Flexibility for Both Parents: Remote Work and the Evolution of Child Penalties *

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PRELIMINARY AND INCOMPLETE

Abstract

Child penalties–the reductions in employment and earnings experienced by women after becoming parents–are a major driver of gender gaps in the labor market. This paper investigates the potential for remote work to mitigate these penalties. We leverage rich administrative data from Sweden to study this question in the context of the rise of remote work during and after the COVID-19 pandemic. We develop a collective model of household labor supply in which each agent can also choose whether or not to work flexibly. In the model, flexibility imposes a trade-off: on the one hand, it reduces commuting frictions; on the other, it may reduce workers' productivity. The model predicts that flexibility reduces motherhood penalties when primarily accessible to women – i.e., if it shifts the *relative* opportunity cost of work for the two parents – but has limited effects when both partners gain flexibility. Consistent with these predictions, we find that remote work has had limited impacts on motherhood penalties in earnings, employment, hours, and wages. Although we find precise but economically small reductions in employment and hours penalties for mothers, the effects on earnings and wage rates are more ambiguous. Furthermore, because remote work exposure is inversely correlated with *ex ante* motherhood penalties, the women who would stand to gain the most from flexibility are also the least likely to have actually gained access to it.

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1 Introduction

Child penalties—the reductions in employment and earnings experienced by women after becoming parents—are a major driver of gender gaps in the labor market. These penalties are large and ubiquitous, even in societies that prioritize gender equality as a goal of public policy: in Sweden, women face a long-run earnings penalty of 26 percent (Kleven et al., 2019b; Kleven, 2022). Gender gaps and child penalties are particularly pronounced in occupations in which returns to hours are convex: when the returns to working very long hours are high, women – who typically supply more household production than men – see their earnings growth slow relative to men even if they do not drop out of the labor force (Goldin, 2014). This gap grows over time on both the intensive and the extensive margin: women drop out of the labor force at higher rates than men after having children, and those that continue to work reduce their hours relative to men. Goldin (2014) hypothesizes that much of the gender gap could be attenuated if jobs accommodated greater *temporal flexibility*: allowing not only reductions in hours but also greater autonomy over *which* hours one works. This hypothesis raises an important question: *can greater job flexibility – particularly in the form of remote work and the temporal autonomy it implies – reduce the motherhood penalty?*

In this paper, we study the effects of the rise of remote work during and after the COVID-19 pandemic on parental labor supply using rich administrative data from Sweden. We find that gains in access to remote work are associated with reductions in the motherhood penalty in employment and hours conditional on working, though effects on wages and earnings are more ambiguous. Importantly, we show that access to remote work *for both parents* matters for the impact of having a child on the mother's labor supply. Our approach combines empirical event-study estimates with a theoretical model of labor supply in which workers can choose whether to adopt flexibility in their jobs. We use data from the EU Labour Force Survey (LFS) to characterize the intensity of remote work adoption at the two-digit occupation level before and after the pandemic; we then measure individuals' exposure to remote work as the percentage change in adoption of habitual working-from-home among workers in their occupation from 2019 to 2021. Our empirical findings motivate a model of a two-member collective household where earnings and home production are shared and each parent chooses hours of labor supply and whether to work flexibly.

Our analysis proceeds in three parts. First, we present three descriptive facts on the heterogeneous adoption of remote work across occupations using survey data from the LFS. First, remote work adoption is concentrated in white-collar jobs, with the greatest exposure in higher-skill and technical roles and moderate exposure in clerical roles. Motivated by this finding, we classify occupations into quartiles of exposure to remote work using our measure from the LFS. The lowest quartile represents workers with minimal potential to work remotely, such as builders and personal care workers; the highest quartile represents those whose capacity to work remotely grew substantially over the pandemic, such as professionals in business, administration, and information technology. Second, because men and women sort differentially across occupations, they are exposed to different degrees of change in the availability of remote work. For both men and women, the plurality of parents is in the bottom exposure quartile – 32.1 percent of mothers and 42.9 percent of fathers. However, women are more likely to have moderate levels of exposure to remote work and men are more likely to have high levels of exposure. 31.9 percent of women are in the third quartile and only 17.1 percent are in the top quartile; in contrast, 24.9 percent of men are in the third quartile and

23.1 percent are in the top quartile. Third, couples exhibit assortative matching on education and earnings. Combined with the education and earnings gradient of exposure to remote work, this generates additional assortative matching on remote work exposure. This assortativity on job *flexibility* motivates us to explore interactions between parents' access to remote work in determining labor supply of each partner.

Second, we connect these empirical insights to a theoretical model of couples' labor supply. This model is a version of the collective household labor supply model with home production (Chiappori, 1992, 1997; Blundell et al., 2005; Cherchye et al., 2012), extended to have two key features. First, there are two types of public goods: public utility, which is enjoyed by both spouses; and children. We solve the model with and without children to provide a structural microfoundation for empirically observed "motherhood penalties". Second, couples jointly choose whether each spouse will work flexibly – in this case this means working remotely – or not. Flexibility affects equilibrium decisions through two channels. On the one hand, occupations are heterogeneous in how adopting flexibility affects the worker's output – the efficiency units of labor produced by the worker for a given number of hours. We model the "flexibility penalty" as a discount to the wage, which is equal to the worker's marginal product. On the other hand, working inflexibly imposes a frictional commuting cost on the worker's time use. Together, these two mechanisms imply that flexibility affects each worker's relative wage and influences the trade-offs the two agents face in choosing who supplies market labor and home production.

We calibrate our model using estimates from Cherchye et al. (2012) to guide our choices of parameters related to household preferences, comparative advantage in home production, and assignment of Pareto weights. We then use the calibration to examine the model's predictions for how couples choose equilibrium labor supply, before and after having children, if working remotely has a greater or lesser impact on each spouse's productivity. Our numerical comparative statics generate three predictions. First, motherhood penalties in hours will decline for women who gain access to flexibility if their partner's access to flexibility remains unchanged. Second, in contrast, if *both* spouses gain access to flexibility in similar ways, motherhood penalties in hours will change little. Intuitively, if the opportunity cost of work changes in a similar way for both parents, the trade-offs they face in sharing time commitments will remain unchanged. Combined with our stylized fact that couples are assortatively matched on exposure to remote work, this finding underscores the limitations of expanding flexibility if it does not *differentially* benefit women. Third, because households prefer to assign more home production to women than to men, even if their wages and access to flexibility are equal, women are more time-constrained by their equilibrium assignments of household labor. This prediction highlights that changing norms around home production would be necessary to fully reap the benefits of increasing women's access to flexibility.

Finally, we leverage variation across occupations in exposure to remote work during and after the Covid-19 pandemic to examine the effect of increased access to flexibility on motherhood penalties across a variety of labor market outcomes: employment, hours, wages, and earnings. We adopt a quasi-experimental triple-difference design similar to the event study approach of Kleven et al. (2019a). We use our framework to estimate child penalties in occupations with different potential to adopt remote work, before and after the pandemic, as well as the differential change in these penalties for occupations with greater or lesser exposure. We measure occupational exposure using quartiles of our remote work adoption measure from

the LFS.

We find that exposure to remote work has limited potential to significantly reduce motherhood penalties. To begin, we document that the size of the *ex ante* child penalties are inversely correlated with remote work exposure. Before the pandemic, women in occupations with the least potential to work remotely experienced income declines of 40.9 percent over the first three years after having a child, whereas those with the most potential to work remotely saw their income drop by 28.7 percent over the same three-year time horizon. Thus, the women who stood to gain the most from structural changes in the organization of work had the least capacity to adopt remote work. Furthermore, as we document in our descriptive facts and microfound in our model, the *joint* distribution of access to flexibility across the two parents also limits the potential positive impacts of remote work on motherhood penalties. Because couples match assortatively on potential to work remotely – a fact that is downstream from assortativity in education and earnings – the most well-off couples are also the couples with the highest joint exposure to remote work. This pattern of matching in couples further mitigates the potential benefits to women with low exposure to remote work, because their partners also tended not to gain access to job flexibility after the pandemic.

Next, we decompose changes in the earnings penalties by estimating the changes in the penalties of employment, hours and wage rates respectively. On each of these margins, we find that changes in motherhood penalties after the pandemic are economically small and not clearly related to exposure to remote work. Employment penalties contracted for women in all occupation groups after the pandemic, and did so to the greatest extent for women who were *least* exposed to remote work. The three-year penalty for the least-exposed women declined from 8.01 percent to 6.22 percent; for the most-exposed women, it declined from 1.90 percent to 1.12 percent. These results suggest that the potential for remote work to reduce the motherhood penalty on the employment margin is limited, though this may be specific to settings in which women who stood to gain the most from remote work were already very unlikely to stop working entirely after having a child. On the hours margin, women in all exposure groups experienced very small changes in the hours penalty after the pandemic. Women in the lower median of our exposure measure experienced an 8.1 percent reduction in hours conditional on working before the pandemic; this gap narrows to a 7.5 percent reduction after the pandemic. Women with the highest intensity of exposure to remote work experienced an 3.4 percent reduction in hours conditional on working before the pandemic, which narrows to a 3.3 percent reduction after the pandemic. Men also appear to experience slightly slower wage growth after having a child after the pandemic, but the effects are economically extremely small.

We also provide novel evidence that the occupational exposure of the father to job flexibility matters for the mother's labor supply. We focus on women whose occupations place them in the highest category of exposure to remote work – including professionals and associate professionals in business, administration, and information technology. We document heterogeneity in employment and hours penalties for similar first-time mothers depending on the degree of flexibility that the father has. Among high-exposure women – who work in high-skill occupations and almost universally hold college degrees – motherhood penalties in employment and hours conditional on working are larger for those whose partner has less access to the flexibility of remote work. High-exposure women with high-exposure partners experienced a decline in the penalty of 1.7 percent, whereas the earnings penalty increased by 1.8 percent for those with medium-

exposure partners and by 3.6 percent for those with low-exposure partners. Consistent with the model prediction, we observe the smallest changes in penalties for couples who are positively assorted. However, this is only true for couples with moderate or high exposure levels. In contrast, the increase in earnings penalties are the largest among couples where both partners have low remote work exposure. Moreover, the change in earnings penalty among high-exposure women with low-exposure partners contradicts the prediction of the model. We view this evidence as suggestive that other factors, such as social norms, are serving as frictions that mitigate the potential effects of remote work on motherhood penalties. Finally, we emphasize that the attenuation of earnings penalties for high-exposure women is quite economically small because their labor supply responses on the employment, wage, and hours margins, were already relatively small before the pandemic. While the model suggests that the father's access to flexibility could play an important role in mothers' labor supply on both intensive and extensive margins, the empirical results highlight the limitations of this channel when couples are assortatively matched.

Our paper advances knowledge in three distinct strands of literature. First, we contribute to the developing literature on child penalties. Goldin (2014) documents that much of the remaining earnings gap between men and women can be explained by child penalties, particularly in occupations with convex returns to hours. In this vein, Bertrand et al. (2010) document that even among MBA graduates, women tend to earn less several years out of graduate school, both because they are more likely to switch to part-time or self-employed work and because they are more likely to not be working at all. Much of this increasing earnings gap over the course of women's careers is driven by changes in labor supply that coincide with having children. In our empirical approach, we build on papers that use panel data and event study designs to estimate child penalties, such as Angelov et al. (2016), Bang (2021), Kleven et al. (2019a,b, 2021), and Kleven (2022). Adda et al. (2017) provides a dynamic life cycle model of fertility and career decisions and provides a framework for how women and men make different labor supply choices in response to the demands of parenting. Hotz et al. (2017) also provide evidence on how family-friendly workplace policies can shift parental labor supply decisions. A review of the literature on children and gender wage gaps is provided by Cortés and Pan (2023). Additionally, a much more extensive review of the broader literature on gender earnings gaps is provided by Blau and Kahn (2017). Our study extends this literature by examining how the rise of remote work reshapes child penalties, leveraging rich administrative data from Sweden to provide precise estimates of labor supply responses across occupations and households. We also examine the role of partners' access to remote work in shaping maternal labor supply, highlighting the joint nature of household labor supply decisions in the presence of job flexibility. By integrating empirical findings with a theoretical model of labor supply and flexibility adoption, we provide a framework to evaluate the broader implications of remote work for gender equality and family policy.

Second, we contribute to the field studying the effects of remote work on productivity and labor supply. Prior to the Covid-19 pandemic, this literature was relatively small, reflecting the limited prevalence of remote work. Bloom et al. (2015) study a field experiment in remote work adoption at a call center in China, finding that working from home can boost productivity for specific tasks. Mas and Pallais (2017a) use a similar setting to estimate workers' willingness to pay for remote work, alongside other flexibility amenities. Mas and Pallais (2020) provide a comprehensive review of the literature on remote work prior

to 2020. Since the pandemic, the literature on remote work has expanded rapidly. Key descriptive studies, such as Barrero et al. (2021b), Aksoy et al. (2022), and Brynjolfsson et al. (2022), use novel survey data to document the adoption of remote work across occupations, industries, and geographies, as well as its impacts on worker satisfaction and self-reported productivity. Other papers, including Bailey et al. (2023), Mongey et al. (2021), and Pabilonia and Vernon (2022), explore pandemic-era labor supply shifts among women and households. Emanuel et al. (2023) and Emanuel and Harrington (2024) focus on the implications of remote work for productivity and human capital accumulation, showing that the effects of this technology depend on job-specific task requirements. Unlike prior studies, which primarily focus on individual workers or descriptive trends, we highlight how remote work shapes household labor supply decisions, emphasizing the importance of joint flexibility for both parents.

Third, we make a substantial contribution to the nascent literature studying the effects of remote work flexibility specifically on *women's* labor supply. Several recent studies highlight the potential of jobs that can be done remotely for increasing women's labor force participation in developing countries (Jalota and Ho, 2024; Jalota et al., 2024). Recent descriptive evidence suggests women's (especially mothers') greater demand for flexibility is associated with greater wage gaps within inflexible occupations (Goldin et al., Forthcoming; Cubas et al., 2023; Noray, 2024), though this work does not address how remote work may or may not attenuate these gaps. Harrington and Kahn (2023) study differential adoption of remote work across occupations in the decade prior to the pandemic using survey data from the United States. They find that the motherhood gap in employment decreased in college majors where remote work increased the most. Additionally, in early stage work using survey data from Brazil, Zarate and Oaquim (2024) document that child penalties are more pronounced in occupations that have less potential for remote work. Relative to other contemporaneous work on the intersection of child penalties and remote work, our paper offers a significant advancement. Our comprehensive administrative data linking workers to their children and spouses allows us to obtain precise estimates of how child penalties change in different occupations over the course of the pandemic. Additionally, because we can link parents to one another, we can examine the importance of partners' occupations in shaping household responses to job flexibility—an area that has not been explored in the existing literature. Furthermore, we complement our empirical analysis with a theoretical model of joint household decision-making under varying levels of job flexibility.

This draft is organized as follows. Section 2 discusses important institutional features of parental leave in Sweden and relevant labor market policy during the COVID-19 pandemic. Section 3 describes our main survey and administrative data sources. Section 4 presents three key descriptive facts about occupational and gender differences in the adoption of remote work during and after the pandemic. Section 5 develops our theoretical framework and Section 6 provides empirical estimates of how motherhood penalties change in response to increased access to remote work. We conduct a number of robustness checks in Section 7. Finally, Section 8 concludes.

2 Institutional setting

2.1 Family policy in Sweden

Swedish family policy is built on the principles of gender equality, work-life balance, and extensive state support for parents, ensuring both mothers and fathers can actively participate in caregiving while maintaining their attachment to the labor market. This study focuses on parents who had their first child between 2010 and 2022. Throughout the time period, there has been subsidized childcare available starting from the child has turned one (but children cannot be enrolled prior to their first birthday).

Parents are entitled to a total of 480 days of paid parental leave per child, with 390 days compensated at 80% of the parent's income (up to a capped amount). The remaining 90 days are paid at a lower flat rate. Each parent is initially allocated 240 days, out of which 90 days for each parent are non-transferable. The 90 days of earmarked parental leave have been gradually implemented (the first month in 1995, the second in 2002, and the third in 2016). The remaining 150 days can be transferred between parents as needed. The system allows parents to take leave in full or partial days, providing flexibility in how leave is used. Additionally, both parents are allowed to take up to 30 days of paid parental leave simultaneously since 2012, providing the opportunity for shared caregiving during the initial stages after childbirth.

Job protection is guaranteed for parents during parental leave, and parents can take paid or unpaid leave with full job protection for up to 18 months. Parents are permitted to use their leave until the child turns 12 years old, but only 96 days can be saved after the child has turned four. Parents to children born before 2014 could only use the parental leave days until the child turned eight, but could use the days flexibly before and after the child turned four. Parents also have the job-protected right to reduce their working hours by up to 25% until the child turns eight.

In addition to parental leave, parents are entitled to temporary parental leave (*VAB*), which allows them to take time off to care for sick children. The VAB benefits provide financial compensation for parents staying home when their child is ill, offering further flexibility in managing work and family responsibilities.

2.2 Policies during COVID-19 Pandemic

Sweden introduced several key policies to support workers during the COVID-19 pandemic. One of the most important measures was the furlough (*korttidspermittering*), which allowed employers to reduce working hours while the government covered a significant portion of the employees' lost wages. This short-term layoff scheme helped many workers to retain their jobs while adjusting to the reduced work hours necessitated by the economic impact of the pandemic. Another important policy was the recommendation for remote work wherever possible, particularly in office-based roles, to limit physical interactions and reduce the spread of the virus. A qualifying day for sick leave was also removed, which meant that employees could receive compensation from the first day they had to stay home due to their own illness.

In addition to these general policies, there were some specific measures that targeted parents with younger children. One crucial policy was the expansion of temporary parental leave (VAB), allowing parents to take paid leave not only when their child was sick, but also if the child was sent home from daycare or preschool due to potential COVID-19 exposure. Contrasting many other countries, preschools and primary

schools remained open throughout the pandemic.

3 Data

The data is collected from two different sources: we use survey data from the EU Labour Force Survey to construct measure for WFH exposure by occupation and education level and field. These aggregate measures are linked to population-wide administrative data on a range of labor market outcomes and background characteristics.

3.1 Administrative data

The administrative data includes the full Swedish population between 1990 and 2022, and draws individual-level information from multiple registers. We use the Register for the Total Population (RTB) to link parents to their children and spouses to each other, as well as to identify the timing of entering parenthood. There is also information on individual background (year of birth, gender, birth location) and annual information on housing and workplace location, including geo-codes by 250 $\times$ 250 (1,000 $\times$ 1,000) meter coordinates in urban (rural) areas. The Longitudinal Integrated Database for Health Insurance and Labor Market Studies (LISA) contains detailed information on education level and field, various earnings measure (including both labor earnings and various benefits such as parental leave and sick leave) and workplace information. There is annual firm and establishment data for the full sample period, but occupation data is only available from 2001 and onwards. Finally, we have the Wage Structure Statistics survey (covering the full population of public sector workers and about half of the population of private sector workers) including monthly wage rates and contracted hours.

We construct a sample of opposite-sex parents who are between ages 19 to 65 at the time of the birth of their first child, and for whom occupational data are available from two years prior to the birth event. This restriction ensures that occupational exposure to remote work is measured before any potential labor market adjustments related to parenthood. In the main analysis, we do not require that both spouses have a reported occupation in t-2.[1] We further restrict the sample to births between 2010 and 2022.

3.2 Measurement of remote work adoption by occupation in the LFS

To classify the intensity of exposure to remote work across different occupations, we leverage a question from the EU Labour Force Survey (LFS). All persons currently in employment are asked whether they *mainly* work at home, *sometimes* work at home, or *never* work at home. The classification of "work at home" is intentionally broad and encompasses any productive work related to the person's current main job that is done at home. A respondent is classified as "mainly" working at home if working at home at least half of the time worked in a reference period of four (to twelve) working weeks preceding the end of the reference week. They are classified as "sometimes" working at home if they worked at home less than half the total time worked in the reference period, but for at least one hour in total.

[1] The occupation variable lists the current occupation type or the latest reported occupation, if an individual does not have a current employer.

Our preferred measure of exposure to remote work is the share of workers in a given 2-digit ISCO-88 occupation who report *mainly* working from home in the reference period.[2] To classify the treatment intensity of exposure to remote work during the pandemic, we compute the change in remote work share by occupation from 2019 to 2021. The ordering of occupational exposure intensity is robust to a variety of other choices of classification: change in occupational share from 2019 to 2021, level of occupational share in 2021, and level of occupational share in 2022. In Appendix Table A.1, we provide the values of work-from-home exposure intensity by two-digit occupation and classify occupations into exposure quartiles. Quartiles are computed using the weighted number of observations in the LFS corresponding to each occupation, so that each quartile represents a roughly equal share of workers.

As with any proxy, this measure will imperfectly capture true exposure to flexibility. The measure excludes workers who adopt regular work-from-home arrangements for less than half their working time, such as those who routinely work from home two days per week. On the other hand, choosing "mainly" WFH and excluding "sometimes" WFH allows us to exclude those whose work performed at home *does not* represent true flexibility in the job. People in many types of occupations work at home not because they have flexibility but because their jobs demand *additional* work outside of the workplace. For example, teachers frequently plan lessons in the evening after school. A substantial share of teachers in the LFS sample report that they sometimes work from home, but this response does not reflect true job flexibility. With these inclusions and exclusions in mind, we view the "mainly WFH" measure as a conservative lower bound for the true intensity of exposure to job flexibility through the WFH channel. Importantly, we argue that this choice of proxy measure is also order-preserving: jobs with higher true flexibility will tend to have higher shares of workers mainly working from home than those with lower true flexibility.

4 Stylized facts on occupational heterogeneity in remote work adoption

4.1 Remote work adoption is concentrated in white-collar jobs, with the greatest exposure in higher-skill and technical roles and moderate exposure in clerical roles

Figure 1 shows a time series of the share of workers in the ten most common two-digit occupations who report mainly working from home. Three key facts emerge. First, exposure to remote work is concentrated among white-collar occupations. Professionals and associate professionals in business and administration; science and engineering; and information, communications, and technology (ICT) have the highest rates of adoption of remote work both at the height of pandemic-induced labor market adjustments in 2021 and in the post-pandemic normalization in 2022. In contrast, those whose job tasks would suggest little scope for remote work – such as sales and personal care workers and health professionals – experienced little to no actual takeup. Notably, teachers saw little change in habitual working from home during the pandemic. This is consistent with the fact that schools did not shut down systematically in Sweden, in stark contrast to the widespread closures experienced in the United States. Teachers' levels of remote work adoption during and

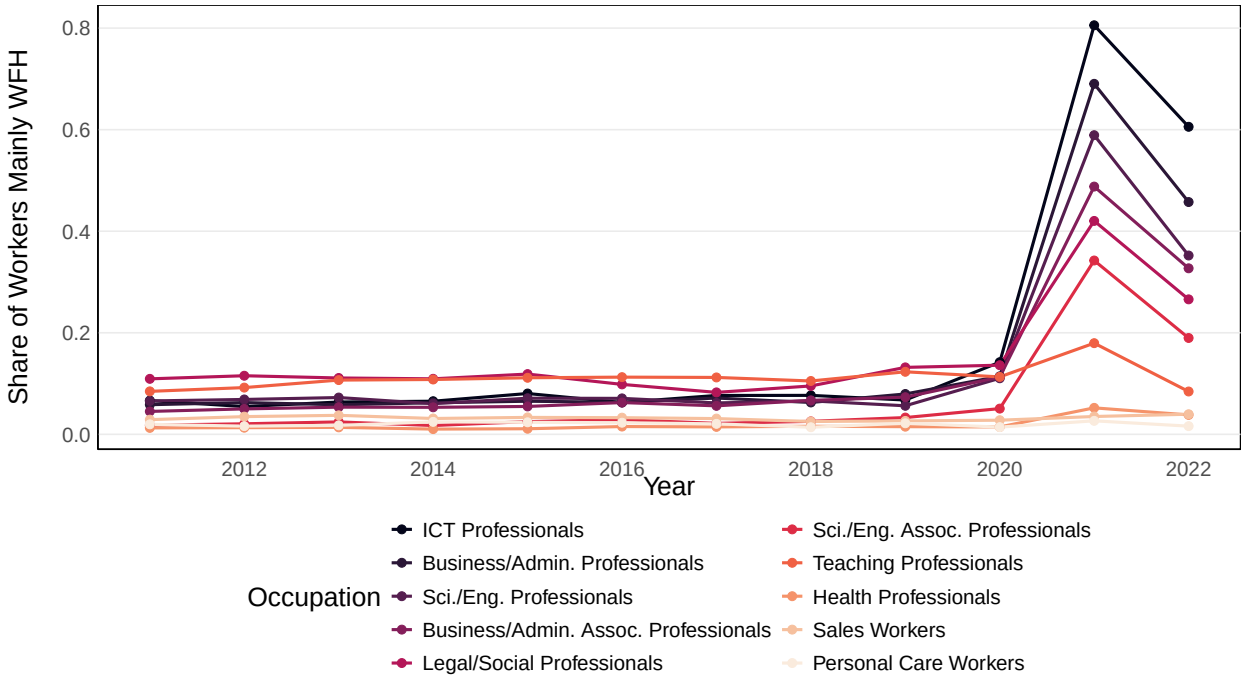
[2] While we have access to information from more detailed occupational classifications – up to 3-digits of the ISCO-08 – we find that computing changes in WFH adoption at the 3-digit level results in noisy estimates for small occupations without materially changing the order of exposure intensity among more common occupations. As a result, the 2-digit classification yields our preferred measure.

after the pandemic are roughly the same, suggesting that they did not experience a broad shift in workplace technology in the way that many white-collar occupations did.

Second, among white-collar occupational categories, higher-skill workers – those classified as "professionals" under the ISCO-08 – tend to have greater takeup of frequent remote work than lower-skill workers – those classified as "associate professionals" or "technicians". For example, in the broad category of workers in business and administrative jobs, about 45 percent of those categorized as professionals mainly worked from home in 2022; in contrast, in the same year, only about 32 percent of those categorized as associate professionals did.

Third, while remote work adoption peaked in 2021, it has remained elevated above pre-pandemic levels in the post-pandemic return to normalcy. All occupations that saw a substantial spike in remote work takeup in 2021 exhibit higher rates of working from home in 2022 than they did in 2019 and earlier. This fact means that our results are robust to classifying occupational work-from-home intensity using changes from before the pandemic to 2021 or from before the pandemic to 2022. Our preferred specification uses changes up to 2021 to reflect differential capacity of remote work adoption across occupations.

Figure 1: Work-From-Home Adoption over Time in Common 2-Digit Occupations



Notes: This figure shows the share of workers age 25-45 in the EU Labour Force Survey (LFS) in Sweden in each year who reported that they mainly worked from home during the reference period in each of the given occupations. Occupations are coded using the ISCO-08 classifications. A worker is considered to be "mainly working from home" if greater than 50 percent of the hours devoted to productive work in their primary job are spent working at home.

4.2 Occupational sorting by gender generates differences in exposure to remote work

Table 1 shows summary statistics of our main sample, separated by quartile of exposure to remote work and gender. The sample consists of parents 19 to 65 for whom we observe an occupation two years prior to the

birth of the first child. Appendix Table A.1 summarizes the two-digit occupations that are included in each exposure quartile. We document three key facts that summarize systematic differences in the demographics of workers with low, moderate, and high exposure to remote work. First, workers with higher occupational exposure tend to be older at the time of the first birth. New fathers in the lowest exposure quartile are, on average, 30.52 years old at the time of the first birth; new mothers in the lowest quartile are, on average, 27.88 years old when they have their first child. In contrast, new parents in the highest quartile are typically 33.83 years old (men) and 32.14 years old (women) when they have their first child. This gradient in age suggests that parents with higher exposure to remote work are likely to be at a slightly more advanced stage in the life cycle than those with less exposure.

Second, there is a strong education gradient in exposure to remote work. Workers with minimal exposure to remote work are by far the most likely to have a high school diploma or less: 81 percent of men and 69 percent of women in the bottom quartile have completed only high school or compulsory schooling. In contrast, workers with the highest levels of exposure almost universally have college degrees: in the top quartile, 82 percent of men and 94 percent of women have at least some college; 64 percent of men and 84 percent of women have completed at least 3 years of college or higher postgraduate work. The exception to this rule is the 16 percent of men in the top quartile who have only a high school degree. These workers are predominantly ICT technicians.

Third, men's and women's differential occupational sorting exposes them to different degrees of remote work. For both men and women, the largest share of all new parents are in the bottom exposure quartile – 32.1 percent of mothers and 42.9 percent of fathers. However, women are more likely to have moderate levels of exposure to remote work and men are more likely to have high levels of exposure. 31.9 percent of women are in the third quartile and only 17.1 percent are in the top quartile; in contrast, 24.9 percent of men are in the third quartile and 23.1 percent are in the top quartile. Thus, among workers with at least moderate exposure – those in the upper median of the occupational distribution – women tend to have more moderate levels of exposure than men do. Additionally, female-dominated occupations tend to be in the middle quartiles: 66 percent (55 percent) of workers in quartile 2 (quartile 3) are women, whereas only 42 percent of workers in the top quartile are women. Taken together, these gender differences underscore that it will be important to consider the heterogeneous occupational incidence of remote work in order to evaluate its impacts on gender disparities among new parents.

4.3 Parents exhibit assortative matching on remote work exposure

Figure 2 shows the composition of occupational exposure to remote work for each member of a parent couple in our sample. On the x axis, we first organize couples by the exposure quartile of the woman; then, within the bins for each of the women's exposure quartiles, we plot the share of all couples where the man's occupation is in each of the four quartiles. For example, the leftmost bar in the figure shows that about 18 percent of all couples in the sample are composed of a woman and a man who are both in the lowest exposure quartile.

The figure illustrates that couples exhibit assortative matching on occupational exposure to remote work. Among women who have virtually no potential to work remotely in their occupation, the plurality are

Table 1: Composition of Remote Work Exposure Quartiles by Gender

ΔWFH **Quartile**	**Quartile 1**		**Quartile 2**		**Quartile 3**		**Quartile 4**	
ΔWFH **Intensity**	**-0.14 - 0.00**		**0.01-0.14**		**0.17-0.31**		**0.41-0.74**	
Gender	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Demographics								
Age at first birth	30.52	27.88	31.70	29.43	32.68	30.81	33.83	32.14
Foreign-born	0.21	0.18	0.18	0.12	0.15	0.12	0.14	0.13
Married	0.24	0.21	0.31	0.25	0.31	0.30	0.37	0.37
Education								
Compulsory schooling	0.17	0.11	0.08	0.04	0.07	0.02	0.02	0.01
High school	0.64	0.58	0.36	0.33	0.35	0.22	0.16	0.06
College <3 years	0.12	0.16	0.13	0.13	0.20	0.17	0.18	0.10
College 3+ years	0.07	0.15	0.44	0.50	0.37	0.59	0.64	0.84
Years since graduation	8.75	5.47	6.56	4.80	8.06	5.44	7.52	5.37
N	188,258	135,585	40,392	79,765	109,157	134,749	101,254	71,954

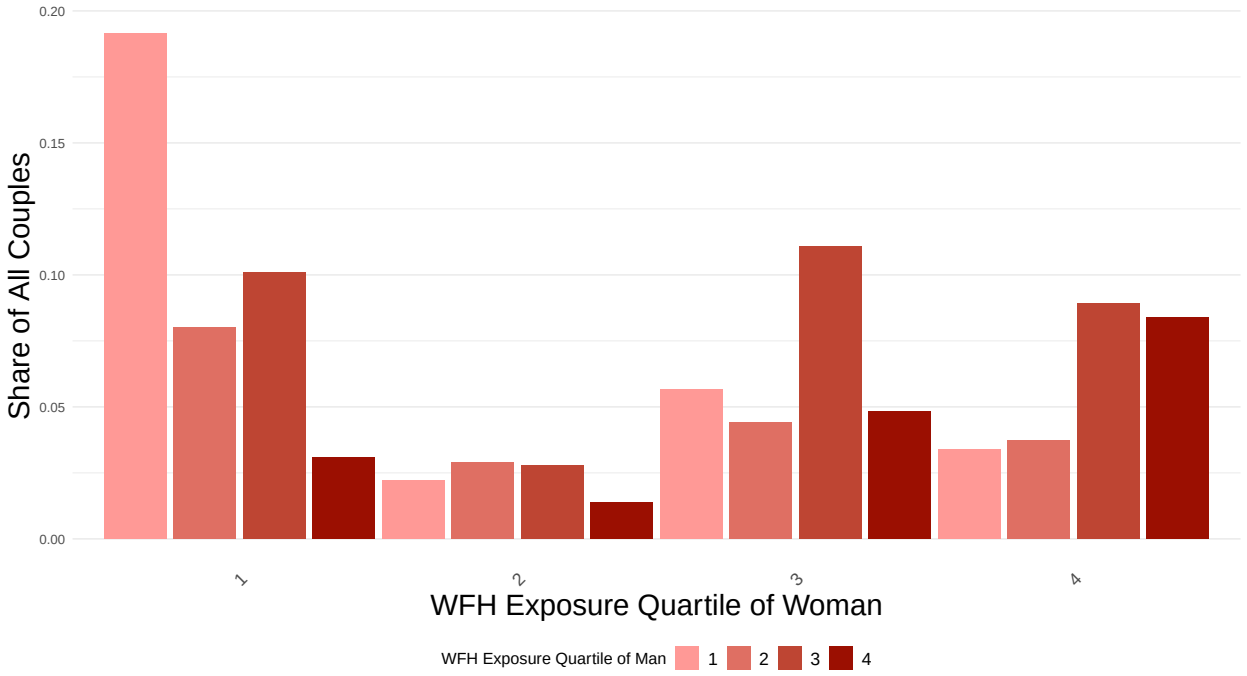
Notes: WFH exposure quartiles for men and women are defined using the change in remote work adoption by 2-digit occupation from 2019 to 2021. The measure is described in detail in section 3.2. "ΔWFH Intensity" refers to the value of the occupation-level change in remote work adoption from 2019 to 2021. The sample consists of opposite-sex parents who have their first child between 2010 and 2022 and are aged between 19 and 65 at the time of the first birth. All variables but two are measured the year prior to the first birth: Age is measured at the year of the first birth. Occupation is measured 2 years prior to the first birth.

matched to men who also have no exposure to working from home. In contrast, the majority of women who have high potential to work from home are matched to men who also have high exposure. Women with moderate exposure levels – those in quartile 3 of the occupational distribution – are also most likely to be matched to men with moderate exposure. This fact suggests that it will be important to consider the interactions between parents' access to flexibility in evaluating the effects of the rise of remote work on child penalties.

5 Theoretical framework: how will job flexibility affect the child penalty?

Collective models are typically used to answer questions about intra-household inequality, and require data on time use and consumption to estimate. In our setting, estimating such a model would not be feasible because of these data requirements. However, we can use a collective model to provide a structural micro-foundation for reduced-form motherhood penalties and to derive empirically testable predictions of how couples' labor supply will respond to the event of having a child, and how flexibility could impact these outcomes. In this section, we develop a collective model of household labor supply, extending the framework of Cherchye et al. (2012) to allow for the possibility that flexibility (a) affects the equilibrium labor supply decisions of both parents and (b) can be endogenously chosen. Flexibility enters the model through two channels: commuting and productivity penalties. On the commuting side, choosing to work flexibly reduces the time cost of market work, raising the effective wage. However, on the productivity side, working flexibly may reduce the marginal product of the worker, reducing her effective wage. Together, these two channels affect the worker's earnings capacity and thus the tradeoffs she faces between market work, home production, and leisure time.

Figure 2: Joint Distribution of Parents' Exposure to Remote Work



Notes: WFH exposure quartiles for men and women are defined using the change in remote work adoption by 2-digit occupation from 2019 to 2021. The measure is described in detail in section 3.2. The sample consists of matched opposite-sex parents who have their first child between 2010 and 2022 and are aged between 19 and 65 at the time of the first birth. Occupation is measured 2 years prior to the first birth. Each bar plots the share of all couples with a given pair of exposure quartiles.

This section proceeds in three parts. First, we develop the two-stage collective problem with and without children to show how the problem differs across the two settings. Second, we summarize how the problem changes when variation in the flexibility parameters is incorporated into the model and the choice of flexibility is endogenized. Third, we calibrate the model using parameter estimates from Cherchye et al. (2012) and develop a series of numerical comparative statics to summarize the model's predictions. While the model admits closed-form solutions for all key equilibrium quantities, their nonlinear form makes them challenging to interpret. The numerical comparative statics are intended to help build intuition for the channels through which flexibility could affect child penalties.

5.1 A collective model of household labor supply with and without children

We leverage the standard result in the collective labor supply literature, due to Blundell et al. (2005), that the household problem can be split into two stages. In the first stage, the agents choose the amount of utility of the public good to produce. The production of public goods is Pareto efficient and thus implies a unique choice of inputs: public-goods consumption and home production from each agent. At this stage, the residual nonwage income $y - c_p - c_k$ is allocated across the two agents according to the sharing rule ρ_i for $i = m, f$. In the second stage, conditional on the sharing rule, each agent chooses his or her own private leisure and consumption. To solve the model, we proceed backwards and begin with the second step.

Stage 2: the individual's problem

To begin, we specify a functional form for the indirect utility of the individual (adult) agents in the second stage of the household problem. We closely follow the framework of Cherchye et al. (2012) and specify the following indirect utility functions for $i = 1, 2$:

$$v_i(w_i, \rho_i, \bar{u}_k, \bar{u}_p) = \frac{\ln(w_i + \rho_i) - \ln a_i(w_i; \bar{u}_k, \bar{u}_p)}{(w_i)^{\beta_i}} \tag{1}$$

where

$$\ln a_i(w_i; \bar{u}_k, \bar{u}_p) = \begin{cases} (\alpha_1^i(\boldsymbol{d}_i) + \alpha_2^i \ln \bar{u}_k + \alpha_3^i \ln \bar{u}_p) \ln w_i & \text{if } K = 1; \\ (\alpha_1^i(\boldsymbol{d}_i) + \alpha_3^i \ln \bar{u}_p) \ln w_i & \text{if } K = 0. \end{cases}$$

We briefly discuss the assumptions that this framework implicitly makes and how they will assist us in identification. First, we assume that each individual's *latent preferences* do not change as a result of having a child. The parameters of the individual's utility function – i.e., the utility contributions of preference shifters and of household labor provided to kids and to the public good – do not vary within a person. This does not shut down selection into parenting on the basis of differences in preferences, nor does it foreclose on the possibility that equilibrium time allocation and consumption will change in response to having children. It only requires that becoming a parent does not shift one's preference parameters as enumerated in the specification. Second, we assume that becoming a parent does not change the wage rate. Again, it may change income in equilibrium, but it does not affect the wage rate directly. As we extend the model to allow

for individuals to endogenously choose to work flexibly, we allow for the possibility that adopting flexibility imposes some known penalty to the wage rate.

Following Cherchye et al. (2012), we apply Roy's identity to the indirect utility functions to obtain the individual demands for leisure and consumption for $i = 1,2$ with and without children:

$$l_i = \begin{cases} \left[(\alpha_1^i(\boldsymbol{d}_i) + \alpha_2^i \ln \bar{u}_k + \alpha_3^i \ln \bar{u}_p) + \beta_i \ln\left(\frac{w_i+\rho_i}{a_i(w_i;\bar{u}_k,\bar{u}_p)}\right)\right] \frac{(w_i+\rho_i)}{w_i} & \text{if } K = 1; \\ \left[\alpha_1^i(\boldsymbol{d}_i) + \alpha_3^i \ln \bar{u}_p) + \beta_i \ln\left(\frac{w_i+\rho_i}{a_i(w_i;\bar{u}_p)}\right)\right] \frac{(w_i+\rho_i)}{w_i} & \text{if } K = 0. \end{cases}$$

$$c_i = \begin{cases} \left[(1 - \alpha_1^i(\boldsymbol{d}_i) - \alpha_2^i \ln \bar{u}_k - \alpha_3^i \ln \bar{u}_p) - \beta_i \ln\left(\frac{w_i+\rho_i}{a_i(w_i;\bar{u}_k,\bar{u}_p)}\right)\right] (w_i + \rho_i) & \text{if } K = 1; \\ \left[(1 - \alpha_1^i(\boldsymbol{d}_i) - \alpha_3^i \ln \bar{u}_p) - \beta_i \ln\left(\frac{w_i+\rho_i}{a_i(w_i;\bar{u}_p)}\right)\right] (w_i + \rho_i) & \text{if } K = 0. \end{cases}$$

Having children affects the conditional demands for leisure and consumption through three channels. First, there is a direct effect on equilibrium demands for consumption and leisure from taking $\bar{u}_k$ into account. As we will see later, we require $\alpha_2^i < 0$ for each i. The direct effect of including the $\bar{u}_k$ term decreases l_i and increases c_i. Second, recalling that $\ln a_i(w_i;\bar{u}_k,\bar{u}_p) = (\alpha_1^i(\boldsymbol{d}_i) + \alpha_2^i \ln \bar{u}_k + \alpha_3^i \ln \bar{u}_p) \ln w_i$, adding the $\alpha_2^i \ln \bar{u}_k$ term reduces $a_i(\cdot)$, which increases l_i and decreases c_i. Third, including children may change the equilibrium ρ_i. To sign this third effect we need to derive expressions for the equilibrium ρ_is in the first stage of the household problem.

Stage 1a: the household's problem *without* children

Now, turning to the first stage, we will separately derive the solutions to the household's problem with and without children to clarify exposition. After deriving equilibrium market and household labor supply for each agent as well as consumption for each agent and the public good, we will compare the predicted labor supply of each spouse before and after having a child, holding fixed the preference parameters, wages, and productivity advantages in home production. The household's problem without children is

$$\begin{aligned} \max_{\rho_1,\rho_2,u_p} \; & \lambda(w_1,w_2,y,\boldsymbol{z}) \left(\frac{\ln(w_1+\rho_1) - \ln a_i(w_1;\bar{u}_p)}{(w_1)^{\beta_1}}\right) \\ & + (1 - \lambda(w_1,w_2,y,\boldsymbol{z})) \left(\frac{\ln(w_2+\rho_2) - \ln a_2(w_2;\bar{u}_p)}{(w_2)^{\beta_2}}\right) \\ \text{s.t. } & \rho_1 + \rho_2 + g_p(w_1,w_2)u_p = y, \end{aligned} \tag{2}$$

where $g_j(w_1,w_2)$ for $j = k,p$ is a constant conditional on wage rates w_1,w_2, given by

$$g_j(w_1,w_2) = \left[(\gamma_j^1)^{\frac{-1}{\varepsilon_j(\boldsymbol{s}_j)-1}} (w_1)^{\frac{\varepsilon_j(\boldsymbol{s}_j)}{\varepsilon_j(\boldsymbol{s}_j)-1}} + (\gamma_j^2)^{\frac{-1}{\varepsilon_j(\boldsymbol{s}_j)-1}} (w_2)^{\frac{\varepsilon_j(\boldsymbol{s}_j)}{\varepsilon_j(\boldsymbol{s}_j)-1}} + (\gamma_j^3)^{\frac{-1}{\varepsilon_j(\boldsymbol{s}_j)-1}}\right]^{\frac{\varepsilon_j(\boldsymbol{s}_j)-1}{\varepsilon_j(\boldsymbol{s}_j)}}.$$

Taking first order conditions where μ is the Lagrange multiplier, we have

$$\begin{aligned}
\frac{\lambda}{(w_1)^{\beta_1}}\frac{1}{w_1+\rho_1} &= \mu \\
\frac{1-\lambda}{(w_2)^{\beta_2}}\frac{1}{w_2+\rho_2} &= \mu \\
-\frac{\lambda}{(w_1)^{\beta_1}}\frac{\alpha_3^1 \ln w_1}{u_p} - \frac{1-\lambda}{(w_2)^{\beta_2}}\frac{\alpha_3^2 \ln w_2}{u_p} &= \mu g_p(w_1,w_2) \\
\rho_1+\rho_2+g_p(w_1,w_2)u_p &= y,
\end{aligned}$$

which can be rearranged to obtain

$$\begin{aligned}
w_1+\rho_1 &= \frac{1}{\mu}\frac{\lambda}{(w_1)^{\beta_1}} \\
w_2+\rho_2 &= \frac{1}{\mu}\frac{1-\lambda}{(w_2)^{\beta_2}} \\
g_p(w_1,w_2)u_p &= \frac{1}{\mu}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2 \ln w_2)\right]
\end{aligned}$$

Adding the first three conditions together and plugging into the budget constraint, we have

$$\begin{aligned}
w_1+w_2+y &= \frac{1}{\mu}\left[\frac{\lambda}{(w_1)^{\beta_1}}[1-\alpha_3^1 \ln w_1] + \frac{1-\lambda}{(w_2)^{\beta_2}}[1-\alpha_3^2 \ln w_2]\right] \\
&\equiv \frac{1}{\mu}X^{NC}(w_1,w_2,\lambda).
\end{aligned}$$

Now we can derive expressions for ρ_1, ρ_2, u_p:

$$\begin{aligned}
\rho_1 &= \frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_1)^{\beta_1}} - w_1 \\
\rho_2 &= \frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{1-\lambda}{(w_2)^{\beta_2}} - w_2 \\
u_p &= \frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2))}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2 \ln w_2)\right].
\end{aligned} \tag{3}$$

Now, using these expressions and the conditional leisure and consumption demands from the solution to the second (individual) stage, we can now derive expressions for the leisure and private consumption of each

agent:

$$l_i = \left[\alpha_1^i(\boldsymbol{d}_i) + \alpha_3^i \ln\left(\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2))}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1\ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2\ln w_2)\right]\right)\right.$$
$$\left. + \beta_i \ln\left(\frac{\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}}{a_i(w_i;\bar{u}_p)}\right)\frac{\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}}{w_i}\right] \tag{4}$$

$$c_i = \left[1 - \alpha_1^i(\boldsymbol{d}_i) - \alpha_3^i \ln\left(\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2)}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1\ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2\ln w_2)\right]\right)\right.$$
$$\left. - \beta_i \ln\left(\frac{\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}}{a_i(w_i;\bar{u}_p)}\right)\right]\left(w_i + \frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}\right). \tag{5}$$

Next, we can apply Shephard's Lemma to the expenditure function $g_p(w_1,w_2)u_p$ to derive the home production choices of each agent:

$$h_p^i = \left(\frac{w_i}{\gamma_p^i}\right)^{\frac{1}{\varepsilon_p(\boldsymbol{s}_p)-1}} (g_p(w_1,w_2))^{-\frac{\varepsilon_p(\boldsymbol{s}_p)}{\varepsilon_p(\boldsymbol{s}_p)-1}} \frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1\ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2\ln w_2)\right]. \tag{6}$$

Stage 1b: the household's problem *with* children

The problem with children is

$$\begin{aligned}\max_{\rho_1,\rho_2,u_p,u_k}\ & \lambda(w_1,w_2,y,\boldsymbol{z})\left(\frac{\ln(w_1+\rho_1) - \ln a_i(w_1;\bar{u}_k,\bar{u}_p)}{(w_1)^{\beta_1}}\right) \\ & + (1-\lambda(w_1,w_2,y,\boldsymbol{z}))\left(\frac{\ln(w_2+\rho_2) - \ln a_2(w_2;\bar{u}_k,\bar{u}_p)}{(w_2)^{\beta_2}}\right) \\ \text{s.t. }& \rho_1+\rho_2+g_k(w_1,w_2)u_k + g_p(w_1,w_2)u_p = y,\end{aligned} \tag{7}$$

where $g_j(w_1,w_2)$ has the same form as in stage 1a without children. To simplify the work in this section, we note that the solutions to our version of the problem with children are identical to those of Cherchye et al. (2012). We thus omit the derivations of intermediate objects and summarize key equilibrium objects: labor supply, home production, and consumption for each agent and for each of the public goods.

First it is helpful to define $X^C(w_1,w_2,\lambda)$, the analogue with children of the object $X^{NC}(w_1,w_2,\lambda)$ in the problem with no children:

$$X^C(w_1,w_2,\lambda) \equiv \left[\frac{\lambda}{(w_1)^{\beta_1}}[1-(\alpha_2^1+\alpha_3^1)\ln w_1] + \frac{1-\lambda}{(w_2)^{\beta_2}}[1-(\alpha_2^2+\alpha_3^2)\ln w_2]\right].$$

Note that for a couple with the same parameters and no changes in wages or Pareto weights, $X^C(\cdot) > X^{NC}(\cdot)$. Intuitively, X^C and X^{NC} capture the weighted average opportunity cost of earnings for the household. After having children, work incurs a higher opportunity cost because time spent on household labor can now

produce utility for children as well. Now we can state the expressions for ρ_1, ρ_2, u_p, and u_k:

$$\rho_1 = \frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{\lambda}{(w_1)^{\beta_1}} - w_1$$

$$\rho_2 = \frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{1-\lambda}{(w_2)^{\beta_2}} - w_2 \tag{8}$$

$$u_p = \frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2))}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2 \ln w_2)\right] \tag{9}$$

$$u_k = \frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2))}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_2^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_2^2 \ln w_2)\right]. \tag{10}$$

and the expressions for l_i, c_i, h_p^i, h_k^i:

$$\begin{aligned} l_i = &\left[\alpha_1^i(\boldsymbol{d}_i) + \alpha_2^i \ln\left(\frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2))}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_2^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_2^2 \ln w_2)\right]\right)\right. \\ &+ \alpha_3^i \ln\left(\frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2))}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2 \ln w_2)\right]\right) \\ &\left.+ \beta_i \ln\left(\frac{\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}}{a_i(w_i;\bar{u}_p)}\right)\right]\frac{\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}}{w_i} \end{aligned} \tag{11}$$

$$\begin{aligned} c_i = &\left[1 - \alpha_1^i(\boldsymbol{d}_i) - \alpha_2^i \ln\left(\frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2)}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_2^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_2^2 \ln w_2)\right]\right)\right. \\ &- \alpha_3^i \ln\left(\frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\frac{1}{g_p(w_1,w_2)}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2 \ln w_2)\right]\right) \\ &\left.-\beta_i \ln\left(\frac{\frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}}{a_i(w_i;\bar{u}_p)}\right)\right]\left(w_i + \frac{w_1+w_2+y}{X^{NC}(w_1,w_2,\lambda)}\frac{\lambda}{(w_i)^{\beta_i}}\right). \end{aligned} \tag{12}$$

$$h_k^i = \left(\frac{w_i}{\gamma_k^i}\right)^{\frac{1}{\varepsilon_k(\boldsymbol{s}_k)-1}}(g_k(w_1,w_2))^{-\frac{\varepsilon_k(\boldsymbol{s}_k)}{\varepsilon_k(\boldsymbol{s}_k)-1}}\frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_2^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_2^2 \ln w_2)\right] \tag{13}$$

$$h_p^i = \left(\frac{w_i}{\gamma_p^i}\right)^{\frac{1}{\varepsilon_p(\boldsymbol{s}_p)-1}}(g_p(w_1,w_2))^{-\frac{\varepsilon_p(\boldsymbol{s}_p)}{\varepsilon_p(\boldsymbol{s}_p)-1}}\frac{w_1+w_2+y}{X^C(w_1,w_2,\lambda)}\left[-\frac{\lambda}{(w_1)^{\beta_1}}(\alpha_3^1 \ln w_1) - \frac{1-\lambda}{(w_2)^{\beta_2}}(\alpha_3^2 \ln w_2)\right]. \tag{14}$$

5.2 Adding the choice of flexibility

Adding job flexibility imposes additional complexity on the problem because it affects individual decisions through two channels. First, flexibility loosens the individual's time budget constraint. The budget constraint will include some fixed time cost of commuting when working inflexibly, and this time cost will be reduced when working flexibly. Second, flexibility imposes a wage penalty if it reduces the worker's marginal product.

We specify the functional form of $q(f_i, m_i)$ as

$$q(f_i, m_i) = \kappa m_i(1 - f_i).$$

where $q(f_i, m_i)$ is a commuting friction that depends on the choice of flexibility and labor supply. If the worker chooses not to work at all or to work entirely from home, $q_i = 0$. For a given worker in a given job, there is some maximum possible time allocated to commuting, q_i^{max}, associated with going to the office every day of the week; flexible arrangements can allow for any commuting time $q_i \in [0, q_i^{max}]$.

We assume competitive output markets, resulting in an equilibrium wage per efficiency unit of labor given by w_i. We allow for the possibility that flexible work arrangements affect the worker's marginal product. Denote the discount to marginal product $\eta_{o(i)}$, which is specific to i's occupation $o(i)$. We allow the discount to depend on the intensivity of flexibility adoption, i.e., $\eta_{o(i)} = \eta_o(f_i)$. We specify the functional form of $\eta_{o(i)}$ as

$$\eta o(f_i) = (1 - \delta_o f_i)^{\theta_o}.$$

Stage 2: the individual's problem

We retain the functional form specification for the indirect utility from the problem without flexibility. The key feature that differs in this version is that the *effective* wage now depends on the choice of flexibility. Using the functional form specifications for commuting time $q(f_i, m_i)$ and wage penalty $\rho_o(f_i)$, we define this effective wage as:

$$w_i^{eff} \equiv \frac{1 - (1 - \delta_o f_i)^{\theta_i}}{1 + \kappa(1 - f_i)} w_i, \tag{15}$$

where w_i is the base wage that the worker earns for each effective unit of labor. The new expression for the effective wage accounts for (i) the reduction in marginal product from adopting flexibility and (ii) the reduction in commuting time from adopting flexibility. Intuitively, if the agent chooses not to work flexibly, her compensation is spread over $(1 + \kappa)m_i$, so the effective wage decreases. However, if she chooses to work flexibly, she incurs no commuting cost but sacrifices the wage penalty $(1 - \delta_o)^{\theta_o}$ on each hour of work because her marginal product is lower. Now, the "price" of leisure is w_i^{eff}. We can apply Roy's identity to the indirect utility function to obtain the individual demands for leisure and consumption:

$$l_i = \begin{cases} \left[(\alpha_1^i(\boldsymbol{d}_i) + \alpha_2^i \ln \bar{u}_k + \alpha_3^i \ln \bar{u}_p) + \beta_i \ln \left(\frac{w_i^{eff} + \rho_i}{a_i(w_i^{eff}; \bar{u}_k, \bar{u}_p)} \right) \right] \frac{(w_i^{eff} + \rho_i)}{w_i^{eff}} & \text{if } K = 1; \\ \left[\alpha_1^i(\boldsymbol{d}_i) + \alpha_3^i \ln \bar{u}_p) + \beta_i \ln \left(\frac{w_i^{eff} + \rho_i}{a_i(w_i^{eff}; \bar{u}_p)} \right) \right] \frac{(w_i^{eff} + \rho_i)}{w_i^{eff}} & \text{if } K = 0. \end{cases}$$

$$c_i = \begin{cases} \left[(1 - \alpha_1^i(\boldsymbol{d}_i) - \alpha_2^i \ln \bar{u}_k - \alpha_3^i \ln \bar{u}_p) - \beta_i \ln \left(\frac{w_i^{eff} + \rho_i}{a_i(w_i^{eff}; \bar{u}_k, \bar{u}_p)} \right) \right] (w_i^{eff} + \rho_i) & \text{if } K = 1; \\ \left[(1 - \alpha_1^i(\boldsymbol{d}_i) - \alpha_3^i \ln \bar{u}_p) - \beta_i \ln \left(\frac{w_i^{eff} + \rho_i}{a_i(w_i^{eff}; \bar{u}_p)} \right) \right] (w_i^{eff} + \rho_i) & \text{if } K = 0. \end{cases}$$

Now, in addition, the individual agent needs to choose $f_i = \{0,1\}$ to maximize conditional (indirect) utility, where utility is given by

$$v_i(w_i^{eff}, \rho_i, \bar{u}_k, \bar{u}_p) = \frac{\ln(w_i^{eff} + \rho_i) - \ln a_i(w_i^{eff}; \bar{u}_k, \bar{u}_p)}{(w_i^{eff})^{\beta_i}}$$

where

$$\ln a_i(w_i; \bar{u}_k, \bar{u}_p) = \begin{cases} (\alpha_1^i(\boldsymbol{d}_i) + \alpha_2^i \ln \bar{u}_k + \alpha_3^i \ln \bar{u}_p) \ln w_i^{eff} & \text{if } K = 1; \\ (\alpha_1^i(\boldsymbol{d}_i) + \alpha_3^i \ln \bar{u}_p) \ln w_i^{eff} & \text{if } K = 0. \end{cases}$$

Simplify the following terms:

$$\begin{aligned} A_i &= (\alpha_1^i(\boldsymbol{d}_i) + \alpha_2^i \ln \bar{u}_k + \alpha_3^i \ln \bar{u}_p) \\ \lambda_0 &= (1+\kappa)^{-1} \\ \lambda_1 &= (1-(1-\delta)^{\theta}) \end{aligned}$$

Then the agent chooses $f_i = 1$ iff

$$\frac{\ln(\lambda_1 \cdot w_i + \rho_i) - A_i \ln(\lambda_1 \cdot w_i)}{(\lambda_1 \cdot w_i)^{\beta_i}} > \frac{\ln(\lambda_0 \cdot w_i + \rho_i) - A_i \ln(\lambda_0 \cdot w_i)}{(\lambda_0 \cdot w_i)^{\beta_i}}. \tag{16}$$

However, the choice of flexibility does not follow a simple threshold rule because the sharing rule ρ_i depends on the choice of flexibility through the channel of the Pareto weight. We have shown in numerical simulations that there is not always a a decentralized Nash equilibrium choice of flexibility for the two agents. Thus we argue that flexibility must be decided by coordinating at the household level. We aim to prove this result formally as this work develops.

Stage 1: the household's problem

The household's problem is similar to the version without flexibility, with the main difference that the effective wage for each agent depends on the choice of flexibility. As argued in our exposition of the individual's problem in this version of the model, the endogenous choice of whether to work flexibly is made as part of the joint decision to maximize household utility. Knowing the solutions to the household problem conditional on the flexibility choices of the man and woman – f_m, f_f, respectively – the spouses choose the combination that maximizes joint household utility.

5.3 Model calibration and numerical comparative statics

As shown in the exposition of the model in the previous subsections, the closed-form expressions for labor, leisure, home production, and utility are quite complicated. To build intuition for the model's predictions, we conduct a series of numerical comparative statics exercises that combine calibrated parameters from the literature with variation in men's and women's wages as well as in the flexibility penalty faced by

each parent. Table 2 summarizes the calibrated parameters drawn from the estimates of Cherchye et al. (2012). While these estimates were obtained using data from the Netherlands, we view them as good first approximations of what we might expect in Sweden since the two countries have similar social norms and safety nets. We omit some of the estimated parameters for simplicity if they were estimated to be zero in the original paper. Furthermore, we shut down three axes of variation in the couple's problem – namely, the role of nonwage income, the age gap between the two spouses, and the number and ages of children – to focus on the model's predictions related child penalties for different combinations of parental wages and productivity costs of flexibility.

In these exercises, we contrast the model's predictions for couples with four combinations of flexibility penalties: $\delta_f, \delta_m \in \{0.1, 0.5\}$. Intuitively, an agent with $\delta_i = 0.1$ has a relatively small penalty to their output productivity when working remotely, while an agent with $\delta_i = 0.5$ loses half of their productivity by working from home. We fix the commuting penalty $\kappa = 0.1$ for both agents. For each exercise, we first fix the man's log wage at 10 and vary the woman's wage; then, we fix the woman's log wage at 10 and vary the man's wage. We then calculate the model's predicted equilibrium quantities for couples with a given set of parameters with and without children to examine how the share of time spent on home production, market work, and leisure change if an "exogenous" child arrives.

Prediction 1: motherhood penalties in hours will decline for women who gain access to flexibility, holding their partner's flexibility constant

To begin, we ask how the share of women's time spent in market work responds differentially to the event of having a child when we vary the woman's access to flexibility δ_f. Figures 3 shows the market labor share of total hours for each partner with and without children, with each panel showing the results for four different combinations of parameters δ_f, δ_m. To examine the effect of increasing the woman's access to flexibility, we compare $\delta_f = 0.5$ to $\delta_f = 0.1$, holding constant the man's access to flexibility at $\delta_m = 0.1$ (comparing panels (a) and (c)) or at $\delta_m = 0.5$ (comparing panels (b) and (d)). In both pairs of panels, we observe that reducing δ_f is associated with a narrowing of the gap in women's market work between the cases with and without children. This is complemented by a slight increase in the gap in men's market work, suggesting that as the woman gains access to flexibility, the man works slightly less. We interpret this to suggest that when the woman experiences a smaller reduction in labor supply after having a child, the man reduces his work as well because the marginal utility of household income declines. Thus, the model predicts that making flexibility more accessible to women in partnered couples should reduce motherhood penalties.

Prediction 2: motherhood penalties in hours will change little if *both* spouses gain access to flexibility

In contrast with the first prediction of the model, we now ask what happens to motherhood penalties when *both* spouses gain access to flexibility at similar treatment levels. To answer this question, we compare panels (a) and (d) of figure 3. We observe that the gaps in market work hours for both men and women are quite similar across the two panels; the main difference between the two is that the total market work share is shifted down slightly for both agents. We interpret this to reflect the fact that when the agents gain *symmetric* access to flexibility, their relative opportunity costs of time remain the same. The trade-off in

Table 2: Calibrated Parameters for Household Labor Supply Model

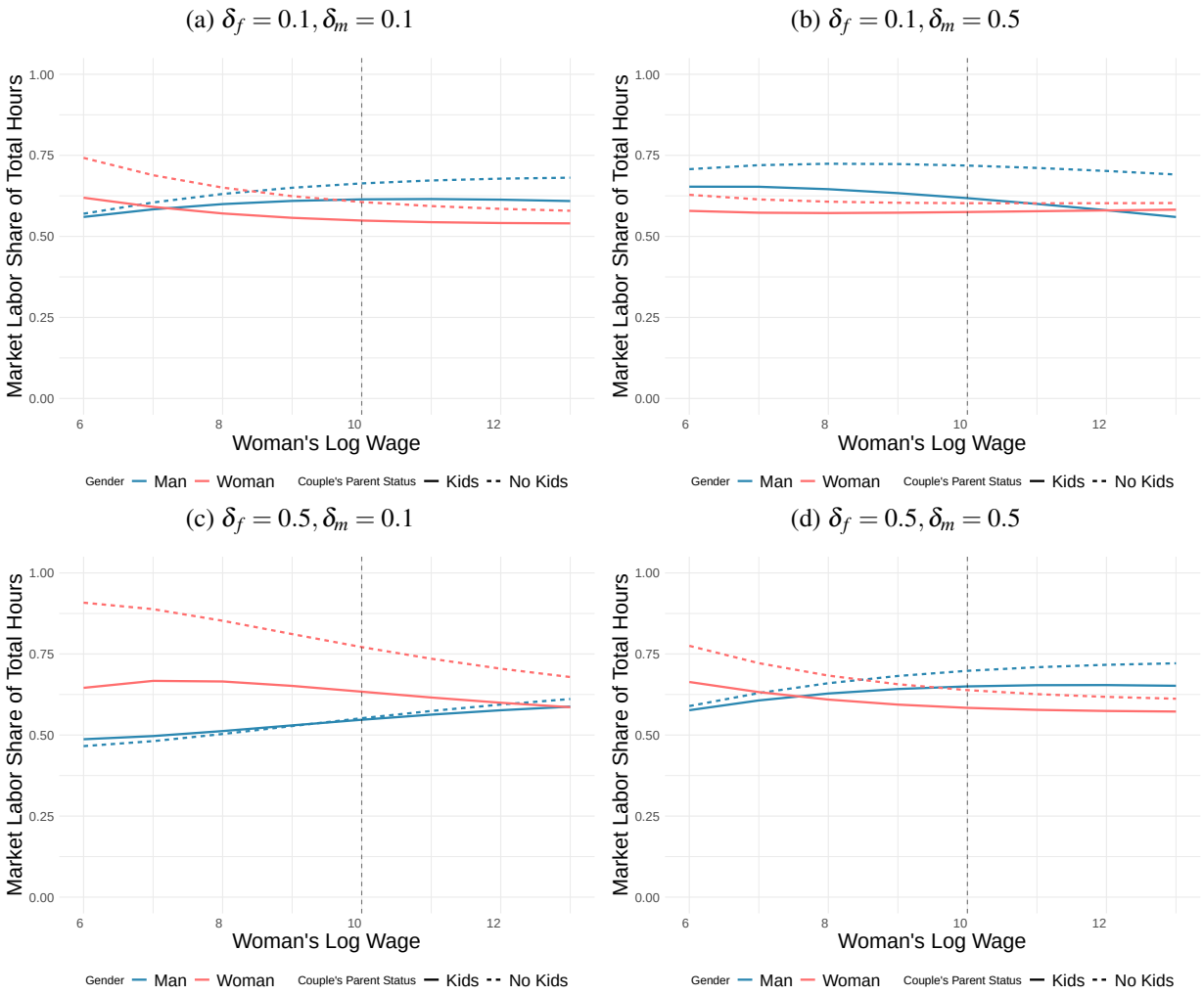
	Model Parameter	Estimate
Preference parameters		
For man's utility		
Preference intercept – man	α_{10}^m	0.826
Effect of u_k on man's preference	$\tilde{\alpha}_k^m$	-2.330
Effect of u_p on man's preference	$\tilde{\alpha}_p^m$	-1.842
Curvature of man's utility of income	β_m	0.209
For woman's utility		
Preference intercept – woman	α_{10}^m	0.881
Effect of u_k on woman's preference	$\tilde{\alpha}_k^f$	-2.486
Effect of u_p on woman's preference	$\tilde{\alpha}_p^f$	-2.876
Curvature of woman's utility of income	β^2	0.159
Household production parameters		
For production of kids' utility		
Productivity of h_m in kids' utility	γ_k^m	0.359
Productivity of h_f in kids' utility	γ_k^f	0.417
Additional productivity parameter in u_k	γ_k^3	0.224
Substitutability of h_m, h_f in kids' utility	ε_1^k	-0.011
For production of public utility		
Productivity of h_m in public utility	γ_p^1	0.196
Productivity of h_f in public utility	γ_p^f	0.204
Additional productivity parameter in u_p	γ_p^3	0.579
Substitutability of h_m, h_f in public utility	ε^b	0.253
Pareto weight parameters		
Baseline Pareto weight	Λ_1	-1.546
Effect of wage ratio on Pareto weight	$\Lambda_2[w_m/w_f]$	1.395

Notes: Calibrated parameters taken from estimates of Cherchye et al. (2012). Some parameters from the original model are omitted for simplicity because they are close to zero or not statistically significant. Parameters $\tilde{\alpha}_j^i$ for $j = k, p$ and $i = f, m$ correspond to α_j^i parameters in the written model through the relation $\alpha_j^i = -\exp(-\tilde{\alpha}_j^i)$. Cherchye et al. (2012) use this specification to impose the restriction that the α preference parameters must be positive. We also omit parameters related to nonwage income as we abstract away from variation in nonwage income in our comparative statics exercises.

time use between the man and the woman remains the same, so their labor supply responses are similar. They also both respond to the increase in flexibility by substituting towards private leisure, which explains the downward vertical shift in market work.

In the context of our descriptive facts, this model prediction highlights a key caveat to the potential of remote work flexibility to reduce child penalties. As discussed in section 4.3, parents match assortatively on the intensity of exposure to increases in remote work – women with high levels of exposure to remote work tend to be partnered to men who also have high levels of exposure to remote work and vice versa – because exposure is positively correlated with income and education. As a consequence, it is empirically more common for couples to experience similar or symmetric changes – like those from panel (d) to panel

Figure 3: Model calibration: share of hours spent in market work with and without children, varying the woman's wage for different levels of flexibility penalties



(a) – than for the woman to gain relatively more access to flexibility – as in the change from panel (c) to panel (a). This prediction highlights that increasing access to flexibility is insufficient to produce major changes in the motherhood penalty if women do not *differentially gain* from this access.

Prediction 3: Women take on more home production than men even with equal wages, and flexibility has a similar effect on home production as on market hours

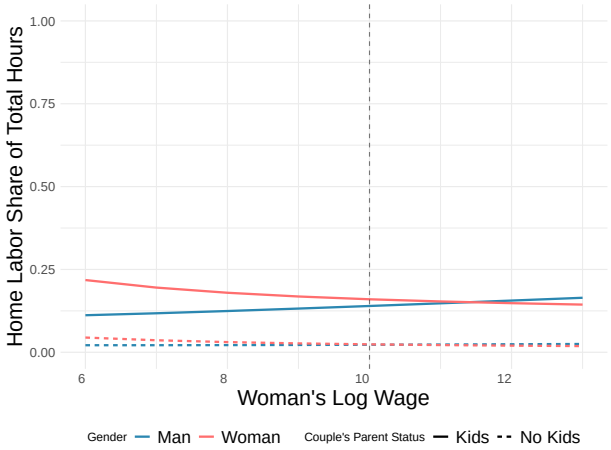
We next ask how the distribution of time spent in home production – especially on childcare – differs for couples with different combinations of access to job flexibility. As in the previous two facts, we summarize these changes by fixing the man's log wage at 10 and varying the woman's log wage for each of four different combinations of (δ_f, δ_m). Figure 4 plots the results, from which two key features emerge. First, when the man and woman have the same flexibility penalty, the woman is typically the partner spends more time on home production unless she substantially outearns the man. For example, if wages are exactly equal –

$w_f = w_m = 10$ on the graph, highlighted by the gray dotted vertical line – the woman spends more time on home production, especially on childcare. For time spent on childcare to be equal, the woman must earn about 15 percent more than the man; such earnings combinations are empirically relatively rare. The result is driven by the calibrated parameters for γ_k^m and γ_k^f: the woman is relatively more productive in producing utility for children than the man is. This "productivity difference" could be microfounded by gender norms – where members of the household gain utility from complying with traditional gender roles – as easily as by true productivity differences. Regardless of its origin, the result is that women spend a disproportionate share of their time on home production, which makes their time scarcer and changes the tradeoff they face between time and market work.

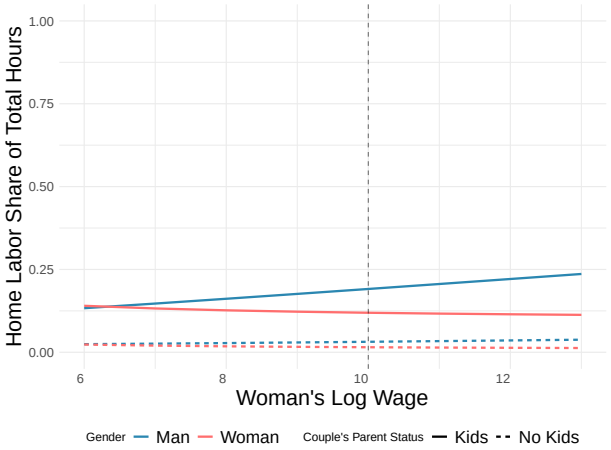
The second feature that emerges from the comparative statics on home production is that increasing the woman's access to flexibility while holding the man's access constant results in a more equal division of home production. Comparing panel (a) to panel (c) and panel (b) to panel (d) in Figure 4, we observe that the woman's time spent on home production decreases and the man's time spent on home production increases as her job is more accommodating of flexibility. This mirrors the comparative statics on market work: as the woman's time budget constraint expands while the man's stays the same, the balance of home production will shift towards gender equity. Analogously, we document a similar pattern to the result on market work when comparing panel (a) to panel (d): when both agents gain greater access to flexibility, the division of childcare remains unchanged. This result underscores that we expect labor supply responses to be muted if men and women gain equally from changes in access to remote work.

Figure 4: Model calibration: share of hours spent in home production with and without children, varying the woman's wage for different levels of flexibility penalties

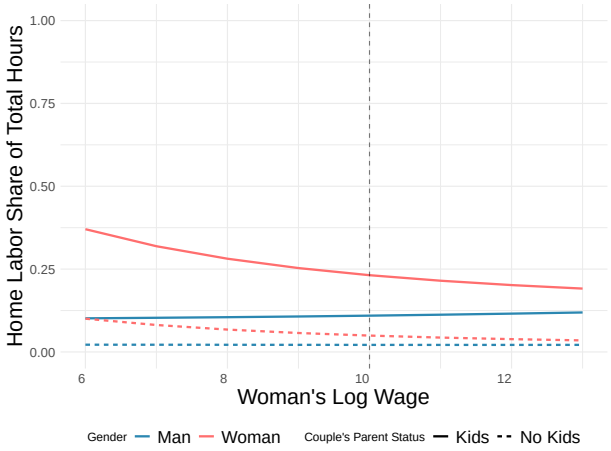
(a) $\delta_f = 0.1, \delta_m = 0.1$



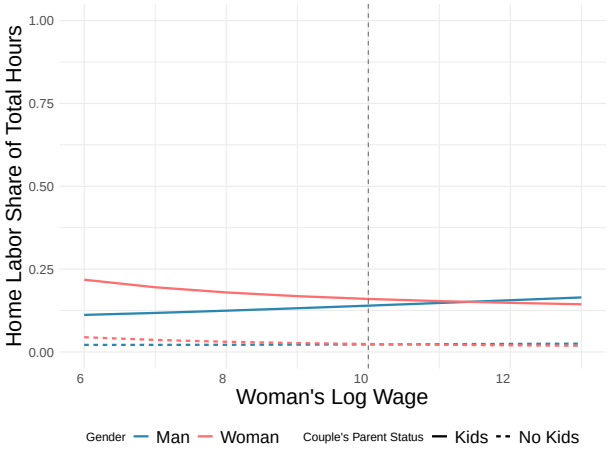
(b) $\delta_f = 0.1, \delta_m = 0.5$



(c) $\delta_f = 0.5, \delta_m = 0.1$



(d) $\delta_f = 0.5, \delta_m = 0.5$



6 Event study estimation of the impact of remote work on child penalties

We exploit quasi-random variation in changes in remote work intensity during the pandemic to answer three empirical questions. First, how did child penalties before the pandemic differ across occupations that have been more or less affected by adoption of working from home? Second, how have child penalties changed since the pandemic in occupations with differential exposure to remote work? Third, what share of the *ex ante* gap in labor market outcomes was closed for workers with differential exposure to remote work?

6.1 Empirical specification

For workers of gender g in occupation group o, we estimate changes in event time effects on employment outcomes Y_{it} by interacting a standard event time specification with indicators for whether the observation is from before or after the pandemic-induced change in remote work adoption:

$$Y_{it}^{go} = \boldsymbol{\alpha}^{go} \cdot \underbrace{D_{it}^{event}}_{\substack{\text{event time} \\ \text{indicators}}} + \varphi^{go} \cdot \underbrace{D_{it}^{post}}_{\substack{\text{post-WFH-} \\ \text{adoption} \\ \text{indicator}}} + \boldsymbol{\delta}^{go} \cdot \underbrace{D_{it}^{event \times post}}_{\substack{\text{event time} \times \\ \text{post-WFH-adoption}}} + \boldsymbol{\beta}^{go} \cdot \underbrace{D_{it}^{age}}_{\substack{\text{age} \\ \text{indicators}}} + \boldsymbol{\gamma}^{go} \cdot \underbrace{D_{it}^{year}}_{\substack{\text{year} \\ \text{indicators}}} + \boldsymbol{\phi}^{go} \cdot \underbrace{X_{it}}_{\text{controls}} + \nu_{it}^{go}. \tag{17}$$

The coefficients δ_t^{go} estimate the difference in child penalty for workers of gender g and occupation o at event-time t relative to the year of first birth. For example, δ_2^{w1} compares the differential change in employment two years after the birth of the first child for women in occupation 1, before and after remote work has been adopted. Effectively, this example coefficient estimates the effect of access to remote work on the labor supply effect of having a child two years after the first birth. At each event time, we normalize the event study and triple-difference estimates by the predicted counterfactual outcome $\mathbb{E}[Y_{it}]$ using age, year, and covariates in the absence of event-time treatment effects. This follows the standard practice in the child penalties literature, first developed by Kleven et al. (2019a), to express the labor supply effect as a percentage of the counterfactual. We define membership in the pre- versus post-pandemic group by birth cohort: parents to children born between 2010 and 2016 are in the pre-pandemic group, and parents to children born between 2017 and 2022. We additionally partition the sub-samples by excluding pre-pandemic event-time years for the post-pandemic group (e.g. all event-time year up to $t+2$ for birth cohort 2017), and post-pandemic years for the pre-pandemic group (e.g. $t+4$ and onwards for birth cohort 2016). As follows, the estimates are obtained with an unbalanced panel.

The ultimate object of estimation is the difference in δ_t^{go} for occupations o and o' with low versus high exposure to remote work. We would expect that workers with little potential to adopt remote work will not see their child penalties change much before and after remote work became popular. This paper aims to test the hypothesis that workers whose occupations make them likely to see a change in their ability to work from home saw a decline in child penalties after remote work became more common.

Identification of the coefficients of interest rests on two parallel-trends assumptions. First, the event-time

estimates require the assumption that labor supply outcomes would have evolved along the same trajectory as the predicted counterfactual if the individual had not had a child. This assumption is standard in the literature on earnings effects of having children. Second, the triple-difference estimates require the assumption that labor supply *penalties* would have remained the same in the absence of exposure to remote work. This is a strong assumption: it implies that differential changes in the child penalty across occupations with heterogeneous exposure to remote work are explained by the increase in flexibility and not by confounding factors. While this assumption cannot be tested directly, we probe its robustness through a placebo test in Section 7.

6.2 Results by individual occupational exposure to remote work

Figure 5 shows the event study estimates of the impact of the first birth on annual wage income before and after the pandemic in the left-hand column; the right-hand column shows the triple-difference estimates. The first row plots estimates for individuals in the lower median of exposure to remote work ($\Delta WFH \in [-0.15, 0.15]$). The second row plots estimates for individuals in the third quartile of exposure ($\Delta WFH \in [0.17, 0.31]$); the third row plots estimates for individuals in the highest quartile of exposure ($\Delta WFH \in [0.41, 0.74]$).[3] The outcome measure is the level of annual real wage income, so individuals with zero wage income are also included. Wage income is normalized using the pre-birth expected value following the convention, allowing the estimates to be interpreted as a percentage penalty relative to pre-birth income.[4]

The left-hand panels illustrate the pre- and post-pandemic effects of childbirth on annual wage income for workers for men and women in each occupational exposure group, and show an inverse relationship between ex ante earnings penalties and eventual exposure to remote work. The right-hand panels show the corresponding triple-difference estimates. Panel (b) shows that the earnings penalty expanded for women with minimal exposure to remote work, with an average short-term expansion of 7.7 percentage points. As exposure intensity increases, the expansion of the earnings penalty decreases: the penalty grew by 3.4 percentage points for moderate-exposure mothers and 1.5 percentage points for high-exposure mothers.

The estimates move in the opposite direction of our hypothesis: While earnings penalties expanded for all women, the differential expansion of the earnings penalty is concentrated among women with the least exposure to remote work; those with greater access fared better than those without it. This notwithstanding, the results are consistent with flexibility mitigating negative earnings effects associated with pregnancy and parenthood during the COVID-19 pandemic. For instance, individuals who are working in risky work environment or with physically demanding jobs are eligible for pregnancy benefits if their employers cannot reallocate them to other tasks during the pregnancy. Women in low-exposure occupations are more likely to use pregnancy benefits, in part because of riskier occupations, in part because they cannot work from home. The incidence of pregnancy benefits take-up also increased during the pandemic, since pregnant women were considered a high-risk group. The take-up of benefits for taking care of sick children in day care is also likely to be differently distributed for working mothers with different levels of remote work exposure.

[3] The separate results for the first and second quartiles are similar, so we pool these groups and show estimates for the lower median for simplicity and ease of comparison across exposure groups.

[4] We present event study results in level changes relative to event-time $t-1$ in Appendix Figures A.1–A.4.

In Section 7, we exclude occupations with unusual pandemic labor market shocks (health and hospitality occupations) and find that the results are robust to excluding these occupations.

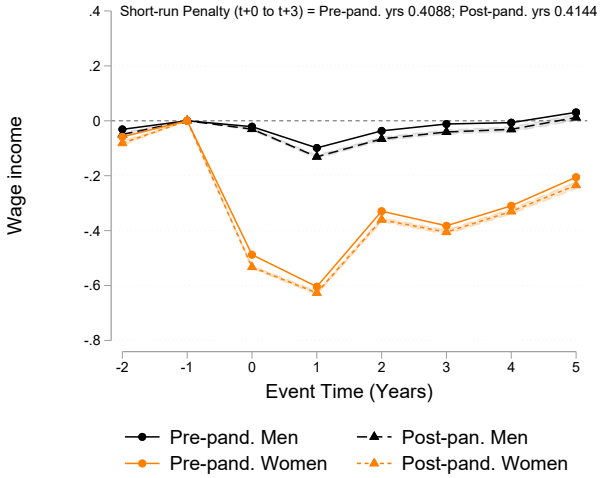
Figure 6 shows the event study estimates of the impact of first birth on the employment margin before and after the pandemic in the left-hand column; the right-hand column shows the triple-difference estimates of the change in event-study outcomes at each event time after the pandemic. The employment outcome is measured as an indicator that the individual is linked to an employer. Importantly, a worker is coded as employed while taking parental leave, even if she does not receive any wage earnings or work any hours. This measurement of the employment outcome is consistent with the argument of Adams-Prassl et al. (2024) that employment penalties should reflect that parents on leave have a right to return to their pre-leave wages and hours after completing a leave spell.

The left-hand panels illustrate that–similar to the earnings penalties–ex ante employment penalties are inversely correlated with eventual exposure to remote work. Before the pandemic, women with the least eventual access to remote work experienced a decline in employment of 8.01 percent over the three years immediately following the first birth. In contrast, during the same period, women with the highest eventual access to remote work experienced a decline in employment of 1.90 percent over the same horizon.

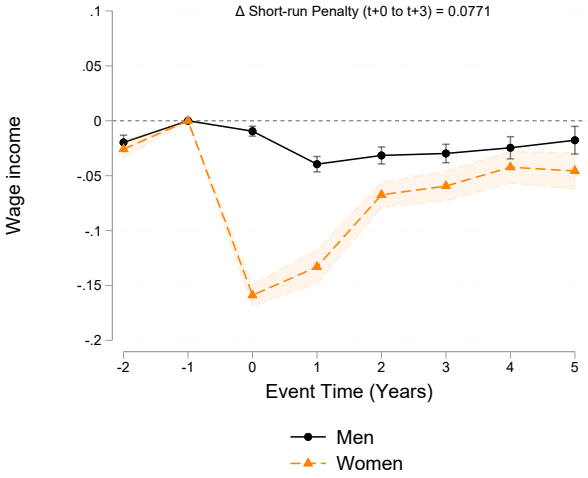
Employment penalties contracted for women in all occupation groups after the pandemic. The three-year penalty for the least-exposed women declined to 6.22 percent; for the most-exposed women, it declined to 1.15 percent. The magnitude of the decline for less-exposed women is larger than the decline for more-exposed women. However, we emphasize that the triple-difference estimate of the closure of the gap in percentage points is much larger for high-exposure women: those with the greatest occupational potential for remote work saw the child penalty close by 0.8 percentage points, 42 percent of the *ex ante* gap. Intuitively, because the employment penalty was smaller before the pandemic for those who became highly exposed to remote work, there was less room for shocks to flexibility to close the gap. In contrast, those with the least potential to adopt remote work based on their occupation saw the penalty close by 2.2 percentage points, or about a 28 percent reduction. Thus there is a monotonically positive correlation between the narrowing of employment declines after the first birth and intensity of exposure to remote work. This provides suggestive evidence that the narrowing of these penalties may be attributable to an increase in the supply of flexibility amenities at these jobs.

Figure 5: Event study and triple-difference estimates of income effects of first birth

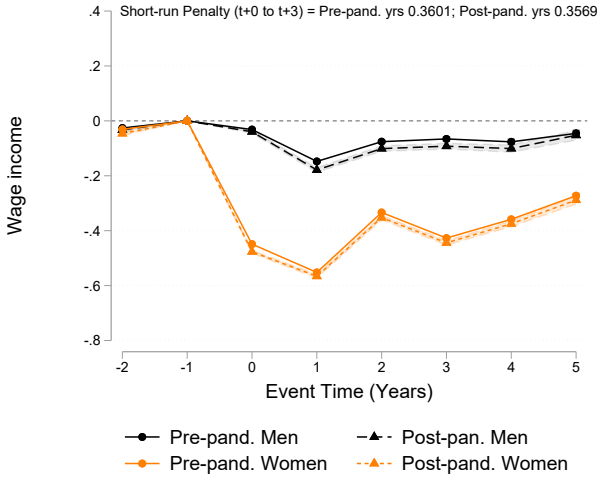
(a) Lower median – event study



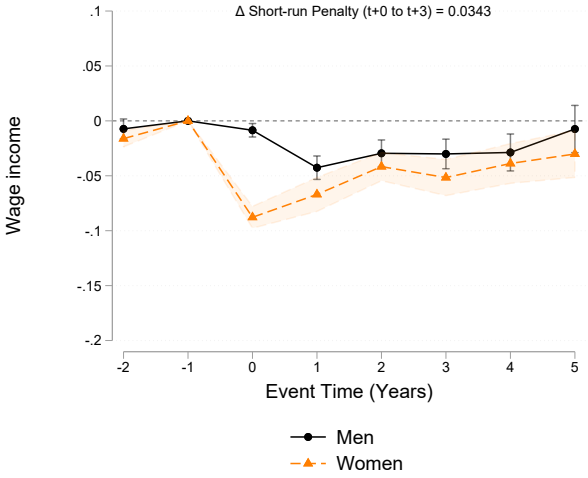
(b) Lower median – triple difference



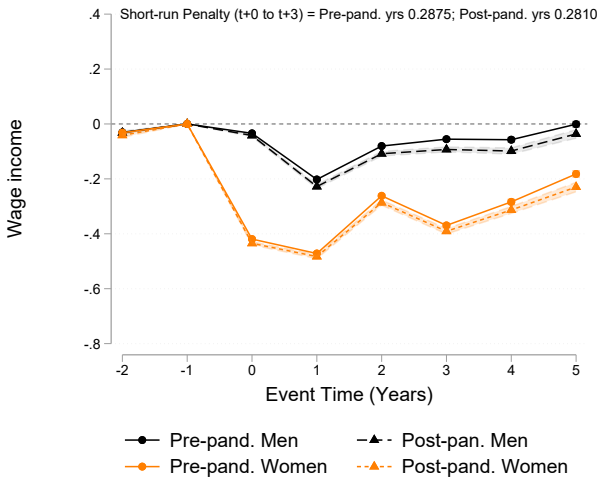
(c) Third quartile – event study



(d) Third quartile – triple difference



(e) Fourth quartile – event study



(f) Fourth quartile – triple difference

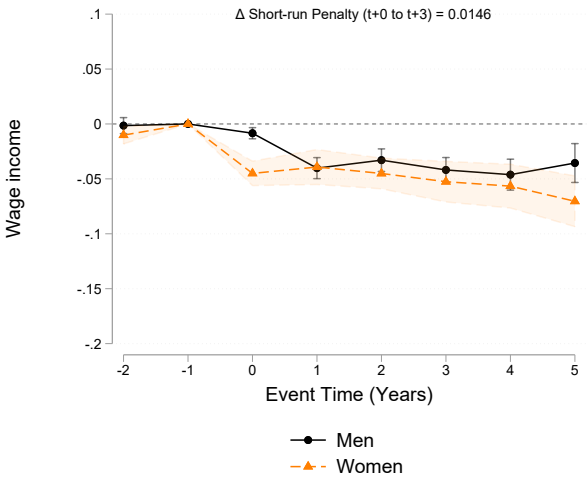
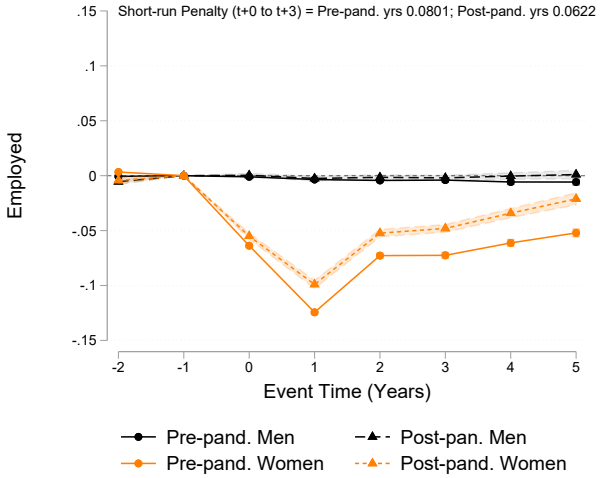
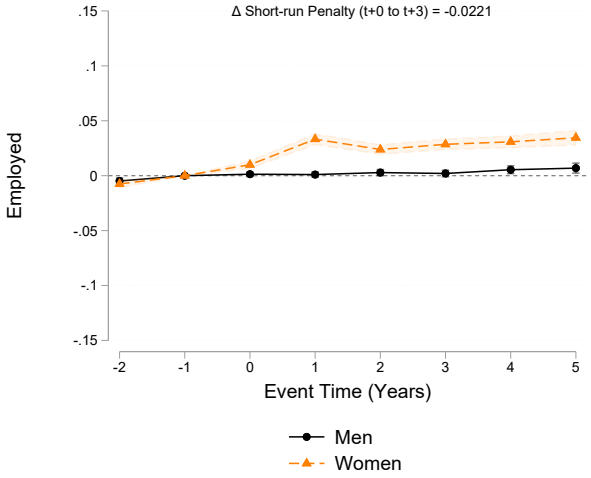


Figure 6: Event study and triple-difference estimates of employment effects of first birth

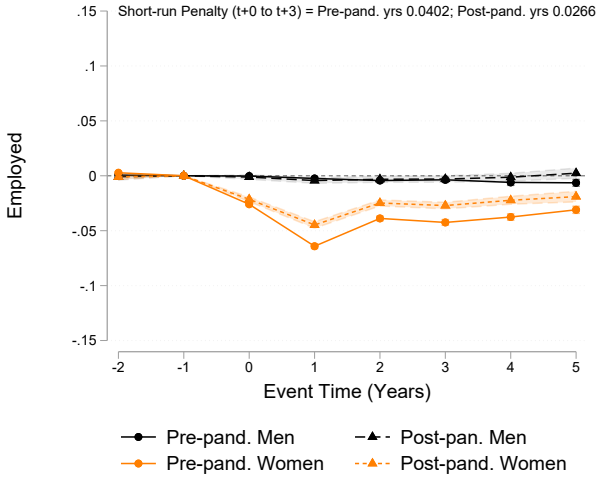
(a) Lower median – event study



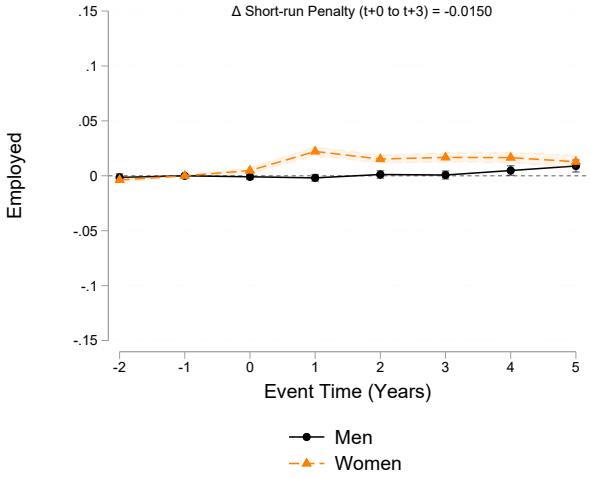
(b) Lower median – triple difference



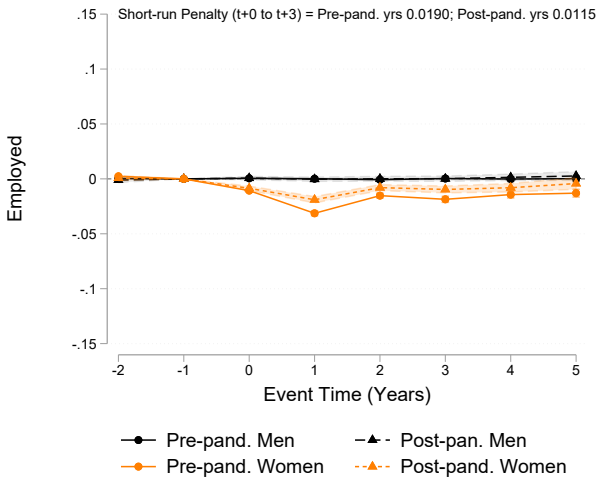
(c) Third quartile – event study



(d) Third quartile – triple difference



(e) Fourth quartile – event study



(f) Fourth quartile – triple difference

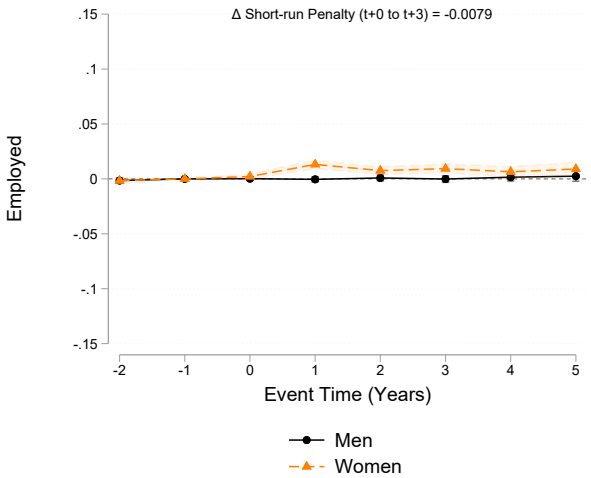


Figure 7 shows the event study estimates of the impact of first birth on hours conditional on working before and after the pandemic in the left-hand column; the right-hand column shows the triple-difference estimates. Hours conditional on working are derived from the Wage Structure Statistics data. The survey covers half of the population of private sector workers, and the full population of public sector workers. Because of the composition of the survey, we may underestimate the child penalty since men are more likely to work in the private sector and private-sector wages tend to be higher than those in the public sector. Employers are surveyed annually and report wages and hours for workers that are currently at work at the firm. Workers who are not at work during the reference period, including those who are on parental leave as well as those who have left the firm, are thus excluded from this measure.[5] We report contracted hours and not actual hours worked.

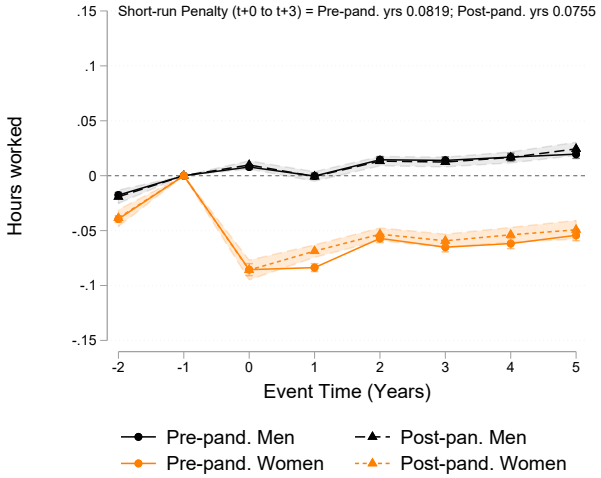
The left hand panels illustrate the pre- and post-pandemic effects of childbirth on hours for workers who remain attached to their jobs for men and women in each occupational exposure group. There is a small but precisely estimated narrowing of the gap for women across all exposure categories. Women in the lower median of exposure to remote work experienced an 8.2 percent reduction in hours conditional on working before the pandemic, which narrows to a 7.6 percent reduction after the pandemic. The triple-difference estimate is a 0.7 percentage point narrowing of the gap, or 8.5 percent of the baseline penalty. Women with moderate exposure to remote work (those in the third quartile) experienced an 5.9 percent reduction in hours conditional on working before the pandemic, which narrows to a 5.3 percent reduction after the pandemic. The triple-difference estimate is a 0.6 percentage point narrowing of the gap. Women with the highest intensity of exposure to remote work (those in the fourth quartile) experienced an 3.4 percent reduction in hours conditional on working before the pandemic, which narrows to a 3.3 percent reduction after the pandemic. The triple-difference estimate is a 0.1 percentage point narrowing of the gap.

Similar to the results on the employment margin, the attenuation of the hours gap after the pandemic is monotonically *decreasing* in the intensity of exposure to remote work, and is small across the exposure distribution. While the penalty in hours conditional on working appears to be narrowing over time across occupational exposure categories, exposure to remote work does not appear to be associated with any differential narrowing of the gap. These empirical findings align with the predictions of our model given that workers tend to match assortatively on exposure to remote work. If most couples consist of two parents who have either high or low exposure to remote work adoption, we would not expect the motherhood penalty in hours to change substantially as a result of introducing remote work. As we discussed in our comparative statics exercises, this result derives from how flexibility impacts both parents' opportunity cost of time. If both parents gain similar levels of access to flexibility, the allocation of time use across the two will not change substantially because their *relative* trade-offs are unchanged. This result motivates our later examination of heterogeneity by partner composition in Section 6.3.

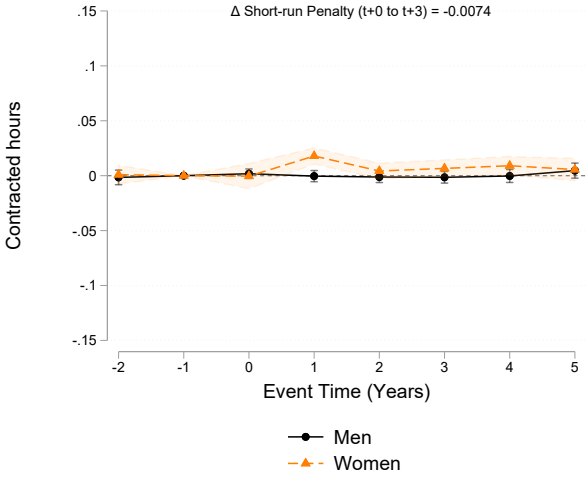
[5] In some cases, firms report zero contracted hours and/or zero wages for workers in their sample. We drop these worker-years from our analysis to exclude all individuals who are not working.

Figure 7: Event study and triple-difference estimates of hours effects of first birth (conditional on working)

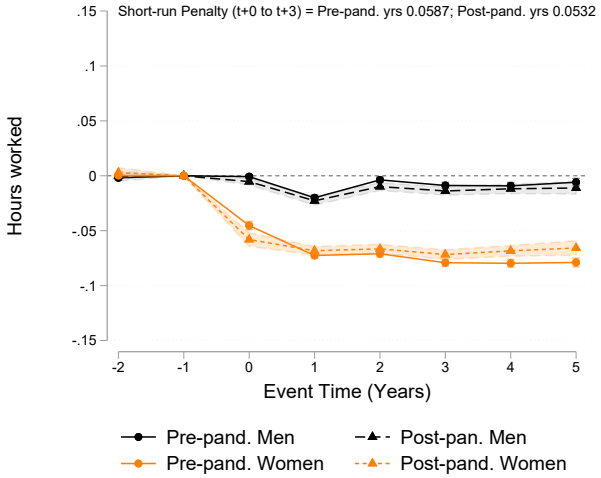
(a) Lower median – event study



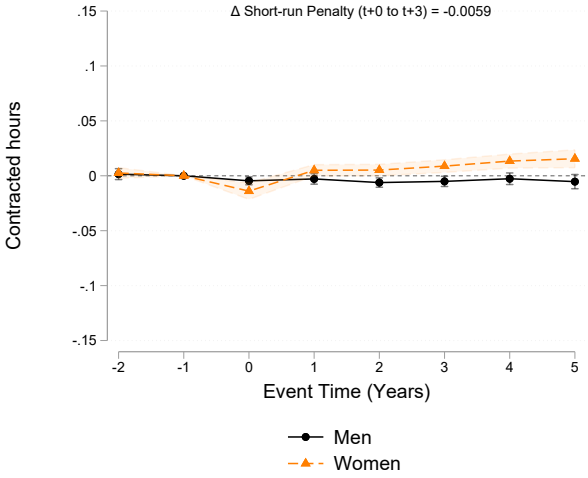
(b) Lower median – triple difference



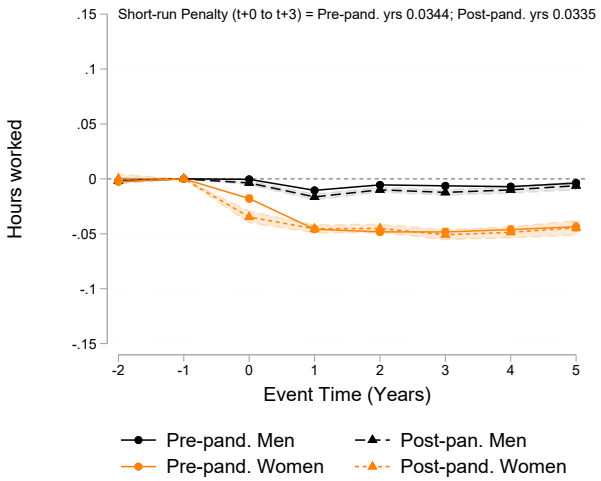
(c) Third quartile – event study



(d) Third quartile – triple difference



(e) Fourth quartile – event study



(f) Fourth quartile – triple difference

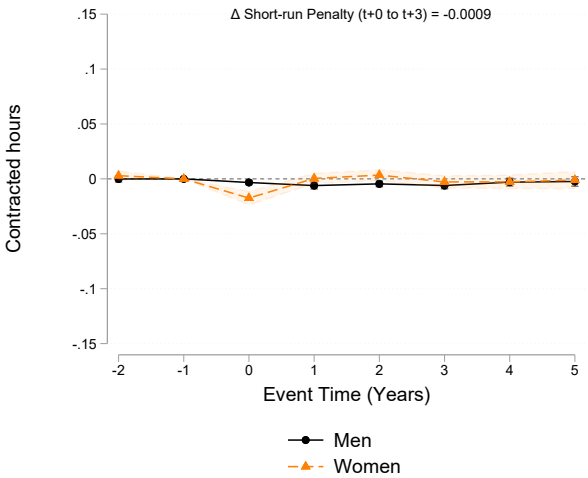


Figure 8 shows the event study estimates of the impact of first birth on wages conditional on working before and after the pandemic in the left-hand column; the right-hand column shows the triple-difference estimates. Wages conditional on working are also derived from the Wage Structure Statistics and thus are subject to the same sample restrictions as the hours outcome measures.

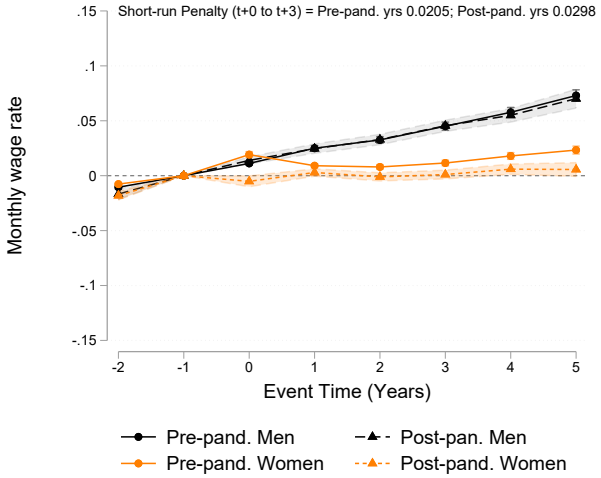
The left hand panels illustrate the pre- and post-pandemic effects of childbirth on wage growth for men and women in each occupational exposure group. Across groups, women experience persistent reductions in real wages over time after accounting for age and year fixed effects. This suggests that women experience slower wage growth than their peers in the years after having a child, with a reduction in wages of 2.05 percent in the first three years for women in the lower median of remote work exposure; the average three-year wage penalty is 2.98 percent for those in the third quartile and 3.53 percent for those with the highest exposure to remote work. In contrast, men experience faster real wage growth after having a child.

In the post-pandemic years, women experience a small but precisely-estimated *increase* in the wage penalty of about 1.3 percent for low-exposure women, whereas moderate-exposure women experience a 0.9 percent decline in the wage penalty and high-exposure women experience a 0.7 percent increase. The differences in wage trajectories could reflect compositional changes in the set of women who remain attached to their jobs after having a child. The results in the previous section establish that employment penalties reduced across groups after the pandemic. This result implies that marginal women – who would have previously chosen not to work – were shifted into remaining attached to their employers. If women who are shifted on the employment margin have lower expected wage growth, the wage trajectory for wages conditional on employment will appear to worsen. Overall, though, the changes in wage penalties are not correlated with exposure to remote work, suggesting that access to remote work does not cause a significant narrowing of the wage gap.

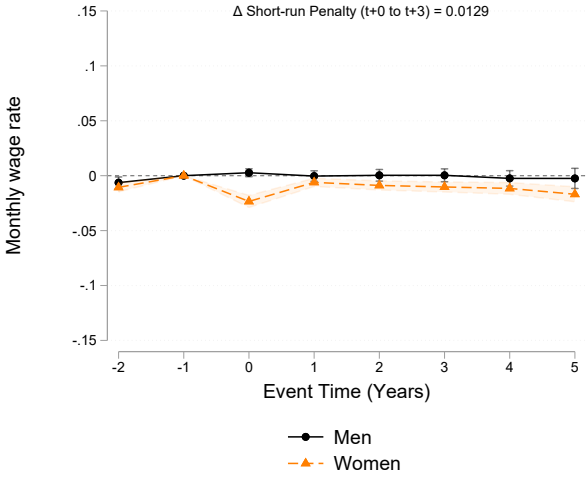
Interestingly, the wage premium for men declines over the same period for the high-exposure groups – men maintain a wage premium, but wage growth slows after the pandemic. Appendix Figure A.17 suggests one possible explanation: men's income from parental leave benefits in the years after the first birth increases across all work-from-home categories after the pandemic. This could reflect an increase in take-up of available benefits rather than an increase in fertility. Appendix Figure A.17 also shows that subsequent fertility remains largely unaffected by the pandemic across occupation categories. Taking up parental leave effectively slows wage growth in the years around leave, so an increase in leave take-up could explain the slowdown in wage growth among men. However, we caveat this argument by noting that we do not observe parental leave spells for men, so the observed increase in the amount of benefits in SEK may not reflect increases in take-up rates.

Figure 8: Event study and triple-difference estimates of wage effects of first birth (conditional on working)

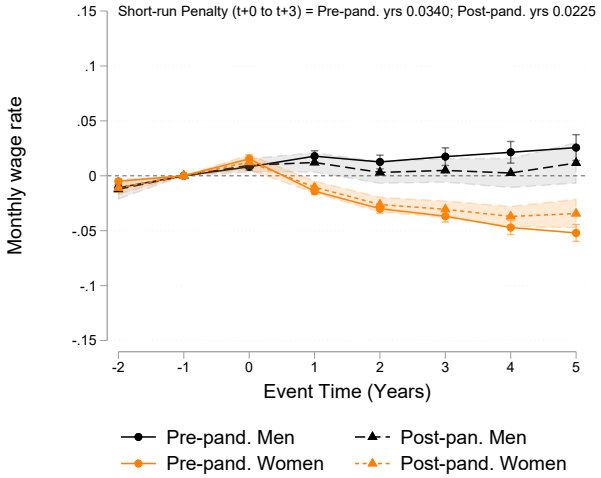
(a) Lower median – event study



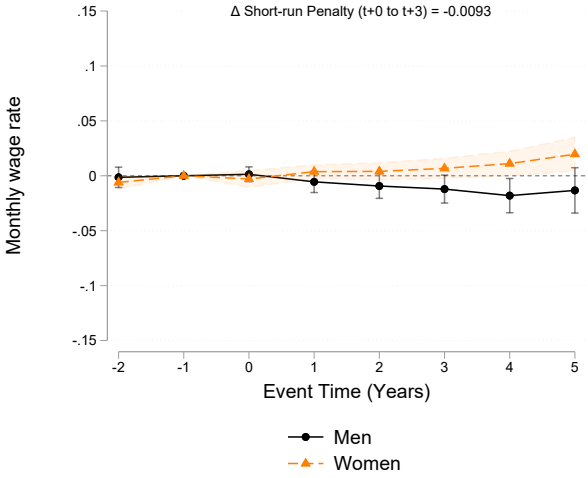
(b) Lower median – triple difference



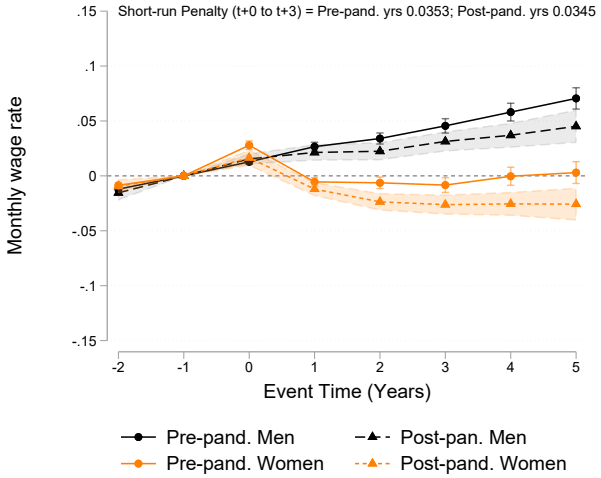
(c) Third quartile – event study



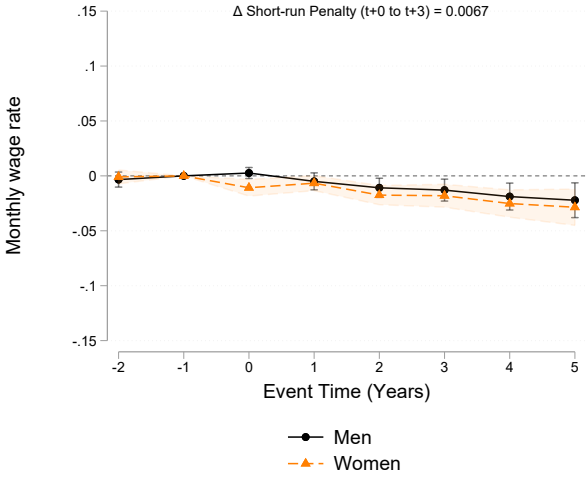
(d) Third quartile – triple difference



(e) Fourth quartile – event study



(f) Fourth quartile – triple difference



6.3 Heterogeneity by couples' exposure composition

We now ask: to what extent do changes in parents' labor market behavior since the pandemic depend on their *partner's* potential to work remotely? To answer this question, we re-estimate our main event study and triple-difference specifications separately for men and women in nine different matched-couple groups: men in the lower median and quartiles 3-4 of remote work exposure matched to women in the lower median and quartiles 3-4 of remote work exposure. In this section, we focus on how women with the highest potential to work remotely experience differential changes in child penalties when partnered with men across the distribution of occupational exposure to remote work. Analogous panels of results for low- and moderate-exposure women are reported in Appendix A.

Before presenting results, it is useful to ask what heterogeneity in labor supply responses we might expect given the earnings and education composition of workers in each exposure quartile and the theoretical predictions from our model. As we discussed in our comparative statics exercises, flexibility impacts both parents' opportunity cost of time. With similar levels of access to flexibility, the allocation of time across the mother and the father will not change substantially as their *relative* trade-offs are unchanged. In other words, the model predicts that we should observe the largest changes among couples who are negatively assorted. Thus, holding all else equal, we might expect high-exposure, high-earning women to be *more* likely to stay in the labor force and less likely to reduce their hours when they have children with less-exposed men.

To start with, Figure 9 shows heterogeneity in the earnings penalty for mothers in the fourth quartile, depending on whether the father to whom she is matched is in the first quartile (top row), third quartile (middle row), or fourth quartile (bottom row) of exposure to remote work. The ex ante earnings penalties are inversely correlated with their partner's eventual exposure to remote work. In fact, the size of the earnings penalties are monotonically decreasing by the father's exposure level for all women. Women in the highest exposure quartile with low-exposure partners experienced earnings penalties of 30.8 percent before the pandemic; women with medium-exposure and high-exposure partners 29.1 percent and 25.8 percent respectively.

While there appears to be a decline in earnings for all high-exposure women and their partners, the changes in the earnings penalties are not precisely estimated. The point estimates suggest there is heterogeneity in the change in the earnings penalties after the pandemic: high-exposure women with high-exposure partners experienced a decline in the penalty of 1.7 percent, whereas the earnings penalty *increased* by 1.8 percent for those with medium-exposure partners and by 3.6 percent for those with low-exposure partners. Consistent with the model prediction, we observe the smallest changes in penalties for couples who are positively assorted. However, this is only true for couples with moderate- or high-exposure levels. In contrast, the increase in earnings penalties are the largest among couples where both partners have low remote work exposure. Moreover, the change in earnings penalty among high-exposure women with low-exposure partners goes in the opposite direction to what the model predicts.

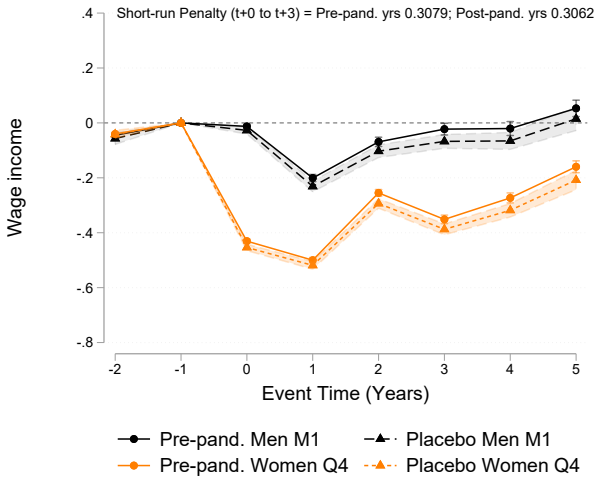
On the employment margin, women whose partners have greater potential to work remotely have similar penalties as those whose partners have minimal potential to do so both before and after the pandemic. Figure 10 shows heterogeneity in the employment penalty for mothers in the fourth quartile, depending on whether the father to whom she is matched is in the first quartile (top row), third quartile (middle row), or fourth

quartile (bottom row) of exposure to remote work. The left-hand panel illustrates the event study estimates for each type of couple. Across groups, the women's employment penalties before the pandemic were already small – as shown in Figure 6, women in the highest exposure quartile only experienced a three-year average penalty of 1.9 percent before the pandemic. The panels document a precisely estimated difference in the pre-pandemic employment effect of the first birth that is similar in raw magnitude across couples with fathers who have different levels of exposure to remote work. Among couples where the father's occupation has minimal potential to adopt flexibility, the high-exposure mother experiences an average pre-pandemic employment penalty of 1.6 percent; among those where both parents have the top level of exposure to flexibility, the mother's pre-pandemic employment penalty is also 1.6 percent. The proportional reduction in the penalty after the pandemic is roughly the same regardless of the father's potential to adopt remote work. High-flexibility mothers with low-flexibility partners saw a 0.7 percentage point reduction in employment penalties after the pandemic to 0.9 percent; those with high-flexibility partners also saw a 0.7 percentage point reduction. Taken together, these results suggest that the father's occupation matters for the mother's decision to remain in the labor market. These results illustrate the limited potential for remote work to affect outcomes on the employment margin, because those who stand to gain the most from potential exposure were already very unlikely to drop out of the labor force completely after having a child.

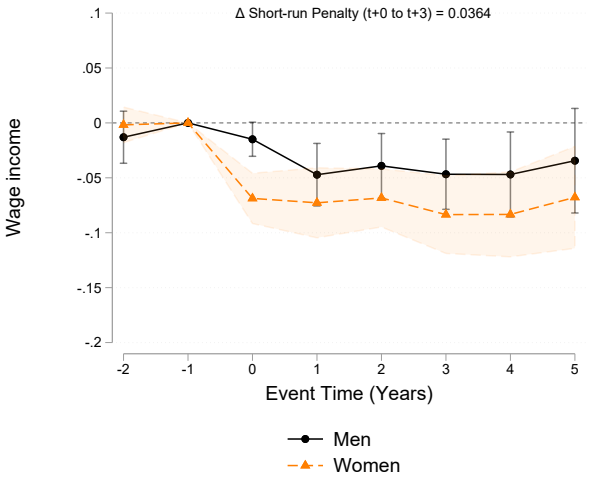
In addition to the differences on the employment margin, conditional on working, mothers whose partners have greater exposure to remote work also have consistently smaller reductions in hours – and saw those penalties narrow to a greater degree after the pandemic. Figure 11 shows the same event study and triple-difference estimates as in figure 10 with hours conditional on working as the outcome. Among mothers with high exposure to remote work, those whose partners have high exposure to remote work have consistently smaller reductions in hours than those whose partners have minimal exposure. The left-hand panel illustrates the event study estimates for each type of couple. Before the pandemic, conditional on working, high-exposure women with low-exposure partners reduced their hours by 4.8 percent in the three years following the birth of the first child. The hours penalty expands slightly but imprecisely for this group of women after the pandemic to 5.9 percent. High-exposure women with moderate-exposure partners saw reductions in hours conditional on working of 2.8 percent before the pandemic and 3.1 percent – again, a small and statistically insignificant difference of 0.3 percent – after the pandemic. While their hours penalties have always been consistently smaller than those of similar women with low-exposure partners, the penalty also remained roughly unchanged after the pandemic. In contrast, similar women with high-exposure partners had hours penalties of 2.8 percent before the pandemic that reduced to 2.1 percent after the pandemic, representing a reduction of 0.7 percentage points. We also note that among high-exposure pairs, men saw a slight reduction in hours after the pandemic, suggesting that high-exposure couples may be substituting more equally across partners in childcare responsibilities. These results suggest that the partner's access to flexibility could influence the hours margin, but again, because those who stand to gain the most from remote work already had very small motherhood penalties, the potential effect is economically quite small.

Figure 9: Event study and triple-difference estimates of income effects of first birth – high-WFH-exposure women, varying partner's exposure

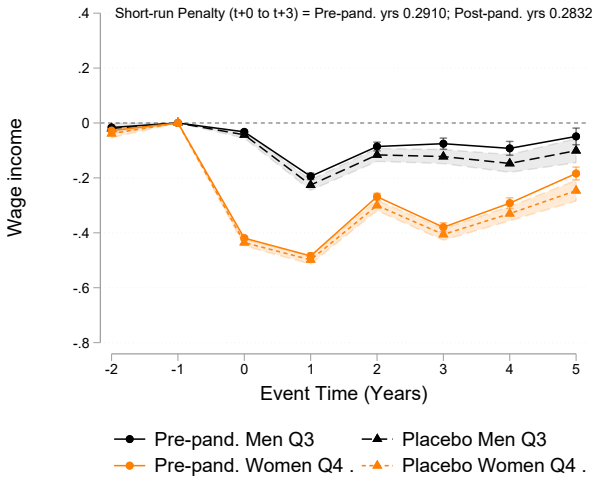
(a) Man in first WFH median – event study



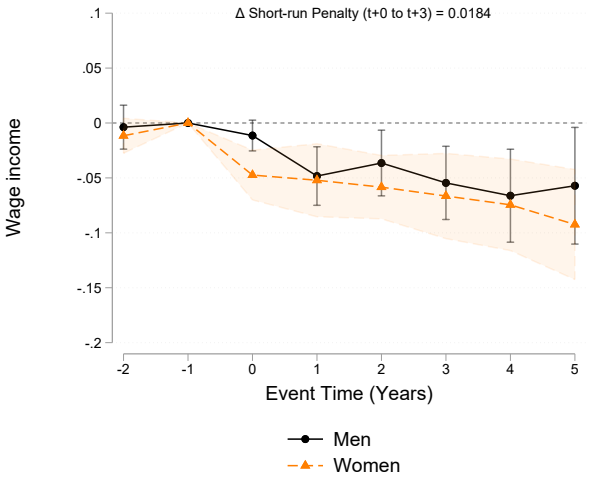
(b) Man in first WFH median – triple difference



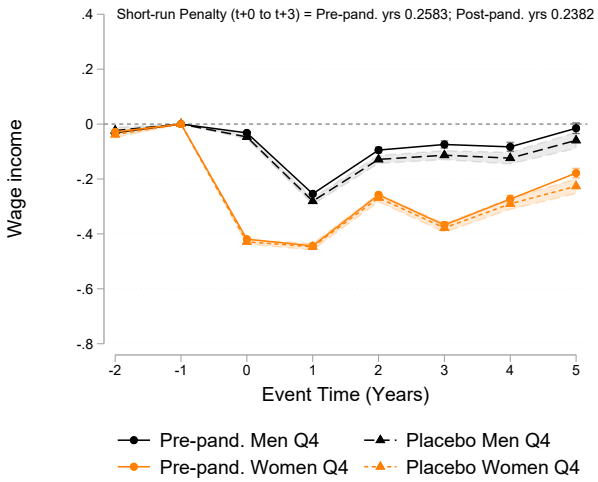
(c) Man in third WFH quartile – event study



(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study



(f) Man in fourth WFH quartile – triple difference

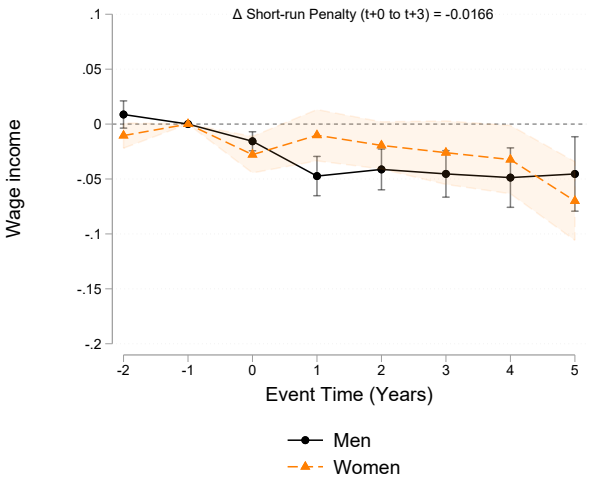
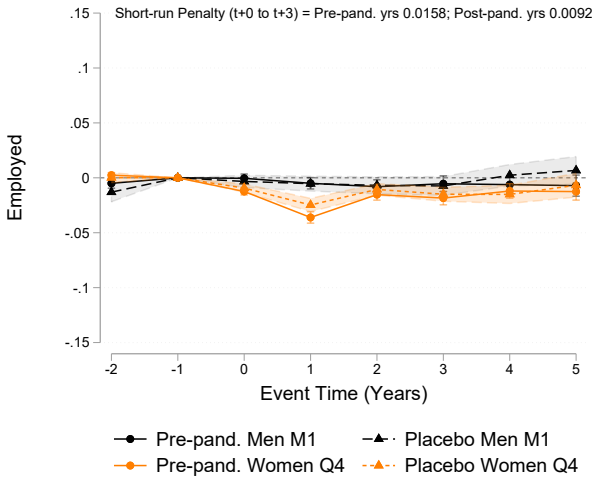
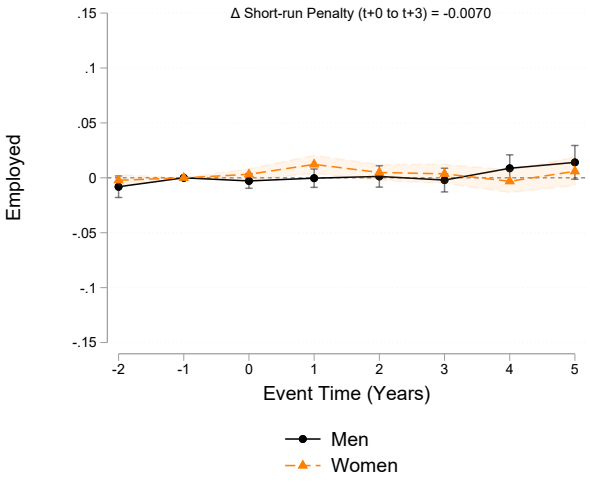


Figure 10: Event study and triple-difference estimates of employment effects of first birth – high-WFH-exposure women, varying partner's exposure

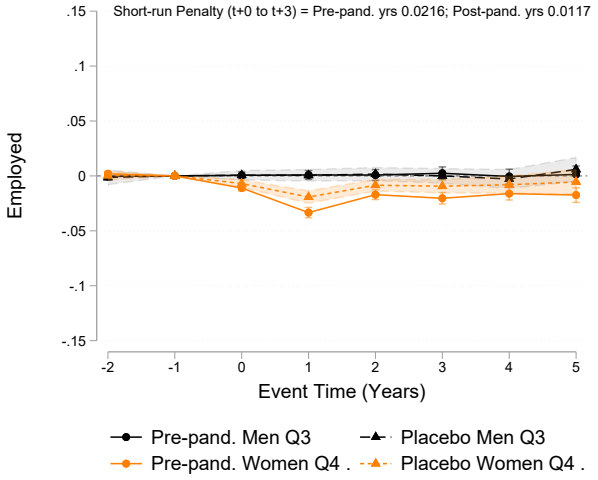
(a) Man in first WFH median – event study



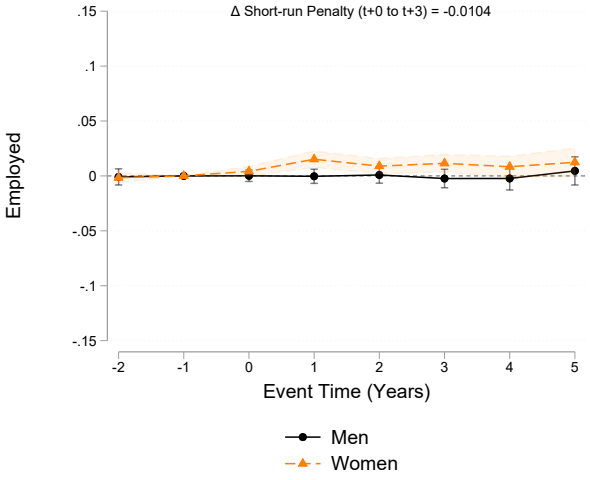
(b) Man in first WFH median – triple difference



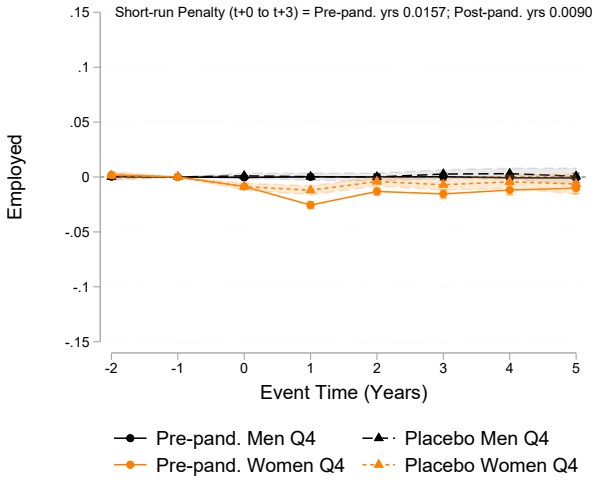
(c) Man in third WFH quartile – event study



(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study



(f) Man in fourth WFH quartile – triple difference

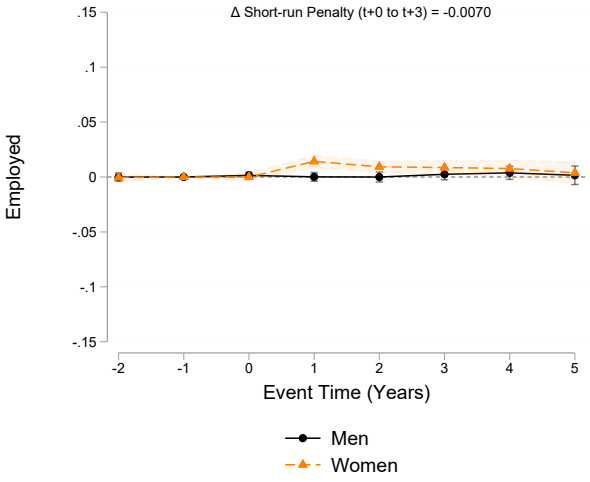
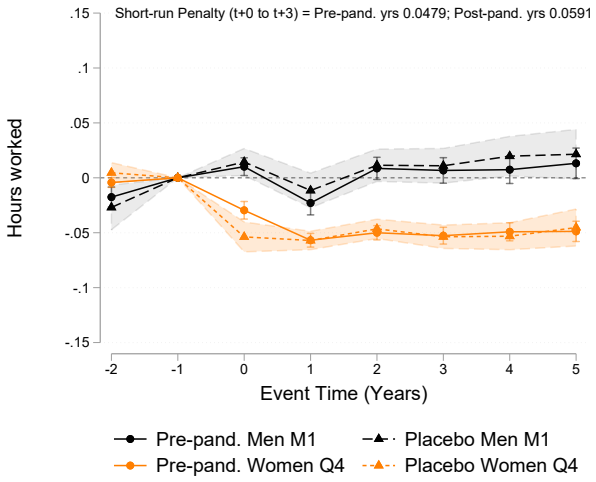
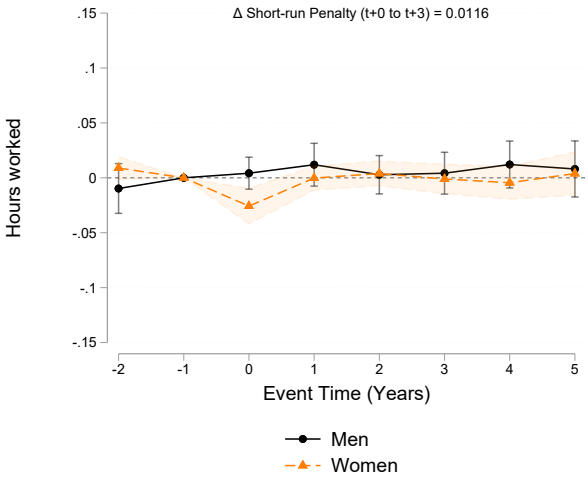


Figure 11: Event study and triple-difference estimates of hours effects of first birth – high-WFH-exposure women, varying partner's exposure

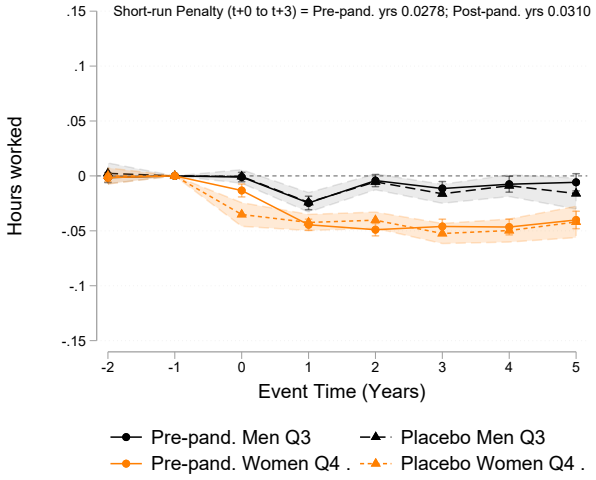
(a) Man in first WFH median – event study



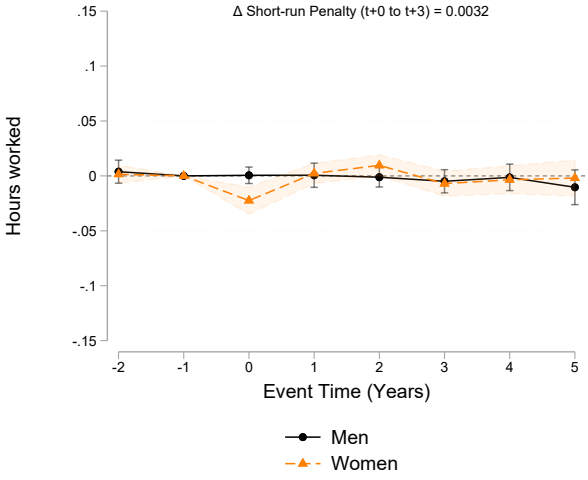
(b) Man in first WFH median – triple difference



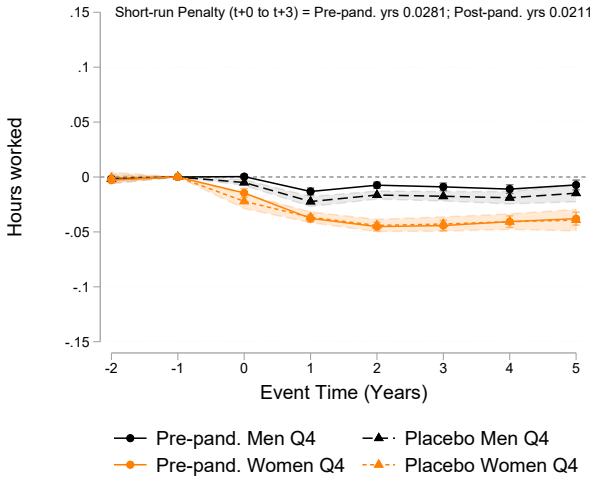
(c) Man in third WFH quartile – event study



(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study



(f) Man in fourth WFH quartile – triple difference

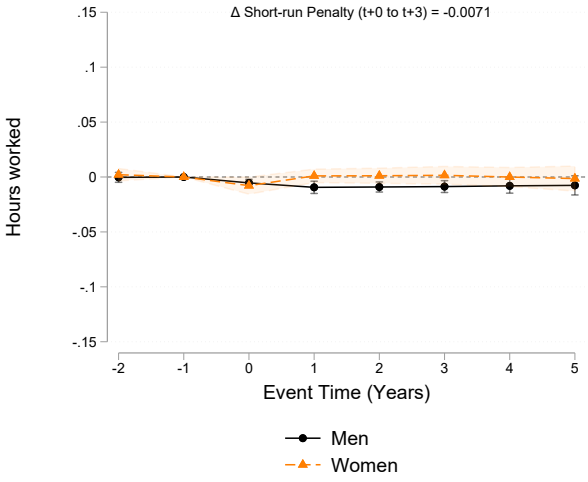
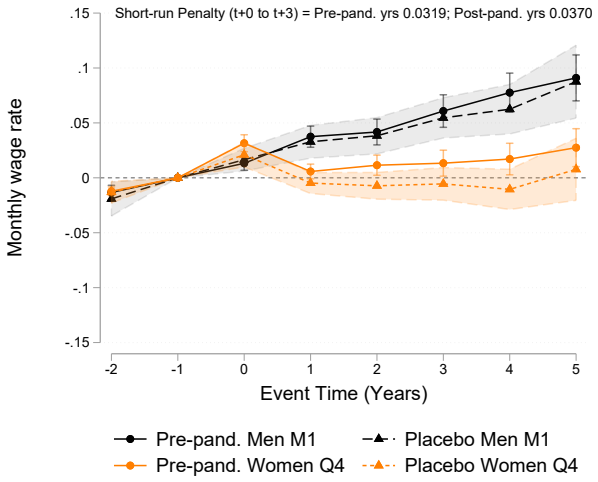
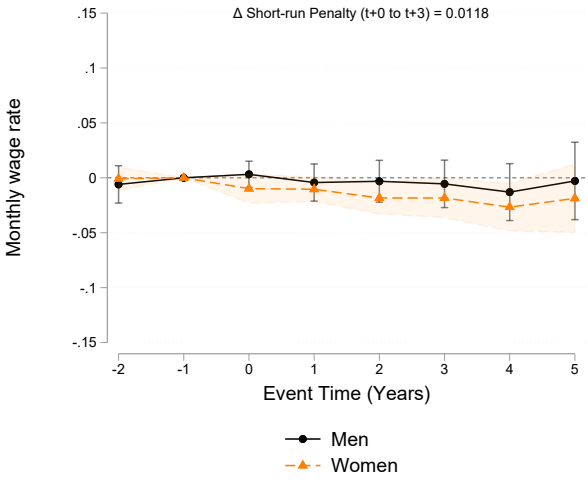


Figure 12: Event study and triple-difference estimates of wage effects of first birth – high-WFH-exposure women, varying partner's exposure

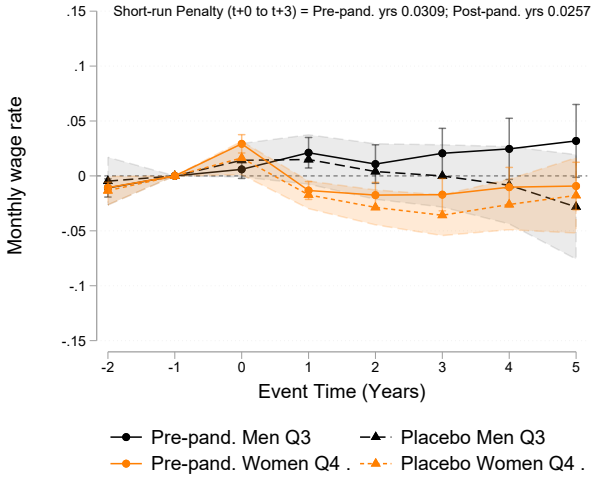
(a) Man in first WFH median – event study



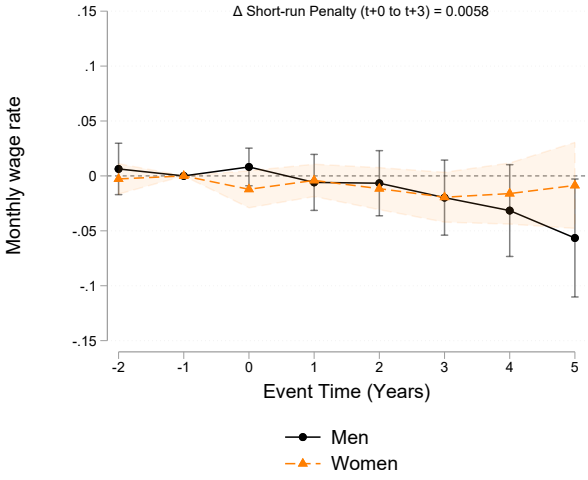
(b) Man in first WFH median – triple difference



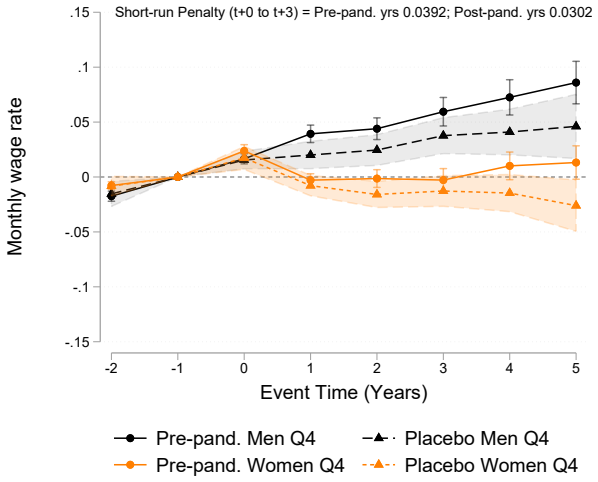
(c) Man in third WFH quartile – event study



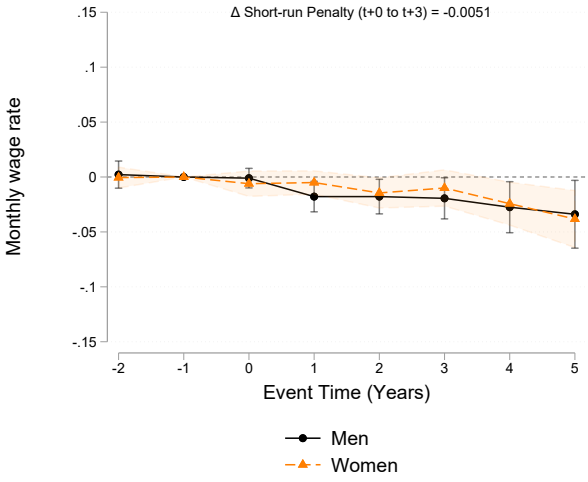
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study



(f) Man in fourth WFH quartile – triple difference



7 Robustness Checks

7.1 Placebo Test

Our identification relies on two parallel trends assumptions. First, the event-time estimates require the assumption that labor supply outcomes would have evolved along the same trajectory as the predicted counterfactual if the individual had not had a child. Second, the triple-difference estimates require the assumption that labor supply penalties would have remained the same in the absence of exposure to remote work. While the first assumption is standard in the literature on earnings effects of having children, the second one is a stronger assumption. It implies that differential changes in the child penalty across occupations with heterogeneous exposure to remote work are explained by the increase in flexibility and not by confounding factors. To address this concern, we are employing a placebo test using not-yet-parents. We outline the sample construction and placebo assignment of child births in Appendix C.

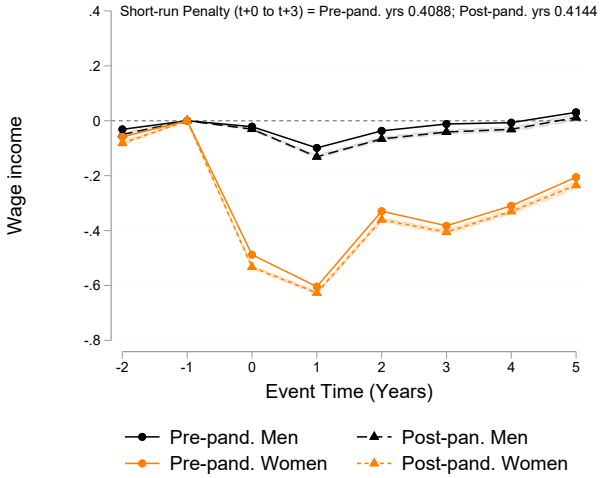
In the placebo test, we re-estimate our event study design for our main outcomes (wage income, employment, contracted hours and wage rates) but instead of comparing the outcomes of pre-pandemic parents to post-pandemic parents, we compare the effects of *placebo parents* before and after the pandemic. This placebo tests aims to disentangle the effects of the pandemic-induced change in remote work adoption on child penalties to other confounding factors.

Figures 13–16 show the event study estimates of the impact of the first birth on our main outcomes (wage income, employment, contracted hours and wage rates) before and after the pandemic. The left-hand column displays the main figures; the right-hand columns compares placebo parents in the pre-period to placebo-parents in the post-period. We are interested in 1) the differences in gender gaps before and after the pandemic for the placebo parents, and 2) differences in the *changes* of the gender gaps following the pandemic for the placebo parents, relative to our main results.

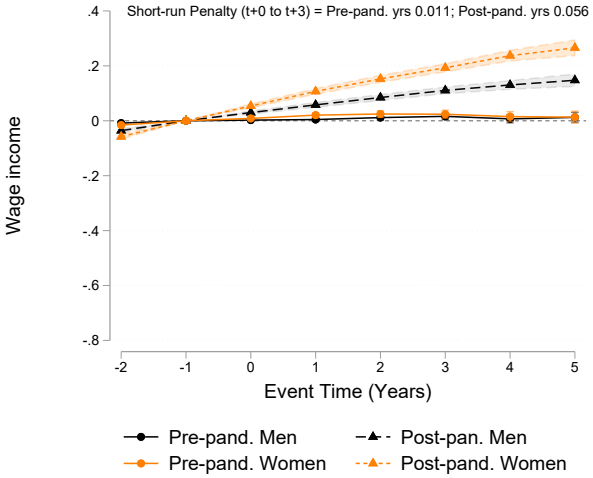
Two results likely follow from the fact that we allocate placebo years of birth (between 2010 and 2022) based on the highest achieved education level in 2022. This means that some individuals are returning to education during the observation period, and they are likely to be overrepresented in the pre-pandemic group. Moreover, individuals who are students or return to studying are also likely to be over-represented in the low-exposure group (as occupation is measured two years prior to placebo year of birth). This sample composition are consistent with the negative trend in employment for the pre-pandemic group, and the growth in earnings, wage and hours, particularly for low-exposure groups. With these caveats in mind, the placebo test largely confirms that while women's and men's careers are differentially impacted by entering parenthood, the pandemic-induced change in remote work adoption seem to have little effect of the size of these child penalties.

Figure 13: Event study estimates of income effects of first birth

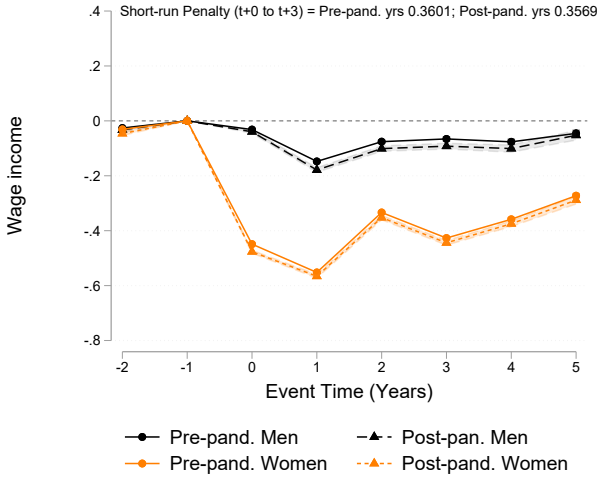
(a) Lower median – main sample



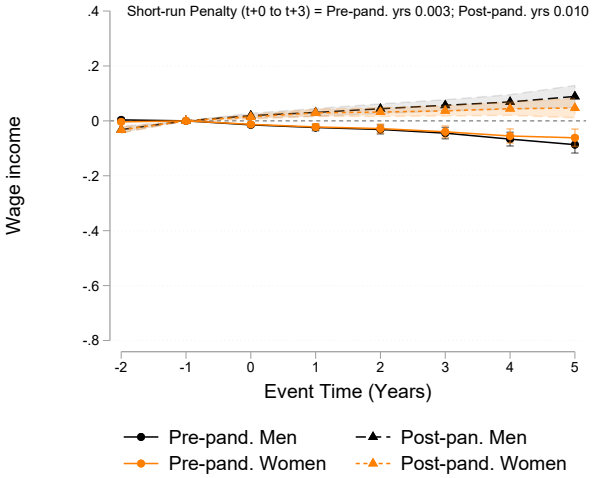
(b) Lower median – placebo sample



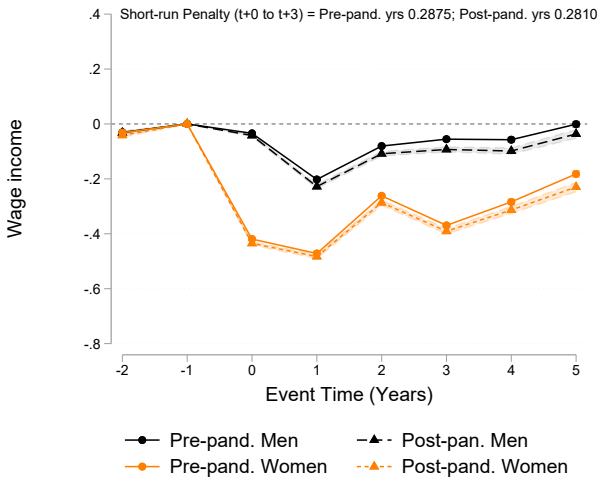
(c) Third quartile – main sample



(d) Third quartile – placebo sample



(e) Fourth quartile – main sample



(f) Fourth quartile – placebo sample

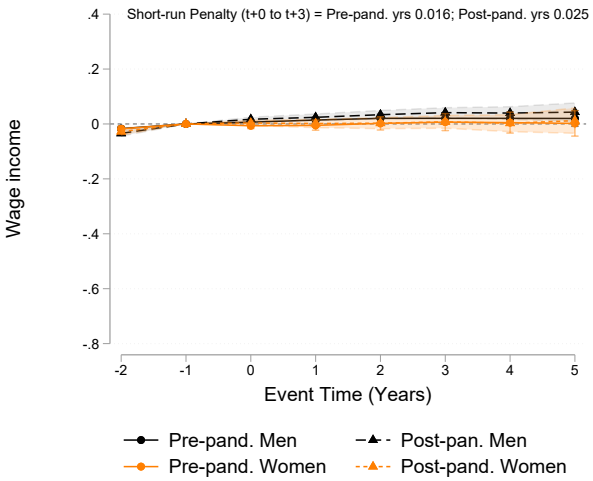
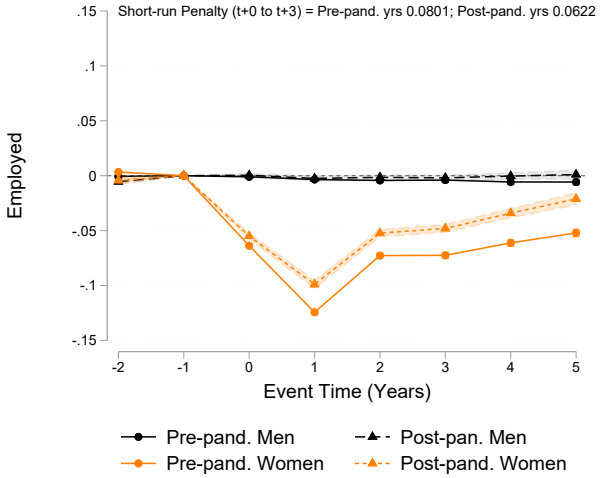
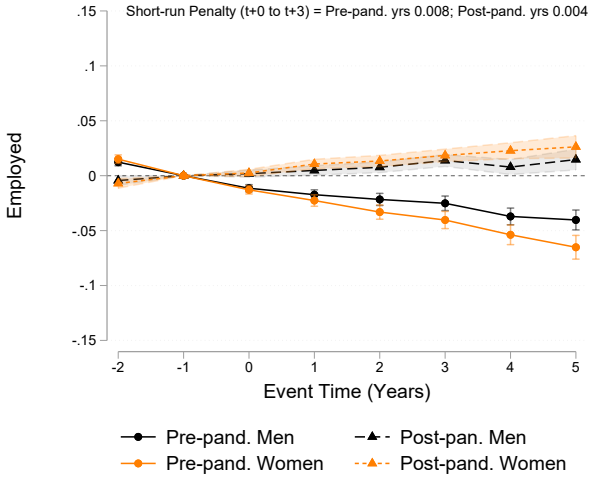


Figure 14: Event study estimates of employment effects of first birth

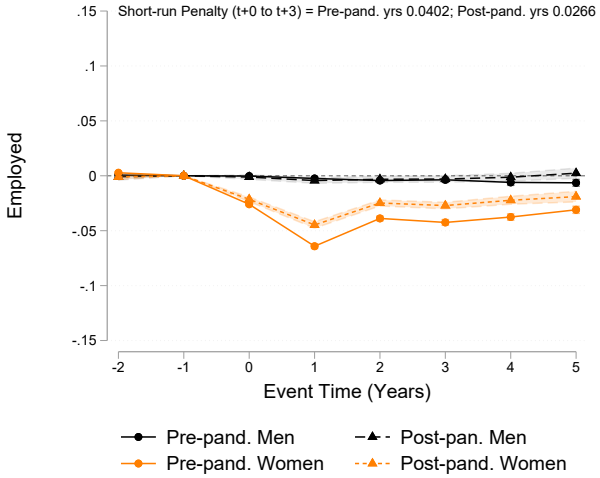
(a) Lower median – main sample



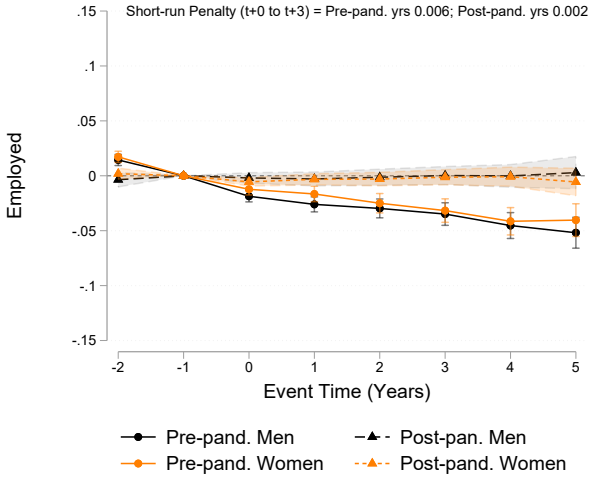
(b) Lower median – placebo sample



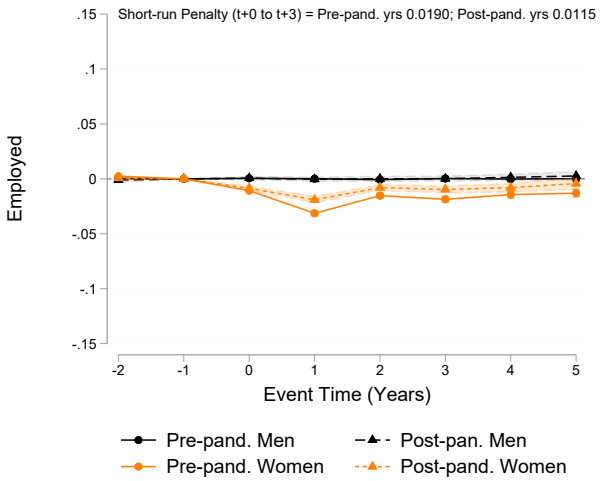
(c) Third quartile – main sample



(d) Third quartile – placebo sample



(e) Fourth quartile – main sample



(f) Fourth quartile – placebo sample

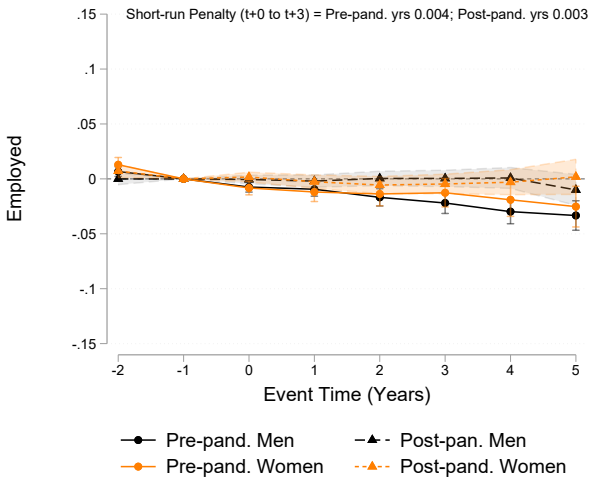
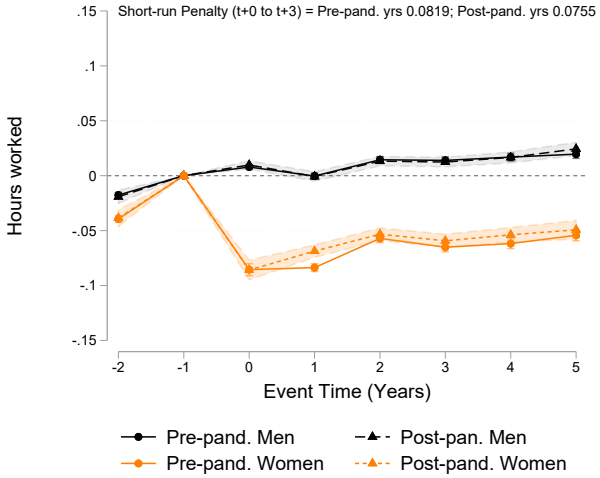
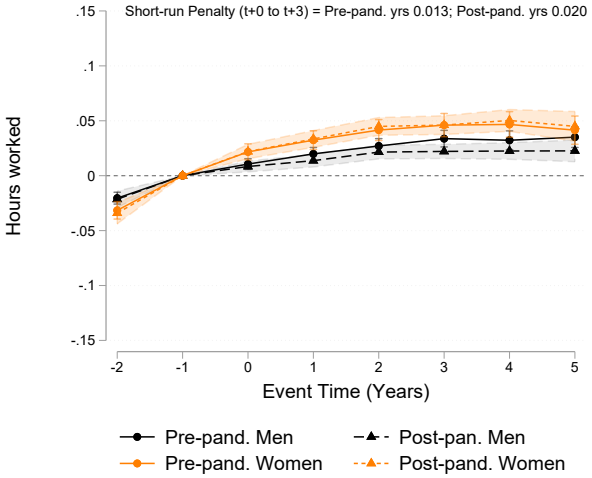


Figure 15: Event study estimates of hours effects of first birth (cond. on working)

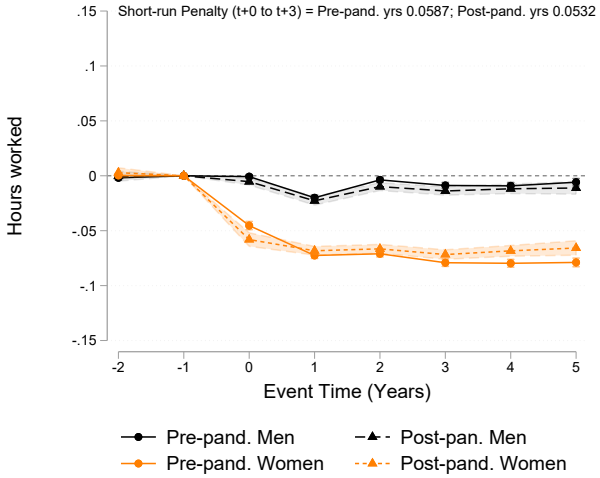
(a) Lower median – main sample



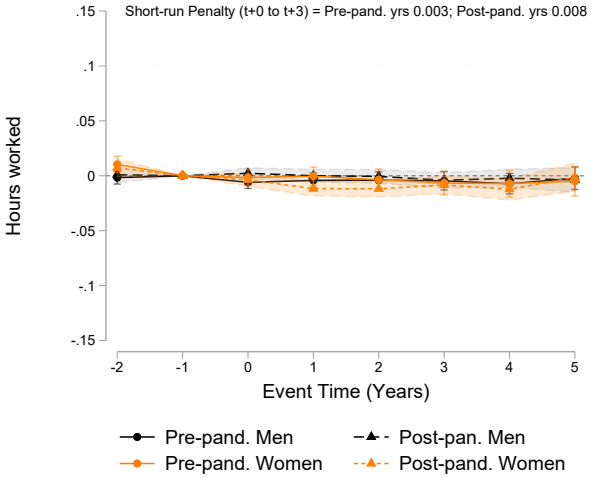
(b) Lower median – placebo sample



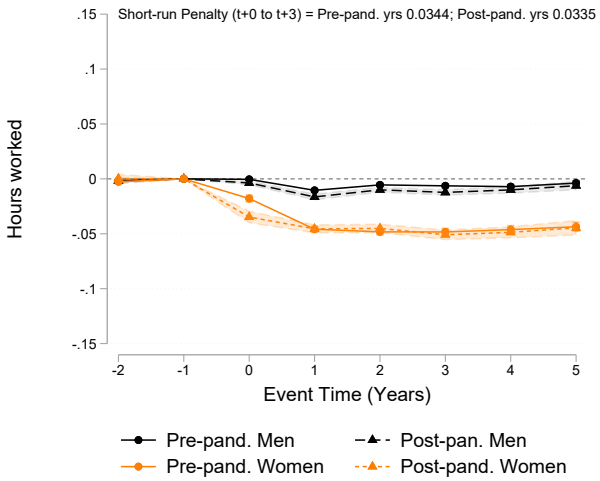
(c) Third quartile – main sample



(d) Third quartile – placebo sample



(e) Fourth quartile – main sample



(f) Fourth quartile – placebo sample

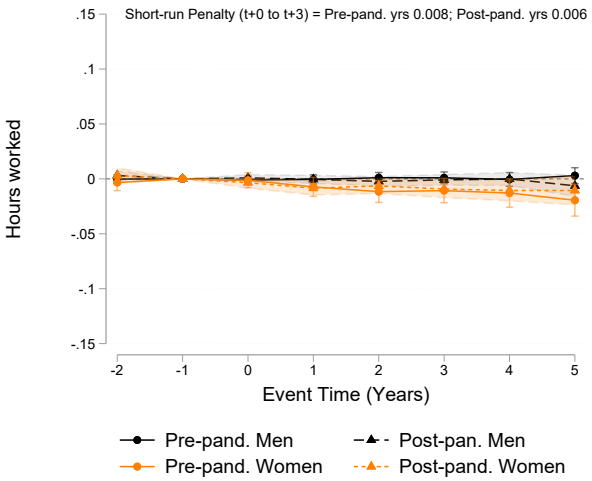
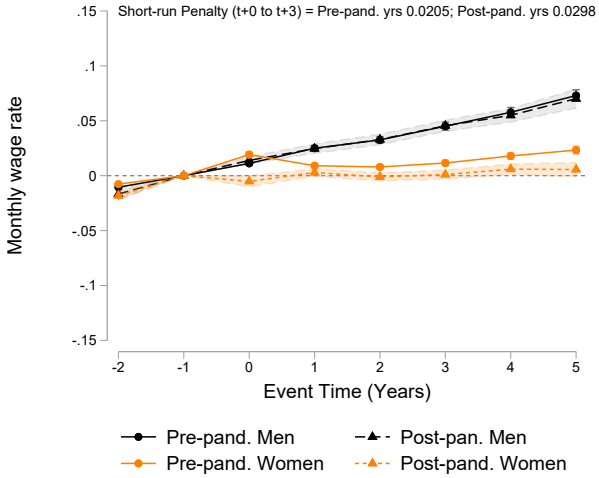
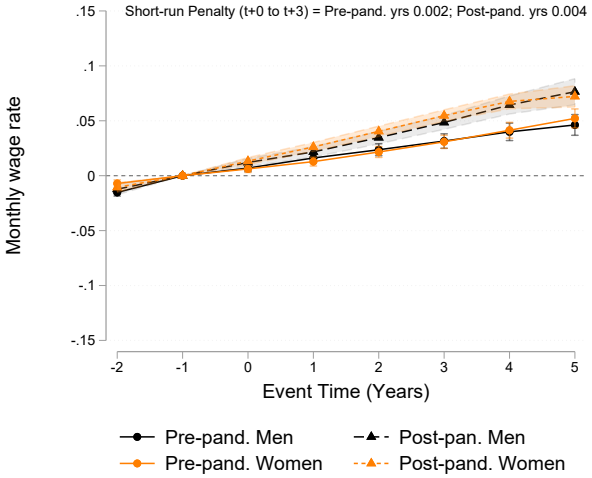


Figure 16: Event study estimates of wage effects of first birth (cond. on working)

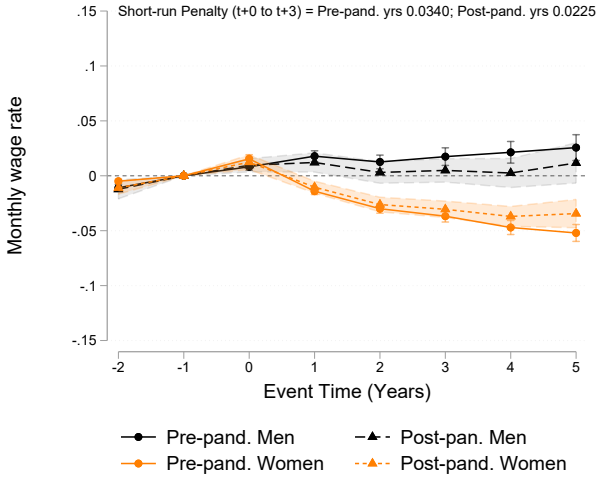
(a) Lower median – main sample



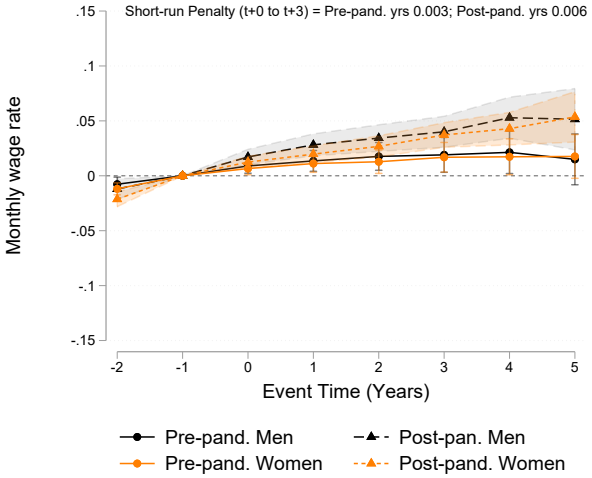
(b) Lower median – placebo sample



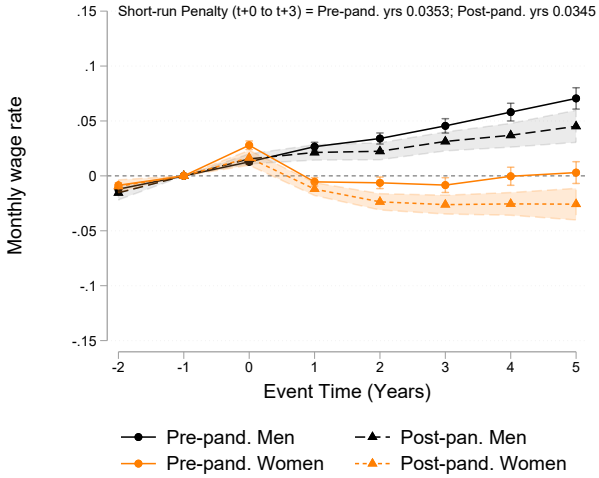
(c) Third quartile – main sample



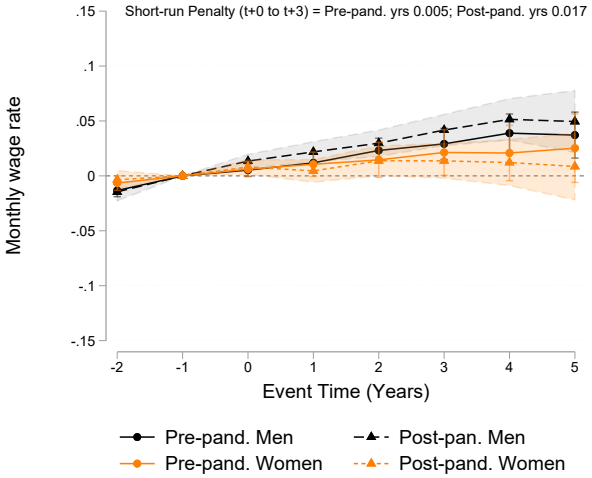
(d) Third quartile – placebo sample



(e) Fourth quartile – main sample



(f) Fourth quartile – placebo sample



7.2 Occupations with unusual pandemic labor market shocks

Sweden did not experience widespread shutdowns during the pandemic, making it relatively unique among developed countries. However, some occupations experienced unusual labor demand shocks that may have disproportionately affected equilibrium labor supply for parents. We focus on two sectors with unusual labor market dynamics during the pandemic. First, increased demand in the health sector may have encouraged an increase in employment, hours, and earnings for healthcare workers. Second, while their workplaces were rarely completely shutdown, workers in the hospitality sector faced a decline in labor demand due to pandemic-related restrictions and precautions. Adermon et al. (2024) document a sharp decline in labor earnings in this sector during the pandemic. While a substantial share of this lost income was replaced by short-time work subsidies that allowed workers to remain employed, differential declines in labor supply for new parents could confound our estimates of child penalties for this group.

To examine whether unusual labor demand shocks to healthcare and hospitality occupations are driving our main results, we re-estimate our main specifications (1) excluding workers in health occupations and (2) excluding workers in hospitality occupations. For the first exercise, we exclude all workers whose occupations at $t-1$ were ISCO-88 codes 22 (Health Professionals, e.g., doctors, nurses, pharmacists) and 32 (Associate Health Professionals, e.g., paramedics, medical assistants, dental technicians). For the second exercise, we exclude all workers whose occupations at $t-2$ were ISCO-88 code 51 (Personal and Protective Services Workers). This second categorization includes most of the hospitality occupations that were most affected by pandemic-induced demand shocks, such as restaurant workers.

Figures A.6–A.8 plot the main event study estimates for each of the remote work exposure groups (lower median, third quartile and fourth quartile, respectively). In each case, the event study estimates – for men and women, before and after the pandemic, in each WFH exposure quartile – are nearly identical when holding out these occupations. We conclude that unusual labor demand shocks that were specific to the pandemic are not driving any of our estimates.

7.3 Total Earnings

The magnitude of the earnings penalty expansion for low-exposure women is somewhat surprising given that the employment declined and wage and hours penalties remained more or less stable (<1 percentage point difference). One question that we cannot yet conclusively address is whether take-up of parental leave or other non-wage benefits expanded substantially during the pandemic. Using our measure, parents are recorded as having zero wage earnings while on parental leave, even if they are guaranteed a bundle of wages and hours upon their return. Adams-Prassl et al. (2024) point out that outcomes set equal to zero during periods of parental leave can cloud interpretation because they incorrectly equate non-earnings due to leave – where the worker remains attached to her job and is guaranteed a particular bundle of wages and hours upon her return – with non-earnings due to leaving the labor force.

While we do not have data on parental spells, we attempt to address the issue of parental leave and benefit take-up by estimating event study and triple-difference specifications for the outcome of *total earnings*, which includes parental leave, sick leave, and unemployment insurance benefits. Figure A.5 shows that

much of the earnings penalty both before and after the pandemic disappears when this alternative measure is used, as does most of the expansion in the earnings penalty across all exposure categories. This alternative income measure partially accounts for the issue of parental leave-taking by measuring the parent's current earning power. However, it does not fully address the concerns of Adams-Prassl et al. (2024) because leave benefits replace wage and salary earnings at a rate of 80 percent up to a cap. Thus, the realized leave benefits still underestimate the earnings to which the worker is *entitled* upon returning to work.

8 Conclusion

This paper examines the relationship between remote work and child penalties, leveraging rich administrative data from Sweden to explore how increased access to job flexibility has reshaped labor market outcomes for mothers and fathers. We develop a model in which couples choose labor supply and remote work adoption, trading off commuting frictions against productivity penalties. The model predicts that flexibility reduces motherhood penalties if women gain more access to flexibility, holding her partner's level constant. However, flexibility has limited effects on child penalties if both partners gain access.

Consistent with these predictions, we find that exposure to remote work has limited potential to significantly reduce motherhood penalties. We find that exposure to remote work is associated with economically small reductions in motherhood penalties in employment, hours worked, and wages. Moreover, as our model suggests, the effects of gaining access to remote work on women's labor supply are mitigated when their partners also increase their ability to work flexibly. Because the trade-off in the opportunity cost of time between the two partners that matters rather than the absolute opportunity cost for a single agent, collective households do not shift market work or home production towards equality when both partners gain flexibility. Because couples are assortatively matched on their ability to work remotely, the incidence of the treatment effect across the population is quite limited.

In addition to our empirical contributions, we advance the theoretical understanding of household labor supply by developing a model of joint decision-making under varying levels of job flexibility. This framework highlights the trade-offs faced by couples as they balance earnings, productivity, and home production responsibilities in the presence of remote work opportunities. By integrating this theoretical model with detailed empirical evidence, our work provides a robust foundation for evaluating policy interventions aimed at reducing child penalties.

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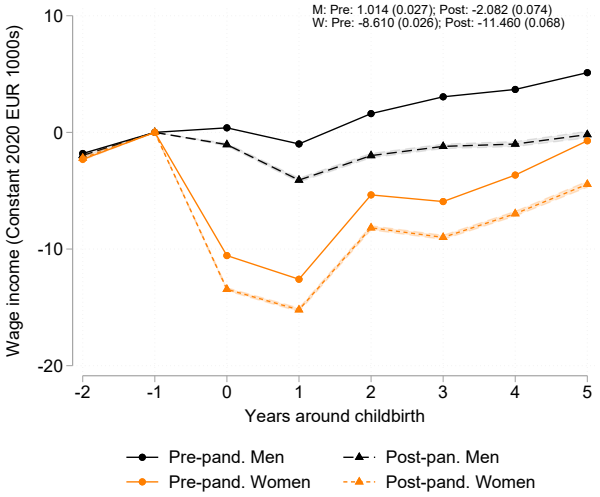
Appendix A Supplemental Tables and Figures

Appendix Table A.1: Occupational Changes in Work-From-Home Adoption

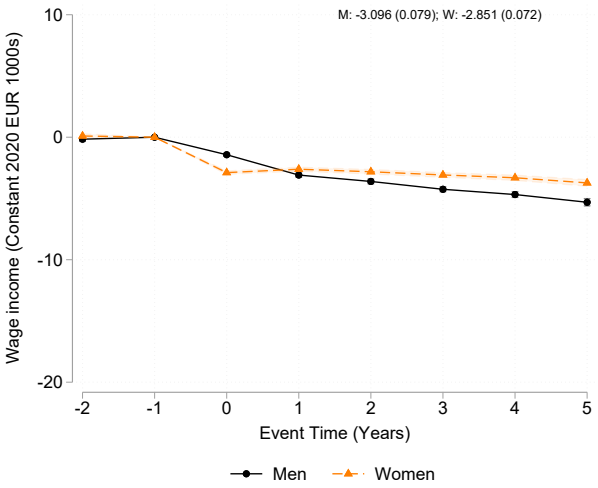
Occupation	**N (LFS)**	**Δ WFH %**
Quartile 1		
Skilled Forestry, Fishery and Hunting Workers	56	-0.139
Food Processing, Woodworking, Garment Workers	203	-0.035
Skilled Agricultural Workers	281	-0.029
Building and Related Trades Workers (excl. Electricians)	1277	-0.016
Cleaners and Helpers	454	-0.012
Drivers and Mobile Plant Operators	933	-0.009
Personal Service Workers	988	-0.007
Labourers in Mining, Construction, Manuf. and Transport	310	0.000
Metal, Machinery and Related Trades Workers	787	0.000
Stationary Plant and Machine Operators	354	0.000
Personal Care Workers	2715	0.005
Quartile 2		
Assemblers	238	0.008
Sales Workers	1213	0.009
Food Preparation Assistants	251	0.009
Electrical and Electronics Trades Workers	422	0.016
Health Professionals	1794	0.037
Refuse Workers and Other Elementary Workers	122	0.051
Teaching Professionals	2235	0.056
Handicraft and Printing Workers	74	0.063
Protective Services Workers	371	0.071
Hospitality, Retail and Other Services Managers	232	0.091
Commissioned Armed Forces Officers	84	0.125
Health Associate Professionals	344	0.128
Armed Forces Occupations, Other Ranks	38	0.143
Quartile 3		
Legal, Social, Cultural Associate Professionals	590	0.171
Numerical and Material Recording Clerks	959	0.208
Production and Specialized Services Managers	825	0.258
General and Keyboard Clerks	257	0.260
Other Clerical Support Workers	196	0.281
Chief Executives, Senior Officials and Legislators	65	0.284
Legal, Social and Cultural Professionals	1613	0.288
Customer Services Clerks	350	0.299
Science and Engineering Associate Professionals	1636	0.309
Quartile 4		
Administrative and Commercial Managers	700	0.408
Business + Administration Associate Professionals	2846	0.415
Information and Communications Technicians	444	0.497
Science and Engineering Professionals	1566	0.533
Business and Administration Professionals	2317	0.611
Info. and Communications Tech. Professionals	1704	0.738

Appendix Figure A.1: Event study and triple-difference estimates of income effects of first birth

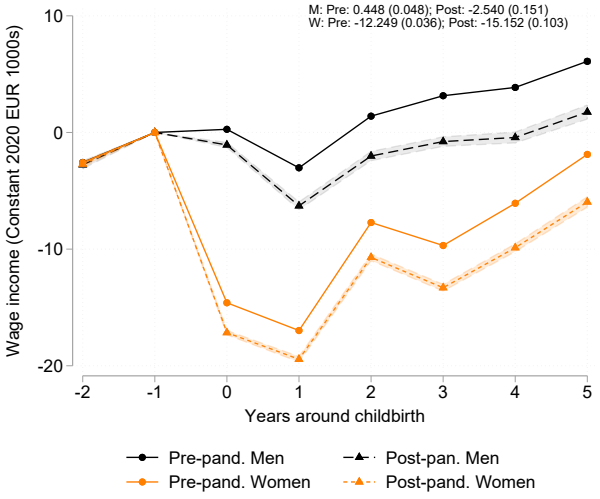
(a) Lower median – event study



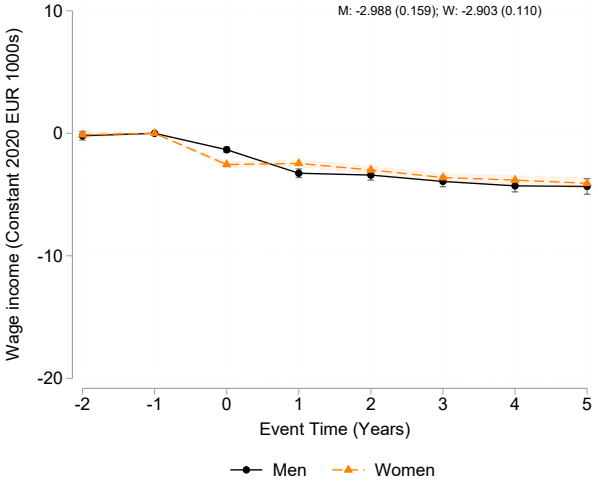
(b) Lower median – triple difference



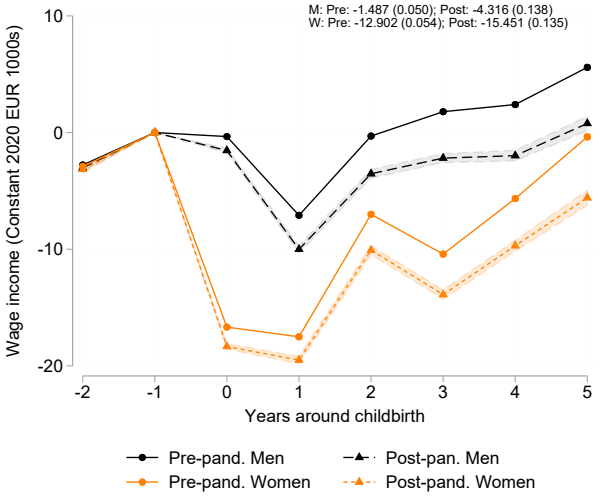
(c) Third quartile – event study



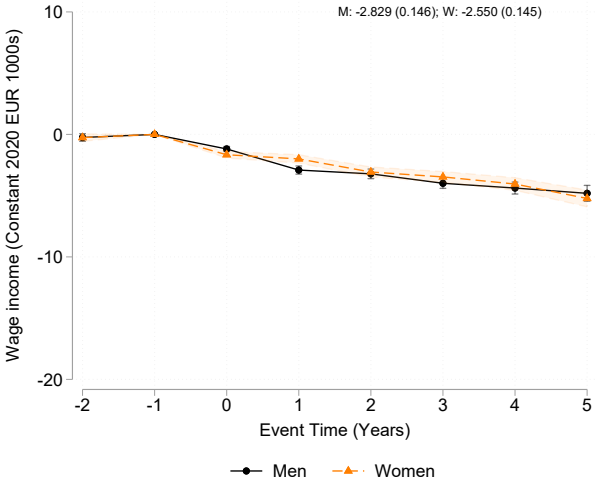
(d) Third quartile – triple difference



(e) Fourth quartile – event study

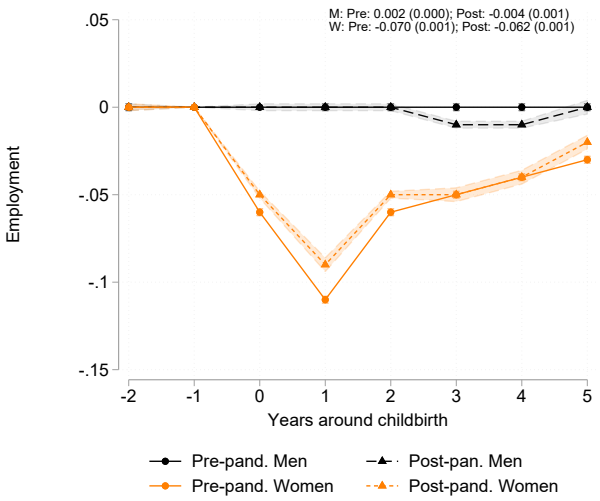


(f) Fourth quartile – triple difference

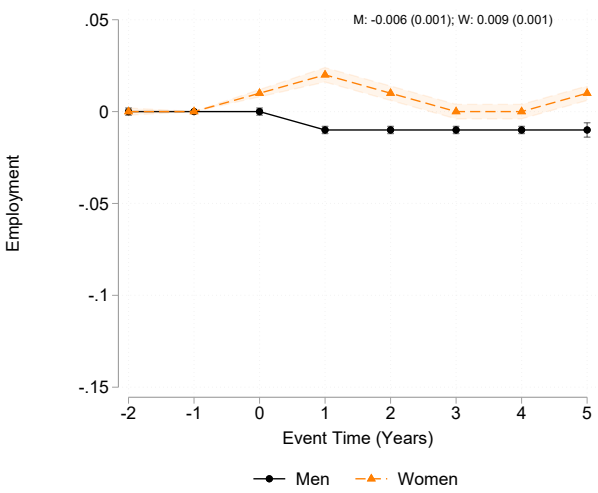


Appendix Figure A.2: Event study and triple-difference estimates of employment effects of first birth

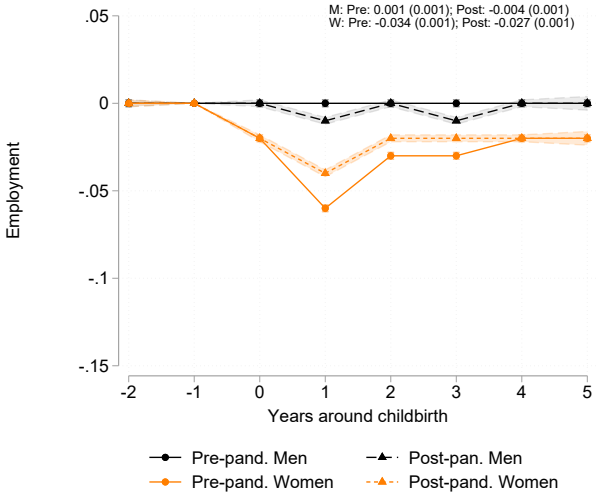
(a) Lower median – event study



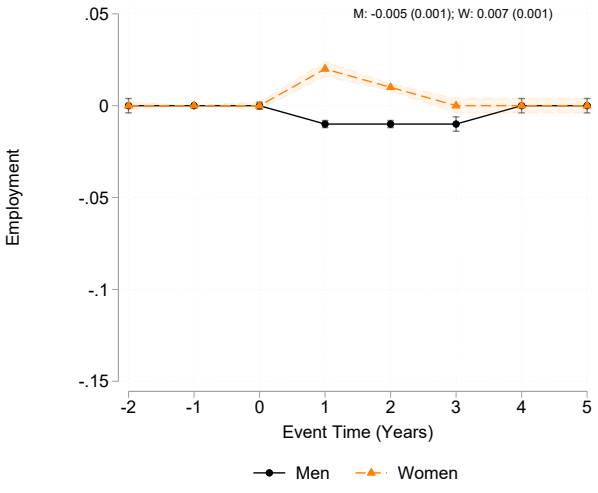
(b) Lower median – triple difference



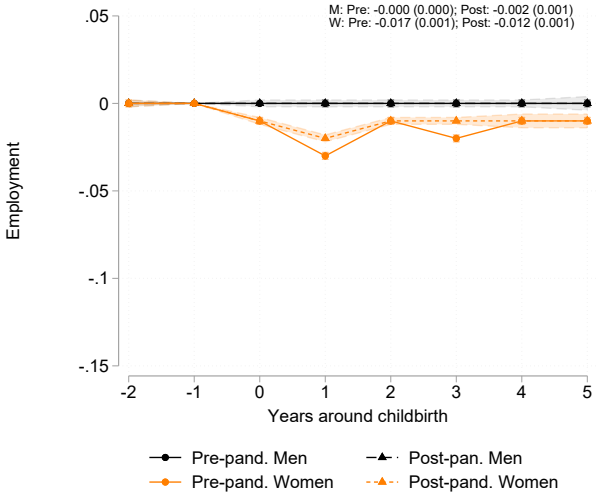
(c) Third quartile – event study



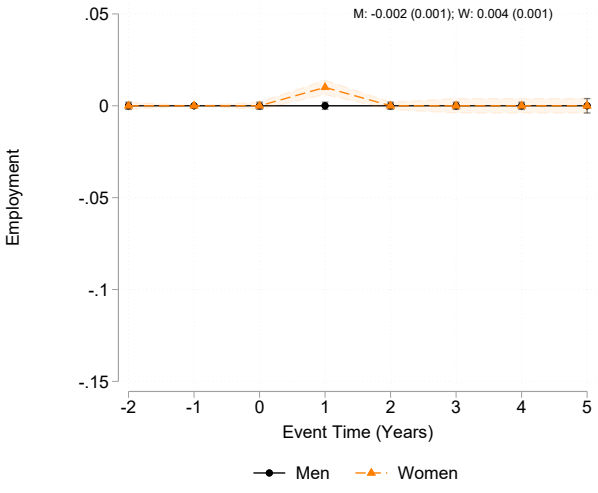
(d) Third quartile – triple difference



(e) Fourth quartile – event study

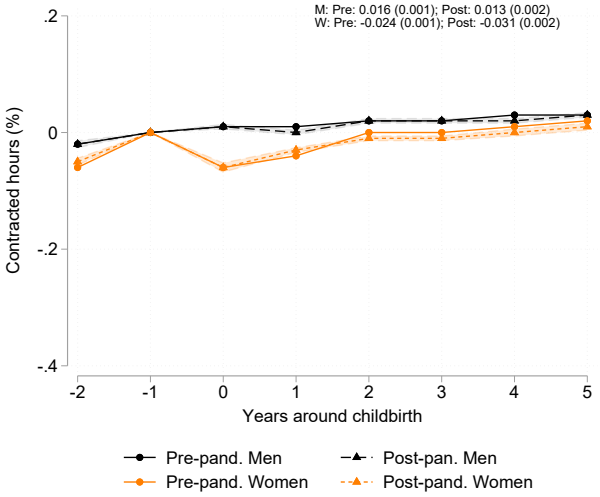


(f) Fourth quartile – triple difference

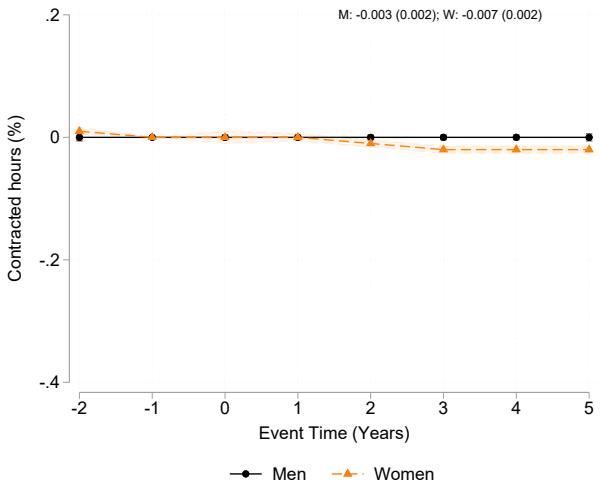


Appendix Figure A.3: Event study and triple-difference estimates of hours effects of first birth (conditional on working)

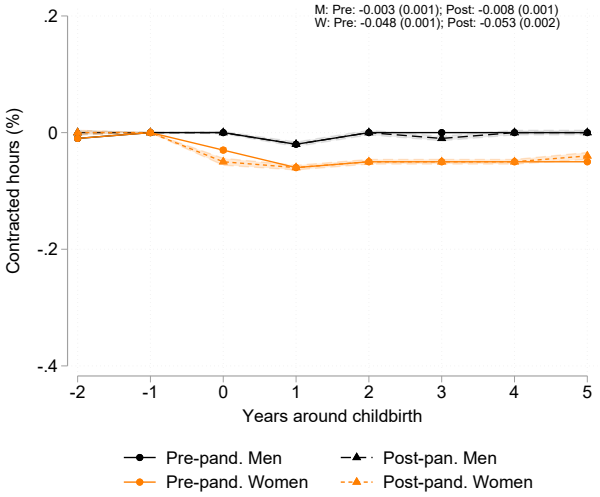
(a) Lower median – event study



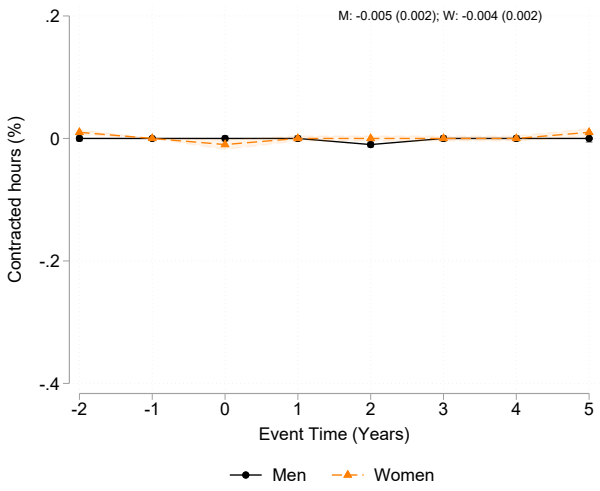
(b) Lower median – triple difference



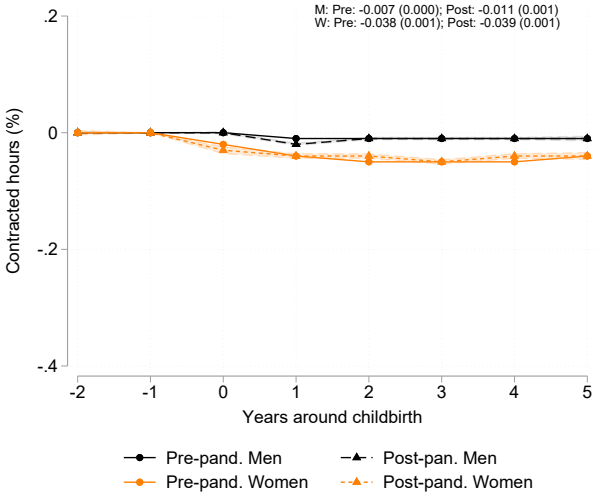
(c) Third quartile – event study



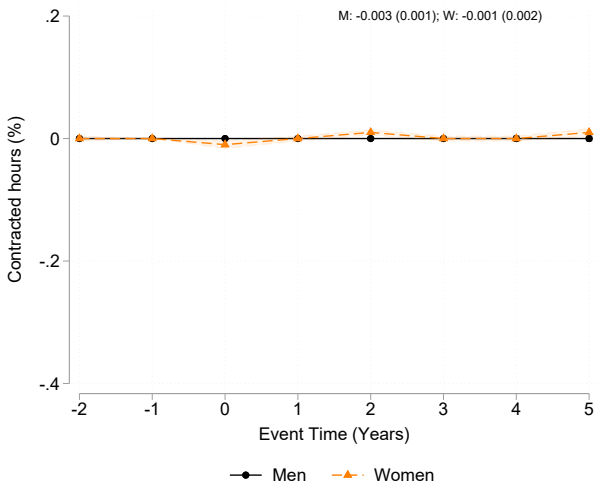
(d) Third quartile – triple difference



(e) Fourth quartile – event study

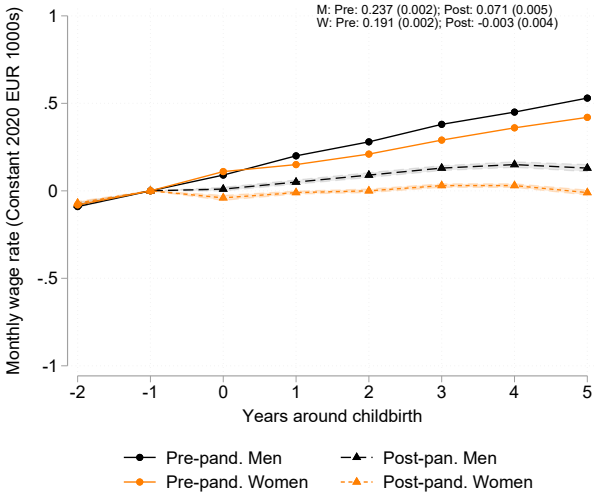


(f) Fourth quartile – triple difference

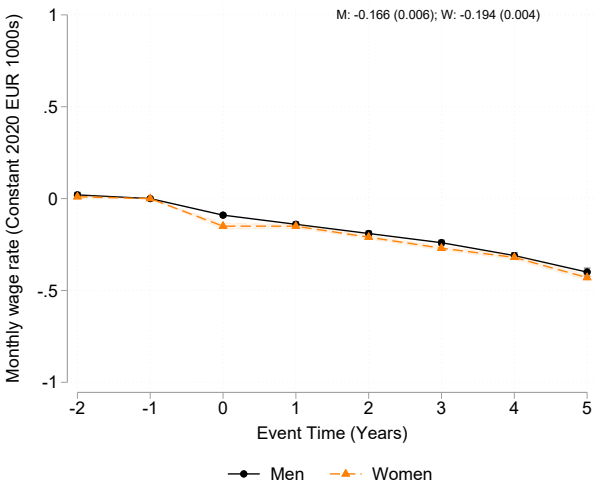


Appendix Figure A.4: Event study and triple-difference estimates of wage effects of first birth (conditional on working)

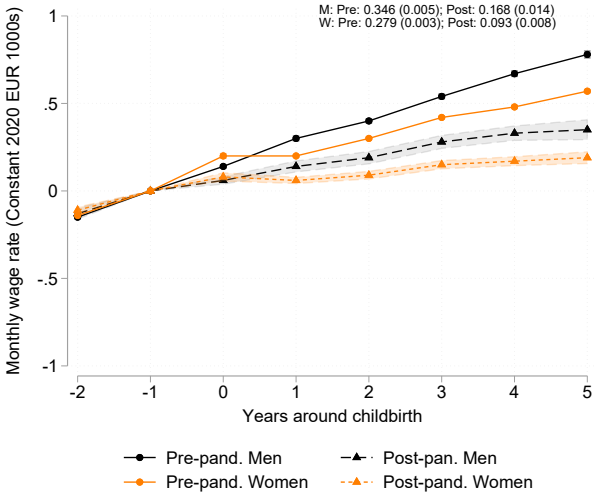
(a) Lower median – event study



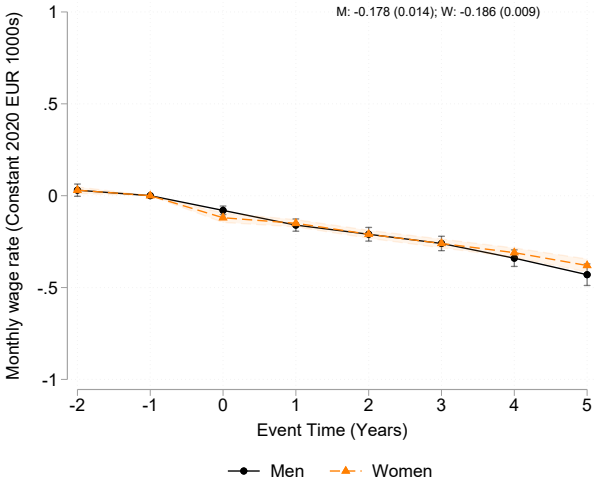
(b) Lower median – triple difference



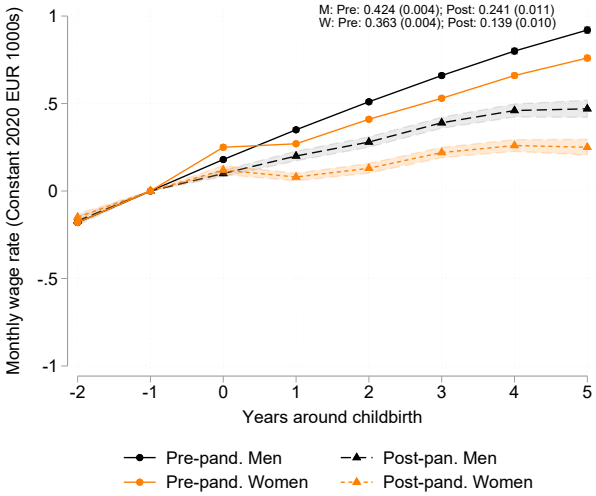
(c) Third quartile – event study



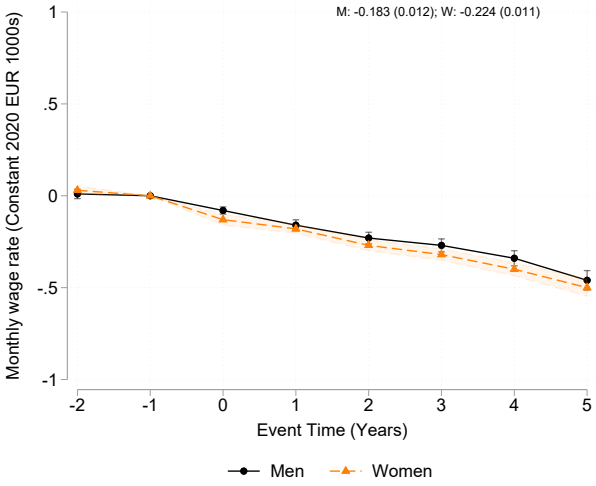
(d) Third quartile – triple difference



(e) Fourth quartile – event study

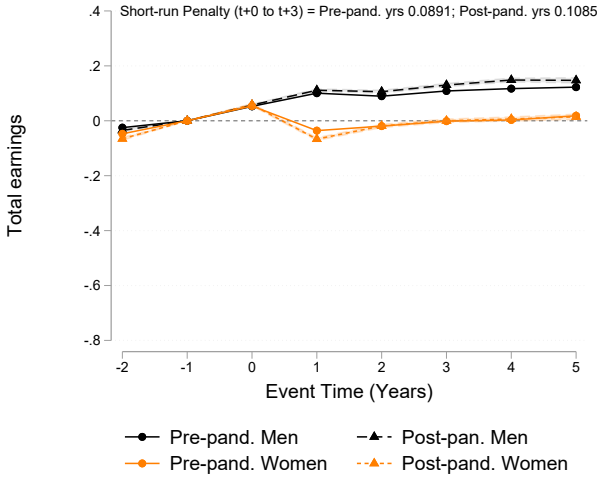


(f) Fourth quartile – triple difference

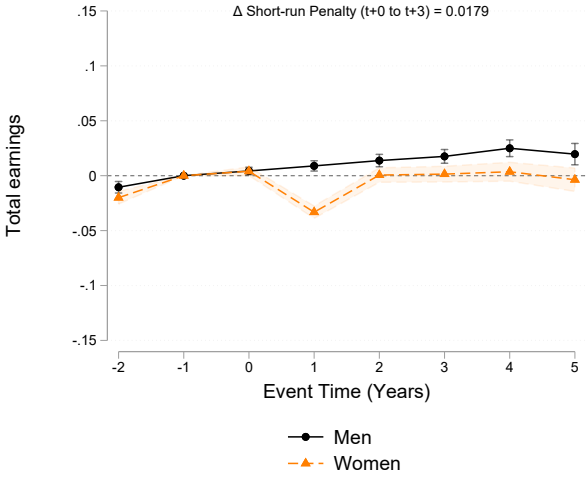


Appendix Figure A.5: Event study and triple-difference estimates of total earnings effects of first birth

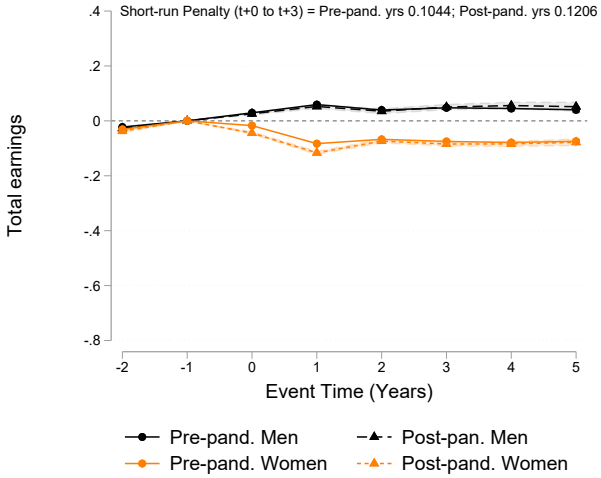
(a) Lower median – event study



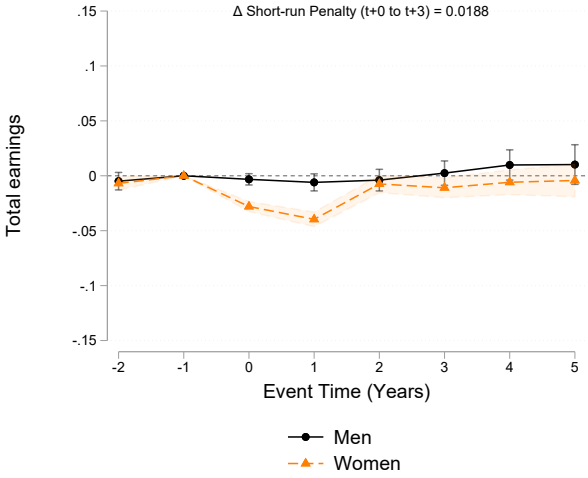
(b) Lower median – triple difference



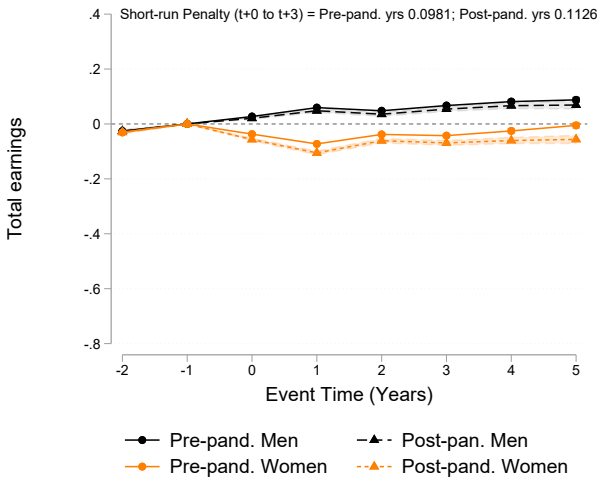
(c) Third quartile – event study



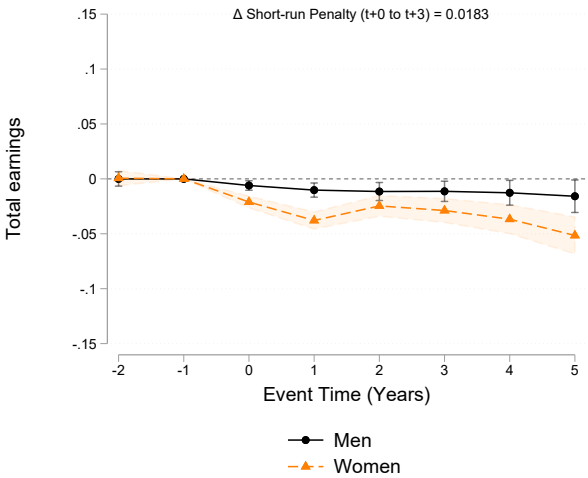
(d) Third quartile – triple difference



(e) Fourth quartile – event study

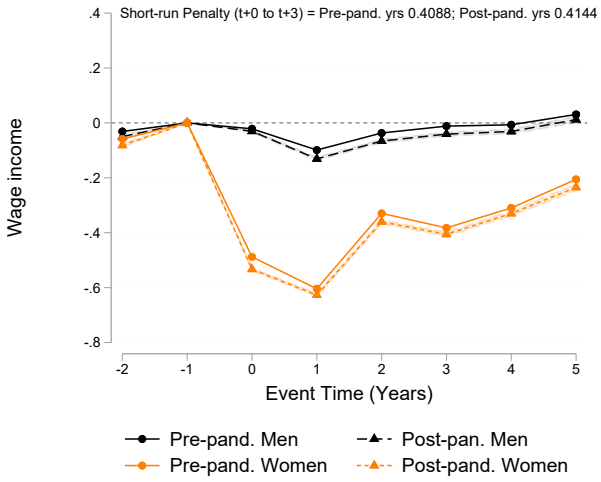


(f) Fourth quartile – triple difference

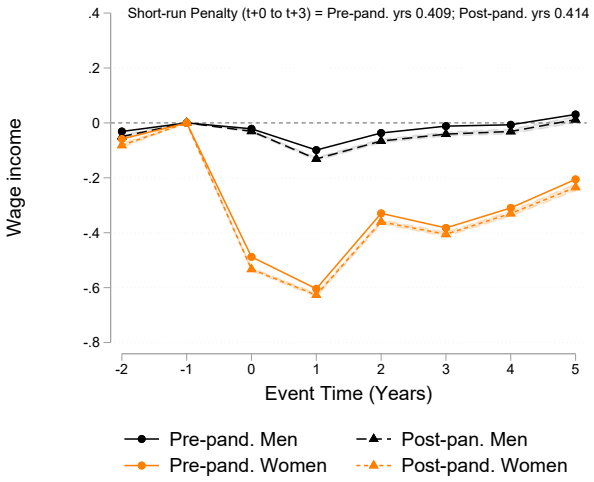


Appendix Figure A.6: Robustness of earnings estimates to exclusion of healthcare and hospitality workers – WFH exposure Lower Median

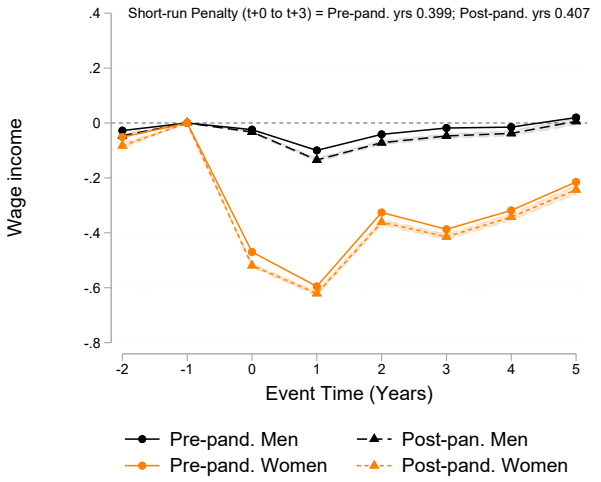
(a) Lower Median - Main



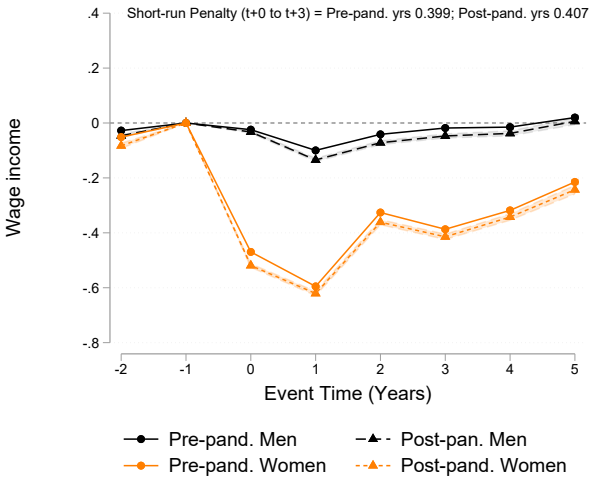
(b) Lower Median - Excl. health



(c) Lower Median - Excl. hospitality

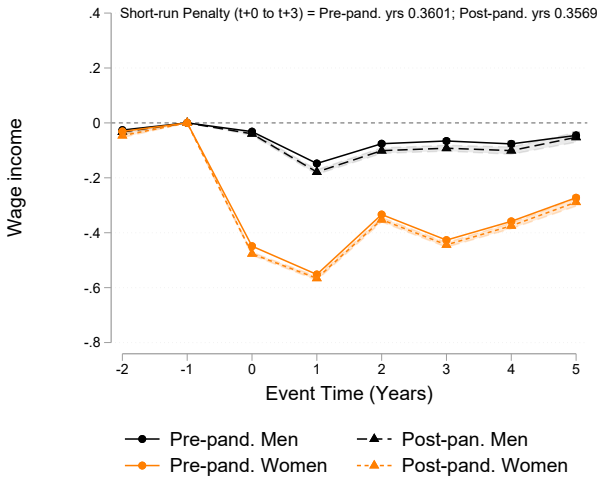


(d) Lower Median - Excl. health and hospitality

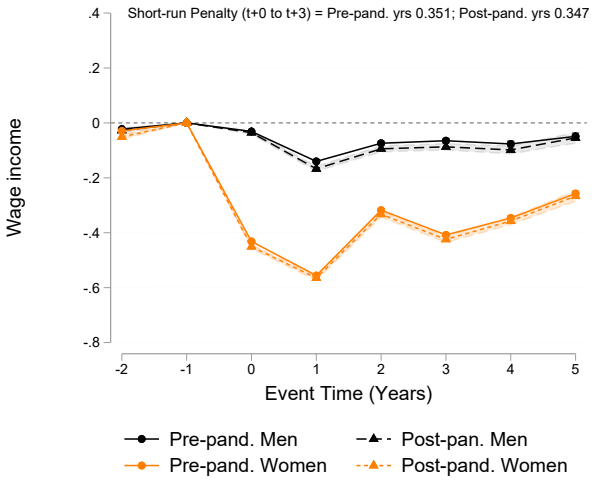


Appendix Figure A.7: Robustness of earnings estimates to exclusion of healthcare and hospitality workers – WFH exposure Quartile 3

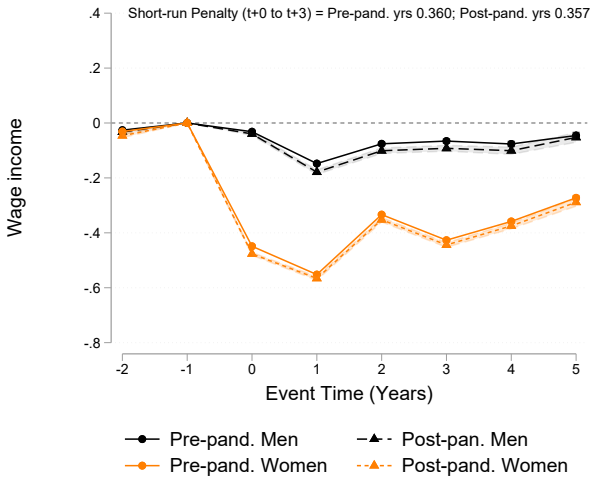
(a) Quartile 3 - Main



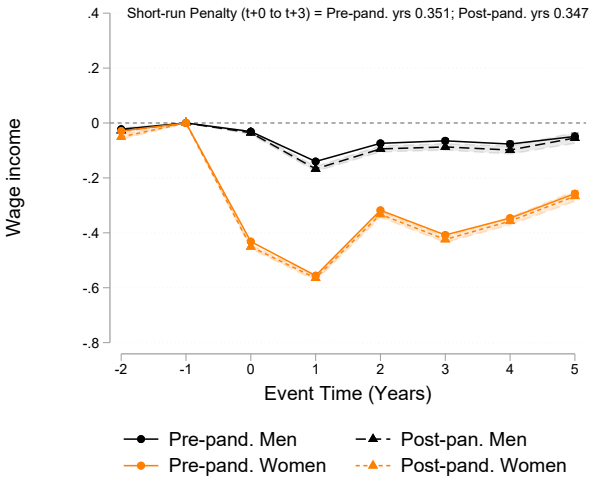
(b) Quartile 3 - Excl. health



(c) Quartile 3 - Excl. hospitality

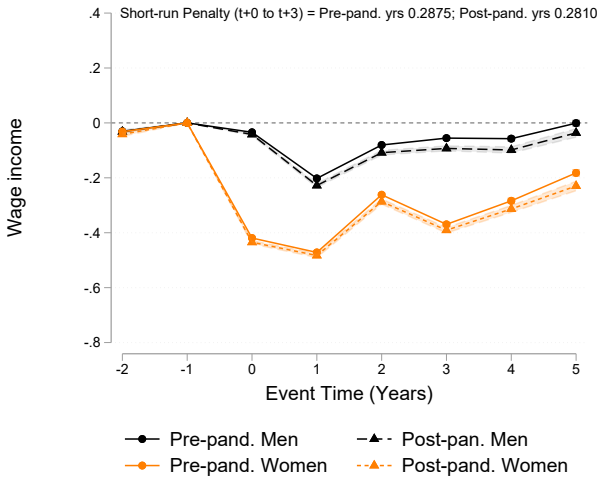


(d) Quartile 3 - Excl. health and hospitality

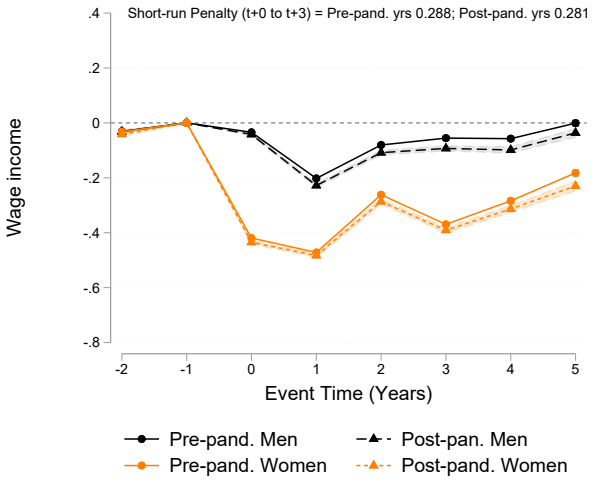


Appendix Figure A.8: Robustness of earnings estimates to exclusion of healthcare and hospitality workers – WFH exposure Quartile 4

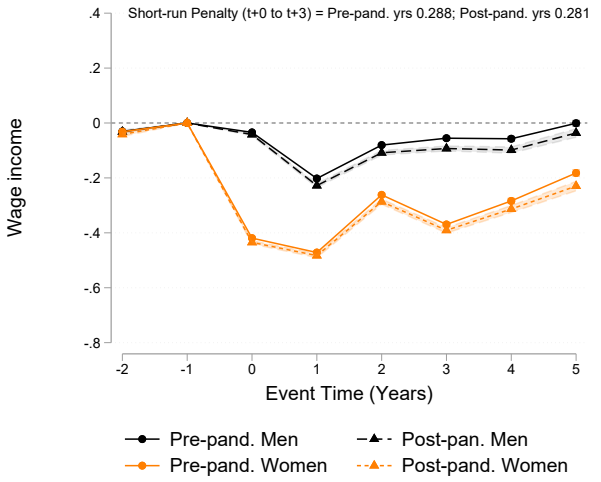
(a) Quartile 4 - Main



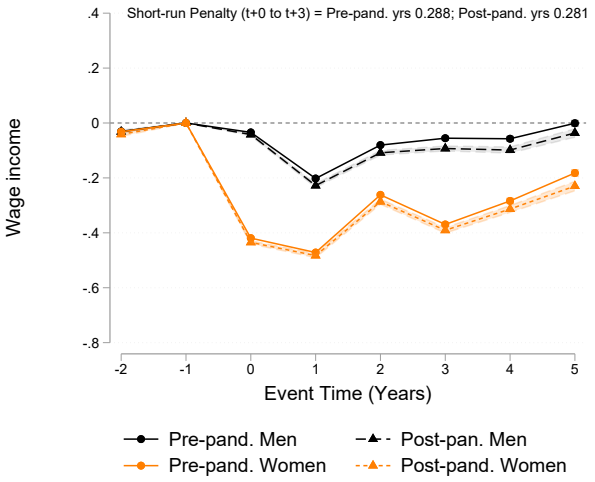
(b) Quartile 4 - Excl. health



(c) Quartile 4 - Excl. hospitality

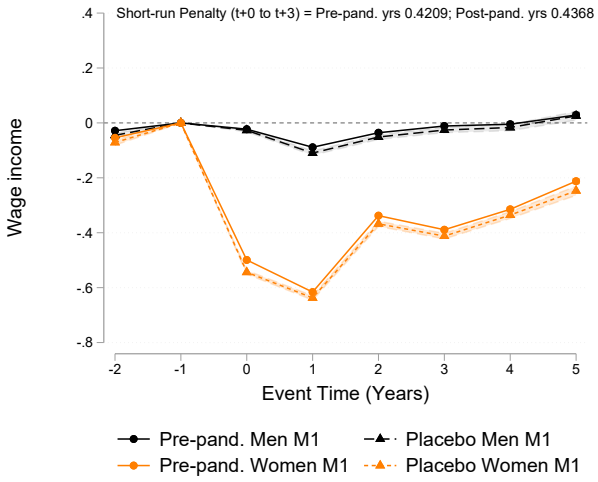


(d) Quartile 4 - Excl. health and hospitality

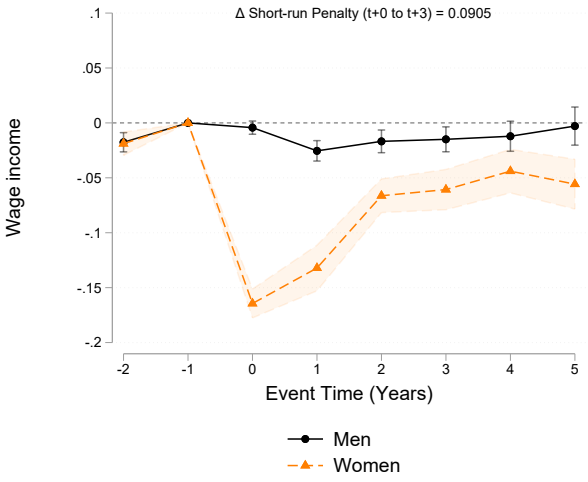


Appendix Figure A.9: Event study and triple-difference estimates of income effects of first birth – low-WFH-exposure women, varying partner's exposure

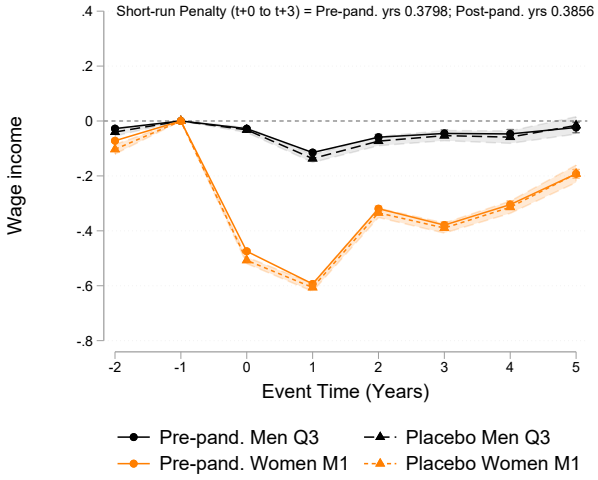
(a) Man in first WFH median – event study



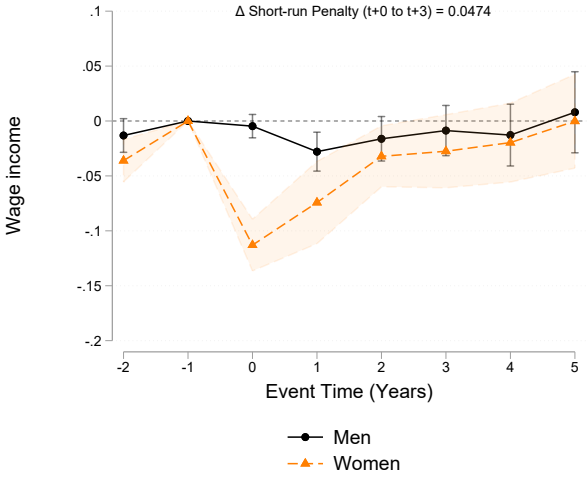
(b) Man in first WFH median – triple difference



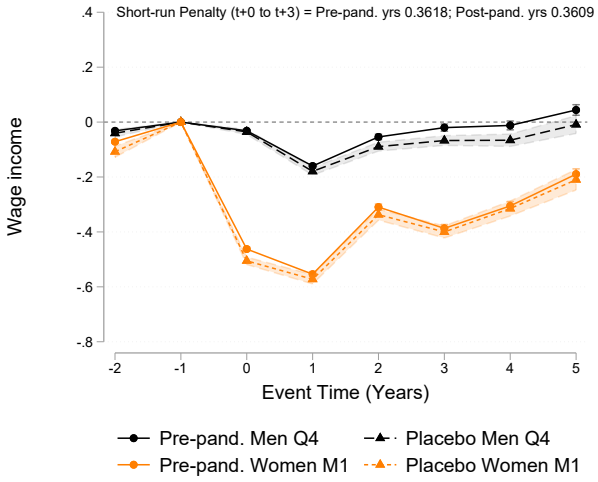
(c) Man in third WFH quartile – event study



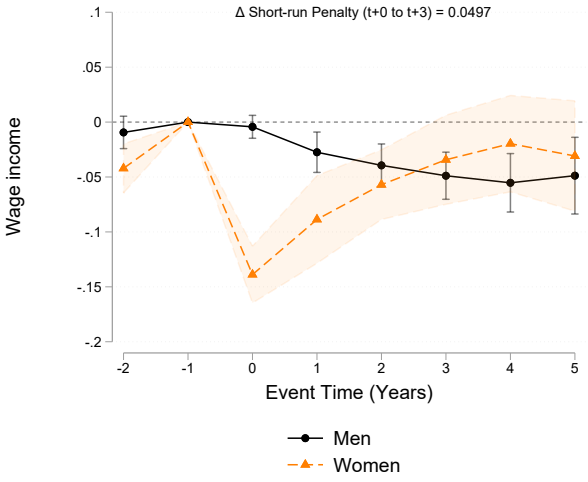
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study

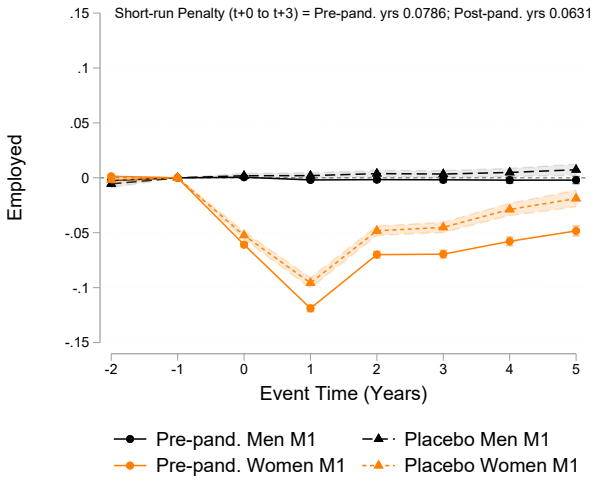


(f) Man in fourth WFH quartile – triple difference

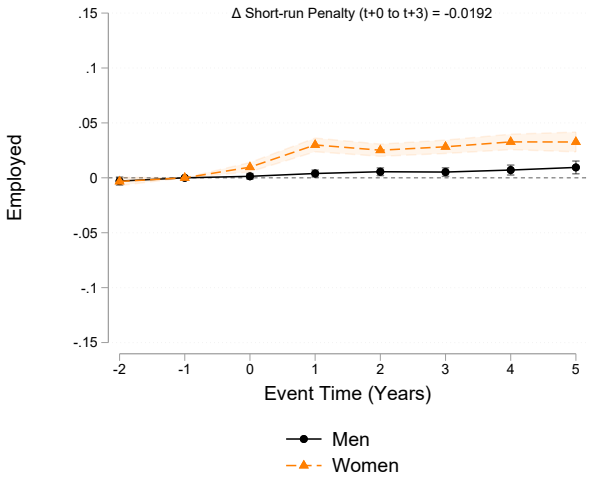


Appendix Figure A.10: Event study and triple-difference estimates of employment effects of first birth – low-WFH-exposure women, varying partner's exposure

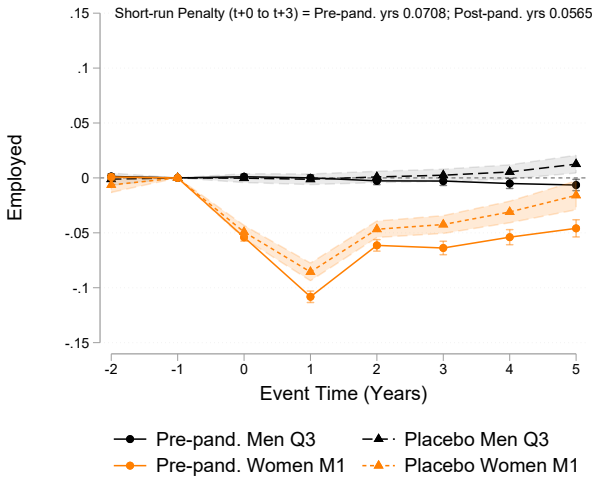
(a) Man in first WFH median – event study



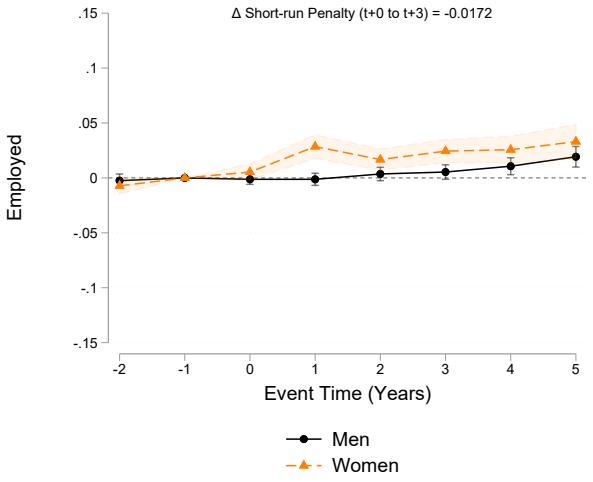
(b) Man in first WFH median – triple difference



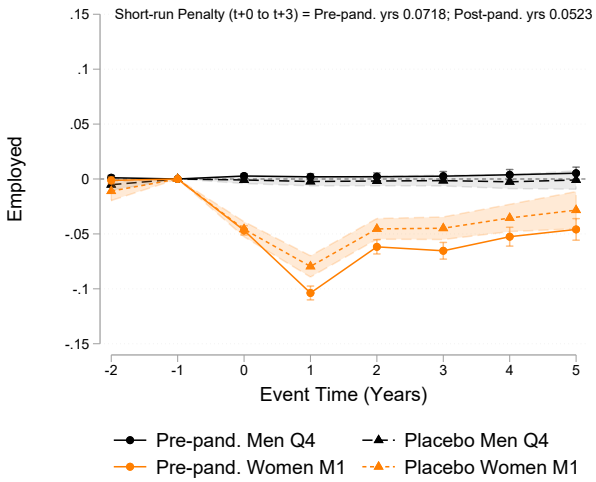
(c) Man in third WFH quartile – event study



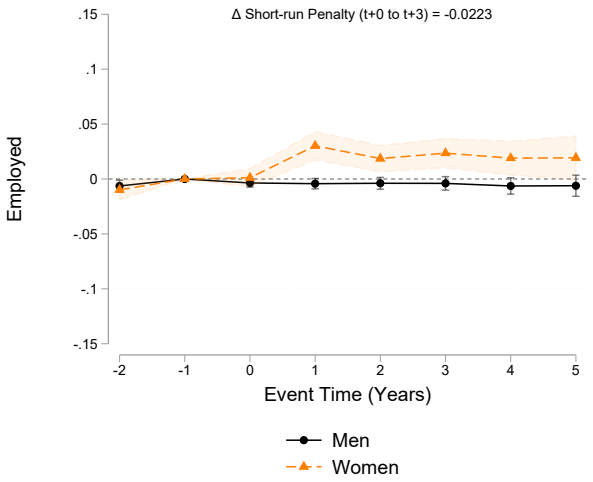
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study

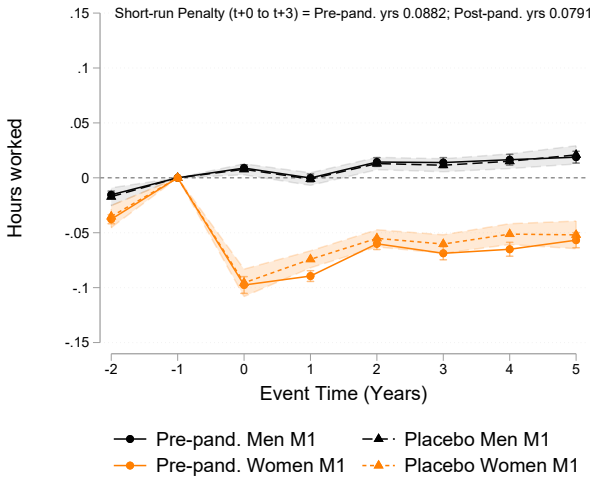


(f) Man in fourth WFH quartile – triple difference

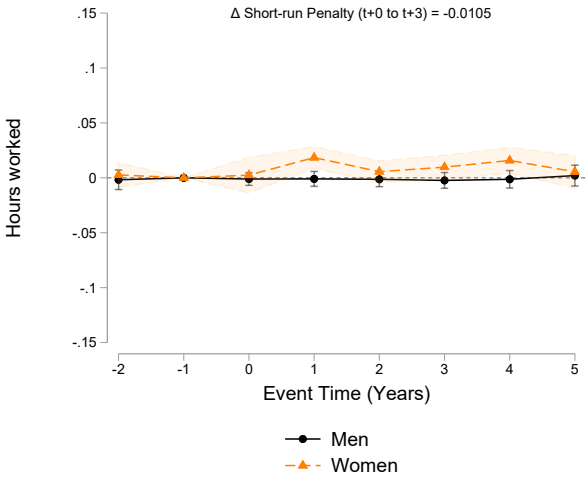


Appendix Figure A.11: Event study and triple-difference estimates of hours effects of first birth – low-WFH-exposure women, varying partner's exposure

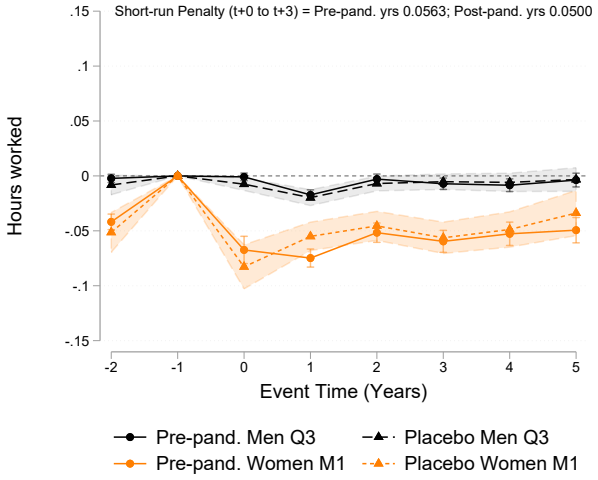
(a) Man in first WFH median – event study



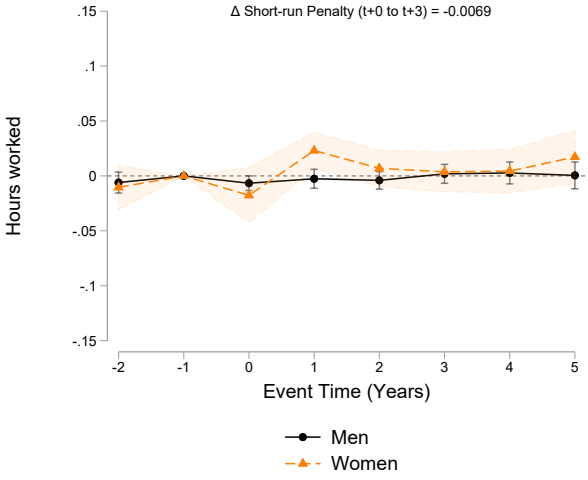
(b) Man in first WFH median – triple difference



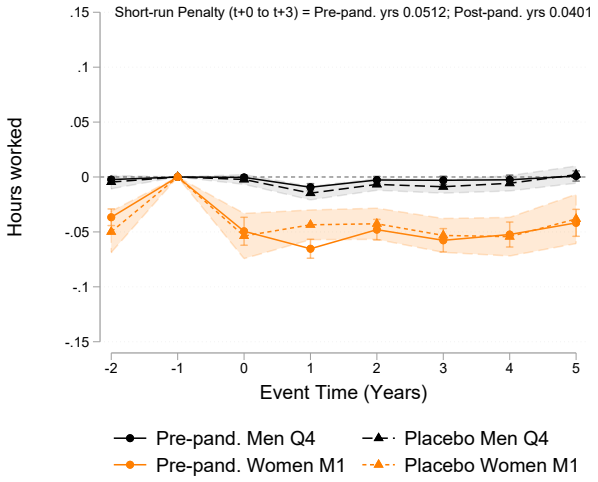
(c) Man in third WFH quartile – event study



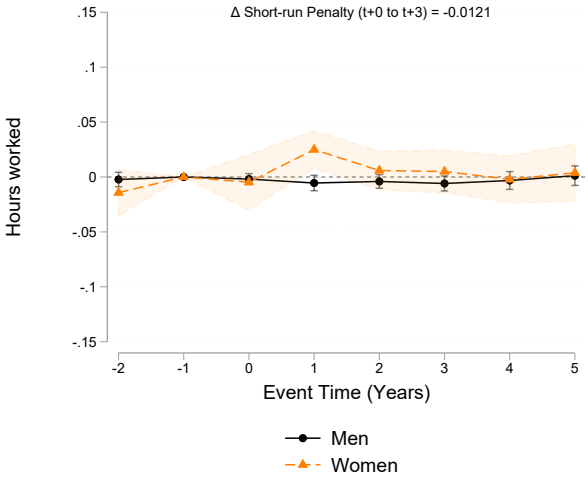
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study

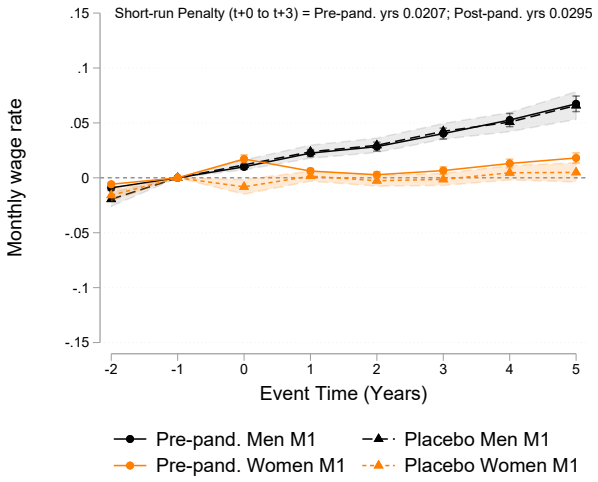


(f) Man in fourth WFH quartile – triple difference

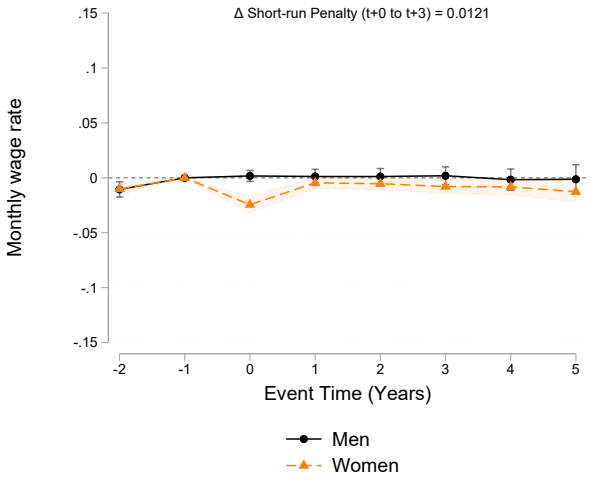


Appendix Figure A.12: Event study and triple-difference estimates of wage effects of first birth – low-WFH-exposure women, varying partner's exposure

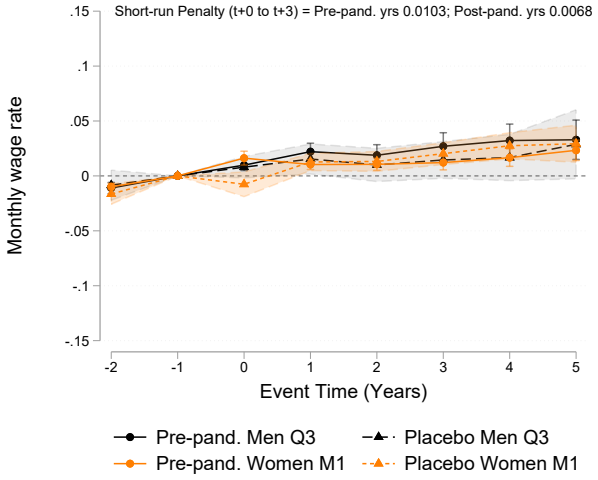
(a) Man in first WFH median – event study



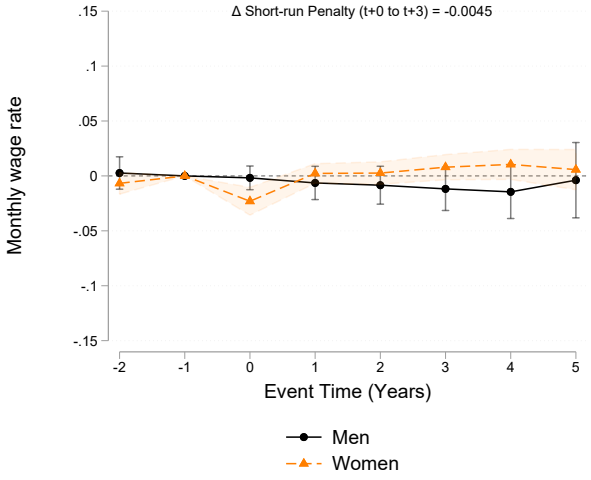
(b) Man in first WFH median – triple difference



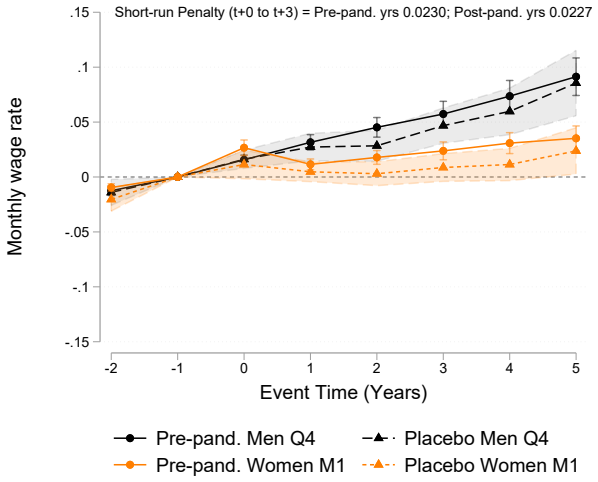
(c) Man in third WFH quartile – event study



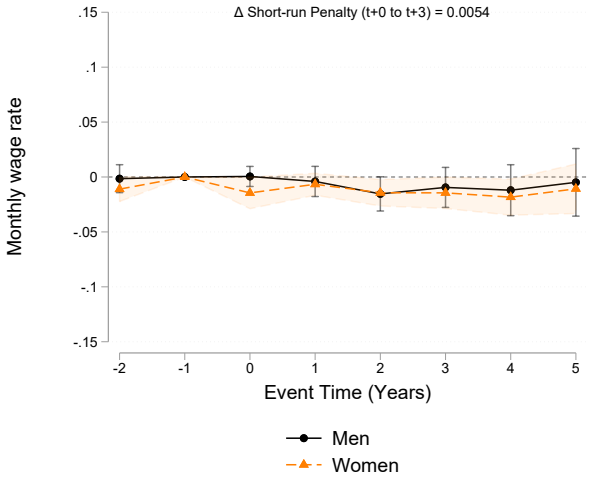
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study

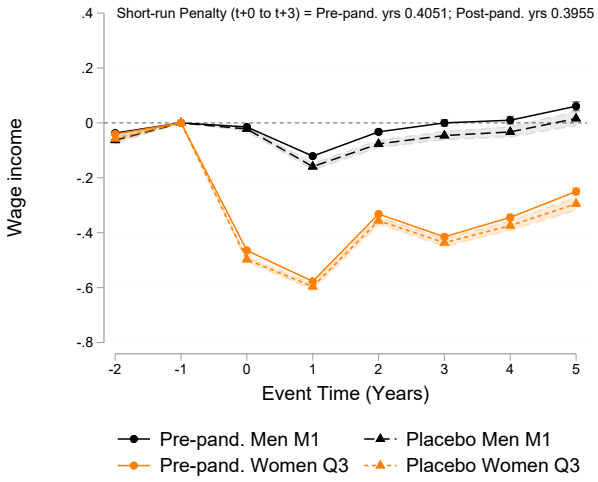


(f) Man in fourth WFH quartile – triple difference

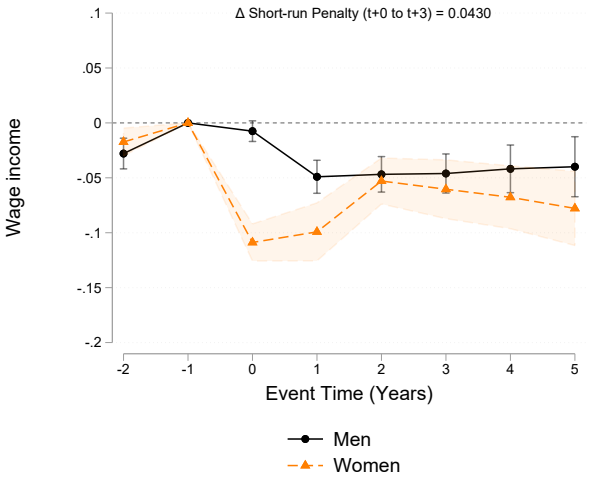


Appendix Figure A.13: Event study and triple-difference estimates of income effects of first birth – medium-WFH-exposure women, varying partner's exposure

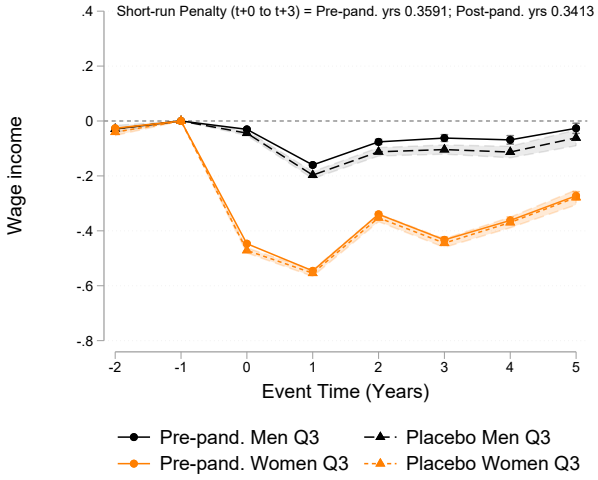
(a) Man in first WFH median – event study



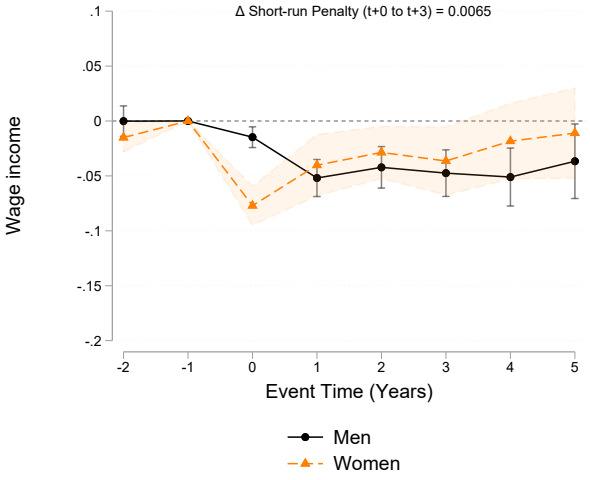
(b) Man in first WFH median – triple difference



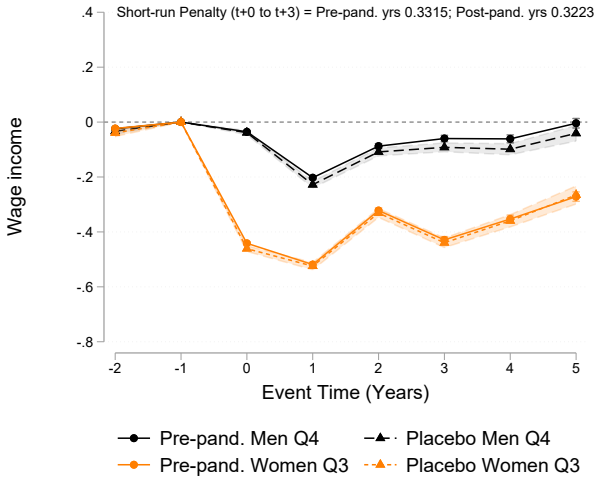
(c) Man in third WFH quartile – event study



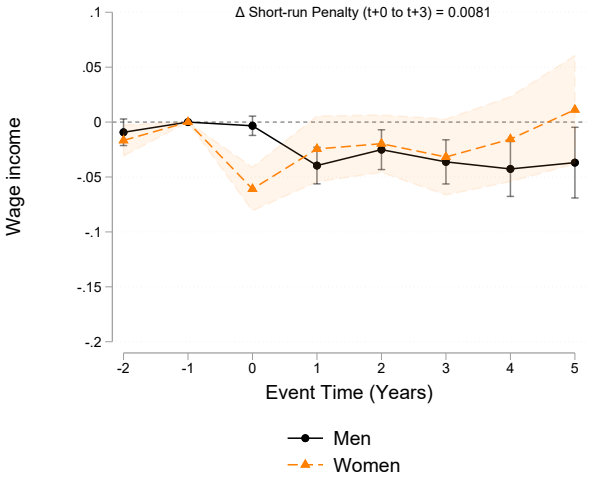
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study

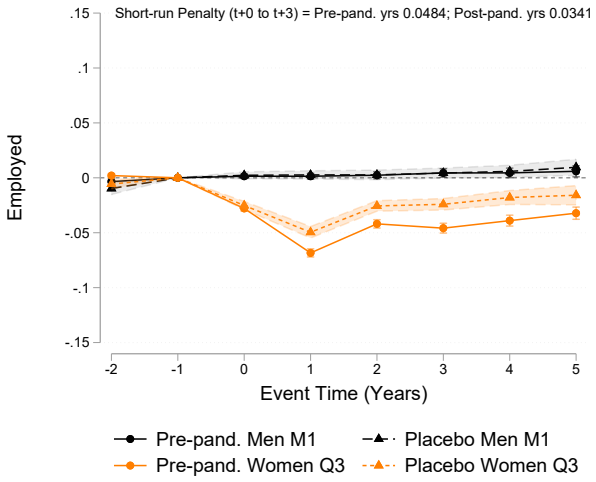


(f) Man in fourth WFH quartile – triple difference

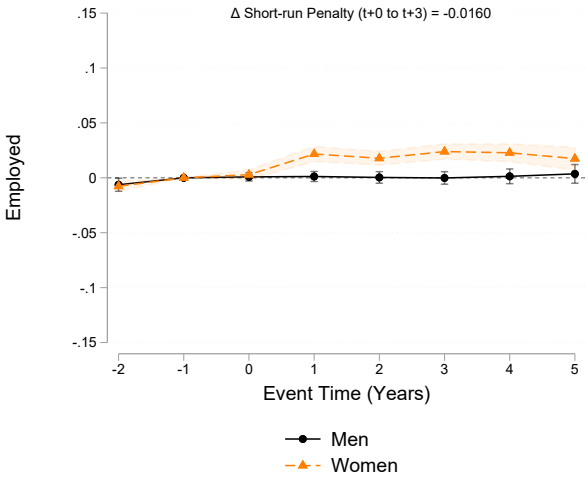


Appendix Figure A.14: Event study and triple-difference estimates of employment effects of first birth – medium-WFH-exposure women, varying partner's exposure

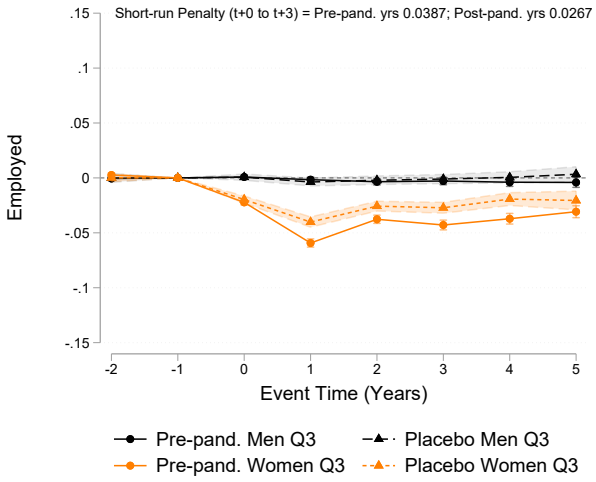
(a) Man in first WFH median – event study



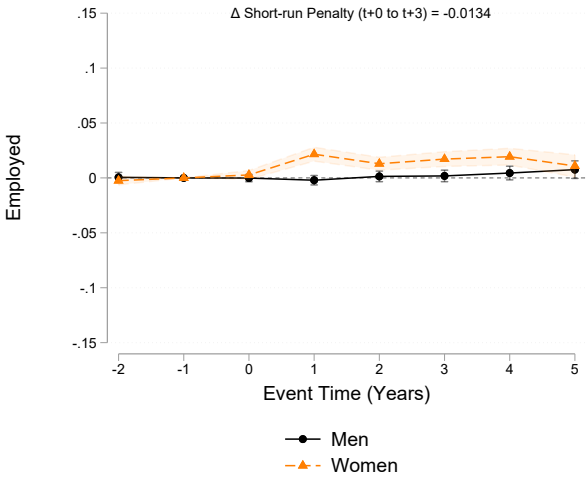
(b) Man in first WFH median – triple difference



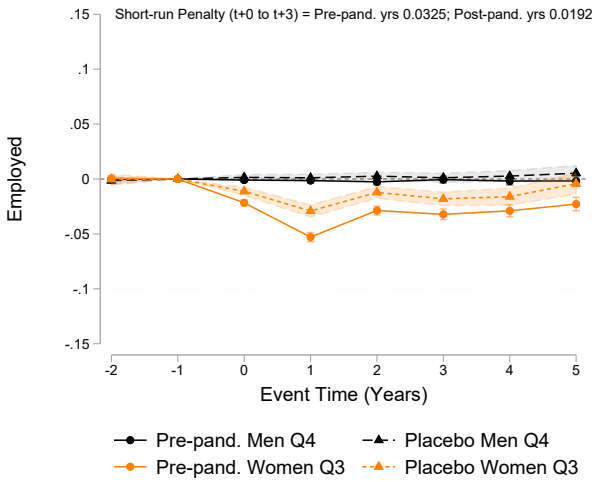
(c) Man in third WFH quartile – event study



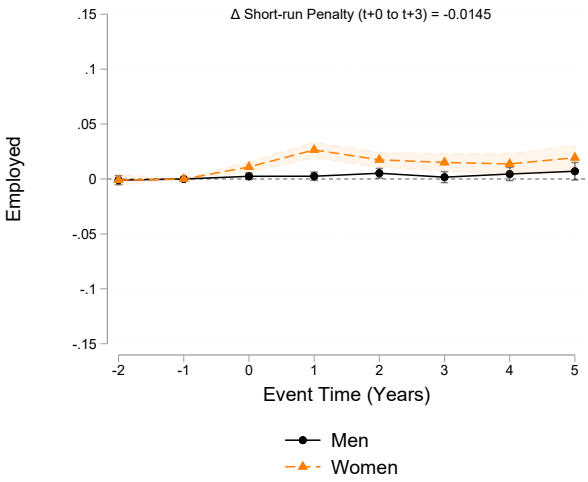
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study

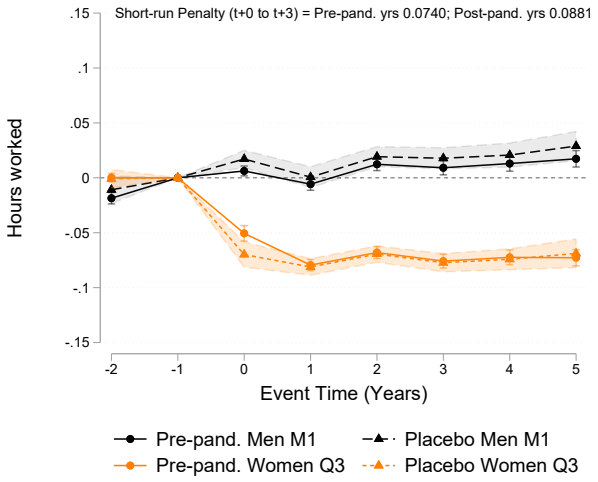


(f) Man in fourth WFH quartile – triple difference

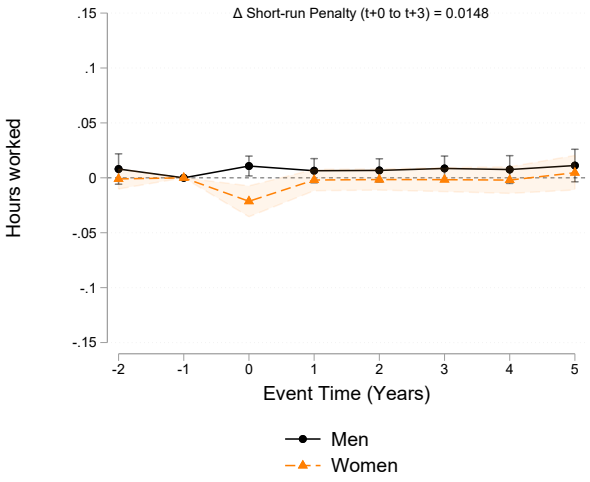


Appendix Figure A.15: Event study and triple-difference estimates of hours effects of first birth – medium-WFH-exposure women, varying partner's exposure

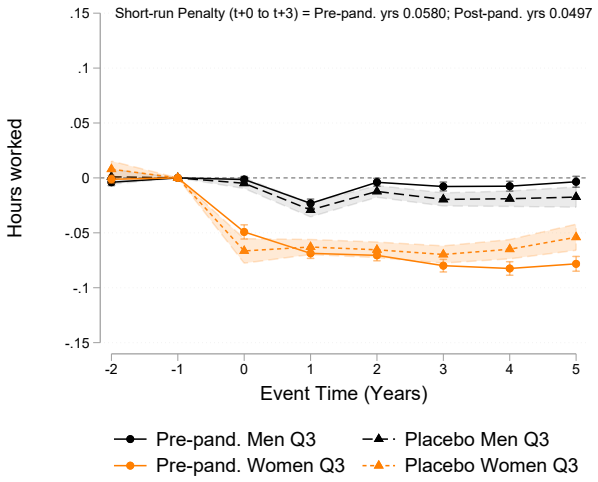
(a) Man in first WFH median – event study



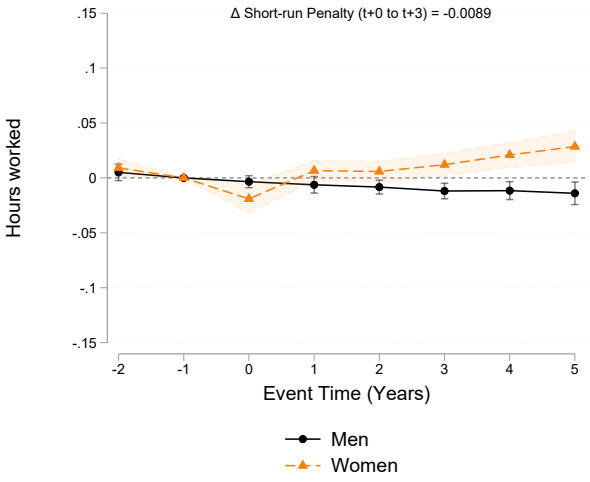
(b) Man in first WFH median – triple difference



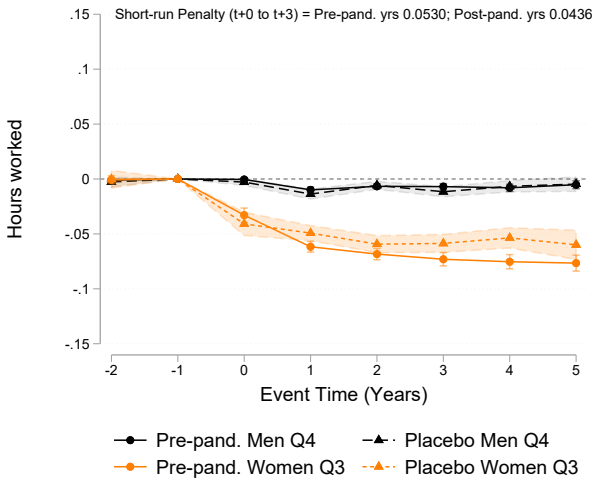
(c) Man in third WFH quartile – event study



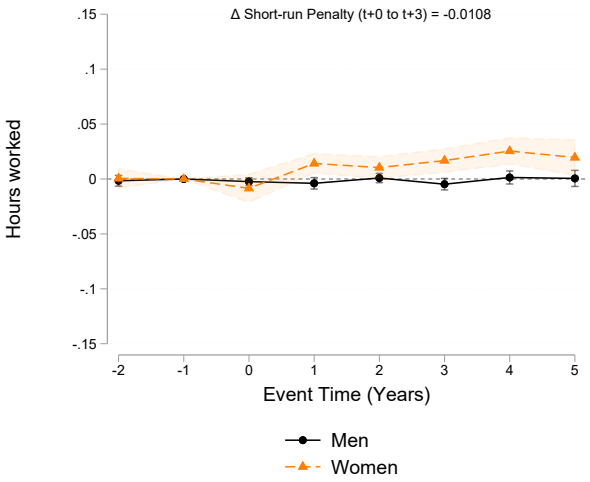
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study

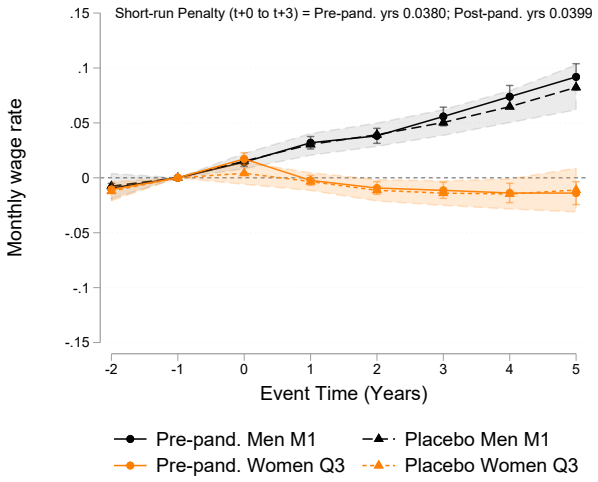


(f) Man in fourth WFH quartile – triple difference

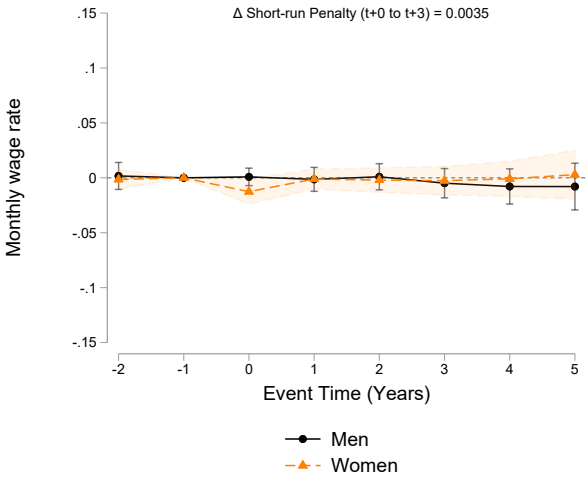


Appendix Figure A.16: Event study and triple-difference estimates of wage effects of first birth – medium-WFH-exposure women, varying partner's exposure

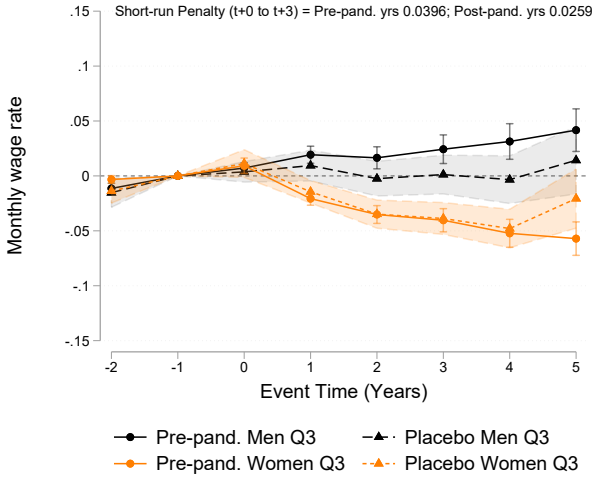
(a) Man in first WFH median – event study



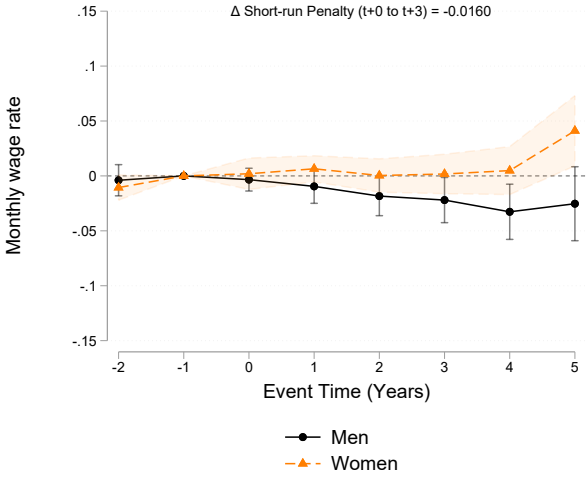
(b) Man in first WFH median – triple difference



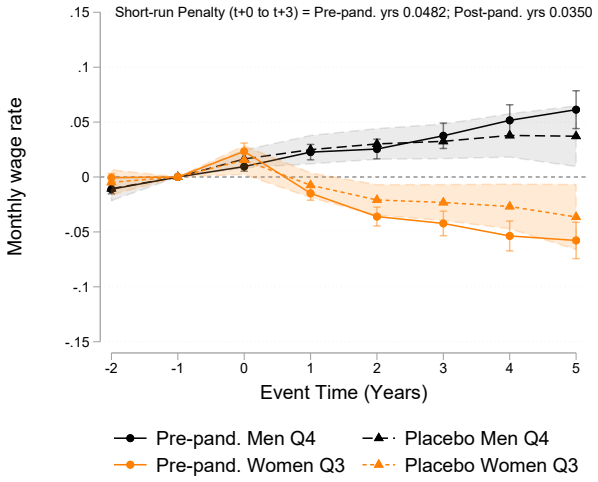
(c) Man in third WFH quartile – event study



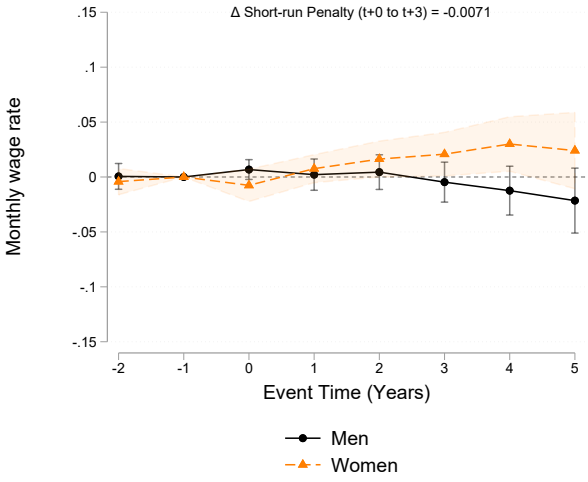
(d) Man in third WFH quartile – triple difference



(e) Man in fourth quartile – event study



(f) Man in fourth WFH quartile – triple difference



Appendix B Fertility timing and takeup of parental leave

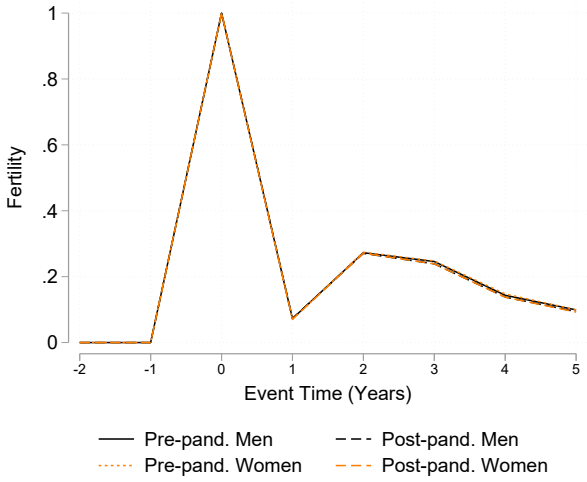
Adams et al. (2024) document that estimates of child penalties are sensitive to the treatment of observed outcomes during periods of parental leave. In particular, they find that much of the total child penalty among Relatedly, Bailey, Currie, and Schwandt (2023) document a slight rise in fertility levels in the United States in 2021, particularly among college-educated mothers. While changes in total fertility in Sweden during the pandemic have yet to be estimated, the combination of these two results raises an important question for our results: are declines in relative earnings after the pandemic explained by increased fertility and associated takeup of parental leave in the years after the first birth?

Figure **??** plots estimates of the probability of having a child at each event time around the birth of the first child. We find precisely estimated zero effects at each event time for each gender and treatment group, illustrating that the pandemic did not meaningfully alter parents' decisions around subsequent fertility after the first birth. Figure A.18 replicates Figure 2.a of Adams et al. (2024), plotting the cumulative number of children in the five years after the first birth across education groups before and after the pandemic. The figure shows that there were virtually no changes in the outcome of interest across education groups. Figure A.19 replicates Figure 2.b of the same paper and shows that, if anything, the cumulative number of children five years after the pandemic *declined* slightly for the highest and lowest educated groups. These results provide strong evidence that increases in subsequent births are highly unlikely to play a role in observed earnings penalties.

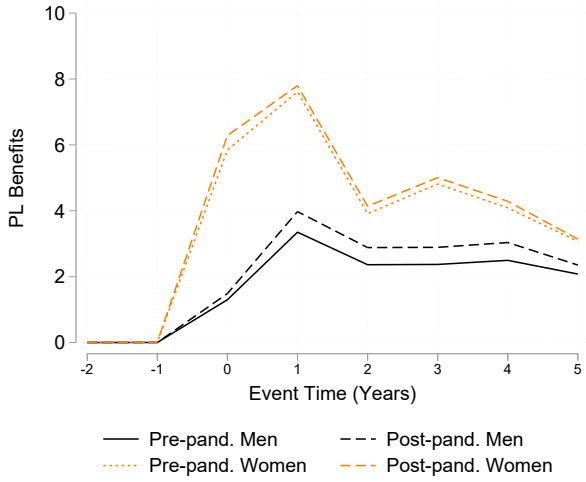
In contrast, Figure A.17 shows that parental leave takeup patterns differ before and after the pandemic. Notably, fathers in both categories of remote work exposure take up parental leave at higher rates in the years after the mother has taken the initial leave spells. This could be explained by changes in the "Daddy Month" policy in 2016.

Appendix Figure A.17: Pre- and post-pandemic fertility rates and parental leave takeup following the first birth

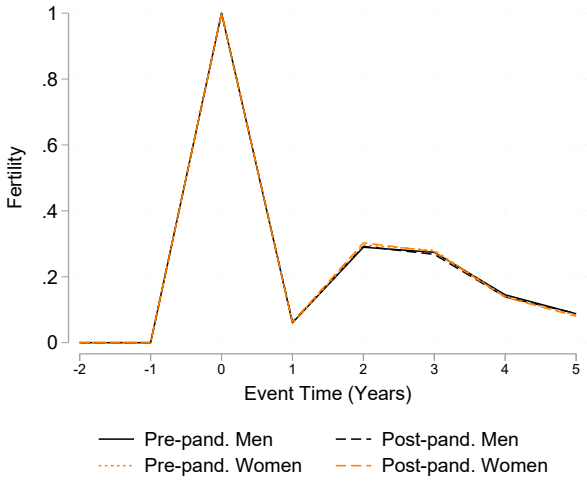
(a) Below-median WFH exposure



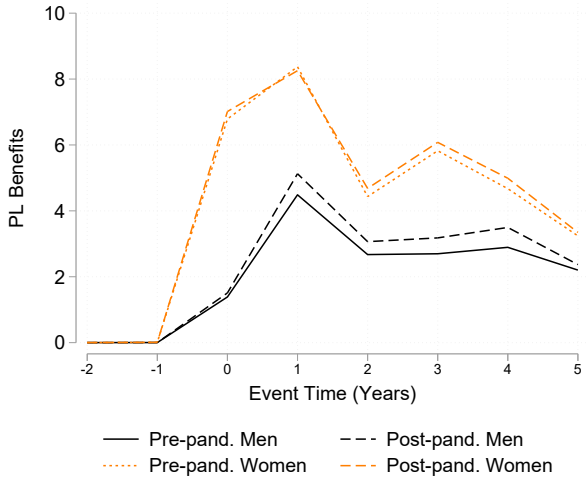
(b) Below-median WFH exposure



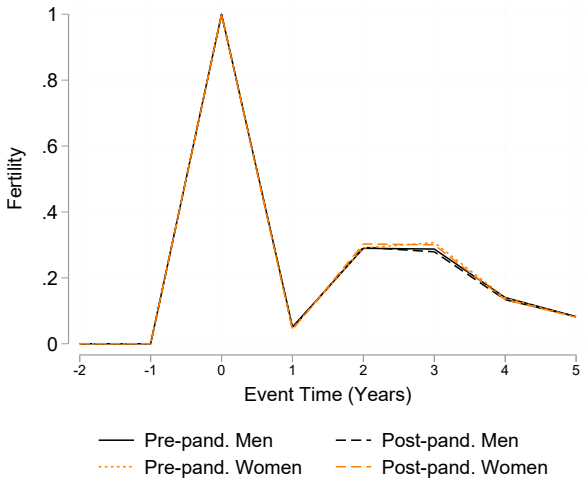
(c) Third Quartile WFH exposure



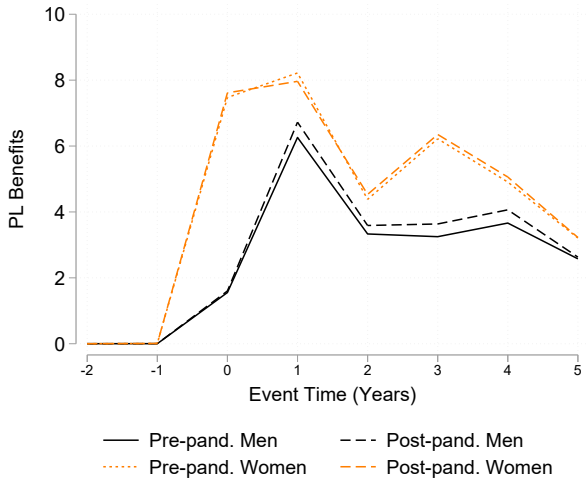
(d) Third Quartile WFH exposure



(e) Fourth Quartile WFH exposure

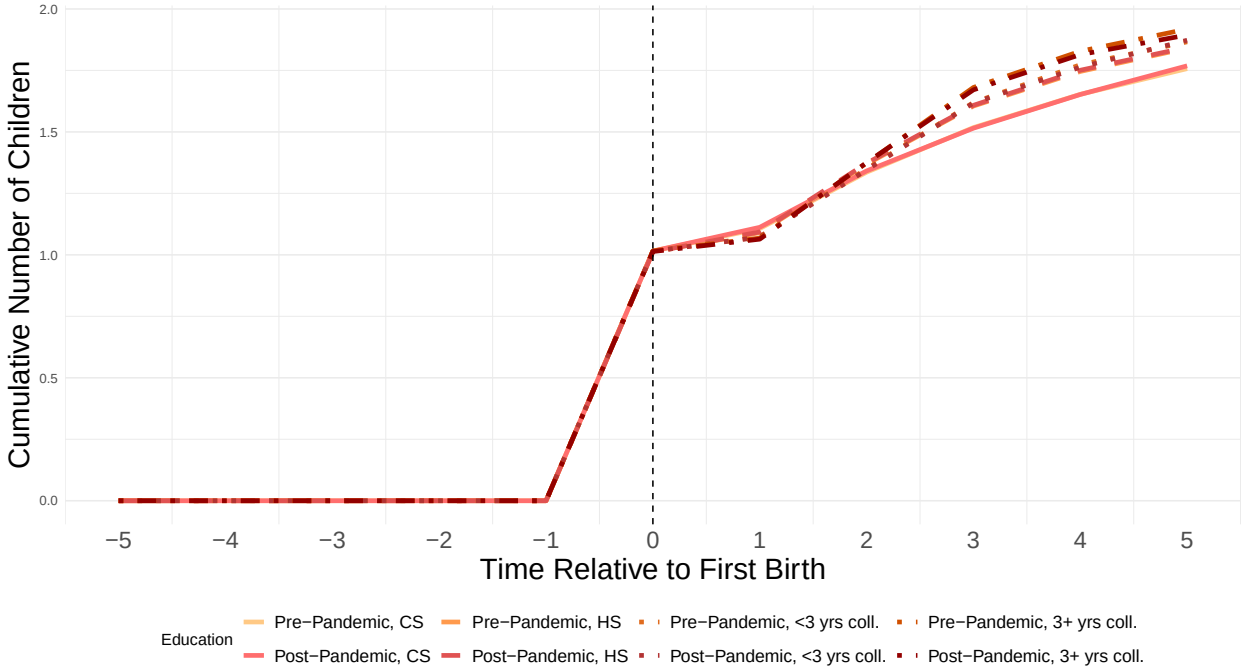


(f) Fourth Quartile WFH exposure

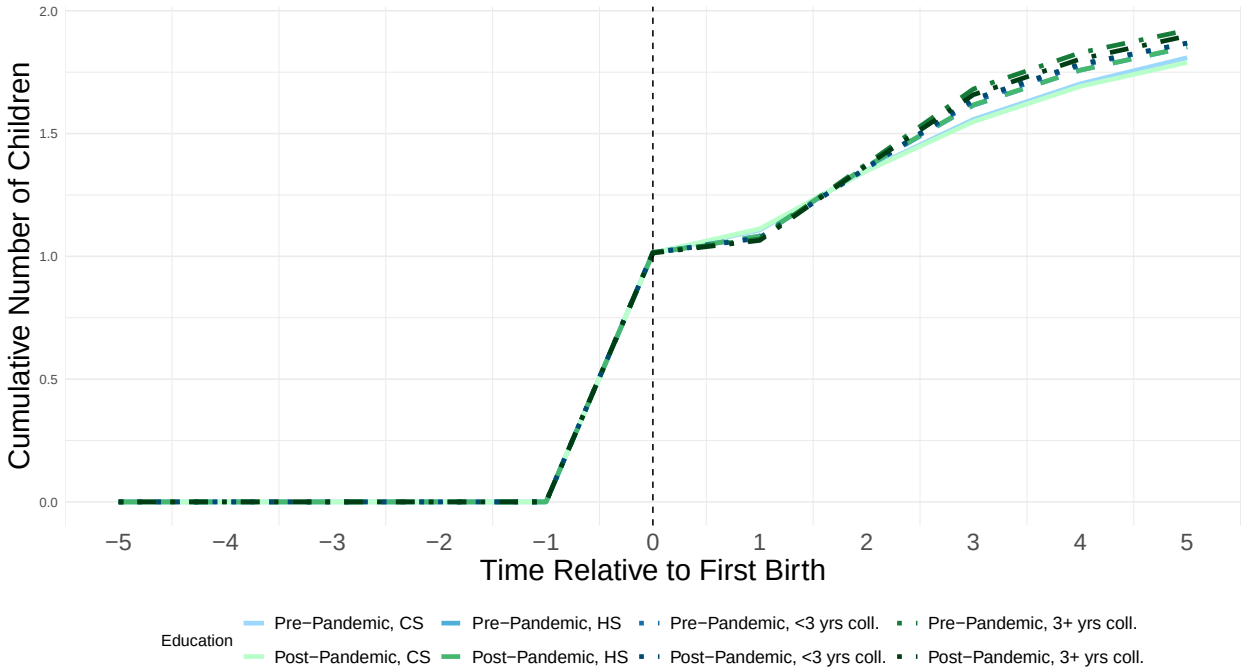


Appendix Figure A.18: Pre- and post-pandemic cumulative fertility by education level

(a) Women

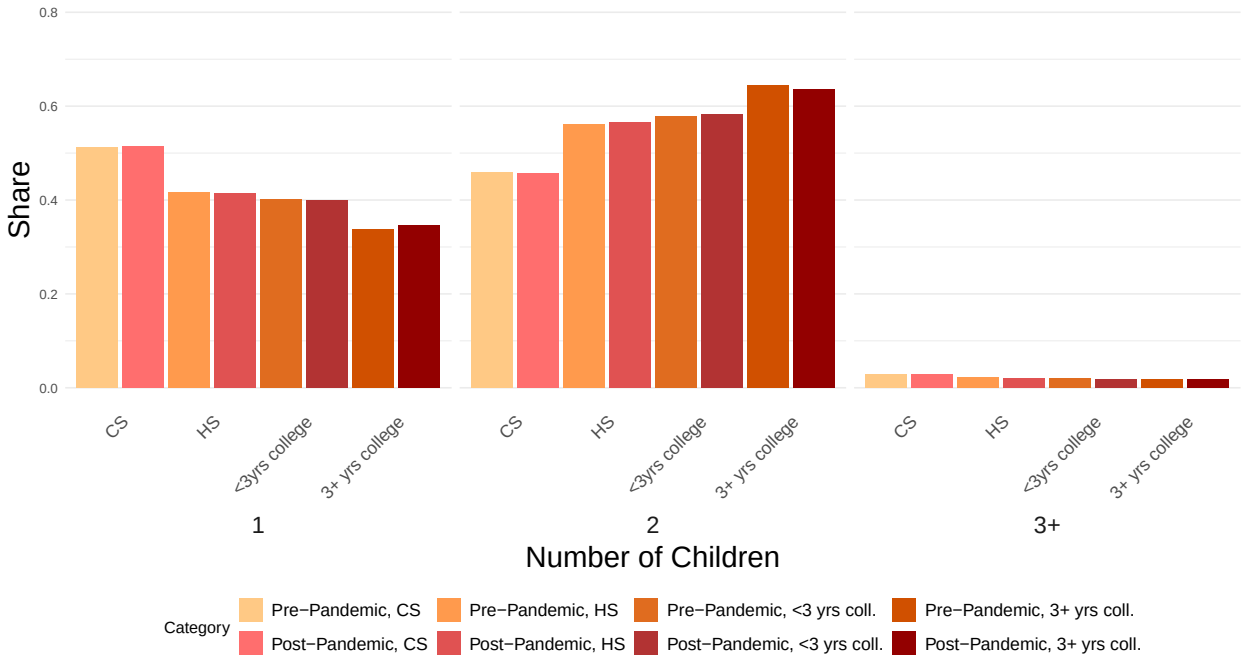


(b) Men



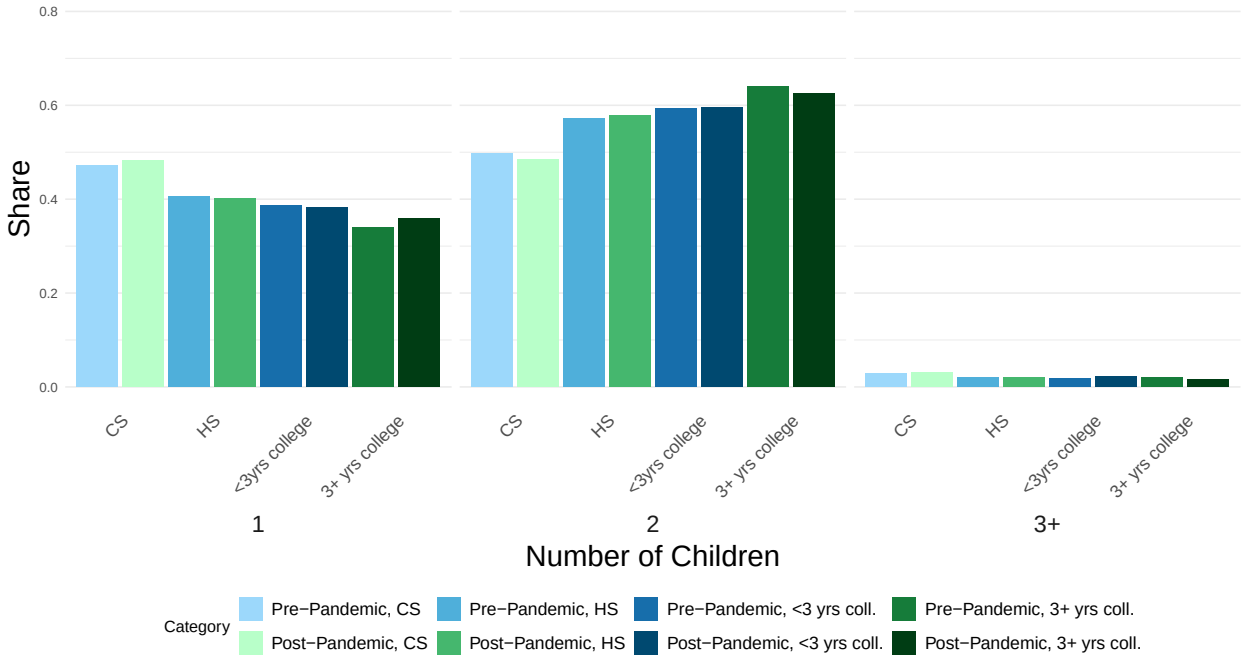
Appendix Figure A.19: Total number of children 5 years after first birth by education level

(a) Women





(b) Men



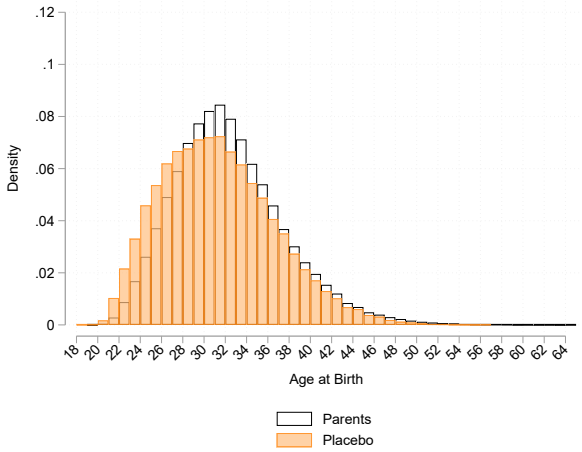
Appendix C Construction of the Placebo Sample

We use a panel of individuals aged 19 to 60 who had not yet had children by 2022. Each individual is randomly assigned to a placebo age at childbirth based on the observed age distribution of actual parents in the corresponding pre- and post-pandemic periods (births from 2010–2016 and 2017–2022, respectively). To ensure a realistic distribution, we fit the assigned placebo ages to a gamma distribution, using parameters estimated from the actual parental age distributions within gender-education level-childbirth year cells. The placebo age at childbirth is matched to the year in which individuals reach that age, and this year is defined as the placebo year of child birth. The year must fall between 2010 and and 2022. Additionally, we exclude individuals who do not have an occupation in placebo event-time $t-2$.

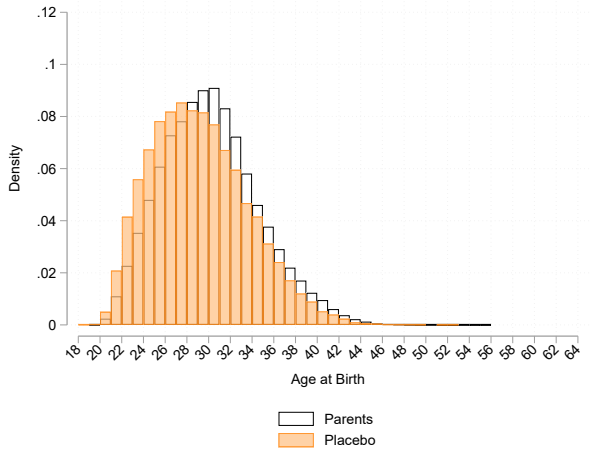
Figure A.20 shows the age distributions of actual and placebo parents by gender. The distributions of placebo parents are slightly left-skewed vis-à-vis the actual age distributions. Table A.2 presents descriptive statistics by gender, remote work exposure quartiles and placebo group. There are three key differences between parents and placebo parents across all remote work quartiles. First, placebo parents tend to be slightly younger than actual parents within each quartile. Second, placebo parents have substantially lower marriage rates. These patterns suggest that actual parents are at more advanced stages in the life cycle compared to placebo parents. However, there remains an age gradient in exposure to remote work, similar to the parent sample. Third, placebo parents are underrepresented at the highest education level. This is because placebo ages at birth are assigned based on the highest education level attained between 2010 and 2022, whereas education in the panel is measured at $t-1$. As a result, some placebo parents are likely still studying (or begin studying) during the sample period, which should be considered when interpreting the results. For instance, similar to the true parents, placebo parents are categorized into remote work exposure quartiles by their $t-2$ occupation. Given the strong gradient in education, individuals who are still studying are more likely to work in low-exposure occupations. Once they have graduated, we would expect them to switch to occupations with higher remote work exposure (and higher earnings).

Appendix Figure A.20: Age Distribution by Placebo Assignment

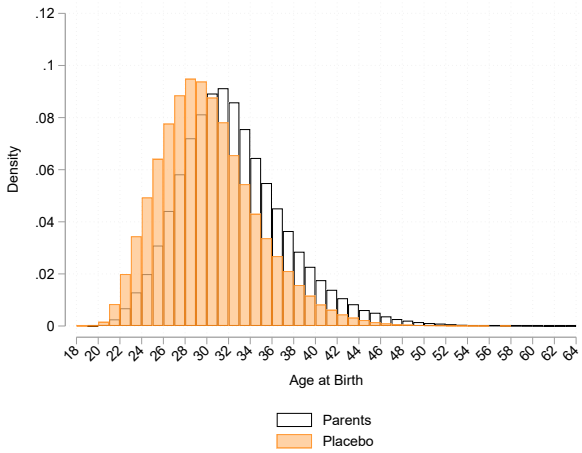
(a) Men, 2010-2016



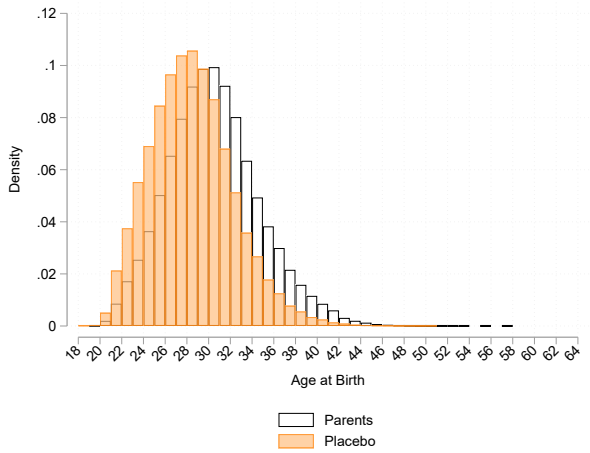
(b) Women, 2010-2016



(c) Men, 2017-2022



(d) Women, 2017-2022



Appendix Table A.2: Composition of Remote Work Exposure Quartiles by Gender & Placebo Assignment

Panel A: Men	**Quartile 1**		**Quartile 2**		**Quartile 3**		**Quartile 4**	
ΔWFH **Intensity**	**-0.14 - 0.00**		**0.01-0.14**		**0.17-0.31**		**0.41-0.74**	
	Parent	**Placebo**	**Parent**	**Placebo**	**Parent**	**Placebo**	**Parent**	**Placebo**
Demographics								
Age	30.52	29.29	31.70	29.64	32.68	30.36	33.83	32.35
Foreign-born	0.21	0.20	0.15	0.16	0.18	0.17	0.12	0.13
Married	0.24	0.05	0.31	0.04	0.31	0.05	0.37	0.07
Education								
CS	0.17	0.18	0.07	0.09	0.07	0.09	0.02	0.03
HS	0.64	0.64	0.36	0.45	0.35	0.45	0.16	0.19
College 3 years	0.12	0.12	0.13	0.16	0.20	0.19	0.18	0.22
College 3+ years	0.07	0.06	0.44	0.30	0.37	0.26	0.64	0.57
Years since grad	8.75	7.64	8.06	6.91	7.52	6.74	5.44	4.59
N	188258	96206	109157	42233	135585	62215	134749	40325
Panel B: Women	**Quartile 1**		**Quartile 2**		**Quartile 3**		**Quartile 4**	
ΔWFH **Intensity**	**-0.14 - 0.00**		**0.01-0.14**		**0.17-0.31**		**0.41-0.74**	
	Parent	**Placebo**	**Parent**	**Placebo**	**Parent**	**Placebo**	**Parent**	**Placebo**
Demographics								
Age	27.88	27.12	29.43	27.76	30.81	29.02	32.14	30.68
Foreign-born	0.18	0.20	0.14	0.18	0.12	0.13	0.13	0.19
Married	0.21	0.05	0.25	0.04	0.30	0.05	0.37	0.07
Education								
CS	0.08	0.09	0.07	0.09	0.02	0.03	0.01	0.01
HS	0.36	0.45	0.35	0.45	0.16	0.19	0.06	0.07
College 3 years	0.13	0.16	0.20	0.19	0.18	0.22	0.10	0.14
College 3+ years	0.44	0.30	0.37	0.26	0.64	0.57	0.84	0.78
Years since grad	5.47	4.75	4.80	4.13	5.37	4.43	5.37	4.43
N	40392	21424	101254	32349	79765	31863	71954	17926

Notes: WFH exposure quartiles for men and women are defined using the change in remote work adoption by 2-digit occupation from 2019 to 2021. The measure is described in detail in section 3.2. "ΔWFH Intensity" refers to the value of the occupation-level change in remote work adoption from 2019 to 2021. The sample consists of opposite-sex parents who have their first child between 2010 and 2022 and are aged between 19 and 65 at the time of the first birth, as well as a sample of individuals who are child-free. All variables but two are measured the year prior to the first birth: Age is measured at the year of the first birth. Occupation is measured 2 years prior to the first birth.