Occupational Heterogeneity of Child Penalty in the United States

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Most recent draft here.

Abstract

I investigate how parenthood reshapes employment patterns across occupations and how this occupational heterogeneity contributes to earning disparities. Using a novel rotating panel approach to estimating child penalties, I document that both women and men lose jobs in some occupations and gain jobs in others after becoming parents. These occupational changes induced by parenthood explain one-third of the income penalty for women, most of the income penalty for men, and most of the wage penalty for both genders. For mothers, these occupational changes are partly driven by preferences for reduced working hours.

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1 Introduction

Since the 1970s, the gender gap in earnings and employment in the United States has narrowed substantially (Goldin, 2024). Nevertheless, significant disparities persist: women participate less in the labor force than men, and when employed, earn lower wages. An extensive literature examines the causes of these persistent gaps. One prominent strand emphasizes occupational segregation, which stands as the single largest factor accounting for the gender pay gap (Blau and Kahn, 2017). Concurrently, a growing literature highlights the importance of child penalties: the differential impact of parenthood on labor market outcomes between women and men. In developed countries, these penalties explain a substantial portion of gender inequality in the labor markets (Kleven et al., 2019a,b, 2021; Cortés and Pan, 2023). However, the intersection between parenthood and occupational choices remains underexplored. This paper addresses this critical gap by examining how parenthood reshapes employment patterns across occupations and how this occupational heterogeneity contributes to earnings disparities. I document that both women and men lose jobs in some occupations and gain jobs in others after becoming parents. These occupational changes induced by parenthood explain one-third of the income penalty for women, most of the income penalty for men, and most of the wage penalty for both genders. For mothers, these occupational changes are partly driven by preferences for reduced working hours.

One challenge to investigating occupational heterogeneity of child penalties is that the vast majority of work on the child penalty uses panel data, which typically do not have enough observations to recover precise estimates of child penalties by sub-groups like occupation. I take advantage of the rotating panels in the Current Population Survey (CPS) – which are two orders of magnitude larger than panel datasets usually used to study the child penalty, such as the National Longitudinal Survey of Youth (NLSY) and the Panel Study of Income Dynamics (PSID) (Kleven et al., 2019b; Bang, 2022; Cortés and Pan, 2023; Kleven, 2025) – to estimate the effects of having children on the probability of being employed in different occupations. My methodological contribution is showing how to use rotating panel datasets, which are both more prevalent and often substantially larger than panel datasets (Donovan et al., 2023), to estimate child penalties with greater precision and without additional assumptions.

I document two new findings on the incidence of child employment penalties. First, the almost zero effect of fatherhood on men, which has been well established in the literature, hides considerable heterogeneity. While men's employment probability decreases by 1.36 percentage points (pp) or by 27% in computer & mathematics, it increases by 1.91 pp (29%) in construction. The positive and negative effects of fatherhood across occupations offset each other, leading to an aggregate estimate of almost zero in the literature. Second, women lose jobs in most occupations but also gain jobs in others. For example, mothers become 4.1 pp (36%) less likely to work in management, whereas their probability of working in personal care and services increases by 0.5 pp (22%). Employment declines in any occupation could represent people who were working in that occupation no longer working or switching to other occupations. However, employment gains in some occupations imply that parenthood definitely causes both genders to change occupations.

Occupational heterogeneity in employment penalties significantly drives child income and wage penalties. Between 1990–2009, motherhood reduced women's income by approximately 23% conditional on working, with 4% attributable to occupational changes. By the 2010s, this penalty decreased to 20%, while income loss from occupational changes increased to 6%. Men experienced virtually no income penalty in the 1990s but gradually incurred larger losses, reaching 9% by the 2010s, almost entirely attributable to fatherhood-induced occupational changes. Both the income penalty for men and its occupational change mechanism represent novel findings, likely because this is a recent phenomenon undetectable in NLSY and PSID. Notably, the occupational change component affects both genders similarly and does not contribute to the child-induced income gap between men and women, which is primarily driven by within-occupation differences.

Similar patterns emerge in wage penalties. Women consistently incurred a 9% wage penalty conditional on working throughout 1990–2019, with half attributable to occupational re-sorting. Men's wage penalties increased over time, driven primarily by parenthood-induced occupational changes. By the 2010s, both genders faced comparable wage penalties, effectively eliminating parenthood's contribution to the wage gap. This finding extends the literature showing that gender wage gaps expand throughout the lifecycle (Blau and Kahn, 2017). The conventional reasoning that parenthood contributes to these widening gaps, as parenthood rates increase with age, was historically accurate but no longer holds. Importantly, the gender wage gap persists but is now equivalent between individuals with and without children.

Lastly, I analyze which occupational attributes explain the heterogeneity in child penalties. The availability of part-time positions enables mothers to remain employed after childbirth and does not affect fathers, thus reducing inequality in employment penalties. This suggests that for mothers, parenthood-induced occupational changes are partly driven by preferences for reduced working hours. These results contribute to the literature studying the role of temporal flexibility in gender inequality (Bertrand et al., 2010; Goldin, 2014; Goldin and Katz, 2016; Bütikofer et al., 2018; Ciasullo and Uccioli, 2023) by demonstrating that flexibility to reduce hours is an important dimension of occupational attributes that affects gender inequality in the labor market.[1] Mothers tend to sort into occupations with part-time options, which ultimately contributes to the pay gap, as these positions typically pay lower wages (Hirsch, 2005).

This paper makes a methodological contribution to the literature on child penalties (Angrist and Evans, 1998; Angelov et al., 2016; Kleven et al., 2019a,b; Cortés and Pan, 2023). Most related to my paper, Kleven (2025) develops a new approach for estimating child penalties using cross-sectional data. His method employs exact matching to predict who will eventually have a child among those without children and uses them as a control group. This pseudo-panel method needs stronger assumptions for identification due to the matching step. However, it enables studying child penalties with precision since large cross-sectional data are widely available.[2] In contrast, the actual

[1] A similar connection between work hours and flexibility was first made by Flabbi and Moro (2012), who defined flexibility as having a part-time job in the context of a search model.

[2] Using this method, Kleven (2025) studies heterogeneity in child penalties across the US states, and Kleven et al. (2024a) study heterogeneity across the globe.

control group is observed in rotating panels. Hence, my method does not need any more identifying assumptions other than the standard *random timing of first child*. Our methods can thus be seen as alternatives with different use cases. When rotating panel data are available, researchers can use my approach to explore child penalties across demographics and job characteristics without using more assumptions. Conversely, when only cross-sectional data are available or when existing panel or rotating panel datasets are too small, researchers can use Kleven (2025)'s methodology to study child penalties.

2 Data

My primary dataset is the basic monthly files of CPS downloaded from IPUMS between the years 1977–2019. I focus on employment, income, and wages. Parental status is determined using the age of the oldest child in the household, with event time assigned based on the child's age. Following convention, I restrict the sample to parents who had their first child between ages 25–45 and include only individuals appearing in both rounds to ensure comparable treatment and control groups.[3] The final dataset includes 474,034 unique parents and 3,078,598 person-month observations.

I validate my rotating-sample design by comparing CPS results with identical specifications using NLSY and PSID data (3,649 and 3,443 unique parents, respectively). These comparisons focus solely on weekly employment outcomes, as income measures differ across datasets (monthly CPS collects weekly income, while NLSY and PSID collect annual income).

For occupational analysis, I examine employment effects across 22 main occupation groups following Standard Occupational Classification (SOC) guidelines (excluding military occupations). I measure temporal flexibility in the main text using part-time availability, which I define as the proportion of workers employed part-time in each occupation. In the Online Appendix, I also explore hour-flexibility, the proportion of workers who can vary their start/end times, calculated from the CPS Work Schedules Supplement (1.6 million observations across 12 years, 1976-2004), and the ratio of women in each occupation. All metrics are calculated using individuals without children, though robustness checks (shown in the Online Appendix) confirm similar results when using all workers or pre-child observations of eventual parents.

[3]CPS follows a 4-8-4 rotation pattern: households are interviewed for four consecutive months, rotate out of the sample for the next eight months, and are then interviewed again for the next four months before rotating out of the sample for good.

3 Identification

3.1 Event study approach

The event-study approach of estimating child penalty uses panel data on men and women who become parents. I run the following specification separately for men and women,

$$Y^g_{iat} = \sum_{j \neq -1} \beta^g_j \Delta D_{i,t-j} + \mu^g_a + \lambda^g_t + \epsilon^g_{it}, \tag{1}$$

where Y^g_{iat} is the outcome for individual i of age a and gender $g = w, m$ at event time t, $\Delta D_{i,t} = 1$ if individual i had first child in time t, μ_a and λ_t are age and year fixed effects that non-parametrically control for lifecycle trends and time trends. The identification assumption is that controlling for age and calendar time fixed effects, the timing of having children is exogenous to potential labor market outcomes of parents. Consistent with this assumption, the event study approach shows little to no pre-trends in the five years before having a child for both men and women (Kleven et al., 2019a). This approach has been widely used to study the effect of the first child on parents' labor market outcomes (Kleven et al., 2019b, 2021; Cortés and Pan, 2023; Kleven et al., 2024b).

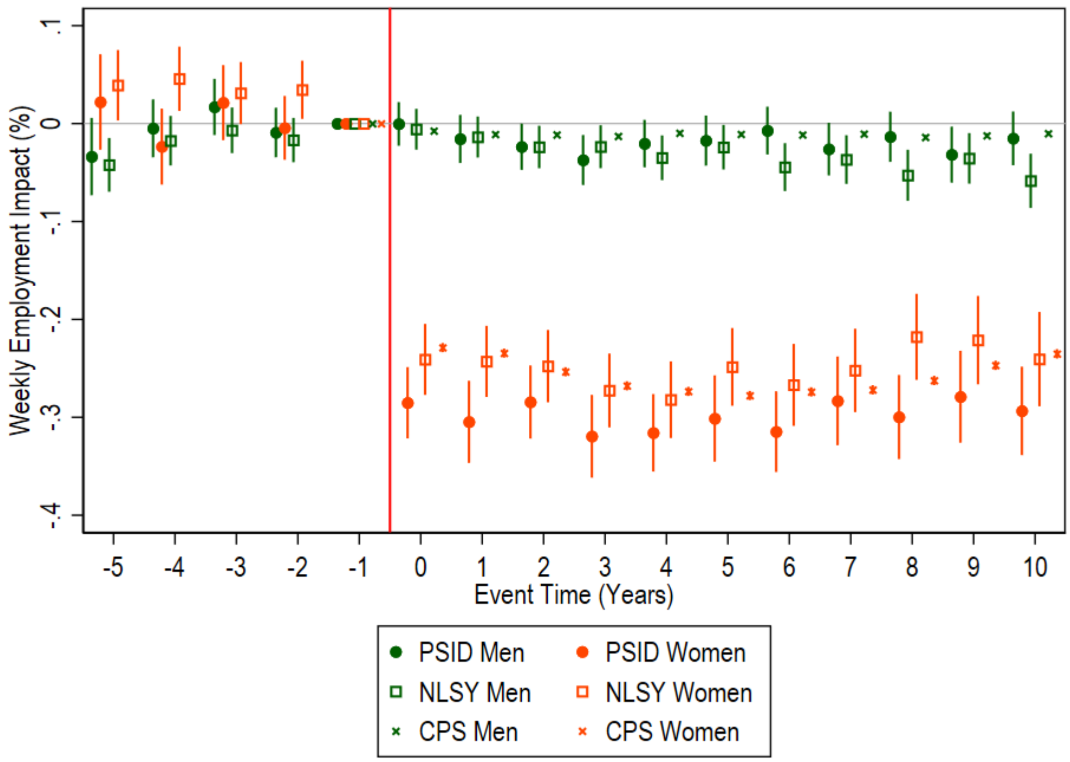
My methodological innovation is predicated on the already established absence of pre-trends in the data, which simplifies the data requirements to only the year before the first child ($t = -1$). Rotating panels like the CPS, where individuals are interviewed in two rounds with a significant time interval between the rounds (eight months in the case of the CPS), are then sufficient to estimate equation 1. Consider an individual who is not a parent during the first round but becomes a parent during the second round of interviews. In the first round, we observe this person at least eight months before having a child, which is enough to index them as $t = -1$.[4]

To validate this approach, I compare the CPS estimates with the NLSY and PSID estimates, the two panel datasets available in the US that have been used to study child penalties. Figure 1 displays the results. The point estimates using CPS are highly comparable to those using PSID and NLSY, providing strong credibility for this method. On average, I find that women lose more jobs than men by 29% using PSID and 24% using NLSY. Using CPS reveals an estimate between the two, a child penalty of 25%. The main difference is that the estimates using CPS are much more precise than those using NLSY and PSID. In fact, the 95% confidence intervals of the CPS estimates are practically invisible in the figure.

I use the event study approach only to validate the CPS as an applicable dataset to study the child penalty. After validation, I continue by estimating occupation-specific child penalties.

[4]Using the "panel" nature of CPS is not novel in the Economics literature, going as far back as Poterba and Summers (1986). However, how the CPS can be used to estimate child penalties has not been shown before. This is likely because the literature on child penalty focuses on long-term effects (as far as ten years after the first child), while the same individual is only observed for sixteen months in CPS. My method enables me to study the long-term effects precisely because it does not exploit changes in the outcome within a person. To estimate the child penalty, we only need to observe $t = -1$ for *some*, not all people in the data.

Figure 1: CPS vs NLSY and PSID



Estimates come from the regression equation $Y_{iat}^g = \sum_{j \neq -1} \beta_j^g \Delta D_{i,t-j} + \mu_a^g + \lambda_t^g + \epsilon_{it}^g$, where Y_{iat}^g is the outcome for individual i of age a and gender $g = w, m$ at event time t, $\Delta D_{i,t} = 1$ if individual i had first child in time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Percentage estimates are obtained by dividing the level estimates β_j^g with predicted outcome absent child effects. The difference in child penalties across men and women (which is often referred to as *the* child penalty in the literature) is estimated as 24% using NLSY, 29% using PSID, and 25% using CPS.

3.2 Differences in means design

To understand how people's occupational choice is impacted by having children, I employ the following design:

$$Employment_{o,iat}^g = \beta_o^g D_{it} + \mu_{o,a}^g + \lambda_{o,t}^g + \epsilon_{o,it}^g, \tag{2}$$

where $Employment_{o,iat}^g$ is a dummy equal to one if individual i of gender g is employed in occupation o at time t. For each gender $g \in \{m, w\}$, I run different regressions using the same sample, where I change only the outcome (if the person i is working as a manager, $Employment_{o,iat}^g$ equals one only for the occupation $o = Manager$, and zero otherwise). To obtain percentage estimates, I divide the level estimates $\hat{\beta}_o^g$ with the predicted outcome absent child effects:

$$\hat{P}_o^g = \frac{\hat{\beta}_o^g}{E\left[\widetilde{Y}_{o,iat}^g\right]}, \tag{3}$$

where $\widetilde{Y}_{o,iat}$ is the predicted employment rate when omitting the contribution of the child effect.[5] The coefficient estimates $\hat{\beta}_o^g$ and $\hat{P}_o^g$ should be interpreted as the effects of having children on the probability of being employed in occupation o for gender g. For example, I find that the probability of working as an engineer decreases by 50% for women. This is the net effect of three separate forces: (i) engineers leaving employment after having children, (ii) engineers transitioning into different occupations, and (iii) people from other occupations and unemployment transitioning into engineering. The lack of a large panel data limits separately identifying these forces, which remains an open question for future work.

Throughout the rest of the paper, I refer to these effects interchangeably as occupational heterogeneity and occupational change. This should not be confused with heterogeneous treatment effects, which would apply only to the first of the three forces I described.

I use the occupation-gender specific child penalty estimates $\hat{\beta}_o^g$ in two ways. First, I compare their magnitudes to document how the effects of having children differ across occupations. Second, I regress these estimates on occupational characteristics, such as part-time availability, to analyze what attributes can explain this heterogeneity. To obtain inference that is robust to multiple hypothesis testing, I employ two additional checks in the Online Appendix. First, I employ the Bonferroni correction to adjust the standard errors of the $\hat{\beta}_o^g$ estimates in a conservative way. Second, I employ the Empirical Bayes shrinkage, which takes into account that occupation-specific child penalties are noisily estimated. All the results presented in the paper remain robust to these adjustments. For simplicity, I present the OLS estimates in the main text and present the robustness checks in the Online Appendix.

4 Results

4.1 Child penalties across occupations

Figure 2 displays child penalty estimates for men and women across the 22 major occupational groups, excluding military service, sorted by the penalty's impact on women. Figure 2a illustrates the effect of children on employment probabilities within each occupation, revealing considerable heterogeneity in child penalties for both genders. There are three main takeaways from this figure.

First, women experience statistically significant employment declines in 14 out of 22 occupations, no significant change in employment probability in 5 occupations, and significant increases in 3 occupations. For example, women become 4.1 pp less likely to work in management, whereas their probability of working in personal care and services increases by 0.5 pp.

Second, the almost zero employment penalty of fatherhood, which has been well documented in the literature, masks a significant heterogeneity across occupations. Men experience statistically significant decreases in employment probability in 10 occupations, no significant change in 5 occu-

[5] An alternative to this linear model would be to use a conditional logit model. Given that there is no integration constraint in the design as the sum of occupations equals the employment probability, which is free to change, assuming a linear probability model should be innocuous.

pations, and significant increases in 7 occupations. For instance, fathers are 1.4 pp less likely to work in computer and mathematics, whereas they are 1.9 pp more likely to work in construction and transportation compared to similar men without children.

Third, the heterogeneity across occupations in child penalties for women is greater than the largest within-occupation difference between genders, highlighting the magnitude of the occupational heterogeneity in child penalties. The most notable within-occupation disparity in levels occurs in management roles, where the likelihood of women holding a management position declines by 4.1 pp, compared to a mere 0.7 pp decline for men, resulting in a 3.4 pp difference in the within-occupation penalties between genders. In comparison, the largest difference in penalties for women across occupations is between personal care and management. In the former, women's employment probability increases by 0.5 pp, leading to a 4.6 pp difference in treatment effects.[6]

Figure 2b presents the employment penalties in percentages. The results remain similar. There is significant heterogeneity in child penalties across occupations for both genders. In percentages, women lose most jobs in engineering, legal, and social sciences while gaining jobs in personal care, food preparation, and cleaning.

These results remain robust to using more conservative confidence intervals or shrinkage estimators. Appendix Figure B.1 plots the updated confidence intervals after applying the Bonferroni correction. Since the parameters are precisely estimated, this conservative correction does not alter the inference. Moreover, Figure C.1 displays the estimates based on Empirical Bayes shrinkage. OLS and Empirical Bayes estimates are highly similar: I document economically meaningful differences in child penalties across occupations for both men and women.[7] Overall, the heterogeneous effects of children on employment probabilities in different occupations are not driven by wrong inference due to multiple hypothesis testing or small samples.

In addition, I study the heterogeneity of child penalties in income and hours, conditional on working. Figure A.1 in the Online Appendix shows that women lose income and hours in nearly all occupations, while men lose income and hours only in a few occupations, if any. Women's penalties differ largely across occupations, while men's penalties do not vary in economically meaningful amounts. Based on Empirical Bayes estimates shown in Figure C.2, women lose 37% income in personal care while losing only 9% income in computer & mathematics.[8] As I show in the next section, this disparity can be explained by personal care occupations allowing mothers to reduce their working hours by working part-time, while computer & mathematics related occupations not providing this flexibility.

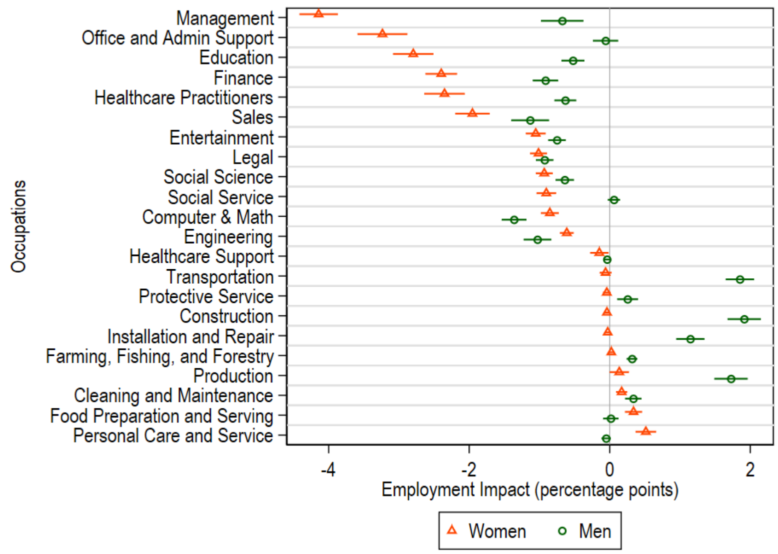
What should we infer from the differences in child penalties in levels and percentages, as de-

[6] The heterogeneity across occupations in child penalties for men is almost equal to the largest within-occupation difference between genders. While men's employment probability decreases by 1.4 pp in computer & mathematics, it increases by 1.9 pp in construction, creating a 3.3 pp difference across occupations.

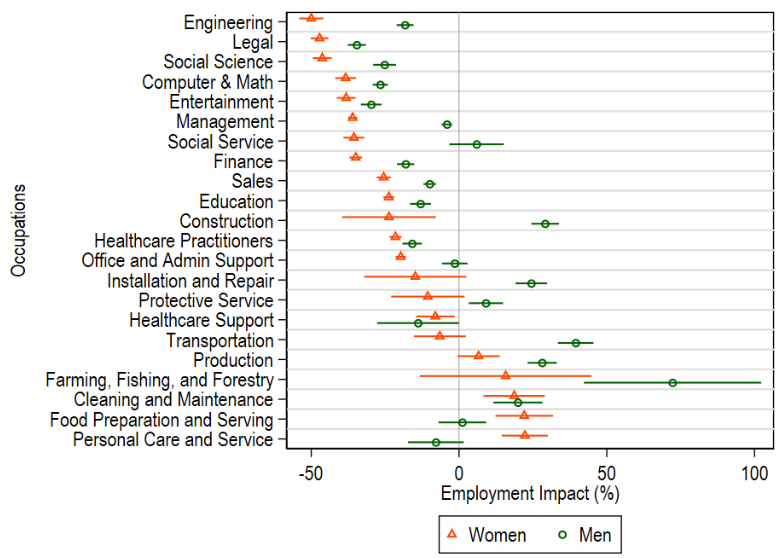
[7] Empirical Bayes shrinkage does not move the OLS estimates by much (except for farming) because the data have high signal-to-noise ratio: the standard deviation in the OLS estimates across occupations is substantially higher than the standard errors of the OLS estimates for each occupation. The Online Appendix Section C provides an in-depth explanation for the interested reader.

[8] Empirical Bayes estimates are more reliable than OLS estimates for income and hour penalties because the OLS estimates are imprecise for these outcomes.

Figure 2: Occupational Heterogeneity in Child Employment Penalty



(a) Employment Penalties (in levels)



(b) Employment Penalties (in percentages)

Note: Results on employment come from the regression $Employment^g_{o,iat} = \beta^g_o D_{it} + \mu^g_{o,a} + \lambda^g_{o,t} + \epsilon^g_{o,it}$, where $Employment^g_{o,iat}$ is a dummy equaling to one if individual i of gender g is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Superscripts mean sample restrictions. For each gender $g \in \{m, w\}$, 22 separate regressions are run for each occupation-specific outcome. Robust standard errors are used to calculate the 95% confidence intervals. To obtain percentage estimates, I divide the level estimates β^g_o with predicted outcome absent child effects: $\hat{P}^g_o = \frac{\hat{\beta}^g_o}{E[\widetilde{Y}^g_{o,iat}]}$, where $\widetilde{Y}_{o,iat}$ is the predicted employment rate when omitting the contribution of the child effect. Standard errors for percentage effects are calculated using the Delta method. 95% confidence intervals are plotted.

picted in Figures 2a and 2b? The employment penalty in levels impacts occupations' role in the gender gap in earnings. For example, management is the third highest-paid occupation during the sample period. Since women lose more management jobs than men after becoming parents, women end up losing more income, increasing the gender gap in earnings. I explore this mechanism in Section 4.2. The percentage penalty helps uncover which occupational attributes can explain employment penalties. For example, women are over-represented in education and under-represented in construction, leading to vastly different employment penalties in levels. However, women leave these occupations at similar rates after becoming mothers, which is informative about which occupational attributes can explain these penalties. I explore this in Section 4.3.

4.2 Effect of occupational sorting on the income penalty

This section studies the effects of child-induced occupational change on the child income and wage penalties. Specifically, I estimate the child penalty on men and women, with and without controlling for 22 major occupation groups, as outlined in equation 4. β_1^g captures the average effect of having the first child on income or wage, conditional on employment.[9] β_2^g captures the *within occupation* child penalty, accounting for the occupational change that both men and women undergo after having children. The differential $\beta_1^g - \beta_2^g$ highlights the influence of these occupational changes on the overall income and wage penalties, indicating how much of the penalty is due to changes in occupations versus income and wage losses within the same occupation,

$$
\begin{aligned}
ln(Y_{iat}^g) &= \beta_1^g D_{it} + \mu_a^g + \lambda_t^g + \epsilon_{it}^g, \\
ln(Y_{iat}^g) &= \beta_2^g D_{it} + \mu_a^g + \lambda_t^g + \theta^g Occ22_i + \eta_{it}^g.
\end{aligned}
\tag{4}
$$

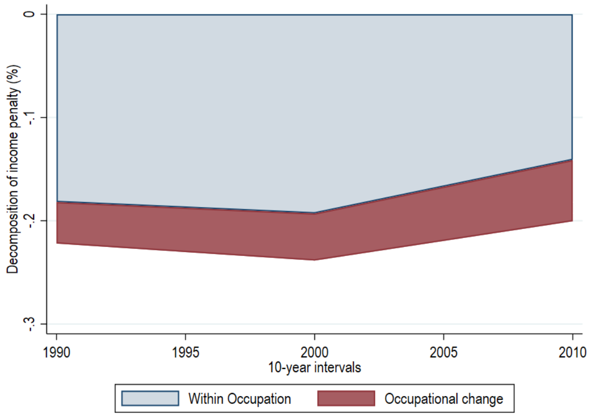
To assess the evolution of these dynamics over time, I calculate these penalties in 10-year intervals from 1990 to 2019. This longitudinal approach allows me to observe how child penalties and the role of occupational adjustments have shifted over the past three decades.

Figure 3a illustrates the evolving dynamics of the income penalty associated with motherhood. My analysis reveals several key trends. In the 1990s and 2000s, mothers faced an income penalty of approximately 23%. This penalty has decreased to around 20% in the 2010s. Notably, parenthood-induced occupational change contributed around 4% in the 1990s, or about one-fifth of the income penalty. However, while the within-occupation component of the income penalty has decreased significantly, the occupational change component has increased to around 6%. Today, one-third of the income penalty for women comes from occupational change.

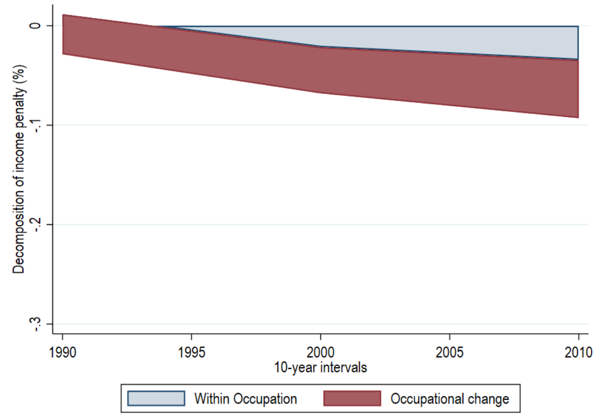
Figure 3b repeats this analysis for men. Interestingly, as women's income penalties decreased overtime, men's income penalties increased, from 3% in the 1990s, to 7% in 2000s and 9% in 2010s. Virtually, most of this income penalty can be attributed to the occupational change induced

[9] While this design faces potential bias from non-uniform employment exits across income and wage distributions, several factors support the reliability of my estimates. First, the minimal reduction in employment rates after fatherhood suggests that compositional biases are negligible at least for men. Second, the stability of women's employment penalty since the 1990s (Kleven, 2025) indicates that such biases would not significantly affect the temporal evolution of my estimates.

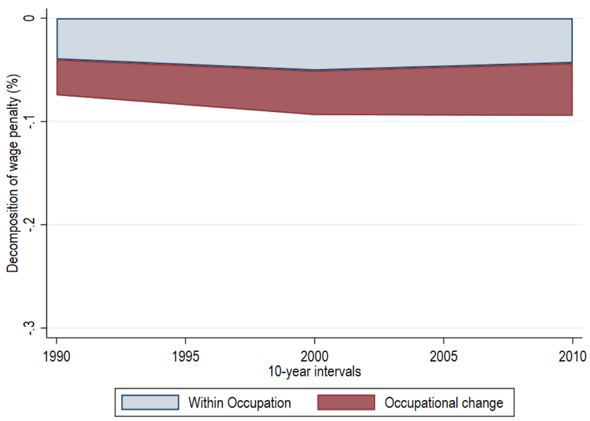
Figure 3: Decomposition of Income and Wage Penalties



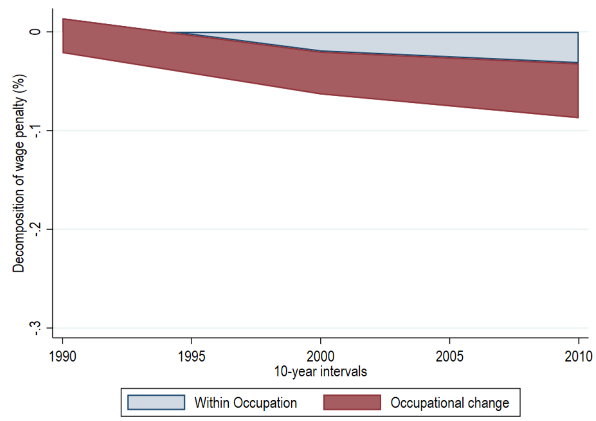
(a) Income penalty for women



(b) Income penalty for men



(c) Wage penalty for women



(d) Wage penalty for men

Note: Within occupation estimates come from the regression: $ln(Y^g_{iat}) = \beta^g_2 D_{it} + \mu^g_a + \lambda^g_t + \theta^g Occ22_i + \eta^g_{it}$, where $ln(Y^g_{iat})$ is the log-income or log-wage of individual i of age a at time t from gender g, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends, $Occ22_i$ is an occupation fixed effect. The "within-occupation" component of child penalty in percentage terms is then defined by $exp(\hat{\beta}_2) - 1$. To obtain the occupational change estimate, I first estimate the child penalty without controlling for occupations from the regression: $ln(Y^g_{iat}) = \beta^g_2 D_{it} + \mu^g_a + \lambda^g_t + \epsilon^g_{it}$. The child penalty that comes from occupational change in percentage terms is calculated by the difference between the two regression estimates: $\exp(\hat{\beta}^g_1) - exp(\hat{\beta}^g_2)$.

by parenthood.[10] Notably, the occupational change component does not lead to an income gap between men and women, as it affects both similarly. In other words, the child-induced income gap between men and women is primarily driven by within-occupation differences.

Figures 3c and 3d repeat this exercise for the wage penalty. The difference between the income and wage penalties is the change in hours. For example, while women incur an income penalty of approximately 20% in the sample period, they incur a wage penalty of around 9%, which implies

[10] One explanation of this increase is given by Appendix Figure A.2, which shows that the fatherhood employment penalty on computer & mathematics-related occupations has been increasing.

that their hours decrease by 11%. In contrast, men incur similar income and wage losses, which implies that they do not lower hours after fatherhood.[11]

This decomposition demonstrates that occupational heterogeneity in child penalties constitutes the primary driver of wage penalties across genders, as both men and women disproportionately exit higher-wage occupations after becoming parents. Remarkably, by the 2010s, wage penalties have converged between genders, a finding that extends the literature documenting that gender wage gaps expand throughout the lifecycle (Blau and Kahn, 2017). The conventional reasoning that parenthood contributes to these widening gaps, as parenthood rates increase with age, was historically accurate but no longer holds. My analysis reveals an unexpected mechanism: rather than women's penalties decreasing, men's penalties have increased substantially, effectively equalizing the impact of parenthood between genders.

These findings do not indicate the absence of a gender wage gap in the 2010s but rather that parenthood no longer contributes significantly to this disparity. Appendix Figure A.3 illustrates this shift by tracking the lifecycle evolution of gender wage gaps among both parents and non-parents within the sample of eventual parents. During the 1990s, the wage gap was consistently larger among parents than non-parents across all age cohorts, demonstrating parenthood's substantial role in gender wage inequality. However, in the 2010s this pattern disappeared for individuals aged 24–34, with parents and non-parents exhibiting statistically identical wage gaps, which explains why parenthood ceased to be a significant factor in wage disparities during this period.

In summary, Figure 3 reveals that occupational heterogeneity in child employment penalties is a major component of income and wage penalties for both genders. Both women and men experience higher exit rates from high-paying occupations relative to low-paying ones, resulting in substantial income and wage reductions. Additionally, my results indicate a structural change in the labor market: while women's income penalties have decreased from 1990s to 2010s, men's income and wage penalties have increased. Since 2010, parenthood no longer functions as a key determinant of the gender wage gap.

4.3 What explains the heterogeneity across occupations?

This section examines which occupational attributes can explain the heterogeneity of child penalties. I focus on part-time availability in the main text, as I find it to be the best explanatory factor. In the Online Appendix I show that other factors, such as the flexibility to determine when to begin and end the work day (hour flexibility hereafter) or the representation on women does not explain the differences between the genders.

I focus on the bivariate relationship between child penalties and part-time availability. Figure 4 shows the three scatterplots of child penalties (on women, men, and the difference in penalties between men and women) and part-time availability. Figure 4a shows that women lose most jobs in occupations with fewer part-time positions and gain jobs in occupations with more part-time

[11] This is also supported by the Appendix Figure A.1, which shows that motherhood reduces women's hours in every occupation, while fatherhood does not change men's hours in most occupations.

positions. For example, less than 5% of workers in management, finance, engineering and legal are part-time, and women lose most jobs relative to their baseline employment rates in these occupations. In contrast, personal care, cleaning, and food preparation are occupations with the highest rates of part-time workers, and women transition into these occupations after becoming mothers.

Figure 4b replicates this analysis on the employment penalties for men. I find no relationship between the fatherhood employment penalty and the availability of part-time work. Figure 4c replicates this analysis on the difference in penalties between men and women and documents that part-time availability is negatively correlated with the inequality-inducing part of child penalties. This is expected since women incur lower penalties in occupations that allow for part-time work, and men are unimpacted. Therefore, there is less inequality between men and women in child employment penalties in occupations with more part-time availability. These results remain robust to using Empirical Bayes estimates instead of OLS estimates, which are reported in Online Appendix Figure C.4. Women lose fewer jobs in occupations with greater part-time availability, while men are largely unaffected. Consequently, there is a smaller gender difference in job loss in occupations with more part-time availability.

Appendix Table A.1 extends this analysis through three dimensions: (1) reporting coefficient estimates from bivariate regressions of child penalties on occupational attributes, (2) expanding dependent variables to include both income and hours penalties, and (3) incorporating additional explanatory variables, specifically hour flexibility and women's representation. This expanded analysis yields two significant findings.

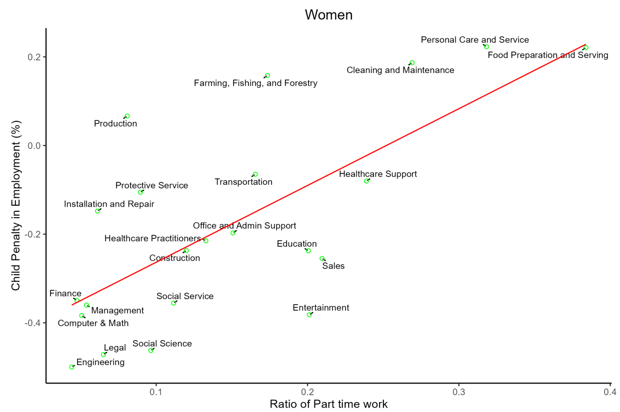
First, occupations with greater part-time availability exhibit larger reductions in women's income and hours worked, though effects on income show less statistical precision. This pattern suggests that part-time availability enables women to maintain employment while reducing hours. This dual effect highlights part-time work's paradoxical role: facilitating continued employment post-childbirth while simultaneously constraining income potential.[12]

Second, neither hour flexibility nor women's occupational representation explains gendered heterogeneity in child employment penalties across occupations. Both genders experience higher job losses in occupations offering greater hour flexibility, resulting in no significant relationship between flexibility and differences in penalties between men and women. Similarly, the proportion of women in an occupation is not correlated with motherhood's employment penalties.

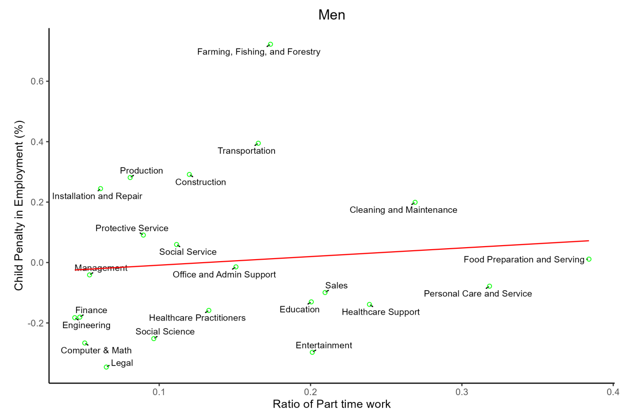
These findings have ambiguous policy implications. A revealed preference approach would conclude that women are better off in terms of welfare when there are part-time options. Otherwise, they would not sort into occupations with part-time positions after childbirth. However, in terms of gender inequality in the labor market, part-time work can increase or decrease the gender income gap. Imagine a model where workers choose between three options: no work, part-time work, and full-time work. My results indicate that women's preference towards part-time work increases, but

[12]Online Appendix Tables B.1 and B.2 show that these results remain robust to defining the explanatory variables using all workers and eventual parents the year before having children.

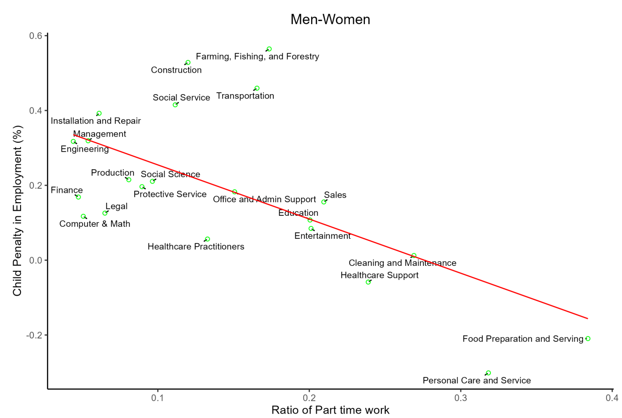
Figure 4: Occupation-level Child Penalties and Part-time Availability



(a) Motherhood penalty



(b) Fatherhood penalty



(c) Gender gap in child penalty

Notes: Part-time availability is calculated using the sample of all workers without kids in the CPS.

my results cannot say whether women would have remained outside of the labor force or worked full-time if part-time wasn't available. If women would have chosen full-time employment, part-time availability would actually *increase* income gaps.

5 Conclusion

This paper demonstrates how rotating panel datasets can be leveraged to estimate child penalties with greater precision and without requiring additional assumptions beyond the standard random timing of the first child. Using this method, I document that occupational segregation between genders, which is the single largest factor accounting for the gender pay gap (Blau and Kahn, 2017), is partly caused by parenthood. Both women and men lose jobs in some occupations and gain jobs in others after becoming parents. These occupational changes induced by parenthood explain one-third of the income penalty for women, most of the income penalty for men, and most of the wage penalty for both genders. For mothers, these occupational changes are partly driven by preferences for reduced working hours, as evidenced by their tendency to transition into occupations with greater part-time availability. Notably, while parenthood contributed to the gender wage gap in the 1990s and 2000s, it no longer does so in the 2010s. This is not because women incur lower wage penalties but because men incur higher penalties.

Several important questions emerge from these findings, which I leave for future work. First, occupational heterogeneity in child penalties incorporates three distinct mechanisms: differential employment exit rates across occupations, direct occupational changes, and transitions from non-employment into specific occupations. Future research with larger panel datasets could disentangle these mechanisms to provide a more nuanced understanding of parenthood's impact on occupational sorting.

Second, the contribution of occupational change to income and wage penalties has increased for both genders over time, even as women's overall income penalties have decreased. This suggests that while improvements have occurred within occupations, the negative impact of occupational re-sorting has intensified. Understanding the causes behind these opposing trends requires further investigation.

Third, the significant increase in men's income and wage penalties over the last twenty years represents a fundamental shift in how parenthood affects labor market outcomes. The causes of this shift, whether changing social norms, economic pressures, or policy environments, merit dedicated study.

Future research might also examine how emerging workplace trends, particularly remote work, affect child penalties. Since motherhood increases the preference for reduced working hours, likely due to women's caregiving roles, remote work flexibility might substitute for part-time arrangements and potentially reduce gender pay gaps by enabling mothers to maintain higher working hours. How this impacts the gender gap in the labor market and women's welfare are interesting avenues for future research.

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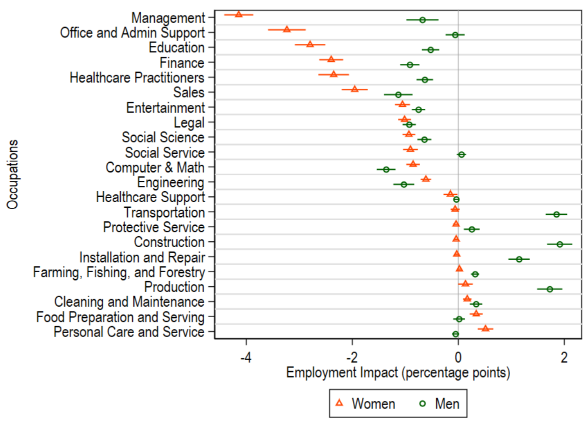
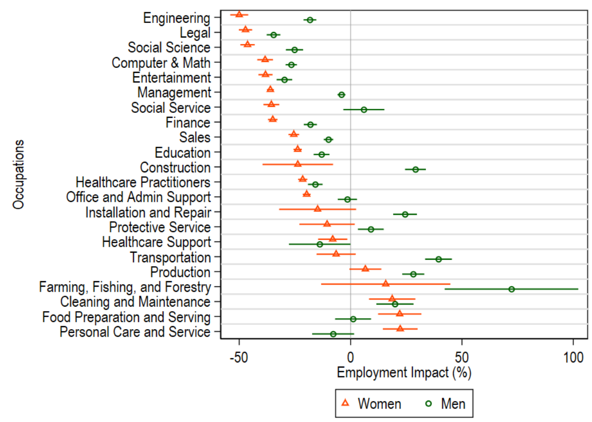
Online Appendix

A Additional Results

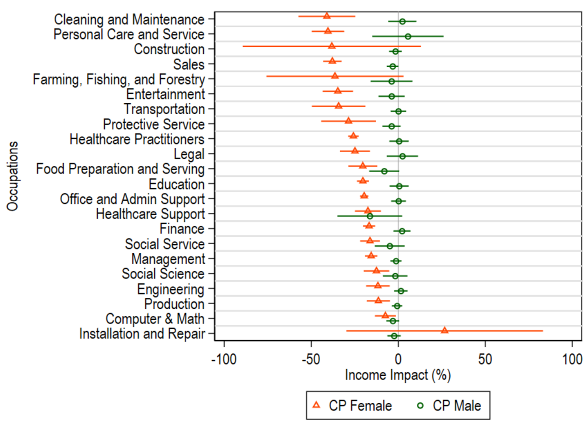
Figure A.1: Occupational Heterogeneity in Child Penalty



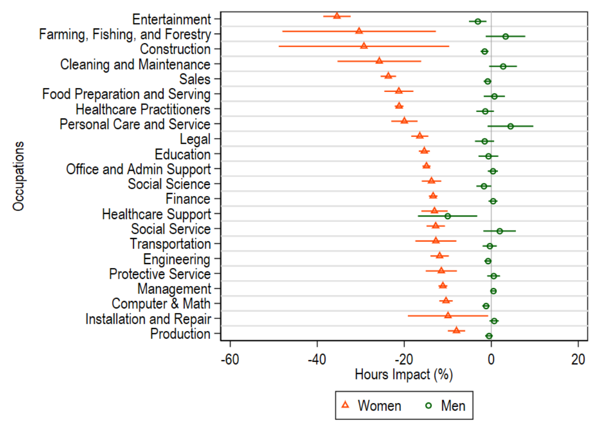
(a) Employment (in pp)



(b) Employment (in %)



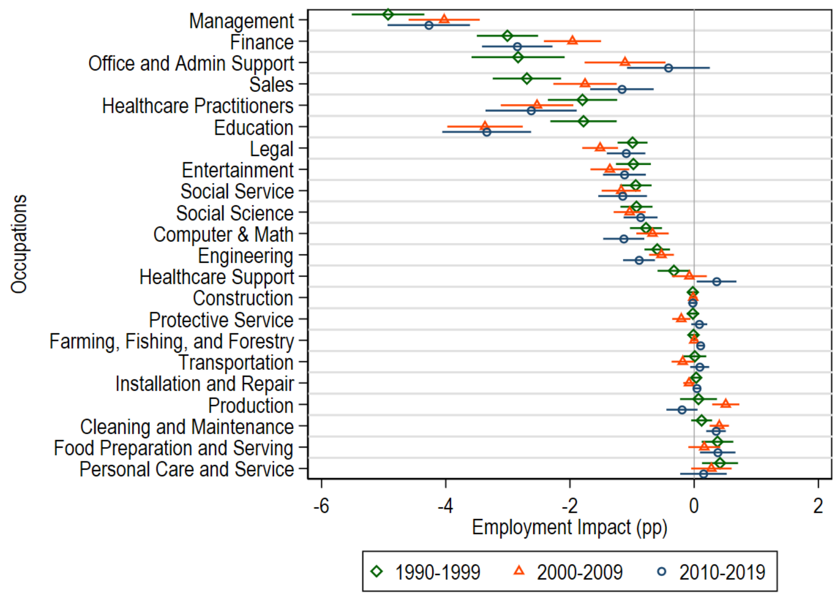
(c) Income (in %)



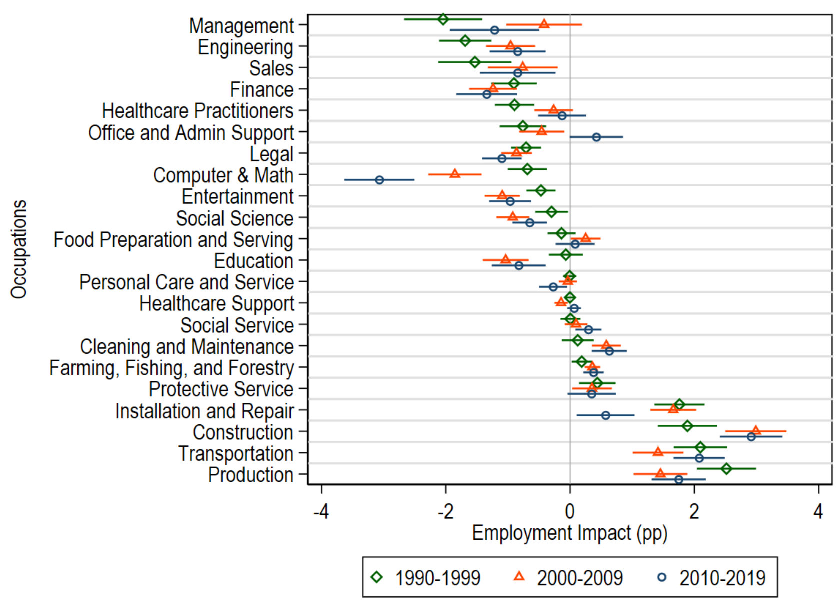
(d) Hours (in %)

Note: Results on employment come from the regression $Employment^g_{o,iat} = \beta^g_o D_{it} + \mu^g_{o,a} + \lambda^g_{o,t} + \epsilon^g_{o,it}$, where $Employment^g_{o,iat}$ is a dummy equaling to one if individual i of gender g is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Superscripts mean sample restrictions. For each gender $g \in \{m, w\}$, 22 separate regressions are run for each occupation-specific outcome. To obtain percentage estimates, I divide the level estimates β^g_o with predicted outcome absent child effects: $P^g_o = \frac{\hat{\beta}^g_o}{E[\widetilde{Y}^g_{o,iat}]}$, where $\widetilde{Y}_{o,iat}$ is the predicted employment rate when omitting the contribution of the child effect. Results on income and hours come from the regression $ln(Y^{o,g}_{iat}) = \gamma^{o,g} D_{it} + \mu^{o,g}_a + \lambda^{o,g}_t + \epsilon^{o,g}_{it}$, where the outcome is either the log income or the log hours worked of an individual i at time t. $\hat{\gamma}^{o,g}$ estimates come from 44 different samples for each occupation-gender combination. 95% Confidence intervals are plotted.

Figure A.2: Evolution of the Occupational Heterogeneity in Child Penalty



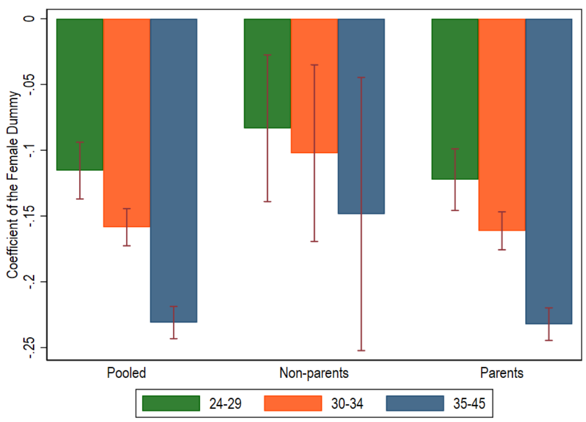
(a) Women



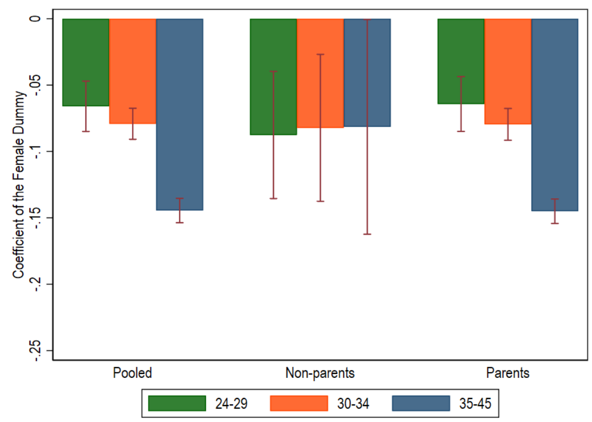
(b) Men

Note: Results on employment come from the regression $Employment^{g,Y}_{o,iat} = \beta^{g,Y}_o D_{it} + \mu^{g,Y}_{o,a} + \lambda^{g,Y}_{o,t} + \epsilon^{g,Y}_{o,it}$, where $Employment_{o,iat}$ is a dummy equaling to one if individual i is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Superscripts mean sample restrictions. For each gender $g \in \{m, w\}$ and decade $Y \in \{1990\text{-}1999, 2000\text{-}2009, 2010\text{-}2019\}$, 22 separate regressions are run for each occupation-specific outcome.

Figure A.3: Decomposition of the Gender Inequality in Wages



(a) 1990–1999



(b) 2010–2019

Note: This figure plots the coefficient estimate from the regression: $ln(wage)^s_{iat} = \beta^s Female^s_i + \mu^s_a + \lambda^s_t + \epsilon^s_{it}$, where $Female$ is a dummy variable, μ_a and λ_t are age and calendar year fixed effects, and superscript s denotes different samples. In particular, I separately estimate β in two decades, three age groups, and using parents and non-parents *within* the sample of eventual parents.

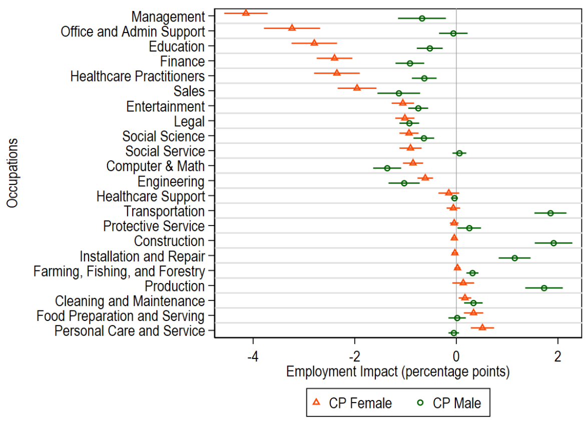
Table A.1: Correlates with Occupation-level Child Penalties
Sample: Workers without children

	Women			Men			Inequality: Men - Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Employment (in %)									
Hour flexibility	-2.024***			-2.220***			-0.196		
	(0.430)			(0.531)			(0.427)		
Share of part time		1.732***			0.285			-1.447***	
		(0.294)			(0.407)			(0.322)	
Share of women			0.005			-0.586***			-0.591***
			(0.171)			(0.179)			(0.142)
Panel B: Income									
Hour flexibility	0.148			0.070			-0.078		
	(0.460)			(0.123)			(0.502)		
Share of part time		-0.808**			-0.106			0.701	
		(0.373)			(0.133)			(0.458)	
Share of women			-0.092			-0.024			0.068
			(0.183)			(0.056)			(0.204)
Panel C: Hours									
Hour flexibility	0.018			0.001			-0.016		
	(0.234)			(0.074)			(0.250)		
Share of part time		-0.399***			0.023			0.423***	
		(0.121)			(0.071)			(0.138)	
Share of women			0.005			-0.028			-0.032
			(0.065)			(0.036)			(0.080)

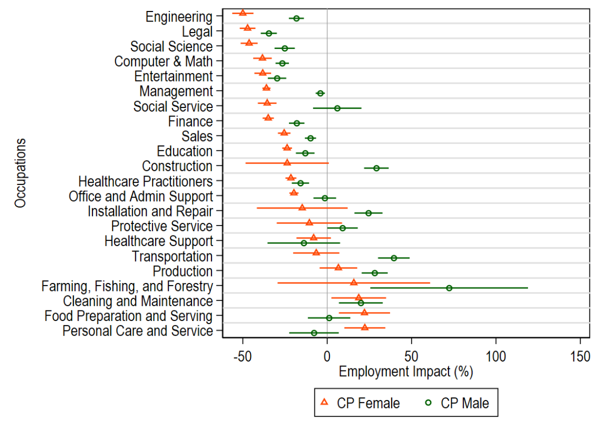
*Notes: Each column shows the estimates of a regression $\hat{\beta}_o = \gamma_0 + \delta W_o + \eta_o$, where $\hat{\beta}_o$ represents the estimated occupation-specific child penalty, and W_o is a vector of occupation attributes, which are (1) the ratio of people who state that their job provides hour flexibility, (2) the ratio of women, and (3) the ratio of part time workers. These attributes are calculated using the sample of all workers without kids. In Panel A, the outcome is the employment penalty estimate in percentages coming from the regression $Employment^g_{o,iat} = \beta^g_o D_{it} + \mu^g_{o,a} + \lambda^g_{o,t} + \epsilon^g_{o,it}$, where $Employment^g_{o,iat}$ is a dummy equaling to one if individual i of gender g is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Percentage effects are calculated by dividing $\hat{\beta}^g_o$ by the predicted outcome absent child effects: $P^g_o = \frac{\hat{\beta}^g_o}{E[\tilde{Y}^g_{o,iat}]}$ In Panels B and C, the outcome variable is the income and hour penalty estimate coming from the regression $ln(Y^{o,g}_{iat}) = \gamma^{o,g} D_{it} + \mu^{o,g}_a + \lambda^{o,g}_t + \epsilon^{o,g}_{it}$. Robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01*

B Robustness Checks

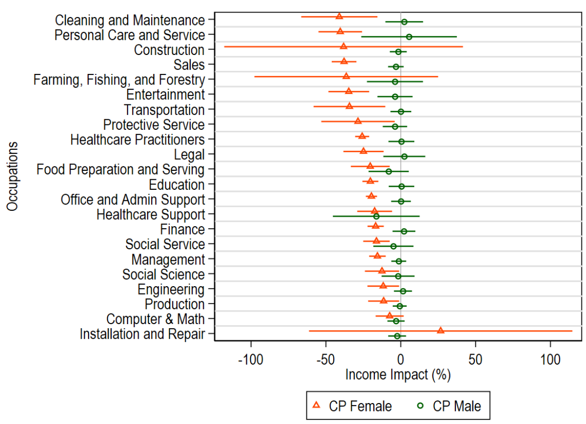
Figure B.1: Occupational Heterogeneity in Child Penalty (Bonferroni corrected confidence intervals)



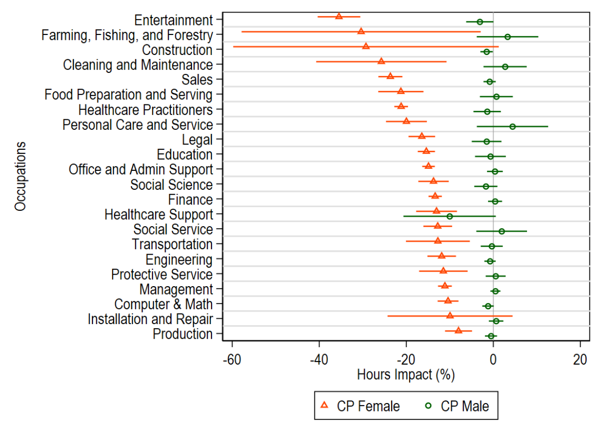
(a) Employment (in pp)



(b) Employment (in %)



(c) Income (in %)



(d) Hours (in %)

Note: Results on employment come from the regression $Employment^g_{o,iat} = \beta^g_o D_{it} + \mu^g_{o,a} + \lambda^g_{o,t} + \epsilon^g_{o,it}$, where $Employment^g_{o,iat}$ is a dummy equaling to one if individual i of gender g is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Superscripts mean sample restrictions. For each gender $g \in \{m, w\}$, 22 separate regressions are run for each occupation-specific outcome. To obtain percentage estimates, I divide the level estimates β^g_o with predicted outcome absent child effects: $P^g_o = \frac{\hat{\beta}^g_o}{E[\widetilde{Y}^g_{o,iat}]}$, where $\widetilde{Y}_{o,iat}$ is the predicted employment rate when omitting the contribution of the child effect. Results on income and hours come from the regression $ln(Y^{o,g}_{iat}) = \gamma^{o,g} D_{it} + \mu^{o,g}_a + \lambda^{o,g}_t + \epsilon^{o,g}_{it}$, where the outcome is either the log income or the log hours worked of an individual i at time t. $\hat{\gamma}^{o,g}$ estimates come from 44 different samples for each occupation-gender combination. 95% Confidence intervals are plotted after adjusting the critical values using Bonferroni correction.

Table B.1: Correlates with Occupation-level Child Penalties
Sample: All workers

	Women			Men			Inequality: Men - Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Employment (in %)									
Hour flexibility	-1.884***			-2.009***			-0.126		
	(0.391)			(0.491)			(0.417)		
Share of part time		1.516***			0.022			-1.493***	
		(0.318)			(0.383)			(0.280)	
Share of women			0.124			-0.465***			-0.590***
			(0.159)			(0.159)			(0.130)
Panel B: Income									
Hour flexibility	0.100			0.067			-0.032		
	(0.422)			(0.108)			(0.457)		
Share of part time		-0.748**			-0.092			0.657	
		(0.347)			(0.130)			(0.429)	
Share of women			-0.117			-0.024			0.093
			(0.170)			(0.054)			(0.192)
Panel C: Hours									
Hour flexibility	0.002			-0.002			-0.003		
	(0.215)			(0.063)			(0.224)		
Share of part time		-0.382***			0.012			0.395***	
		(0.119)			(0.073)			(0.137)	
Share of women			-0.013			-0.021			-0.008
			(0.059)			(0.035)			(0.075)

*Notes: Each column shows the estimates of a regression $\hat{\beta}_o = \gamma_0 + \delta W_o + \eta_o$, where $\hat{\beta}_o$ represents the estimated occupation-specific child penalty, and W_o is a vector of occupation attributes, which are (1) the ratio of people who state that their job provides hour flexibility, (2) the ratio of women, and (3) the ratio of part time workers. These attributes are calculated using the sample of all workers. In Panel A, the outcome is the employment penalty estimate in percentages coming from the regression $Employment^g_{o,iat} = \beta^g_o D_{it} + \mu^g_{o,a} + \lambda^g_{o,t} + \epsilon^g_{o,it}$, where $Employment^g_{o,iat}$ is a dummy equaling to one if individual i of gender g is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Percentage effects are calculated by dividing $\hat{\beta}^g_o$ by the predicted outcome absent child effects: $P^g_o = \frac{\hat{\beta}^g_o}{E\left[\tilde{Y}^g_{o,iat}\right]}$ In Panels B and C, the outcome variable is the income and hour penalty estimate coming from the regression $ln(Y^{o,g}_{iat}) = \gamma^{o,g} D_{it} + \mu^{o,g}_a + \lambda^{o,g}_t + \epsilon^{o,g}_{it}$. Robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01*

Table B.2: Correlates with Occupation-level Child Penalties
Sample: Eventual parents at $t = -1$

	Women			Men			Inequality: Men - Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Employment (in %)									
Hour flexibility	-0.638			-0.485			0.153		
	(0.414)			(0.577)			(0.406)		
Share of part time		1.903***			0.001			-1.902***	
		(0.374)			(0.418)			(0.296)	
Share of women			-0.003			-0.495***			-0.492***
			(0.157)			(0.152)			(0.139)
Panel B: Income									
Hour flexibility	-0.081			0.091			0.172		
	(0.268)			(0.089)			(0.312)		
Share of part time		-0.740*			-0.158			0.582	
		(0.419)			(0.198)			(0.558)	
Share of women			-0.068			-0.022			0.046
			(0.151)			(0.051)			(0.172)
Panel C: Hours									
Hour flexibility	-0.085			0.047			0.132		
	(0.148)			(0.055)			(0.184)		
Share of part time		-0.359***			-0.016			0.343	
		(0.147)			(0.125)			(0.226)	
Share of women			-0.001			-0.023			-0.022
			(0.056)			(0.033)			(0.070)

Notes: Each column shows the estimates of a regression $\hat{\beta}_o = \gamma_0 + \delta W_o + \eta_o$, where $\hat{\beta}_o$ represents the estimated occupation-specific child penalty, and W_o is a vector of occupation attributes, which are (1) the ratio of people who state that their job provides hour flexibility, (2) the ratio of women, and (3) the ratio of part time workers. These attributes are calculated using the sample of eventual parents before they had a child. In Panel A, the outcome is the employment penalty estimate in percentages coming from the regression $Employment^g_{o,iat} = \beta^g_o D_{it} + \mu^g_{o,a} + \lambda^g_{o,t} + \epsilon^g_{o,it}$, where $Employment^g_{o,iat}$ is a dummy equaling to one if individual i of gender g is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Percentage effects are calculated by dividing $\hat{\beta}^g_o$ by the predicted outcome absent child effects: $P^g_o = \frac{\hat{\beta}^g_o}{E[\tilde{Y}^g_{o,iat}]}$ In Panels B and C, the outcome variable is the income and hour penalty estimate coming from the regression $ln(Y^{o,g}_{iat}) = \gamma^{o,g} D_{it} + \mu^{o,g}_a + \lambda^{o,g}_t + \epsilon^{o,g}_{it}$. Robust standard errors are shown in parenthesis.
** p<0.10, ** p<0.05, *** p<0.01*

C Empirical Bayes Correction

This section replicates the main results of the paper using Empirical Bayes.

Let β_j be the child penalty in occupation j for gender g, where I suppress g for notational purposes. Let $\hat{\beta}_j$ be an estimate of β_j. For example, Figure 2 in the main text shows the OLS estimates of Child employment penalties across the 22 major occupations separately for both men and women. Assume that the identification strategy is correct, hence $\hat{\beta}_j$'s are unbiased estimators of unknown β_j's:

$$\hat{\beta}_j|\beta_j \sim N(\beta_j, s_j^2)$$

Let F denote the distribution of occupation-specific child penalties. Suppose F is a normal distribution and independent of s_j's. This gives the following hierarchical model:

$$\begin{aligned}
\hat{\beta}_j|\beta_j, s_j &\sim N(\beta_j, s_j^2) \\
\beta_j|s_j &\sim N(\mu_\beta, \sigma_\beta^2)
\end{aligned}$$

In this normal/normal model, the posterior mean and variance for β_j given $\hat{\beta}_j$ is given by

$$\begin{aligned}
\beta_j^* &\equiv E[\beta_j|\hat{\beta}_j] = \left(\frac{\sigma_\beta^2}{\sigma_\beta^2 + s_j^2}\right)\hat{\beta}_j + \left(\frac{s_j^2}{\sigma_\beta^2 + s_j^2}\right)\mu_\beta \\
s_j^{2*} &\equiv E[s_j^2|\hat{s}_j^2] = \frac{s_j^2\sigma_\beta^2}{s_j^2 + \sigma_\beta^2}
\end{aligned}$$

I use the following estimators for the hyperparameters $\mu_\beta, \sigma_\beta^2$.

$$\begin{aligned}
\hat{\mu}_\beta &= \frac{1}{J}\sum_{j=1}^{J}\hat{\beta}_j \\
\hat{\sigma}_\theta^2 &= \frac{1}{J}\sum_{j=1}^{J}\left[(\hat{\beta}_j - \hat{\mu}_\beta)^2 - s_j^2\right]
\end{aligned}$$

Replacing the unknown parameters by their estimates, I obtain the Empirical Bayes posterior mean and variance:

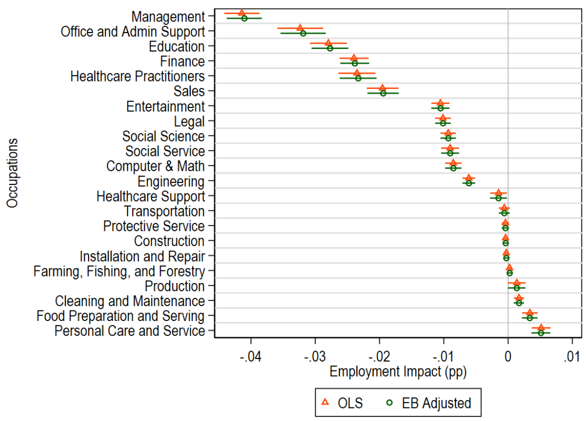
$$\begin{aligned}
\hat{\beta}_j^* &= \left(\frac{\hat{\sigma}_\beta^2}{\hat{\sigma}_\beta^2 + s_j^2}\right)\hat{\beta}_j + \left(\frac{s_j^2}{\hat{\sigma}_\beta^2 + s_j^2}\right)\hat{\mu}_\beta \\
\hat{s}_j^{2*} &= \frac{\hat{s}_j^2\hat{\sigma}_\beta^2}{\hat{s}_j^2 + \hat{\sigma}_\beta^2}
\end{aligned}$$

Using the posterior distribution of occupation child penalties, I replicate Figures 2 and 4 of the main text. Figure C.1 plots the 95% confidence intervals of the child employment penalties for the 22 major occupation groups. Notice that OLS and EB estimates are similar. This is because child penalties are precisely estimated compared to the observed variation in point estimates across occupations. Therefore, EB updating assigns most of the weight to the data and less of the weight to the prior. This is different for the income and hour penalties, which are plotted in Figure C.2. As the hour and income penalty estimates are less precise and the observed variation across occupations is less prevalent, EB and OLS estimates differ. For example, EB assigns practically all the weight to the prior for Men's income penalties.

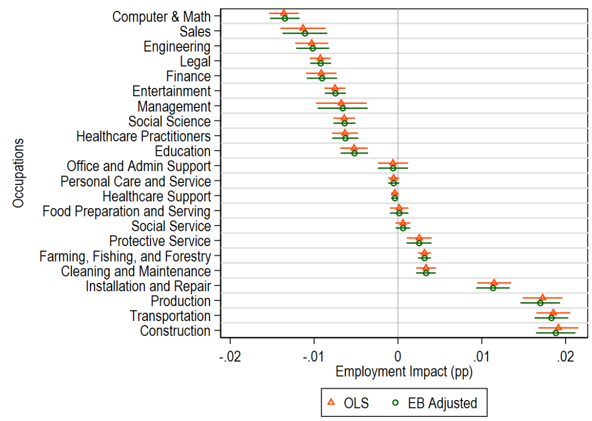
How much the EB adjustment moves the OLS estimates can also be seen in Figure C.3, which displays the scatter plot of OLS and EB estimates of child penalties. As employment effects are precisely estimated in OLS, EB and OLS estimates mostly align on the 45 degree line. However, as the hour and income penalty estimates are less precise, EB estimates are visibly different from OLS estimates.

Figure C.4 replicates Figure 4 using EB adjusted child penalty estimates. Results remain robust. Both men and women lose more jobs after becoming parents in occupations with more temporal flexibility. Consequently, the inequality-inducing part of the child penalty (i.e., the relative impact on women compared to men) remains the same. In contrast, women lose fewer jobs in occupations with more part-time availability, and men are largely unaffected. Therefore, there is a smaller difference across genders in occupations with more part-time availability.

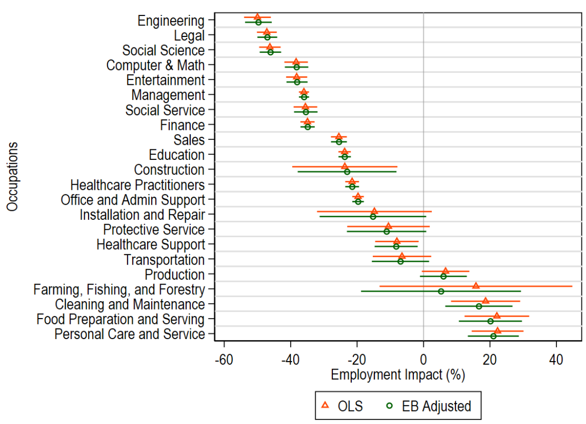
Figure C.1: Occupational Heterogeneity in Child Employment Penalty: OLS vs EB estimates



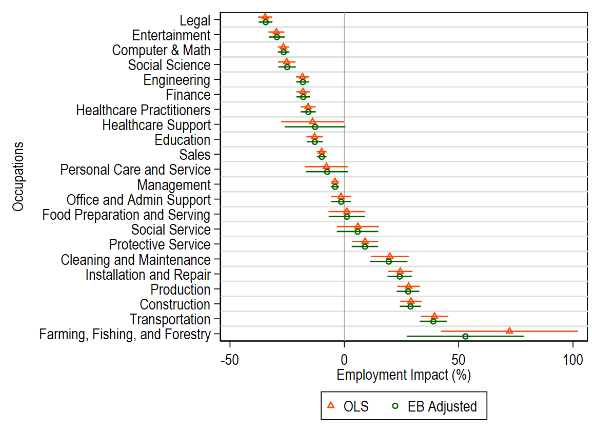
(a) Employment penalties for women (in pp)



(b) Employment penalties for men (in pp)



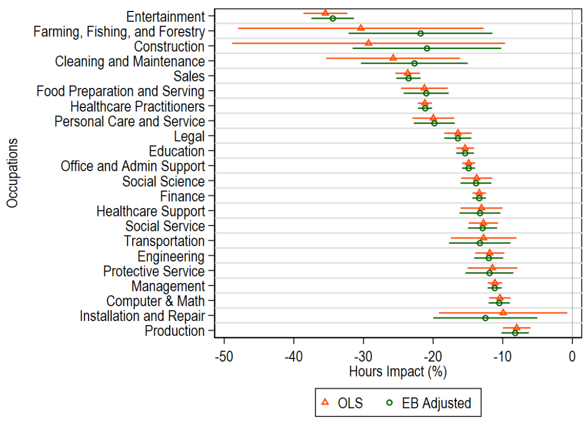
(c) Employment penalties for women (in %)



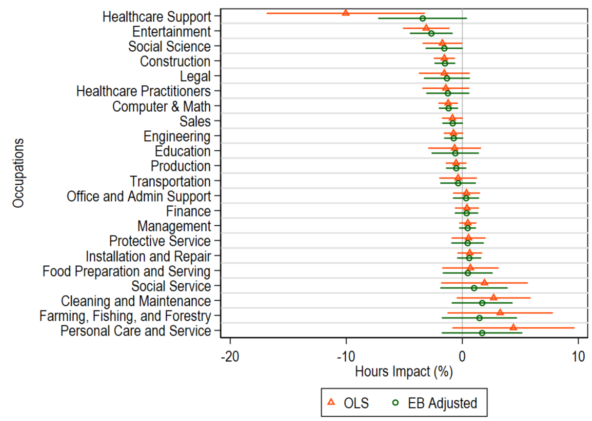
(d) Employment penalties for men (in %)

Note: This figure plots the OLS estimates alongside the estimated mean and the 95% confidence interval of the occupation-gender specific child penalties based on the Bayesian posterior, where the distibution for the occupation penalties (for each gender) is assumed to be normal with known mean and variance. Posterior is obtained using empirical bayes, separately for each gender.

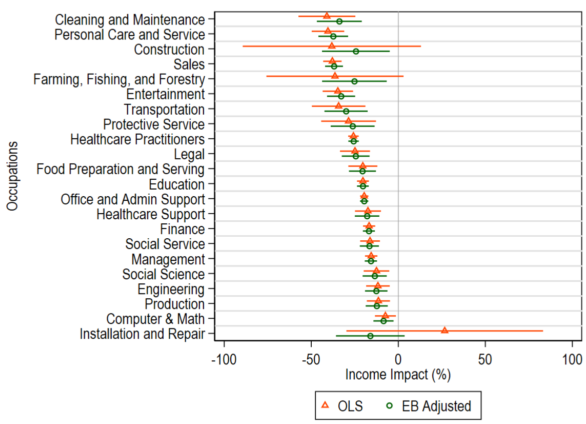
Figure C.2: Occupational Heterogeneity in Child Income and Hour Penalties: OLS vs EB estimates



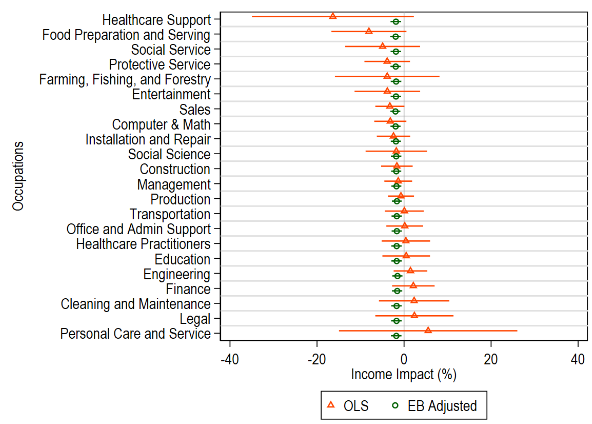
(a) Hours penalties for women (in %)



(b) Hours penalties for men (in %)



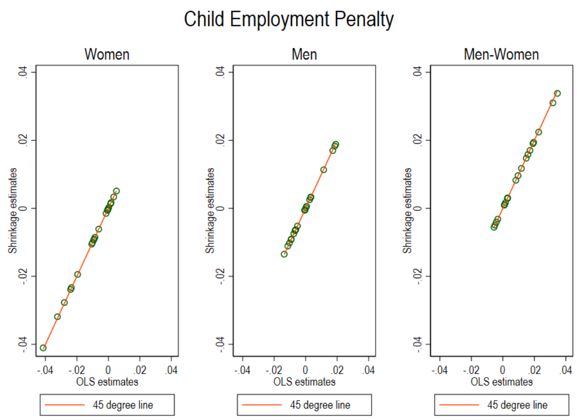
(c) Income penalties for women (in %)



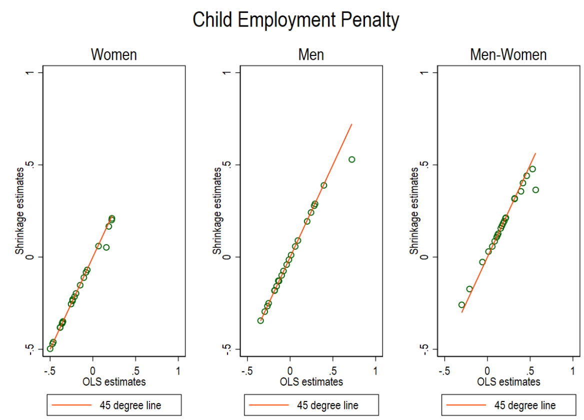
(d) Income penalties for men (in %)

Note: This figure plots the OLS estimates alongside the estimated mean and the 95% confidence interval of the occupation-gender specific child penalties based on the Bayesian posterior, where the distibution for the occupation penalties (for each gender) is assumed to be normal with known mean and variance. Posterior is obtained using empirical bayes, separately for each gender.

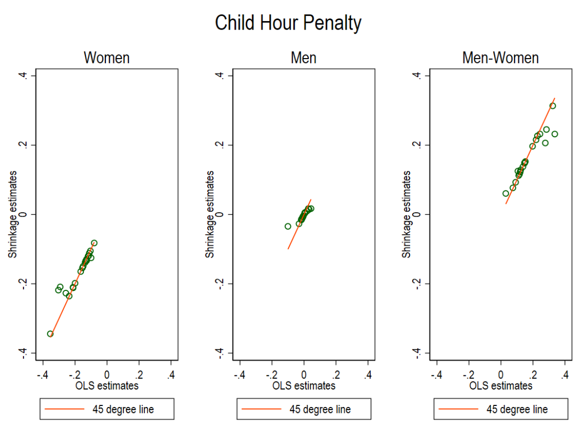
Figure C.3: Comparison of OLS and EB estimates



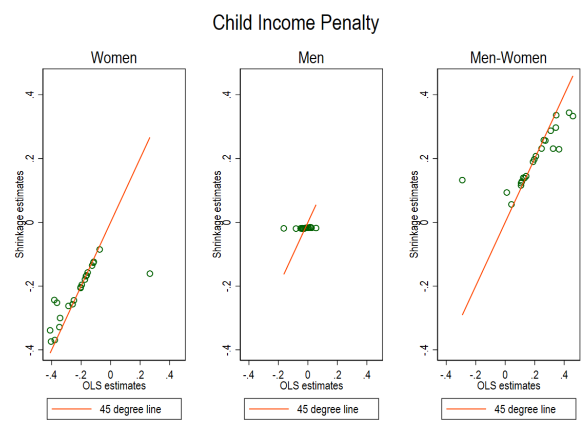
(a) Employment Penalties (in pp)



(b) Employment Penalties (in %)



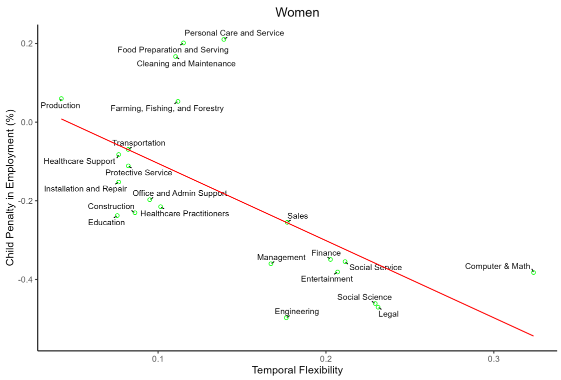
(c) Hour Penalties (in %)



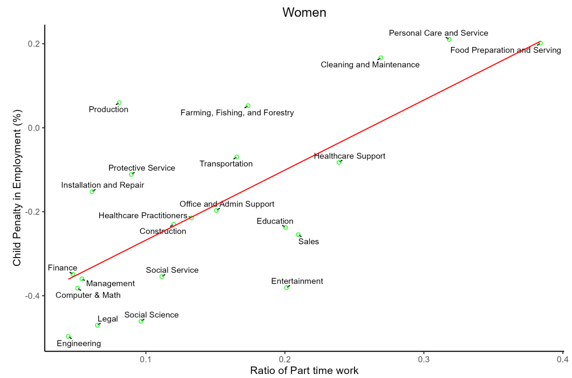
(d) Income Penalties (in %)

Note: OLS estimates on employment come from the regression $Employment^g_{o,iat} = \beta^g_o D_{it} + \mu^g_{o,a} + \lambda^g_{o,t} + \epsilon^g_{o,it}$, where $Employment^g_{o,iat}$ is a dummy equaling to one if individual i of gender g is employed in occupation o at time t, μ_a and λ_t are age and year fixed effects that control non-parametrically for lifecycle trends and time trends. Superscripts mean sample restrictions. For each gender $g \in \{m, w\}$, 22 separate regressions are run for each occupation-specific outcome. To obtain percentage estimates, I divide the level estimates β^g_o with predicted outcome absent child effects: $P^g_o = \frac{\hat{\beta}^g_o}{E[\widetilde{Y}^g_{o,iat}]}$, where $\widetilde{Y}_{o,iat}$ is the predicted employment rate when omitting the contribution of the child effect. Results on income and hours come from the regression $ln(Y^{o,g}_{iat}) = \gamma^{o,g} D_{it} + \mu^{o,g}_a + \lambda^{o,g}_t + \epsilon^{o,g}_{it}$, where the outcome is either the log income or the log hours worked of an individual i at time t. $\hat{\gamma}^{o,g}$ estimates come from 44 different samples for each occupation-gender combination. EB estimates update the OLS estimates using a normal prior with known mean and variance. The exact equations can be found in the Online Appendix.

Figure C.4: Correlates with Occupation-level Child Penalties (with Empirical Bayes correction)



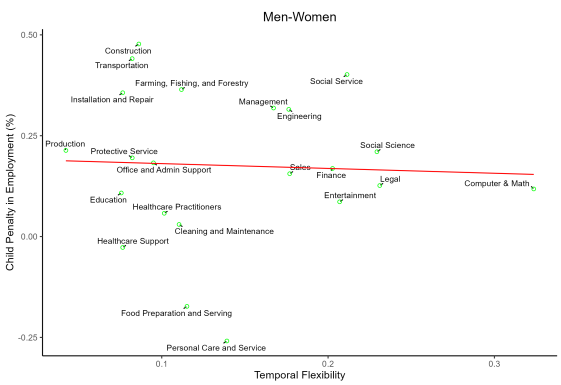
(a) Female penalty: hour flexibility



(b) Female penalty: availability of part-time

(c) Male penalty: hour flexibility

(d) Male penalty: availability of part-time



(e) Child penalty: hour flexibility

(f) Child penalty: availability of part-time

Notes: The occupational correlates are (1) the ratio of people who state that their job provides hour flexibility and (2) the ratio of part-time workers. These attributes are calculated using the sample of all workers without kids in the CPS. Empirical Bayes corrected child penalty estimates are used.

Table C.1: Correlates with Occupation-level Child Penalties

	Women			Men			Inequality: Men - Women		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Employment (in %)									
Hour flexibility	-1.961***			-2.156***			-0.120		
	(0.412)			(0.503)			(0.381)		
Share of part time		1.668***			0.264			-1.334***	
		(0.287)			(0.387)			(0.275)	
Share of women			0.025			-0.538***			-0.496***
			(0.159)			(0.155)			(0.123)
Panel B: Income									
Hour flexibility	0.246			-0.003			-0.221		
	(0.262)			(0.003)			(0.286)		
Share of part time		-0.519***			-0.004			0.371	
		(0.223)			(0.003)			(0.254)	
Share of women			-0.036			0.000			0.012
			(0.064)			(0.001)			(0.072)
Panel C: Hours									
Hour flexibility	-0.033			-0.031			0.026		
	(0.205)			(0.034)			(0.214)		
Share of part time		-0.358***			0.021			0.376***	
		(0.095)			(0.031)			(0.105)	
Share of women			-0.031			-0.008			0.014
			(0.039)			(0.014)			(0.054)

*Notes: Each column shows the estimates of a regression $\hat{\beta}_o = \gamma_0 + \delta W_o + \eta_o$, where $\hat{\beta}_o$ represents the estimated occupation-specific child penalty, and W_o is a vector of occupation attributes, which are (1) the ratio of people who state that their job provides hour flexibility, (2) the ratio of women, and (3) the ratio of part time workers. These attributes are calculated using the sample of all workers without kids. The outcome variables are the Empirical Bayes estimates of child penalties. Robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01*