Childcare and Female Labor Supply in the Era of Remote Work: Evidence from Administrative Tax Data*

Yana Gallen Stephanie Karol Dmitri Koustas Ithai Lurie

March 24, 2026

PRELIMINARY AND INCOMPLETE. DO NOT CITE OR CIRCULATE

Abstract

We study how the rise of remote work has changed childcare use and gender inequality in the labor market. Using newly available administrative tax data on childcare arrangements in the United States, we document that paid childcare has fallen by roughly 10 percent since the pre-Covid period, despite persistently high maternal labor force participation. The decline is broad-based across child ages, largest for higher-income households, and closely matches survey-based measures. A decomposition shows that mothers' access to remote work accounts for more than half of this decline, far outweighing other observed factors such as fathers' characteristics, universal pre-k expansions, grandparental caregiving, platform work, and childcare-sector supply conditions. We next identify two distinct channels through which remote work affects households. First we study the effect of being at a firm that allows remote work. Linking firm remote-work policies to the administrative tax records, we show that parents exposed to remote-work firms are less likely to use paid childcare than comparable parents exposed to in-person firms. However, remote work does not improve mothers' earnings relative to non-mothers and thus does not reduce the gender wage gap; if anything, fathers benefit more from the potential to work remotely. Second, using plausibly random variation in school-entry cutoffs around age 5 relative to children's birth dates, we show that when children leave the home for school, earnings rise for mothers in remote work-friendly occupations who had previously been using little paid childcare. There was no effect of school eligibility on mother's earnings in the years before the remote-work era among similar mothers. Together, the results suggest that remote work has reduced paid childcare use by allowing parents to substitute toward caring for children while working, but that this substitution offsets potential career gains for mothers.

Keywords: Work from home, Gender Pay Gap, Childcare

JEL Codes: J13; J22; J24; J31

*Gallen: University of Chicago, Harris School of Public Policy and IZA. E-mail: yana@uchicago.edu. Koustas: University of Chicago, Harris School of Public Policy. Email: dkoustas@uchicago.edu. Karol: The US Department of the Treasury, Office of Tax Analysis. Email: stephanie.karol@treasury.gov. Lurie: The US Department of the Treasury, Office of Tax Analysis. Email: ithai.lurie@treasury.gov. We thank Gustavo Luchesi for his excellent research assistance. This research was conducted while Gallen, Karol, Koustas and Lurie were employees at the U.S. Department of the Treasury or the Internal Revenue Service (IRS). The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors and do not necessarily reflect the views or the official positions of the U.S. Department of the Treasury or the IRS. Any taxpayer data used in this research was kept in a secured IRS data repository, and all results have been reviewed to ensure that no confidential information is disclosed.

1 Introduction

Despite substantial growth in female employment and wages in the last half of the twentieth century, women's progress in the labor market has stalled since the mid-1990 (England et al., 2020). A large body of evidence links the remaining gap to the arrival of children. Women's earnings, hours, and advancement fall persistently after childbirth, while men's outcomes change little (Kleven et al., 2019). These patterns point to childcare and the difficulty of combining demanding jobs with family responsibilities as central constraints on women's careers (Goldin, 2014). The Covid-19 pandemic introduced a potentially important change to these constraints. Remote and flexible work arrangements expanded rapidly and remain far more common than before the pandemic. By allowing workers to perform their jobs from home, remote work may ease the tension between careers and family responsibilities and reshape the tradeoffs that have historically slowed women's progress in the labor market.

The shift to remote work has altered market and non-market work within the household. When parents perform paid work from home, they can simultaneously work and care for children. This reduces the incentive to purchase childcare services. Consistent with this incentive, we document a new stylized fact: since the pre-COVID period, paid childcare use has declined by roughly 10 percent. Analyzing IRS tax data on childcare use not previously available to researchers, we show declines in use of paid childcare across all child ages, with the largest declines among higher-income households, falling by over 6 percentage points. We validate our tax-data-based measures of childcare with survey-based measures of childcare usage, finding that the tax data yields very similar trends over time. Paid childcare usage measured in the Current Population Survey (CPS) shows the same 10 percent decline through 2024, further validating that the decline in childcare usage is not driven by a reporting phenomenon in the tax data.

A decomposition of the factors accounting for the decline in use of paid childcare suggests that the most important determinant—accounting for more than half of the decline—is whether a mother's occupation is amenable to remote work, based on the pre-2020 O*NET task mix measure from Dingel and Neiman (2020). Factors attributed to fathers play only a secondary role, with more of the decline coming from fathers attributable to occupations with non-teleworkable tasks. The second most important correlate is the low-skill immigration share (Cortes, 2008; Cortés and Tessada, 2011), which accounts for around 30 percent of the decline and may reflect a changing role of immigrants in childcare provision since 2020. We are able to rule out a large role for other explanations, including expansions in Universal Pre-Kindergarten (UPK), expanded gig work, and pandemic-induced early retirements by grandparents. A high-level examination of supply-side factors reveals that profits and employment remain higher throughout the industry, suggesting that Covid-related supply pressures are unlikely to explain the observed decline in paid childcare usage.

In summary, the ability to work remotely is by far the most important factor driving the decline in our decomposition, outweighing all other observed factors we investigated.

Next, we turn to understanding the consequences of working remotely while caring for children on parents' careers. We take two complementary approaches: one exploits variation in access to remote or hybrid work arrangements, and the other exploits variation in whether a child is at home with a potentially teleworking parent. First, we link information on the remote work policies of firms in the Fortune 500 with administrative tax data to (a) show that remote work access affects use of paid childcare, and (b) that remote work has little effect on the earnings of mothers relative to non-mothers, but is associated with a relative increase in the earnings of fathers compared to non-fathers. We link data from the Flex Index database, which records remote-work arrangements as of 2024, to administrative tax data, focusing on companies in the Fortune 500. We identify workers employed at these firms in 2019 and follow those individuals from 2017 to 2024, regardless of where they work in later years. Our empirical design therefore assigns workers to treatment based on whether their 2019 employer still allows remote work in 2024, which provides an intent-to-treat measure of exposure to remote-work policies. Firm characteristics are relatively balanced in 2019 by eventual remote work policy, suggesting that similar workers are plausibly randomly exposed to different policies.

We find that parents who are assigned to firms that allow remote work are less likely to report using paid childcare than parents working in in-person firms. This effect is driven by parents of school age children. We also show that remote-work policy is not associated with statistically significant differences in fertility or job switching.

While remote work arrangements may affect firms in many ways, the shift in childcare responsibilities associated with remote work affects only parents at these firms. To study the effect of remote work arrangements on earnings, we compare the earnings trajectories of parents assigned to firms that allow remote work to non-parents at those firms, separately for male and female employees. We find that earnings of workers assigned to firms which are fulltime in office grew relative to earnings of workers assigned to firms allowing remote work, but for women, there is no differential effect of parenthood: mothers assigned to these firms do just as well as non-mothers. If anything, men with children benefit substantially more from remote work than men without children. While remote work may expand the hours individuals are able to work, it also induces some workers into combining time spent at work with time spent on childcare. Extrapolating from our estimates for workers from Fortune 500 companies to the rest of the population, we conclude that on net remote work policies do not reduce the gender wage gap.

Next, we examine how mothers' careers respond when their youngest child becomes eligible to start public kindergarten—an event which makes childcare outside of the home free—in the remote-work era. Following a research design similar to Fitzpatrick (2010), but focusing on employed women in teleworkable occupations

after the advent of remote-work, we compare mothers whose youngest child's birthday falls just before versus just after the school starting-age cutoff. Relative to women in non-teleworkable jobs, mothers in teleworkable jobs show (1) larger decline in paid childcare overall and (2) a smaller change in paid childcare use when their child becomes eligible for school in the post-Covid years. This pattern is consistent with remote work allowing families to substitute toward providing childcare while working from home. If watching children while working constrains parents' productivity, we would expect that removing children from the home increases earnings. Focusing on mothers using little paid childcare (so conditioning on the subset of women who are more likely to be caring for children while working), we find the wages rise by nearly 4 percent when children are eligible to start school. Importantly, in the years before the remote work era, there was *no such relationship* and women in teleworkable jobs who were using little paid childcare saw no impact of having children start school. This result suggests that indeed, when mothers are able to work remotely and watch their children simultaneously, their careers are constrained relative to the case when these children are out of the home.

Taken together, our results suggest that remote work changes the tradeoff between caring for children and working in a way that does not translate to a reduction in the gender pay gap. The expansion of remote work reduced reliance on paid childcare, particularly among households where mothers hold teleworkable jobs. At the same time, the evidence indicates that working from home often coincides with parents providing childcare during the workday. This substitution appears to offset potential career benefits of remote work for women. While remote access expands flexibility and may increase fathers' earnings, mothers' earnings trajectories do not improve relative to non-mothers. Additional evidence from school entry cutoffs reinforces this interpretation: when children leave the home for school, earnings rise among mothers who previously combined remote work with providing childcare. Together, these patterns suggest that remote work relaxes the need to purchase childcare but does not eliminate the underlying tension between childcare responsibilities and career advancement. As a result, the widespread adoption of remote work alone is unlikely to close the remaining gender gaps in pay and career progression.

Our paper contributes to several literatures. First, our study of the impact of public school eligibility on parental earnings is related to prior research studying the impact of access to public school on female labor supply. Gelbach (2002) provides a seminal study of maternal labor supply in the 1980 census using child's quarter of birth to examine eligibility. However, changes in census data collection made follow-up studies using public census data for more recent cohorts impossible. Like Gelbach (2002), Cascio (2009) finds substantial response of earlier cohorts of mothers to their children's school eligibility. Fitzpatrick (2010) uses restricted data from the 2000 Census to estimate the impact of being eligible for Geogia's and Oklahoma UPK, and finds no impact on female labor supply. Cascio (2009) studies state-level introductions of kindergarten

in the 20th century. One potential reason that the effects on maternal labor supply may be small is that these programs tend to be short, and do not provide the type of full-day care that working parents need. Two recent papers Gibbs et al. (2024) and Humphries et al. (2024) document a substantial female employment and hours response to full day public childcare. Our contribution is to study the substitution away from paid childcare, to examine differential responses by whether the mother's task mix is amenable to remote work, pre- and post- the remote work revolution, and especially among households who work but report not using paid childcare.

Recent and complementary work on the impact of remote work on parents' labor supply includes Harrington and Kahn (2024), which studies the decline in employment associated with motherhood and how it is mitigated in careers where women can work from home. Our paper makes use of panel data and identification of specific firm policies to connect the ability to work from home with wage growth and career progression. On the one hand, work-from-home policies allow women to remain employed rather than leave the labor force when they become mothers. On the other hand, if work from home induces women to substitute away from care arrangements which take place out of the home and towards care arrangements which take place inside the home, there may be substantial productivity costs and career consequences associated with the shift towards working from home post-Covid (Adams-Prassl et al., 2023; Gallen, 2023).

2 Data

2.1 IRS Tax Data

We link mothers of children under 13 to the universe of US tax records. In particular, we combine tax records on paid childcare usage with tax records on maternal labor supply. We also further examine the filings of firms where mothers work, and examine the location of grandparents in the tax data based on multi-generation mother-child SSA links. We describe each of these data elements in turn. Many labor market and childcare variables of interest are available back to 2000. We draw on these data to show trends over time. Given our main interest is more recent changes, our main empirical analysis will be conducted on a panel from 2018 to 2024, the latest data currently available.

2.1.1 Birth Records

We begin with a spine based on birth records, where both the mother and child have been issued a Social Security Number (SSN). When someone files for a SSN, often at birth in the United States, the SSA also

collects the SSNs of mothers and fathers, when available.[1] These data are shared with the IRS by the SSA. The coverage of these data begin with births in 1983. In earlier years, these data may be supplemented based on tax filing information.

2.1.2 Paid Childcare in Tax Data

U.S. tax data provide a unique link between a household, their dependent children and care providers. To our knowledge, we are the first to analyze the tax data recording childcare usage. These data are collected when tax units with children claim the Child and Dependent Care Tax Credit (CDCC) or a Dependent Care Flexible Spending Account (DCFSA).

The United States has had a federal CDCC since 1976. From 2003-2025, a tax unit could receive up to $2,100 from the CDCC. Under the One Big Beautiful Bill Act (OBBBA), the maximum CDCC was expanded to $3,000. The American Rescue Plan Act (ARPA) temporarily but substantially increased the generosity for tax year 2021 only. In this temporary expansion, the credit was made fully refundable, the maximum spending threshold rose to $16,000, and subsidy generosity increased to as much as 50 cents per dollar spent for households with adjusted gross income less than $125,000. In addition, many states offer top ups to the federal credit. The most generous are in Minnesota, Pennsylvania and New York, which double the value of the federal credit.

Qualifying tax units are those with any childcare or dependent care expenses that allow the filer (or spouse) to work, look for work, or go to school. Qualifying children must be under 13 years old.[2] The credit amount is a percentage of the first $3,000 of qualifying expenses, or $6,000 for two or more qualifying children. The federal credit is nonrefundable, and is therefore only relevant for tax units with tax liability. We will return to this point when we compare counts from the tax data with other sources of data on paid childcare usage. Another related tax benefit is the DCFSA, which has been available since 1982. Through 2025, filers could contribute up to $2,500 into DCFSAs, per filer, pre-tax ($5,000 for a married couple).[3] Taxfilers with a DCFSA may also claim the CDCC, but the DCFSA amount is deducted from the cap on qualifying CDCC expenses.

The CDCC is claimed by filing a tax form known as Form 2441, and tax units receiving a DCFSA also file this form. The important elements of this form are shown in Appendix Figure A.1. Tax units list each care provider, the SSN or EIN of the care provider, and amount paid. They also list the expenses for each of their eligible children.

[1] Mother SSNs are rarely missing, but may be missing if the mother has not been issued an SSN, such as when a foreigner gives birth in the U.S. Father's SSNs can be missing in the case the father is not known or similarly has not been issued a SSN.

[2] While our focus is on mothers with young children, qualifying dependents can be any age if they cannot provide care for themselves.

[3] This was expanded to $7,500 under OBBBA.

2.1.3 Construction of Panel of Mothers

We begin with all mothers with children under 13 at any point since 2000. In some of our analyses, we rely on a 10 percent random sample for computational purposes. We collapse the data to the mother level, tracking the total number of children under 13 for each mother, and their ages. We also link to fathers based on SSA records.[4] If a mother has multiple children under 13 with different fathers, we attach father's characteristics for the mother's youngest child.

We also look one generation further back, linking the mothers and fathers to their parents (thus identifying the grandparents of the children). Given that we see links beginning in 1983, the oldest a mother can be in a mother-child pair with a grandparental link by the beginning of our 2018 panel would be 35. For older mothers, we further supplement the SSA links based on dependent claiming in 1996 1040 filings. For instance, if a mother in our panel was claimed as a dependent in 1996, we can link her to her parents. This allows us to further construct a grandparental link for most mothers as old as 40 as of 2018 (who would have been 18 in 1996).

Our main focus is on working mothers. We consider female labor supply both from employee and non-employee income. Our main measure of female labor supply comes from receiving a W2 for wage and salary income. We also consider self-employment income, as indicated by the filing or Form Schedule SE, or the receipt of a 1099 from a gig economy payer (Garin et al., 2022).

We also extract self-reported occupation on the 1040, when available. Around half of 1040s have a self-reported occupation that is mappable to a six digit O*NET occupation code. We use this occupation to classify jobs based on whether they can be done remotely, using a methodology discussed in more detail below. Geographic location (zipcode and state) is determined based on the 1040 address.

We also add mortality, geographic location, labor supply and retirement status of the grandparents. First, we link to death dates, as recorded by the SSA (if applicable). We note whether the grandparents work as employees based on receipt of W2, or are retired, based on receipt of Social Security income (1099-SA) or pension/retirement account withdrawals (1099-R). We identify the location of grandparents based on 1040 filings or information returns received in a tax year.

2.2 Identifying Telework

We are interested in the relationship between telework and paid childcare. We thus need to identify telework. Unfortunately, there is no flag in the tax data for telework. We use the index from Dingel and Neiman (2020), which classifies occupations based on their feasibility for remote work using O*NET survey data on

[4] Another alternative is to assign a father based on tax filing information using the 1040, but this requires the household to file and to file as married filing jointly. For this reason, we prefer the SSA links.

job characteristics. We can apply this index to occupations self-reported on 1040s. The main limitation of this approach is that we cannot compare teleworkability across firms within occupation. We have a separate research design exploiting return-to-office policies across firms, that allows us to take advantage of this firm variation, which we discuss below.

2.3 Comparisons to Public-Use Data

2.3.1 CPS ASEC

We complement some of our tax data analysis with public use data from the CPS ASEC for a similar period, from 2000 to the present.[5] In particular, we will use the CPS to validate our measure of paid childcare over time.[6] We validate cross-sectional statistics when possible in both the CPS and tax data. There are a number of potentially desirable properties of the CPS data for this purpose. Households can report using paid childcare in the CPS whether or not they are tax filers. In addition, there is no incentive in the CPS to conceal "under the table" childcare. There are also no tax credit-induced incentives to over-report spending. Unlike the tax data, however, there is no further information about the childcare purchased. Beyond the small sample relative to the tax data, another potential drawback is that individuals may not accurately recall the cost of childcare when asked by an enumerator, compared to when filling out their taxes under the potential risk of audit.

2.3.2 National Survey of Early Care and Education (NSECE)

An additional source on the childcare arrangements of households is the National Survey of Early Care and Education (NSECE). We construct a complementary measure of paid childcare use in the United States using publicly available data from the 2012, 2019, and 2024 waves of the NSECE. The NSECE is a nationally representative survey funded by the Office of Planning, Research, and Evaluation in the Administration for Children and Families of the U.S. Department of Health and Human Services and conducted in partnership with NORC. It offers a comprehensive look at the U.S. childcare landscape, collecting information from households with a child under age 13, childcare providers, and members of the childcare workforce. We use the household data, which report the types of care used by families and their out-of-pocket childcare costs in the week prior to the survey (this time-frame presumably minimizes recall error), to estimate the number of

[5] One possible concern during the immediate Covid period is that response rates declined dramatically. However, we are looking at a longer period through the latest data available.

[6] Between 2001 and 2006, the CPS asked: Did (you/anyone in this household) pay for the care of (your/their) (child/ children) while they worked in [year]? [include preschool and nursery school; do not include kindergarten or grade/elementary school]. From 2007 onwards, the question became: Did (you/ anyone in this household) pay for the care of (your/their) (child/children) while (you/they) worked in [year] [include: all child care expenses including preschool and nursery school expenses before and after school care, and summer care. Do not include: cost of kindergarten or grade/elementary school.]

households with a child under age 13 that pay for childcare and average weekly spending among households with positive costs. Because the CPS and tax data only observe annual childcare spending, we annualize weekly NSECE costs by multiplying them by 52. Since families may not rely on paid childcare throughout the whole year, we interpret this measure as a plausible upper bound on annual childcare expenditures.

2.3.3 ATUS

Finally, we complement our analysis in the tax data with time-use data from the American Time Use Survey (ATUS) for the years 2003 to 2024. The ATUS is a nationally representative sample drawn from households that have completed their eighth and final CPS interview. In each household that takes part in the ATUS, one individual is selected as a "designated person" and is invited to complete a time-dairy, which is a report of all activities they engaged in specified 24-hour periods.[7] In addition to tracking how the designated person spends their time, the ATUS records where and with whom they were while engaging in each activity. The ATUS also includes rich demographic and economic information linked from the last CPS monthly interview.

We use the ATUS to analyze an alternative measure of the prevalence of remote work among fathers and mothers of children under 14 across the years. Given that the survey asks respondents to specify where they performed each activity, we are able to calculate, for parents that worked on diary day, what share of working hours was done remotely.[8] Specifically, we define remote work in the ATUS as any work time spent in a location other than the designated person's workplace.[9] Additionally, the ATUS also allows us to document how working parents have managed childcare throughout the years. Childcare in the ATUS can be reported in two ways. First, it may be recorded as a primary activity when the designated person is directly engaged with a child, such as helping with homework, playing together, or preparing meals.[10] Childcare may also be recorded as a secondary activity when the designated person reports having supervised a child under 13 while engaged in other activities. We use both of these childcare definitions to look at how working parents adjusted their childcare provision in response to the telework-related shifts in work arrangements.

[7] Unfortunately, the ATUS does not collect time-use data for household members other than the designated person.

[8] For each activity, respondents also specify where it took place. The ATUS interviewer asks: "Where were you while you were [ACTIVITY]?"

[9] To estimate the amount of work being performed from home, we focus on two specific activities: "Work, main job" and "Work, other job(s)". The activity codes for these activities are 050101 and 050102, respectively

[10] We classify three groups of activities as primary childcare: "Caring for and Helping Household Children", "Activities Related to Household Children's Education", and "Activities Related to Household Children's Health". The activity codes for these groups are 030100, 030200, and 030300, respectively

3 Stylized Facts about Paid Childcare and Maternal Labor Supply

3.1 Use of Paid Childcare has Declined Post-2020

We begin with trends in maternal labor supply for mothers in the tax data. Figure 1(a) plots the share of mothers with any employment over the course of the year, against the share with paid childcare, as measured in the tax data. Employment of mothers was increasing between 2015-2019, and the share with paid childcare increased slightly. Any paid childcare dramatically declined in 2020 due to Covid related disruptions. Paid childcare measured in tax data increased in 2021 (some of this increase for 2021 is undoubtedly due to the credit expansion for 2021 only), before declining again in 2022 and 2023. Following a decline in 2020-2021, employment on the other hand has continued to increase. Figure 1(a) presents the main "puzzle" at the heart of our paper: the labor supply of mothers is at an all-time high, while paid childcare usage is at an all-time low. Appendix Figure A.2 examines paid childcare usage back to 1999 by youngest child age, showing trends were mostly stable, with a slight upward trend for moms of younger children.

Figure 1 Panel (b) examines the decline in paid childcare by mothers' earnings.[11] For the lowest earning mothers, paid childcare increases in 2021 (the year of the temporary expansion in generosity from ARPA), before returning to previous levels. For all other earnings levels, paid childcare drops. The largest drops in percentage point terms comes from higher earners, falling over 6 percentage points. We further break out the decline in childcare out by age of the youngest child in Figure 1, panel (c), comparing ages 1-4 who would not yet be in school, with ages 5-12. The declines in paid childcare occur across all child age groups.

Appendix Figure A.4 examines trends by state. The decline in paid childcare is seen across all states: no state has higher rates of paid childcare as of 2024 compared to 2019. However, there is variation across states in the magnitude of the decline, with states like Rhode Island and Connecticut seeing very small declines relative to 2019, and states like New Mexico and Hawaii showing declines of 20 to 30 percentage points.

Appendix Figure A.5 examines childcare expenses reported on Form 2441 by number of children, for 2019. Given the structure of the CDCC, there is no incentive to report more than $3,000 in expenses among households who have one eligible child, or $6,000 in expenses among households with two or more eligible children. However, there is little evidence of bunching at these thresholds. More than 40 percent of households report more than these thresholds.

Appendix Figure A.6 provides additional descriptive evidence on childcare usage in the United States, using data from 2019, examining the role of grandmother distance. Panel (b) examines the share with paid childcare, for those with at least $50,000 in earnings, by distance to a grandmother. The share rises from

[11] Appendix Figure A.3 examines employment by mothers' earnings and youngest child age. Employment is at an all time high across all groups of mothers.

around 55 percent for those in the same zipcode, to 75 percent for grandmothers who are more than 1 hour away. The increase in paid childcare usage appears more or less linear in distance. Panel (a) shows that over 30 percent of mothers live in the same zipcode as their mother. Only 20 percent of mothers live more than 100 miles away. These facts highlight the importance of grandmothers for childcare in the United States.

To benchmark our numbers to an outside source, we next compare the tax data to CPS and NSECE measures of paid childcare usage. Figure 2 examines trends over time. While the CPS measure is noisier, trends in the tax data follow the CPS extremely closely. Importantly, both series show the same 10 percent decline in paid childcare usage between 2019 and 2024. Appendix Figure A.8, panel (a), plots the total number of tax units reporting paid childcare in tax data, alongside the comparable measure in the CPS and NSECE. The tax data on average cover 88 percent of paid childcare usage in the CPS, and 79 percent of the NSECE. Panel (b) reports the dollars spent, conditional on having paid childcare, which is available in the CPS since 2009. The tax data capture on average 77 percent of the dollars spent in the CPS, and 62 percent of the NSECE (expenses last week*52, which is likely an upper bound). Figure A.7, Panel (a) examines any paid childcare usage by mother's earnings and child age in the tax data, for 2019. For small earners, paid childcare usage and CDCC filing is low, only around 10 percent. As maternal income rises, the share using paid childcare increases dramatically, reaching around 50 percent for earners of around $50,000, and 70 percent for earners above $100,000. Panel (b) examines this same income gradient to the CPS. The CPS shows more usage of paid childcare for mother's earning less than $25,000. This is perhaps unsurprising given that lower-income households without tax liability will not benefit from filing the CDCC. However, above $25,000 in maternal earnings, the rates of paid childcare are very similar, and are even slightly higher in the tax data, particularly for older children ages 4-12. To summarize, our measure in the tax data appears to follow similar trends as the CPS and cover the majority of paid childcare usage in the United States.

3.2 Changes in Parental and Grandparental Labor supply

We next discuss trends in parental and grandparental labor supply. First, we examine the ability to do remote work. Appendix Figure A.9, panel(a) examines the share of mothers with teleworkable jobs, according to the Dingel and Neiman (2020) measure. The share rises by around 1 percentage points post Covid for mothers with younger children, suggesting some sorting into occupations that are compatible with teleworking. As shown in Panel (b), there is a similar increase for fathers. Even if the jobs are amenable to teleworking, firm policies vary. Figure A.11 shows that nearly all Fortune 500 firms switched to remote work in the year of the Covid pandemic. Over time, a subset steadily switch back to fulltime in-person policies. By the end of

2024, around twenty percent of Fortune 500 firms have a full-time in office policy.[12]

Platform gig work has been rising dramatically since 2012, and experienced major growth during Covid. As shown in Figure A.9, panel(c), platform gig work rose tripled from fewer than 1 percent of mothers in 2019 to 4 percent by 2024. This was largely driven by growing demand for gig services during Covid, and demand has remained persistently higher since. Panel (d) shows a smaller but still substantial rise for fathers. Outside of platform gig work, other types of self-employment have been largely stable (or even declined) in recent years (Garin et al., Forthcoming, 2023). Given the unique characteristics of platform gig jobs and their dramatic growth, we can test whether paid childcare usage among platform gig workers differs from more traditional forms of self-employment.

Finally, we examine changes in the availability of grandparental care in Panels (e)-(f). There were actually subtantial trends in grandmother distance and the share of grandmothers who were alive and retired prior to the start of Covid. These trends appear to slow after 2020. Nevertheless, as of 2024, grandmothers are further away and more likely to be alive and retired than they were in 2019.

3.3 Role of Childcare Providers and Other Supply-Side Factors

Explanations for the decline in paid childcare may lie on the supply side, if many centers permanently shut down and never returned. We investigate these trends on the supply side at a high level by examining the firm tax filings of the childcare centers themselves. We proceed in two ways: linking EINs furnished by tax units on Form 2441 and separately studying firm tax filings for NAICS 624410 "Child Day Care Services." More details are provided in Appendix C.

Examining aggregate real profits and payroll, we find that while profits fell during 2020 for all provider types except nonprofits, industry profits (real, $2019) have since rebounded and now surpass 2019 levels. Payrolls, which declined in 2020 and 2021, also recovered across provider types by 2023—with the childcare industry experiencing smaller payroll declines and a more robust recovery than restaurants or hotels, culminating in 2023 payrolls that are 20 percent higher than pre-pandemic levels in real-terms. These positive trends are likely explained by critical government support during the pandemic, as providers benefited from emergency measures such as the Paycheck Protection Program (PPP), Child Care Stabilization Fund block grants, and expanded eligibility for the Employee Retention Credit. Nonprofits in particular received other targeted relief that helped preserve essential community services and likely contributed to their unique profit increases in 2020. These interventions appear to have offset revenue losses, maintained payrolls, and prevented widespread provider exit. While concerns remain about a "Childcare Cliff" as federal relief funds phase

[12] In the figure this is closer to ten percent because this figure focuses on the subset of firms for which we can find return to office date through public announcement or earnings calls. The figure is closer to twenty percent for firms overall. We discuss this in more detail in Section 4.

out in late 2023, our analysis suggests that supply-side factors, such as provider exit or reduced capacity, are unlikely to explain the observed decline in paid childcare usage, at least through 2023.

We also consider two other supply-side factors: Universal Pre-Kindergarten (UPK) and the low-skill non-native share of the labor force. Aggregate trends are shown in Appendix Figure A.10. National UPK enrollment was lower between 2020-2021, but is higher by 2024. The low-skill non-native share declined during 2020-2023, but was also higher by 2024.

3.4 A Decomposition of the Decline in Paid Childcare

To understand the main causes of the decline in paid childcare over time, we next conduct a simple statistical decomposition, as follows:

$$PaidChildcare_{it} = \sum_{z \in Z} \beta_z^{pre} z_{it} + \sum_{z \in Z} \beta_z^{post} z_{it} \times post_t + Controls + \epsilon_{it} \tag{1}$$

This decomposition answers, "What is association between paid childcare usage and each factor, z", which includes teleworkable occupation (for mother and father); self-employed in platform gig work; Grandmother retired; Grandmother distance; UPK availability, and the low-skill non-native share, in year t. The regression is estimated using data from 2018-2019 and 2023-2024 only, and we define *Post* as 2023-2024. We exclude 2020-2022 from the estimation given the unique disruptions such as school closures that occurred in these years. We can also consider interactions between our main explanatory variables of interest—i.e. to capture if grandparental availability becomes more important when a worker is in a teleworkable job or is self-employed. Our main estimation sample is all mothers with children under 13. In some specifications we will restrict to non-missing occupation and grandmother link (as discussed above, this requires the mother to be 40 or younger). Since a mother will appear in the data in more than one year, we cluster standard errors on mother. We include flexible controls for mother's age, youngest child age, number of children, and, in specifications with grandmother, grandmother's age.

Using the estimates from Equation 1, the share of the decline in paid childcare that can be explained by factor z can be decomposed using a Oaxaca-decomposition into changes in levels and changes in β:

$$zShare = \frac{\Delta \overline{z} \cdot \beta_{z,Pre}}{\Delta \overline{PaidChildcare}} + \frac{\overline{z}_{pre} \cdot \beta_{z,Post}}{\Delta \overline{PaidChildcare}} \tag{2}$$

Where $\overline{X}$ denotes the sample average. As this decomposition shows, there are two main ways (not mutually exclusive) that these factors may contribute to the decline in paid childcare. First, as indicated by term on the left, the share of workers that these factors affect could be increasing over time. Second, the importance

of any of these factors could be increasing in the post period (this change will be captured by our post coefficient), as shown by the term on the right.

3.5 Decomposition Result

Table 1 implements specification (1) examining how our factors of interest are related to paid childcare over time. Columns (1)-(4) examine groups of factors separately. Column (5) combines all factors together in one regression. Panel (a) of Table 1 reports the pre-period main effects, while Panel (b) reports the post-period interactions.

We find that prior to 2020, teleworkable jobs were more likely to be associated with paid childcare. Most likely, this is because these are more likely to be full-time white collar jobs with substantial responsibility and in-office norms. The post effect indicates that by 2023-2024, however, teleworkable jobs among mothers are associated with a large 3.1 percentage point decline in paid childcare. There is a smaller decline among fathers, and no additional effect on the interaction (both mother and father are in teleworkable jobs). However, we also see a comparable decline among fathers working in a non-teleworkable job. Platform gig work by mothers has a large negative main effect. The fact that more workers are engaged in platform gig work in the post period will contribute to a decline in paid childcare. We next turn to factors associated with grandmothers. As we saw in Appendix Figure A.6, grandmother distance is positively associated with childcare. A retired grandmother has a large negative effect on paid childcare usage of -2.3 to -3.4 percentage points. However, this effect nearly halves in the post period. The effect of UPK in Column (5) is actually positive, suggesting some crowd-in to paid childcare, perhaps for after school activities. The effect of the non-native share on paid childcare is large and negative in Column (5), and this effect gets larger in the post period.

Figure 3 reports the implied share of decline explained by our decomposition results, plugging the regression results and level changes into Equation 2.[13] By far, the most important factor is that the mother's job is teleworkable. Mothers jobs being teleworkable explains 51 percent of the decline in paid childcare overall. Teleworkable jobs among fathers explains another 9 percent, and changes among non-teleworkable jobs explains an additional 21 percent of the decline. The rise of gig work explains about 5 percent between mothers and fathers.

The role of grandmothers is more complicated. A grandmother being retired is substantially less important in the post period and distance increases. The overall role of grandmothers for the decline in paid childcare goes in the opposite direction, predicting an increase in paid childcare. This suggests grandparents are playing less of a role in the post period.

[13] We use the estimates from Column (5), but the calculations are similar using estimates from Columns (1)-(4).

As expected given its limited impact only on 3- and 4-year olds, UPK is not found to be an important part of the story. However, the low-skill non-native share does explain a substantial share of the decline– around 30 percent, making it the second most important factor in our decomposition. This comes entirely from changes in the loading factor, rather than changes in levels. As this is only an association, we cannot say for sure what the underlying mechanism is behind the increase in the loading factor.

Overall, we can explain 90.2 percent of the decline in paid childcare with the factors discussed above, with 59 percent of the decline attributable to teleworkable jobs among parents. Our decomposition is of course only suggestive, since we do not know if mothers are actually working remotely. Our exercise in the next section will compare differences across firms that allow for remote work with those that do not. Before we move on, we first briefly discuss supporting evidence from the ATUS.

3.6 Supporting Evidence From the ATUS

Figure 4 shows evidence from the ATUS. Panel (a) shows that the share of work hours engaged in remote work, stratified by whether an occupation is teleworkable according to the same Dingel and Neiman (2020) measure used above. We see that the share of hours engaged in remote work doubles between 2019 and 2020, from around 20 percent to nearly 50 percent, before settling to just under 40 percent by 2024. We also see an increase even for jobs that are supposedly "non-teleworkable," but this increase is small in percentage points, only 5 percentage points. The differential increase for teleworkable compared to non-teleworkable is 16 percentage points.

Panel (b) examines childcare. Parents are providing substantially more childcare, around 18 percent more hours for mothers and 20 percent more for fathers (albeit the increase among fathers is from a much lower level). At the same time, grandmothers are providing around 20 percent fewer hours of childcare.

4 Return to Office Mandates

We next directly study the effect of remote-work policies, comparing the evolution of outcomes for workers at firms with different remote work policies by 2024.

4.1 RTO Data and Research Design

We collect data on the return-to-office (RTO) policies of Fortune 500 companies using two complementary but distinct methods. First, we using publicly available information from news articles, management statements, and earnings calls available on Factiva. For each firm in each year between 2020 and 2025, we code whether

the firm allowed full-time remote work, allowed hybrid work, or required workers to be full-time person. We assume firms were remote in 2020 and stayed remote until an announcement about a shift to hybrid arrangements or a return to office is made, unless the announcement contains more detailed information about past policies. We are able to identify the time-series of policies for 227 of the Fortune 500 companies. These policies help us to understand the timing of shifts in workplace policies surrounding remote work. Appendix Figure A.11 plots the share firms which are fully remote, hybrid, and fully in-person over time, among the subset of Fortune 500 firms for whom we can find information on the timing of policy changes. We see that the rate of return to office has been fairly smooth over the years 2021-2024 among these companies, and that only about ten percent of firms are fully in-person by 2024.

We supplement the data on announcements with information from the Flex Index database, an online platform documenting work-from-home policies for over 10,000 companies. This website tracks the real-time policies of almost all of the companies in the Fortune 500. We collected the data in 2024, and assign to each firm the policy we observe at that time. The database includes details about the type of policy adopted (fully flexible, hybrid, or full-time in-office), the minimum number of required in-office days per week, and whether specific days are mandated for attendance (e.g., Monday through Wednesday or other weekday combinations). These data are based on employee reports, announcements, and verification by HR representatives of the companies. A drawback of this dataset is that we are unable to trace firm polices over time.

To link firm policies with employee outcomes, we match firms in the Fortune 500 as of 2024 to both the Flex Index database and to employer records in the tax data. Specifically, we search the universe of large W-2 payers in the 2019 tax year for firms listed in the Flex Index, using employer names to identify their Employer Identification Numbers (EINs). We are able to identify 432 of the Fortune 500 firms using this name-matching method. Of these identified firms, 348 have some remote work possible in 2024, according to Flex Index. We then identify workers employed by those firms and follow these individuals in the tax records from 2017 to 2024, regardless of which firm employs them in later years.

We study how the remote-work policy of a firm affects use of paid childcare and, ultimately, parental earnings. We first compare the characteristics of firms which allow remote work to full time in-office firms. To avoid capturing the effect of remote work itself on productivity, we make this comparison in a year when all of these firms had in-person workplace policies, 2019. Table 2 compares the characteristics of Fortune 500 firms that still allowed remote work in 2024 with those that required employees to work in person full time. We present means by workplace policy for financial characteristics, employee ratings of workplace development, wellness, and family-friendliness, and CEO gender and age. We see that adding 2 digit industry controls, firms are similar by remote work policy for almost all financial characteristics and available employee ratings

(column labeled NAICS FE).[14] The relative balance across these firms in the year before remote work became common suggests that firms may be adopting these policies for reasons largely unrelated to their business practices and financial health at that time. Interestingly, one factor that is different is the female CEO share, which is over 3 times higher for the non-remote firms.

We leverage an intent-to-treat style assignment of women to firms in 2019, before firms formulated remote-work policies, to study the impact of workplace policy on outcomes. We estimate coefficients from the regression:

$$y_{it} = \sum_{k=1 \in T \setminus 2019} \beta_k \mathbf{1}\{\text{Remote}(j)\}\mathbf{1}\{t = k\} + \gamma_i + \gamma_{NAICS(j)\times t \times State(i)} + \epsilon_{it} \tag{3}$$

where y_{it} is the outcome (using paid childcare, earnings, or having a child) of individual i in year t, $Remote(j)$ indicates whether i's firm in 2019 allows remote work, γ_i are individual fixed effects, and $\gamma_{NAICS(j)\times t \times State(i)}$ are 2019 firm NAICS by year by state of residence fixed effects. The coefficients of interest are β_k, which trace out effect of working at a firm in 2019 which allows some remote work by 2024, relative to a firm which is in-person in 2024. We cluster standard errors at the firm level.

Table 3 presents characteristics of our sample of 2019 Fortune 500 company employees. We see that these employees are on average 45 years old, a slight majority are male, and they are relatively high earning: earnings are on average nearly seventy-two thousand dollars annually. Importantly, we see that 47% of workers are at the same firm in 2024 as in 2019 when they are "assigned" to remote firm treatment. When discussing the impacts of remote work policy based on 2019 firm assignment, it is important to keep in mind that only about half of workers are still in their 2019 firm by the end of our period. Unfortunately we do not observe the remote work arrangements of all firms and so we do not know the actual remote work arrangements workers are exposed to, unless they remain in their 2019 firm.

4.2 The Effect of Return-To-Office Policies

Consistent with the aggregate trend that we highlight—workers who juggle both childcare and workplace responsibilities drive the decline in use of paid childcare, mothers employed in Fortune 500 firms (in 2019, pre-Covid) that allow remote work reduced their use of paid childcare in the post-COVID years relative to mothers employed in firms that require in-person work. Figure 5, panels (a) and (b) present the effect of 2019 assignment to a firm which allows remote work on use of paid childcare among mothers and fathers, respectively, with teleworkable occupations and children 0-13 years old. Mothers who worked in remote-work

[14] The exceptions are that firms which eventually are in-person have higher 2019 employee ratings of wellness and social environment, higher 2019 log market value and are less likely to be run by a female CEO in 2019.

firms in 2019 used 1-2 percentage points less paid childcare in the post-COVID years than mothers whose 2019 firms later required full-time in-person work. There is no trend in the use of paid childcare across these firm types in the years before Covid. We see similar, though more muted patterns for fathers in panel (b).

The differential use of paid childcare by remote work policy of parents' 2019 firm is not driven by differential fertility or by differential job-switching behavior. Panel (c) of Figure 5 shows no significant effect of remote work policy on fertility, though point estimates in the last years are meaningful and suggest that women in remote work firms are relatively less likely to have children. Beyond statistical significance, differential fertility does not seem to explain the trends in use of paid childcare because the relative decline is use of paid childcare is driven by women whose youngest child is school-age, as shown in Appendix Figure A.12. We also see no significant trends in job-switching behavior, though these estimates are very noisy.

Although Table 2 shows little evidence that firms adopting remote work policies differ systematically from firms requiring full-time in-person work, many factors remain unobserved and policy choices may reflect worker demand. As a result, the wage path of parents employed at in-person firms may be a poor counterfactual for the wage path of parents employed at firms that allow remote work. To address this concern, we compare parents and non-parents within the same firms. Firm-wide factors such as how remote work affects office costs, productivity, or profits should influence similar workers within a firm in similar ways. By contrast, if remote work allows parents to substitute between childcare and market work, then parents may respond differently than non-parents. We compare parents and non-parents across firms with different remote work policies in order to isolate the role of childcare demands in wage responses to remote work. To do this, we estimate equation (3) interacting the time-varying indicators for remote work policy with whether an employee has children age 13 and under.[15]

Comparing parents of 0-13 year old children to other employees, we find that among men, being assigned a remote work firm is associated with substantially higher levels of earnings for fathers of children 0-13 but the same is not true among women. In general, earnings of individuals initially employed in remote work firms are lower in the post-Covid period (panel (a) of Figure 6). This can be explained by several sources. First, remote work may reduce productivity (Emanuel and Harrington (2024)). Second, even if productivity is not reduced, if firms have some wage-setting power and workers value remote work, then firms able to offer this amenity reduce monetary employee compensation. Finally, a lower productivity trajectory may cause firms to adopt remote work policies. These explanations are not the focus of our paper, but we present

[15] We estimate the following regressions, separately for men and women:

$$y_{it} = \sum_{k \neq 2019} \delta_k \mathbf{1}\{\text{Remote}(j)\}\mathbf{1}\{t = k\}\mathbf{1}\{Parent\} + \sum_{k \neq 2019} \alpha_k \mathbf{1}\{\text{Remote}(j)\}\mathbf{1}\{t = k\} + \gamma_i + \gamma_{NAICS(j) \times t \times State(i)} + \gamma_{Age} + \epsilon_{it} \tag{4}$$

some evidence consistent with the final explanation in the appendix. When comparing the *relative* impacts of remote work policy on parents of 0-13 year old children compared to non-parents or parents of older children, we see that women follow similar earnings trajectories regardless of whether they have children. Figure 6 panel (b) shows that in terms of earnings, mothers are no better or worse of than non-mothers if they were assigned to remote-work firms instead of fulltime in-person firms. In contrast, fathers seem to substantially benefit from being assigned remote firms relative to non-fathers—by 2024, there relative earnings gain is about ten percent of their baseline earnings. This may reflect the fact that for fathers, remote work gives access to longer hours that are otherwise incompatible with fatherhood, without a compensating reduction in wage. For mothers this does not seem to be the case. If remote work increases flexibility in ways that women value, this is associated with compensating reductions in productivity while working which on net do not increase mothers earnings.

5 The Effect of Working From Home When Children Are Not Home

We next implement a separate research design that estimates how earnings respond when children are no longer in the home during the workday. To do this, we leverage plausibly random variation in children's birthdates relative to cross-district variation in kindergarten eligibility age. We study the impact of having a child eligible for school one year early on women's careers among those who worked. We present results for women in teleworkable occupations who would most plausibly be able to remote work and for women in non-teleworkable occupations, pre (2018-2019) and post the remote work revolution (2023-2024).

5.1 Data and Regression Discontinuity Research Design

We draw on birth cutoff data data from National Center of Education Statistics Database,[16] and in some cases manually collect state-level kindergarten age cutoff dates for through 2024. Using annotated state codes and statutes, we first document the cutoff dates and then identify any changes over the sample period.[17]

To estimate the causal effect of potentially having (and then removing) young children in the home while working on maternal earnings, we use a Regression Discontinuity (RD) design. This approach leverages quasi-random variation in children's birthdates relative to state-level birth eligibility cutoffs, and occupational heterogeneity in remote work potential.

[16] https://nces.ed.gov/programs/statereform/tab5_3.asp

[17] Eight states—Colorado, Massachusetts, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, and Vermont—do not have a uniform statewide cutoff date and instead allow local school agencies to set their own cutoff dates. For these states, we impute a state-level kindergarten cutoff date using the weighted mode of district cutoff dates, where the weights are based on the population of 5–17-year-olds served by each district. Our list of school districts by state and the estimated population of 5–17-year-olds served by each school district come from the U.S. Census Bureau's Small Area Income and Poverty Estimates (SAIPE) Program. We then apply this imputed date to all years in the sample.

We examine our outcomes of interest at the mother-child level, across years. We drop mothers with multiple births (twins, triplets, etc) in the same year, so that our estimation sample contains only one mother with a child turning 5 in the current year. We will examine mothers with children turning 5 in 2018 (pre) and 2023 (post). This allows us to examine both the effect in the current year, which would be the effect of children going to school for approximately four months if students start school around September 1, and a subsequent year, which would capture the remainder of the effect of children starting school one year earlier. Approximately 3.5 percent of mothers have a child turning 5 in both 2018 and 2023, but in 96.5 percent of cases we compare different mothers in the pre- and post- periods.

Our baseline RD estimate is examines outcomes around birth cutoffs, as follows:

$$Y_i^g = \alpha^g + \beta^g Older_i + f^g(B_i - K_{s,t}) + \gamma^g X_i + \delta_s^g + \epsilon_i \tag{5}$$

where Y_i is our outcome of interest, e.g. any paid childcare or a measure of maternal employment/earnings for mother-child pair i. We estimate effects separately for groups $g \in \{teleworkable, non-teleworkable\} \times \{2018, 2023\}$. $Older_i = B_i < K_{st}$ is an indicator for whether the child is older the cutoff for state s and year t and hence eligible for kindergarten in year t in district/state s; $f(B_i - K_{st})$ is a flexible function of the running variable (our baseline specification is separate linear trends on each side of the cutoff); X_i is a vector of controls (mother's age, lagged values of the outcome); and δ_s are state fixed effects. In this setup, β estimates the intent-to-treat effect of school eligibility on the outcome of interest. We can run this separately by whether a mother's occupation is amenable to telework in the period before remote work was common (2018) and the period after remote work was common (2023). We also consider results stratifying by whether or not paid childcare was extensively used in the year prior, when children turned 4. We define this as having less than $3,000 in paid childcare usage, which would indicate incomplete takeup of the CDCC, typically when only part-time paid childcare was used.

Identification of the causal effect relies on several standard assumptions. First, near the cutoff, children's birthdates are quasi-randomly assigned, making mothers just above and below the cutoff comparable. Potential outcomes and covariates should vary smoothly in $B_{ij} - K_{ct}$ in the absence of treatment. To assess this, we examine the distribution of births and find that birthdates are smooth around the cutoff. Our main specification also incorporates a doughnut hole of 7 days around the cutoff to mitigate measurement error due to minor exceptions, enhancing power though not affecting the intent-to-treat interpretation.

We will show results for cohorts of children turning 5 in 2018 and 2023, to show how effects have changed over time. A formal RD-DiD framework would require that in the absence of the remote work revolution, the discontinuity for teleworkable and non-teleworkable occupations would have evolved similarly over time

(parallel trends). We view this as a strong assumption that is difficult to test given the Covid disruption, which likely also impacted the labor supply of mothers between 2020-2022. Thus, we simply present the differences over time as suggestive. Our analysis focuses on the effect of children going to school on mothers who work but use little paid childcare in the time-period when aggregate statistics imply that many of these mothers were working from home.

5.2 RD Results

We run the RD regressions in specification 5 for mother's with teleworkable and non-teleworkable jobs (defined in the year prior), separately for 2018 and 2023 cohorts of children turning five. The outcomes we consider are years of paid childcare and mother's log earnings. We define years of paid childcare is the sum of indicators for having any paid childcare in year t and $t+1$, and log earnings is log of the sum of mother's earnings in year t and $t+1$.

Figure 7 examines years of paid childcare around the birth cutoff. The figure plots raw data; we also report the RD coefficient estimated from specification 5 on the figure itself. First we note that we see reductions in paid childcare over time on both sides of the birth cutoff, consistent with the overall stylized facts. Consistent with the decomposition, the decline between 2018 and 2023 is larger for mothers in teleworkable jobs versus non-teleworkable jobs: to the right of the cutoff, the decline is 10.2 percentage points, compared to 3.8 percentage points for mothers in non-teleworkable jobs. In 2018, the decline in years of paid childcare for children to the left of the birth cutoff was similar for mothers in teleworkable and non-teleworkable jobs: households with children just to the left of the cutoff experience a decline of approximately 0.062 years of paid childcare for both teleworkable and non-teleworkable mothers. Over time, the RD coefficient remains relatively stable for mothers in teleworkable jobs. In contrast, the RD effect increases by roughly one-third for mothers in non-teleworkable jobs, suggesting use of paid childcare is more sensitive to public school eligibility in the later period among non-teleworkable mothers. One story potentially consistent with these result is the lack of workplace flexibility of mothers in non-teleworkable jobs, interacted with increasing costs of childcare.

Figure 8 examines the RD estimates for earnings. Earnings are defined as the log of the sum of mothers earnings in the year that the children turn five, as well as the next year. Earnings are adjusted for inflation using the CPI. In these figures, we restrict to mothers who were not using little paid childcare in the year prior, defined as using reporting less than \$3,000 in expenses (expenses below the CDCTC threshold for subsidies). Compared to mothers in households reporting higher levels of paid childcare in the prior year, these mothers are more likely to be working from home while caring for their children.

In 2018, we observe no statistically significant discontinuity in earnings around the school-entry birth cutoff for mothers in either teleworkable or non-teleworkable occupations. This suggests that, prior to the expansion of remote work, children starting school had little short-run effect on the earnings trajectories of working mothers. Earnings rise substantially between 2018 and 2023 for both groups, reflecting overall wage growth during this period. However, in 2023 we estimate a positive and statistically significant earnings increase of 3.9 percent for mothers in teleworkable jobs whose children turn five before the public school eligibility cutoff, relative to those on the other side of the cutoff whose children are likely to be home for an additional year before starting public school. This pattern is consistent with the interpretation that when children begin school—and are therefore out of the home for part of the day—mothers in teleworkable jobs experience an increase in productivity. We find no comparable effect for mothers in non-teleworkable jobs, who are less likely to combine paid work with childcare during the workday.

6 Conclusions

This paper documents a shift in the ability of households to combine work and childcare that has resulted in a decline in use of paid childcare by ten percent in aggregate since the Covid pandemic. We find no evidence that this remarkable shift in the technology of production has closed the "last chapter" of the gender pay gap (Goldin, 2014). We estimate two distinct margins though which remote work affects households. First, we estimate the effect of being at a firm that allows remote work. Next, we estimate the effect of caring for children at home with access to remote work. Overall the earnings of mothers exposed to more remote work based on their 2019 firm's eventual adoption of remote or hybrid work policies are similar over time to the earnings on non-mothers at these firms. If anything, the gender gap among parents grows, as fathers appear to increase their earnings relative to men without children at remote-friendly firms. To identify the second effect, we exploit school start-date cutoffs and show that among mothers who may be plausibly caring for their children while working a remote job, earnings improve when children become eligible for school. This pattern was not present in the pre-Covid period.

These findings speak to broader questions about how technological change reshapes the division of labor within households. Remote work removes the link between paid work and a need for childcare, but it does not eliminate the underlying time and attention constraints associated with caring for children. Instead, remote work changes how these constraints manifest, shifting some childcare from formal markets into the home, but simultaneously reducing parents'—in particular, mothers'—market work, relative to a counterfactual where children are not at home.

Although remote work may not reduce the wage gap, the ability to combine work and childcare saves

households thousands of dollars per year. In addition, Chen et al. (2023) documents that individuals value these arrangements, especially post-Covid. Further study of the welfare effects of remote work, especially among households struggling to combine childcare and work, could clarify how much these arrangements improve household well-being.

References

Adams-Prassl, Abi, Kotaro Hara, Kristy Milland, and Chris Callison-Burch, "The Gender Wage Gap in an Online Labor Market: The Cost of Interruptions," *The Review of Economics and Statistics*, 02 2023, pp. 1–23.

Apps, Patricia and Ray Rees, "Optimal family taxation and income inequality," *International Tax and Public Finance*, 2018, *25* (5), 1093–1128.

Berlinski, Samuel, Maria Marta Ferreyra, Luca Flabbi, and Juan David Martin, "Childcare Markets, Parental Labor Supply, and Child Development," *Journal of Political Economy*, 2024, *132* (6), 2113–2177.

Cascio, Elizabeth U., "Maternal Labor Supply and the Introduction of Kindergartens into American Public Schools," *Journal of Human Resources*, 2009, *44* (1), 140–170.

Chen, Yuting, Patricia Cortes, Gizem Kosar, Jessica Pan, and Basit Zafar, "The Impact of COVID-19 on Workers' Expectations and Preferences for Remote Work," *AEA Papers and Proceedings*, May 2023, *113*, 556–561.

Cortes, Patricia, "The Effect of Low-Skilled Immigration on U.S. Prices: Evidence from CPI Data," *Journal of Political Economy*, June 2008, *116* (3), 381–422.

Cortés, Patricia and José Tessada, "Low-Skilled Immigration and the Labor Supply of Highly Skilled Women," *American Economic Journal: Applied Economics*, July 2011, *3* (3), 88–123.

Cunha, Flavio, James J. Heckman, and Susanne M. Schennach, "Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Econometrica*, 2010, *78* (3), 883–931.

Dingel, Jonathan I. and Brent Neiman, "How many jobs can be done at home?," *Journal of Public Economics*, 2020, *189*, 104235.

Emanuel, Natalia and Emma Harrington, "Working Remotely? Selection, Treatment, and the Market for Remote Work," *American Economic Journal: Applied Economics*, October 2024, *16* (4), 528â59.

England, Paula, Andrew Levine, and Emma Mishel, "Progress toward Gender Equality in the United States Has Slowed or Stalled," *Proceedings of the National Academy of Sciences of the United States of America*, 2020, *117* (13), 6990–6997.

Fitzpatrick, Maria D., "Preschoolers Enrolled and Mothers at Work? The Effects of Universal Prekindergarten," *Journal of Labor Economics*, 2010, *28* (1), 51–85.

Gallen, Yana, "Motherhood and the Gender Productivity Gap," *Journal of the European Economic Association*, 10 2023, *22* (3), 1055–1096.

Garin, Andrew, Emilie Jackson, and Dmitri Koustas, "Is Gig Work Changing the Labor Market? Key Lessons from Tax Data," *National Tax Journal*, 2022, *75* (4), 791–816.

_ , _ , and _ , "New Gig Work or Changes in Reporting? Understanding Self-Employment Trends in Tax Data," *American Economic Journal: Applied Economics*, Forthcoming.

_ , _ , Dmitri K. Koustas, and Alicia Miller, "The Evolution of Platform Gig Work, 2012-2021," Working Paper 31273, National Bureau of Economic Research May 2023.

Gelbach, Jonah B., "Public Schooling for Young Children and Maternal Labor Supply," *American Economic Review*, March 2002, *92* (1), 307â322.

Gibbs, Chloe R., Jocelyn Wikle, and Riley Wilson, "A Matter of Time? Measuring Effects of Public Schooling Expansions on Families' Constraints," CESifo Working Paper 11200, CESifo 2024.

Goldin, Claudia, "A Grand Gender Convergence: Its Last Chapter," *American Economic Review*, April 2014, *104* (4), 1091â1119.

Harrington, Emma and Matthew Kahn, "Has the Rise of Work-from-Home Reduced the Motherhood Penalty in the Labor Market?," *Working Paper*, 2024.

Humphries, John Eric, Christopher Neilson, Xiaoyang Ye, and Seth D Zimmerman, "Parents' Earnings and the Returns to Universal Pre-Kindergarten," Working Paper 33038, National Bureau of Economic Research October 2024.

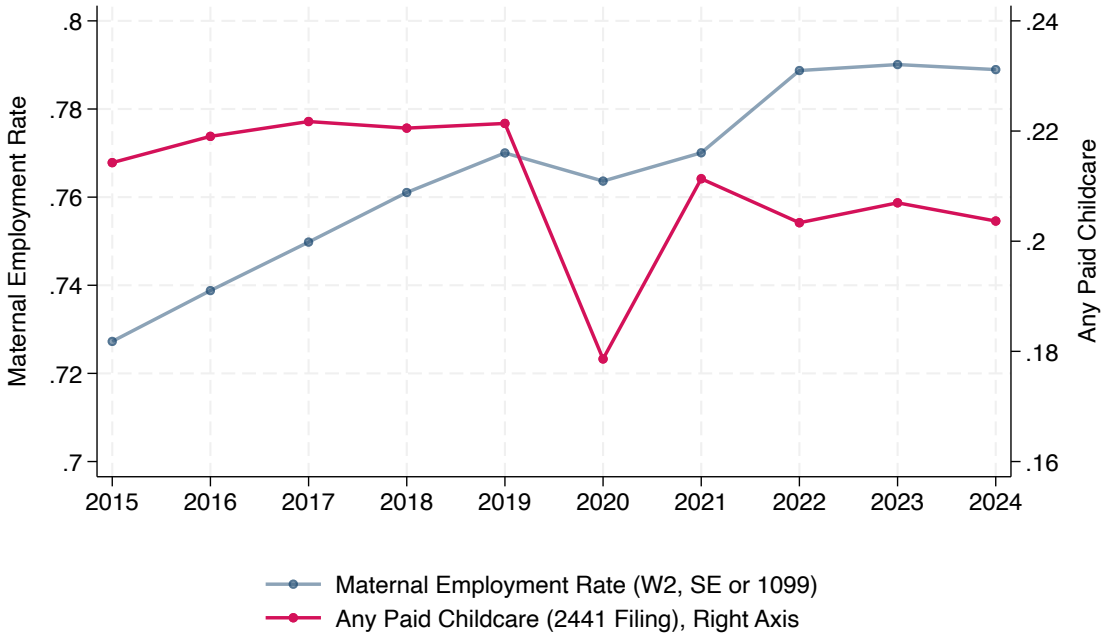
Ichino, Andrea, Martin Olsson, Barbara Petrongolo, and Peter Skogman Thoursie, "Economic Incentives, Home Production and Gender Identity Norms," IFN Working Paper 1283, IFN – Research Institute of Industrial Economics 2019.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard, "Children and Gender Inequality: Evidence from Denmark," *American Economic Journal: Applied Economics*, 2019, *11* (4), 181–209.

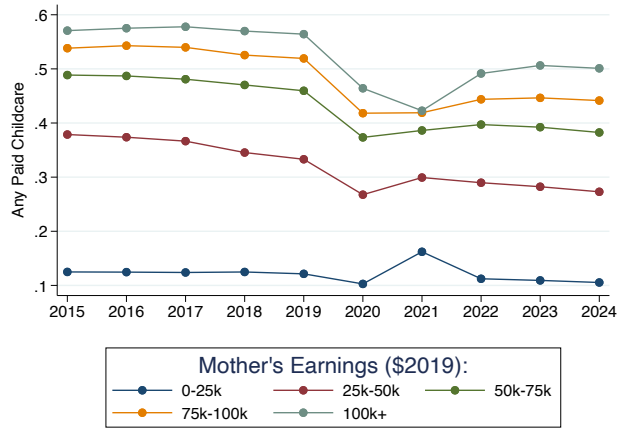
Figures

Figure 1: Employment and Paid Childcare Usage Among Mothers, 2015-2024

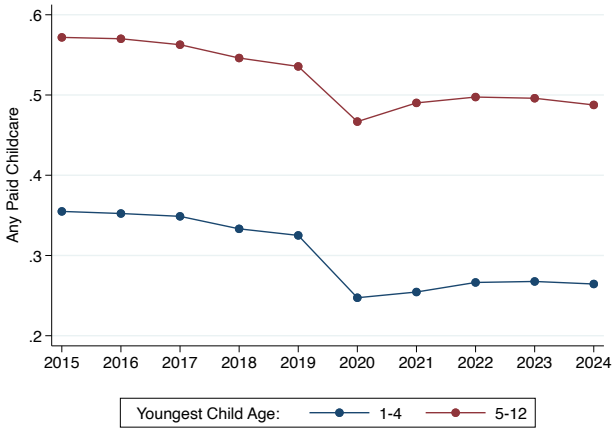
(a) Share of Mothers Working versus Using Paid Childcare



(b) Paid Childcare by Mothers' Earnings

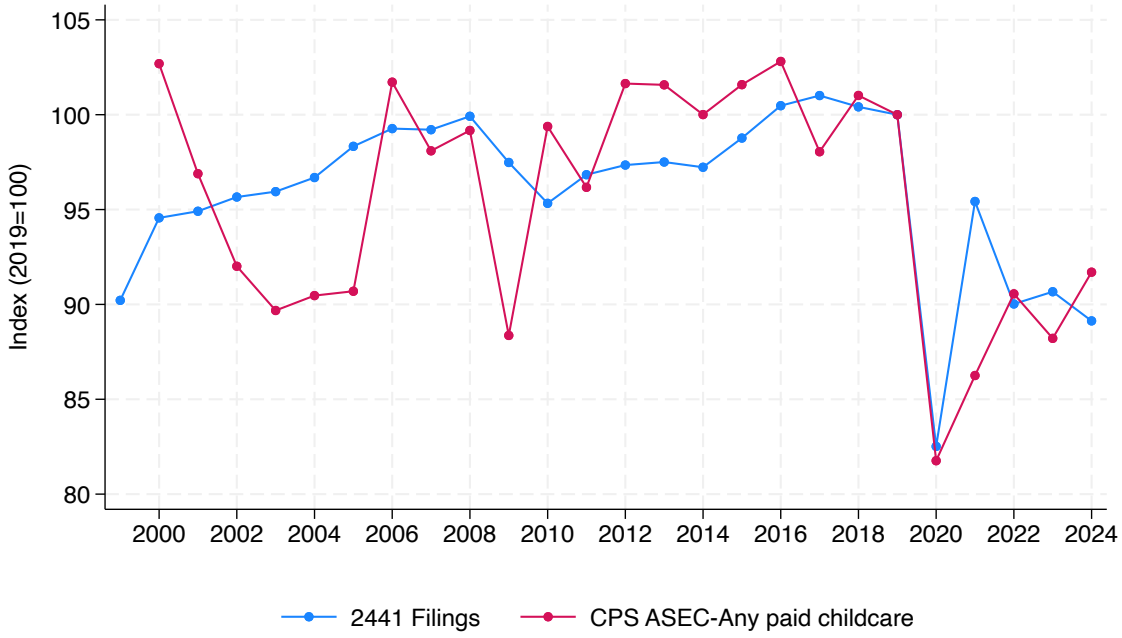


(c) Paid Childcare by Age of Youngest Child



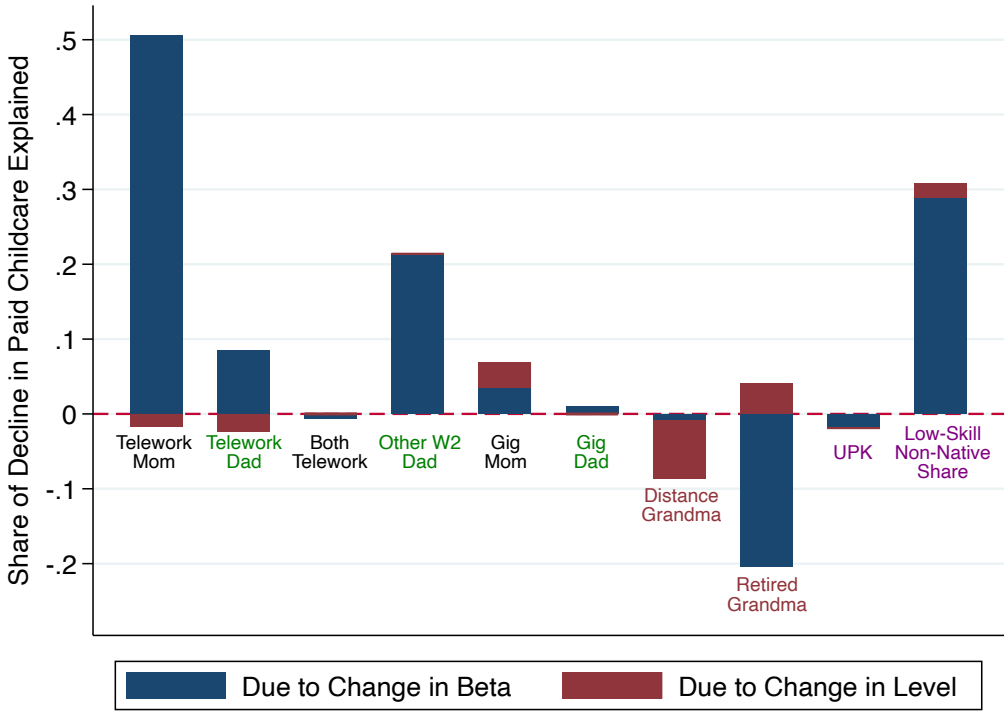
Notes: Mothers with children under 13. Earnings includes wage/salary plus reported self-employment profits. Panel (c) restricted to mothers with at least $25,000 ($2019) in earnings.

Figure 2: Decline in Paid Childcare, CPS Evidence



Notes: The CPS question asks, "Did (you/ anyone in this household) PAY for the care of (your/their) (child/children) while (you/they) worked in [YEAR] [INCLUDE: ALL CHILD CARE EXPENSES INCLUDING PRESCHOOL AND NURSERY SCHOOL EXPENSES, BEFORE AND AFTER SCHOOL CARE, AND SUMMER CARE. DO NOT INCLUDE: COST OF KINDERGARTEN OR GRADE/ELEMENTARY SCHOOL.]."

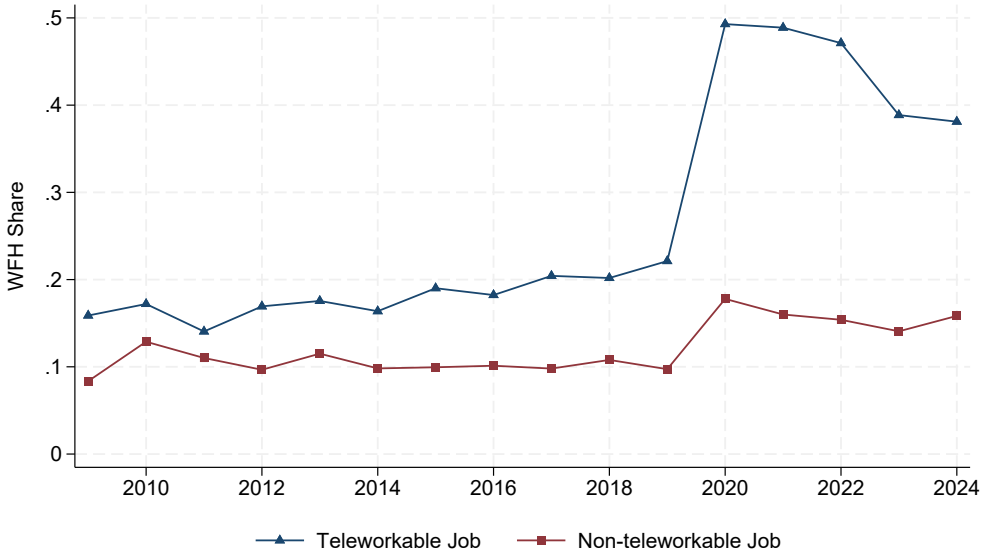
Figure 3: Decomposition of Decline in Paid Childcare, 2023-2024 v 2018-2019



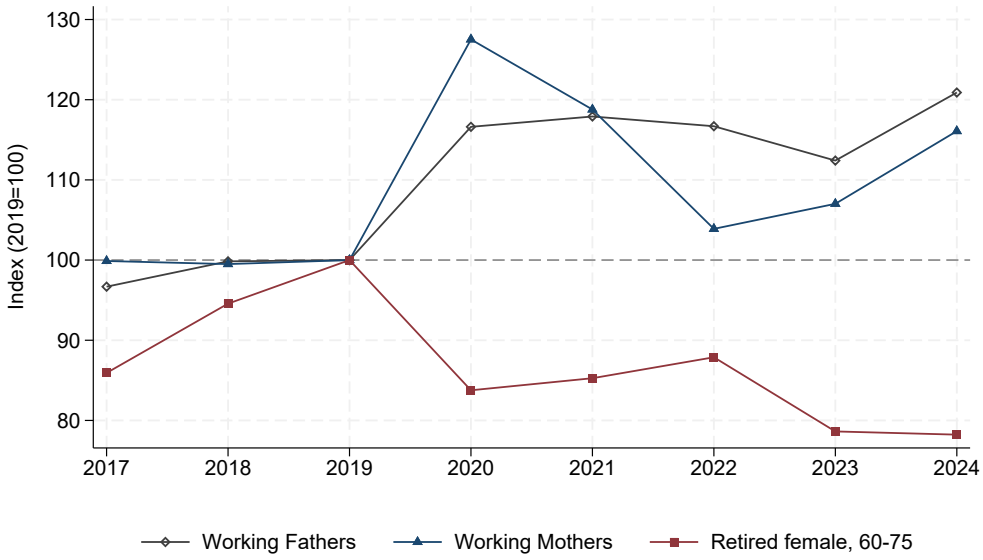
Notes: This figure shows the contribution from each factor to the decline in paid childcare, following equation **??** in the text.

Figure 4: Supporting Evidence from the ATUS

(a) Remote Work Hours



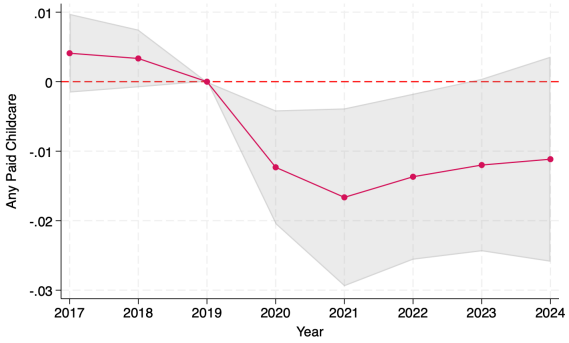
(b) Hours of Childcare



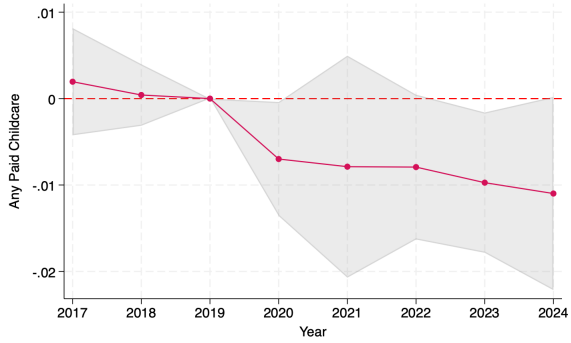
Notes: This figure presents descriptive statistics constructed from the ATUS. In panel (a), we show the average share of regular work hours (8 a.m. to 5 p.m.) worked from home on non-holiday weekdays for all adults who were employed and reported positive work hours on the diary day. We split the sample by work-from-home feasibility using the index in Dingel and Neiman (2020). Work hours are defined as time spent in the following activities: "Work, main job" and "Work, other job(s)". In panel (b), we report total childcare hours relative to 2019 separately for working fathers, working mothers, and women ages 60 to 75 who reported being out of the labor force. For the working fathers and working mothers series, the sample is restricted to parents with a child under age 14 in the household who worked a positive number of hours on the diary day. For the series on women ages 60 to 75, the sample includes all women in this age range who reported being out of the labor force. Total childcare hours include both primary and secondary childcare. Primary childcare includes the following activity groups: "Caring for and Helping Household Children", "Activities Related to Household Children's Education", and "Activities Related to Household Children's Health". Secondary childcare refers to time spent supervising a child under age 13 while performing the following activities: "Work, main job" and "Work, other job(s)". All estimates are weighted using the ATUS sampling weights.

Figure 5: Use of Paid Childcare Among Parents by Remote Work Policy

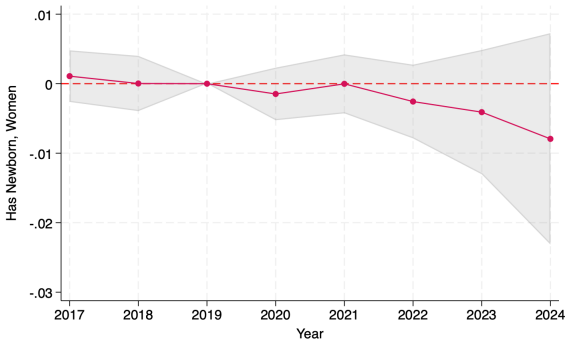
(a) Mothers (0-13), Use of Paid Childcare



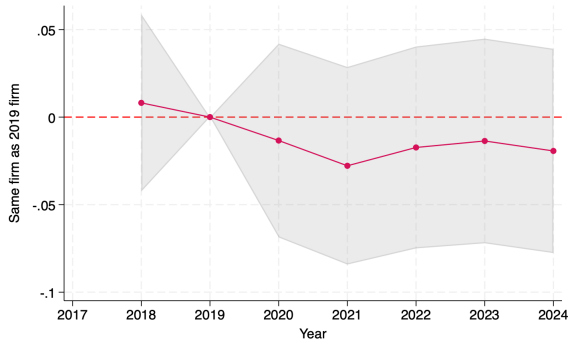
(b) Fathers (0-13), Use of Paid Childcare



(c) Women, Newborn



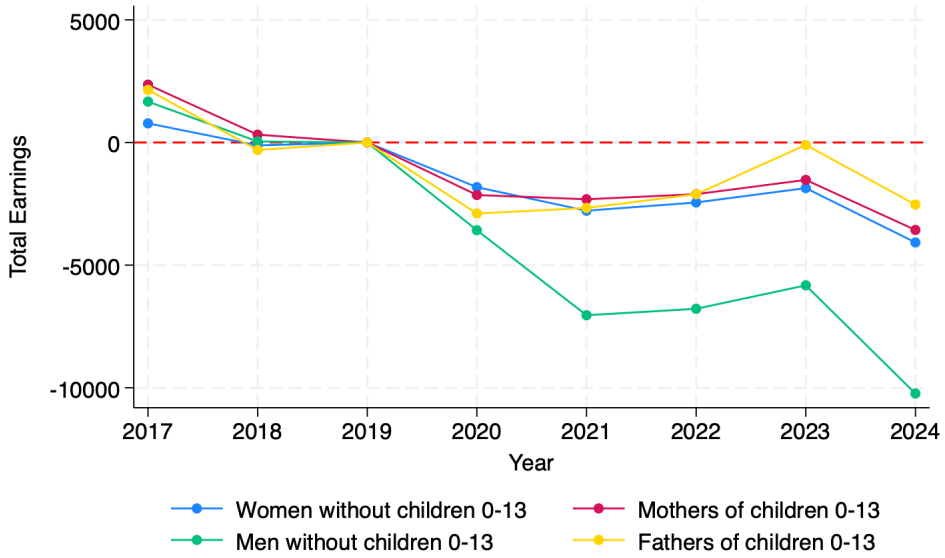
(d) Mothers (0-13), Same Firm as 2019 Firm



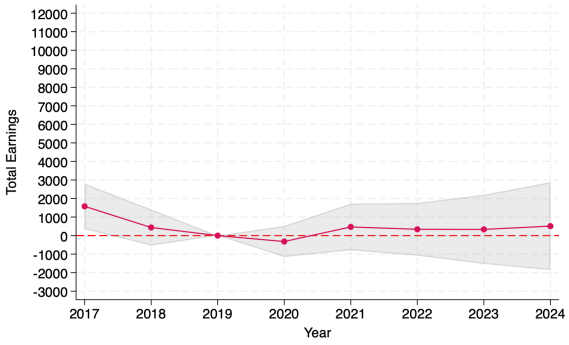
Notes: This figure presents estimates of β_k from equation (3) where the outcome is an indicator of reporting paid childcare expenses in panels (a) and (b), is the presence of a 0 year old child claimed as a dependent in panel (c), and is an indicator for whether an employees has the same employer as their focal 2019 employer, based on which treatment is assigned. β_k give the difference in outcomes among parents who in 2019 worked in firms allowing remote work (as measured in 2024) compared to parents who in 2019 worked in firms which have returned to full-time in person work by 2024. Panel (a) reports the results of the regression restricted to mothers of children 0-13 years old with teleworkable jobs, panel (b) reports the results for fathers of children 0-13 years old with teleworkable jobs, panel (c) reports the results of the regression among all women with teleworkable jobs, and panel (d) reports the results of the regression among mothers of children 0-13 years old with teleworkable jobs. Teleworkability is measured in 2019. Additional controls include individual fixed effects, and 2019-firm NAICS by year by state of residence fixed effects. Standard errors are clustered at the firm level.

Figure 6: Earnings for Parents vs. Other Employees, by Remote Work Policy

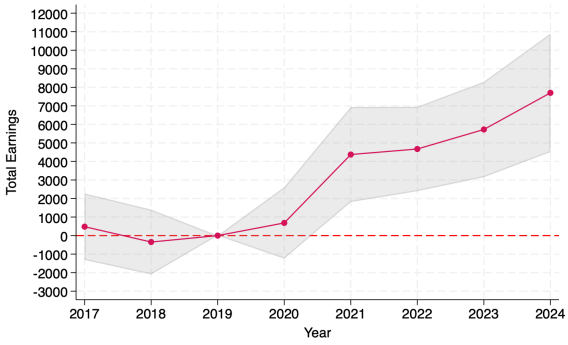
(a) All Employees



(b) Women, Mothers (0-13) Relative to Others



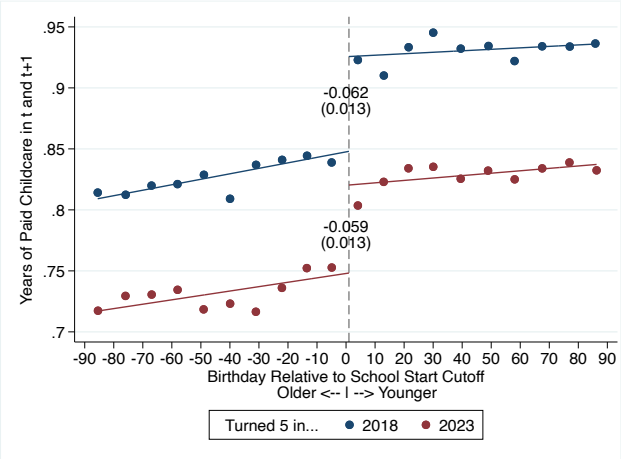
(c) Men, Fathers (0-13) Relative to Others



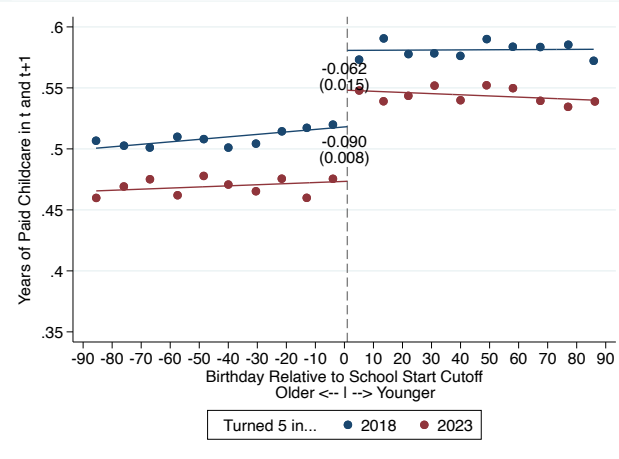
Notes: This figure presents estimates β_k from (3) in panel (a), separately by whether an individual is a parent of a 0-13 year old child and by gender. This gives the difference in earnings among those who in 2019 worked in firms allowing remote work (as measured in 2024) compared to those who in 2019 worked in firms which have returned to full-time in person work by 2024. Panels (b) and (c) present estimates of δ_k from equation (4) where the outcome is annual earnings. This gives the interaction effect on being a parent of a 0-13 year old and the remote work policy times year indicators. All regressions restrict to individuals with teleworking jobs in the baseline (2019) period. Additional controls include individual fixed effects, 2019-firm NAICS by year by state of residence fixed effects, remote work policy and parenthood indicator, and age. Standard errors are clustered at the firm level.

Figure 7: Paid Childcare, Regression Discontinuity Around School Start Birthdate Cutoffs, by Teleworkable

(a) Teleworkable



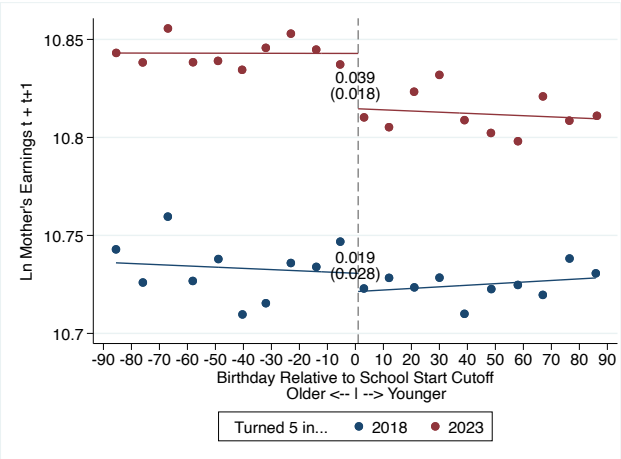
(b) Non-Teleworkable



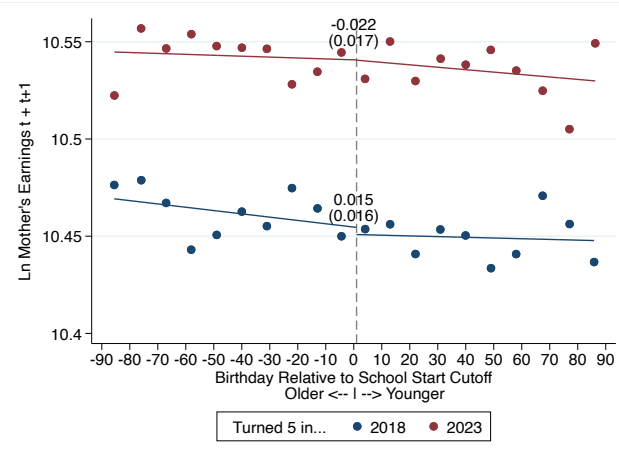
Notes: Mothers with W2 earnings in year and/or year+1. Figure shows vintiles of raw means of years of paid childcare. Regression discontinuity estimated on a 45 day bandwidth with a doughnut of 7 days, and includes controls for mothers age, and state-by-year. Standard error clustered on state in parentheses.

Figure 8: Mother's Earnings, Regression Discontinuity Around School Start Birthdate Cutoffs, Part-time or No Paid Childcare in t-1

(a) Teleworkable



(b) Non-Teleworkable



Notes: Mothers with W2 earnings in year and/or year+1, with less than $3,000 in dependent care expenses in t-1. Figure shows vintiles of raw means of earnings. Earnings adjusted for inflation using the CPI. Figure shows raw data. Regression discontinuity estimated on a 45 day bandwidth with a doughnut of 7 days, and includes controls for mothers age, and state-by-year. Standard error clustered on state in parentheses.

Tables

Table 1: Factors Contributing to Change in Any Paid Childcare Among Working Mothers, 2022-2023 v. 2018-2019

(a) 2018-2019 Estimates

	(1)	(2)	(3)	(4)	(5)
Main Effects:					
Mother Teleworkable	0.106	0.082			0.079
	(0.001)	(0.001)			(0.002)
Father Teleworkable		0.097			0.079
		(0.002)			(0.003)
Mother and Father Teleworkable		0.001			-0.000
		(0.003)			(0.005)
Father Other W2		0.107			0.087
		(0.001)			(0.002)
Mother Platform Gig Work		-0.058			-0.030
		(0.005)			(0.009)
Father Platform Gig Work		-0.015			0.000
		(0.005)			(0.009)
Grandma Distance * 10			0.011		0.011
			(0.000)		(0.000)
Grandma Retired			-0.023		-0.034
			(0.002)		(0.002)
State UPK Enrollment				-0.004	0.014
				(0.003)	(0.008)
State Low-Skill Non-Native Share				0.015	-0.170
				(0.007)	(0.019)
Pre-Mean	0.315	0.333	0.298	0.302	0.342

Notes: Table shows estimates for 2018-2019 from running Specification 1 in the text. "Pre-mean" refers to 2018-2019. Teleworkable refers to a job being classified as teleworkable according to the Dingel and Neiman (2020) measure. Platform gig work refers to receiving a 1099-NEC or 1099-K from a platform-gig company. Grandmother distance is the Haversine distance in miles between zipcode centroids of the mother and grandmother. Grandmother retired refers to a grandmother who is alive and either not working or receiving Social Security, pension or IRA withdrawals. A mother can appear in the data for multiple years so long as the youngest child's age is between 1-12. Regressions include controls for mother's age, age of youngest child, number of children earnings and grandmother age. Standard errors clustered on mother.

(b) Interacted Post Coefficients, Identifying Change in Coefficients in Post Period (2023-2024) Compared to pre-period (2018-2019)

	(1)	(2)	(3)	(4)	(5)
Post Effects:					
1{Post}	-0.015	0.002	-0.048	-0.018	-0.021
	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)
×Mother Teleworkable	-0.031	-0.027			-0.032
	(0.001)	(0.001)			(0.002)
×Father Teleworkable		-0.016			-0.011
		(0.002)			(0.004)
×Mother and Father Teleworkable		0.001			0.001
		(0.003)			(0.005)
×Father Other W2		-0.017			-0.007
		(0.001)			(0.002)
×Mother Platform Gig Work		0.003			-0.002
		(0.006)			(0.009)
×Father Platform Gig Work		-0.030			-0.024
		(0.004)			(0.009)
×Grandma Distance * 10			-0.000		-0.001
			(0.000)		(0.000)
×Grandma Retired			0.014		0.014
			(0.001)		(0.002)
×State UPK Enrollment				-0.022	0.013
				(0.003)	(0.008)
×State Low-Skill Non-Native Share				-0.116	-0.095
				(0.008)	(0.023)
Observations	4,151,980	2,356,985	3,546,759	7,439,230	964,978

Notes: Table shows the coefficients interacted with post (i.e. the change in the estimates between 2023-2024 and 2018-2019) from running Specification 1 in the text. 2020-2022 are omitted from the regression due to Covid-related disruptions in these years. Teleworkable refers to a job being classified as teleworkable according to the (Dingel and Neiman, 2020) measure. Platform gig work refers to receiving a 1099-NEC or 1099-K from a platform-gig company. Grandmother distance is the Haversine distance in miles between zipcode centroids of the mother and grandmother. Grandmother retired refers to a grandmother who is alive and either not working or receiving Social Security, pension or IRA withdrawals. A mother can appear in the data for multiple years so long as the youngest child's age is between 1-12. Regressions include controls for mother's age, age of youngest child, number of children earnings and grandmother age. Standard errors clustered on mother.

Table 2: Balance: Remote Work Possible vs Fully in Person Work Policies

Variable	Mean		P-value		Sample Size (N)	
	Remote Work Possible (N=407)	Fully in Person (N=93)	No Controls	NAICS FE	Remote Work Possible	Fully in Person
2019 Financial Variables						
Log Current Assets	8.405	8.621	0.113	0.616	312	77
Log Total Assets	9.916	10.218	0.064	0.522	377	89
Log Total Revenue	9.735	9.629	0.361	0.242	377	89
Log Number of Employees	10.129	10.234	0.489	0.752	370	88
Log Market Value	9.532	10.059	0.001	0.022	341	85
Log Fiscal Price Close	4.102	4.310	0.087	0.372	367	88
Log Sales	9.735	9.628	0.360	0.241	377	89
Log Net Property, Plant and Equipment	8.565	8.136	0.019	0.299	373	88
2019 InHerSight Ratings						
Overall Score	2.844	3.079	0.040	0.336	98	18
Personal Development	2.617	2.871	0.078	0.347	98	18
Career Opportunities	3.111	3.185	0.588	0.897	98	18
Family Support	2.828	3.112	0.069	0.684	98	18
Telecommute Ability	2.233	2.643	0.034	0.661	97	18
Equal Opportunities	3.194	3.440	0.057	0.277	97	18
Family Growth Support	2.628	2.998	0.042	0.171	97	18
Flexible Work Hours	2.628	3.065	0.004	0.108	97	18
Management Opportunities	3.250	3.344	0.465	0.811	97	18
Maternity Leave	3.133	3.375	0.136	0.702	97	18
Paid Time Off	3.494	3.634	0.375	0.702	97	18
Salary Satisfaction	2.933	2.993	0.675	0.522	97	18
Social Environment	2.317	2.677	0.028	0.035	97	18
Mentorship	2.222	2.512	0.046	0.263	97	18
People You Work With	3.250	3.384	0.208	0.708	97	18
Wellness	2.678	3.004	0.110	0.044	97	18
Women in Leadership	3.039	3.085	0.770	0.964	97	18
2019 CEO Characteristics						
Female CEO	7.4%	2.3%	0.086	0.079	380	86
Actual CEO Age	58.66	58.31	0.678	0.545	370	85
Predicted CEO Age	58.56	58.43	0.883	0.839	374	84

Note: This table displays means among firms in which remote work is possible vs. those in which it is not possible (as measured in 2024), as well as p-values for the test of whether these means are difference both without any controls and after controlling for 2-digit NAICS industry codes. We test for differences across the levels of these characteristics in 2019. Columns 5 and 6 present the number of observations with non-missing data for each characteristic. We note that there are substantially fewer observations for InHerSight Ratings because the researchers had collected these ratings in 2019 as part of another project, and only for a subset of companies. Unfortunately, the data are not archived for all firms in the Wayback machine or any other online sources which we could find. Actual CEO age and gender were collected from WRDS Execucomp database from 2019. Predicted CEO age (available for a slightly larger subset of firms) is based on ChatGPT responses to the prompt "Provide a predicted birth year for this individual" and uploading a professional headshot. Professional headshots were collected using the following protocol: (1) official corporate website photos were prioritized, (2) LinkedIn profile photos were used when corporate photos were unavailable or low quality, and (3) clear, professional-quality images from reputable sources such as news interview sites were used as a final alternative. All images were collected in January 2026.

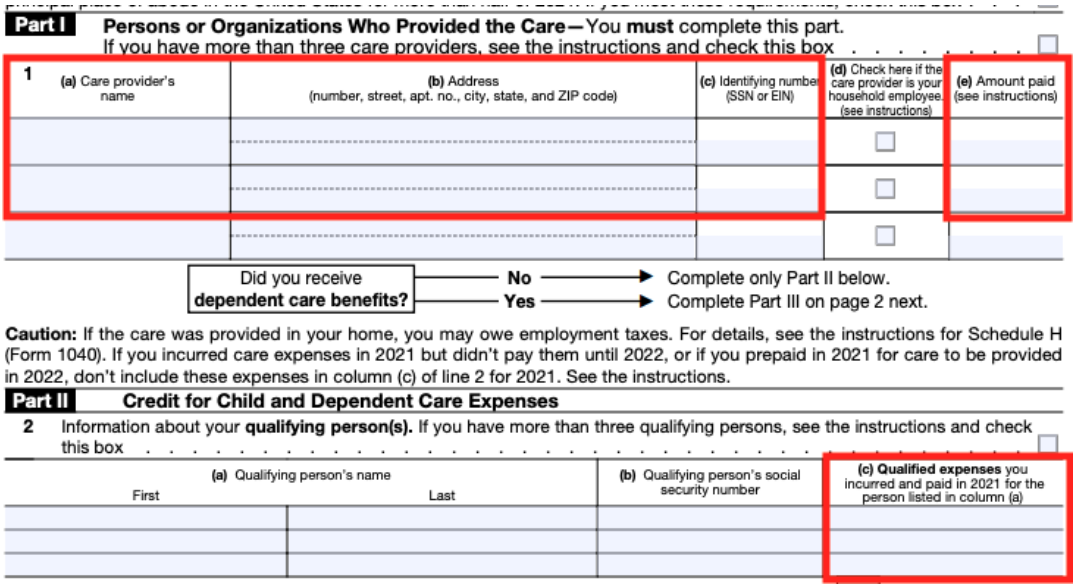
Table 3: Summary Statistics for Fortune 500 Remote Work Policy Sample

Variable	Mean	Std. Dev.	Median	N
Female	0.464	0.499	0	7,110,699
Age	45.75	13.82	44	7,110,658
Parent of Child 0-13	0.205	0.404	0	7,208,802
Youngest Child Age	19.91	11.69	19	4,312,556
Newborn Indicator	0.011	0.104	0	7,208,802
Total W2 Earnings	71,942.15	97,168.37	42,445.84	7,208,802
Firm Allows Remote Work	0.672	0.470	1	7,208,802
2024 Firm Same as 2019 Firm	0.466	0.499	0	7,208,802
Any Paid Childcare	0.070	0.255	0	7,208,802

Note: This table reports summary statistics for the Fortune 500 remote work policy analysis sample. All variables are measured in 2024 (so Newborn Indicator measures whether an individual had a baby in 2024). Remote firm indicates whether the worker was employed at a firm in 2019 that allowed remote work as of 2024. Paid childcare indicates whether the household reports any paid childcare expenditures.

A Appendix Figures and Tables

Figure A.1: Form 2441 Child and Dependent Care Expenses



Part I **Persons or Organizations Who Provided the Care**—You **must** complete this part.
If you have more than three care providers, see the instructions and check this box

1 (a) Care provider's name	(b) Address (number, street, apt. no., city, state, and ZIP code)	(c) Identifying number (SSN or EIN)	(d) Check here if the care provider is your household employee. (see instructions)	(e) Amount paid (see instructions)
			☐	
			☐	
			☐	

Did you receive **dependent care benefits?** — **No** → Complete only Part II below.
— **Yes** → Complete Part III on page 2 next.

Caution: If the care was provided in your home, you may owe employment taxes. For details, see the instructions for Schedule H (Form 1040). If you incurred care expenses in 2021 but didn't pay them until 2022, or if you prepaid in 2021 for care to be provided in 2022, don't include these expenses in column (c) of line 2 for 2021. See the instructions.

Part II **Credit for Child and Dependent Care Expenses**

2 Information about your **qualifying person(s).** If you have more than three qualifying persons, see the instructions and check this box ☐

(a) Qualifying person's name First	Last	(b) Qualifying person's social security number	(c) **Qualified expenses** you incurred and paid in 2021 for the person listed in column (a)

Figure A.2: Paid Childcare Usage Among Mothers, 2000-2024, By Child Age

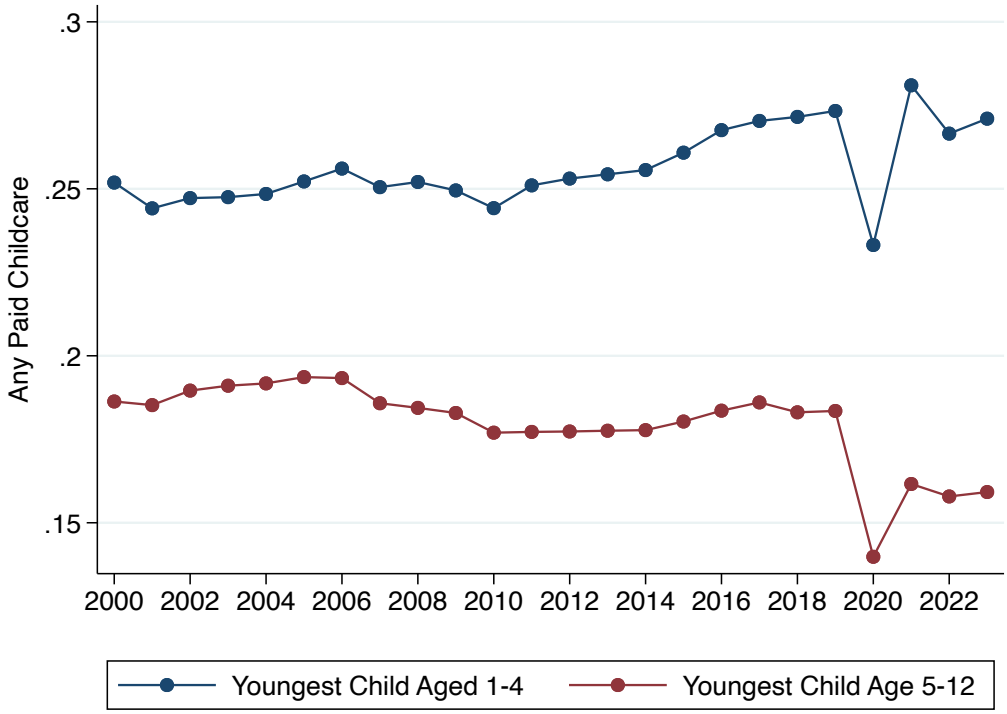
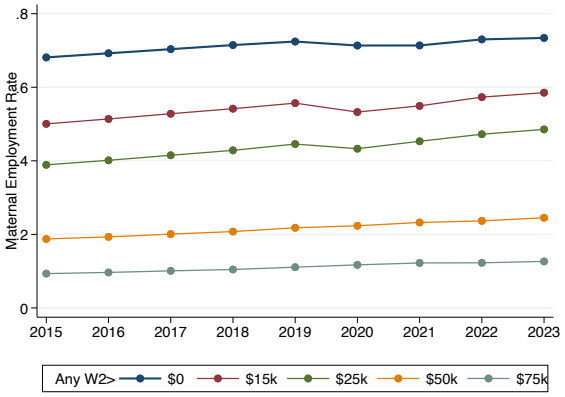


Figure A.3: Trends in Maternal Employment

(a) By Mother's Earnings ($2019)



(b) By Age of Youngest Child

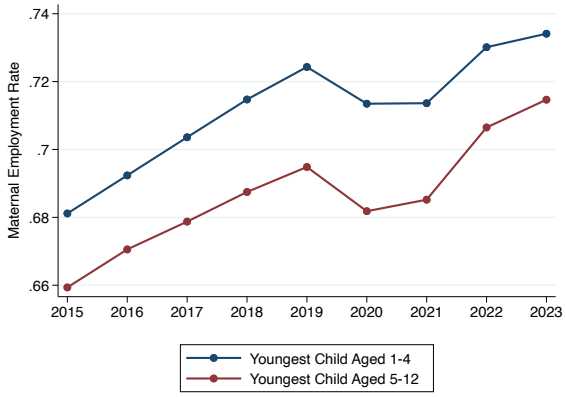


Figure A.4: Paid Childcare Usage by State, 2015-2024

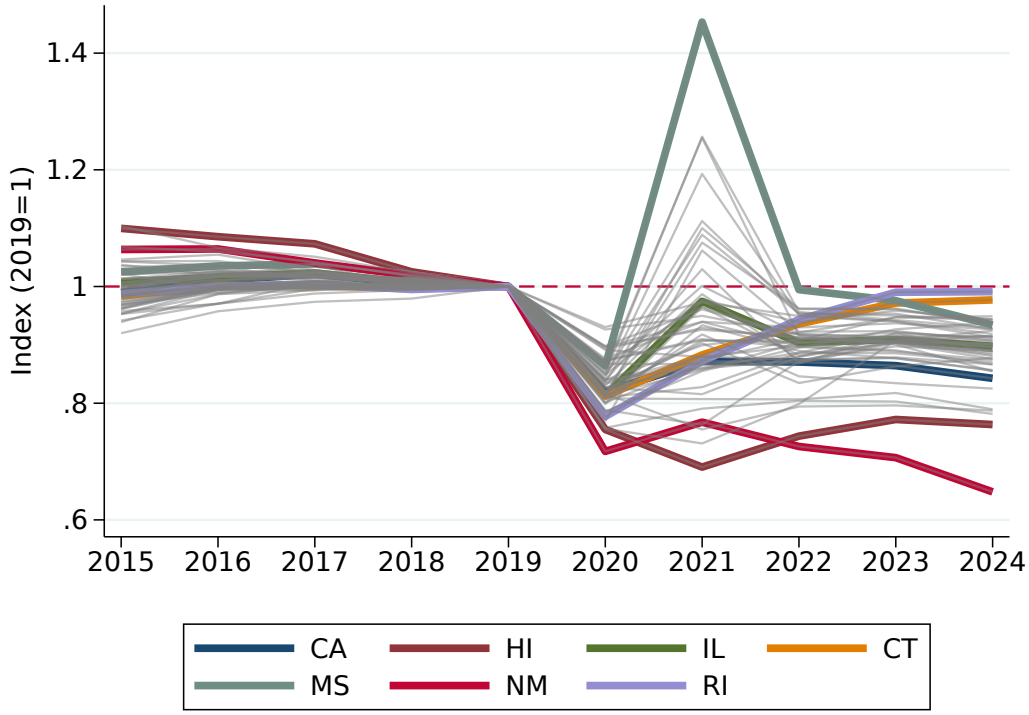
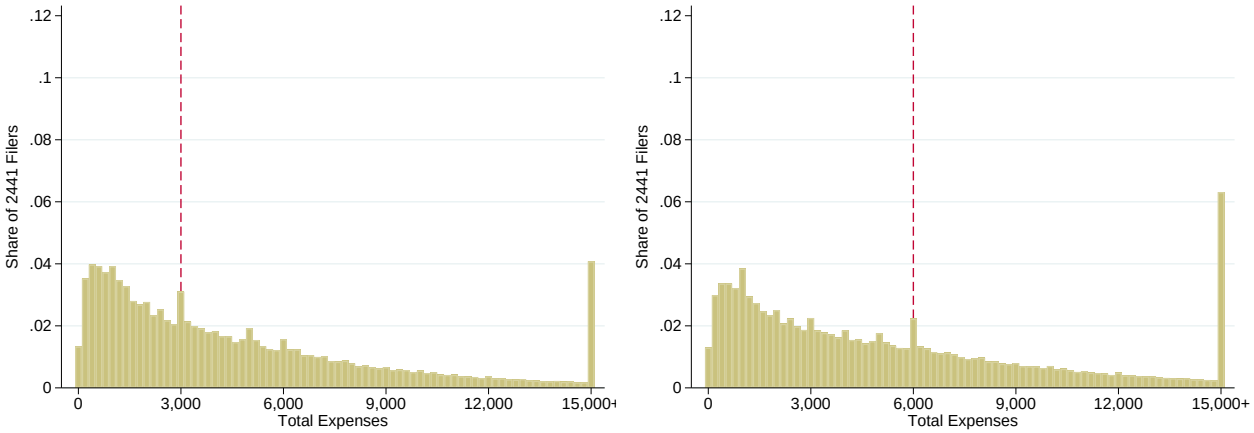


Figure A.5: Expenses Reported on 2441 (2019)

(a) One Child

(b) Two or More Children

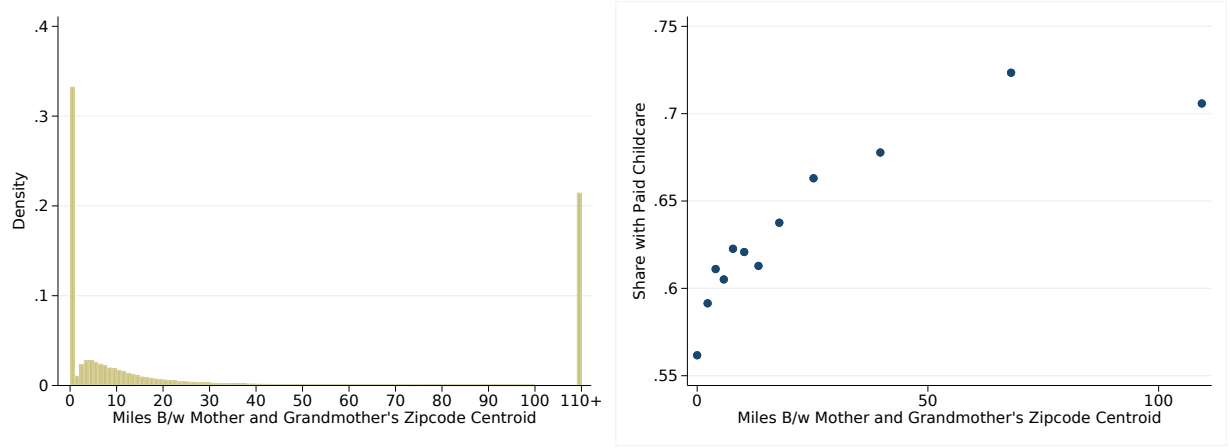


Note: 2019. The vertical line indicates the maximum expenses eligible for the CDCC.

Figure A.6: Childcare Usage and Grandmother Distance, 2019

(a) Distance to Grandmother

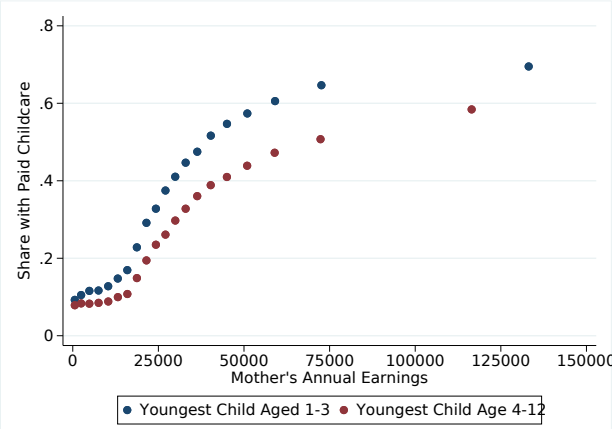
(b) Usage of paid childcare by grandmother distance



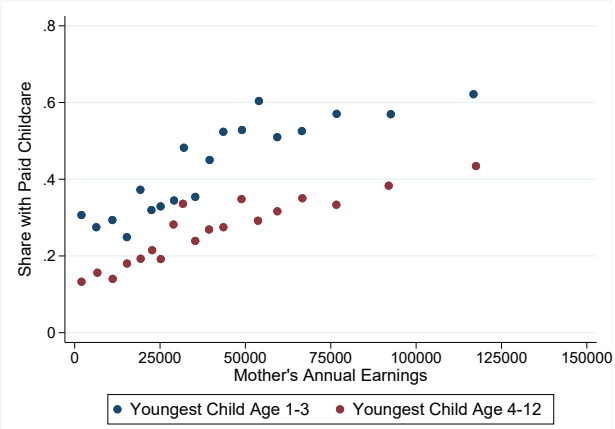
Note: Panel (a) shows the distribution of mother-grandmother distance in the tax data. Distance is defined as the number of miles between the centroids of the mother's and grandmother's zip codes. Panel (b) plots paid childcare use against distance to grandmother in the tax data for mothers with earnings $\geq$50,000.

Figure A.7: Childcare Usage by Mothers' Earnings, Tax Data versus CPS (2019)

(a) Tax Data



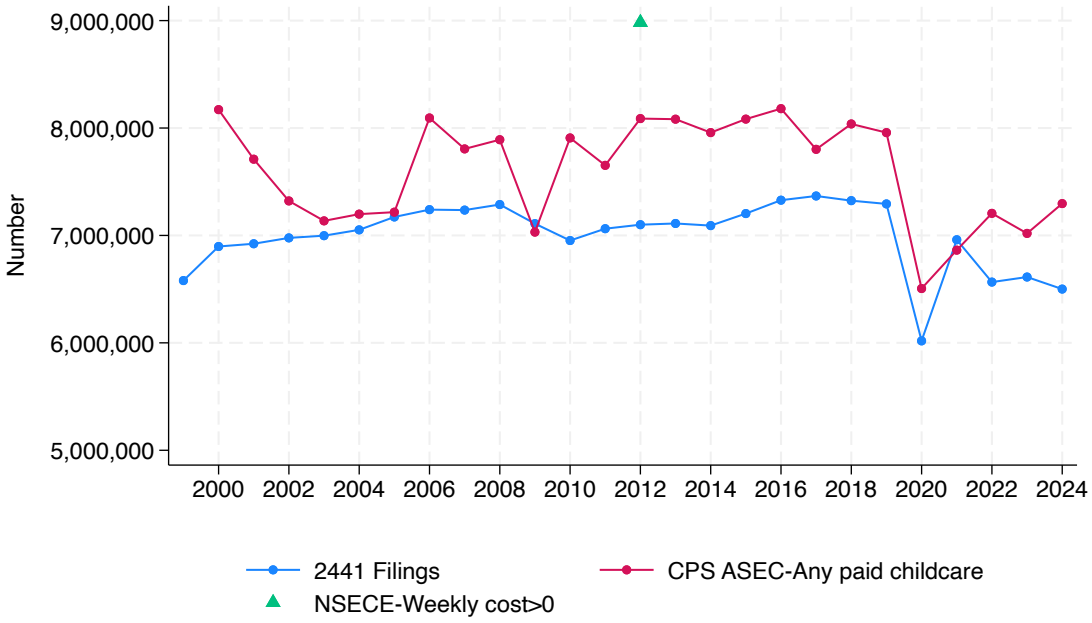
(b) CPS



Note: Panel (a) plots paid childcare use against mothers' earnings in the tax data. Panel (b) shows the analogous binscatter using 2019 CPS-ASEC data. The CPS sample includes mothers with a child under age 13 who worked during 2019 and had positive earnings. CPS earnings are winsorized at the 95th percentile, and all estimates use CPS sampling weights.

Figure A.8: Use of Paid Childcare: IRS data v Current Population Survey

(a) Counts



(b) Dollars

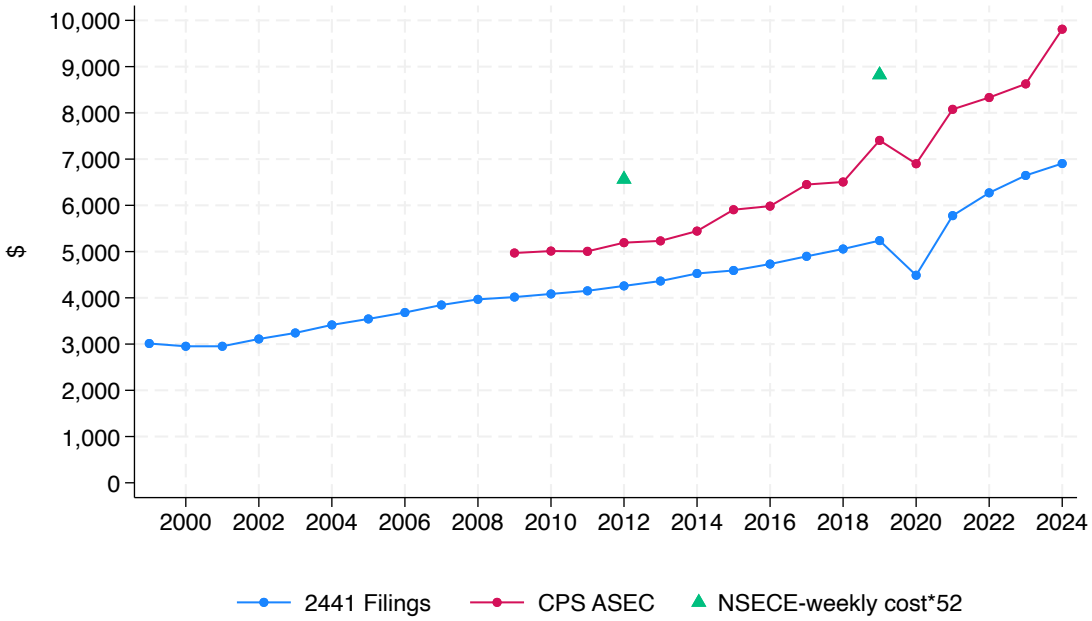
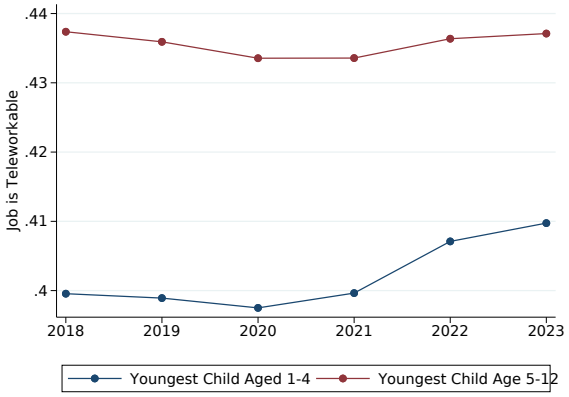
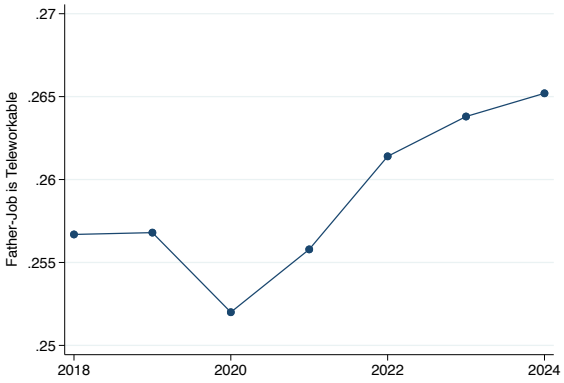


Figure A.9: Changes in Parental and Grandparental Labor Supply

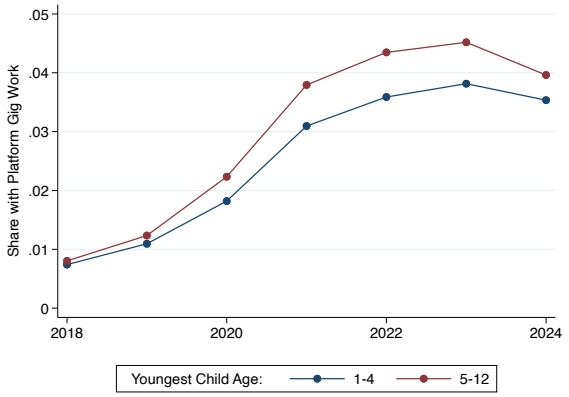
(a) Mother Teleworkable



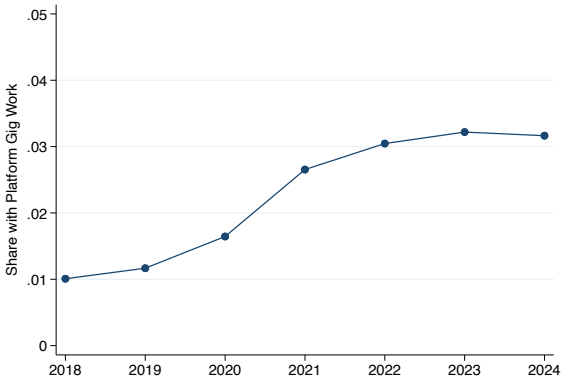
(b) Father Teleworkable



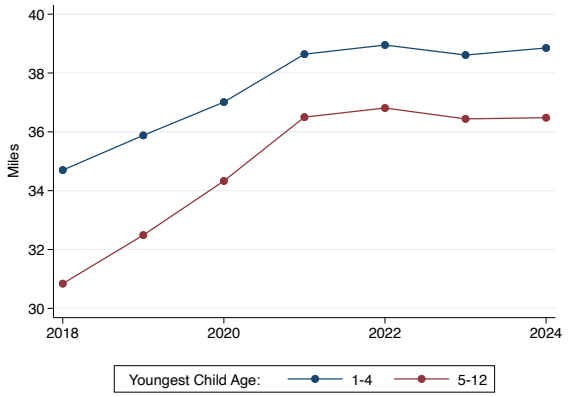
(c) Mother-Any Platform Gig Work



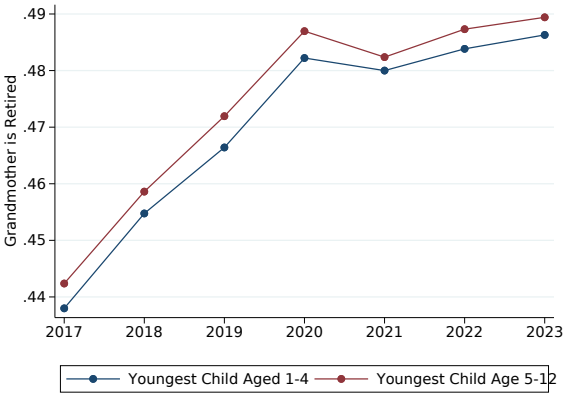
(d) Father-Any Platform Gig Work



(e) Grandmother-Distance



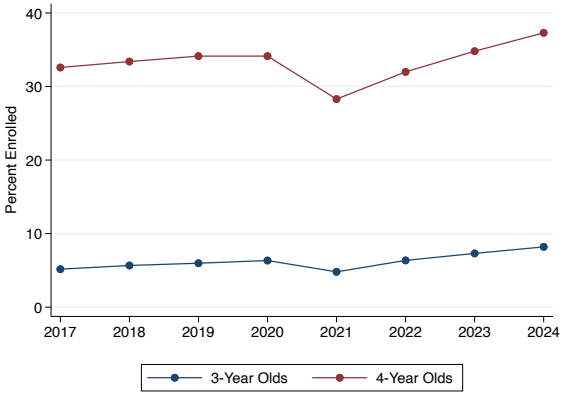
(f) Grandmother-Alive and Retired



Notes: Mothers with children under 13. Teleworkable refers to a job being classified as teleworkable according to the (Dingel and Neiman, 2020) measure. Platform gig work refers to receiving a 1099-NEC or 1099-K from a platform-gig company. Grandmother retired refers to a grandmother who is alive and either not working or receiving Social Security, pension or IRA withdrawals. Panels (e)-(f) are restricted to mothers aged 18-38.

Figure A.10: The Role of Other Supply-Side Factors

(a) Universal Pre-Kindergarten



(b) Low-Skill Non-Native Share

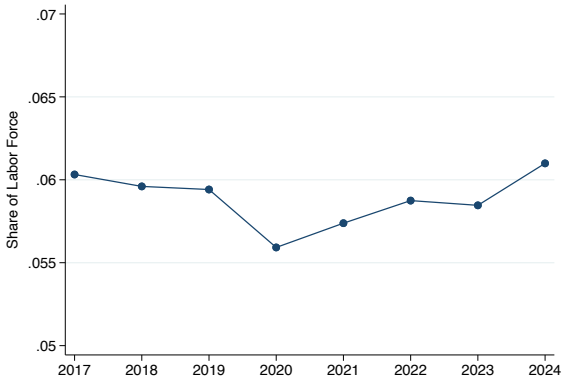


Figure A.11: Fortune 500 Firm Remote Work Policies Over Time

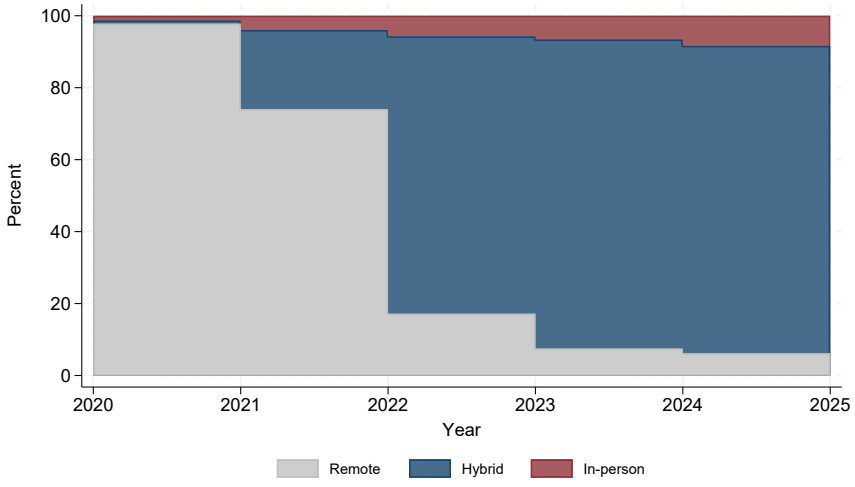
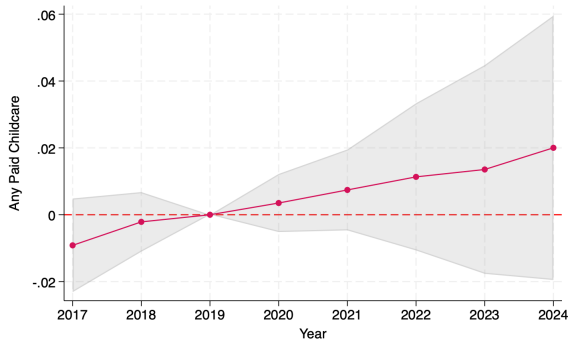
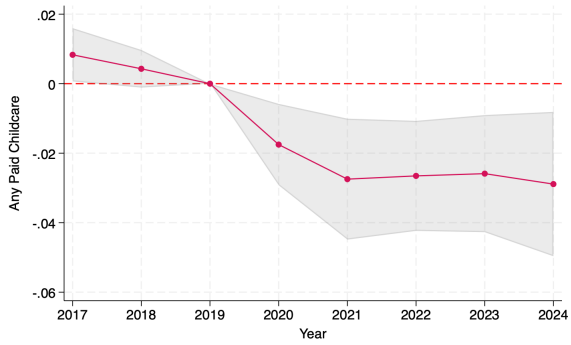


Figure A.12: Use of Paid Childcare Among Parents by Remote Work Policy and Child Age

(a) Mothers, Use of Paid Childcare



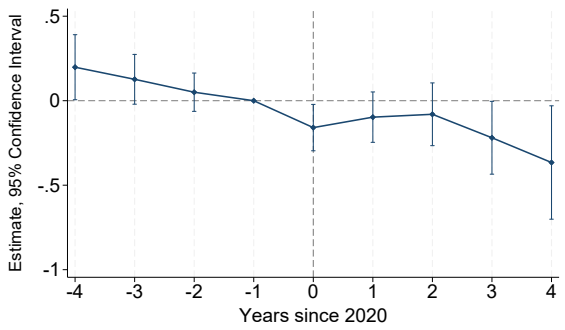
(b) Mothers, Use of Paid Childcare



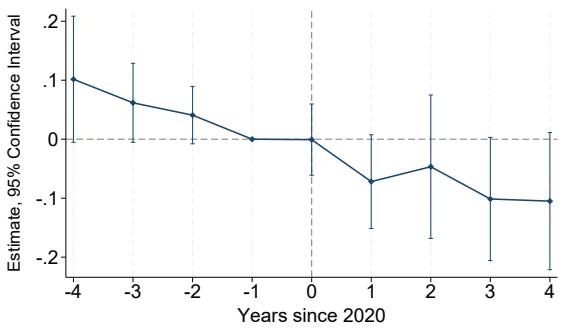
Notes: This figure presents estimates of β_k from equation (3) where the outcome is an indicator of reporting paid childcare expenses. β_k give the difference in outcomes among parents who in 2019 worked in firms allowing remote work (as measured in 2024) compared to parents who in 2019 worked in firms which have returned to full-time in person work by 2024. Panel (a) reports the results of the regression restricted to mothers of children 0-4 years old with teleworkable jobs, panel (b) reports the results for mothers of children 5-13 years old with teleworkable jobs. Teleworkability is measured in 2019. Additional controls include individual fixed effects, and 2019-firm NAICS by year by state of residence fixed effects. Standard errors are clustered at the firm level.

Figure A.13: Fortune 500 Firms Characteristics Over Time

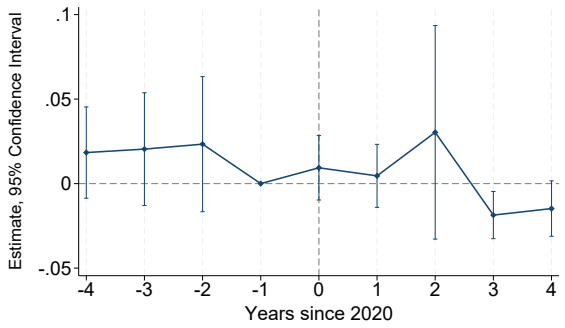
(a) Log of Total Market Value



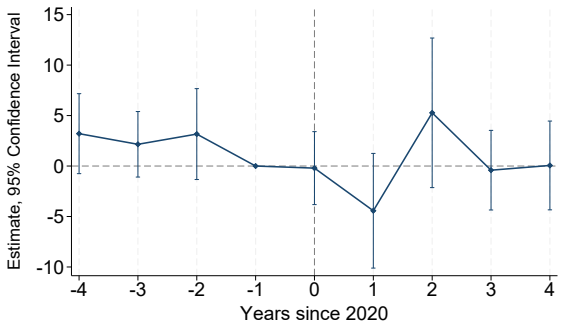
(b) Log of Total Revenue



(c) Profit



(d) Earnings Per Share



B Appendix: Theoretical Framework

Households produce a home good, denoted H, and work in the market to purchase consumption goods.[18] In our framework, the home good captures child quality. Parents produce this good by combining time with the mother H_m, time with the father, H_f, and time in market childcare, K, through a nested CES technology.

$$H = \left[s_P \left(s_m H_m^{\frac{\beta_P - 1}{\beta_P}} + (1 - s_m) H_f^{\frac{\beta_P - 1}{\beta_P}} \right)^{\frac{\beta_P}{\beta_P - 1} \cdot \frac{\beta_K - 1}{\beta_K}} + (1 - s_P) K^{\frac{\beta_K - 1}{\beta_K}} \right]^{\frac{\beta_K}{\beta_K - 1}}.$$

We assume an elasticity of substitution β_P between mother's and father's time spent on childcare, and relative productivity s_m for mothers compared to $1 - s_m$ for fathers. We assume parental childcare is imperfectly substitutable with market childcare, with elasticity of substitution β_K and productivity parameter s_P.

Utility of the household is given by

$$\max_{H_m, H_f, K, C} U(H, C)$$

where households are constrained by their income in consumption and purchase of childcare.

No Remote Work

In a world where remote work is not possible, every unit of time spent on childcare cannot be spent on work.

$$C \leq w_m(1 - H_m) + w_f(1 - H_f) + pK$$

We next derive the marginal rate of substitution between H_m, H_f, and K under a remote work vs. a no-remote work regime. It is useful to define the parental composite

$$P \equiv \left(s_m H_m^{\frac{\beta_P - 1}{\beta_P}} + (1 - s_m) H_f^{\frac{\beta_P - 1}{\beta_P}} \right)^{\frac{\beta_P}{\beta_P - 1}}$$

Taking the ratio of FOCs for mother's to father's time, we obtain the relationship between relative wages and relative childcare time. This model generates the traditional household specialization explanation of why mother's spend more time on non-market work than fathers:

$$\frac{s_m}{1 - s_m} \left(\frac{H_f}{H_m} \right)^{\frac{1}{\beta_P}} = \frac{w_m}{w_f}$$

The MRS between mother's time spent on childcare and purchase of formal childcare is similarly related to the ratio of the total earnings impact of mother's time spent on childcare and the price of market childcare.

$$\frac{s_P s_m}{1 - s_P} P^{\frac{1}{\beta_P} - \frac{1}{\beta_K}} H_m^{-\frac{1}{\beta_P}} K^{\frac{1}{\beta_K}} = \frac{w_m}{p}.$$

Remote Work

When remote work is possible, households may work while caring for children. However, working while caring for children may have direct implications on the wage.[19] In this case, the budget constraint is

$$C \leq w_m(H_m) + w_f(H_f) + pK$$

We model remote work as taking away the mechanical relationship between hours spent on childcare and household income: when remote work is possible, individuals can both work and produce childcare time at

[18] This CES formulation for home good production (or childcare quality) follows Berlinski et al. (2024); Cunha et al. (2010); Apps and Rees (2018) and Ichino et al. (2019), among others.

[19] Our model is not dynamic, but this can be thought of as capturing the present value of wages which includes potential future promotions directly depending on current work hours.

once. This means that the relevant "price" of parental time is only $w_g'(H_g)$.

In this model, the *level* of wages no longer affects the allocation of household time spent on childcare between mothers and fathers (except through the income effect). The decision of who provides relatively more childcare depends on the relative wage impacts of time spent in childcare and relative productivity. If men work in jobs which are more flexible, but higher wage, then we may expect a reversal in the within-household allocation of labor to childcare, and a reduction in the gender wage gap.

$$\frac{s_m}{1-s_m}\left(\frac{H_f}{H_m}\right)^{\frac{1}{\beta_P}} = \frac{w_m'(H_m)}{w_f'(H_f)}.$$

The use of market childcare in the era of remote work is also related to the wage impact of time spent on childcare:

$$\frac{s_P s_m}{1-s_P} P^{\frac{1}{\beta_P}-\frac{1}{\beta_K}} H_m^{-\frac{1}{\beta_P}} K^{\frac{1}{\beta_K}} = \frac{-w_m'(H_m)}{p}.$$

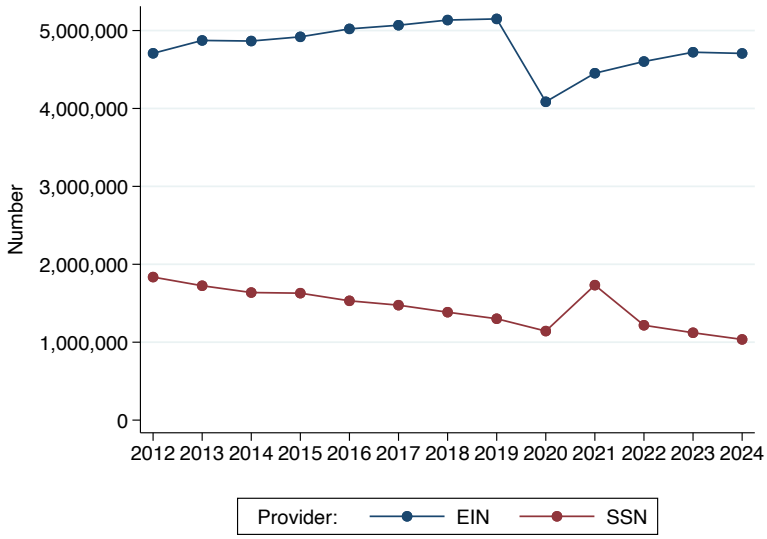
A prediction of this model is that mothers who face a steeper decline in wages associated with time spent on childcare (large and negative $w'(H_g)$), would use similar levels of K even when they have access to remote work.

C Appendix: Tax Filings of Child Care EIN Providers

We study the supply side using two complementary approaches: (1) matching and following the EINs furnished by tax units on Form 2441, and (2) separately studying the universe of firm tax filings of NAICS 624410 "Child Day Care Services."

Figure B.1 breaks out 2441 filings by whether they list an EIN or SSN. EIN providers are by far more common, and represent 70 percent of filings. Moreover, there has been a decline over time in SSN providers appear on Form 2441, with a slight increase in EIN providers. Most of the drop we observe since 2020 appears to come from EIN providers.

Figure B.1: 2441 Filings, Numbers of EIN and SSN Providers



Notes: Electronically filed 2441 returns.

We are able to match 67 percent of these EINs to business returns (1065 Partnerships, 1120 Corporate, 990 Non-Profits or Schedule C Sole-Proprietor).

We also separately examine the universe of firm returns with NAICS code 624410. 69 percent of all firm returns with NAICS 624410 appear on a 2441. This rises to 82 percent when excluding Schedule C's.

Table B.1 examines the distribution of business returns from our two complementary approaches. The most common type of provider is a corporation. Among firms with NAICS 62441, the second most common is a nonprofit. The next most common are Schedule C filers. Partnerships are the least common, representing fewer than 10 percent of providers.

Table B.1: Distribution of Businesses Providing Childcare

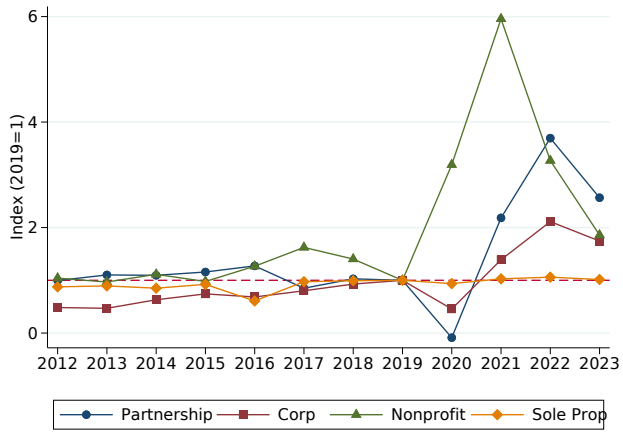
	Percent of returns	
	(1) Firms with NAICS 62441	(2) 2441 EINs matched to business returns
Corporation (1120)	47.8	37.1
Nonprofit (990)	28.2	26.3
Sole Proprietor (Schedule C)	15.4	29.7
Partnership (1065)	8.7	7.0

We next examine aggregate profits and payroll in the childcare industry. To do this, we use the second approach, following all firms in NAICS 624110, since this should provide complete coverage, at least for this NAICS code. In Figure B.2, we examine profits and payroll by type of firm filing. In 2020, profits fell for all providers except nonprofits, who saw a dramatic increase in profits. In all other years, profits in the industry have increased relative to 2019. Total payrolls fell in 2020 and continued to be lower in 2021, but since recovered for across types of providers by 2023.

In figure B.3, we compare the experience of the childcare industry to full-service restaurants (NAICS 722511) and hotels and motels (NAICS 721110). Childcare saw less dramatic declines in profits in 2020 compared to restaurants. While restaurants had a higher increase in aggregate profits in 2021, the childcare industry had higher profits in 2022 and 2023. Childcare also had smaller declines in aggregate payroll compared to restaurants and hotels, and by 2023 payroll was 20 percent higher than in 2019, similar to restaurants and well above hotels.

Figure B.2: Childcare Industry, Aggregate Profits and Payroll

(a) Aggregate Profits



(b) Aggregate Payroll

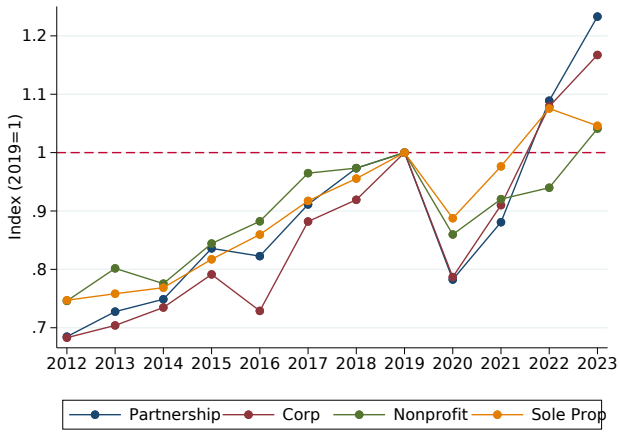
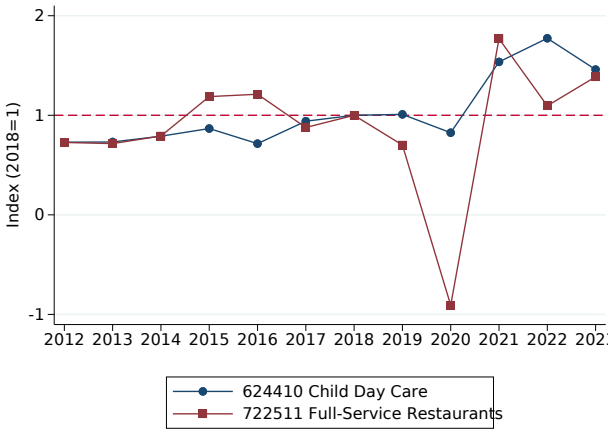


Figure B.3: Comparison to Other Industries

(a) Aggregate Profits



(b) Aggregate Profits

