Intra-Household Decisions and Labor Market Outcomes - Evidence from Shared Parental Leave*

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December 2024

Abstract

This paper examines the impact of intra-household decisions over the split of childcare duties on labor market outcomes. We study the introduction of shared parental leave in Portugal, which allows parents to decide on the allocation of leave days. Using a model of the household, we show that introducing shared parental leave leads to an increase in women's wages, as they are allocated a lower of childcare duties when compared with the allocation before shared parental leave is introduced. Moreover, this wage increase should be more pronounced for high-productivity women. Using a novel data set which combines household data with matched employer employee data, we find that the monthly wages of women increase by 1 percent relative to the wages of men. We also find that most of this increase is driven by women which are the primary earners in their household. Our results suggest that the effectiveness of childcare policies in mitigating gender inequality in the labor market may be determined by intra-household decisions.

Keywords: Gender wage gap, intra-household decisions, child penalty

JEL Codes: D13, J16, J31

*We thank Ramin Baghai, Bence Bardóczy, Matthias Doepke, Luigi Guiso, Simon Jäger, Adam Jørring, Laura C. Murphy, Michèle Tertilt, and Luana Zaccaria for helpful comments and discussions. We also thank seminar participants at EIEF and at the SED for helpful comments. Andrea Ferrara thanks the Northwestern Buffett Institute for Global Affairs for financial support.

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1 Introduction

Women earn less than men. This wage gap is present across most developed countries and occupations (Bertrand et al., 2010a; Goldin, 2014) but is not constant across the life cycle. Upon the birth of a child, women experience wage losses in the short- and long-run, while men tend to experience wage gains (Goldin, 2006; Kleven et al., 2019a,b; Goldin et al., 2022). This disparity suggests that childbirth and the associated burden of childcare are important drivers of gender inequality. However, deciding who takes on childcare duties and the associated wage losses is the outcome of a decision process within the household. Therefore, this decision process links intra-household task allocation and labor market outcomes. This paper studies how this intra-household decision process affects gender inequality in the labor market.

We take advantage of a change in Portuguese law in 2009 that introduced the concept of shared parental leave. Before 2009, mothers had a maternity leave of 90 days, while fathers had a very short paternity leave (less than 10 days). During this leave, individuals still earn their base wage, paid by the government, at no cost to firms. There is a strong incentive to use these days of leave as childcare in Portugal is relatively expensive. With the introduction of shared parental leave, parents now have access to 120 days of leave, which they can allocate to either parent. Furthermore, this legislation provides strong incentives towards an equitable sharing of leave days by increasing the number of leave days if parents share the leave. One consequence of this legislation is that it may shift the allocation of childcare duties away from women. In fact, in 2010, nearly 15 percent of the total leave days were taken by men, which suggests that compliance was significant. Before 2010, this share was close to zero. In 2022, this share was around 22 percent. We also show that, with the introduction of shared parental leave, the average number of days women take declines by around 15 percent. Both empirical facts are evidence that the introduction of shared parental leave led to a change in the allocation of childcare duties.

To understand the impact of the introduction of shared parental leave on labor market outcomes, we rely on the Portuguese matched employer-employee data set, allowing us to track workers (and firms) over time. We observe wages and hours for each worker and several demographic characteristics (including gender) and occupation. We also use a novel data set, which includes information on all births in Portugal. For each birth, we observe several characteristics of the parents: gender, age, region of residence, educational attainment, and occupation. We cannot directly link workers and parents, so we rely on a statistical merge between the two data sets. This merging procedure allows us to build synthetic households, which we validate using survey and Portuguese Census data. As a result, we can track individuals and households over time and observe their labor market outcomes and the probability that the household produces a child.

We first consider a simple theoretical framework for analyzing the link between intra-household decision-making and labor market outcomes. The model will be helpful in understanding the impact of shared parental leave on wages and in generating predictions we can test in the data. We focus on a partial equilibrium analysis. Households comprise two individuals, each with their labor productivity and a newborn child. Households choose consumption and the allocation of a fixed amount of childcare duties across individuals. Individuals derive utility from consumption and from time spent with the child. We adopt a collective approach in which the household chooses consumption and the allocation of childcare duties across individuals by maximizing the sum of the individuals, weighted by a Pareto weight. Therefore, households are making Pareto-efficient decisions. We assume that childcare duties decrease an individual's labor productivity. Hence, childcare duties have a benefit – the utility gain of spending time with the child – as well as a cost from the human capital loss associated with childcare.

In our model, the introduction of shared parental leave leads to an increase in women's wages. This increase is driven entirely by the fact that women are no longer allocated the duties associated with childcare, and therefore, they experience smaller losses in productivity. Moreover, we show that in households where women are more productive, they are allocated a lower share of childcare duties when compared to other women. Therefore, the increase in women's wages is more pronounced for women who are more productive than the men they are matched with. This happens because the allocation of childcare duties to women declines with the woman's human capital, holding the man's human capital fixed. This occurs because the household wishes to maximize its overall labor income, and keeping the most productive individual outside of the labor market carries a high cost in terms of overall labor income.

The model also predicts that women with high bargaining power inside the household experience smaller wage increases when compared with women who have low bargaining power inside the household. The intuition for this result is simple – as individuals derive utility from spending time with their child, they are allocated a larger share of childcare duties if they have a higher bargaining power. In fact, we show that the allocation of childcare duties to women never decreases with the Pareto weight of the woman.

The model also allows us to make predictions about the child penalty, which is the change in women's wages after childbirth relative to men's wages. We show that the child penalty increases with the share of childcare duties allocated to women. Therefore, introducing shared parental leave decreases the child penalty, decreasing the gender wage gap.

Finally, we can use the model to consider the consequences of introducing shared parental leave for wage inequality. The model predicts that wage inequality should decrease due to the introduction of shared parental leave. A decline in within-household inequality should drive this decrease, while across-household inequality should not change. This prediction is borne out in the data. Using our data on Portuguese wages, we find that overall wage inequality, measured as the variance of wages, decreased by 24 percent between 2008 and 2012. In the same period, within-household inequality decreased by almost 37 percent.

We turn to the data to test the model's predictions. We use the adoption of shared parental leave in Portugal as a source of quasi-random variation and compare the evolution of wages of women (the treated group) relative to men (the control group) in a difference-in-differences design. We include occupation-year fixed effects, which allows us to fully absorb sector- and occupation-level shocks that may affect men and women differently due to occupation choice. We also include individual fixed effects to account for permanent differences in skills or preferences. Finally, we include two third-degree polynomials of age and tenure to account for differences across the life and tenure cycles. Therefore, our empirical strategy allows us to identify the variation in women's relative wage (compared to men) driven by the introduction of shared parental leave.

Women's relative monthly wage increased by 1.2 percent between 2008 and 2012. This increase represents an annual increase of about 130 Euros or a reduction of around 5 percent of the wage gap in 2008 (23 percent in 2008, the last year before the introduction of shared parental leave). We find minimal effects on women's hours worked, which increased only by 0.2 percent relative to men between 2008 and 2012. Therefore, the wage increase is driven entirely by the monthly wage increase. We argue that this is consistent with increased human capital or productivity associated with a lower childcare burden for women.

Our results also include a great deal of heterogeneity across sectors. We split our sample into two groups: individuals working in greedy sectors and other sectors. We define greedy sectors as in Goldin (2014) – sectors where the elasticity of wages to hours is very high. This decomposition is important because it has been argued that these sectors drive much of the wage gap as women have a lower endowment of hours, possibly due to childcare duties. We show that, before 2009, the gender wage gap was much more significant for greedy sectors than other sectors. However, women's relative wage increase is driven by women working in greedy sectors. Between 2008 and 2012, the relative monthly wage of women rose by 1.8 percent for women working in greedy sectors, while the relative wage of women working in other sectors did not change.

We then turn to the second prediction of the model – that women's wages should increase more for women with a higher level of human capital relative to their partners. To do this, we turn to our data on synthetic households. We introduce a third difference in our empirical design – whether an individual is a primary earner, measured before the introduction of shared parental leave. We think of the primary earner as the individual with the highest productivity in the household. Therefore, we compare the evolution of the relative wage of women who are the primary earners with the relative wage of women who are not the primary earners. We find that most of the increase in women's relative wages is driven by women who were the primary earners in the household before the introduction of shared parental leave. This result is in line with our model predictions. Moreover, note that, according to our model, if the primary earner also was the individual with the highest bargaining power inside the household, we should expect the wage increase to be smaller for women who are primary earners. Therefore, cross-sectional variation in bargaining power cannot explain these results.

Finally, we turn to our data on synthetic households to test this last model prediction. We compute the child penalty as in Kleven et al. (2019b) by comparing the evolution of women's wages relative to men's wages after the birth of their first child. We find that, before the introduction of shared parental leave, the child penalty in wages was around 1 percent – after the birth of their first child, wages of women fell by 1 percent relative to wages of men. The introduction of shared parental leave effectively undoes the child penalty in wages. This finding is consistent with men's significant take-up of leave days after the introduction of shared parental leave. We also find that the introduction of shared parental leave undoes the child penalty in hours worked and probability of employment.

Our results suggest that the intra-household decision-making process is vital in determining the effectiveness of shared parental leave in reducing gender inequality in the labor market. If women are ex-ante less productive than their partners, they are still allocated a large share of childcare duties and therefore will not observe significant wage increases. Thus, policymakers should consider the other causes of gender disparity in productivity when setting up shared parental leave policies.

Related Literature. This paper relates to a large body of literature on the gender wage gap - the difference in wages between women and men - and its determinants. In this literature, Goldin (2014) has shown that not only is there a gap between wages of men and women, but that this gap also widens with age. This increase is larger for more educated individuals, as shown in Bertrand et al. (2010a), and following the birth of a child, as shown in Goldin (2006). In fact, many in the literature have referred to the increase in the gap between wages of men and women as the *child penalty* (Kleven et al., 2019b,a; Goldin et al., 2022). This literature has found that, following the birth of a child, women experience losses in wages, hours worked, and probability of being employment, and that these losses tend to be quite persistent. For example, Angelov et al. (2016) show that 15 years after the birth of a child, the wage gap between men and women increases by 10 percentage points. They also argue that the magnitude of this effect is driven by the share of labor income within the household. In contrast, as shown in Goldin et al. (2022) or Brewer et al. (2022) or Lim and Duletzki (2023), men experience an increase in wages upon the birth of a child (the fatherhood premium). The child penalty is a phenomenon which can be found in multiple settings and countries, as documented in Kleven et al. (2023). We contribute to this literature by studying how intra-household decisions shape the overall child penalty.

Our work is also related to a literature that studies universal childcare and childcare subsidies, with somewhat mixed results. On one side, some studies have found positive effects of universal childcare on female labor supply. An example is Baker et al. (2008) who use the introduction of universal childcare in Quebec and find that female labor supply increases substantially. In related work, Lefebvre and Merrigan (2008) find that hours worked by mothers increased by 231 hours per year. In contrast to these results, González (2013) finds that the introduction of a sizable child benefit in Spain in 2007 leads to a decrease in female labor force participation, as well as an increase in fertility rates. Finally, Havnes and Mogstad (2011) finds that, following an expansion of subsidized child care in Norway, female labor supply experience no change. On the side of fathers, the results are equally mixed. Using Swiss administrative data and looking at childcare expansion in Bern, Krapf et al. (2020) find that public childcare provisions reduce the fatherhood premium in low-income households. In contrast, Andresen and Havnes (2019) and Brewer et al. (2022) have found no significant impact of public provision of childcare on fathers. Finally, Lim and Duletzki (2023) find that early childcare expansion increases fathers' take up of parental leave and reduces father labor supply. In our paper, we argue that these mixed results may be driven by different outcomes of intra-household decisions.

We also relate to a large literature that seeks to understand how intra-household decision making affects labor supply and fertility decisions. This literature goes as far back as the seminal contribution of Becker (1973), who begins the development of the *collective model* of the household, which is formalized in Chiappori (1988, 1992) or Blundell et al. (2005). In this approach, the household makes its labor supply decisions (and other possible decisions) by moving along the utility possibilities frontier, which implies that the decisions made by the household are Pareto-efficient. An alternative methodology within the collective approach involves modelling household decision-making as a bargaining problem, which is the approach in Doepke and Kindermann (2019), who study the optimal fertility decision of households. This approach stands in contrast to the unitary model of household decision making, like in Becker and Barro (1988) and Barro and Becker (1989) where there is no disagreement.

Outline. Section 2 describes the data and the introduction of shared parental leave. Section 4 presents our main empirical results. In Section 3, we present a simple model. Section 5 presents our results on the child penalty. Section 6 concludes.

2 Shared Parental Leave in Portugal

2.1 Shock

We take advantage of a change in Portuguese law in 2009.[1] Before 2009, mothers were entitled to a maternity leave of up to 90 days while fathers were only entitled to take up to 10 days after the birth of a child. During the period of the leave, the government pays for the entirety of the base wage and so this comes at no cost for the firm.[2] In 2009, both paternity and maternity leaves are abolished and replaced by a 120-day parental leave which can be shared by both parents according to their needs. To ensure a equitable allocation of the leave across parents, the Portuguese government introduced a sharing bonus - if the father takes 4 weeks or more of the parental leave (after the mother has taken 6 weeks of leave), the government will pay for an additional month of fully-compensated parental leave. Therefore, there is an incentive to share the leave between both parents. Under the new policy, fathers' leave periods have become longer, and fathers' use of initial parental leave has increased substantially.

In Figure 1, we present results on the take-up of shared parental leave by men. We compute the share of total leave days taken by men. On impact, we see a large increase

[1] This change is introduced by Law Decree number 91 in April 2009 and by Law number 7 of February 2009.

[2] There are other forms of compensation in Portugal, such as meal subsidies, which the firm must pay to all of its full-time employees. During the period of the leave, the firm is not obliged to pay these other forms of compensation, and the government does not pay them to the worker. Therefore, taking a leave does involve some loss in terms of income for the worker.

in the share of leave days taken by men - it increases from around 0 to close to 15 percent. This share then continues to increase until it reaches around 22 percent in 2022. Therefore, before the reform, households faced a binding constraint in terms of how they allocated leave days between men and women.

We also use data from the European Social Survey to verify that households comply with the introduction of shared parental leave. The European Social Survey is a cross-country survey of households in European countries run every two years.[3] For each wave of the survey, and for Portuguese households, we can compute the share of households in which men do not participate in childcare duties. In Figure 2, we find that the share of households in which men do not participate in childcare is stable until the introduction of shared parental leave. After the introduction of shared parental leave, this share declines, which suggests household start to allocate more of childcare duties towards men.

We can also look at the average number of leave days taken by women, which we plot in Figure 3. Before 2009, women were entitled to 90 days of paid leave and the average woman took more than this limit. With the introduction of shared parental leave, which increases the total number of leave days to 120 (to be shared between men and women), the number of days women take up decreases. In fact, between 2008 and 2010, the average number of days women take declines by around 15 percent. This is again suggestive of the fact that, from the perspective of the household, women were taking too many days of leave. Moreover, it also suggests that the number of days women take is not solely driven by preferences towards spending time with children. If that were the case, women would not change their behavior between 2008 and 2010.

2.2 Data

Our data set is built from two data sources: a matched employer-employee panel data set and a data set containing information on all births in Portugal. Our data covers the period between 2004 and 2012. As we explain below, the matched employer-employee data virtually cover the universe of firms, while the data set on births covers the universe of births and households. Appendix A includes further descriptions of these data sets.

[3]The goal of the survey is to measure attitudes, beliefs and behaviour patterns of diverse populations. For each survey wave, the organizers of the survey choose a new set of representative households. Therefore, the survey is not a panel, but a repeated cross-section of households.

2.2.1 Matched employer-employee data

We start with the matched employer-employee panel data set, which comes from *Quadros de Pessoal*, which is made available by the Ministry of Employment of Portugal. The source of these data is a compulsory annual census of all firms in Portugal that employ at least one worker.[4] *Quadros de Pessoal* collects data on about 500,000 firms and 4 million employees. Upon entering the database, each firm and each worker is assigned a unique, time-invarying identifying number, which we can use to follow firms and workers over time.[5] For the firm, we observe the firm's geographical location, industry, total employment, and total sales. The worker-level data cover information on all workers working for the reporting firms in a reference week in October of each year. This includes information on occupation, hourly wages, and hours worked (normal and overtime).[6] We also observe demographic information about the worker, such as gender, age, educational attainment, and nationality.

We present some summary statistics for 2008 in Table I. While men and women have, on average, the same number of work hours per month, men are much more likely to do overtime. On average, men work almost two extra hours per month. The wages of women are also lower on average - the average monthly wage is 25 percent smaller than the average monthly wage for men, and the hourly wage is 24 percent smaller. Women are on average younger and with a lower tenure at their current job. Moreover, while women are more likely to have a college degree, they are less likely to occupy managerial positions.

[4]These data excludes public administration and nonmarket services. *Quadros de Pessoal* have been used by Blanchard and Portugal (2001) to compare the US and Portuguese labor markets; Cabral and Mata (2003) to study the evolution of the firm size distribution; and Caliendo et al. (2020) to investigate the response of productivity to firm reorganization.

[5]The Ministry of Employment implements a number of checks to ensure that a firm that has already reported to the database is not assigned a different identification number. Similarly, each worker also has a unique identifier, based on a worker's social security number. The administrative nature of the data and their public availability at the workplace — as required by law — imply a high degree of coverage and reliability. It is well known that employer-reported wage information is subject to less measurement error than worker-reported data. The public availability requirement facilitates the work of the services of the Ministry of Employment that monitor the compliance of firms with the law.

[6]We observe several components of earnings: base wage (gross pay for normal hours of work), seniority-indexed components of pay, other regularly paid components (meal subsidies, for example), overtime work, and irregularly paid components. Following Caliendo et al. (2020), our results are based on monthly earnings, which we define as the sum of total regular earnings (base wage and regular benefits) and irregular earnings (irregular benefits and overtime payments). We define hours as the sum of regular hours and overtime hours. Our results are also robust to the definition of monthly earnings and hours.

2.2.2 Household data

We use a novel data set which has information on all live births in Portugal. This data set is maintained by the Portuguese National Institute of Statistics. For each birth, we observe some information about the parents: their gender, their age, their area of residence, their occupation, and their educational attainment. In the period between 2004 and 2012, we observe 900 thousand births. However, we cannot merge each individual in this data set with the individuals in *Quadros do Pessoal*. Therefore, we employ a statistical matching procedure in which we build *synthetic households*.

Our goal is to compute four variables for each household: whether or not a child was born, the income of both household members, and total household income. In our method, for each worker in the matched employer-employee data set, we can compute the probability that they had a child in year t as well as an estimate for the income of their partner. We briefly describe the algorithm below, and provide more details in Appendix B.

Algorithm. We group the births data according to parent-level information on gender, age, region of residence, occupation, and year. For each group, we compute the number of births. Let the set of groups be $\mathcal{G}$. Similarly, we group the matched employer-employee data set according to the same groups and compute the number of individuals. We define the probability that an individual in a group g had a child as the ratio of the number of births to the number of individuals. To compute the estimated wage of the partner of an individual in group g, we start by considering all groups $\tilde{g} \in \mathcal{G}$ to which the partner might belong. For each group $\tilde{g}$, we compute the number of pairings with group g in the births data, $n_{g,\tilde{g}}$ and the average wage $w_{\tilde{g}}$ in the matched employer-employee data set. We define the estimated wage of the partner as the weighted average across all $w_{\tilde{g}}$, using the $n_{g,\tilde{g}}$ as the weights. For each group g, we compute the estimated wage as the average wage across all individuals in group g in the matched employer-employee data set.[7] Finally, we define household income as the sum of the estimated wage of an individual and the estimated wage of their partner.

Validation with census data. We validate the relative size of our groups using Portuguese Census data for the year 2011, which we obtain from the Portuguese National

[7]In our results in Section 4, we will use the share of household income attributable to the individual as a sorting variable. We decided to use the estimated wage rather than the actual observed wage in order to make the numerator and denominator consistent. Our results do not change if we instead use the observed wage.

Institute of Statistics. We use a random 5 percent sample of households that answer the Census and build groups. We define a group's relative size as the number of individuals in the group divided by the total number of individuals. In Figure B.1, we plot the distribution of groups sizes in our synthetic household data and in census data. We find that the two distributions look very similar and that they both have a large spike around zero, which suggests that groups are generally quite small. In Figure B.2, we plot group sizes in the census data in the horizontal axis against group sizes in our synthetic household data in the vertical axis, along with a dashed 45-degree line. We find that most data points are clustered around zero and very close to the 45-degree line which suggests that our synthetic household data is representative of the overall population.

Validation with household survey. We also obtain data from two waves of a survey on Portuguese households, called the *Inquérito às Despesas das Famílias (IDEF)*. We have data from the 2004-2006 and the 2010-2011 waves. This survey is run every five years and it includes around 10 thousands households in each wave.[8] This survey has information on the wages of each member of the household, which allows us to compare the distribution of the female share in our data on synthetic households with the distribution of the female share of the household income on the survey data. To compute the female share in the survey data, we consider households where (1) there are two individuals who are either married or cohabiting, and (2) both the head of the household and their partner are employed.[9] For these households, we define the female share as the share of the woman's labor income in overall household labor income.[10] We then compare the distribution arising from each wave with the distribution for the same year coming from the data on synthetic households, which we present in Figure B.4. With the exception of an extra mass on the left tail, the distributions look very similar. In fact, for 2006, the median female share is 0.43 in the household survey and 0.44 in the data set with synthetic households. In 2011, the median female share is 0.44 in the household survey and 0.46 in the data set with synthetic households. Therefore, we are confident that our data set on synthetic households is capturing the overall distribution of the female share of household labor income.

[8]This survey is not a panel and so we only observe each household once.

[9]The head of the household is determined by the entity running the survey and is usually defined as the individual with the highest labor income.

[10]In this survey, we also observe non-labor income. Since our data on synthetic households only has information on labor income, we exclude non-labor income from the comparison.

Comparison with literature. Most of the literature which uses household data has either relied on samples of households, as Kleven (2022) or Kleven et al. (2023), for which they observe the event of having a child or considers the whole population, like Kleven et al. (2019a) for Denmark, but does not contain information on the income of the household. Our method builds on a large administrative data set like Kleven et al. (2019a) with two differences. First, unlike in their data, we do not observe the birth of a child. Instead, we are forced to compute a probability of having had a child. Second, we are able to compute an estimated wage of the partner for each individual. Therefore, we are able to provide insights into how household characteristics shape the labor outcomes of women in response to the birth of a child.

3 Model

In this Section, we present a simple model of the household. The model will be helpful in understanding the effects of shared parental leave on women's wages and in generating predictions we can test on the data.

3.1 Environment

Consider a household with two members $i = \{m, f\}$, where the man is individual m and the woman is individual f. Each individual has an endowment of human capital, which we denote w_i. We exclude the possibility of separation, i.e., no household member can exit.[11] The household is hit with an exogenous fertility shock – or "stork shock" – and a child is born. As a consequence, members of the household will need to devote one unit of time to childcare.

We assume a collective model of the household. The household makes choices of consumption for each member and allocates childcare duties. Each member of the household derives utility from consumption c_i according to the function $u(c_i)$, which is increasing and concave and from time spent with the child x_i according to the function $\alpha_i v(x_i)$ where $\alpha_i \geq 0$ and $v(\cdot)$ is increasing and concave. If individual i spends x_i amount of time with the child, their human capital decreases and becomes $H(w_i, x_i)$, which we will refer to as the wage. Therefore, when choosing the allocation of childcare duties, the household must consider both preferences for spending time with children and the human capital loss associated with childcare.

[11] We will later relax this assumption with a model with exogenous separation. For reasonable probabilities of separation, our results remain unchanged.

Assumption 1 *The wage is increasing in human capital and decreasing in time spent with children -* $H_w(w,x) > 0$ *and* $H_x(w,x) < 0$*. The human capital cost of spending time children increase with human capital and with time spent with children -* $H_{x,w}(w,x) \leq 0$ *and* $H_{xx}(w,x) \leq 0$*.*

This Assumption summarizes our functional form assumptions. We assume the wage increases in the human capital endowment and decreases in the time spent on childcare duties. The crucial assumption is the one we make on the cross-derivatives. First, we assume that human capital losses increase in the time spent on childcare duties. Second, we assume that the human capital losses associated with childcare duties increase in the human capital endowment.

Because the household must supply one unit of time for childcare, we focus on the share which is allocated to the woman, which we define as $\delta = x_f$. The household solves the following problem:

$$\begin{aligned}
&\max_{c_m, c_f, \delta} \mu \left[u(c_m) + \alpha_m v(1-\delta)\right] + (1-\mu)\left[u(c_f) + \alpha_f v(\delta)\right] \\
&\text{s. to} \\
&c_m + c_f = (1+\gamma)\mathcal{W} \\
&\delta \in [0,1] \\
&\mathcal{W} \equiv H(w_m, 1-\delta) + H(w_f, \delta),
\end{aligned}$$

where $\delta \in [0,1]$ is the share of childcare duties the household allocates to the woman, and $\gamma \geq 0$ is the agglomeration externality, which is a common assumption in the literature. We also allow for different Pareto weights for the members of the household. We use the μ parameter to mimic changes in bargaining power.

3.1.1 Discussion

We also assume an efficient decision-making process within the collective model of the household as defined by Chiappori (1988, 1992), i.e., a model in which the household is choosing a point in its utility possibilities frontier. An alternative formulation involves assuming that individuals within a household solve a bargaining problem, as in Mazzocco (2007) or Doepke and Kindermann (2019), to determine consumption and labor supply. In this second class of models, individuals may leave the household if the allocation that arises from the bargaining process is worse than some outside option. If the outside option is increasing in the individual's human capital φ_i, then we should also expect to see a decreasing relation between the allocation of childcare duties and one's labor productivity. However, in the data we do not see large separation rates for couples who have just a child. Therefore, we view our adoption of the unitary model as a simplifying assumption that does not greatly affect our ability to understand intra-household decisions.

Despite the fact that our model is in the "collective" family of household models, it can still speak to the possibility that our empirical results are driven by bargaining power. In fact, we can interpret the Pareto weights as the bargaining power of each individual in an equivalent Nash bargaining model.[12]

In our model, we have chosen to model time spent in childcare as a reduction in productivity or human capital. This choice is in line with some of the literature in the child penalty (Goldin, 2006; Kleven et al., 2019b,a; Goldin et al., 2022) which present evidence of a drop in wages of women following the birth of a child. However, those wage losses tend to take place over several years, while our model is static. Therefore, we think of our structure as representing a long-run decision by the household, and we must interpret the w_i terms as lifetime human capital. We are also silent on the causes of this drop in human capital. One possibility is that time away from the labor market depreciates human capital of women (and men). Another possibility is that time spent away from the labor prevents women from climbing the job ladder. Then, our model can be thought of as a reduced form representation of this loss. Another explanation is that, even though firms do not have to pay the wages of women while they are taking the leave, it is costly for firms to have women take the leave. This cost comes from the fact that overall firm output decreases, and if hiring is costly, the firm must incur additional costs to cover this loss.

We have abstracted from labor supply decisions in our model. In particular, the household does not choose the number of hours each individual works or whether or not the individual participates in the labor market. We exclude both decisions from the problem because we find that the introduction of shared parental leave has no impact on either hours or the probability of employment, as we show in Section 4.

One important simplifying assumption we make is that fertility is not a choice in our model but rather a shock. This is at odds with most of the literature studying fertility, like Rasul (2008) or Doepke and Kindermann (2019), who view fertility decisions as the outcome of a bargaining process between men and women where the allocation of childcare duties plays an important role. For example, in Doepke and Kindermann (2019), women

[12] If we consider a Nash bargaining problem where the objective function is given by $[c_m - \alpha_m(1-\delta) - u_m]^{\mu}[c_f - \alpha_f \delta - u_f]^{1-\mu}$, where u_m, u_f denote the outside options, we will obtain the exact same result for the allocation of childcare leave.

are more likely to agree to have a child if men agree to take on more of the childcare duties. We instead model fertility as an exogenous shock that hits some households. We do this because the introduction of shared parental leave has no effect on fertility rates which remain low and decreasing over time after the introduction of this policy. Therefore, households are not changing their fertility decisions because of the introduction of shared parental leave. Hence, modeling fertility as a choice would make the model more complex adding no further understanding of the intra-household decision process.

3.2 Solution

Before presenting the solution of the model, it is useful to consider a simplified model to build intuition. Consider a simplified model with linear utility ($u(c_i) = c_i$) and where men do not derive utility from spending time with children ($\alpha_m = 0$). The following Proposition summarizes the equilibrium in this model.

Proposition 1 *Assume $u(c_i) = c_i$ and $\alpha_m = 0$. Then, the optimal choice for the share of childcare which is allocated to women, $\delta^\star$, is not a function of the Pareto weight μ. Instead, the optimal choice is the solution to*

$$\alpha_f v'(\delta^\star) = (1+\gamma)\left(H_2(w_m, 1-\delta^\star) - H_2(w_f, \delta^\star)\right). \tag{1}$$

Proof. In Appendix C. ■

Equation (1) is the first order condition associated with the allocation of childcare duties across household members. On the left hand side, we have the benefits of an additional unit of childcare being allocated to the woman. On the right hand side, we have the costs. If the household shifts one additional unit of childcare towards the woman, overall household income increases by $-H_2(w_m, \delta)$ as the woman's human capital increases. However, there is also a decrease driven by a decline in the man's human capital, which is captured by $H_2(w_m, 1-\delta)$. Because utility of consumption is linear, this net effect is also expressed in utility units.

The intuition behind this equation is simple, and can be described through a bargaining interpretation of the collective model of the household. Men care only about consumption and so wish to both increase household income and to increase their consumption share. Women care about consumption but also care about spending time with children. Therefore, men can offer some childcare to women in exchange for a greater share in consumption. However, men will not allocate all childcare duties to women as that will lead to a large decline in household labor income.

Equation (1) also implies that the optimal choice of childcare duties does not depend on the Pareto weights of the members of the household. Therefore, if we compare two households with identical human capital endowments but different Pareto weights, we should not expect to see differences in the allocation of childcare and, as a consequence, no differences in the relative wage of women. The result in Proposition 1 also highlights the role of preferences for time spent with children. As the woman's preferences towards time spend with children increase, *i.e.*, as α_f increases, the allocation of childcare duties to women increases. [13]

We now turn to the general model, which we solve numerically. We assume the following functional forms:

$$u(c_i) = \log c_i, \quad v(x_i) = \log(1 + x_i), \quad H(w, x) = 2w - x - wx.$$

We begin by showing that the choice of $\delta^\star$ is never decreasing with the Pareto weight of the woman. If this was the case, our results could be explained by the bargaining channel - as women have more bargaining power, they obtain a lower share of childcare duties, increasing their wages. We consider three cases: (1) $\alpha_m = \alpha_f > 0$, (2) $\alpha_m = 0$ and $\alpha_f > 0$, and (3) $\alpha_m = \alpha_f = 0$. We also consider three levels for w_f: (1) identical to w_m, (2) smaller than w_m, and (3) larger than w_m. We present the result of this numerical exercise in Figure 4.

Consider first the case when $w_m = w_f$. If both individuals care about spending time with children, then the share of childcare allocated to women $\delta^\star$ is increasing in the Pareto weight of the woman as she can shift most of the time to her, thus increasing her utility. In contrast, if only women care about spending time with children, then men don't spend any time with their child and obtain a larger share of consumption. Finally, if neither individual benefits from spending time with children, the optimal solution is to allocate 50 percent of the time to each to maximize total household income. If women are less productive ($w_m > w_f$), then for each level of $1 - \mu$, they always receive a larger share, when compared to the case where $w_m = w_f$, because that maximizes household income. Finally, if women are more productive, they only have $\delta^\star = 1$ for high Pareto weights because that leads to a significant drop in overall household income.

We can also show that the allocation of childcare to women is decreasing in the human capital of women, holding the human capital of men fixed. We present the results of this analysis in Figure 5. In panel (a), we see that as the human capital of women in-

[13] To see this, note that the right hand side of equation (1) is increasing in δ while the left hand side is decreasing in δ. Therefore, an increase in α_f shifts the left hand side up, which leads to an increase in the equilibrium value of δ.

creases, the amount of time women spend with children declines, and that the shape of this relation does not depend on the Pareto weights. In panel (b), we conclude that the preferences towards spending time with children are also crucial to obtain a decreasing relation between $\delta^\star$ and the relative wage of women. Even if no individual derives utility from spending time with children, i.e., if $\alpha_m = \alpha_f = 0$, women who are the primary earners will still take on a lower share of childcare duties when compared to women who are not the primary earners.

3.3 The introduction of shared parental leave

We will now use our model to understand how the introduction of shared parental leave affects the allocation of childcare duties and its impact on women's relative wages. Before the introduction of shared parental leave, women were allocated the entirety of childcare duties, so the wage of a woman with human capital w was $H(w, 1)$.

Prediction 1 *The introduction of shared parental leave leads to a increase in women's wages.*

The introduction of shared parental leave implies that the new wage of the woman is $H(w, \delta)$. Given the conditions we assumed, the solution for δ is interior, and so, as $H_2(w, \delta) < 0$, the wage of the woman increases. Moreover, the wage of a man with human capital w that is in another household will also decrease from w to $H(w, 1 - \tilde{\delta})$, where $\tilde{\delta}$ is the optimal solution for the second household. Therefore, the wage gap will decline due to the introduction of shared parental levels.

3.3.1 Heterogeneity across women

Given the functional form, we assume for the $H(\cdot, \cdot)$ function, the change in the wage of women is given by $(1 - \delta^\star)(1 + w_f)$. Our empirical findings show that this increase is increasing on w_f, holding w_m fixed. We conduct two exercises to distinguish between the bargaining and household income channels. First, we compute the change in women's wages for different levels of the Pareto weight. Second, we compute the change in women's wages for varying levels of w_f / w_m. We present the results of this analysis in Figure 6.

Prediction 2 *With the introduction of shared parental leave, wage growth is larger for women with higher human capital, holding men's human capital constant. In contrast, wage growth should be smaller for women with a higher bargaining power in the household.*

Consider the case of Pareto weights first. In our empirical exercise, we compare the wage increase for women who are the primary earners with the increase observed by women who are not the primary earners. If this reflects bargaining power, we compare the average woman in households where $\mu < 0.5$ with the average woman in households where $\mu > 0.5$. In the model, if $\alpha_m = \alpha_f > 0$, women with high bargaining power should observe a lower wage increase when compared with women with low bargaining power. If $\alpha_m = 0$ or $\alpha_m = \alpha_f = 0$, the there should be no difference in terms of wage increase between women with a high or low bargaining power.

Consider now panel (b). If both individuals in the household derive utility from spending time with children, the increase in wages for women is increasing women's human capital. Therefore, we expect women with high human capital to exhibit a larger wage growth. This result is driven entirely by the fact that, if women have high human capital, the household does not wish to keep them outside of the labor force as this would reduce overall household income.

Model with separation. In our baseline model, individuals care more about overall household income than their human capital. Their human capital is only important to determine δ, so if $\alpha_f = \alpha_m$, their own human capital is irrelevant for a given level of $\mathcal{W}$. In Appendix C, we consider a two-period model in which individuals may separate with some exogenous probability θ in the second period, but they inherit the wage of the first period. We find that our results remain unchanged for small levels of θ. If θ is sufficiently large, women with higher bargaining power observe larger wage increase, when compared to other women. This is driven by their desire to hedge against a possible separation. However, women with higher human capital also observe larger wage increases.

3.3.2 Child penalty

Another important statistic the literature has focused on is the child penalty. Following Kleven et al. (2019a), we will define the child penalty as the difference between the change in women's wages following childbirth and the change in men's wages following childbirth. If we consider a man and a woman with the same human capital w, the child penalty is given by

$$\text{Child penalty} \equiv (H(w,\delta) - w) - (H(w,1-\delta) - w) = H(w,\delta) - H(w,1-\delta).$$

Prediction 3 *With the introduction of shared parental leave, the child penalty in wages should decrease.*

From our assumptions, we can see that the child penalty is decreasing in δ. Therefore, the introduction of shared parental leave should lead to a decrease in the child penalty and it is this decrease that then leads to an increase in women's relative wages. In Section 5, we show empirically that the introduction of shared parental leave leads to a decrease in the child penalty.

3.3.3 Effect on Inequality

Our model also has implications for inequality. With the introduction of shared parental leave, as women are allocated a smaller share of childcare duties, within-household inequality is likely to decrease. However, the effects on overall inequality are not obvious, as inequality across households may either increase or decrease.

To understand the effects of the introduction of shared parental leave on inequality, we consider an economy populated by many households, each characterized by a vector (w_m, w_f). We assume all other parameters are identical across households and present a detailed calibration in Appendix C. We draw the levels of human capital from a joint log-normal distribution. We calibrate the average and standard deviation using the empirical distribution of wages in 2008. We then consider various levels for the correlation coefficient ρ.

Our measure of inequality is the variance of wages. This variance can be decomposed into (1) within-household inequality and (2) across-household inequality. Using the results from our simulated economy, we can present the change in inequality for different levels of the correlation coefficient ρ. We can also compute these measures in the data using our data set of synthetic households, where we compare 2008 (the last year before the introduction of shared parental leave) with 2012. We present the results of this exercise in Figure 7.

In terms of the model, we see that, for all levels of ρ, the model predicts an overall decline in inequality. Moreover, this decline is driven by a sharp fall in within-household inequality. In our preferred specification (where $\rho = 0.75$), across-household inequality declines very little, while within-household inequality falls sharply. Our model results are qualitatively similar to those in the data. Between 2008 and 2012, there was a decline in overall wage inequality in Portugal – wage inequality in 2012 was only 76 percent of the one observed in 2008. Most of this decline is driven by a decrease in within-household inequality, which falls by almost 37 percent.

4 Effect on wages

We now turn to the data to test the first two predictions of our model. The first prediction is that women's wages should increase after the introduction of shared parental leave. The second prediction is that this increase should be more pronounced for women who have a higher level of human capital relative to their partner.

4.1 Empirical Design

We use a difference-in-differences design, where we compare the evolution of wages of women (the treated group) with the evolution of wages of men (the control group). We estimate the following equation

$$\log w_{it} = \mu_i + \lambda_{o(i)t} + \beta X_{it} + \sum_{m=-4, m\neq -1}^{4} \gamma_m \mathbf{1}\left\{m = t - 2009\right\} \mathbf{1}\left\{i \in \text{Female}\right\} + \varepsilon_{it}, \quad (2)$$

where the outcome variable is the logarithm of the monthly wage. We include individual fixed effects μ_i to fully absorb permanent characteristics (gender, educational attainment, etc...) and occupation-year fixed effects $\lambda_{o(i)t}$ to control for potential shocks that affect occupations differently.[14] The vector of controls X_{it} includes a 3rd degree polynominal on age and a 3rd degree polynominal on tenure at the current job. Our parameters of interest are the γ_m, which capture the change in the relative wage of women m years after 2009. Following the event study literature, the year before the introduction of shared parental leave (2008) is the excluded period. We cluster errors by worker.

Our approach relies on two key assumptions. First, we assume that there is no other shock taking place in this period which has differential effects on men and women. Our sample periods includes the beginning of the sovereign debt crisis in Europe, which had a significant effect in the Portuguese economy.[15] There are two potential effects coming from the crisis which could bias our results. First, the crisis led to a drop in real wages. However, this should be captured in our occupation-year fixed effects and there is no

[14] We define an occupation as a pair occupation-sector. In our data, we observe 11 occupations. In principle, we could observe more, but due to a change in the occupation classification in 2009, we can only consider 11 occupations to make the classification consistent over time. We observe 20 sectors. This yields a total of 220 occupations.

[15] There are two different shocks associated with the sovereign debt crisis - the crisis itself and the bailout by the IMF, and the subsequent adoption of austerity measures. Between 2008 and 2012, the Portuguese real GDP per capita fell by 7 percent and the unemployment rate rose from 7.6 percent to 16.5 percent. The increase in the unemployment rate is larger for men than it is for women. Eichenbaum et al. (2017) provide an excellent overview of the Portuguese economy in this period.

reason to believe that this drop should be different for men and women. A second possibility is related to migration. Between 2009 and 2013, the number of emigrants from Portugal more than doubles as it changes from around 18,000 in 2009 to over 50,000 in 2013. The share of women in total emigrants also increases in this period. However, most of this outflow consists of individuals with high educational attainment. Therefore, while it is true that women emigrate at a higher rate than men, the average productivity of the women that remain is likely declining. This should lead to a decrease in average wages for women, which would dampen our effects.

The second identification assumption is that men are a good control group for women. Men and women differ along a large number of characteristics: age, tenure, educational attainment, ability to form social networks in the workplace, elasticity of labor supply to the birth of a child, etc... Many of these characteristics are permanent (or very persistent) and should therefore be captured by the individual fixed effects. Therefore, conditional on the inclusion of individual fixed effects (and controls), men are an appropriate control group.

4.1.1 Results

We present the results of estimating equation (2) in Figure 8. We find that the average wage of women, relative to the wage of men, increases by 1.2 percent between 2008 and 2012.[16] This increase represents an increase of 9 euros per month (or 130 euros per year).[17] If we look at unconditional moments, the wages of women grew by 10 percent between 2008 and 2012, while the wages of men grew by 7 percent in the same period. Therefore, our estimates explain about half of the unconditional changes in wages in this period.

We also find that the increase in wages is not immediate and is quite persistent. Between 2008 and 2009, the relative monthly wage of women only increases by 0.5 percent, which represents almost a third of the overall effect we find. We can attribute this slow increase in wages of women to the also slow adoption of shared parental leave by men. We documented in Figure 1 that in 2009 only 10 percent of households had allocated parental leave to men. This share increased to around 30 percent in 2012, which also means that compliance in 2009 was a third of compliance of 2012, which is line with our estimated effects for wages.

[16] In Appendix D, we also show that our results are robust to different assumptions on the structure of fixed effects.

[17] Portuguese workers receive 14 monthly wages per year.

Pretrends. Our results in Figure 8 display pretrends, i.e., the coefficients associated with the periods before 2008 are statistically different from zero. We observe a reversal in the trend for female wages - before 2008, the relative wage of women was decreasing, while the introduction of shared parental leave coincides with an increase in the relative wage of women. In this sense, the presence of pretrends is an econometric problem, but not an economic problem. Our mechanism is consistent with a reversal in the gender wage gap trend.[18] If women are now expected to take fewer days off work, and if this change is strong enough, we would expect the gender wage gap to display a reversal in its long-run trend. Moreover, we also find that pretrends are a feature across a variety of subgroups of workers. In Appendix D, we split the sample according to educational attainment, hierarchical position, new hires vs. incumbents, average wage of occupation, and services vs. other sectors, and we find that for all of these subgroups, we observe a pretrend. Therefore, we are confident that the pretrend is not caused by specific shocks that affect a share of the workforce, but are rather the product of aggregate long-run phenomena.

However, pretrends are an econometric problem. The usual assumption in event studies is that nontreatment trends are zero after treatment. To test this assumption, we usually impose an additional assumption - that nontreatment trends are constant over time. Under this additional assumption, we can then test the hypothesis that nontreatment trends are zero after treatment. This assumption is clearly violated in our design. Therefore, we need an alternative assumption to identify the average treatment effects. The literature has proposed three potential alternatives: (1) assume that nontreatment trends follow a linear trend as in Wolfers (2006), (2) detrend the data as in Goodman-Bacon (2018), or (3) conduct inference which is robust to the presence on non-zero nontreatment trends as Manski and Pepper (2018) and Rambachan and Roth (2023). We adopt the third solution, which allows us to obtain confidence intervals for partially identified treatment effects.[19] We consider three different sets of assumptions. First, we allow nontreatment trends to have a linear trend. Second, we allow nontreatment trends to follow a trend which may experience deviations from linearity. Third, we allow nontreatment trends to follow an arbitrary trend, but assume that the changes in these effects are bound by a constant. We present confidence sets for all of these alternative assumptions in Appendix D and show that we still obtain a positive and statistically significant effect on wages of

[18] In Appendix D, we show that there is a long run trend of an increase in the wage gap before 2008, and that after this period, the gender wage gap starts to decline.

[19] Assuming linear trends is potentially problematic as it imposes very strict assumptions on the distribution of treatment effects, as shown in Roth and Sant'Anna (2023). The approach followed by Goodman-Bacon (2018) also has potential drawbacks. In that approach, the data used to estimate the event study is itself the product on a model, which may make inference difficult.

women, even if nontreatment trends are positive. That is, even if we assume that the non-treatment trend would have experienced a small reversal in 2008, we still find that the introduction of shared parental leave increases the wages of women relative to men.

Importance of job-to-job transitions. Our data also allow us to decompose the changes in the relative wages of women between the changes driven by individuals that do not change jobs (remainers) and those driven by individuals that change jobs (switchers). We estimate equation (2) on both of these two groups of individuals and present the results in Figure 9. We find that most of the increase in the relative wage of women is driven by women that change jobs after the introduction of shared parental leave. This finding is consistent with either the presence of contractual frictions which make changing nominal wages for existing workers costly or with the presence of high bargaining power for firms in the wage-setting process.

Other outcome variables. We also estimate equation (2) using as outcomes the logarithm of total monthly hours (which includes both regular hours and overtime), the logarithm of the hourly wage, and a dummy variable that takes value one if the individual is employed and zero if otherwise. We present estimates for all of these specifications in Appendix D. In Figure D.2, we find that effects on hours are very small - between 2008 and 2012, hours worked by women increased only by 0.2 percent. Therefore, most of the effect we document in Figure 8 is driven by an increase in the hourly wage, not hours worked. In fact, in Figure D.3, we show that the hourly wage of women increases by 1.1 percent relative to men between 2008 and 2012.

The shock we consider - the introduction of shared parental leave - includes two different treatments. The introduction of shared parental leave allows parents to decide on the split of total leave days but also increases the overall length of the leave from 90 to 120 days. The increase in the size of the leave could also explain some of the results we observe in wages. If 90 days is not a sufficiently large period of time for a mother to attend to the initial childcare duties, the woman's wage could be lower in the following periods because she works fewer hours.[20] Therefore, the simple extension of the parental leave, even without a new allocation of leave days across members of the household, could lead to an increase in wages due to an increase in hours. However, we find no economically significant increase in hours, which suggests that the extension of the number of leave days is not the main driving force of our results. Instead, our results suggest that

[20] In fact, it has been argued in the literature, like in Kleven et al. (2019a) and Goldin et al. (2022), that after the birth of a child, women work fewer hours than men.

the introduction of shared parental leave shifts the allocation of leave days away from women, which reduces their human capital losses post childbirth and therefore leads to an increase in their wages.

4.2 Heterogeneity across households

We now turn to the test of the second prediction. To test this, we conduct a triple difference exercise.[21] In our previous analysis, we relied on two sources of variation: (1) time series variation, where we compare the years after the introduction of shared parental leave with those before, and (2) cross-sectional variation, where we compare women with men. We introduce a second source of cross-sectional variation, where we compare primary earners with non-primary earners. Using our synthetic households, we define an individual as a primary earner if their labor income is more than half of the total household labor income.[22] We then augment equation (2) with a third difference as

$$\begin{aligned}
\log w_{it} = & \sum_{m=-4, m\neq -1}^{4} \gamma_m \mathbf{1}\{m = t-2009\} \mathbf{1}\{i \in \text{Female}\} \\
& + \sum_{m=-4, m\neq -1}^{4} \eta_m \mathbf{1}\{m = t-2009\} \mathbf{1}\{i \in \text{Primary}\} \\
& + \sum_{m=-4, m\neq -1}^{4} \theta_m \mathbf{1}\{m = t-2009\} \mathbf{1}\{i \in \text{Female}\} \mathbf{1}\{i \in \text{Primary}\} \\
& + \mu_i + \lambda_{o(i)t} + \beta X_{it} + \varepsilon_{it},
\end{aligned} \tag{3}$$

where include a set of coefficients θ_m which captures the variation *within women*, where we compare primary earners with non-primary earners. We present the results of our estimation of θ_m in Figure 11.

Results. We find that women which are primary earners drive the increase in the relative wages of women. In fact, within women, between 2008 and 2010, relative wages of primary earners increase almost 1 percent more than the relative wages of non-primary earners. We also do not find evidence of a difference in relative wages between primary and non-primary earners (within women) before 2009, which is consistent with our view

[21]This exercise also has another advantage. In our difference-in-differences design, the presence of pretrends makes inference difficult. A triple difference design which eliminates pretrends will not face the same problem.

[22]In Figure B.3, we present the distribution of the wage share of women inside the household. The median share in 2008 is 0.45.

that the pretrends in Figure 8 are driven by a trend which is common across all women.

Discussion. Our model predicts that women's wages should increase and that this increase should be more pronounced for women who have a higher human capital relative to their partner. Therefore, if we interpret our triple difference design as one in which we compare women with high relative human capital with women with low relative human capital, the data shows that Prediction 2 is correct. Therefore, there is a household income channel in which the household allocates leave with the goal of maximizing overall labor income in the household. This channel can also explain why most of the increase in the relative wage is concentrated among households with lower household income, as we show in Figure B.6 in Appendix B. These are also the households where increasing income is most valuable.

However, some models of intra-household bargaining show that primary earners also have higher bargaining power. If this is the case, then maybe the triple difference design compares women with high bargaining power with women with low bargaining power. If this were the case, then the model predicts that the coefficients would be negative as women with high bargaining power choose to take a longer leave as they derive utility from spending time with children. Therefore, as the coefficients are positive, it cannot be that the triple difference design is capturing differences in bargaining power.

4.3 Heterogeneity across sectors

One of the chief causes of wage differences between men and women is the existence of convex pay structures. In particular, there are many sectors where the elasticity of wages to hours worked is high and has become higher, as shown in Goldin (2014). As women have either a lower endowment of hours due to home production or childcare, the presence of convex pay structures generates wage differences within occupations and sectors. Shared parental leave interacts with this phenomenon - if women are able to take on a lower share of childcare activities, their wages should increase more than their increase in hours if pay structures are convex.

To test this hypothesis, we begin by computing a measure of the convexity of the pay structure for every sector, or "greediness". Following Goldin (2014), and using data between 2004 and 2008, we regress the logarithm of the monthly wage on a 4th degree polynominal of age, educational attainment fixed effects, year fixed effects, occupation-gender fixed effects, and the interaction between the logarithm of total hours worked (including overtime) and an occupation fixed effect.[23] Our measure of greediness is the coefficient associated with the interaction between the occupation fixed effect and the logarithm of hours worked. We define a sector as greedy if its greediness is above the median. We then estimate equation 2 on three samples: (1) using all observations, (2) using observations for greedy sectors, and (3) using observations for non-greedy sectors. We present the results of this estimation in Figure 10.

We find that all of the increase in monthly wages for women is driven by greedy sectors. Between 2008 and 2012, the average monthly wage of women increases by 1.8 percent relative to men, while the wages of women do not change (relative to men) for non-greedy sectors. This finding is consistent with our mechanism: as women become responsible for a lower share of childcare activities, they are able to be more present in the labor market, either by taking on more hours or by taking fewer days of leave, and so their wages increase relative to men.[24] It's also important to note that, in the period before 2008, both greedy and non-greedy sectors display the same increasing trend in the gender wage gap. Therefore, pretrends are not driven by differences between sectors in terms of the convexity of the pay structure.

Other sources of heterogeneity. We explore other sources of heterogeneity in the data - educational attainment, hierarchical position, new hires vs. incumbents, average income of occupation in 2008, and sectoral heterogeneity - and present results in Appendix D. We find that the increase in the relative wages of women is driven by workers with low educational attainment in Figure D.5 or workers which are not in managerial positions in Figure D.6. We also find that there are no differences in the evolution of the relative wages of women when we compare new hires with incumbent workers, as we see in Figure D.7. In Figure D.8, we find that most of the wage increases women observe after the introduction of shared parental leave is driven by occupations with lower wages. In Figure D.9, we find that there is not difference in the evolution of monthly wages when we compare service sectors with other sectors. For all of these decompositions, we also find no heterogeneity in the behavior of pretrends.

These results suggest that the effects within sectors and across sectors are substantially different. Within sectors, we find that low-income women exhibit a larger increase in

[23]We provide more details on how we compute this measure, as well as some summary statistics in Appendix A.

[24]In Figure D.4, we estimate an event study on hours worked. We find that hours worked do not increase by more for greedy sectors than they do for non-greedy sectors (the change in hours worked between 2008 and 2012 for women is around 0.2 percent). Therefore, the difference in the change in wages is either explained by differences in the elasticity of wages to hours worked or by a difference in the elasticity of wages to days of leave.

relative wages after the introduction of shared parental leave. However, when we look across sectors, the average woman in greedy sectors exhibits a larger increase in relative wages. Therefore, within-sector wage inequality for women is decreasing, but this same wage inequality is increasing across sectors.

5 Effect on child penalty

We have shown that the introduction of shared parental leave leads to an increase in the wages of women relative to the wage of men. Moreover, we have provided evidence that most of this increase is driven by so-called greedy sectors, which are sectors in which the pay structure is strongly convex in hours. However, the model has generated another prediction we have not yet tested - that the introduction of shared parental reduces the child penalty.

The child penalty is usually defined as the costs women experience after childbirth, as documented by Bertrand et al. (2010b), Angelov et al. (2016), or Kleven et al. (2019a). This penalty involves losses in terms of wages, hours worked, and probability of employment for women, relative to men, after having a child. This literature has shown that the child penalty is a key driver of the gender wage gap. Moreover, the shock we explore implies a tight link between the child penalty and the evolution of the gender wage gap. In this section, we estimate the change in the child penalty after the introduction of shared parental leave.

5.1 Empirical design.

Our goal is to identify the difference in labor market outcomes between men and women after the birth of a child. The standard approach, as Kleven et al. (2023), is to estimate two event studies - one for men and another for women - using the birth of the first child as an exogenous shock. The child penalty is then defined as the difference between the effect on women and the effect on men. In our data set, we do not directly observe the birth of a child. Therefore, we define treatment as the earliest time period in which individual i has a strictly positive probability of having had a child.[25]

We augment the approach in Kleven et al. (2023) by allowing the treatment effects to vary with the introduction of shared parental leave. Therefore, we estimate the following

[25]In our sample, 90 percent of individuals are treated - 95 percent of women are treated and 82 percent of men are treated. We also show in Figure B.8 that the probability of having a child is decreasing in this period, in line with the trends in fertility. Moreover, in Appendix B, we show that our results are robust to the threshold we choose for the probability of having a child.

equation for each gender $g \in \{\text{men, women}\}$:

$$
\begin{aligned}
Y_{it} = \mu_i^g + \lambda_{ot}^g + \beta^g X_{it} + \sum_{m \neq -2} \gamma_m^g \times \mathbf{1}\{t - E_i = m\} \\
+ \sum_{m \neq -2} \delta_m^g \times \mathbf{1}\{t - E_i = m\} \times \mathbf{1}\{t \geq 2009\} + \varepsilon_{it}^g,
\end{aligned} \tag{4}
$$

where the outcome variable is the logarithm of the monthly wage, the logarithm of the number of total monthly hours, or an indicator variable which takes the value of one if individual i is employed in year t, and zero if otherwise. We include worker fixed effects and occupation-year fixed effects as in our estimation of equation 2. We also include a vector of controls, which includes a 3rd degree polynominal on age and a 3rd degree polynominal on tenure at the current place of employment. We define E_i as the year in which individual i is treated, i.e, the year in which individual i has their first child.[26] Therefore, coefficient γ_m^g allows us to identify the effect on outcome Y m periods after having had their first child, before the introduction of shared parental leave. We use period $m = -2$ as the excluded year, as in Kleven (2022). Coefficient δ_m^g instead allows us to identify the change in the treatment effect as a consequence of the introduction of shared parental leave. We cluster errors at the worker level.

Following Kleven (2022), we define the child penalty before the introduction of shared parental leave for a given outcome variable Y as

$$
\text{Child penalty}(Y) = \sum_{m \geq 0} (\gamma_m^{\text{women}} - \gamma_m^{\text{men}}) - \sum_{m \leq -1} (\gamma_m^{\text{women}} - \gamma_m^{\text{men}}), \tag{5}
$$

which involves adding up all the treatment effects for women, net of the same sum for men, for all periods after the event, and subtracting the equivalent sum for all periods before the event.[27] We define the change in the child penalty for a given outcome variable Y as

$$
\Delta\text{Child penalty}(Y) = \sum_{m \geq 0}^{M_1} (\delta_m^{\text{women}} - \delta_m^{\text{men}}) - \sum_{m \leq -1} (\delta_m^{\text{women}} - \delta_m^{\text{men}}), \tag{6}
$$

where we instead focus on the δ_m^g coefficients.

[26] The standard approach is to consider only the birth of the first child in order to avoid individuals being treated multiple times in our sample period.

[27] Note that by adding up all the *cumulative* treatment effects, we are computing an average child penalty over the M_1 periods that follow the birth of the first child.

5.2 Results

We estimate equation (4) separately for men and women for the period between 2004 and 2012, using as outcome variables the logarithm of the monthly wage, the logarithm of total monthly hours (including overtime), and an indicator variable which takes the value of one if the individual is employed and zero if otherwise.

Effect on wages. Figure 12 presents the estimates for the child penalty on wages. Panel (a) shows the estimates for the child penalty before the introduction of shared parental leave. After the birth of the first child, men experience a large increase in wages. This finding is also present in other settings, and has been dubbed the ”fatherhood premium” by Goldin et al. (2022). In contrast, women experience a small but very persistent drop in earnings. For example, if we compare female earnings one year after the birth of the first child with earnings two years before giving birth, we observe a drop of 0.4 percent. However, as men experience a 0.4 percent increase in wages in the same period, the child penalty one year after the birth of the first child is 0.8 percent. In our results, it takes four years for women to recover their pre-birth wages. However, four years after the birth of a child, men make almost 1 percent more than they did before having had a child. Our estimate for the overall child penalty is 1.03 percent, and this child penalty is mostly driven by the fatherhood premium.

The introduction of shared parental leave changes both the wages of fathers and mothers, as we shown in panel (b). For fathers, we observe a drop in earnings two years before the birth, following by an increase after birth. In contrast, women do not experience wage gains in the periods that follow birth, but they do experience wage gains three and four periods after births. This last finding is consistent with women taking less time off after giving birth, which implies that their human capital does not depreciate as much as it did before the introduction of shared parental leave. All in all, we find that the child penalty in wages is almost undone - the child penalty decreases by 0.92 percentage points, which almost undoes the 1.03 percent child penalty we observe before 2009.[28]

Effect on other outcomes. We also look at the effects on the child penalty on hours and employment. Figure E.1 presents our estimates for the child penalty in hours. We find that the introduction of shared parental leave undoes the child penalty in hours for women. However, this effect is not enough to explain the reduction in the child penalty

[28] In Figure B.9, we present the child penalty and the change in the child penalty if we use different thresholds on the probability of having a child to define the treated and control groups. We find that we always recover a decrease in the child penalty in wages after the introduction of shared parental leave.

in wages as the child penalty in hours before the introduction of shared parental leave is 0.45 percent, which is roughly half of our child penalty in monthly wages. In Figure E.2, we present our results for the child penalty in employment. We find that the probability of employment for women increases by 0.4 percentage points in the year before birth, and so the child penalty in employment is also undone by the introduction of shared parental leave.

6 Conclusion

This paper studies how intra-household decisions affect labor market outcomes by examining the introduction of shared parental leave in Portugal. We begin by writing a model of intra-household decision-making. This model has three key predictions: (1) women's wages should increase, (2) the increase in women's wages should be more pronounced for high-productivity women, and (3) the child penalty should decrease. The second prediction is explained by the fact that high-productivity women are allocated a lower share of childcare duties as the household wishes to maximize overall labor income. In contrast, we also show that women with a larger bargaining power should experience a smaller wage increase.

We then turn to the data to test these hypotheses. To do this, we create a novel data set that combines the matched employer-employee data set with data on all births. After introducing the policy in 2009, women's relative monthly wages increased by 1.2 percent from 2008 to 2012, translating to an annual uplift of around 130 Euros or a 5 percent reduction in the pre-existing wage gap. Notably, this wage increase is primarily concentrated among women working in sectors with elastic wage-hours relationships. Additionally, we find that the wage increase is concentrated in women who are the household's primary earners, per the model's predictions. Finally, we show that introducing shared parental leave also leads to a decrease in the child penalty.

Our paper focuses on the short-run implications of shared parental leave on labor market outcomes. There are a variety of other consequences of this policy change in the long run. This may affect the occupation choice of women who have not yet entered the labor market. For example, these women might choose occupations that require high hours if they expect that they will need to bear a lower share of childcare duties. In the marriage market, women may prefer to match with more productive men if they have stronger preferences towards spending time with children, which may affect assortative matching. There are also implications for children. Suppose children inherit the productivity of the parent who takes on the largest share of childcare duties. In that case, introducing shared parental leave may reduce their future productivity as high-productivity women no longer take on a large share of childcare duties. These questions require data on children's long-run outcomes, and we leave them for future research.

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Figures

FIGURE 1: Take-up of shared parental leave by men

We plot the share of total leave days that is taken by men. For the period before the introduction of shared parental leave, we compute this ratio by dividing the number of days men take under paternal divided by the total number of days taken by men under paternal leave and the total number of days taken by women under maternal leave. The data comes from the Portuguese Social Security Administration.

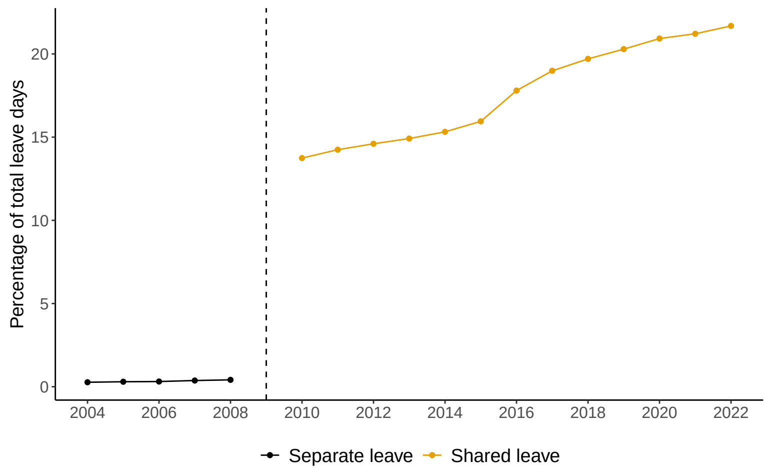


FIGURE 2: Share of households where men do not take-up childcare

We use data from the European Social Survey for Portugal. We consider households where the respondent lives with a partner or spouse, and where they have at least on child living at home. We also consider only households in which at least one individual (either the respondent or their partner) has done childcare in 7 days prior to the interview. We then classify a household as one in which men do not take on childcare duties if (1) the respondent is male and the respondent has not taken on childcare duties in the last 7 days (according to variable `hswrk`), or (2) the respondent is female and the respondent's partner has not taken on childcare duties in the last 7 days (according to the variable `hswrkp`). We then compute the share of households in which men do not take on childcare duties across all households in the same survey wave. We present the results for all households in panel (a). In panel (b), we present results for all households in which both the respondent and their partner are employed.

(a) All households

(b) Both partners work

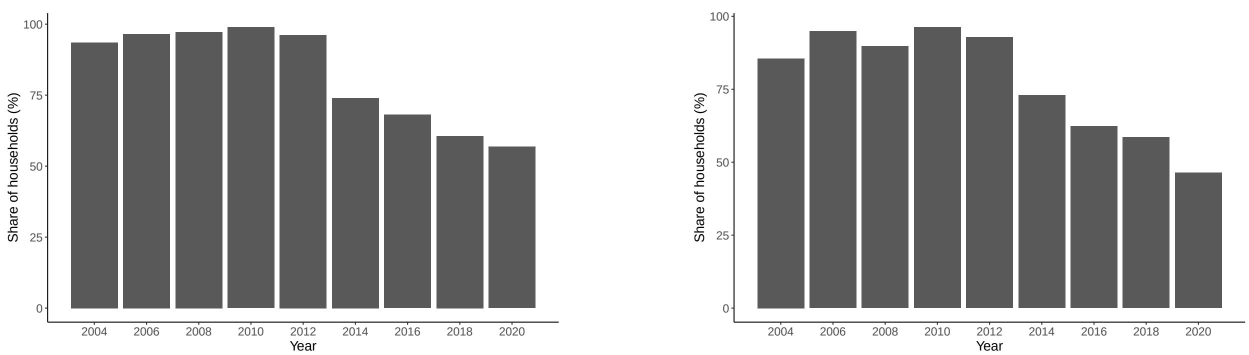


FIGURE 3: Average leave taken by women

We plot the average number of leave days taken by women. Before 2009, we compute this by counting the total number of maternal leave days and dividing it by the number of women who are eligible. After 2009, we compute it by counting the number of days taken by women under parental leave and dividing it by the number of eligible women.

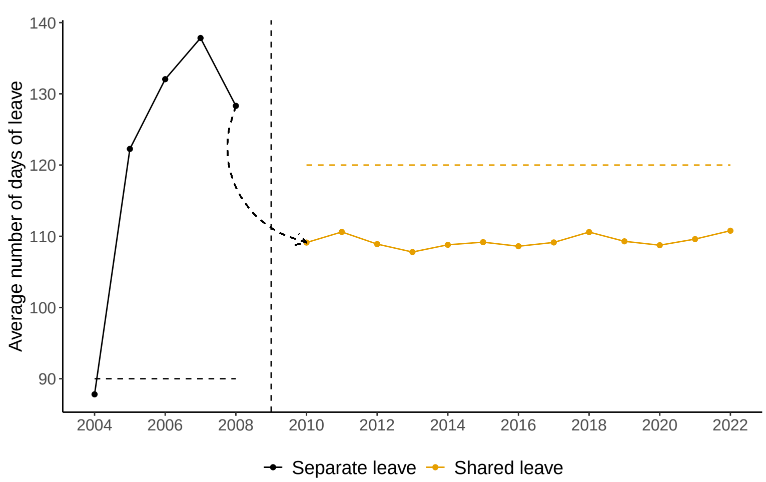


FIGURE 4: Allocation of childcare to women as a function of Pareto weights

This figure presents the optimal allocation of childcare duties to women as a function of the Pareto weight of the woman. We consider three cases: (1) identical levels of human capital, (2) human capital of the woman is lower, and (3) human capital of the woman is higher. For each case we consider three possibilities: (1) $\alpha_m = \alpha_f > 0$, (2) $\alpha_m = 0 < \alpha_f$, and (3) $\alpha_m = \alpha_f = 0$.

(a) $w_m = w_f$ (b) $w_m > w_f$ (c) $w_m < w_f$

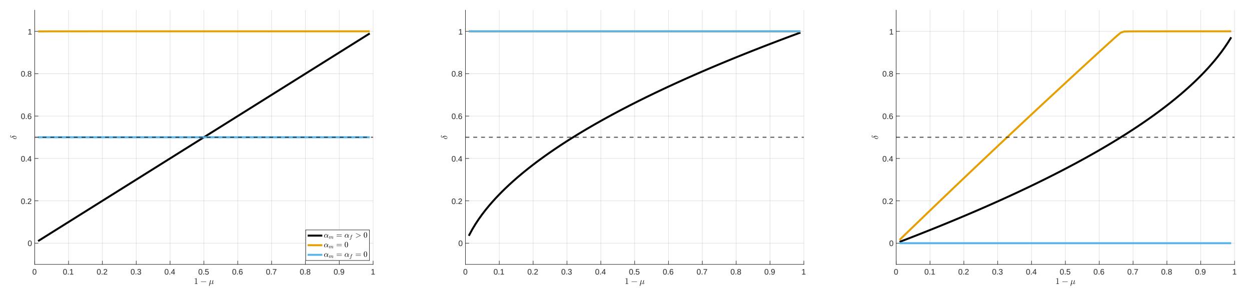


FIGURE 5: Allocation of childcare to women as a function of wages

This figure presents the optimal allocation of childcare duties to women as a function of the relative wage of women. In panel (a), we consider three cases: (1) $\mu = 0.75$, (2) $\mu = 0.5$, and (3) $\mu = 0.25$. In panel (b), we consider three other cases: (1) $\alpha_m = \alpha_f > 0$, (2) $\alpha_m = 0 < \alpha_f$, and (3) $\alpha_m = \alpha_f = 0$.

(a) Role of Pareto weights (b) Role of α_i

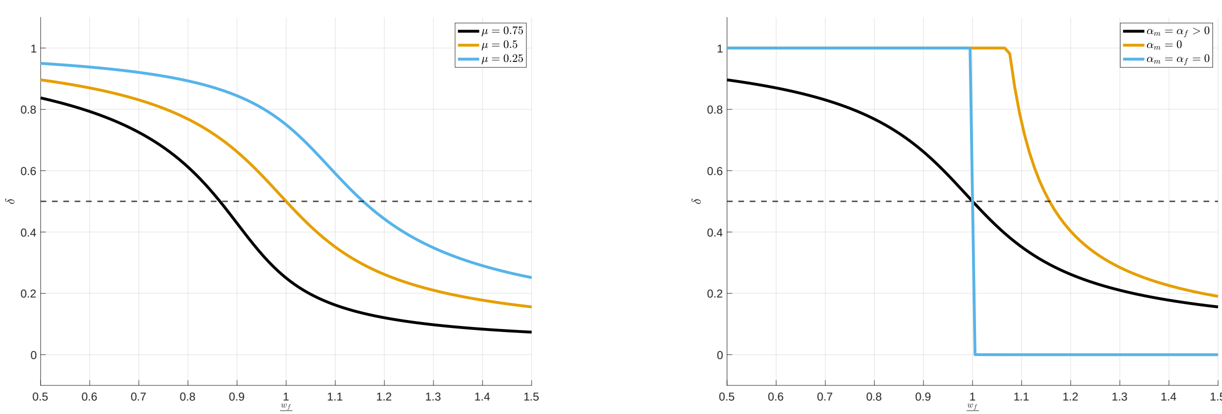


FIGURE 6: Effect on women's wages

This Figure presents the change in the logarithm of women's wages after the introduction of shared parental leave. We consider three cases: (1) $\alpha_m = \alpha_f > 0$, (2) $\alpha_m = 0 < \alpha_f$, and (3) $\alpha_m = \alpha_f = 0$. In panel (a), we vary the Pareto weight of women $1 - \mu$ while assuming $w_f = w_m$. In panel (b), we vary the relative wage of women while assuming $\mu = 0.5$.

(a) Role of Pareto weights

(b) Role of human capital

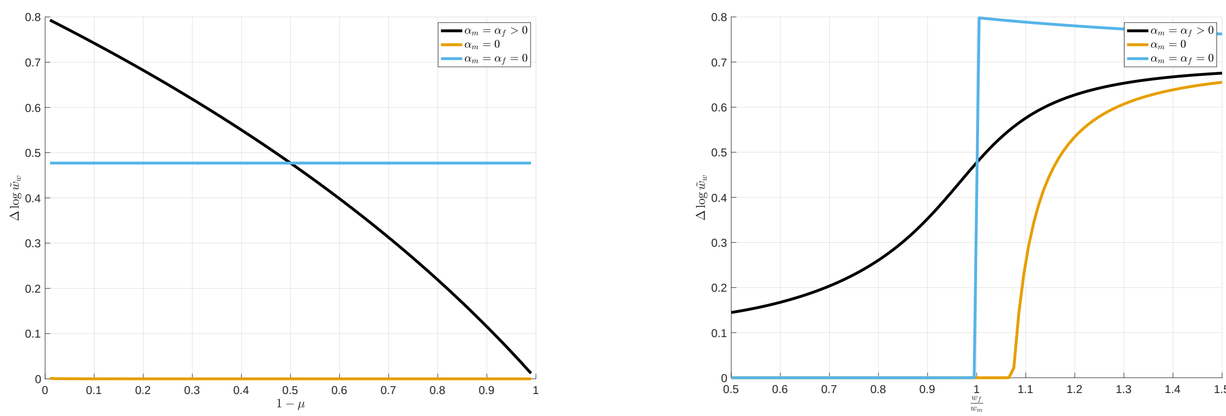


FIGURE 7: Evolution of inequality within and across households

We plot the change in wage inequality as a result of the introduction of shared parental leave. Our measure of inequality is the variance of wages, which can be decomposed as the sum of the within-household variance and the variance across households. We present results for five cases. The first four cases are the result of a model simulation. We simulate an economy with 10,000 households that only vary according to the human capital pair (w_m, w_f), which we draw from a joint lognormal distribution. The coefficient ρ is the correlation between the two random variables. The last series represents the data. Using our data set on synthetic households, we compute the variance decomposition for wages between 2008 and 2012.

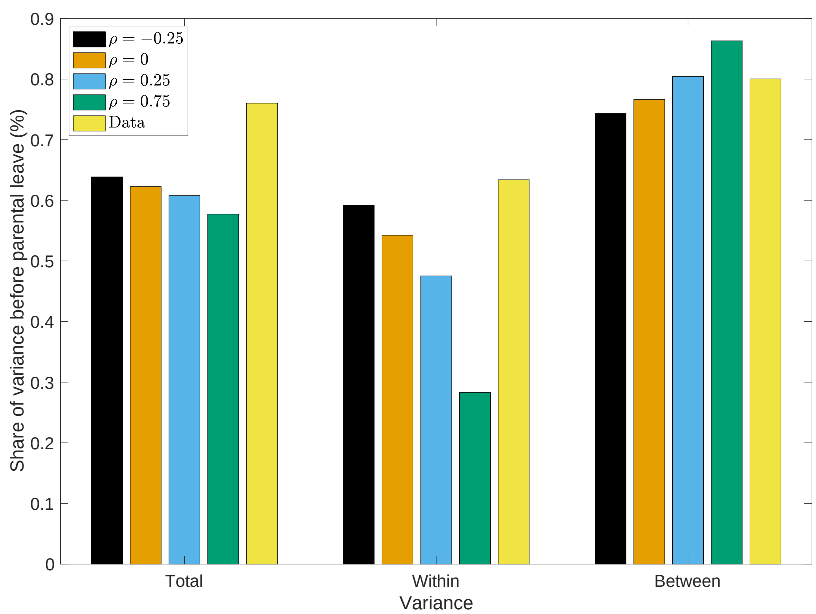


FIGURE 8: Effect on wages of women relative to men

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

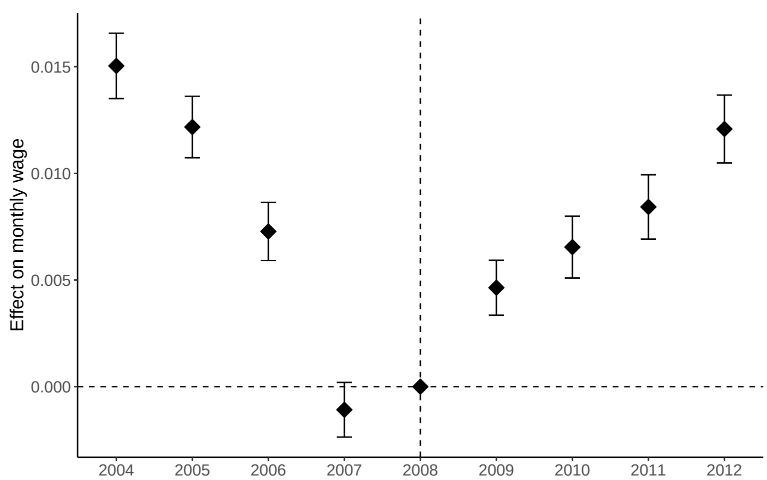


FIGURE 9: Effect on wages of women relative to men - switchers vs. remainers

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We conduct this estimation in two different samples: (1) using workers that switch jobs (switchers), and (2) using only workers that do not change jobs (remainers). We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

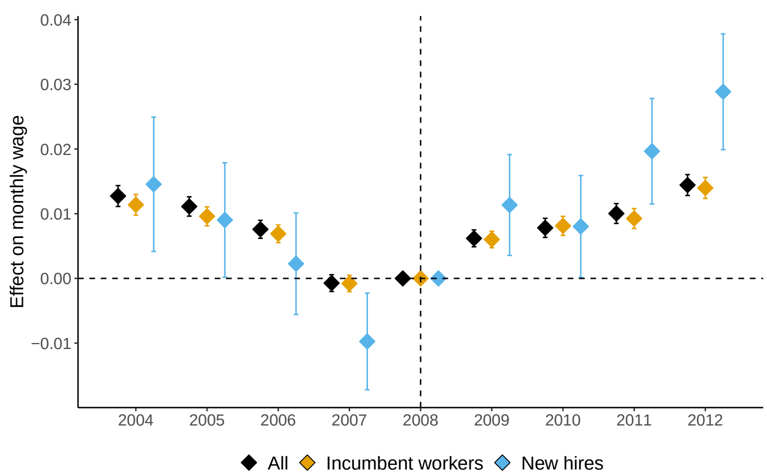


FIGURE 10: Effect on wages of women relative to men - decomposition by sectors

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. To compute sector greediness, we regress the logarithm of the monthly wage on a 4th degree polynominal of age, educational attainment fixed effects, year fixed effects, occupation-gender fixed effects, and the interaction between the logarithm of total hours worked (including overtime) and an occupation fixed effect, using data from 2004 and 2008, following Goldin (2014). Our measure of greediness is the coefficient associated with the interaction between the occupation fixed effect and the logarithm of hours worked. We define a sector as greedy if its greediness is above the median. We then estimate equation 1 on three samples: (1) using all observations, (2) using observations for greedy sectors, and (3) using observations for non-greedy sectors. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

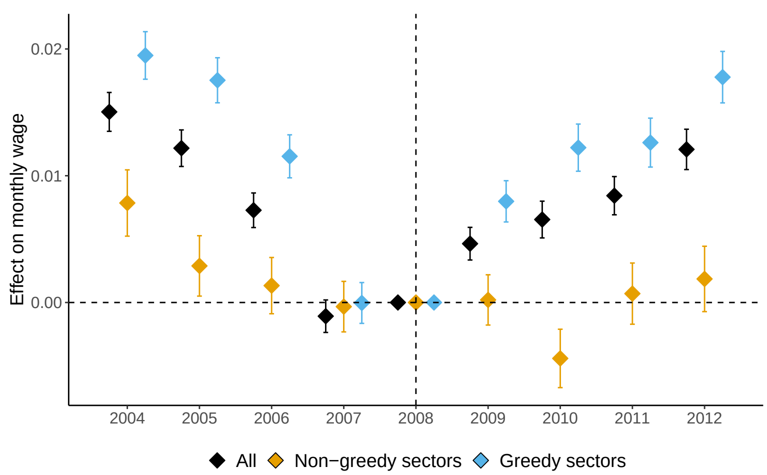


FIGURE 11: Effect on wages of women relative to men - primary earners vs. non-primary earners

This figure presents the results of estimating equation (3) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We include a set of coefficients which multiply an indicator variable which takes the value of one if the worker is a woman, and zero if otherwise, with an indicator which takes the value of one if the year is *m* periods away from 2009. We use the year 2008 as the excluded year. We also include a set of coefficients which multiply three indicator variables: (1) an indicator variable which takes the value of one if the worker is a woman, and zero if otherwise, (2) an indicator which takes the value of one if the year is *m* periods away from 2009, and (3) an indicator which takes the value of one if the worker's monthly wage is at least 50 percent of total household labor income. We present estimates for this last set of coefficients, which compares the relative wage of women who are the household's primary earners with the relative wage of women who are not the household's primary earners. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

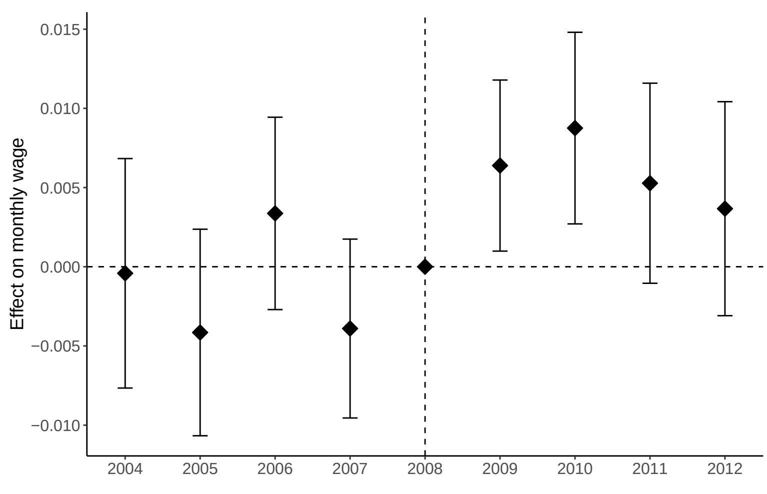
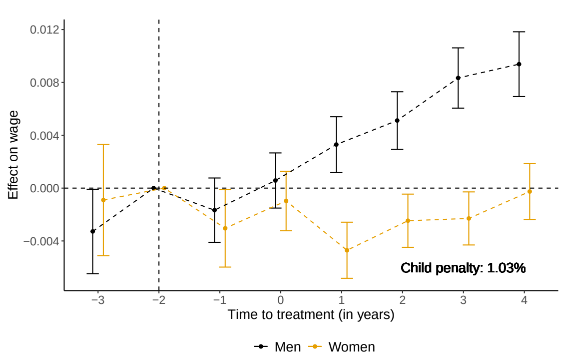


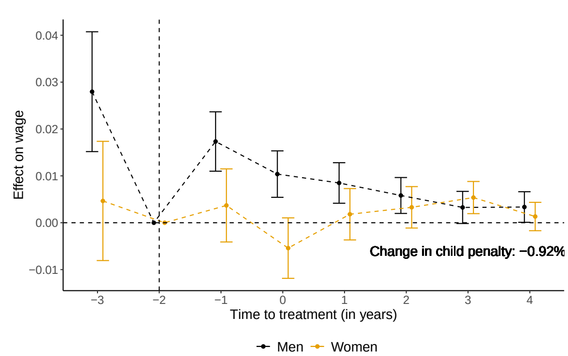
FIGURE 12: Child penalty - monthly wages

This figure presents the results of estimation equation (4) on our data set between 2004 and 2012. The outcome variable is the logarithm of the monthly wage. We estimate (4) separately for men and women. The regression includes worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a 3rd degree polynominal on age and a 3rd degree polynominal on tenure at the current place of employment. For each individual, we define treatment as having had their first child. The event time is the year in which the individual has their first child. We include a set of coefficients γ_m^g, where $g \in \{\text{men}, \text{women}\}$, which multiply an indicator variable which takes the value of one if the individual is m periods away from the time of treatment. We use $m \neq -2$ as the excluded period. We present estimates for these coefficients for men and women, which estimate the treatment effect of the birth of the first child before the introduction of shared parental leave, in panel (a). In panel (a), we also present our estimate for the child penalty, which is defined as $\sum_{m\geq 0}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}}) - \sum_{m\leq -1}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}})$ as in equation (5). We also include a set of coefficients δ_m^g, where $g \in \{\text{men}, \text{women}\}$, which multiply an indicator variable which takes the value of one if the individual is m periods away from the time of treatment and an indicator which takes the value of one if the year is after 2009, and zero if otherwise. We present estimates for these coefficients for men and women, which estimate the change in the treatment effect of the birth of the first child with the introduction of shared parental leave, in panel (b). In panel (b), we also present our estimate for the change in the child penalty, which is defined as $\sum_{m\geq 0}(\delta_m^{\text{women}} - \delta_m^{\text{men}}) - \sum_{m\leq -1}(\delta_m^{\text{women}} - \delta_m^{\text{men}})$ as in equation (6). We cluster errors at the worker level and also present 95 percent confidence intervals.

(a) Before introduction of shared parental leave



(b) Change with introduction of shared parental leave



Tables

TABLE I: Summary Statistics

This table presents summary statistics for the matched employer-employee data set for the year 2008. We consider three groups: all workers, men, and women. For each group we present the cross-sectional average of: regular monthly hours, total hours in a month, monthly wage, hourly wage, age, tenure at the current place of employment in years, an indicator variable that takes the value of one if the individual has a college degree and zero if otherwise, and an indicator variable that takes the value of one if the individual is a manager and zero if otherwise. We also present the difference in means between women and men. For each difference, we compute the t-statistic and present the significance level of the difference where ***, **, and * denote significance at the 5, 1, or 0.1 percent level, respectively.

	All workers	Men	Women	Difference
Hours (regular)	160	160	160	0.00
Hours (total)	167	168	166	-1.56***
Monthly wage	925.76	1,030.48	771.67	-258.82***
Hourly wage	5.66	6.27	4.77	-1.50***
Age	37.8	38	37	-1.25***
Tenure (in years)	6.3	6.4	6.2	-2.70***
Has a college degree	0.09	0.08	0.11	0.03***
Is a manager	0.08	0.09	0.07	-0.02***
Observations	2,224,348	1,324,330	900,018	

Online Appendix

A Additional Details about Data, Tables and Figures

A.1 Description of data

The matched employer-employee data set is the result of a survey carried out by the National Institute of Statistics. The survey includes data for all firms with at least one employed worker, which the exception of entities of the central government, local government, or other institutions, as well as firms in nonmarket services, such as domestic work. Firms answer the survey every October, and use this month as the reference. Therefore, all variables are relative to October.

We define the monthly wage as total labor earnings paid in a month, which includes: (1) regular wage, (2) regular benefits, such as meal subsidies, (3) irregular benefits, and (4) payment for overtime. We define monthly hours as total hours worked in a month, which includes regular hours and overtime. The hourly wage is the ratio of the monthly wage to total hours worked. Tenure is defined as the number of years in the current place of employment.

The matched employer-employee data set also provides data on the profession of each worker. Before 2009, this variable uses the the 1985 *Classificação Nacional de Profissões*. After 2009, the National Institute of Statistics changes to the 2010 *Classificação Portuguesa de Profissões*, which is in line with the E.U. classification of occupations. However, there is no easy one-to-one match between the two classifications. We therefore are forced to create a coarse classification for which there is a one-to-one match. We end up with 11 different professions. We define a sector as a section according to the *Classificação das Actividades Económicas* (rev. 3). We therefore end up with 20 sectors. We define an occupation as a pair of profession-sector, which implies we end up with 220 occupations.

For each worker, we define educational attainment as: (1) has less than a high-school diploma, (2) has a high-school diploma, and (3) has a college degree. Firms also report the hierarchical position of each worker. We define managers as workers which belong either to the *Quadro superior* (high-level manager) or *Quadro médio* (middle-level manager).

We also observe the region of the firm. We use the NUTS 2 regions classification: (1) Lisbon, (2) *Centro*, (3) *Norte*, (4) *Alentejo*, (5) *Algarve*, (6) Azores, and (7) Madeira.

FIGURE A.1: Number of individuals in sample

This figure presents the number of individuals present in our matched employer-employee dataset. In panel (a), we present the number of individuals in our sample per year. In panel (b), we present the number of individuals in our sample per year as a share of the total employed Portuguese population.

(a) Number of workers

(b) Share of employed population

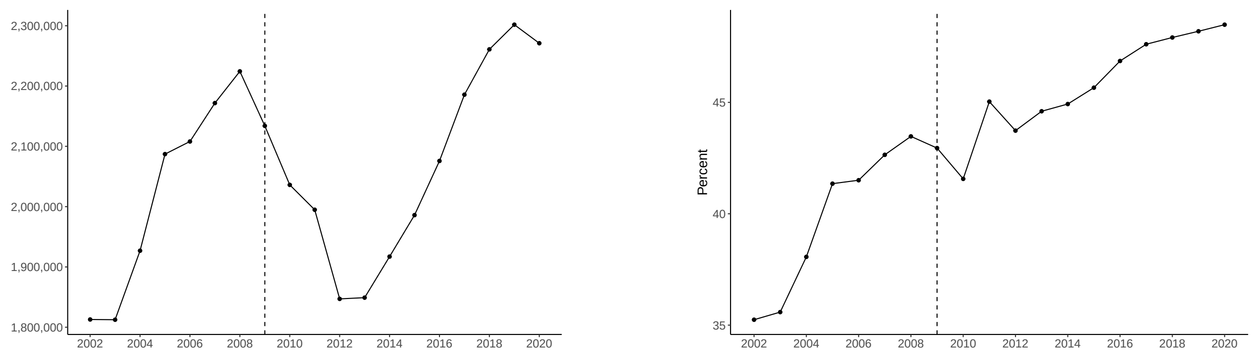


FIGURE A.2: Number of women in sample

This figure presents the number of female workers present in our matched employer-employee dataset. In panel (a), we present the number of female workers in our sample per year. In panel (b), we present the number of female workers in our sample per year as a share of the total number of employed Portuguese women.

(a) Number of women

(b) Share of employed population

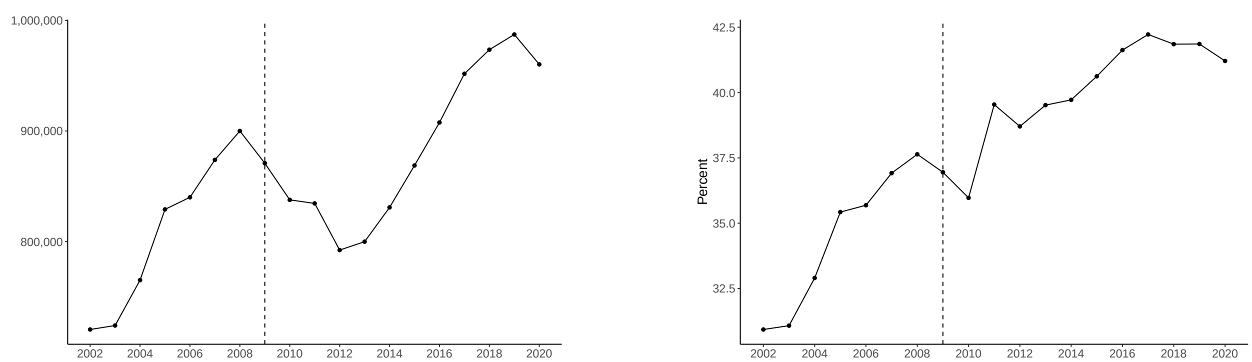
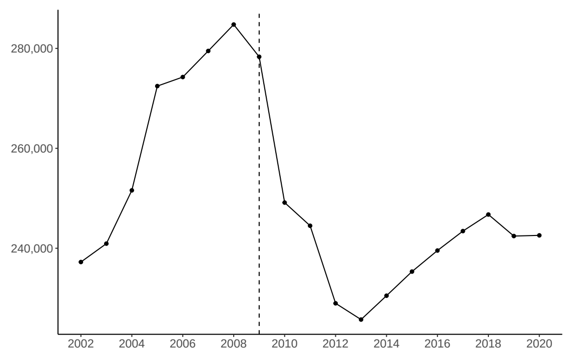


FIGURE A.3: Number of firms and firm size

This figure presents the number of firms and average firm size per year. In panel (a), we present the number of firms in our sample each year. In panel (b), we present the average firm size per year, which we define as the average number of workers per firm.

(a) Number of firm



(b) Size of firm

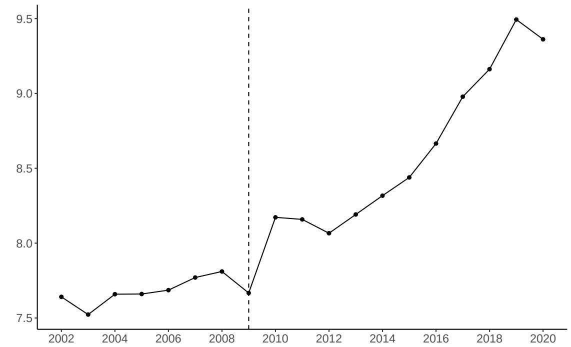
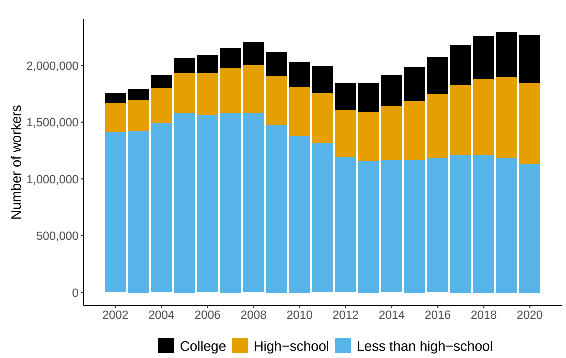


FIGURE A.4: Number of workers - decomposition by educational attainment

This figure presents a decomposition of the number of workers according to their educational attainment. We classify workers into three workers: (1) workers with less than a high-school diploma, (2) workers with a high-school diploma, and (3) workers with a college degree. In panel (a), we present a decomposition of the number of workers according to their educational attainment. In panel (b), we present a decomposition of the wages of workers according to their educational attainment.

(a) Number of workers



(b) Wages

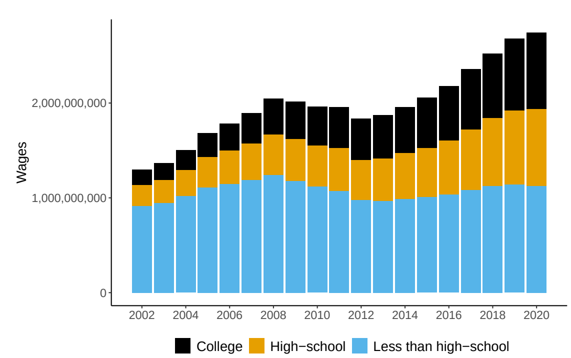
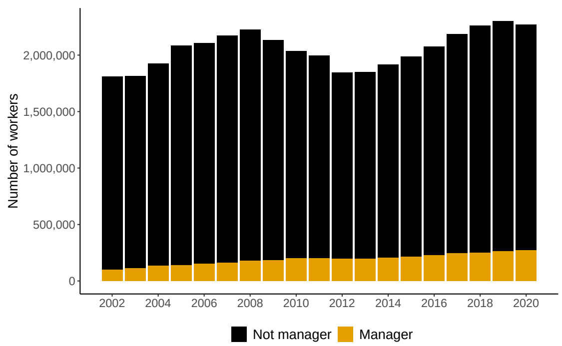


FIGURE A.5: Number of workers - decomposition by hierarchical position

This figure presents a decomposition of the number of workers according to their hierarchical position within the firm. We classify workers as managers or non-managers. In panel (a), we present a decomposition of the number of workers according to their hierarchical position within the firm. In panel (b), we present a decomposition of the wages of workers according to their hierarchical position within the firm.

(a) Number of workers



(b) Wages

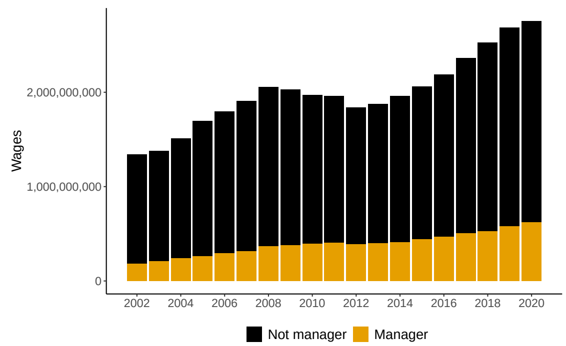
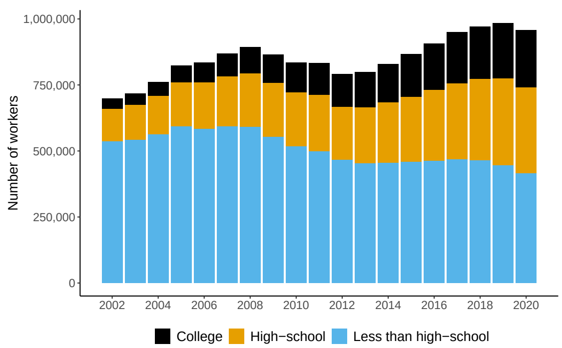


FIGURE A.6: Number of women - decomposition by educational attainment

This figure presents a decomposition of the number of female workers according to their educational attainment. We classify workers into three workers: (1) workers with less than a high-school diploma, (2) workers with a high-school diploma, and (3) workers with a college degree. In panel (a), we present a decomposition of the number of female workers according to their educational attainment. In panel (b), we present a decomposition of the wages of female workers according to their educational attainment.

(a) Number of workers



(b) Wages

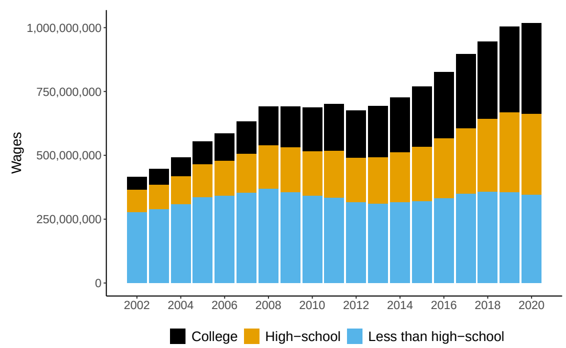
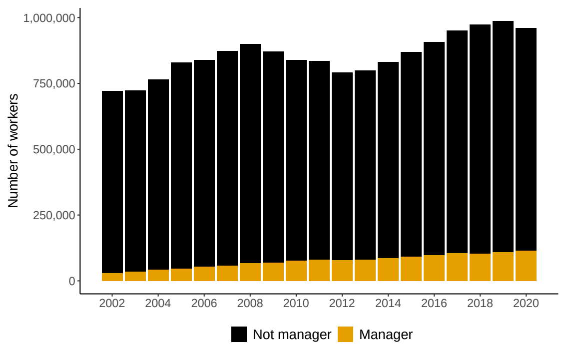


FIGURE A.7: Number of women - decomposition by hierarchical position

This figure presents a decomposition of the number of female workers according to their hierarchical position within the firm. We classify workers as managers or non-managers. In panel (a), we present a decomposition of the number of female workers according to their hierarchical position within the firm. In panel (b), we present a decomposition of the wages of female workers according to their hierarchical position within the firm.

(a) Number of workers



(b) Wages

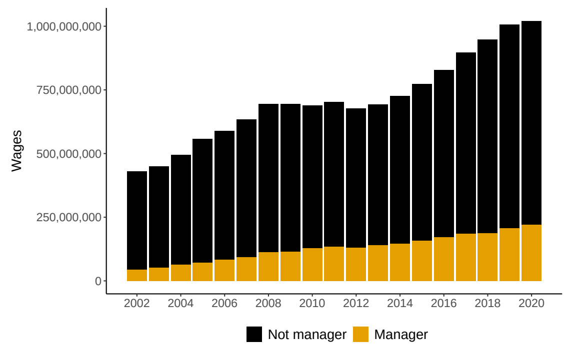
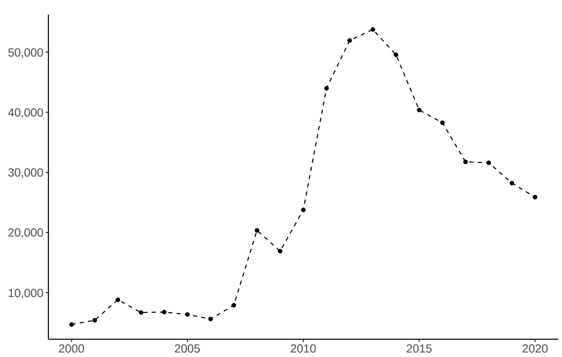


FIGURE A.8: Number of emigrants

This figure presents the evolution of the number of emigrants. In panel (a), we report the number of new emigrants per year. In panel (b), we report the share of women within the total number of new emigrants per year.

(a) Number of emigrants



(b) Share of women

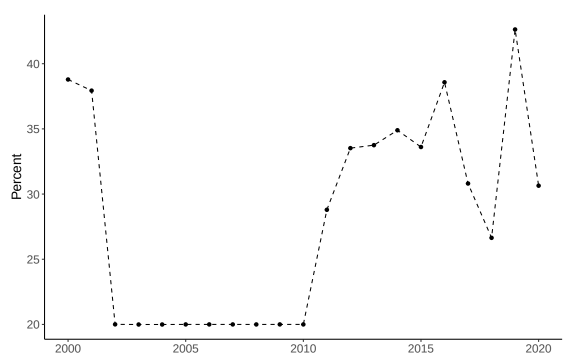


FIGURE A.9: Distribution of wages by gender

This figure presents the distribution of the logarithm of the monthly wages by gender in 2008.

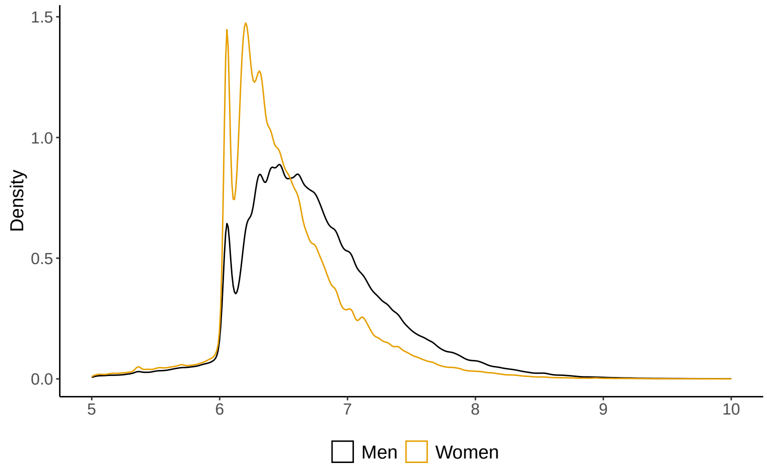


FIGURE A.10: Wage gap over time

This figure presents the evolution of the wage gap over time. For each year, we compute the wage gap by regressing the logarithm of the monthly wage on a 3rd degree polynominal of age, a 3rd degree polynominal on tenure at the current place of employment, an occupation fixed effect, and a gender dummy. We define the gender gap as the coefficient associated with the gender dummy. We cluster errors at the worker level. We present 95 confidence intervals.

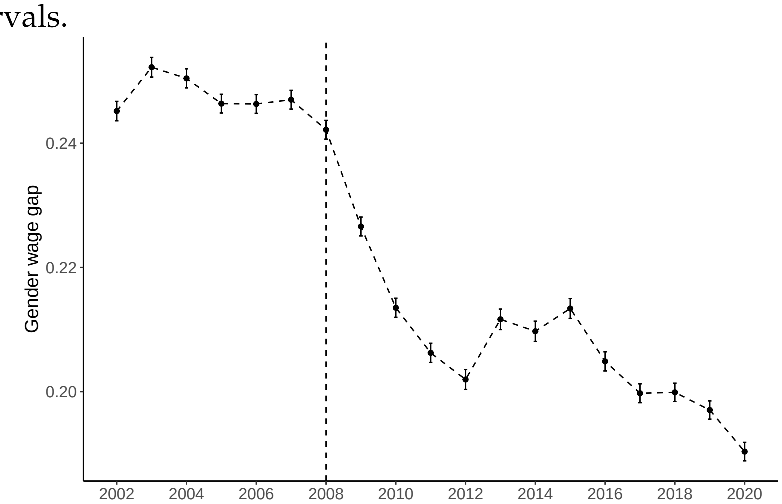
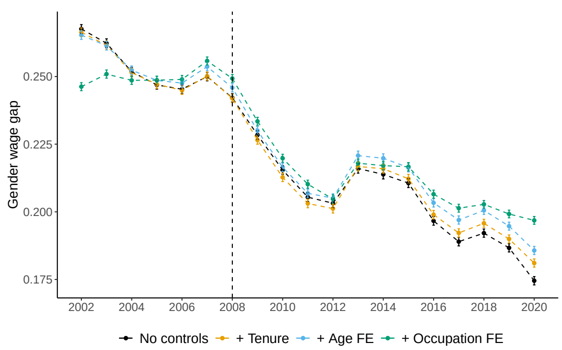


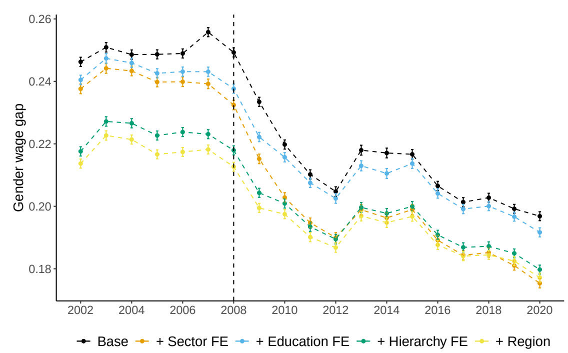
FIGURE A.11: Wage gap over time - robustness

This figure presents the evolution of the wage gap over time. For each year, we compute the gender gap as the coefficient associated with the regression of the logarithm of the monthly wage on the gender dummy. In panel (a), we consider four cumulative specifications: (1) no controls, (2) including logarithm of tenure as a control, (3) further including an age fixed effect, (4) further including a profession fixed effect. in panel (b), we consider four cumulative specifications: (1) including the logarithm of tenure as a control, an age fixed effect, and a profession fixed effect, (2) further including a sector fixed effect, (3) further including an educational attainment fixed effect, and (4) futher including a hierarchical position fixed effect. In panel (c), we consider four alternative specifications starting from a base specification with the logarithm of tenure, an age fixed effect, a profession fixed effect, a sector fixed effect, an educational attainment fixed effect, and a hierarchical position fixed effect: (1) base case, (2) adding a firm fixed effect, (3) adding the firm-level share of female workers as a control, and (4) adding the firm-level share of female wages as a control. We cluster errors at the worker level. We present 95 confidence intervals.

(a) First group



(b) Second group



(c) Third group

A.2 Creating a measure of greediness

To compute a measure of "greediness", or the elasticity of monthly wages to hours worked, we follow Goldin (2014) and, using our sample for the years between 2002 and 2008, estimate the following equation

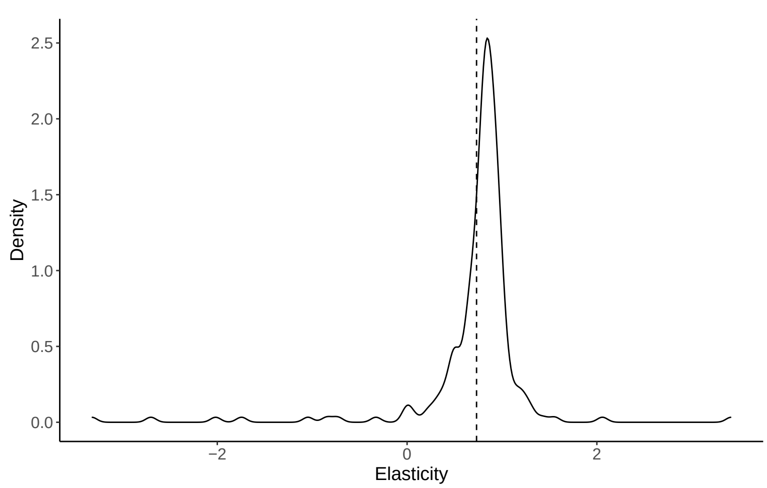
$$\log w_{it} = \beta X_{it} + \mu_{\text{education}} + \lambda_t + \alpha_{\text{occupation, gender}} + \theta_{\text{occupation}} \times \log h_{it} + \varepsilon_{it}$$

where the outcome variable is the logarithm of the monthly wage of worker i in year t. We include a vector of controls which includes a 4th order polynominal on age. We further include educational attainment fixed effects, year fixed effects, and a occupation-gender fixed effect. We interact an occupation fixed effect with the logarithm of the number of hours worked. We define the occupation's greediness as the occupation-specific elasticity of wages with respect to hours worked.

In Figure A.12, we plot the distribution of the elasticities, or "greediness" of the occupations in our data. Most of the elasticities are positive and the median is slightly less than one.

FIGURE A.12: Distribution of occupation greediness

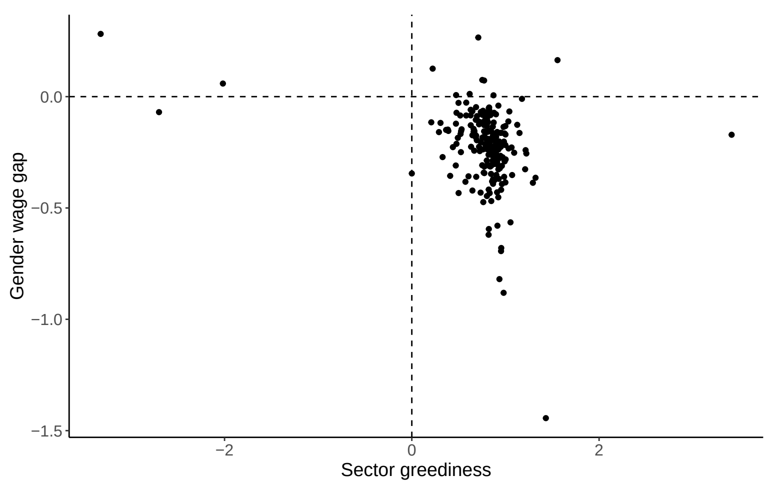
This figure presents the distribution of the occupation greediness. To compute sector greediness, we regress the logarithm of the monthly wage on a 4th degree polynominal of age, educational attainment fixed effects, year fixed effects, occupation-gender fixed effects, and the interaction between the logarithm of total hours worked (including overtime) and an occupation fixed effect, using data from 2004 and 2008, following Goldin (2014). Our measure of greediness is the coefficient associated with the interaction between the occupation fixed effect and the logarithm of hours worked. The vertical dashed line represents the median of the distribution.



We also compare the greediness of each occupation with the gender wage gap in that occupation. For each occupation, we regress the logarithm of the monthly wage on year fixed effects and a gender dummy, which captures the gender wage gap of the occupation. In Figure A.13, we present a scatter plot of the greediness of the occupation against the gender wage gap. The two measures are negatively correlated, as shown in Goldin (2014) - sectors with more convex pay structures observe lower wages for women relative to men.

FIGURE A.13: Occupation greediness and the gender wage gap

This figure plots occupation greediness against the occupation-level gender wage gap. To compute occupation greediness, we regress the logarithm of the monthly wage on a 4th degree polynominal of age, educational attainment fixed effects, year fixed effects, occupation-gender fixed effects, and the interaction between the logarithm of total hours worked (including overtime) and an occupation fixed effect, using data from 2004 and 2008, following Goldin (2014). Our measure of greediness is the coefficient associated with the interaction between the occupation fixed effect and the logarithm of hours worked. The vertical dashed line represents the median of the distribution. To compute the occupation-level gender wage gap we regress, for each occupation, the logarithm of the monthly wage on year fixed effects and a gender dummy, which captures the gender wage gap of the occupation.



A.3 Creating a data set to study participation

We also use the matched employer-employee data set to create a data set to study the participation of workers in the labor market. As a starting point, we create a balanced data set at the worker-year level - each worker has an observation for each year. We define a worker as non-employed if, for a particular year, there is no record of employment for that worker in the matched employer-employee data set.

We then wish to merge this balanced data set with worker characteristics. We assume gender is a permanent characteristic and merge it. We also use the first observation for the worker in the matched employer-employee data set as well as the difference in years between the balanced data set and the matched employer-employee data set to compute the worker's age.

We also want to have information on occupation and educational attainment. For workers who are currently employed, we can simply use the information on the matched employer-employee data set. For the remaining observations, we use the observation for the same worker on the matched employer-employee data set which is closest in terms of absolute difference in years.

Finally, we exclude observations where the worker's age is less than 16 or larger than 65.

B Building synthetic households

B.1 Description of algorithm

We start with by creating a data set on all births in Portugal between 2000 and 2019, where each observation is a birth. In this time period, we observe 1,979,479 births.

For each birth, we observe the date of the birth, the educational attainment of the father and the mother (defined as in Appendix A), the age of the father and the mother, the region in which the father or the mother live, and the profession of the father and the mother (defined as in Appendix A).

Our goal is to obtain a panel on households. For each household, we observe the wages of both members, as well as whether or not they had a child in that year. As we cannot do this at the individual level, we adopt a probabilistic approach, or we build *synthetic households*. Using the births data set, we create groups according to the Cartesian product between all professions, all ages of parents in the data set, all regions, all years between 2002 and 2012, and both genders. We end up with 1,278,720 observations, or 63,936 observations. Each observation is an individual.

Probability of having a child. In an ideal data set, we would observe the event of child-birth. In this data set, we will need to adopt a probabilistic approach. To compute the probability of having a child, we divide the number of births in group by the number of individuals in the group in the matched employer-employee data set. This approach will overstate the probability of having a child as the true number of individuals in the group is weakly larger than the number of individuals we observe in the matched employer-employee data set. Therefore, the value of the probability is not very informative. We address this issue by using these probabilities to compute two bins: (1) individuals for whom the probability is zero, and (2) individuals for whom the probability is not zero. Note that a zero probability implies that there are no births, and therefore the size of the group in the matched employer-employee data set is irrelevant.

Wage of partner. Let $\mathcal{G}$ denote all the groups in our sample. Consider a group g. We want to have a measure of the wage of the partner of the individual in group g. In our births data, group g may appear matched with many other groups, i.e., there may be births involving group g and group g', group g'', etc... Define $G(g) \in \mathcal{G}$ as the set of groups matched with group g. For each group $g' \in G(g)$, we can compute $w_{g'}$ as the average wage in that group in the matched employer-employee data set. We can also compute $n_{g,g'}$ as the number of births involving group g and $g' \in G(g)$. Note that, for all $\tilde{g} \notin G(g)$, $n_{g,\tilde{g}} = 0$. Define $N_g \equiv \sum_{g' \in G(g)} n_{g,g'}$ as the total number of births involving group g. We then define the estimated wage of the partner as $(N_g)^{-1} \sum_{g' \in G(g)} n_{g,g'} w_{g'}$.

Labor income of household. For each individual in the matched employer-employee data set, we observe the actual income but we need to estimate the income of the partner. In the end, we are concerned with the individual's share of income in the household. However, our measure of the income of the partner has measurement error. We assume that this measurement error is multiplicative and similar across individuals. Therefore, to avoid measurement error in the share of income, we will also use the estimated value for the wage of the individual. Therefore, the labor income of the household is the sum of the estimated wage of the individual and the estimated wage of the partner.

Merging with matched employer-employee data set. We match the data with the matched employer-employee data set according to the groups we created.

B.2 Figures

FIGURE B.1: Distribution of group size

This figure plots the distribution of group sizes for our synthetic households and for the census data. The orange line plots the distribution of relative group size (number of individuals in the group divided by the total number of individuals in the sample) for our synthetic households data for 2011. The black line plots the distribution of relative group size for the 2011 Portuguese Census, for which we have a 5 percent random sample of households.

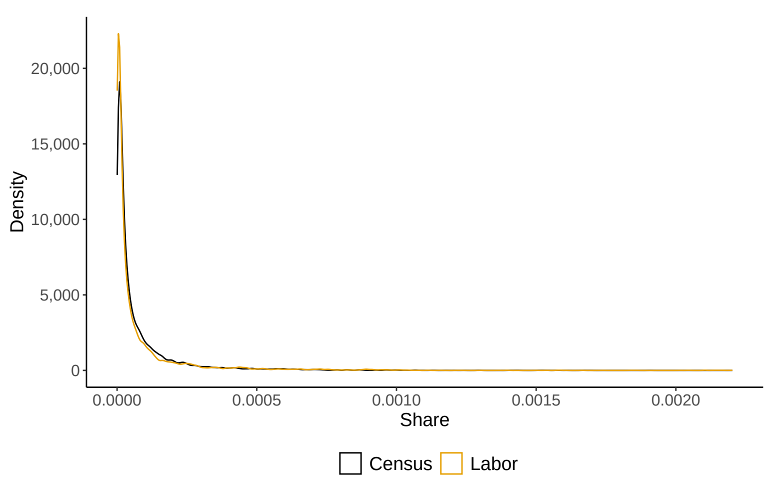


FIGURE B.2: Validation of group sizes

This figure plots the relative group size (number of individuals in the group divided by the total number of individuals in the sample) for our synthetic households data for 2011 against the relative group size for the 2011 Portuguese Census, for which we have a 5 percent random sample of households. We also plot dash black 45-degree line, as well as the linear fit line in blue. We present the coefficient associated with the regression of the relative group size in the synthetic household data on the group size in the census data, as well as the R^2.

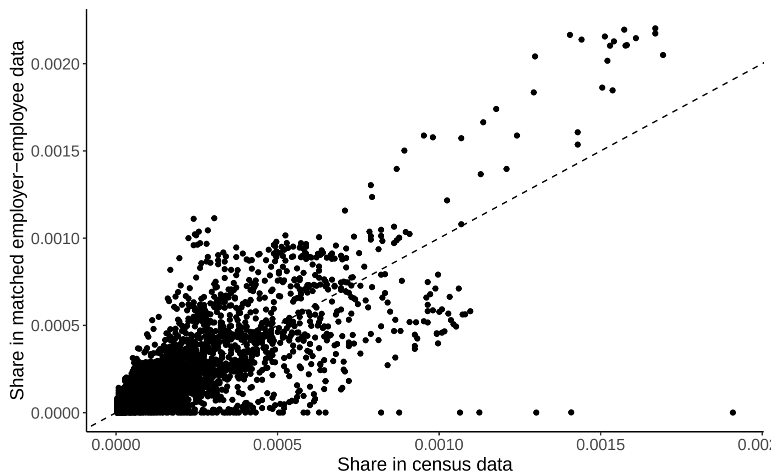


FIGURE B.3: Distribution of female share of household income in 2008

For each household, we compute the female share of labor household income as the ratio of the monthly wage of the woman to the sum of the monthly wages of both members of the household. We present the distribution of this indicator for 2008. The vertical dashed line represents the median.

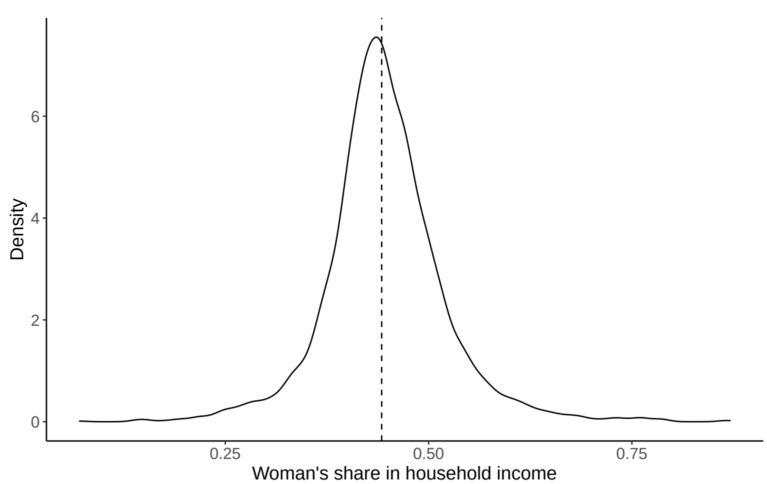


FIGURE B.4: Validation of distributions of female share of income

This figure plots the distribution of the female share of labor income for both the household survey and our synthetic household data. We define the female share of labor income as the labor income of the woman divided by the total labor income of the household. For the household survey, we consider households where (1) there are two individuals who are either married or cohabiting, and (2) both the head of the household and their partner are employed. The dashed lines represent the medians of each distribution. Panel (a) presents the comparison of the distributions for the 2005-2006 wave of the household survey and the 2006 distribution of the synthetic household data. Panel (b) presents the comparison of the distributions for the 2010-2011 wave of the household survey and the 2011 distribution of the synthetic household data.

(a) 2006

(b) 2011

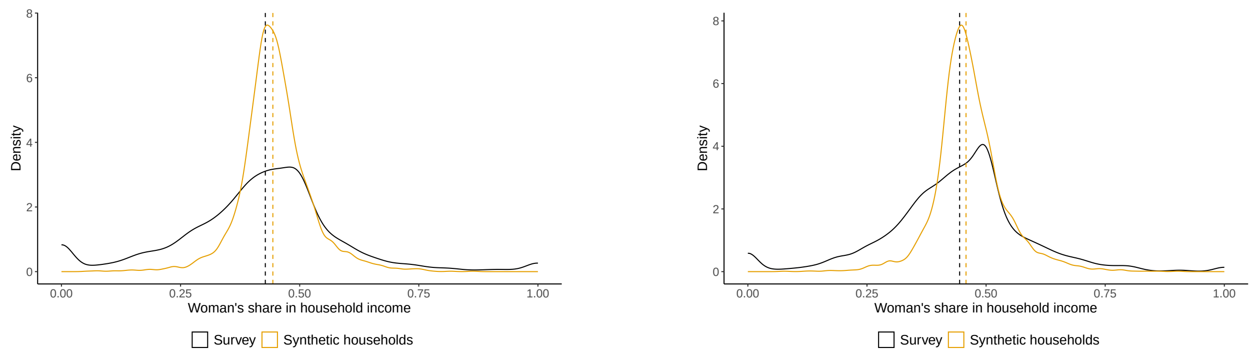


FIGURE B.5: Number of births

This figure plots the number of births per year.

FIGURE B.6: Correlation between labor share of women and other measures

This figure plots the correlation between the labor share of women and the estimated income of women, the estimated income of their partner, and the estimated labor income of the household. We define the labor share of women as the estimated income of women divided by the estimated labor income of the household. For each year, we regress the labor share of women against the logarithm of one of the three variables. We present the coefficients from that regression along with a 95 confidence interval.

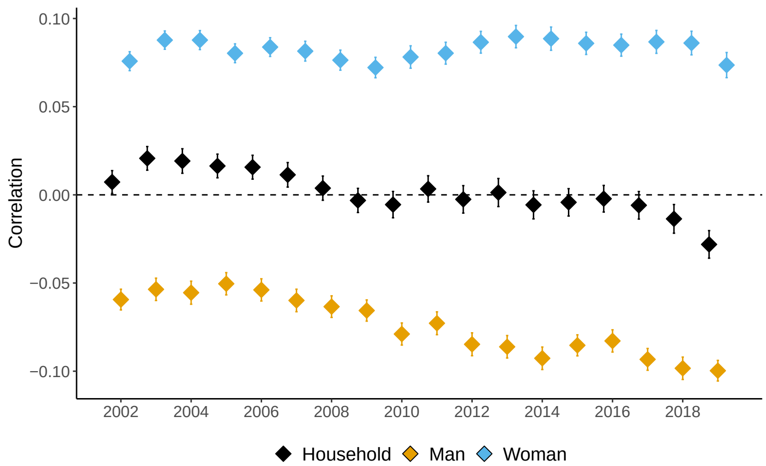


FIGURE B.7: Degree of assortative mating

This figure plots the correlation between the estimated income of women and the estimated income of their partners. For each year, we regress the logarithm of the estimated income of women on the logarithm of the estimated income of their partners. We present the coefficients from that regression along with a 95 confidence interval.

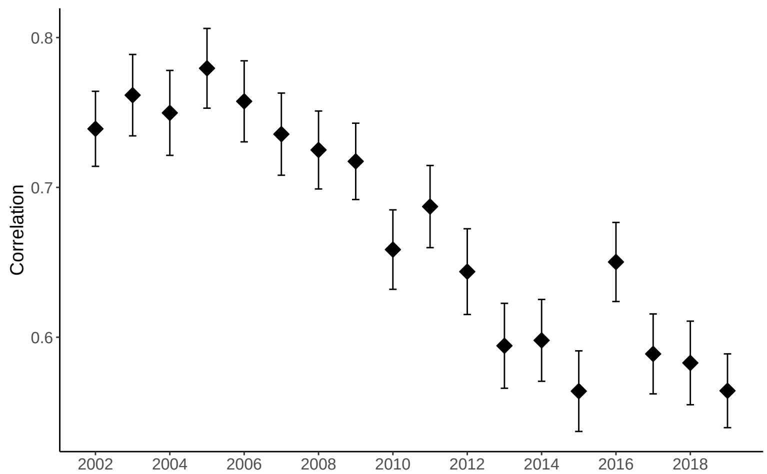
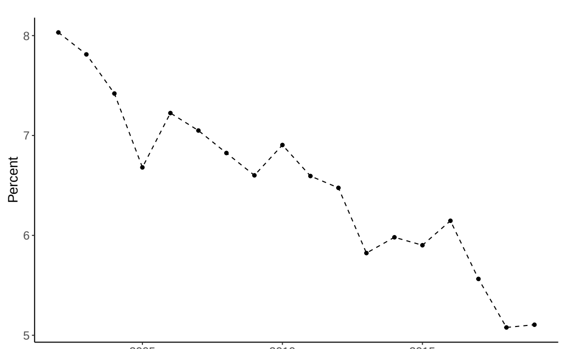


FIGURE B.8: Probability of having a child

This figure plots the probability that a woman has a child in a given year. In panel (a), we present the probability of having had a child using our synthetic household data. In panel (b), we present the probability of having had a child using aggregate data where we divide the number of births by the total number of women in the population.

(a) Synthetic households



(b) Aggregate data

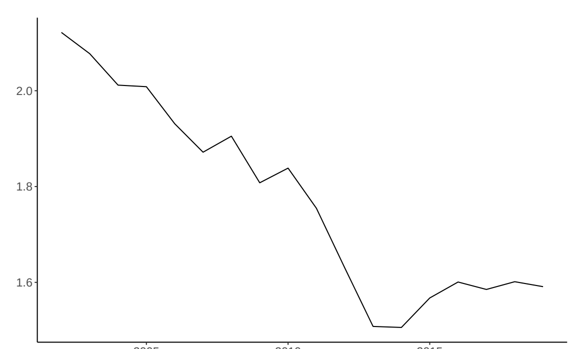
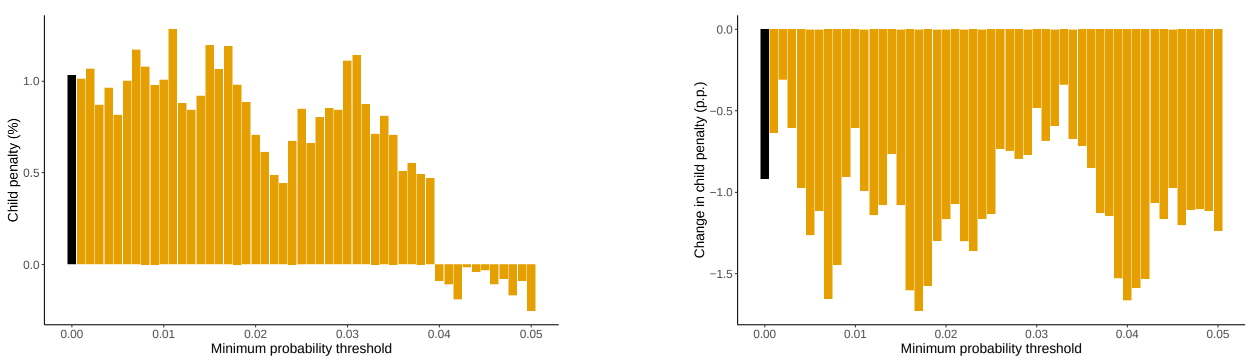


FIGURE B.9: Child penalty - monthly wages

This figure presents the results of estimation equation (4) on our data set between 2004 and 2012, using different thresholds in the probability of having a child to define treatment (having a child). The outcome variable is the logarithm of the monthly wage. We estimate (4) separately for men and women. The regression includes worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a 3rd degree polynominal on age and a 3rd degree polynominal on tenure at the current place of employment. For each individual, we define treatment as having had their first child. The event time is the year in which the individual has their first child. We include a set of coefficients γ_m^g, where $g \in \{\text{men}, \text{women}\}$, which multiply an indicator variable which takes the value of one if the individual is m periods away from the time of treatment. We use $m \neq -2$ as the excluded period. In panel (a), we present our estimates for the child penalty, which is defined as $\sum_{m\geq 0}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}}) - \sum_{m\leq -1}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}})$ as in equation (5). In panel (b), we also present our estimate for the change in the child penalty, which is defined as $\sum_{m\geq 0}(\delta_m^{\text{women}} - \delta_m^{\text{men}}) - \sum_{m\leq -1}(\delta_m^{\text{women}} - \delta_m^{\text{men}})$ as in equation (6). In both plots, the black bar represents the baseline case where we define treatment as having a stricly positive probability of having a child.

(a) Before introduction of shared parental leave

(b) Change with introduction of shared parental leave



C Model

C.1 Model with separation

We now present a version of the model in Section 3 which features exogenous separation. The goal of this model is to consider an environment in which individuals care about their individual human capital beyond its effect on δ.

There is a single household that lives for two periods. The first period is identical to the model we described in Section 3. In the second period, the household separates with probability θ. If the household does not separate, the second period is a repetition of the first period - the household inherits the choice of δ and just chooses consumption. As household income will be identical in the second period, the choice of consumption is the same as in the first period. If there is separation, each individual becomes single. They inherit the post-childcare wage of the first period and, as they do not have savings, this determines their wage. Individuals also inherit the childcare share of the first period.

We assume the household solves the problem jointly in the first period. Therefore, the household solves the following problem:

$$
\begin{aligned}
&\max_{c_m, c_f, \delta} \mu \left[u(c_m) + \alpha_m v(1-\delta)\right] + (1-\mu)\left[u(c_f) + \alpha_f v(\delta)\right] \\
&\quad + \beta(1-\theta)\left\{\mu\left[u(c_m) + \alpha_m v(1-\delta)\right] + (1-\mu)\left[u(c_f) + \alpha_f v(\delta)\right]\right\} \\
&\quad + \beta\theta\left\{\mu\left[u(H(w_m, 1-\delta)) + \alpha_m v(1-\delta)\right] + (1-\mu)\left[u(H(w_f, \delta)) + \alpha_f v(\delta)\right]\right\} \\
&\text{s. to} \\
&c_m + c_f = (1+\gamma)\mathcal{W} \\
&\delta \in [0, 1] \\
&\mathcal{W} \equiv H(w_m, 1-\delta) + H(w_f, \delta),
\end{aligned}
$$

and so the individual levels of human capital enter the problem of the household directly.

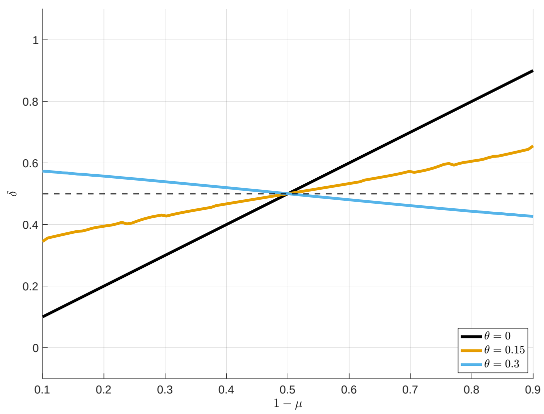
In this model, if θ is large enough, a woman with a large Pareto weight will wish to take on a lower share of childcare in order to hedge against the possibility of separation. To see this we solve the model for different levels of $1-\mu$ conditional on various levels of θ. We also solve the model for different human capital ratios. We present the results of this exercise in Figure C.1.

Note that, for low levels of θ, we recover the results in our baseline model - women with a high Pareto weight obtain a larger share of childcare duties and women with a higher human capital obtain a lower share of childcare duties. However, when the prob-

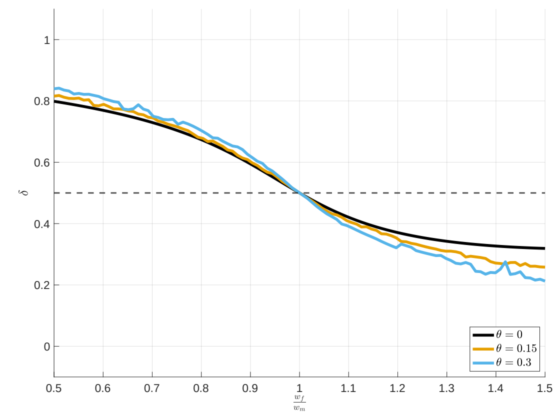
FIGURE C.1: Allocation of childcare to women in a model with separation

This figure presents the optimal allocation of childcare duties to women. We consider three levels for θ: 0, 0.15, and 0.3. In panel (a), we present the optimal allocation of childcare duties to women as a function of the Pareto weight of women. In panel (b), we present the optimal allocation of childcare duties to women as a function of the relative human capital of women.

(a) Role of Pareto weights



(b) Role of human capital



ability of separation is high, women with a high Pareto weight will choose a lower share of childcare duties in order to hedge against the possibility of separation. However, even for high values of θ, it is still true that more productive women spend less time with their children.

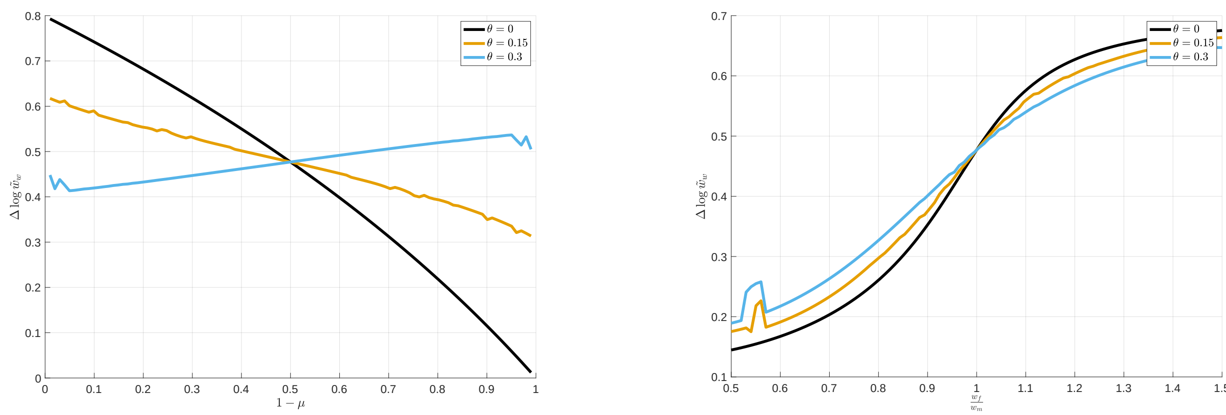
We can also present the effects of the introduction of shared parental leave in this model by looking at the wage increases experienced by women as a function of their Pareto weight and their relative human capital. We present the results of this exercise in Figure C.2.

For low values of θ, we still conclude that our empirical results can only be explained by the household income channel because, as the Pareto weight of the woman increases, the wage increase is lower. However, if θ is large enough, we now observe a positive relation between the wage increase of women and their Pareto weight as these woman obtain a lower share of childcare duties. However, even in this case, the household income channel is still present as more productive women observe a larger increase in wages. Therefore, if θ is large, we cannot distinguish between the two channels in the data.

FIGURE C.2: Effect on women's wages in a model with separation

This Figure presents the change in the logarithm of women's wages after the introduction of shared parental leave. We consider three cases: (1) $\theta = 0$, (2) $\theta = 0.15$, and (3) $\theta = 0.3$. In panel (a), we vary the Pareto weight of women $1 - \mu$ while assuming $w_f = w_m$. In panel (b), we vary the relative wage of women while assuming $\mu = 0.5$.

(a) Role of Pareto weights (b) Role of human capital



C.2 Proofs

C.2.1 Proof of Proposition 1

Using the budget constraint and the definition of $\mathcal{W}$, we can rewrite the problem of the household as

$$\max_{c_m, \delta} \mu \left\{ (c_m) + \alpha_m v(1-\delta) \right\} + (1-\mu) \left\{ \left((1+\gamma) H(w_m, 1-\delta) + (1+\gamma) H(w_f, \delta) - c_m \right) + \alpha_f v(\delta) \right\},$$

and the first order condition with respect to δ is given by

$$\mu \alpha_m v'(1-\delta) = (1-\mu) \left\{ (1+\gamma) \left(H_2(w_f, \delta) - H_2(w_m, 1-\delta) \right) + \alpha_f v'(\delta) \right\}.$$

Now, suppose that $\alpha_m = 0$. In this case, the first order condition can be rewritten as

$$\alpha_f v'(\delta) = (1+\gamma) \left(H_2(w_m, 1-\delta) - H_2(w_m, \delta) \right),$$

as we wanted to show. Note that this expression does not depend on the Pareto weights.

D Effect on relative wages of women

FIGURE D.1: Effect on wages of women relative to men - several specifications

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present results for five specifications: (I) including year and worker fixed effects, (II) including worker and profession-year fixed effects, (III) including worker and sector-year fixed effects, (IV) including worker and education-year fixed effects, and (V) including worker and occupation-year fixed effects. We define occupation as a pair profession-sector. Specification (V) is our main specification, which we present in Figure 8. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. We also present 95 percent confidence intervals.

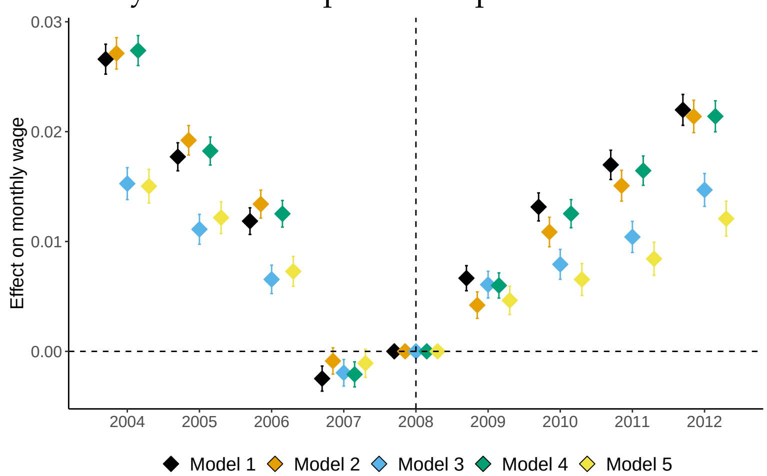


FIGURE D.2: Effect on hours worked of women relative to men

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of total hours worked in a month, including overtime. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

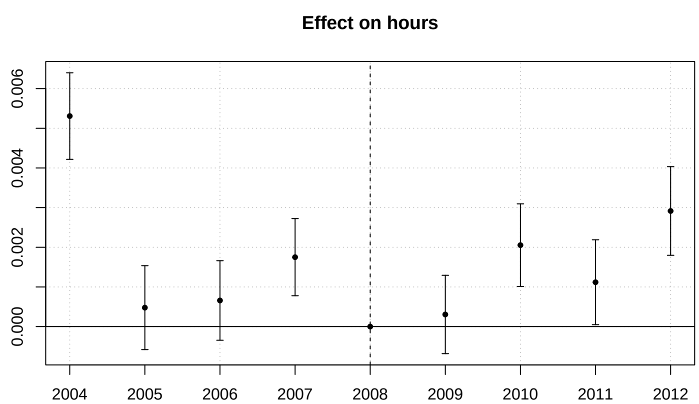


FIGURE D.3: Effect on hourly wages of women relative to men

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker or the logarithm of the hourly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

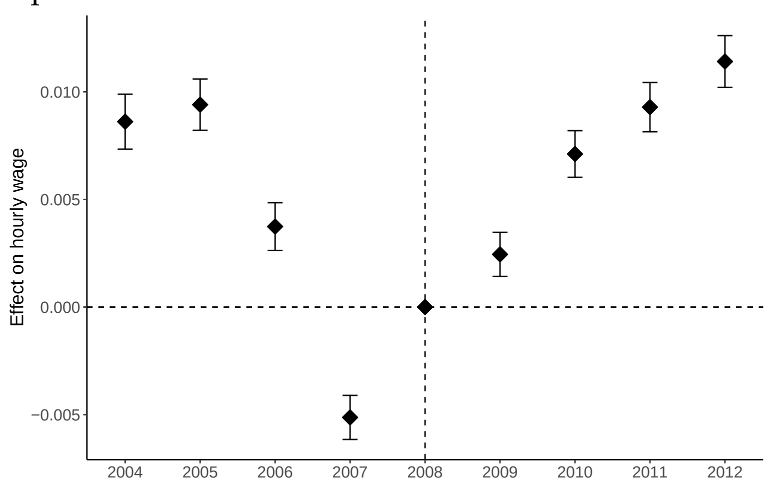


FIGURE D.4: Effect on hours worked of women relative to men - decomposition by sectors

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of total hours worked in a month, including overtime. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. To compute sector greediness, we regress the logarithm of the monthly wage on a 4th degree polynominal of age, educational attainment fixed effects, year fixed effects, occupation-gender fixed effects, and the interaction between the logarithm of total hours worked (including overtime) and an occupation fixed effect, using data from 2004 and 2008, following Goldin (2014). Our measure of greediness is the coefficient associated with the interaction between the occupation fixed effect and the logarithm of hours worked. We define a sector as greedy if its greediness is above the median. We then estimate equation 1 on three samples: (1) using all observations, (2) using observations for greedy sectors, and (3) using observations for non-greedy sectors. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

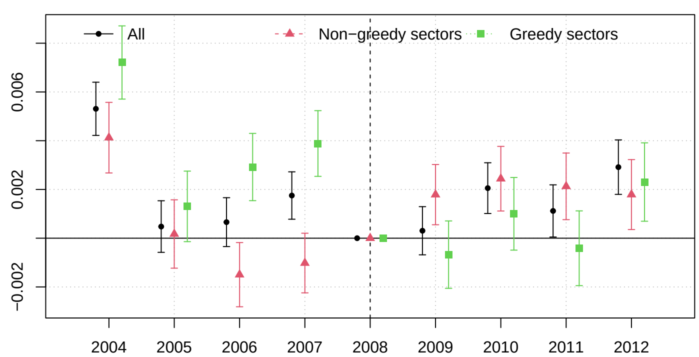


FIGURE D.5: Effect on wages of women relative to men - role of educational attainment

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. We estimate equation 8 for four samples: (1) using all observations, (2) using only observations for workers with less than a high-school degree, (3) using only observations for workers with a high-school degree, and (4) using only observations for workers with a college degree. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

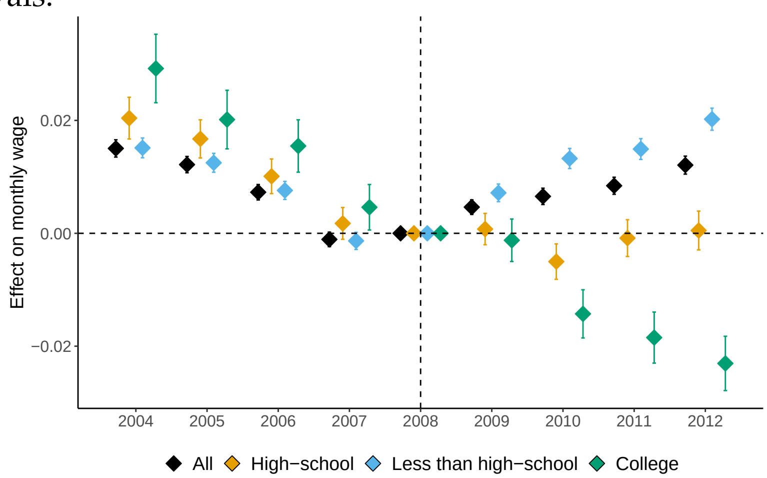


FIGURE D.6: Effect on wages of women relative to men - role of hierarchical position

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. We estimate equation 8 for three samples: (1) using all observations, (2) using only observations for workers which occupy managerial positions, and (3) using only observations for workers which do not occupy managerial positions. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

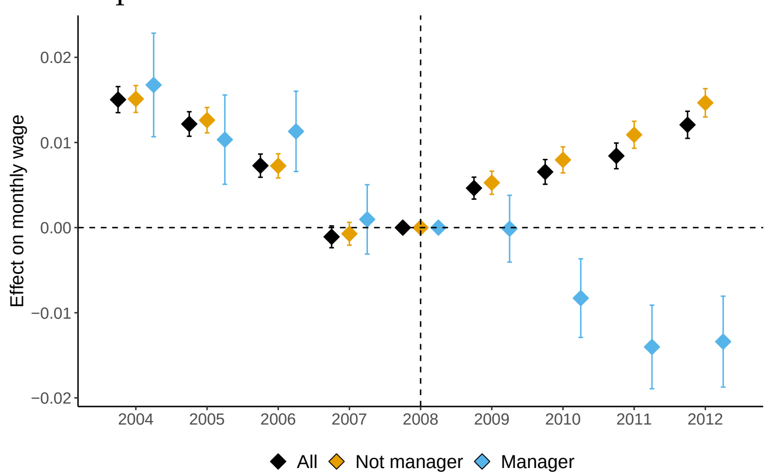


FIGURE D.7: Effect on wages of women relative to men - role of new hires

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. We estimate equation 8 for three samples: (1) using all observations, (2) using only observations for new hires, and (3) using only observations for incumbent workers. Errors are clustered at the worker level. We also present 95 percent confidence intervals.

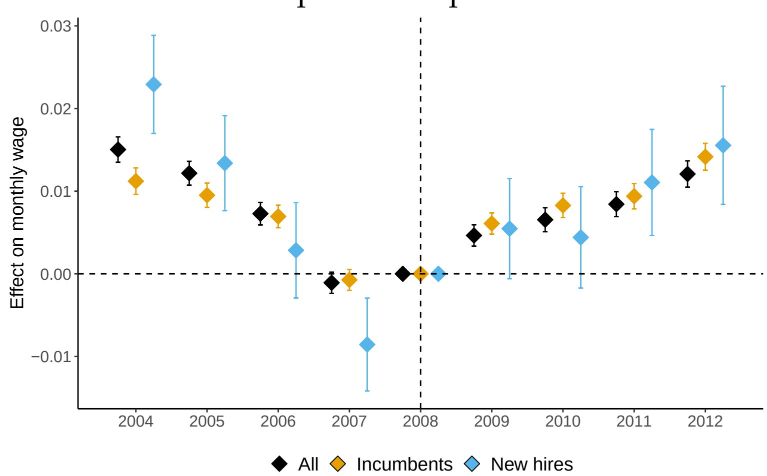


FIGURE D.8: Effect on wages of women relative to men - role of wage levels

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. For each occupation, we compute the average monthly wage in 2008. We then split occupations into four quartiles using the average monthly wage in 2008. We estimate equation 8 for five samples: (1) using all observations, (2) using only observations for occupations in the first quartile, (3) using only observations for occupations in the second quartile, (4) using only observations in the third quartile, and (5) using only observations in the fourth quartile. We also present 95 percent confidence intervals.

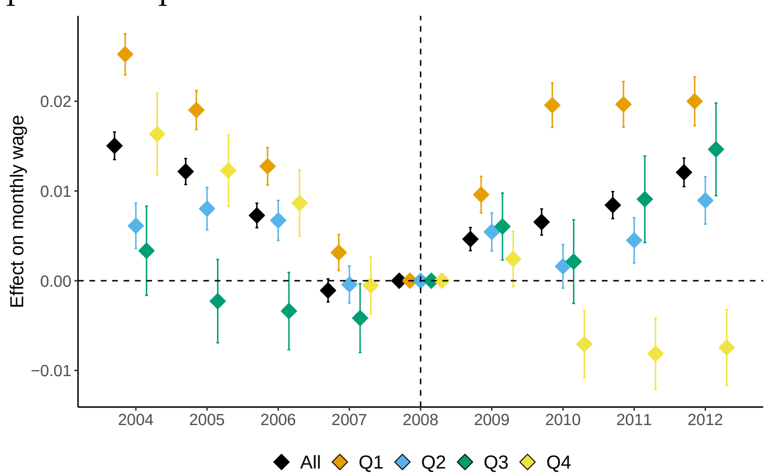
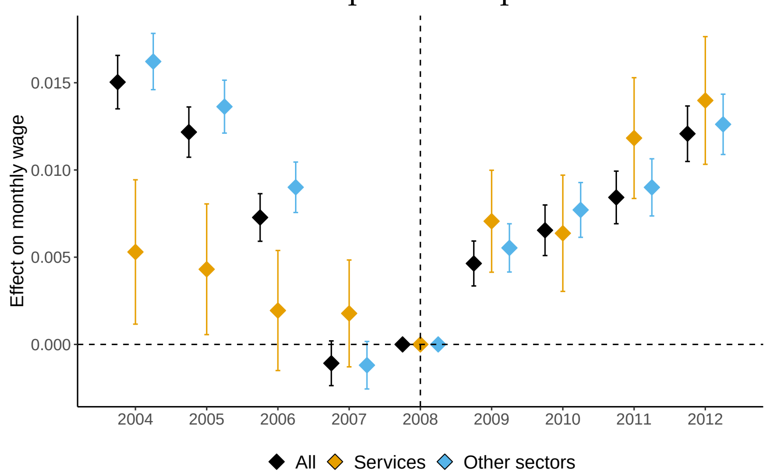


FIGURE D.9: Effect on wages of women relative to men - role of services

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We present estimates for the average treatment effect on women relative to men. We use the year 2008 as the excluded year. We estimate equation 8 for three samples: (1) using all observations, (2) using only observations for service sectors, and (3) using only observations for non-service sectors. Errors are clustered at the worker level. We also present 95 percent confidence intervals.



D.1 Addressing pretrends

In an event study regression, the estimated coefficients can be decomposed as

$$\gamma_t = \tau_t + \delta_t,$$

where γ_t is the coefficient we estimate in equation (2). According to this decomposition, as shown in Rambachan and Roth (2023), the coefficient can be decomposed as the sum of two components: (1) the treatment effects τ_t, and (2) a nontreatment differential trend δ_t. Under the usual assumption of no-anticipation, $\tau_t = 0$ for $t < 2009$. Therefore, we can only identify the nontreatment trends separately for $t < 2009$. This is the standard identification challenge in an event study. The usual assumption is the parallel trends assumption, under which $\delta_t = \delta = 0$. This assumption provides us both with the identification of τ_t and with a test for $\delta = 0$, using the nontreatment trends for the period before the introduction of shared parental leave.

However, it is possible to deviate from the parallel trends assumption in settings where the assumption may be too restrictive. In Figure X, we show that wage differences between men and women are time-varying. Moreover, as there are causes of these wage differences other than childcare activities, there is no reason to believe that the parallel trends assumption should hold.

There are several possible alternatives to the parallel trends assumption. A possible solution is to assume a functional form for δ_t. For example, we could assume a linear trend for δ_t, which would then allows us to point-identify the treatment effects. This method is similar to a detrending of the data like the one used in Goodman-Bacon (2018). Another possibility is to make minimal assumptions for nontreatment trends as in Manski and Pepper (2018) or Rambachan and Roth (2023). This second method will, in general, not allow us to obtain point identification of the nontreatment trends and the treatment effects. We will adopt this second method as it allows us to show how our results vary with different assumptions. We will consider two classes of assumptions as in Rambachan and Roth (2023): relative magnitude restrictions and smoothness restrictions. Moreover, we will also be able to construct confidence sets on treatment effects using the methods developed in Rambachan and Roth (2023).

Relative magnitude restrictions. The first assumption we make is that the confounding factors which produce non-parallel trends in the post-treatment periods are not too much larger in magnitude than the confounding factors in the pre-treatment periods. This is the assumption used in Manski and Pepper (2018) and formalized in Rambachan and Roth

(2023). Under this assumption, the identification set for nontreatment trends is given by

$$\Delta^{\mathrm{RM}}(\bar{M}) \equiv \left\{ \delta : t \geq 2009, |\delta_{t+1} - \delta_t| \leq \bar{M} \cdot \max_{s<2009} |\delta_{s+1} - \delta_s| \right\}, \tag{D.1}$$

where $\Delta^{\mathrm{RM}}(\bar{M})$ bounds the maximum post-treatment violation of parallel trends between consecutive periods by $\bar{M}$ times the maximum pre-treatment violation of parallel trends. This assumption is particularly appealing in our setting because we can think of it as bounding other causes of fluctuations in the wage gap using the pre-treatment trends. Moreover, we can show robustness of our findings to different values of $\bar{M}$. In Figure D.10, we present confidence sets for the treatment effect for the year 2012 (relative to 2008) under different values for $\bar{M}$.

We find that, for relative magnitudes which are not larger than 30 percent, we still recover a positive and statistically significant effect on the relative wages of women after the introduction of shared parental leave. Note that the relative magnitudes assumption we describe in equation (D.1) does not restrict the sign of the discrete analogue of the first derivative and so this method allows for reversals in the pre-treatment trend we observe in Figure 8. If $\bar{M}$ is larger than 30 percent, our estimates are no longer statistically significant.

Smoothness restrictions. A second class of assumptions deals with potential confounders which come from secular trends which evolve smoothly over time. For example, researchers often impose group-specific linear trends as Wolfers (2006). However, this assumption can be relaxed as we can impose only that the differential trends evolve smoothly over time by bounding the extent to which its slope may change across consecutive periods. This can be formalized as

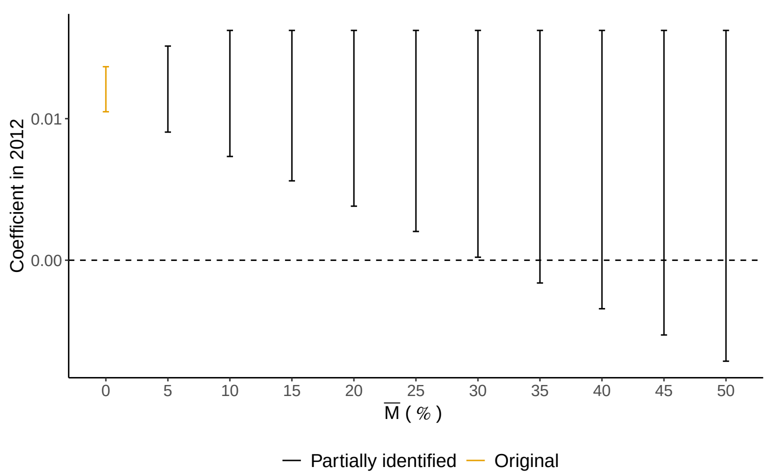
$$\Delta^{\mathrm{SD}}(M) \equiv \{\delta : |(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leq M\}, \tag{D.2}$$

where the parameter M governs the amount by which the slope of δ can change between consecutive periods, and thus bounds the discrete analogue of the second derivative. In contrast, the relative magnitude restriction in (D.1) bounds the discrete analogue of the first derivative. In the special case where $M = 0$, $\Delta^{\mathrm{SD}}(0)$ requires that the difference in trends be exactly linear, which corresponds with the assumption underlying the parametric linear specification common in applied work. We present our estimates for the treatment effect in 2012 under this class of assumptions in Figure D.11.

We find that, if we assume that nontreatment trends follow a linear trend as it is com-

FIGURE D.10: Effect on wages of women relative to men - imposing relative magnitude restrictions

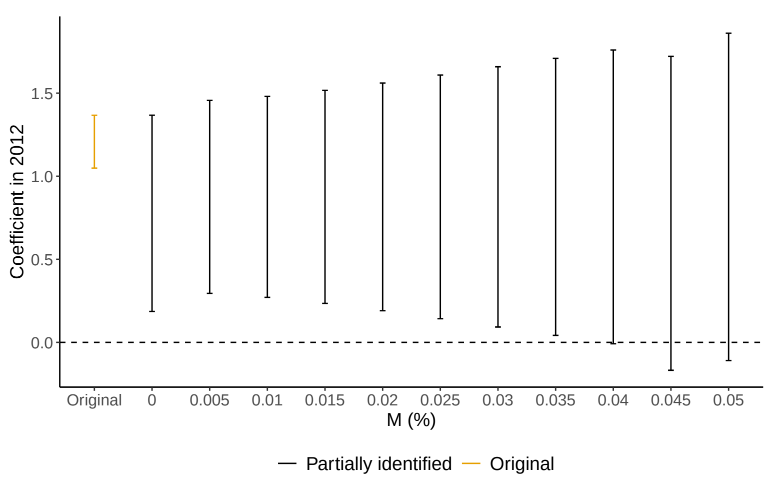
This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We use the year 2008 as the excluded year. This two-way fixed effects regression allows us to estimate the sum of the nontreatment trends and the treatment effects. We imposed relative magnitude restrictions of the form $\Delta^{RM}(\bar{M}) \equiv \{\delta : t \geq 2009, |\delta_{t+1} - \delta_t| \leq \bar{M} \cdot \max_{s<2009} |\delta_{s+1} - \delta_s|\}$, where δ_t denote nontreatment trends, as in Rambachan and Roth (2023). Using this identified set, we then build an identified set for the treatment effects, which are defined as the difference between the coefficients we estimate in the two-way fixed effect regression and the nontreatment trends δ_t. We present 95 percent confidence sets for the treatment effects for the year 2012 for different values of $\bar{M}$. When $\bar{M} = 0$, we recover the parallel trends assumption.



mon in the literature, we still recover a positive and statistically significant treatment effect for the year 2012. Moreover, if we allow for small but reasonable deviations from linearity, we still recover treatment effects which are statistically different from zero.

FIGURE D.11: Effect on wages of women relative to men - imposing smoothness restrictions

This figure presents the results of estimating equation (2) on a sample of 3,970,338 workers between 2004 and 2012. The outcome variable is the logarithm of the monthly wage for each worker. We use women as the treated group and men as the control group. We include worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a third degree polynominal on worker age and a third degree polynominal on worker tenure at the current place of employment. We use the year 2008 as the excluded year. This two-way fixed effects regression allows us to estimate the sum of the nontreatment trends and the treatment effects. We imposed smoothness restrictions of the form $\Delta^{\text{SD}}(M) \equiv \{\delta : |(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leq M\}$, where δ_t denote nontreatment trends, as in Rambachan and Roth (2023). Using this identified set, we then build an identified set for the treatment effects, which are defined as the difference between the coefficients we estimate in the two-way fixed effect regression and the nontreatment trends δ_t. We present 95 percent confidence sets for the treatment effects for the year 2012 for different values of M. When $M = 0$, we impose linear trends.

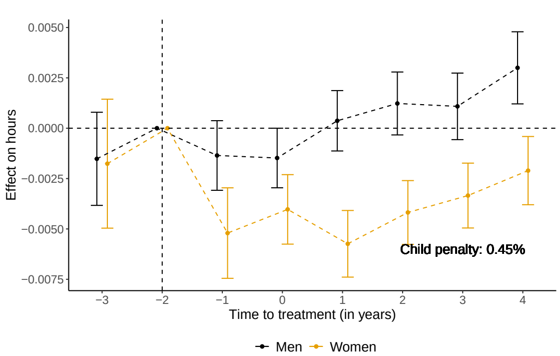


E Additional results for child penalty

FIGURE E.1: Child penalty - monthly hours worked

This figure presents the results of estimation equation (4) on our data set between 2004 and 2012. The outcome variable is the logarithm of the monthly hours worked, including overtime. We estimate (4) separately for men and women. The regression includes worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a 3rd degree polynominal on age and a 3rd degree polynominal on tenure at the current place of employment. For each individual, we define treatment as having had their first child. The event time is the year in which the individual has their first child. We include a set of coefficients γ_m^g, where $g \in \{\text{men, women}\}$, which multiply an indicator variable which takes the value of one if the individual is m periods away from the time of treatment. We use $m \neq -2$ as the excluded period. We present estimates for these coefficients for men and women, which estimate the treatment effect of the birth of the first child before the introduction of shared parental leave, in panel (a). In panel (a), we also present our estimate for the child penalty, which is defined as $\sum_{m\geq 0}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}}) - \sum_{m\leq -1}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}})$ as in equation (5). We also include a set of coefficients δ_m^g, where $g \in \{\text{men, women}\}$, which multiply an indicator variable which takes the value of one if the individual is m periods away from the time of treatment and an indicator which takes the value of one if the year is after 2009, and zero if otherwise. We present estimates for these coefficients for men and women, which estimate the change in the treatment effect of the birth of the first child with the introduction of shared parental leave, in panel (b). In panel (b), we also present our estimate for the change in the child penalty, which is defined as $\sum_{m\geq 0}(\delta_m^{\text{women}} - \delta_m^{\text{men}}) - \sum_{m\leq -1}(\delta_m^{\text{women}} - \delta_m^{\text{men}})$ as in equation (6). We cluster errors at the worker level and also present 95 percent confidence intervals.

(a) Before introduction of shared parental leave



(b) Change with introduction of shared parental leave

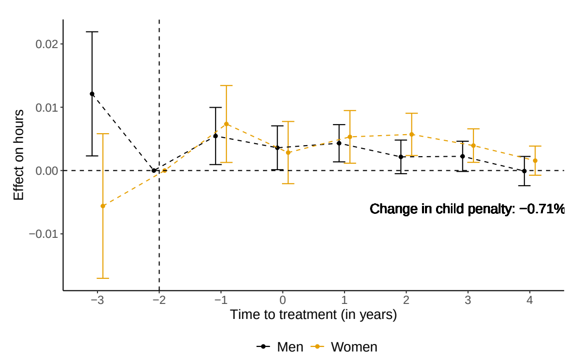
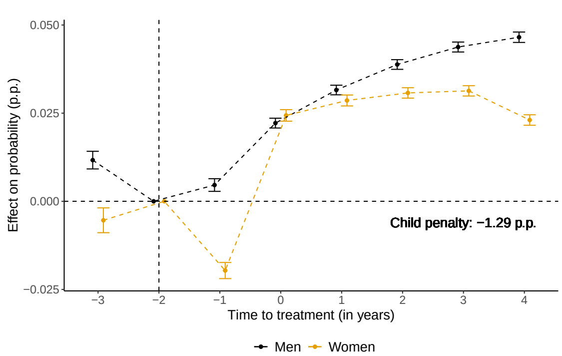


FIGURE E.2: Child penalty - employment

This figure presents the results of estimation equation (4) on our data set between 2004 and 2012. The outcome variable is an indicator variable which takes the value of one if the individual is employed, and zero if otherwise. We estimate (4) separately for men and women. The regression includes worker fixed effects, occupation-year fixed effects, and a vector of controls which includes a 3rd degree polynominal on age and a 3rd degree polynominal on tenure at the current place of employment. For each individual, we define treatment as having had their first child. The event time is the year in which the individual has their first child. We include a set of coefficients γ_m^g, where $g \in \{\text{men, women}\}$, which multiply an indicator variable which takes the value of one if the individual is m periods away from the time of treatment. We use $m \neq -2$ as the excluded period. We present estimates for these coefficients for men and women, which estimate the treatment effect of the birth of the first child before the introduction of shared parental leave, in panel (a). In panel (a), we also present our estimate for the child penalty, which is defined as $\sum_{m\geq 0}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}}) - \sum_{m\leq -1}(\gamma_m^{\text{women}} - \gamma_m^{\text{men}})$ as in equation (5). We also include a set of coefficients δ_m^g, where $g \in \{\text{men, women}\}$, which multiply an indicator variable which takes the value of one if the individual is m periods away from the time of treatment and an indicator which takes the value of one if the year is after 2009, and zero if otherwise. We present estimates for these coefficients for men and women, which estimate the change in the treatment effect of the birth of the first child with the introduction of shared parental leave, in panel (b). In panel (b), we also present our estimate for the change in the child penalty, which is defined as $\sum_{m\geq 0}(\delta_m^{\text{women}} - \delta_m^{\text{men}}) - \sum_{m\leq -1}(\delta_m^{\text{women}} - \delta_m^{\text{men}})$ as in equation (6). We cluster errors at the worker level and also present 95 percent confidence intervals.

(a) Before introduction of shared parental leave



(b) Change with introduction of shared parental leave