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Gender Convergence in Couples' Time Use Following the COVID-19 Pandemic

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Abstract

This paper uses American Time Use Survey data to show that prime-age men's and women's average weekly work hours followed parallel trends from 2011-19, but then abruptly converged in the years following the COVID-19 pandemic. This convergence was driven by the changing behavior of couples, for whom the gender gap in weekly hours of paid work closed by 4.3 on a base of 14.7 (29.3%). While historical gender convergence has been driven by wives, husbands accounted for three-quarters (all) of the recent convergence in paid work (unpaid housework). I find that two labor market factors associated with the pandemic—sectoral reallocation and remote work-exposure—explain little of observed time-use changes in samples of husbands and fathers, although they explain 44% of the shrinking college-noncollege gap in paid work observed among fathers. These results suggest an ongoing shift in labor supply factors associated with fatherhood that may be stronger among the college-educated.

JEL classification

E24, J16, J21, J22

Keywords

time use, employment, labor supply, housework, remote work, leisure, fatherhood, gender norms, COVID-19

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1. Introduction

In 1965, husbands devoted most of their productive time to paid employment and relatively little to unpaid housework such as cooking, cleaning, and childcare. Wives' time use was almost the negative image of this. During the next few decades, married women rapidly entered the paid workforce and reduced their housework time in response to large economic and social shifts (Goldin, 1990, 2006; Bianchi et al., 2006), an epoch described by Claudia Goldin as a "quiet revolution." Husbands' employment and time use changed comparatively little during this period.

Between 2000 and 2019, women's progress continued although at a slower pace (Blau and Kahn, 2006; Goldin, 2014). Then, the COVID-19 pandemic halted progress altogether. Unlike in prior recessions, women's employment declined by more than men's during the pandemic recession (Heggeness, 2020; Albanesi and Kim, 2021; Alon et al., 2022; Stantcheva, 2022; Lim and Zabek, 2024). This was due to their specialization in high-contact service occupations and to the extra childcare burden they shouldered when schools closed (Giurge et al., 2021; Augustine and Prickett, 2022; Lyttelton et al., 2023; Atalay, 2023).

Yet, this reversal appears to have been short-lived. As schools reopened, remote work became commonplace, and demand for personal services rose again, female employment quickly rebounded. As shown in Appendix Figure B.1, by the first half of 2022, the employment-to-population ratio of women aged 25-54 already exceeded its level from the first half of 2019, while comparable men's employment lagged behind its 2019 level.

Using data from the American Time Use Survey, this paper shows that as the pandemic continued to recede, there occurred—for the first time in 25 years—a notable gender convergence in time use. Whereas wives were the protagonists of earlier convergence, the present episode featured husbands reducing their long days on the job, devoting more time instead to housework and leisure. The husband-wife gap in weekly hours of paid work declined by 4.3 on a pre-pandemic base of 14.7 (29.3%), with 3.2 of these hours coming from husbands' decreases in paid work and 1.1 coming from wives' increases.[1] There were also important differences by fatherhood and education statuses. Husbands with preschool-aged children experienced larger increases in housework time and smaller changes in leisure than those without. Husbands with college education experienced a larger reduction (increase) in paid work (housework) time than those without. This suggests a realignment of priorities surrounding fatherhood, particularly among the most-educated, who have traditionally been most attached to long-hours careers.

What were the drivers of this male-driven gender convergence? I use a simple decomposition framework to investigate the roles of post-pandemic changes in the occupation distribution and in remote-work incidence in accounting for these patterns. These variables help explain the changes in college-educated husbands' paid work and housework time *relative* to those without college. This is because the latter group experienced a shift from lower- to higher-hours sectors, while the former group experienced a disproportionate increase in remote work. However, the effects of remote-work on work time are estimated to be modest (matching prior work of Pabilonia and Vernon, 2023, 2025, 2026). Ultimately, these two variables explain little of the aggregate change in husbands' or fathers' time use.

I speculate that the primary effect of the pandemic involved a shift in household demand for husbands' flexible scheduling and time at home, even conditional on occupation and remote-work status. The potential for the pandemic to reshape gender norms in response to childcare binds, family stress, and contactless technology was first suggested in April 2020 by Alon et al. (2020). While further research is needed to fully evaluate this hypothesis in more years of post-pandemic data, the patterns identified here suggest an important and abrupt gender convergence that is not easily explained by observed labor-market conditions.

[1] This is based on comparing 2017-19 to 2022-24 aggregates, as described in detail in the next section.

2. Data

I utilize two U.S. household surveys to form a nationally-representative sample of men and women aged 25-54.[2] My starting point is the Current Population Survey (CPS). This is a monthly survey of around $60,000$ households that has been fielded by the Census Bureau since 1948, and analyzed and published by Bureau of Labor Statistics since 1959.[3] This survey provides information on some of the key indicators released each month in the U.S. jobs report. It also records various economic and demographic information at the individual and household levels.

The CPS sampling design involves a rotating panel of households. Approximately 2-5 months after CPS households complete their final interviews, a random subsample of around 3% of these households are interviewed in a follow-up survey called the American Time Use Survey (ATUS).[4] The ATUS randomly selects one adult individual from the CPS household and updates their key economic and demographic variables from the last CPS interview. Then, for a randomly-selected day, respondents fill out a 24-hour time diary recording information on activities engaged in, durations and types of those activities, where each activity took place, and who was present. Although the practice of interviewing just one member of each household means we cannot examine gender differences in time use within the same household, we can still examine broad population changes in time use and compare them across gender, presence of children, and other demographic variables.

I access the harmonized public-use versions of survey microdata from the Integrated Public-Use Microdata Series Time Use module (Flood et al., 2025).

[2]The present analysis focuses on prime-working-age individuals (age 25-54), as this group supplies the bulk of paid work and unpaid childcare hours, and married women in this group were the subjects of earlier gender convergence literature. Forsythe et al. (2022); Montes et al. (2022); Cortes and Forsythe (2023) identified an important rise in retirements during the pandemic. Tracking the continuation or reversal of this rise is out of scope for the present paper, but is a worthy endeavor for other research.

[3]https://www.census.gov/programs-surveys/cps/about/history-of-the-cps.html.

[4]https://www.bls.gov/tus/atususersguide.pdf#page=11

2.1. Sample characteristics

Given the relatively small sample size of the ATUS and my desire to investigate time-use patterns separately by gender and family structure types, I pool the data into three-year bins. My main sample consists of $11,572$ men and $12,880$ women aged 25-54, covering three years on either side of the pandemic years of 2020 and 2021: 2017-19 versus 2022-24. All results focus on this pre- versus post-pandemic comparison. In some cases I extend comparisons backward to 2011 by constructing 2011-13 and 2014-16 time points as well.

Appendix Table B.1 records selected summary statistics of the main sample. Men and women are aged 39.3 on average (SD: 8.7). Nearly two-thirds of individuals report living with a romantic partner. Around 46% of men and 54% of women have a child present in the household, and 19% (22%) have a child aged 0-5 living in the home. Around 41% of men and 48% of women have a 4-year college degree, reflecting known gender differences in educational attainment. Finally, 84% of men and 71% of women were employed and not absent from work in the week they were surveyed. Among those who employed, shown in Panel B, men work more usual weekly hours than women and have higher average and median earnings. The gender ratio in median weekly earnings is $830/1080 = 76.9\%$, which matches typical recent estimates.

2.2. Analytical specifications

I aggregate time-use activities into 4 mutually exclusive and exhaustive categories: paid work, housework,[5] work-related travel, and the REST (Relaxation, Entertainment, Sleep, and personal care, or "TLC"). The ATUS elicits time use for one randomly-selected day: to conform with weekly concepts typically asked about on household surveys, I multiply daily observations by 7 and then average across individuals within a group. With ATUS sampling weights, each day accounts for 1/7 of the data.

The CPS was the primary source of data analyzed in studies of the U.S. labor market

[5] Housework is defined in this paper as any unpaid task (except traveling, which is in the next category) associated with household maintenance or the care of other household individuals such as children.

during the pandemic. I verified that my ATUS sample contained similar rates of employment and full-time employment as the analogous CPS sample. However, the rates were not identical. To eliminate the possibility that the ATUS became less representative of the CPS following the pandemic, I adjust the ATUS survey weights in a reweighting procedure described in Appendix A.1. Within each time aggregate, this procedure ensures that the ATUS sample replicates CPS-derived employment and full-time employment rates by gender, in the full population as well as in key demographic subgroups. In practice, this adjustment had little effect on the results.

3. Main Descriptives

I begin by considering changes in the employment-to-population ratio by gender, extending the comparison backward to 2011 to establish pre-existing trends prior to the pandemic. As shown in Panel A of Figure 1, the male and female employment-to-population ratios increased in tandem by about the same amount between 2011 and 2019. Thereafter, male employment stagnated between 2017-19 and 2022-24, while female employment increased by 1.7 percentage points. Note that the graph plots male and female outcomes on separate axes to focus on differential trend breaks following the pandemic. That is, men's employment to population ratio still exceeded women's after the pandemic, but the gender gap shrunk from 13.8 percentage points pre-pandemic to 12.0 points post-pandemic.

This change in the gender gap in employment, on its own, predicts a modest change in the gender gap in time spent in paid work. Specifically, if the marginal employed individual works 35 hours per week, the $\sim$ 2-percentage-point gender convergence in employment translates into a $.02 \cdot 35 = 0.7$-hour convergence in weekly hours. But this benchmark ignores the *intensive* margin, i.e., movements in paid work hours among those already employed. Indeed, Panel B shows a substantially larger gender convergence, of 2.9 weekly paid work hours on a base of 10.7 (or a 27.1 % convergence). This convergence was driven primarily by a decline in men's paid work hours, despite their unchanging employment rate. As shown in Appendix

Figure B.2, we find very similar patterns when we omit non-working individuals, exclude weekends from the data, or both. This establishes the importance of employed men reducing their work hours (and to a lesser extent, employed women increasing their work hours) in the overall post-pandemic gender convergence.

Panels C and D of Figure 1 record trends by gender in weekly hours spent in housework and in REST. As for employment and weekly paid work hours, we note similar trends by gender in these time use categories prior to the pandemic. Thereafter, while women's time spent in housework and REST changed little, men experienced a substantial increase in the former and a modest increase in the latter. The gender gap in weekly hours of housework shrank from 11.9 to 10.4 (or a 12.6 % convergence), while gender gap in REST changed from around 0.5 hours to 2.2 hours in favor of men.

The remaining category is work-related travel, i.e. commuting to a job as well as travel associated with household errands such as shopping. Trends in this category are presented in Appendix Figure B.3. Although there have been notable post-pandemic declines in this category, they have been similar by gender and so are not a meaningful component of change in gender differences in time use. This category is also by far the smallest category.

3.1. Focusing on couples

Much of the post World War II convergence between men and women's time use occurred within married couples (e.g. Goldin, 2006). To the extent that the above patterns resulted from changes in the gender division of labor within the household, we would expect to see larger changes among couples. Figure 2 assesses this possibility by plotting trends in weekly hours of work for singles and for couples. We use relationship identifiers available in IPUMS to capture all cohabitants in romantic unions, not just legally married couples, although the patterns are similar in this subset as well.

Panel A of Figure 2 shows that unpartnered men and women experienced similar and modest declines in weekly paid work hours between pre- and post-pandemic. On the other hand, panel B shows a large decrease in paid work hours for partnered men combined with a moderate increase for partnered women. Overall, the gender gap declined by 4.3 hours, from 14.7 to 10.4: a 29.3% reduction.

This is quite a large gender convergence over a horizon of only 5 years. To put the recent convergence in perspective, Appendix Figure B.4 plots couples' average weekly paid work hours during the late 1960s - early 1990s. This was a unique period of rapid gender convergence that many researchers have studied (eloquently synthesized by Goldin, 2006). According to the CPS data on hours worked for pay "last week" that are available during this period, the gender gap in married couples' average weekly paid hours declined from 29.2 to 15.4 between 1969 and 1992, or a rate of 0.60 hours per year. The gender convergence observed between pre- and post-pandemic was even faster than this, at 0.83 hours per year (4.3 hours / 5 years).[6]

It is important not to over-interpret this comparison, since the weekly work hours concept is measured in different ways in the earlier versus the more-recent period (ATUS time-diary data only became available in 2003). It also seems unlikely that gender gaps continue to evolve as quickly after 2025 as they did in the immediate years following the pandemic. Nonetheless, the comparison highlights the gravity of the recent change in the couples' division of labor. It also shows that while the increase in wives' paid work hours was the dominant force behind the earlier gender convergence, the more-recent one has been driven by husbands reducing their work hours.

3.2. Caring for young children

The presence of preschool-aged children in the household has long been associated with wider gender gaps in time use. Figure 3 shows the evolution of the gender gap in couples' paid

[6] The same conclusion holds when we measure the gender gap in terms of percentages rather than raw hours. The gender gap in married couples' average weekly hours of paid work stood at 67.4% in 1969 (i.e. the average wife worked 67.4% fewer hours than did the average husband) and 38.3% in 1992. This amounts to a convergence of 29.1 percentage points, or 29.1/23 = 1.27 percentage points per year. In comparison, the gender gap in couples' average weekly paid work hours was 36.7 % in the pre-pandemic period and 28.3 % in the post-pandemic period: a convergence of 8.4 percentage points, or 1.68 percentage points per year.

work hours (panels A and B) and in housework hours (panels C and D) according to whether the couple has a child aged 0-5 living in the household.[7] For example, panel A shows in gray a 13.7-hour gender gap in weekly paid work hours, among couples without young children, in the pre-pandemic period. This gap then shrunk by 4.4 weekly hours, to 9.3, in the post-pandemic period. 3.3 hours of this convergence came from a reduction in men's work hours (blue region), while 1.1 came from an increase in women's hours (maroon region). Panel B shows a similar pattern of change among couples with young children: the gender gap in weekly paid work hours shrunk by 4.1, driven primarily by fathers reducing their work time.

On the other hand, panels C and D show a divergence in the evolution of housework gaps between couples without and with young children. Among those without, the gender gap in weekly hours of housework declined only from 11.1 hours to 10.4 hours. However, among those with young children, the gender gap declined from 18.6 to 14.8 hours—a 3.8-hour (20.5%) reduction. This change was driven almost entirely by an increase in fathers' housework hours. In sum, while partnered men without young children replaced their reduced paid work hours primarily with more REST, those with young children—whom I'll refer to as "young fathers" henceforth—completely offset their reduction in paid work hours with more housework.[8]

Appendix Figure B.6 shows a breakdown of the gender gap in overall housework hours among young parents into two categories: "active" childcare (i.e. direct supervision of or helping the child, as opposed to passive monitoring while doing some other primary activity) and all other activities. Two points stand out. First, half of the pre-pandemic gender gap in housework was generated by gender differences in active childcare, while the other half came from gender differences in other household tasks. Second, the post-pandemic convergence in overall housework was driven by meaningful changes in both sub-categories, but relatively more so by the non-childcare category (1.6-hour convergence in active childcare versus 2.4-

[7] For a comparable set of graphs that considers the full sample of couples, see Appendix Figure B.5.

[8] I did not find meaningful differences in pre-pandemic time use patterns, nor in the effects of the pandemic on time use, between couples without any children at all and couples without young children but with older children. Accordingly, I pooled those two groups together.

hour convergence in other household tasks).

This increase in time spent on other household tasks substantially exceeds the overall increase in housework time observed among men without young children (Figure 3 panel c). This indicates that the post-pandemic change in young fathers' housework reflects not just more-equal sharing of the childcare burden, but also a more general shift in their home involvement. It remains to be seen whether this pattern is a transitory effect that will fadeout as children age and become less dependent on parents, or a persistent effect that signals an enduring shift in fatherhood roles among recent cohorts.

3.3. Heterogeneity by education status

I close this section by examining how the recent gender convergence in couples' time use varies by socioeconomic status. I use the sub-sample of young parents for this analysis, although qualitative patterns are identical in the full sample of couples.

I measure socioeconomic status with a simple binary variable indicating the completion of a 4-year college degree. Note that the pre-pandemic sample contains 1,703 (1,829) partnered men (women) with young children, and the post-pandemic sample contains 1,107 (1,116). Approximately half of each of these groups had completed a 4-year college degree, so samples remain of reasonable size with this binary categorization.

Figure 4 displays the results. Looking at panel A, the gender gap in weekly hours of paid work changed little after the pandemic among less-educated young parents. Within this group, young fathers experienced almost no change in average paid work hours, while young mothers slightly increased their paid work time. In contrast, panel B shows a large decline in college-educated young fathers' paid work time, of over 6 weekly hours, alongside almost no change for college-educated young mothers. The overall gender gap declined from 16.7 weekly hours to 10.6 weekly hours; or in percentage terms, from 40.6% to 28.6%.

This decline of 12 percentage points, or nearly 30% of the pre-pandemic gap, is large for just a 5-year span. This narrowing of the college-noncollege gap in men's paid work is unexpected given the widening of inequality in male employment and wages that occurred in decades prior (Binder and Bound, 2019). Moreover, this narrowing does not show up in comparisons of post-pandemic changes in the employment rate. College-educated fathers have remained strongly attached to the labor force, but are no longer working as intensively as they did prior to the pandemic.

Panels C and D present results for housework. In contrast to panels A and B, we see that both less- and more-educated young fathers experienced substantial increases in housework time. Given that noncollege-educated fathers did not change their average paid work time, the 2.6-hour increase in housework time implies a reduction in REST time. On the other hand, while college-educated fathers experienced a larger post-pandemic increase in housework time (roughly 4.4 hours), this was exceeded by their reduction in paid work time, such that their REST time increased modestly. In sum, post-pandemic cohorts of young fathers have taken on a greater share of household chores regardless of socioeconomic status; noncollege fathers have accommodated this shift through decreased REST, while college fathers have accommodated it through decreased paid work.

4. Analyzing the Role of Sectoral Shifts and Remote Work

The descriptive results so far indicate an important gender convergence in time use following the pandemic that i) was more concentrated among couples, ii) was driven by men's changing behavior as opposed to women's, iii) involved reductions in paid work and increases in housework that were more pronounced among young-father and college-educated subgroups (especially the interaction of the two). In the space that remains, I trace out a simple decomposition framework that delivers a partial account of changes in partnered men's paid work and housework.

4.1. Decomposition setup

The pandemic was associated with two important labor-market changes that we can measure in the ATUS data. First, there was a reallocation of individuals across labor-market sectors, featuring growth in healthcare, other personal services, construction, and transportation. Second, there was an increase in the availability of remote work within the average sector. I measure labor-market sector with two sets of dummy variables recording the occupation and the industry of each employed individual, based on the `occ2` and `ind2` codes available in IPUMS. Nonemployed individuals are not asked about their (current or former) sector of work, so I impute these values based on a rich set of demographic and economic characteristics as described in Appendix A.

I measure remote-work status as

$$\mathbf{1}\{\text{individual engaged in} \geq 30 \text{ mins paid work and exactly 0 mins commuting}\} \tag{1}$$

with statuses initially set to missing for those working fewer than 30 minutes on their ATUS day.[9] I then imputed remote-work statuses to these individuals using an analogous procedure as for the sectoral imputations. One can think of these imputations as "potential" remote-work statuses, were the individual to have been employed and chosen to work on the given day. With this information in hand, we can examine the relationship between remote-work exposure and time use in the full population—not just those who chose to work on the given day—as well as map out population changes in remote-work exposure.[10]

To execute the decomposition, I begin by estimating the following regression:

$$y_{it} = \alpha + \beta' \mathbf{X_i} + \gamma \mathbf{1}\{t = POST\} + \epsilon_{it} \tag{2}$$

[9] I verified the results were robust to other minimum paid-work thresholds as described in Appendix A.

[10] Because the ATUS records just one random day's worth of time use, it is impossible to distinguish individuals who are full-time remote from those who are remote on some days and in-office on others. Pabilonia and Vernon (2026) recently leveraged a novel CPS module available only after the pandemic to examine work-from-home intensity over the course of the week. They found that hybrid versus fully-remote arrangements exerted similar effects on men's paid work and housework.

where y is an outcome (paid work or housework), t indexes time (pre- or post-pandemic), $\mathbf{X}$ is a vector of exogenous characteristics, $\mathbf{1}\{t = POST\}$ is a post-pandemic indicator variable, and ϵ captures idiosyncratic determinants of time use. Specifically, $\mathbf{X}$ contains a quadratic in age, race-ethnicity indicators, education indicators, Census region indicators, and a weekend versus weekday indicator. Thus, γ provides a baseline estimate of the post-pandemic change in male time use after accounting for changes in sample composition plausibly unrelated to the pandemic. (In practice, these background controls mattered little for the results.)

Next, I add in a set of occupation and a set of industry fixed effects. The change in the γ coefficient upon the addition of these controls is an estimate of the portion of observed change due to the changing sectoral distribution. I.e. if men switch from high-hours to low-hours sectors as a result of the pandemic, γ would become less negative upon inclusion of sector controls, indicating that sectoral reallocation helps account for the post-pandemic decline in men's paid-work hours. Finally, I added a remote-work indicator to the regression model. The remaining γ value after including these controls is the portion left unexplained by background variables, sectoral reallocation, and remote-work shifts.

I perform this decomposition for paid work and housework hours, and separately for the following groups: all partnered men, partnered men with young children (i.e. young fathers), college-educated young fathers, and noncollege-educated young fathers. Subtraction of the fourth decomposition from the third also provides an estimate of how sectoral reallocation and remote-work exposure have shaped the evolution of the *college-noncollege gap* in young fathers' time use.

4.2. The college-biased rise in men's remote work

Before we discuss the decomposition results, Figure 5 compares pre- and post-pandemic prevalence of remote work among the four groups of men. Panel A considers the subsample of individuals for whom we can directly observe remote work status. It shows almost no pre-pandemic differences in remote-work incidence across the four groups, with 10-12 percent of days worked remotely by men in each group. In the full sample of partnered men, this figure had doubled to over 23 percent by the post-pandemic period. The post-pandemic incidence of remote work for young fathers was slightly higher at around 26.2 percent. The last two bars show an uneven increase in remote work by education status: while 36.9 percent of days were worked remotely among college-educated young fathers in 2022-24, the corresponding figure was only 17.7 percent for the less-educated group.

Panel B presents the same statistics, as estimated in the full sample of men—i.e. with imputed remote-work statuses assigned to those men working under 30 minutes on their ATUS day. The bar graphs look quite similar to Panel A, indicating that the imputation procedure is not altering any key conclusions.[11]

It is worth noting that even for the college-educated group, the post-pandemic prevalence of remote work was far below 100%. This reflects a considerable degree of return to hybrid or full-time in-office schedules from pandemic highs, as reported on in NCSES (2025).

4.3. Decomposition results

Panel A (B) of Table 1 records decomposition results for paid work (housework). Each panel contains four rows corresponding to the four groups of partnered men described above, plus a fifth row recording a decomposition of the post-pandemic change in the *college-noncollege gap* in young fathers' time use.

Looking at the first four rows of each panel, we see that sectoral reallocation and rising remote-work incidence account for almost none of the observed time-use changes in each group. College-educated fathers (row 3) is the mild exception, but even so, the two variables account for only 0.75 hours (or 13.8%) of the 5.44 weekly hour decline in paid work and 1.07 hours (or 25.5%) of the 4.19 weekly hour increase in housework. Given this group's large uptick in remote-work incidence shown in Figure 5, one implication of these results is that

[11] Two minor points of difference: first, the pre-pandemic bars in Panel B are all a few percentage points higher, suggesting that individuals who chose not to work on the given day had greater exposure to remote work than those who did; second, the post-pandemic gap in remote work between college and noncollege fathers is slightly higher in Panel B.

men's work time is insensitive to the ability to work remotely. Indeed, in the full sample of partnered men, we find that remote work is associated with only a 1.62 weekly hour decline in paid work and 1.92 weekly hour rise in housework. For college-educated young fathers, the effect estimates are -2.17 hours for paid work and 2.89 for housework. (All estimates statistically significant at the 10% level.)

For noncollege-educated young fathers, we see that sectoral reallocation predicts an *increase* in paid work and small *decrease* in housework, which are opposite to the observed changes. As shown in row 5, sectoral reallocation and remote-work exposure account for 1.74 hours (or 43.7%) of the 3.98 hour decline in the college-noncollege gap in young fathers' paid work hours. They also account for 1.24 hours—essentially all—of the rise in the college-noncollege gap in housework hours. Therefore, while these two labor-market changes help explain why the pre-pandemic gap in time use between more- and less-educated men began to close, they offer no insight into aggregate movements in men's or fathers' time use. This suggests, although does not prove, a broad-based shift in labor-supply factors associated with fatherhood, which Alon et al. (2020) hypothesized might occur as a result of the pandemic. Such a narrative is also consistent with the outsized effect of the pandemic on gender convergence in couples'—but not singles'—time use (Figure 2).

5. Conclusion

Using American Time Use Survey Data from immediately before and after the COVID-19 pandemic (2017-19 versus 2022-24), I find early evidence of a gender convergence much different than that which preceded it. Instead of wives converging toward husbands in paid employment while reducing their time spent in housework, I find husbands—especially those with young children—converging toward wives in housework time, while reducing their time in paid employment. Couples' gender convergence in paid work time between pre- and post-pandemic was even faster than that observed during the "quiet revolution" of the late 60s-early 90s, amounting to a 4.3 weekly-hour reduction in the gap in paid work hours over just a 5-year span.

I also showed that husbands' reduction in paid work hours and increase in housework hours occurred unevenly across education statuses. While both college- and noncollege-educated partnered men experienced important increases in housework time, the college group experienced a larger increase, and also experienced a much larger reduction in paid work hours. As a result, the college-noncollege gap in husbands' paid work hours shrunk during the aftermath of the pandemic. This is notable given the large widening in employment and hours worked between college and noncollege men that occurred in decades prior (Binder and Bound, 2019). Contemporary college-educated fathers are taking more leisure and rest time than they used to, while their less-educated counterparts have substituted housework for REST.

I attribute almost half of the shrinking college-noncollege gap in husbands' paid work hours to the combination of i) the reallocation of noncollege men toward higher-hours sectors of the labor market and ii) the disproportionate growth of remote work among college men. However, these factors do a poor job of accounting for time-use changes in the full population of husbands or fathers. It is possible that much of the gender convergence in time use following the COVID-19 pandemic reflects a reconsideration of contemporary fathers' household roles, with associated effects on their labor supply curves. Further research is needed to evaluate whether the time-use changes identified here persist or revert as the years continue to unfold.

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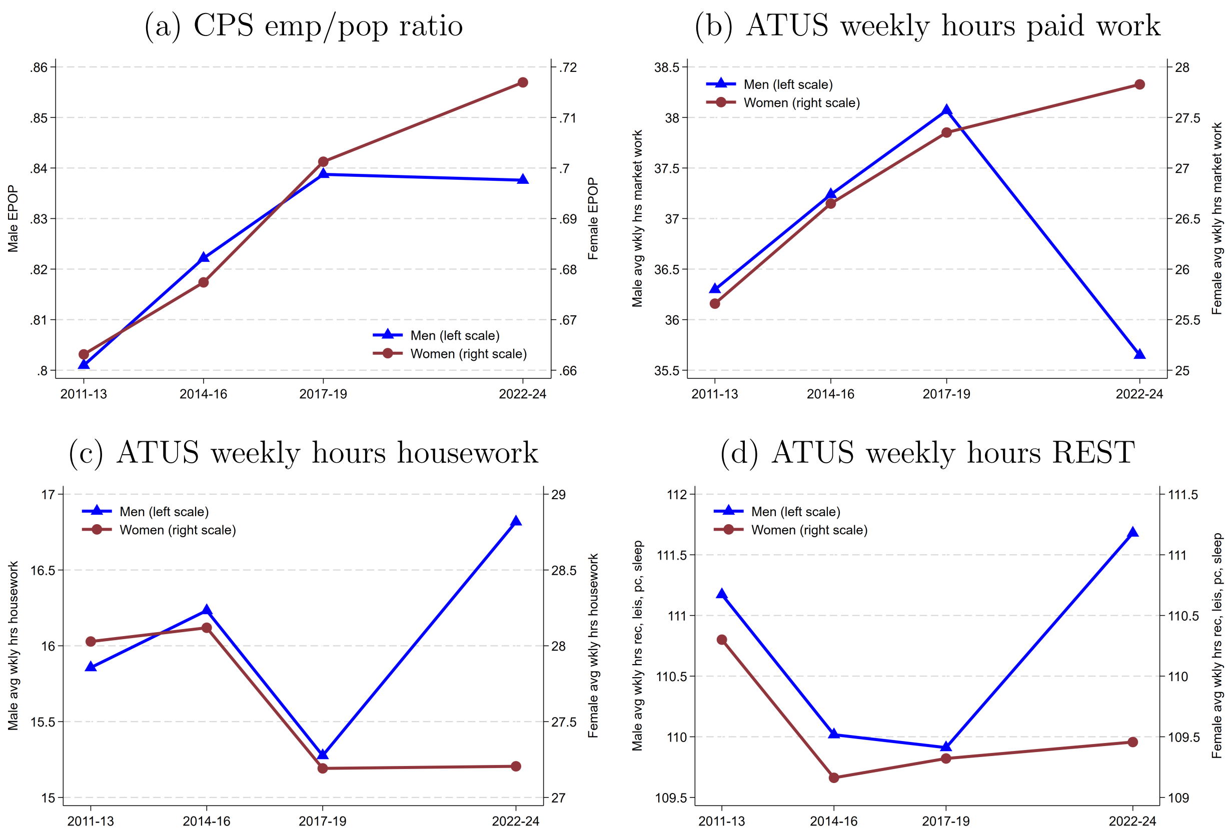
Figures and Tables

Figure 1: Trends in Employment and Time Use by Gender

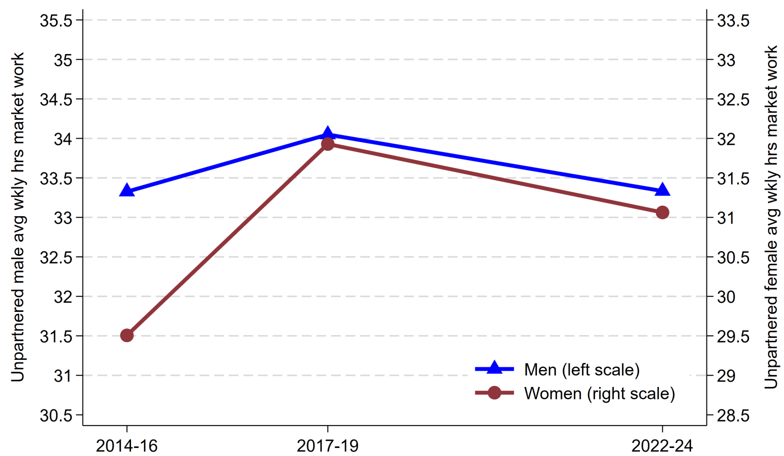


Source: 2011-2019, 2022-2024 Current Population and American Time Use Surveys, as accessed through IPUMS.

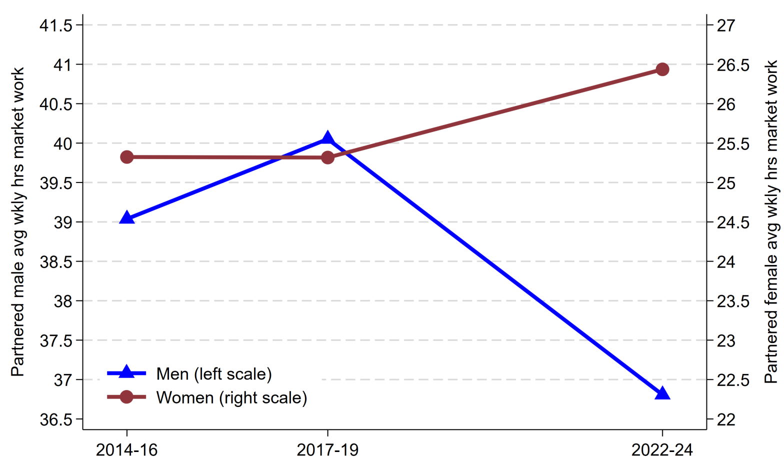
Note: ATUS weekly statistics are computed by multiplying daily observations by 7 and then taking the average across respondents. Survey weights ensure that each day contributes 1/7 to the total weekly average. "REST" encompasses recreation, entertainment, sleep, and personal care (or "TLC") and is the balance of time not spent in paid work, housework, or work-related travel. As shown in Appendix Figure B.3, there have been notable changes in work-related travel, but this is a small category relative to other uses of time and observed changes do not differ much by gender.

Figure 2: Trends in Weekly Work Hours by Gender and Partnership Status

(a) Unpartnered

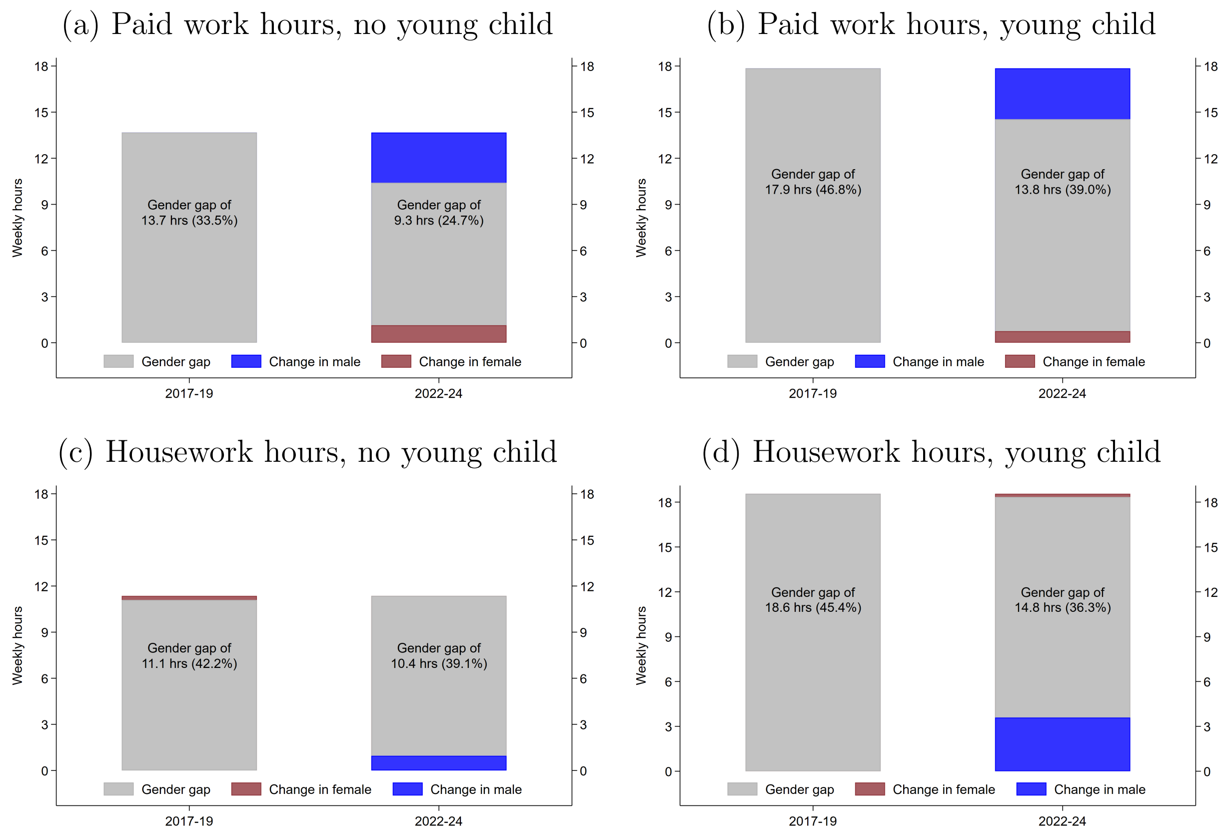


(b) Partnered



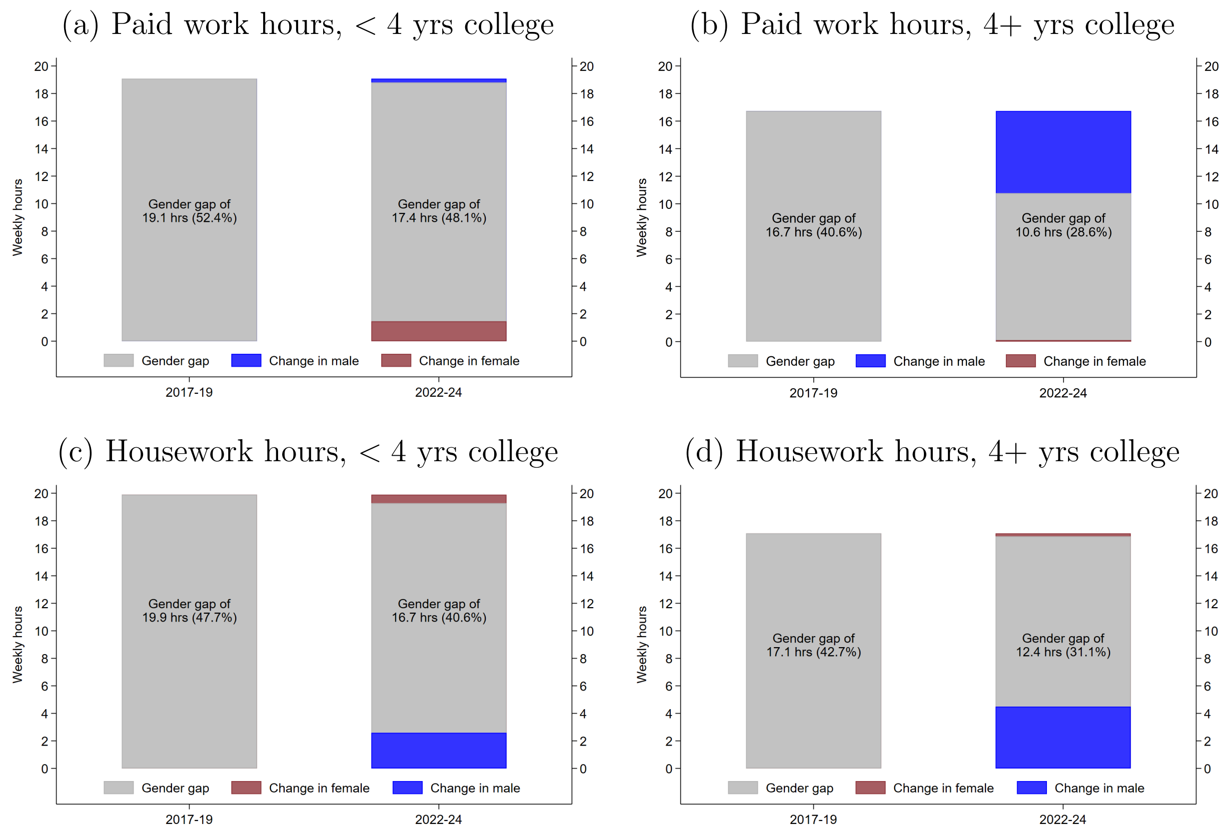
Source: 2017-2019, 2022-2024 American Time Use Surveys, as accessed through IPUMS.
Note: ATUS weekly statistics are computed by multiplying daily observations by 7 and then taking the average across respondents. Survey weights ensure that each day contributes 1/7 to the total weekly average.

Figure 3: Change in Gender Gap in Paid Work and Housework,
by Presence of Young Children



Source: 2017-2019, 2022-2024 American Time Use Surveys, as accessed through IPUMS.
Note: Sample restricted to partnered individuals. A "young" child is aged 0-5. ATUS weekly statistics are computed by multiplying daily observations by 7 and then taking the average across respondents. Survey weights ensure that each day contributes 1/7 to the total weekly average.

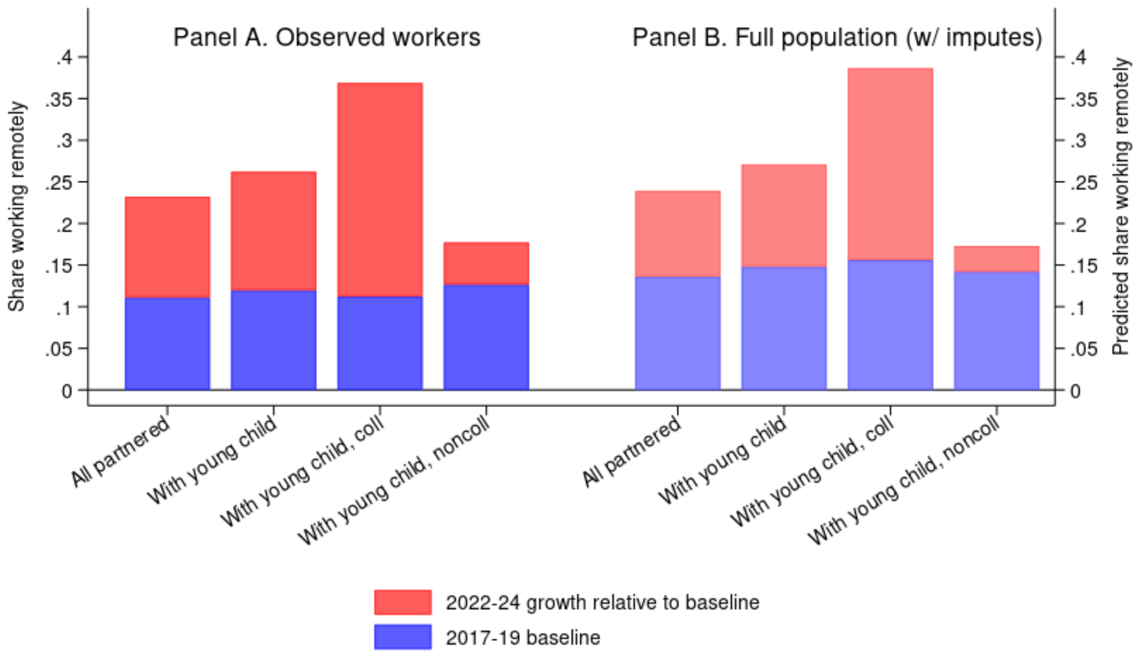
Figure 4: Change in Gender Gap in Paid Work and Housework
among Young Parents, by College Status



Source: 2017-2019, 2022-2024 American Time Use Surveys, as accessed through IPUMS.

Note: Sample restricted to partnered individuals with at least one child aged 0-5 living in the household. ATUS weekly statistics are computed by multiplying daily observations by 7 and then taking the average across respondents. Survey weights ensure that each day contributes 1/7 to the total weekly average.

Figure 5: Changes in Remote-Work Incidence among Partnered Men



Source: 2017-19, 2022-24 American Time Use Surveys as accessed through IPUMS.
Note: Panel A considers all individuals who performed at least 30 minutes of paid work on the day they were surveyed, while Panel B considers the full population. See Section 4.1 and Appendix A.4 for descriptions of the imputations behind Panel B.

Table 1: Decompositions of Average Changes in Paid Work and Housework Hours among Partnered Men, by Demographic Subgroup

	Baseline change	Sector	Remote work	Residual
	Panel A. Weekly hours of paid work			
1) All partnered men	-3.11	0.08	-0.20	-3.00
	(0.44)	(0.72)	(0.10)	(0.52)
2) With young children	-3.42	0.17	-0.01	-3.46
	(0.71)	(1.17)	(0.18)	(0.84)
3) With young children	-5.44	-0.19	-0.56	-4.69
and 4+ yrs college	(0.83)	(1.39)	(0.35)	(1.03)
4) With young children	-1.46	0.91	0.08	-2.45
and < 4 yrs college	(1.15)	(1.93)	(0.12)	(1.38)
5) With young children	-3.98	-1.10	-0.64	-2.24
coll-noncoll gap: 3) - 4)				
	Panel B. Weekly hours of housework			
1) All partnered men	1.52	-0.02	0.23	1.31
	(0.30)	(0.50)	(0.07)	(0.36)
2) With young children	3.75	-0.12	0.30	3.57
	(0.55)	(0.92)	(0.14)	(0.66)
3) With young children	4.19	0.33	0.74	3.12
and 4+ yrs college	(0.68)	(1.14)	(0.29)	(0.85)
4) With young children	2.94	-0.24	0.07	3.11
and < 4 yrs college	(0.88)	(1.48)	(0.09)	(1.07)
5) With young children	1.25	0.57	0.67	0.01
coll-noncoll gap: 3) - 4)				

Source: 2017-2019, 2022-2024 American Time Use Surveys as accessed via IPUMS.

Note: All demographic groups considered refer to partnered men, not just group 1. "Baseline change" is the average observed change in time use between 2017-19 and 2022-24 after controlling for exogenous characteristics (age, education, race/ethnicity, region, and weekend indicator). "Sector" is the average change explained by the changing distribution of individuals across occupations and industries between 2017-19 and 2022-24 (after controlling for exogenous characteristics). "Remote work" is the average change explained by within-sector growth in remote-work exposure between 2017-19 and 2022-24 (i.e. after controlling for exogenous characteristics and occupation and industry effects). As described in Section 4 and in Appendix A.2-A.4, this decomposition requires imputing sector and remote-work statuses to those with missing information. This is done probabilistically on the basis of 250 independently-drawn implicates. Standard errors appear below point estimates in parentheses and account for baseline variance as well as between-implicate variance.

A. Appendix: Data and Methodology Details

A.1. Reweighting to match CPS employment rates

The ATUS stratified-randomly samples from the CPS. Given that its sample size is rather small relative to the CPS, this implies that its employment composition should be close to, but not necessarily exactly the same as, the CPS universe. Because the CPS underlies the official jobs reports and was the primary source of data analyzed in COVID-19 literature on the U.S. labor market, I reweight my ATUS sample to match CPS employment statistics.

Specifically, for each demographic subgroup D and time t, I considered the CPS employment-status usual weekly hours questions. This information exists in the ATUS data as well as in the CPS: the survey instrument pre-populates the respondent's original CPS responses from 2-5 months ago, and updates the values if they have changed. Using the provided survey weights, I computed the share belonging to each status in both the full CPS sample and the ATUS subsample: non-employed (n), part-time employed (p: less than 35 usual weekly hours), full-time employed (f: at least 35 usual weekly hours). Next, I multiplied each ATUS respondent i's survey weight by the ratio of the CPS share to the ATUS share, where the share in question matches i's observed employment status. Denoting i's given ATUS survey weight as bw_i ("base" weight), the final weight I use in analyses is:

$$fw_i^{Dt} = bw_i^{Dt} \times \begin{cases} \frac{n_{CPS}^{Dt}}{n_{ATUS}^{Dt}} & \text{if } i \text{ is not employed} \\ \frac{p_{CPS}^{Dt}}{p_{ATUS}^{Dt}} & \text{if } i \text{ is part-time employed} \\ \frac{f_{CPS}^{Dt}}{f_{ATUS}^{Dt}} & \text{if } i \text{ is full-time employed.} \end{cases} \tag{A.1}$$

I consider 18 demographic subgroups D, formed by the interaction of gender, education status (high school or less, some college without a Bachelor's degree, Bachelor's degree or higher), and presence of children (0, 1, 2+). As discussed in the main text, I pool ATUS years into 3-year bins to increase sample size and the ability to analyze smaller subgroups. Thus, I iterate the reweighting routine across the the pre-pandemic period (2017-

2019), post-pandemic period (2022-2024) and two "pretrend" periods of 2011-2013, 2014-2016. Ultimately, the routine guarantees that the ATUS replicates national CPS employment statistics in each of these 3-year aggregates, both in the full prime-age population and within each D subgroup.

Without this weighting adjustment, I find even slightly larger time-use changes between pre- and post-pandemic than what is reported in the main text. However, the results are quantitatively similar and the qualitative narrative remains unchanged.

A.2. Weekly earnings edits and imputations

Although weekly earnings are not directly considered in the analysis, I use them as an input to imputation models of labor-market sector and remote-work takeup (described below).

First, I edited top-coded values. Reported weekly earnings are top-coded at \$2884.61, a value which has not changed since 2003. I replaced top-coded weekly earnings in year y with the value $2884.61 \cdot (1.5 + (y - 2003) \cdot .05)$.

Next, I estimated an imputation model to allocate weekly-earnings values to non-employed men. I conditioned the model on a quadratic in age, metropolitan status (central city, non-central city, nonmetro), tenure of ownership (owned, rented), state, race/ethnicity, education, partnership status (married, non-marital cohabitation, single), presence of children, presence of young children, and year. Following Juhn et al. (1993) and related work, instead of assigning nonworkers the mean weekly earnings value conditional on this information, I assigned the 25^{th} percentile based on a quantile regression. This choice assumes that non-employed men have lower-than-typical potential earnings conditional on observed characteristics, which Juhn et al. (1993); Juhn and Murphy (1997) and others have validated.

A.3. Occupation and industry imputations

Occupation and industry values are missing for non-employed individuals, who are not typically asked about their current (or former) sector of work on household surveys. Because non-employment is heavily correlated with observed weekly hours of work, and I wish to consider the role of sectoral reallocation in the observed time-use patterns, I must impute labor-market sectors to these non-workers.

Given that my sample size is not huge, I used the `occ2` and `ind2` codes available in IPUMS, of which 22 mutually exclusive and exhaustive codes exists for occupation and 51 exist for industry. I used the same list of variables as for the weekly earnings imputation, with a couple of modifications. I substituted region effects in for state effects and aggregated-year effects (i.e. 2017-2019 versus 2022-2024) in for single-year effects to avoid overfitting. I also utilized log weekly earnings (imputed for non-workers as above) as an additional regressor in the model. Based on the assumption that non-workers have low potential wages conditional on observables, including this variable in the model pushes non-workers toward lower-paying sectors. That is, the model reasonably assumes that non-workers have lower sectoral distributions than observably similar workers.

The imputation procedure ran as follows:

1. Estimate S different linear probability models in terms of the imputation regressor described above, one for each sector s. (Thus, $S = 22$ for occupation and 51 for industry.) Based on these models, predict the probability of working in each sector s for each non-worker i.

2. Set negative predicted probabilities to 0 if they exist, and normalize the sum of predicted probabilities to be 1 if it is not 1.

3. Weighted-randomly assign a sector to each non-worker i based on i's vector of predicted probabilities.

A.4. Remote-work imputations

As discussed in the main text, we can only observe the take-up of remote work on a day in which a non-trivial amount of paid work was performed. I used a threshold of 30 minutes in this paper, but verified that the results were robust to alternative thresholds (e.g. 20

minutes, 40 minutes, one hour). In order to consider the role of remote-work exposure in average time-use behavior, not just behavior conditional on the 30-minute threshold, I must impute remote-work status to individuals who work less than this amount. For employed individuals observed not to work due to a weekend or a leave, this imputation predicts exposure to remote work in the job they already have. For non-employed individuals observed not to work because they do not have a job, this imputation predicts "potential" exposure to remote work, just as a wage imputation for this group captures their potential wage offer.

I imputed remote-work exposure according to the same variables used for the weekly earnings imputations, with three modifications. First, I included (imputed) log weekly earnings information. Second, I included a weekend indicator variable. Third, I allowed education, weekend, and weekly-earnings effects on remote work propensity to vary with time, to allow for changing provision of / selection into remote work on the basis of these statuses. I estimated a linear probability model in terms of these variables and then predicted a remote-work probability for each individual i observed to work less than 30 minutes. I then weighted-randomly assigned i's remote work status based on their predicted probability.

A.5. Bootstrap

Notice that these imputation procedures are stochastic in nature—i.e. they weighted-randomly assign a category to an individual based on his imputed probabilities of belonging to each category. Accordingly, I use a bootstrap procedure to account for this uncertainty, in which I independently generate 500 implicate datasets, perform 500 decompositions, and average the results across implicates. Standard errors account for the extra variability induced by this step.

B. Additional Tables and Figures

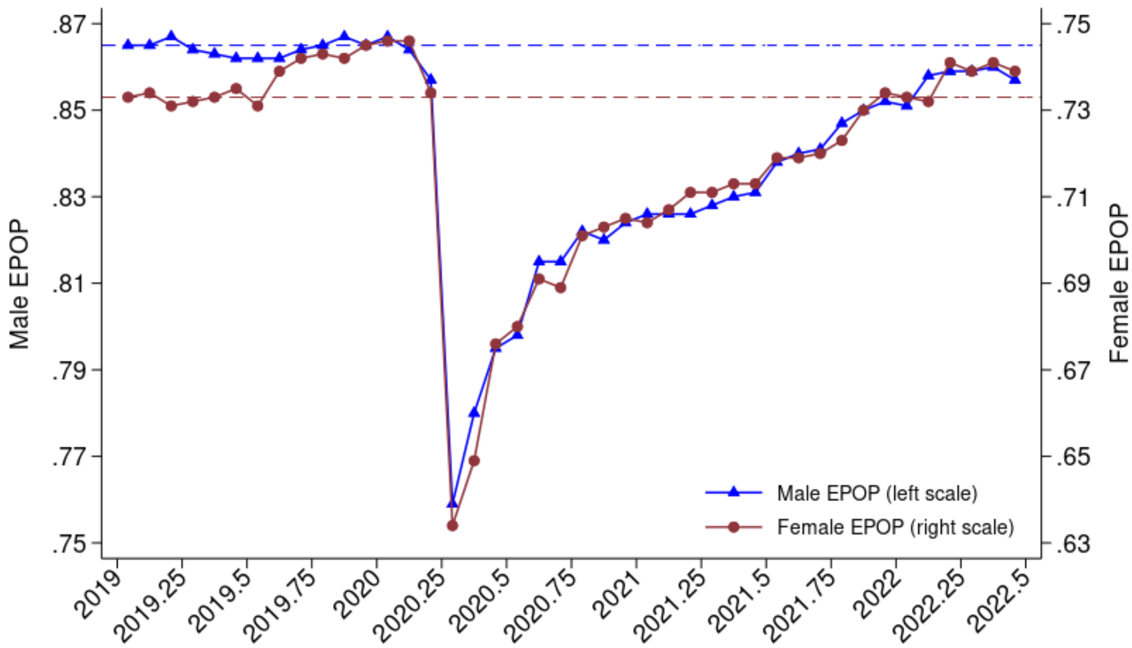
Table B.1: Summary Statistics

	Men		Women	
	Mean	SD	Mean	SD
	Panel A. All			
Age	39.3	8.7	39.3	8.7
Partnered	0.65	0.48	0.66	0.48
Child present	0.46	0.50	0.54	0.50
Young child present	0.19	0.40	0.22	0.42
College degree	0.41	0.49	0.48	0.50
Employed not absent	0.84	0.37	0.71	0.45
	Panel B. Workers			
Mgmt/biz/prof occupation	0.45	0.50	0.56	0.50
Serv/sales/adsup occupation	0.23	0.42	0.38	0.48
Other occupation	0.32	0.46	0.07	0.25
Usual weekly hours	43.8	9.8	39.6	10.2
Weekly earnings ($2018)	1600	1610	1170	1250

Source: 2017-2019, 2022-2024 American Time Use Surveys as accessed via IPUMS.

Note: A "young" child is a child aged 5 or younger. "Mgmt/biz/prof" is short for management, business, or professional occupations. "Serv/sales/adsup" is short for services, sales, or administrative support occupations. "Other" records all other occupations. Weekly earnings are rounded to the nearest 10. Mean earnings may not be representative due to skewness of the distribution: median values are 1080 for men and 830 for women.

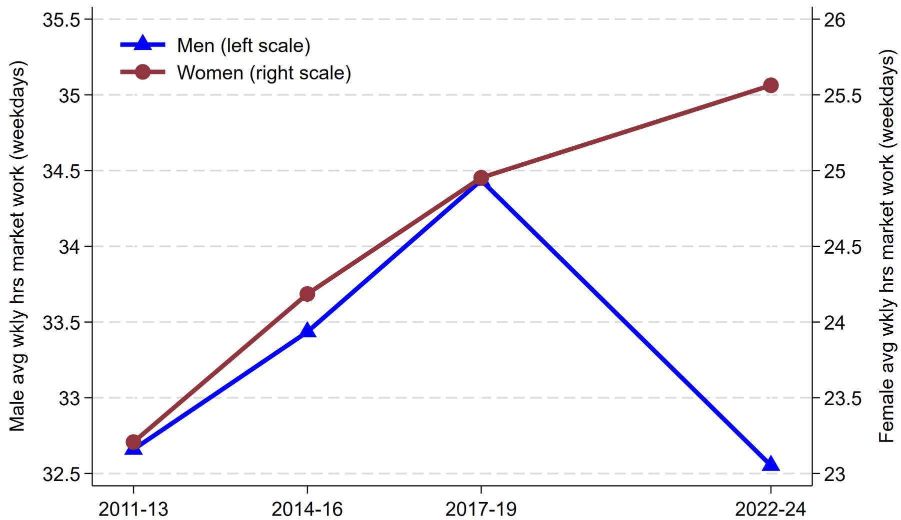
Figure B.1: Prime-age Men's and Women's Employment-to-Population Ratio, 2019-2022



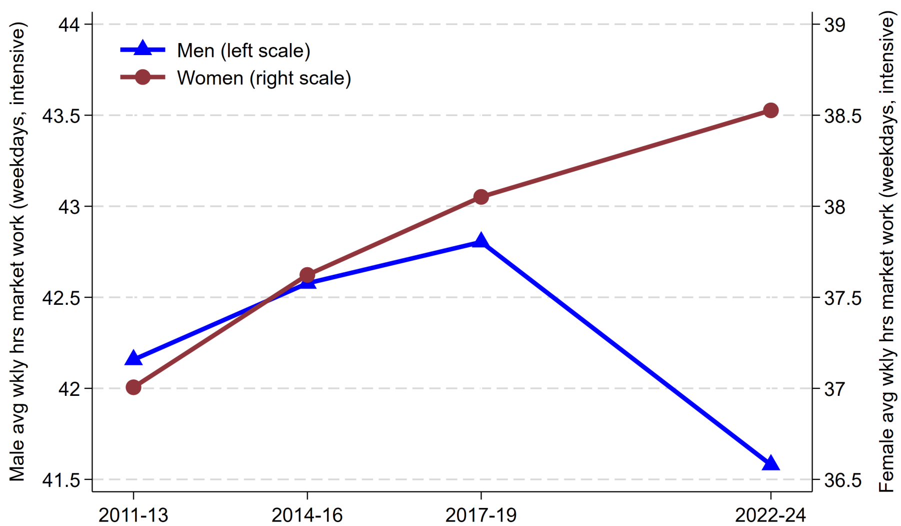
Source: Bureau of Labor Statistics.
Note: Prime-age range is 25-54.

Figure B.2: Weekly Work Hours with Non-Workers or Weekends Excluded

(a) Excluding weekends

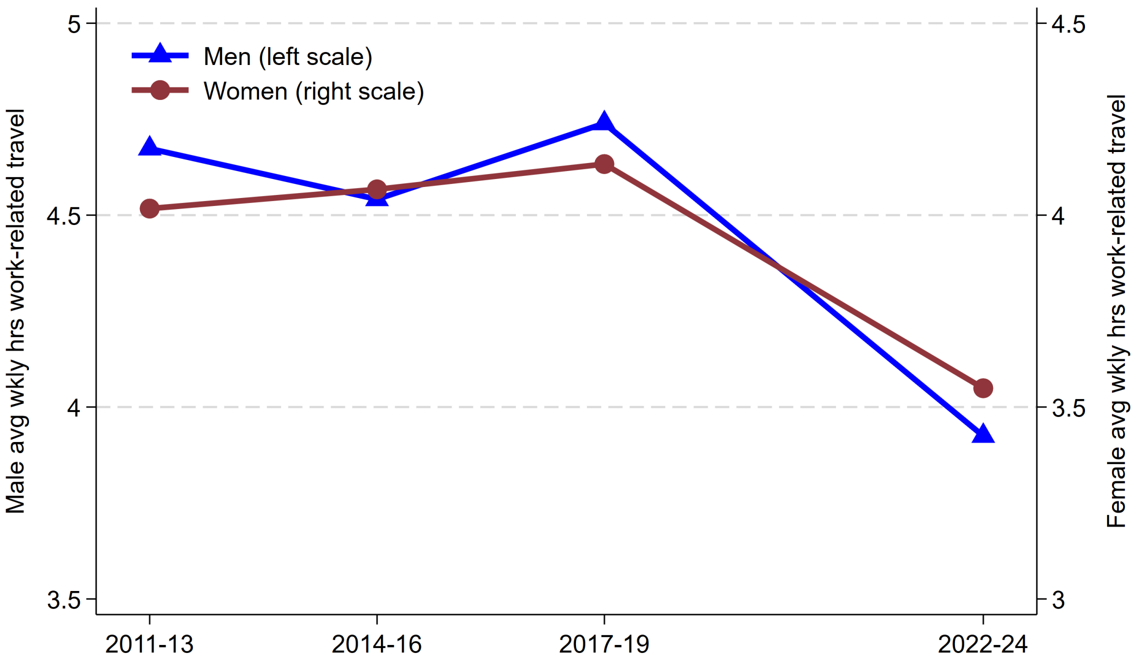


(b) Excluding non-workers and weekends



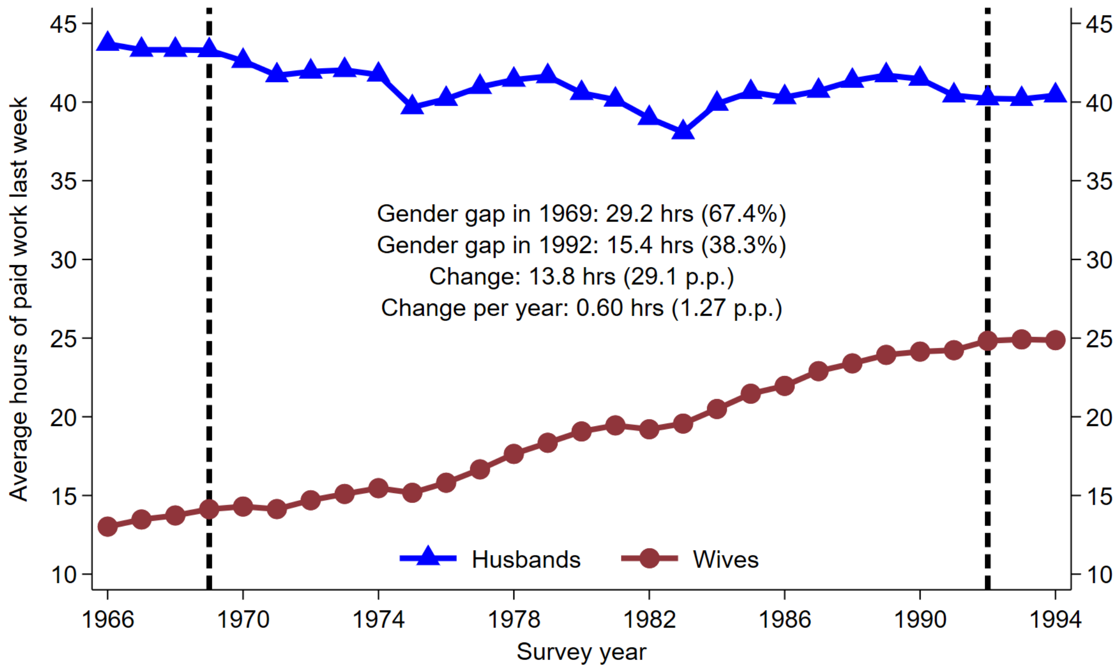
Source: 2011-2019, 2022-2024 American Time Use Surveys, as accessed through IPUMS.
Note: ATUS weekly statistics are computed by multiplying daily observations by 5 and then taking the average across respondents. Survey weights ensure that each weekday contributes 1/5 to the total weekly average.

Figure B.3: Weekly Hours of Work-Related Travel



Source: 2011-2019, 2022-2024 American Time Use Surveys, as accessed through IPUMS.
Note: ATUS weekly statistics are computed by multiplying daily observations by 7 and then taking the average across respondents. Survey weights ensure that each day contributes 1/7 to the total weekly average.

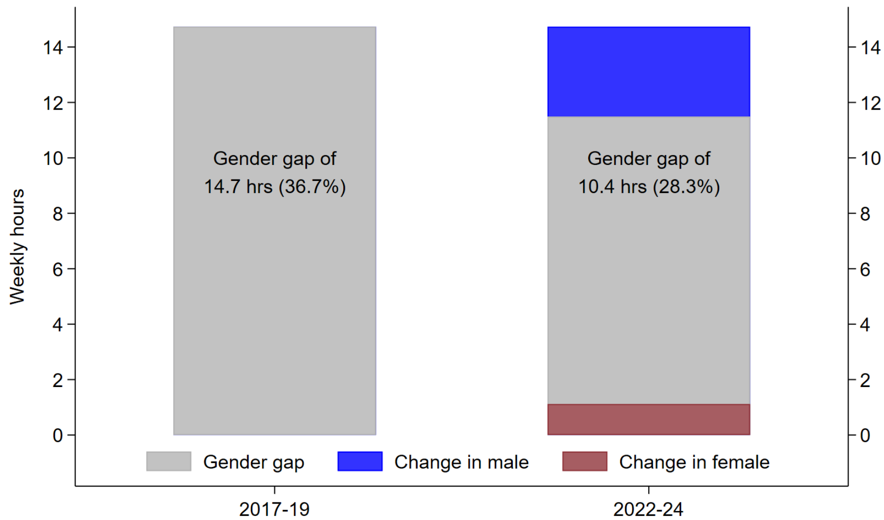
Figure B.4: Couples' Average Paid Work Hours during the "Quiet Revolution" Period



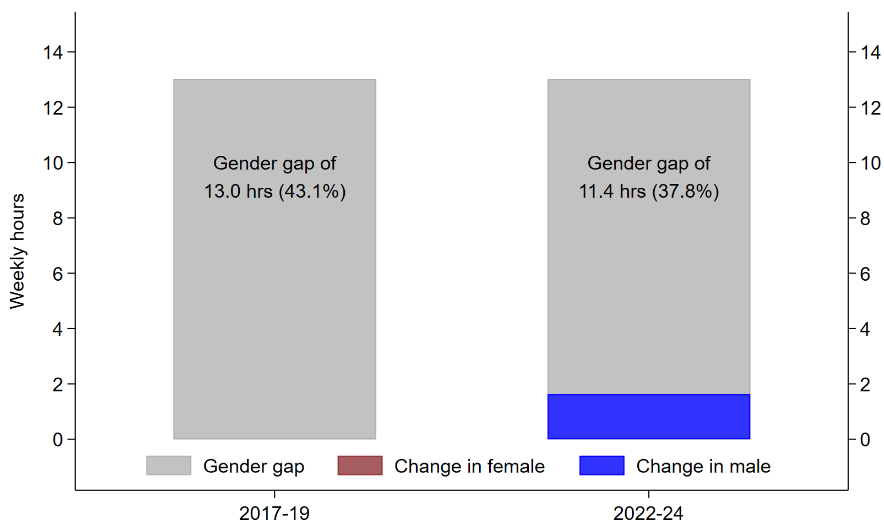
Source: 1996-1994 Current Population Surveys (March Supplement).
Note: The basic monthly CPS was not archived in its entirety until 1976–this graph considers the month of March only, which has been archived back into the 1960s as part of the Annual Social and Economic Supplement (ASEC) to the CPS. The "usual weekly hours of work" question was not asked until 1994; the hours-worked data comes from the "hours worked last week" questions, with 0s assigned to the non-employed.

Figure B.5: Change in Gender Gap in Paid Work and Housework,
Full Sample of Partnereds

(a) Paid work hours



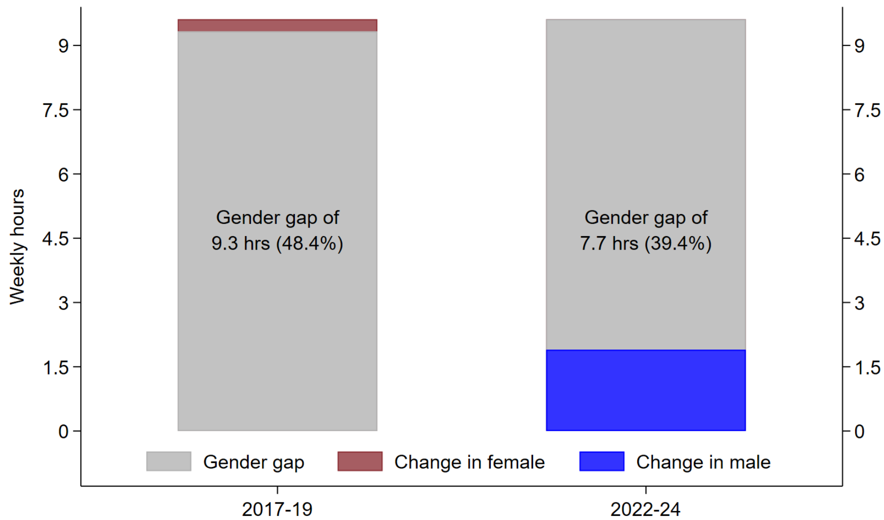
(b) Housework hours



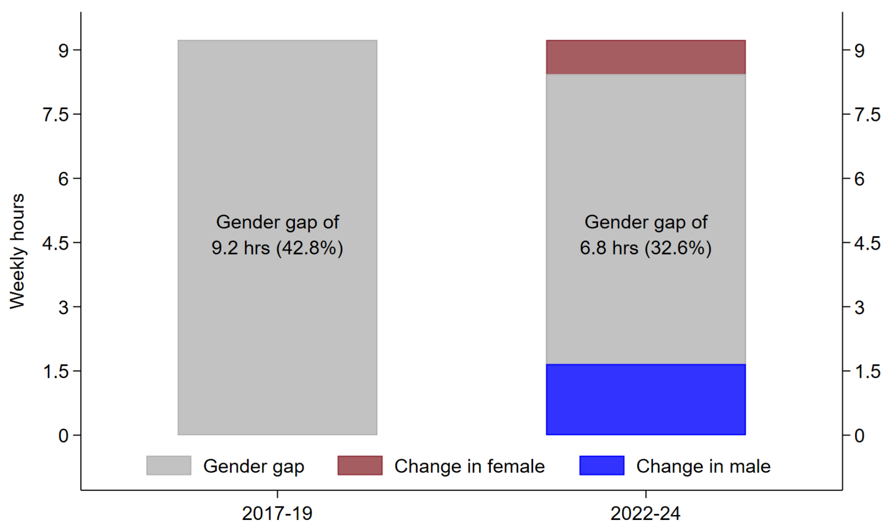
Source: 2017-2019, 2022-2024 American Time Use Surveys, as accessed through IPUMS.
Note: ATUS weekly statistics are computed by multiplying daily observations by 7 and then taking the average across respondents. Survey weights ensure that each day contributes 1/7 to the total weekly average.

Figure B.6: Split of Young Parents' Housework Trends into Active Childcare versus Other

(a) Active childcare hours



(b) Other housework hours



Source: 2017-2019, 2022-2024 American Time Use Surveys, as accessed through IPUMS.
Note: ATUS weekly statistics are computed by multiplying daily observations by 7 and then taking the average across respondents. Survey weights ensure that each day contributes 1/7 to the total weekly average.