are more compatible with child-rearing responsibilities.

Concluding, this paper provided the quantification of the motherhood penalty and a better understanding of the mechanisms behind it. In the future, it would be interesting to further understand and explore the role of firms' heterogeneity and what is behind the sorting observed, namely which factors influence mothers and non-mothers in their decision of firm and occupations and the differences between them.

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9 Appendix

Table A.1: Percentage of women without children by age group

Age group	18 - 25	26 - 30	31 - 35	36 - 40	41 - 45	46 - 50
% without children	95.18%	69.39%	33.74%	18.41%	14.58%	14.99%

Source: INE, Inquérito à Fecundidade 2019

Table A.2: Descriptive Statistics - Social Security Data

	(1) Mothers	(2) Non-Mothers
Age (years)	25.43	24.77
	(2.97)	(3.04)
Actual experience (months)	45.39	37.45
	(29.48)	(26.77)
Tenure (months)	22.04	18.29
	(19.19)	(17.42)
Real monthly total wage (in 2012 prices)	651.84	701.76
	(274.64)	(325.44)
Real monthly base wage (in 2012 prices)	640.56	686.82
	(267.38)	(314.74)
Observations	209512	203887
Number of individuals	4533	5897

Table A.3: Descriptive Statistics - Quadros de Pessoal

	(1) Mothers	(2) Non-Mothers
Age (years)	27.62	25.88
	(3.84)	(3.75)
Tenure (years)	4.03	2.30
	(3.76)	(2.93)
Real hourly total wage (in 2012 prices)	5.60	5.47
	(3.12)	(3.02)
Real monthly total wage (in 2012 prices)	952.12	934.26
	(517.45)	(509.18)
Real monthly base wage (in 2012 prices)	748.02	726.34
	(343.66)	(313.49)
Monthly total hours	171.01	171.67
	(8.80)	(8.74)
Observations	217809	1592158
Number of individuals	31374	381259

Table A.4: Motherhood penalty across the wage distribution using Quadros de Pessoal

	Base model			Full Model		
	Percentiles			Percentiles		
Variables	10	50	90	10	50	90
	(1)	(2)	(3)	(4)	(5)	(6)
First specification						
Year after first childbirth						
1	-0.0106***	-0.0290***	-0.0652***	-0.0359	-0.0294	-0.0217
	(0.0019)	(0.0020)	(0.0047)	(0.0892)	(0.0441)	(0.0548)
2	-0.0135***	-0.0372***	-0.0839***	-0.0314	-0.0266	-0.0210
	(0.0021)	(0.0022)	(0.0052)	(0.0999)	(0.0494)	(0.0614)
3	-0.0203***	-0.0481***	-0.1027***	-0.0303	-0.0276	-0.0244
	(0.0023)	(0.0025)	(0.0059)	(0.1136)	(0.0562)	(0.0698)
4	-0.0229***	-0.0535***	-0.1136***	-0.0312	-0.0298	-0.0281
	(0.0027)	(0.0029)	(0.0068)	(0.1308)	(0.0647)	(0.0804)
5	-0.0319***	-0.0608***	-0.1177***	-0.0350	-0.0341	-0.0331
	(0.0032)	(0.0034)	(0.0080)	(0.1518)	(0.0751)	(0.0933)
6	-0.0336***	-0.0622***	-0.1186***	-0.0361	-0.0312	-0.0253
	(0.0037)	(0.0040)	(0.0094)	(0.1814)	(0.0898)	(0.1115)
7	-0.0411***	-0.0779***	-0.1505***	-0.0326	-0.0318	-0.0309
	(0.0044)	(0.0047)	(0.0110)	(0.2178)	(0.1077)	(0.1339)
8	-0.0512***	-0.0890***	-0.1636***	-0.0375	-0.0355	-0.0330
	(0.0054)	(0.0058)	(0.0136)	(0.2713)	(0.1342)	(0.1668)
9	-0.0488***	-0.0963***	-0.1901***	-0.0314	-0.0346	-0.0385
	(0.0067)	(0.0072)	(0.0169)	(0.3487)	(0.1725)	(0.2144)
10	-0.0383***	-0.1025***	-0.2289***	-0.0127	-0.0204	-0.0297
	(0.0093)	(0.0101)	(0.0236)	(0.5094)	(0.2521)	(0.3132)
Second specification						
After childbirth	-0.0228***	-0.0517***	-0.1086***	-0.0334	-0.0289	-0.0235
	(0.0010)	(0.0011)	(0.0026)	(0.0925)	(0.0465)	(0.0618)

Note: The dependent variable is the natural logarithm of real monthly total wages. Controls for age (and its square), tenure (and its square), and time dummies were included in both models. Columns 1-3 report the base model regression coefficient estimates for the 10, 50, and 90 percentile, respectively. In the full model, worker and firm fixed effects were included. Columns 4-6 report the full model regression coefficient estimates for the 10, 50, and 90 percentile, respectively. Specification 1 reports the estimates of the motherhood penalty for each year after childbirth. Specification 2 aggregates the ten years after childbirth and presents an estimate for the overall motherhood penalty. The estimates were obtained using Machado and Santos Silva's (2019) method of moments estimator.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.5: Motherhood penalty across the wage distribution using Social Security data

	Base model			Full Model		
	Percentiles			Percentiles		
Variables	10	50	90	10	50	90
	(1)	(2)	(3)	(4)	(5)	(6)
First specification						
Year after first childbirth						
1	-0.0119***	-0.0493***	-0.1558***	-0.0080	-0.0071	-0.0061
	(0.0013)	(0.0016)	(0.0048)	(0.1895)	(0.0803)	(0.0496)
2	-0.0199***	-0.0677***	-0.2035***	-0.0068	-0.0090	-0.0112
	(0.0014)	(0.0017)	(0.0052)	(0.2266)	(0.0960)	(0.0593)
3	-0.0205***	-0.0790***	-0.2449***	-0.0096	-0.0110	-0.0126
	(0.0016)	(0.0020)	(0.0059)	(0.2779)	(0.1177)	(0.0727)
4	-0.0232***	-0.0958***	-0.3019***	-0.0114	-0.0136	-0.0160
	(0.0019)	(0.0023)	(0.0068)	(0.3382)	(0.1432)	(0.0884)
5	-0.0277***	-0.1157***	-0.3657***	-0.0089	-0.0168	-0.0251
	(0.0023)	(0.0027)	(0.0082)	(0.4251)	(0.1800)	(0.1112)
6	-0.0410***	-0.1334***	-0.3959***	-0.0038	-0.0112	-0.0188
	(0.0036)	(0.0043)	(0.0130)	(0.6301)	(0.2669)	(0.1648)
7	-0.0712***	-0.1707***	-0.4535***	-0.0194	-0.0361	-0.0535
	(0.0223)	(0.0267)	(0.0804)	(3.0091)	(1.2744)	(0.7870)
Second specification						
After childbirth	-0.0224***	-0.0747***	-0.2222***	-0.0252	-0.0184	-0.0113
	(0.0008)	(0.0010)	(0.0029)	(0.0259)	(0.0258)	(0.0632)

Note: The dependent variable is the natural logarithm of real monthly total wages. Controls for experience (and its square) and time dummies were included in both models. Columns 1-3 report the base model regression coefficient estimates for the 10, 50, and 90 percentile, respectively. In the full model, worker and firm fixed effects were included. Columns 4-6 report the full model regression coefficient estimates for the 10, 50, and 90 percentile, respectively. Specification 1 reports the estimates of the motherhood penalty for each year after childbirth. Specification 2 aggregates the seven years after childbirth and presents an estimate for the overall motherhood penalty. The estimates were obtained using Machado and Santos Silva's (2019) method of moments estimator.
** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.6: Understanding the role of occupational heterogeneity

Variables	Base model (δ_{0j})	Full model (δ_{1j})	Decomposition		
			Worker FE	Firm FE	Occupation FE
	(1)	(2)	(3)	(4)	(5)
First specification					
Year after first childbirth					
1	-0.0339***	-0.0287***	-0.0003	-0.0013	-0.0035***
	(0.0022)	(0.0013)	(0.0015)	(0.0011)	(0.0004)
2	-0.0435***	-0.0256***	-0.0079***	-0.0043***	-0.0058***
	(0.0025)	(0.0015)	(0.0016)	(0.0013)	(0.0005)
3	-0.0554***	-0.0262***	-0.0131***	-0.0082***	-0.0080***
	(0.0029)	(0.0017)	(0.0019)	(0.0015)	(0.0006)
4	-0.0616***	-0.0284***	-0.0160***	-0.0082***	-0.0090***
	(0.0033)	(0.0020)	(0.0022)	(0.0017)	(0.0007)
5	-0.0685***	-0.0324***	-0.0195***	-0.0074***	-0.0092***
	(0.0039)	(0.0023)	(0.0025)	(0.0020)	(0.0008)
6	-0.0698***	-0.0290***	-0.0225***	-0.0079***	-0.0104***
	(0.0046)	(0.0028)	(0.0029)	(0.0023)	(0.0009)
7	-0.0877***	-0.0293***	-0.0332***	-0.0128***	-0.0123***
	(0.0054)	(0.0033)	(0.0034)	(0.0028)	(0.0011)
8	-0.0991***	-0.0324***	-0.0360***	-0.0177***	-0.0129***
	(0.0066)	(0.0040)	(0.0041)	(0.0035)	(0.0014)
9	-0.1090***	-0.0313***	-0.0426***	-0.0184***	-0.0167***
	(0.0083)	(0.0050)	(0.0051)	(0.0043)	(0.0017)
10	-0.1195***	-0.0181**	-0.0586***	-0.0208***	-0.0221***
	(0.0115)	(0.0072)	(0.0070)	(0.0062)	(0.0023)
R-squared	0.1338	0.8620	0.3720	0.0058	0.0444
Second specification					
After childbirth	-0.0593***	-0.0277***	-0.0164***	-0.0066***	-0.0086***
	(0.0021)	(0.0012)	(0.0015)	(0.0011)	(0.0004)
R-squared	0.1339	0.8620	0.3729	0.0058	0.0446
Observations	1,773,144	1,773,144	1,773,144	1,773,144	1,773,144

Note: The dependent variable is the natural logarithm of real monthly total wages. Controls for age (and its square), tenure (and its square), and time dummies were included in both models. Column 1 reports the base model regression coefficient estimates. Column 2 reports the full model regression coefficient estimates in which worker, firm, and occupation fixed effects were included. Column 3 presents the contribution of the worker-fixed effects to the variation in the estimated coefficient from the base to the full model. Column 4 presents the contribution of the firm fixed effects to the variation in the estimated coefficient from the base to the full model. Column 5 presents the contribution of the occupation fixed effects to the variation in the estimated coefficient from the base to the full model. The decomposition was performed according to the method described in section 5. Specification 1 presents the estimates for each year after childbirth. Specification 2 aggregates the ten years after childbirth and presents an estimate for the overall motherhood penalty. Standard errors are clustered at the worker level.
** p<0.01, ** p<0.05, * p<0.1