The Summer Drop in Female Employment*

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Abstract

We provide the first systematic account of summer declines in women's labor market activity. From May to July, the employment-to-population ratio among prime-age US women declines by 1.1 percentage points, whereas male employment rises; women's total hours worked fall by 9.8 percent, more than twice the decline among men. School closures for summer break—and corresponding lapses in implicit childcare—provide a unifying explanation for these patterns. The summer drop in female employment aligns with cross-state differences in the timing of school closures, is concentrated among mothers with young school-aged children, and coincides with increased time spent engaging in childcare. Decomposing the gender gap in summer work interruptions across job types defined by sector and occupation, we find large contributions from both gender differences in job allocation and gender differences within job types in the propensity to exit employment over the summer. Women's summer work interruptions contribute to gender gaps in pay: while men's weekly earnings are stable during the summer months, women's earnings decline by 2.2 percent.

Keywords: gender gap, seasonality, labor force participation, childcare, time use, school closure
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1 Introduction

Women and men differ markedly in the intensity and timing of their work. Relative to men, women work fewer hours per week, have more conventional work schedules, work less overtime, and experience more career interruptions.[1] These differences in labor supply along the extensive and intensive margins can explain a considerable portion of gender gaps in wages and earnings (Goldin, 2014; Blau and Kahn, 2017). But despite decades of research into gender disparities in labor supply, surprisingly little is known about gender gaps in the timing of work *throughout the year*. As a starting point, Figure 1 plots non–seasonally adjusted labor force participation rates for women and men, with June, July, and August shaded gray. A striking seasonal pattern emerges: summer after summer, women's labor force participation drops sharply, whereas men's participation is comparatively stable.

This paper provides the first systematic account of summer declines in female labor market activity. Using Current Population Survey data spanning 1989–2019, we first show that the employment-to-population ratio among prime-age US women falls by an average of 1.1 percentage points from May to July, with equal contributions from increased unemployment and diminished participation. This yearly decline is economically meaningful, amounting to almost one third of the decline in prime-age female employment during the Great Recession. In contrast, employment among prime-age men rises slightly over the summer. Declines in female work activity along the intensive margin reinforce those along the extensive margin: conditional on being employed, both women and men work fewer hours over the summer (primarily reflecting summer vacations), but for women the drop is larger and includes a sizable increase in unpaid time off. Combining both margins, women's total hours worked fall by 9.8 percent from May to July, more than twice the decline among men.

[1] See, for example, Bertrand, Goldin, and Katz (2010); Mas and Pallais (2017); Wiswall and Zafar (2018); Cortés and Pan (2019); Bolotnyy and Emanuel (2022); Cubas, Juhn, and Silos (2022); and Wasserman (2023).

School closures for summer break—and corresponding lapses in implicit childcare—provide a unifying explanation for these patterns. During the summer, parents use a patchwork of childcare arrangements, from summer school and camps to informal care by relatives, to account for the six to seven hours per weekday that children previously spent in school (Hoyer and Sparks, 2017). Because women shoulder a disproportionate share of childcare—as evidenced by observed patterns of parental time use as well as gender differences in single parenthood—their labor supply is likely to be more heavily influenced by seasonal reductions in access to external childcare. In addition, leisure complementarities—i.e., preferences for taking time off while their children are on summer break—may lead women to reduce employment over the summer.

To establish the central role of school closures, we show that the summer drop in female employment (1) is tightly synchronized with cross-state differences in the timing of schools' summer breaks; (2) is concentrated among mothers, especially those with young school-aged children; (3) is driven by an increase in non-participants who cite household or family duties as their main activity while out of the labor force; and (4) coincides with an increase in women's time spent engaging in childcare. These regularities are absent or much less evident among men. While these patterns are consistent with both childcare constraints and leisure complementarities, we provide evidence that leisure complementarities can explain at most half of the summer drop in female employment.

The gender gap in summer employment is driven in roughly equal parts by gender differences in sorting across sectors/occupations and by gender differences conditional on job type. First, women are disproportionately represented in the education sector, where employment plummets each summer. Although women may choose to work in the education sector for many reasons, working mothers may find jobs in that sector especially attractive because their work schedules are aligned with school calendars. Indeed, we show that women's propensity to work in education peaks precisely when their children are of school-going age. Second, both within and outside of the education sector, women are more likely to work in occupations that contract more sharply over the summer. Third, alongside these sorting effects, women in a given occupation also exit employment each summer at rates higher than their male counterparts. Within education, female teachers, managers, and bus drivers all work less over the summer than men in the same occupation. Outside education, too, women exit employment each summer at higher rates than men.

School closures for summer break may contribute to gender gaps in pay by reducing women's annual hours worked, curbing productivity, impeding human capital accumulation, or influencing job choices. We provide evidence for two such channels. First, we estimate that the summer drop in women's employment and hours leads to a contemporaneous earnings loss of 2.2 percent, whereas men's earnings remain unchanged. Second, among occupations represented both within and outside the education sector, we show that women systematically sort into education jobs. Since jobs in education typically pay less than comparable jobs outside of education, women may be trading off compensation for access to summer flexibility.

This paper contributes to the voluminous literature that studies gender disparities in labor market activity along both the extensive and intensive margins. Women's differential demand for temporal flexibility in work schedules—arising from actual or anticipated conflicts between work and childcare responsibilities—is one of the leading explanations for the remaining gender gaps in pay (Goldin, 2014; Wiswall and Zafar, 2018; Cortés and Pan, 2019; Cubas, Juhn, and Silos, 2022; Adams-Prassl et al., 2023; Wasserman, 2023).[2] Temporal demands are typically defined as the number and timing of hours worked per day or week, the predictability and location of those hours, and the extent to which the employer (versus the employee) has discretion over those hours (Mas and Pallais, 2017; Blau and Winkler, 2018; Wiswall and Zafar, 2018; Bolotnyy and Emanuel, 2022). Our paper focuses on an un-

[2]The differential effects of having children on women relative to men—the motherhood penalty—can explain the majority of gender gaps in earnings (Cortés and Pan, 2023). Parenthood causes steep declines in women's earnings and employment, while men's is largely unchanged (Angelov, Johansson, and Lindahl, 2016; Kleven, Landais, and Søgaard, 2019).

derexplored dimension of temporal flexibility—the timing of work throughout the year—and shows that childcare considerations prompt women both to gravitate to jobs that provide summer flexibility and to reduce their summer employment within a given job.

A closely related literature studies the labor market ramifications of school availability and timing. Expansions in the availability of schooling generally have positive effects on mothers' labor supply (Gelbach, 2002; Cascio, 2009; Fitzpatrick, 2012). With regard to the timing of schooling, Duchini and Van Effenterre (2022) find gains in the continuity of maternal employment when France's school week switched from having Wednesdays off to running Monday through Friday.[3] In a similar vein, Graves (2013) documents that year-round school schedules—which chop up the school year into smaller intervals of schooling—have negative effects on maternal employment. Focusing on parental time use throughout the year, Handwerker and Mason (2017) and Cowan, Jones, and Swigert (2023) find that mothers decrease time spent working and increase time spent in the presence of children when school is not in session. We contribute to this research by showing how a pervasive feature of educational systems—summer break—shapes the timing of women's employment, labor force participation, hours, and earnings.

Our paper also complements the literature on the gendered labor market effects of the COVID-19 pandemic.[4] Despite clear parallels, the school closures that occur each summer differ in important respects from those caused by the pandemic. While pandemic school closures were unanticipated, summer school closures are predictable events to which career choices have ample time to respond. In addition, while pandemic school closures were unprecedented events, school closures due to annual summer breaks are a longstanding fixture

[3] Philippe and Skandalis (2023) go on to show that mothers' job search tracks school schedules: mothers search for jobs more than non-mothers during the school day, and the same French reform increased mothers' job search on Wednesdays.

[4] See, among others, Heggeness (2020); Albanesi and Kim (2021); Alon et al. (2021); Goldin (2022); and Hansen, Sabia, and Schaller (2022).

of the US educational system.

Finally, we contribute to a body of research analyzing seasonal regularities both in the macroeconomy (e.g., Barsky and Miron, 1989; Olivei and Tenreyro, 2007; Geremew and Gourio, 2018) and among individual workers and households (Del Bono and Weber, 2008; Coglianese and Price, 2020). A recurring theme in these papers is that seasonal phenomena—though routinely regarded as statistical nuisances to be adjusted away—can have important real-world consequences that go unnoticed in adjusted or annualized data. Sounding the same theme, we demonstrate how seasonal lapses in publicly provided implicit childcare shape the timing and continuity of women's labor market activity.

2 Data and Methodology

We trace seasonal shifts in labor market activity using the Current Population Survey (CPS) and, secondarily, the American Time Use Survey (ATUS). We describe the CPS here, with further details in Appendix B.1. We defer discussion of the ATUS until later in the paper.

2.1 Sample construction

The CPS is a representative survey of US households conducted monthly by the US Census Bureau. From basic CPS extracts provided by IPUMS (Flood et al., 2023a), we assemble a person $\times$ year-month panel of civilians aged 25–49 spanning the years 1989–2019. By restricting our sample to prime-age adults, we largely abstract from seasonality in labor supply linked to individuals' own school enrollment and retirement decisions.[5] Our analysis period begins in 1989, when the CPS first reports actual hours worked during the reference week, and ends on the eve of the COVID-19 pandemic, which upended typical seasonal patterns. Appendix Table A.1 reports summary statistics for our CPS sample.

CPS households are in-sample for four consecutive months, out-of-sample for eight

[5]Our age restriction excludes most students from the sample: data from the 1989–2019 October CPS supplements show that just 6.8 percent of prime-age women and 4.9 percent of prime-age men are enrolled in school on a full-time or part-time basis.

months, and then back in-sample for a final four months. We use the cross-sectional dimension of the CPS to trace seasonality in labor market stocks, and we use the longitudinal dimension to track labor market flows both month-to-month and year-to-year (Drew, Flood, and Warren, 2014). For cross-sectional analyses, we use IPUMS sampling weights to ensure that our estimates are representative of the prime-age US population. For longitudinal analyses, we construct sex-specific raked sampling weights that ensure consistency between labor market stocks and flows throughout our analysis period (Frazis et al., 2005).

We observe household characteristics and labor market activity as of the survey reference week, which usually includes the 12th day of the month. We partition individuals into those employed, those unemployed, and those not participating in the labor force. To account for vacation/leave-taking during the summer months, we separately analyze whether individuals are employed and at work or employed but absent from work. Tracking whether or not individuals are employed and at work also sidesteps the subtleties of how education sector employees report spells of non-work during the summer months. We also leverage CPS data on industry, occupation, earnings, and actual hours worked during the reference week; stated reason for absence as well as paid versus unpaid leave for those absent from work; and reasons for non-participation or unemployment among those not employed.

We distinguish between individuals who are (i) married, with a spouse present, versus (ii) unmarried, separated, or married with an absent spouse. We define parental status based on the presence or absence in the household of one or more own children under age 18. This definition includes adopted and step-children as well as biological children; it excludes other children residing in the household as well as children who have already moved out.

2.2 Main specifications

We employ simple regression specifications that recover the typical seasonal movements in a given time series. Because the variation of interest is cross-month, we aggregate our data to the year-month level for each population we consider. To trace seasonal shifts in labor market activity, we then estimate time-series specifications of the form

$$y_t = \alpha + \sum_{m \neq 5} \beta_m \cdot \mathbb{1}\{M(t) = m\} + f(t) + \gamma \cdot weeks_t + \varepsilon_t \tag{1}$$

where y_t is an outcome in year-month t, $M(t) \in \{1, 2, \ldots, 12\}$ returns the calendar month, $f(t)$ controls for lower-frequency trends, and $weeks_t$ is the number of weeks elapsed since the previous month's reference week. Because our focus is on summer work interruptions, we normalize β_5 to zero, so that the coefficients of interest β_m capture average differences in an outcome relative to May—just before the start of summer break.[6]

To account flexibly but parsimoniously for secular trends and business-cycle dynamics that might otherwise bias estimation of seasonal patterns, we specify $f(t)$ as a linear spline in calendar time, with knots at roughly five-year intervals corresponding to turning points in the prime-age employment and participation rates (see Appendix B.2 for details). Our spline function flexibly allows for non-parametric time trends in these and other outcomes. We also control for the number of weeks elapsed between successive months' reference weeks, since these time intervals are correlated with month length and holiday timing. We estimate Equation (1) separately for each of the demographic groups we consider, since trend and cyclical movements in labor market outcomes vary strongly with sex and household structure.

Equation (1) is designed for use with stock variables, such as employment rates. When examining labor market flows, we estimate the first-differenced analogue of Equation (1):

$$\Delta y_t = \sum_{m \neq 5} \delta_m \cdot \mathbb{1}\{M(t) = m\} + \Delta f(t) + \theta \cdot \Delta weeks_t + \Delta \varepsilon_t \tag{2}$$

where Δy_t represents gross inflows, gross outflows, or net flows into employment as a share of the relevant population. Here, the coefficients of interest δ_m capture the magnitude of flows between months $m - 1$ and m relative to April–May flows, and the differenced spline

[6] Only the June, July, and August reference weeks are affected by summer break: the share of 16-year-old CPS respondents currently enrolled in school hovers between 94 and 95 percent from September through May.

terms allow for structural breaks in flow rates at the knot dates.

In both stock and flow specifications, we allow for heteroskedastic and autocorrelation-consistent standard errors correlated up to a maximum lag of 26 months, a horizon suggested by the automatic lag selector of Newey and West (1994).[7] When our interest lies in transformations of the estimated coefficients, we construct confidence intervals via the delta method.

3 Summer Declines in Female Employment and Hours

This section establishes that women's labor market activity contracts each summer—along both extensive and intensive margins—in ways much less evident among men.

3.1 Women's employment drops in the summer

We start with the extensive margin. Figure 2 plots coefficients $\widehat{\beta}_m$ from estimating Equation (1) for employment, unemployment, and non-participation, separately for men and women, with each measure expressed as a percentage of the corresponding population. As shown in the left panel, the prime-age female employment-to-population ratio (EPOP) declines by 1.1 percentage points (p.p.) between May and July—amounting to 1.5 percent of its May level—and then rebounds strongly in the fall. Unemployment and non-participation contribute equally to the summer reduction in women's employment, with each rising 55 basis points from May to July. The drop in employment appears relatively stable over time, with no obvious trend or cyclical variation in its magnitude (Appendix Figure A.1), and it occurs consistently across age, education, and racial and ethnic groups (Appendix Figure A.2).

The summer drop in female employment is sizable, equaling almost one third of the decline in prime-age female EPOP in the wake of the Great Recession.[8] If these summer

[7]We chose the lag structure of 26 months by running our main specification separately by sex and by sex $\times$ household structure for key outcome variables. Across specifications, the optimal maximum lag often equaled (and never exceeded) 26 months.

[8]Prime-age female EPOP fell 3.7 p.p. from the start of the Great Recession in December 2007 (72.4 percent) to its nadir in September 2011 (68.7 percent). Source: BLS Labor Force

rates held at their May levels throughout June, July, and August, women's average annual EPOP and labor force participation rate would be 0.2 p.p. and 0.1 p.p. higher, respectively.

In contrast to these patterns, prime-age male employment actually *rises* slightly over the summer months. We note that another seasonal downturn occurs during winter, when men's employment falls more sharply than women's. Prior research attributes the winter downturn to two main factors: cold and inclement weather, which triggers job losses in sectors like construction and agriculture, and a post-holiday retreat in consumer spending, which reduces labor demand not only in retail but also in complementary sectors like manufacturing and transportation (Barsky and Miron, 1989; Beaulieu and Miron, 1992; Geremew and Gourio, 2018). The bulk of the drop in male employment between October and January originates in winter-sensitive sectors, particularly construction (Appendix Figure A.3). Because the main drivers of the winter downturn—adverse weather and the winter holidays—are not operative in the summer months, we confine our analysis to summer work interruptions, though we continue to show year-round seasonal movements to place the summer in context.

3.2 The employment drop mostly stems from increased outflows

The summer drop in female employment could reflect weak inflows to employment, strong outflows from employment, or both. Along the inflow margin, some women might choose to delay labor market entry until the end of the summer or conduct only a limited job search over the summer. Along the outflow margin, women may be subject to summer layoffs or choose to quit their jobs at the start of the summer. In Appendix C.1, we show how the flow coefficients $\widehat{\delta}_m$ from estimating Equation (2) for gross inflows and outflows can be transformed to express month-to-month changes in employment rates as *excess inflows* minus *excess outflows*. Intuitively, employment falls between two consecutive months if monthly outflows exceed their annual average and/or if inflows fall short of their annual average.

Figure 3 decomposes month-to-month changes in EPOP into these respective margins.

Statistics, series LNS12300062.

The left panel shows that the summer drop in female employment is primarily a story of summer exits: elevated May–June and June–July outflows (relative to the annual average) drive female employment rates down by a combined 0.9 p.p. from May to July, while depressed inflows contribute an additional 0.2 p.p. The summer decline reverses in autumn, when employment is buoyed by a wave of entries.

For many women, summer exits are a recurring phenomenon, rather than one-time occurrences. Following Coglianese and Price (2020), we find that women who exit employment between May and June in a given year are 4.9 p.p. more likely to experience another such separation exactly 12 months later than would be expected based on separation rates 11 and 13 months after baseline (see Appendix Figure A.4 and Appendix E.1 for details).

3.3 Summer hours contract more for women than for men

The summer drop in female employment is also evident in average hours worked during the reference week. To encompass shifts in labor market activity along both extensive and intensive margins, we code non-employed individuals as working zero hours. As shown in the left panel of Figure 4, women's hours fall by an average of 2.6 per week between May and July. Men's hours also decrease, but only by 1.4 per week. Since women work considerably fewer hours than men on average—owing to both lower employment rates and shorter workweeks—expressing hours in levels understates the magnitude of the gender gap. The right panel shows a much steeper drop in log hours among women (equivalent to 9.8 percent) than among men (3.6 percent).

To decompose the summer drop in hours between the extensive and intensive margins, Appendix Table A.2 tallies up changes in hours worked among respondents observed from May through July as they shift between three statuses: employed and present at work, employed but absent, and non-employed. In line with their drop in employment, women experience a modest reduction in hours along the extensive margin. This change is reinforced by much larger reductions on the intensive margin, reflecting both increased week-long absences from work and a small reduction in hours worked conditional on working in both May and July. For men, the entirety of the decline in summer hours comes via intensive margin changes, again primarily in the form of increased absences. For both groups, the increase in summer absences is driven by workers who say they are taking vacation or personal days. Men's elevated absences, however, are almost entirely paid time off, whereas women's also reflect a sizable increase in unpaid absences (Appendix Figure A.5).

Women also experience *prolonged* summer work interruptions at higher rates than men. We define non-work as being either non-employed or absent from work during a month's reference week. During the summer months, women and men experience similarly sharp upticks in periods of non-work that encompass exactly one reference week. But women experience a much larger uptick than men in non-work that encompasses two or more consecutive months' reference weeks. These patterns suggest that men's intensive-margin changes in summer hours are almost entirely due to brief, paid vacations, whereas women's also include unpaid absences from work and longer periods of non-work (Appendix Figure A.6).

4 School Closures as a Unifying Explanation

Why does female employment fall over the summer? School closures for summer break—which disrupt implicitly provided childcare—provide a unifying explanation. Below we give an overview of summer childcare arrangements, then outline a model of labor supply that incorporates school closures and yields predictions as to employment and sectoral allocation.

4.1 School closures and summer childcare arrangements

Childcare needs change substantially over the summer. During the school year, working parents of school-aged children need to arrange childcare before and after school hours as well as during weekend and overnight shifts. When schools close for summer break, parents must additionally account for the six to seven hours per weekday their children previously spent in school (Hoyer and Sparks, 2017). Working parents use a panoply of summer care arrangements, the most common of which are organized care (such as summer camps and summer schools), care by relatives, and having children look after themselves (Capizzano, Adelman, and Stagner, 2002). Since most summer programs do not span the full length of summer, nor cover the full work day, families often require multiple types of care.

Over 40 percent of working parents with school-aged children pay for childcare over the summer months (Capizzano, Adelman, and Stagner, 2002). The cost of summer programs varies by state and municipality; five weeks of summer programs for two children range from $1,400 in Wisconsin to $6,700 in Nevada (Novoa, 2018). In a survey conducted by the Center for American Progress, half of parents report that costs are a barrier to finding adequate summer care. An even higher percentage report that at least one parent plans to make a job sacrifice—in the form of reduced hours worked, fewer days worked, use of unpaid time off, or leaving the labor force—to accommodate summer childcare needs (Novoa, 2019).

4.2 Conceptual framework

To frame our subsequent analysis, we describe a two-period model with career choices and childcare considerations that can rationalize the summer drop in female employment as a byproduct of the traditional school calendar. We formalize the model in Appendix D.

Model setup. We consider a two-period partial equilibrium model in which individuals decide whether and in which sector to work at different points throughout the year and throughout their lives. Each period represents a distinct phase of the life cycle—pre-parenthood or parenthood—and is subdivided into two seasons, the summer and the school year. In each season, an individual may choose to (i) work in the education sector, (ii) work in the non-education sector, or (iii) not work. We highlight two key assumptions.

First, we assume that jobs differ in the extent to which they reward continuous employment or (equivalently) penalize interrupted employment. Jobs in the education sector provide *summer flexibility*: education workers may choose whether or not to work during summer break without affecting their earnings during the school year. By contrast, non-education jobs offer a continuity bonus for full-year employment.[9] Together, these assumptions imply

[9]Some employers might only hire workers who commit to full-year employment; others

that the earnings penalty for summer work interruptions is smaller in the education sector. While the sectors differ in their treatment of *within-year continuity*, both sectors reward *career continuity*: individuals who stay in the same sector throughout their careers receive an earnings premium for doing so, reflecting factors such as specific human capital, backloaded salary scales, or the vesting of pension benefits.

Second, we allow the disutility of work to vary across seasons. In particular, some parents find it especially costly to work over the summer for either (or both) of two possible reasons. The first is *childcare constraints*: while schools provide implicit childcare during the school year, working parents must arrange costly childcare arrangements when schools are closed for the summer. The second is *leisure complementarities*: parents may especially dislike working over the summer because they forgo opportunities to spend time with their children. In keeping with observed patterns of parental time use (Handwerker and Mason, 2017), we assume that mothers shoulder a disproportionate share of these utility costs, since they are more likely to be single parents and, if married, are less likely to have a non-working spouse available to cover childcare. Within two-earner households, gender gaps in earnings and gender norms regarding the division of labor could lead women, rather than men, to curtail their summer employment.

Model predictions. Our framework yields three intuitive predictions regarding how schools' summer breaks shape employment patterns throughout the year and over the life cycle.

1. Summer childcare costs lead to a summer employment drop among women generally and among mothers in particular.
2. Conditional on working in a given sector during the school year, women are less likely to work over the summer than are their male counterparts. These gender differences arise in both the education sector and the non-education sector.
3. Summer childcare costs induce some women to sort into education jobs in pursuit of summer flexibility. Such sorting takes two forms. The first is *contemporaneous sorting*:

might offer a lower-paying career track for those who seek fewer hours/weeks per year.

some women work in non-education early in their careers, then switch to education jobs once they have school-aged children. The second is *anticipatory sorting*: due to the returns to career continuity, some women sort into education jobs earlier in their careers in anticipation of future childcare considerations.

We explore these predictions empirically throughout the rest of the paper.

5 Timing and Incidence of the Summer Drop

In this section, we provide a constellation of evidence that the summer drop in female employment stems from school closures. First, we show that the timing of the drop lines up with cross-state differences in the timing of schools' summer breaks. Second, we show that mothers of school-aged children are especially likely to experience summer declines in employment. Third, these declines are accompanied by an uptick in time spent on childcare.

5.1 The summer drop in female employment tracks school calendars

We exploit cross-state variation in the timing of school closures to establish that the summer drop in female employment is inextricably tied to school summer breaks.[10] To determine when schools typically close in each state, we leverage information about how many 16-year-old CPS respondents report being enrolled in high school during the May, June, and July reference weeks. For each state, we compute the average decline in school enrollment rates from May to July during our analysis period. We then classify as "early-closure states" those in which at least two thirds of this decline occurs between May and June; we classify as "late-closure states" those in which less than one third of the decline occurs between May and

[10] A small share of public schools use year-round schooling, in which schools replace summer break with shorter breaks throughout the year. The share was 6.1 percent in 1999–2000 but fell to 3.0 percent by 2017–18 (National Center for Education Statistics, 2018). The summer drop in female employment is unchanged if we exclude California, which has a particularly high share of students in year-round schools.

June. The remaining states have "mixed closures".[11] Our measure lines up closely with an alternative classification based on teachers' presence at school (see Appendix Figure A.8).[12]

Applying this classification, the right panel of Figure 5 plots the summer drop in female employment separately for each group of states. In states where the large majority of K–12 schools have closed by the June reference week, female employment starts to decline in June. By contrast, in states where most closures occur between the June and July reference weeks, female employment instead holds steady in June and starts its decline in July.[13] In both cases, female employment rebounds by September, as schools have reopened nationwide by the September reference week. The tight synchronization between school summer breaks and low female employment points to school closures as the underlying cause.[14]

5.2 The summer drop is largest for women with young school-aged children

Our conceptual framework predicts that summer declines in employment will be most pronounced among women who experience lapses in externally provided childcare during the summer months. To test this prediction, the left panel of Figure 6 examines heterogeneity in women's seasonal employment patterns by the presence/absence of a spouse interacted with the presence/absence of an own child under 18 in the household. Within both spousal groups, the presence of children amplifies the summer drop in female employment. The

[11] Most states in the US interior and the South Atlantic have early school closures, while much of the Northeast and Washington state have late school closures (Appendix Figure A.7).

[12] State-level differences in closure timing are also quite stable over time. If we compute our classification separately in the first and last decades of our sample period, 46 of 51 states (and DC) would receive the same classification.

[13] These patterns do not stem from cross-state differences in climate: we find similar patterns when comparing late-closure states in the Northeast to early-closure states at similar latitudes in the East North Central Census division.

[14] As shown in Appendix Figure A.9, male EPOP rises rapidly in the spring and stabilizes over the summer, but the inflection point comes a month earlier in early-closure states.

decline is steepest, at 1.6 percentage points, among married mothers residing with their children. These patterns align with a life-cycle fact: the summer drop in female employment is larger during women's prime child-rearing years (Appendix Figure A.10).[15]

Childcare needs are most likely to constrain summer employment when children are old enough to attend school from fall through spring, but too young to be left unattended for extended periods of time. Since childcare constraints are likely to be determined by a mother's youngest child, the right panel of Figure 6 stratifies mothers (of any marital status) by the age of that child: children under 6 years old, who have yet to enter the K–12 education system; those aged 6–12, who attend school and require supervision when not in school; and those aged 13–17, who attend school and require less supervision when not in school. Mothers of children aged 6–12 experience the largest drop in employment, of 2.3 percentage points. For this group, the annual average EPOP and labor force participation rates would be 0.5 p.p. and 0.3 p.p. higher, respectively, if these rates were to hold at their May levels through the months of June, July, and August. Declines in summer employment are also substantially larger for women with two children relative to one child, especially for those aged 6–12 (Appendix Figure A.11). By contrast, no subgroup of men experiences a decline in summer employment (Appendix Figure A.12 and Appendix Figure A.13).

Joint employment patterns among opposite-sex married couples confirm that—within a couple—women reduce their employment during the summer (Appendix Figure A.14). During the summer months, the share of married households with both spouses employed falls by 1.3 percentage points, driven almost entirely by an increased share of households with only the husband employed.[16] The shift from two-earner to husband-only households

[15] The summer drop is also present among women who are 60–65 years old, consistent with grandmothers reducing employment to care for grandchildren (Frimmel et al., 2022).

[16] These patterns could arise if couples sort into jobs with offsetting seasonal characteristics (or match on seasonality), either to smooth out household income or to promote continuity in childcare availability throughout the year. In practice, however, spouses instead tend to

is especially pronounced among couples with young school-aged children.

5.3 Women spend more time on childcare in the summer months

Our assertion that childcare responsibilities account for women's reduced summer employment is consistent with their self-reported summer activities. Beginning in 1994, the CPS reports each non-participant's major activity while not in the labor force. As shown in the top panel of Figure 7, both for prime-age women as a whole and for mothers of school-aged children in particular, the increase in non-participation is almost fully accounted for by an increase in the share of women who report that they are "taking care of house or family".[17] In contrast, women without children in the household exhibit no summer change in labor force participation (and only a slight increase in their propensity to cite household duties in the event of non-participation). Men show little change over the summer in non-participation linked to taking care of house or family (Appendix Figure A.15.)

Some of the summer increase in female unemployment may also reflect women providing childcare while waiting to be called back to work. As shown in the bottom panel of Figure 7, the uptick is driven—especially for mothers—by a jump in the share of respondents who are job losers on temporary layoff (i.e., awaiting recall). Since temporary summer layoffs are concentrated in the education sector, they are likely to align closely with the span of time for which a laid-off worker's children are on summer break.[18]

To further probe the role of childcare in women's time allocation during the summer months, we turn to the American Time Use Survey (Flood et al., 2023b). We compute total childcare time by summing time spent on primary childcare (childcare as one's main activity)

work in sectors with similar seasonal patterns.

[17] A small share of prime-age women are enrolled in school, and we observe a partly offsetting decline in the number of non-participants whose major activity is being in school.

[18] The education sector accounts for 59.8 percent of the summer increase in the share of women who are unemployed on temporary layoff (Appendix Figure A.16), with additional summer layoffs in child day care services and bus service and urban transit.

and secondary childcare (childcare while doing other tasks) (see Appendix B.3 for details). We decompose secondary childcare according to the primary tasks that accompany it: leisure activities, household activities, or other activities. Motivated by our earlier results, we focus on parents whose youngest child is aged 6–12.

Consistent with summer school closures prompting women to shift their time use from employment to childcare, the left panel of Figure 8 shows that mothers' total time spent on childcare rises by 8.8 hours per week from May to July, with similarly elevated levels in June and August. This overall increase embeds a sharp rise in secondary childcare partly offset by a reduction in primary childcare.[19,20] Consistent with the more modest drop in men's hours worked primarily associated with summer vacations (Figure 4), the right panel of Figure 8 shows that fathers experience a smaller—and more fleeting—rise in total childcare time, owing mainly to increased secondary childcare while engaged in leisure activities.

5.4 Childcare constraints or leisure complementarities?

The above patterns demonstrate tight linkages between school closures, summer declines in women's employment, and disproportionate shifts in women's summer time use toward childcare. These patterns are consistent with two non–mutually exclusive explanations. The first is childcare constraints: female employment may decline over the summer because of lapses in the implicit childcare provided by schools. The second is leisure complementarities: women may take time off from work over the summer because their preference for leisure is

[19]This pattern is consistent with other research finding a summer decline in primary childcare involving educational activities, such as helping children with their homework (Handwerker and Mason, 2017; Cowan, Jones, and Swigert, 2023).

[20]Appendix Figure A.17 shows that, relative to May, total time spent on childcare is stable over the summer and declines a bit during the rest of the year for parents whose youngest child is under 6. Primary childcare time is near constant throughout the year for mothers whose youngest child is 13–17 (the ATUS does not report secondary childcare for this group).

stronger when children are off from school.

We provide evidence that leisure complementarities are unlikely to be the primary determinant of the decline in women's summer employment. In Appendix Figure A.18 we examine seasonality in vacation-related absences from work, a proxy for leisure. Mothers of children aged 6–12 and 13–17 exhibit nearly identical increases in vacation-taking during the summer months, suggesting that preferences for spending time with children when they are off from school are similar across these groups. But mothers of children aged 6–12—who incur the largest increase in childcare costs over the summer—experience a 1.1 percentage point larger reduction in summer employment than mothers of children aged 13–17 (Figure 6). Under the (strong) assumption that the entire decline in employment among mothers of children aged 13–17 is due to leisure complementarities, the excess decline among mothers of children aged 6–12 can be attributed to childcare constraints. Using the estimates from Figure 6, only half of the decline in employment among mothers of children aged 6–12 can be explained by leisure complementarities. Given that employment also declines for women without children in the household, we view this calculation as an upper bound on the potential contribution of leisure complementarities.

Demographic differences in women's summer employment patterns do not militate clearly in favor of either hypothesis (Appendix Figure A.2 and Appendix Table A.3). First, relative to high school graduates, college graduates exhibit a larger summer drop that can be fully explained by their greater propensity to work in education. Controlling for attachment to the education sector, college graduates are, if anything, *more* likely to keep working over the summer, consistent with the possibility that they can better afford externally provided childcare. Second, women with less than a high school education exhibit no significant summer drop; furthermore, relative to white women, Black women exhibit a smaller summer drop that is only partly explained by differences in household structure or sectoral affiliation. These patterns may suggest that groups with fewer financial resources have less scope to reduce their labor income over the summer.[21]

6 Job Sorting and Within-Job Gender Differences

Our conceptual framework in Section 4 yields predictions about the sectoral allocation and within-sector employment patterns of individuals for whom summer work is especially costly. In this section, we show that the gender gap in summer work interruptions reflects gender differences both in sorting across jobs and in employment conditional on job type. Using a formal decomposition, we find roughly equal contributions from both channels.

6.1 Job sorting contributes to the summer drop

Women are disproportionately employed in the education sector—which accounts for 13.3 percent of female workers in May, compared with just 4.7 percent of male workers. Because employment in education contracts sharply over the summer, while employment in other sectors expands (Appendix Figure A.19), gender differences in sectoral sorting may contribute to the summer drop in female employment.[22] Even *within* education, women are more likely to work in occupations that shed more workers over the summer. For example, the share of women employed in education who work as primary school teachers is nearly twice that of men, while the reverse is true for secondary school teachers (Appendix Table A.4). Averaging male and female separation rates, primary school teachers are 1.7 p.p. more likely than

[21]We find that greater *family* resources—proxied by family income and spousal education—do not consistently correspond to larger drops in mothers' employment during the summer. The effect of family resources on the summer drop is theoretically ambiguous: greater resources may enable women either to continue working over the summer (by purchasing external childcare) or, instead, to reduce work over the summer (to spend time with their children).

[22]The summer drop in education employment is also found in the Current Employment Statistics, which measures the number of employees paid during the pay period that includes the reference week (Appendix Figure A.19).

secondary school teachers to exit employment from May to July.

These patterns are consistent with women seeking out jobs with summer flexibility to navigate summer lapses in school-provided childcare. But women might gravitate toward the education sector for other reasons, such as tastes, comparative advantage, historical path dependence in occupational choice, or norms. To test whether childcare demands contribute to women's sorting into education, we examine the propensity to work in education based on the age of one's youngest child (Appendix Figure A.20). Relative to mothers with a newborn, the share of working mothers employed in education first declines with child age, rises as the youngest child reaches school age, peaks when the youngest child is 10 years old, and then declines as the youngest child progresses through adolescence. In contrast, fathers' propensity to work in education is invariant to the age of their youngest child.

6.2 Within-job differences contribute to the summer drop

Our model predicts that—both in and outside of the education sector—women will be less likely to work over the summer than men in similar jobs. In the education sector, we observe gender differences even within narrowly defined occupations: as shown in Figure 9a, female primary school teachers, secondary school teachers, managers in education, and school bus drivers are all more likely to exit employment each summer than their male counterparts.

A potential concern with these comparisons is that women and men who work in education may—conditional on their objective status—differ in their likelihood of reporting being non-employed versus employed but absent from work.[23] If we instead measure the rate of transitioning from positive hours worked in the reference week to zero hours worked, without distinguishing between absence and non-employment, the same qualitative picture emerges, and the gender gaps are generally even larger in absolute terms (Appendix Figure A.21).

[23] Among individuals employed in the education sector as of May, 55.8 percent are employed and present at work in July. School employees may keep working over the summer by, for example, teaching summer classes, coaching sports, or finding work in another sector.

Outside of the education sector, women are also more likely than men to exit employment during the summer. The left panel of Figure 9b shows that, in each summer month (relative to May), the rate of exiting employment for workers outside of the education sector is higher for women than for men. This gender difference is not simply incidental: the right panels show that women's rates of exiting non-education employment are tightly connected to school calendars. Using our earlier classification of early- and late-closure states, we observe that outside of the education sector, women experience an upswing in exits from employment precisely when schools in their state close for summer break.

Which occupations—outside of the education sector—contribute to the summer decline in women's employment? When we consider 23 broad occupational categories (detailed in Appendix B.1), we find that six of them experience substantial net flows of women into non-employment: teachers (outside of the education sector), personal services, other administrative support, secretaries and records clerks, sales, and food services. These six occupations also offer more flexibility than the non-contributing occupations in terms of lower actual and usual hours worked and higher rates of part-time employment.

To corroborate that non-education jobs contribute to the summer drop in female employment, we estimate our baseline specification in a subsample of women who had no connection to the education sector during their first four months in the CPS and are now being observed one year later (Appendix Figure A.22). Imposing this sample restriction attenuates the summer drop in employment to 0.6 p.p., which continues to be both economically and statistically significant. The estimates are little changed if we exclude two additional groups of women whose previous jobs might potentially be structured around the school calendar: teachers outside of the education sector as well as workers in child day care services.

6.3 Quantifying the roles of job-sorting and within-job effects

What share of the gender gap in summer work interruptions reflects gender differences in job sorting, and what share reflects gender differences conditional on job type? To answer this question, we develop a nested Kitagawa-Oaxaca-Blinder decomposition that quantifies contributions from six distinct channels. We describe the decomposition verbally here and formalize it in Appendix C.

Consider the May–July change in women's EPOP minus the same change among men. Men and women differ in their allocation across job types, which in turn differ in their propensity to generate net outflows from employment between May and July. Conditional on job allocation, men and women also differ in their propensity to exit employment. By the standard Kitagawa-Oaxaca-Blinder logic, we can thus decompose the gender gap in summer work interruptions as

$$\text{overall gender gap} = \text{between jobs} + \text{within jobs} \tag{3}$$

We define "jobs" on the basis of both sector and occupation (Appendix B.1). Within the education sector, we distinguish five job types: (i) pre-K, kindergarten, and primary school teachers; (ii) secondary school teachers; (iii) postsecondary teachers; (iv) other staff in elementary and secondary schools; and (v) other staff in education. Outside of education, we distinguish 23 job types using the same broad occupation groups used in Section 6.2. Using these job groupings, we can subdecompose the "between" component as

$$\begin{aligned} \text{between jobs} = \; & \text{sorting into education versus non-education} \\ & + \text{sorting across occupations within education} \\ & + \text{sorting across occupations outside of education} \\ & + \text{baseline differences in EPOP} \end{aligned} \tag{4}$$

The first of these terms captures gender differences in sorting into education, coupled with the fact that education contracts each summer relative to non-education. The second term captures gender differences in sorting across education jobs, which likewise differ in their seasonal patterns; for example, primary school teachers are more likely to exit employment each summer than are secondary school teachers. The third term captures gender differences in sorting in the rest of the labor market; for example, men are disproportionately employed in the construction trades, which expand every summer, relative to health services, which are comparatively stable through the summer months. The final term, a scaling component that adjusts for gender differences in baseline EPOP, is of little economic interest and is quantitatively small in practice.

The within-job component, in turn, can be expressed as a share-weighted average of the gender difference in employment seasonality observed within each job type. Summing these differences across education and non-education jobs, we obtain

$$\text{within jobs} = \text{within education jobs} + \text{within non-education jobs} \tag{5}$$

Differences in the propensities of male and female secondary school teachers to exit employment over the summer will be credited to the within-education term. Likewise, differences between male and female salespeople will be credited to the within-non-education term.

Figure 10 implements this decomposition, with the methodology extended to span the full calendar year.[24] Between May and July, female EPOP declines by 1.1 p.p. while male EPOP rises by 0.1 p.p., yielding a 1.2 p.p. gap to explain. Consistent with the evidence presented in Section 6.1 and Section 6.2, each of the five components emphasized above contributes to this overall gap. Sorting into education explains 32 percent of the overall change, while sorting across jobs within the education sector contributes an additional 7 percent. Sorting outside of education (e.g., between construction trades and health services) explains 21 percent of the total. Finally, gender differences within education and non-education jobs account, respectively, for 26 percent and 21 percent of the total. All in all, gender differences in job sorting explain a little over half of the gender gap in summer work interruptions, and gender differences conditional on job type explain a little under half.[25]

[24] Appendix Table A.5 presents point estimates and standard errors. Appendix Figure A.23 presents analogous results using an indicator for being employed and present at work.

[25] The shares attributed to these five components sum to a little over 100 percent, owing to the small baseline EPOP scaling term acting in the opposite direction.

7 Implications for the Gender Pay Gap

We next provide evidence that summer drops in employment and hours reduce female earnings and consequently contribute to the gender pay gap. While we focus our discussion on the role of summer childcare constraints in generating declines in women's earnings, we note that leisure complementarities would yield similar implications for pay.

7.1 Potential channels for summer childcare constraints to affect earnings

Summer childcare constraints may decrease women's earnings through several channels. First, reductions in work activity along the extensive and intensive margins could directly reduce women's earnings if they are not compensated for time off.[26] Second, conditional on working, women might disproportionately seek out employment in the education sector, which offers summer flexibility but lower compensation; likewise, they may seek work in other sectors (such as retail) that accommodate intermittent employment but offer few opportunities for career advancement. Third, summer reductions in work activity may diminish women's productivity. Fourth, summer work interruptions could reduce future earnings by impeding human capital accumulation or signaling less commitment to the employer.[27] We provide evidence on the first two channels below.

7.2 Reduced work contributes to gender gaps in pay

We quantify the direct effect on earnings using data from the CPS Outgoing Rotation Groups. First, we assign non-employed individuals zero weekly earnings. Second, for those who worked positive hours during the reference week, we set weekly earnings equal to (i) hourly

[26] Anticipation of these constraints could also dissuade some women from participating in the labor force if there are steep costs associated with summer childcare or substantial penalties associated with taking time off for childrearing (Bertrand, Goldin, and Katz, 2010).

[27] If employers expect female workers to engage in summer childcare, they may statistically discriminate against women by offering fewer hours or more flexible work arrangements at the expense of less flexible work with better career prospects.

wage times actual hours worked, if paid hourly, or (ii) *usual* weekly earnings, if salaried. Third, for those absent *with* pay, we use their usual weekly earnings. Lastly, for those absent *without* pay, we assign zero earnings. Our earnings measure captures the summer spike in uncompensated time off (Appendix Figure A.5), while conservatively assuming that all workers receive full compensation if absent with pay.

Figure 11 plots seasonality in weekly earnings in both levels and logs. Consistent with the decline in female employment and hours worked, women's weekly earnings fall sharply over the summer: relative to May, the average drop over June/July/August is $12.43, or 2.2 percent of the May level.[28] Notably, half of this decline in women's earnings stems from uncompensated time off among salaried workers. By contrast, men's earnings are stable over the summer months, implying that the gender gap in pay widens over the summer.

A conceptual question here is how to treat teacher compensation, since many teachers who only work during the school year have their salaries paid out in equal installments throughout the year.[29] At one extreme, we could view teachers as generating earnings only when they are actually working, regardless of when they receive paychecks. At the other extreme, we could view teachers as generating earnings smoothly throughout the year, again regardless of pay timing. Since our baseline estimates take teachers' self-reported pay status at face value, we implicitly adopt an intermediate assumption. If we instead assign positive earnings to teachers who are absent without pay, we obtain a 1.3 percent summer decline in

[28]The summer drop in women's earnings may increase the variability of household income. In particular, while unemployment insurance partly offsets earnings losses for many seasonally unemployed workers (Coglianese and Price, 2020), layoffs from the education sector are subject to special federal rules that render many unemployed school employees ineligible for benefits (US Department of Labor, 2023).

[29]The 1999–2000 Schools and Staffing Survey shows that almost 90 percent of school districts employ teachers on 9- or 10-month contracts. Many districts disburse teachers' salaries across 12 months or give teachers the option of doing so (Schmitz, 2018).

women's weekly earnings (and an insignificant summer increase in men's earnings).[30]

However, this alternative calculation may understate gender gaps in summer earnings by smoothing out differences among teachers themselves. In Appendix Figure A.24 and Appendix E.2, we use data from the 1999–2000 Schools and Staffing Survey (Tourkin et al., 2004) to show that male teachers earn, on average, $2,600 during the summer from supplemental work in or outside of schools. Women, by contrast, earn less that half that amount. Because our alternative calculation puts teachers who are employed but absent on equal footing with (disproportionately male) teachers who are present at work, it likely understates the contribution of summer earnings disparities to the gender gap in annual earnings.

7.3 Job sorting contributes to gender gaps in pay

Women's disproportionate representation in the education sector, in part due to its provision of summer flexibility, may also contribute to gender gaps in *annual* earnings.[31] In Figure 12a we select 29 two-digit occupations present in both the education and non-education sectors, then compute the female share of each occupation, by sector. The female share is higher in the education sector for 24 out of 29 occupations, often by a wide margin.[32] Using these same occupations, we then estimate the education-sector earnings premium or penalty in each occupation by estimating a Mincer regression on annual *male* earnings in the Annual Social

[30] Among education-sector teachers who are absent from work in July, 68 percent are absent with pay and assigned positive earnings in our baseline analysis. The rest are absent without pay and assigned zero earnings. In the alternative calculation, we assign usual weekly earnings to education-sector teachers who are salaried and absent without pay.

[31] It is also possible that motherhood penalties are smaller in the education sector, in which case such sorting could reduce gender gaps in pay (Fontenay, Murphy, and Tojerow, 2023).

[32] Appendix Figure A.25 shows that the education sector provides flexibility during the school year as well. In 24 of the 29 occupations, the prevalence of part-time employment outside of the summer months is substantially higher among men in the education sector than among those outside of education.

and Economic Supplement to the March CPS. As shown in Figure 12b, a large majority of occupations display an earnings penalty associated with working in education, suggesting that women may be trading off compensation for summer flexibility (among other amenities). These earnings penalties are driven largely by lower hourly wages in education jobs (Appendix Figure A.26).

8 Conclusion

This paper documents pervasive summer declines in women's labor market activity. Extending prior research into the causes and consequences of interruptions to women's careers, we show that the employment-to-population ratio among prime-age US women declines by 1.1 percentage points from May to July, while their total hours worked fall by 9.8 percent. In contrast, men's employment increases slightly over the summer, and their hours fall less than half as much. We establish the central role of school closures in driving these patterns. Importantly, these interruptions contribute to gender gaps in pay: women's weekly earnings fall by 2.2 percent over the summer months, whereas men's earnings remain unchanged.

The heavy imprint of school summer breaks on female labor force participation, employment, hours, and earnings highlights the potential need for policy solutions to alleviate the remaining barriers to women's equal participation in the labor market. Moreover, the ramifications of lengthy summer breaks extend beyond the labor market: education researchers have long documented that students lose skills and knowledge during summer breaks (Quinn and Polikoff, 2017). Policy options such as extending the school year, providing universal access to summer school, or increasing federal support for summer childcare could simultaneously address both labor market and educational impacts of summer school closures.

References

Adams-Prassl, Abi, Kotaro Hara, Kristy Milland, and Chris Callison-Burch. 2023. "The Gender Wage Gap in an Online Labor Market: the Cost of Interruptions."

Review of Economics and Statistics, forthcoming: 1–23.

Albanesi, Stefania and Jiyeon Kim. 2021. "Effects of the COVID-19 Recession on the US Labor Market: Occupation, Family, and Gender." *Journal of Economic Perspectives*, 35(3): 3–24.

Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt. 2021. "From Mancession to Shecession: Women's Employment in Regular and Pandemic Recessions." In *NBER Macroeconomics Annual*. Vol. 36.

Angelov, Nikolay, Per Johansson, and Erica Lindahl. 2016. "Parenthood and the Gender Gap in Pay." *Journal of Labor Economics*, 34(3): 545–579.

Barsky, Robert B. and Jeffrey A. Miron. 1989. "The Seasonal Cycle and the Business Cycle." *Journal of Political Economy*, 97(3): 503–534.

Beaulieu, J. Joseph and Jeffrey A. Miron. 1992. "A Cross Country Comparison of Seasonal Cycles and Business Cycles." *Economic Journal*, 102(413): 772–788.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2010. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics*, 2(3): 228–255.

Blau, Francine D. and Anne E. Winkler. 2018. "Women, Work, and Family." In *The Oxford Handbook of Women and the Economy*. Oxford University Press.

Blau, Francine D. and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature*, 55(3): 789–865.

Bolotnyy, Valentin and Natalia Emanuel. 2022. "Why Do Women Earn Less than Men? Evidence from Bus and Train Operators." *Journal of Labor Economics*, 40(2): 283–323.

Capizzano, Jeffrey, Sarah Adelman, and Matthew Stagner. 2002. "What Happens When the School Year Is Over? The Use and Costs of Child Care for School-Age Children During the Summer Months." Urban Institute Occasional Paper Number 58, available at https://www.urban.org/sites/default/files/publication/60111/310497-What-Happens-When-the-School-Year-Is-Over-.PDF.

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

Coglianese, John and Brendan M. Price. 2020. "Income in the Off Season: Household Adaptation to Yearly Work Interruptions." Federal Reserve Board Finance and Economics Discussion Series No. 2020-084.

Cortés, Patricia and Jessica Pan. 2019. "When Time Binds: Substitutes for Household Production, Returns to Working Long Hours, and the Skilled Gender Wage Gap." *Journal of Labor Economics*, 37(2): 351–398.

Cortés, Patricia and Jessica Pan. 2023. "Children and the Remaining Gender Gaps in the Labor Market." *Journal of Economic Literature*, 61(4): 1359–1409.

Cowan, Benjamin W., Todd R. Jones, and Jeffrey M. Swigert. 2023. "Parental and Student Time Use Around the Academic Year." NBER Working Paper No. 31177.

Cubas, German, Chinhui Juhn, and Pedro Silos. 2022. "Coordinated Work Schedules and the Gender Wage Gap." *Economic Journal*, 133(651): 1036–1066.

Del Bono, Emilia and Andrea Weber. 2008. "Do Wages Compensate for Anticipated Working Time Restrictions? Evidence from Seasonal Employment in Austria." *Journal of Labor Economics*, 26(1): 181–221.

Drew, Julia A. Rivera, Sarah Flood, and John Robert Warren. 2014. "Making Full Use of the Longitudinal Design of the Current Population Survey: Methods for Linking Records Across 16 Months." *Journal of Economic and Social Measurement*, 39(3): 121–144.

Duchini, Emma and Clémentine Van Effenterre. 2022. "School Schedule and the Gender Pay Gap." *Journal of Human Resources*, 58(4).

Fitzpatrick, Maria Donovan. 2012. "Revising Our Thinking About the Relationship Between Maternal Labor Supply and Preschool." *Journal of Human Resources*, 47(3): 583–612.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Megan Schouweiler, and Michael Westberry. 2023a. "IPUMS CPS: Version 11.0 [dataset]." Minneapolis, MN: IPUMS. https://doi.org/10.18128/D030.V11.0.

Flood, Sarah M., Liana C. Sayer, Daniel Backman, and Annie Chen. 2023b. "American Time Use Survey Data Extract Builder: Version 3.2 [dataset]." College Park, MD: University of Maryland and Minneapolis, MN: IPUMS. https://doi.org/10.18128/D060.V3.2.

Fontenay, Sébastien, Thomas Murphy, and Ilan Tojerow. 2023. "Child Penalties Across Industries: Why Job Characteristics Matter." *Applied Economics Letters*, 30(4): 488–495.

Frazis, Harley J., Edwin L. Robison, Thomas D. Evans, and Martha A. Duff. 2005. "Estimating Gross Flows Consistent with Stocks in the CPS." *Monthly Labor Review*, 128: 3–9.

Frimmel, Wolfgang, Martin Halla, Bernhard Schmidpeter, and Rudolf Winter-Ebmer. 2022. "Grandmothers' Labor Supply." *Journal of Human Resources*, 57(5): 1645–1689.

Gelbach, Jonah. 2002. "Public Schooling for Young Children and Maternal Labor Supply." *American Economic Review*, 92(1): 307–322.

Geremew, Menelik and François Gourio. 2018. "Seasonal and Business Cycles of US Employment." *Economic Perspectives*, 42(3): 1–28.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review*, 104(4): 1091–1119.

Goldin, Claudia. 2022. "Understanding the Economic Impact of COVID-19 on Women." *Brookings Papers on Economic Activity*, Spring: 65–110.

Graves, Jennifer. 2013. "School Calendars, Child Care Availability, and Maternal Employment." *Journal of Urban Economics*, 78: 57–70.

Handwerker, Elizabeth Weber and Lowell Mason. 2017. "BLS Spotlight on Statistics: Differences in Parents' Time Use Between the Summer and the School Year." Available at https://www.bls.gov/spotlight/2017/differences-in-parents-time-use-between-the-summer-and-the-school-year/pdf/differences-in-parents-time-use-between-the-summer-and-the-school-year.pdf.

Hansen, Benjamin, Joseph J. Sabia, and Jessamyn Schaller. 2022. "Schools, Job Flexibility, and Married Women's Labor Supply: Evidence From the COVID-19 Pandemic." NBER Working Paper No. 29660.

Heggeness, Misty L. 2020. "Estimating the Immediate Impact of the COVID-19 Shock on Parental Attachment to the Labor Market and the Double Bind of Mothers." *Review of the Economics of the Household*, 18(4): 1053–1078.

Hoyer, Kathleen Mulvaney and Dinah Sparks. 2017. "Instructional Time for Third- and Eighth-Graders in Public and Private Schools: School Year 2011–12." US Department of Education Stats in Brief, available at https://nces.ed.gov/pubs2017/2017076.pdf.

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

Mas, Alexandre and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review*, 107(12): 3722–3759.

National Center for Education Statistics. 2018. "Percentage of Public Schools Operating on Any Type of 12-Month Cycle." Available at https://nces.ed.gov/surveys/sass/tables/sassmulti_21050301_s1n.asp (1999–2000 tabulation) and https://nces.ed.gov/surveys/ntps/tables/ntps1718_20050401_s1n.asp (2017–18 tabulation).

Newey, Whitney K. and Kenneth D. West. 1994. "Automatic Lag Selection in Covariance Matrix Estimation." *Review of Economic Studies*, 61(4): 631–653.

Novoa, Cristina. 2018. "Families Can Expect to Pay 20 Percent of Income on Summer Child Care." Center for American Progress Report, available at https://www.americanprogress.org/article/families-can-expect-pay-20-percent-income-summer-child-care/.

Novoa, Cristina. 2019. "When Parents Can't Find Summer Child Care, Their Work Suffers." Center for American Progress Report, available at https://www.americanprogress.org/article/parents-cant-find-summer-child-care-work-suffers/.

Olivei, Giovanni and Silvana Tenreyro. 2007. "The Timing of Monetary Policy Shocks." *American Economic Review*, 97(3): 636–663.

Philippe, Arnaud and Daphné Skandalis. 2023. "Motherhood and the Cost of Job Search." IZA Discussion Paper No. 16669.

Quinn, David M. and Morgan Polikoff. 2017. "Summer Learning Loss: What Is It, and What Can We Do About It?" Brookings Institution report, available at https://www.brookings.edu/articles/summer-learning-loss-what-is-it-and-what-can-we-do-about-it/.

Schmitz, Kirsten. 2018. "Do Teachers Get Paid over the Summer?" Teacher Pensions Blog, available at https://www.teacherpensions.org/blog/do-teachers-get-paid-over-summer.

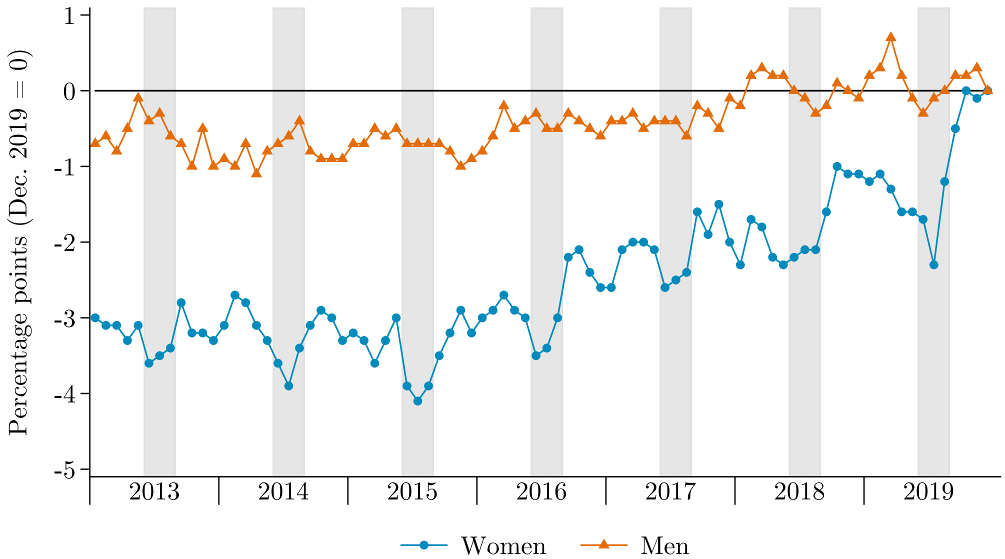
Tourkin, S.C., K.W. Pugh, S.E. Fondelier, R.J. Parmer, C. Cole, B. Jackson, T. Warner, G. Weant, and E. Walter. 2004. "1999–2000 Schools and Staffing Survey (SASS) Data File User's Manual (NCES 2004-303)." US Department of Education. Washington, DC: National Center for Education Statistics.

US Department of Labor. 2023. "Conformity Requirements for State UC Laws." https://oui.doleta.gov/unemploy/pdf/uilaws_termsdenial.pdf.

Wasserman, Melanie. 2023. "Hours Constraints, Occupational Choice, and Gender: Evidence from Medical Residents." *Review of Economic Studies*, 90(3): 1535–1568.

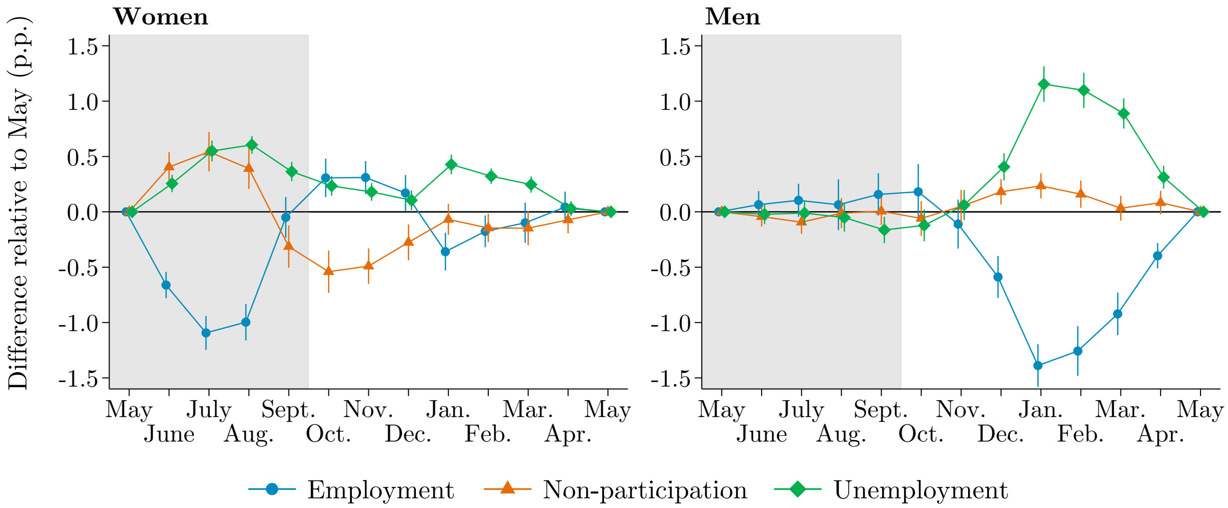
Wiswall, Matthew and Basit Zafar. 2018. "Preference for the Workplace, Investment in Human Capital, and Gender." *Quarterly Journal of Economics*, 133(1): 457–507.

Figure 1: The summer drop in prime-age female labor force participation



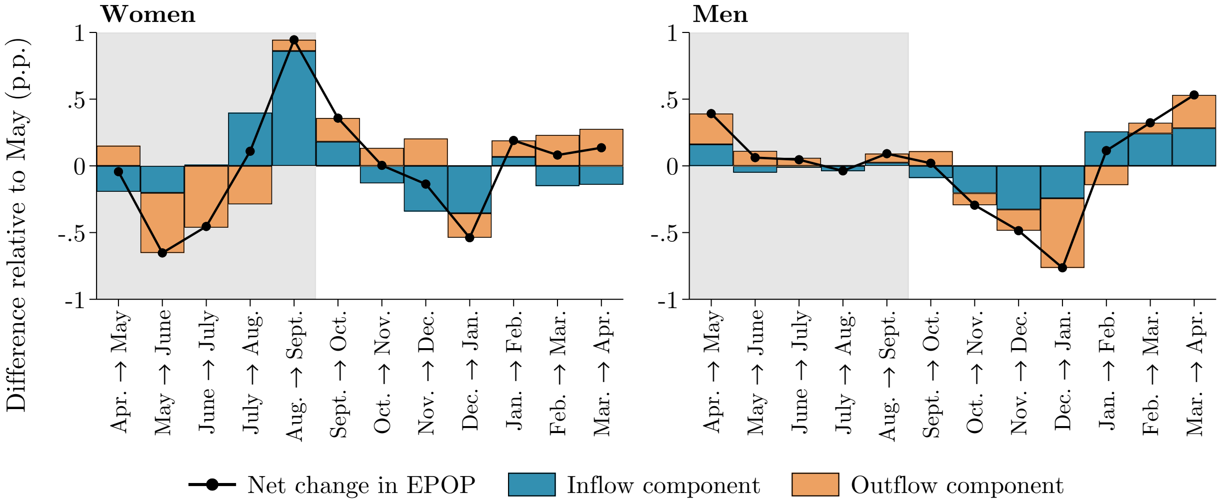
Source: Bureau of Labor Statistics, Labor Force Statistics, series LNU01300061 (men) and LNU01300062 (women).
Notes: Non–seasonally adjusted labor force participation rates among individuals aged 25–54, normalized to zero in December 2019. Shaded regions correspond to the months of June, July, and August.

Figure 2: Seasonal changes in employment, unemployment, and non-participation



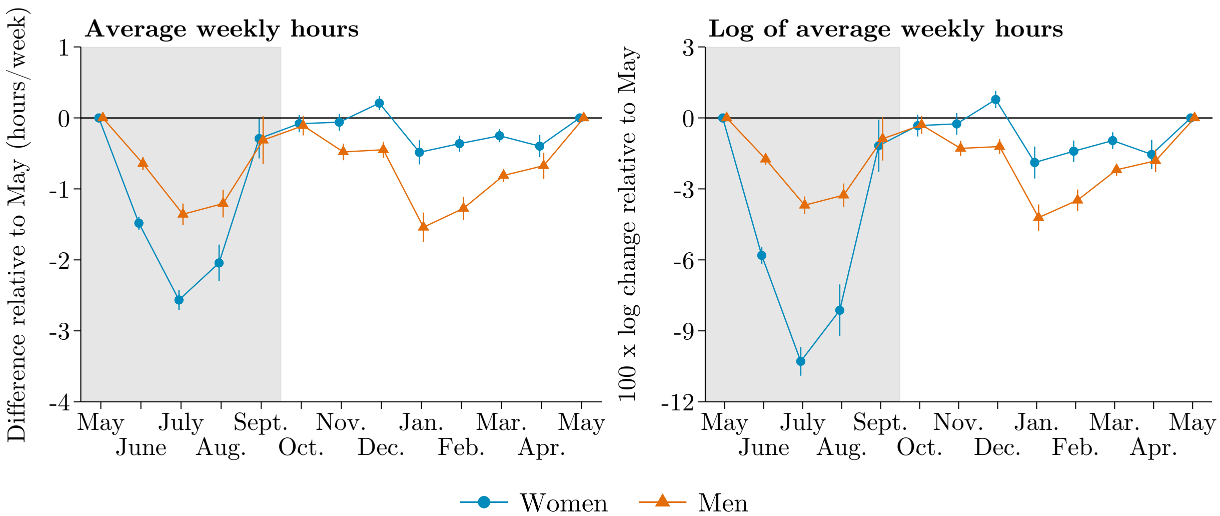
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1), separately by sex, for respondents aged 25–49 grouped to the year-month level. Each measure is expressed as a share of the corresponding population. Bars show 95 percent confidence intervals based on Newey-West standard errors. In this and many subsequent figures, coefficients for May are normalized to zero, and plotted points are offset horizontally for visual clarity.

Figure 3: Contributions of inflows versus outflows to seasonal changes in employment



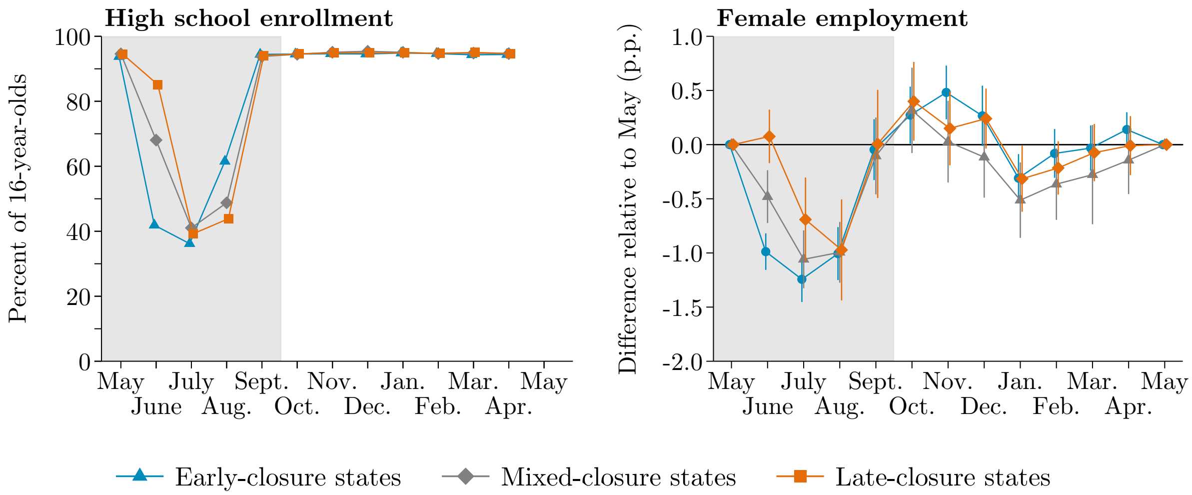
Source: Current Population Survey.
Notes: Additive decomposition of month-to-month changes in EPOP into contributions from above-average inflows and below-average outflows. Excess flows are transformations of the coefficients $\widehat{\delta}_m$ obtained by estimating Equation (2) using gross monthly transitions into or out of employment (see Appendix C). Positive bar segments (respectively, negative segments) indicate that a given margin boosts (lowers) EPOP between two months. In this and subsequent flows-based analyses, the sample is restricted to individuals with valid longitudinal links.

Figure 4: Seasonal changes in weekly hours worked



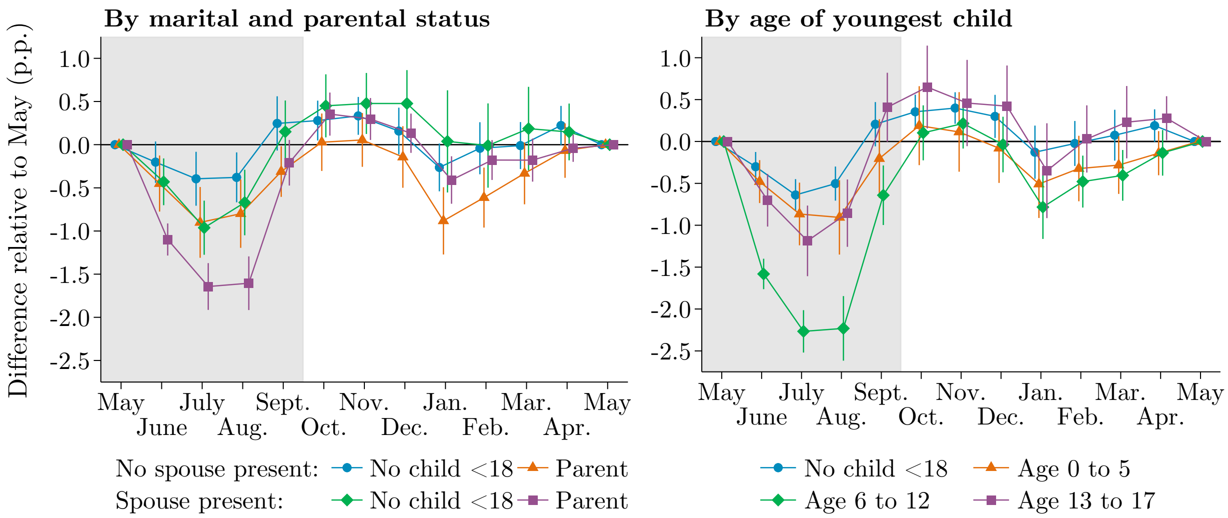
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for average hours worked during the reference week and for the log of hours worked. Non-employed individuals are assigned zero hours, so that the measure reflects both intensive and extensive margins of hours worked. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Figure 5: Cross-state synchronization of school closures with the summer drop in female employment



Source: Current Population Survey.
Notes: Left panel shows the percentage of 16-year-olds who report being enrolled in high school in the indicated month in states with early school closures (mostly in effect by the June reference week), late school closures (mostly in effect only as of July), or mixed school closures (in between). Right panel shows coefficients $\widehat{\beta}_m$ from estimating Equation (1) for female EPOP separately in each group of states. Bars show 95 percent confidence intervals based on Newey-West standard errors.

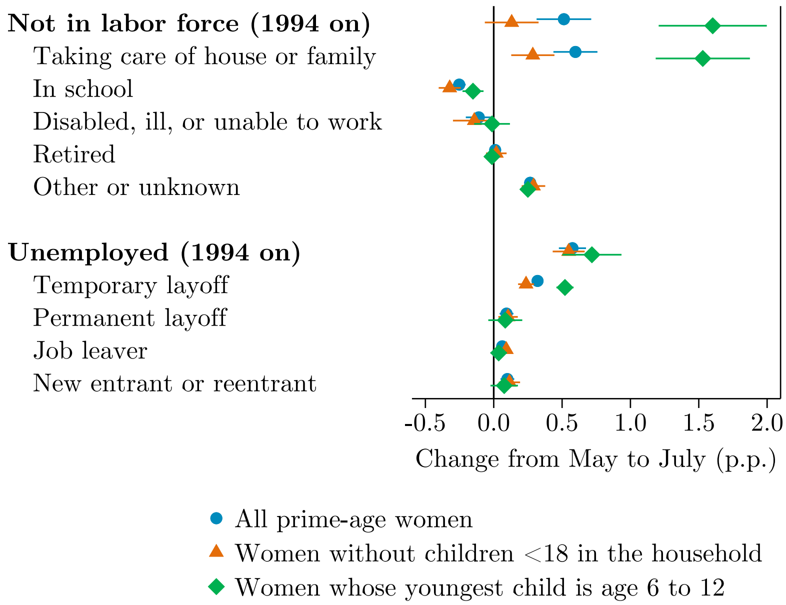
Figure 6: Seasonal changes in female employment by marital and parental status



Source: Current Population Survey.

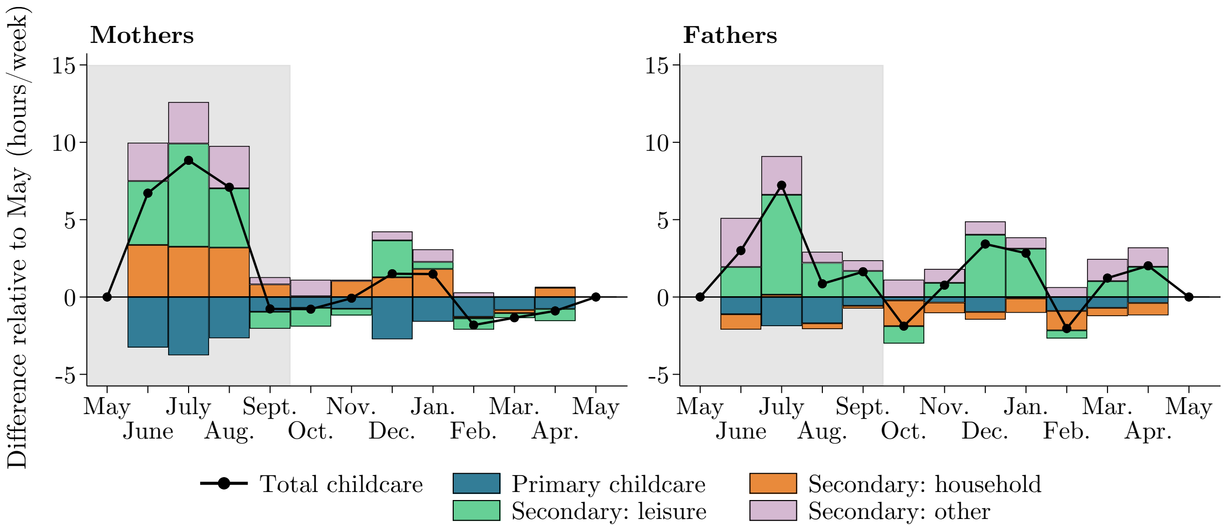
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for female EPOP separately by marital and parental status. "Spouse present" refers to married individuals residing in the same household as their spouse; parental status is defined relative to an individual's own children, including adoptees and step-children. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Figure 7: Decomposition of May–July changes in female non-employment



Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_7$ (representing May–July changes) from estimating Equation (1) for subcategories of non-participation and unemployment. The survey years are limited to 1994–2019 as types of non-participants are not distinguished before 1994. Non-participation status denotes a respondent's major activity during the reference week. Unemployment status denotes a respondent's reason for being unemployed. Bars show 95 percent confidence intervals based on Newey-West standard errors.

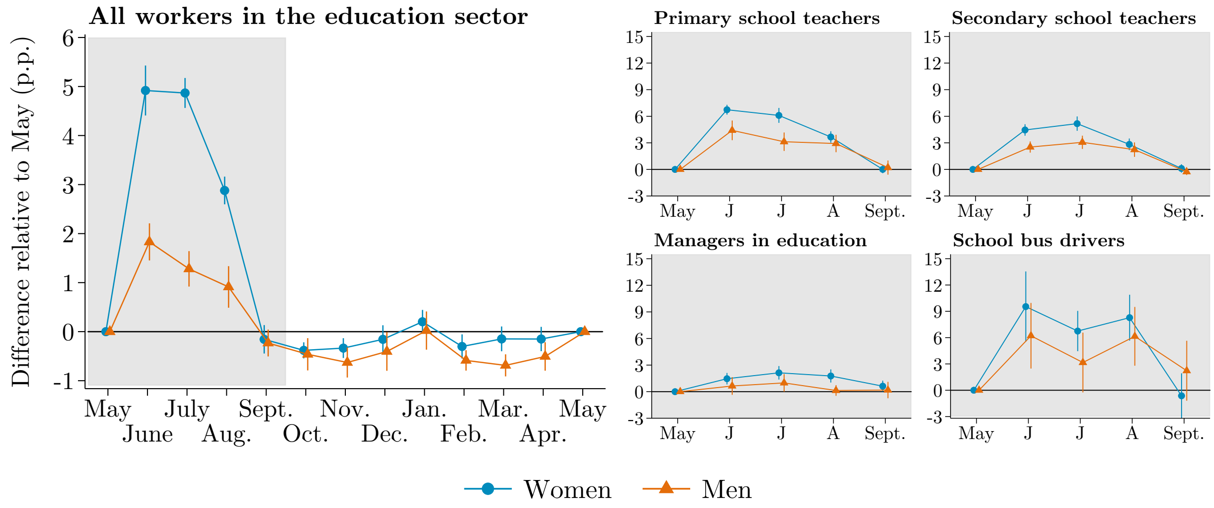
Figure 8: Decomposition of total childcare time among parents of school-aged children



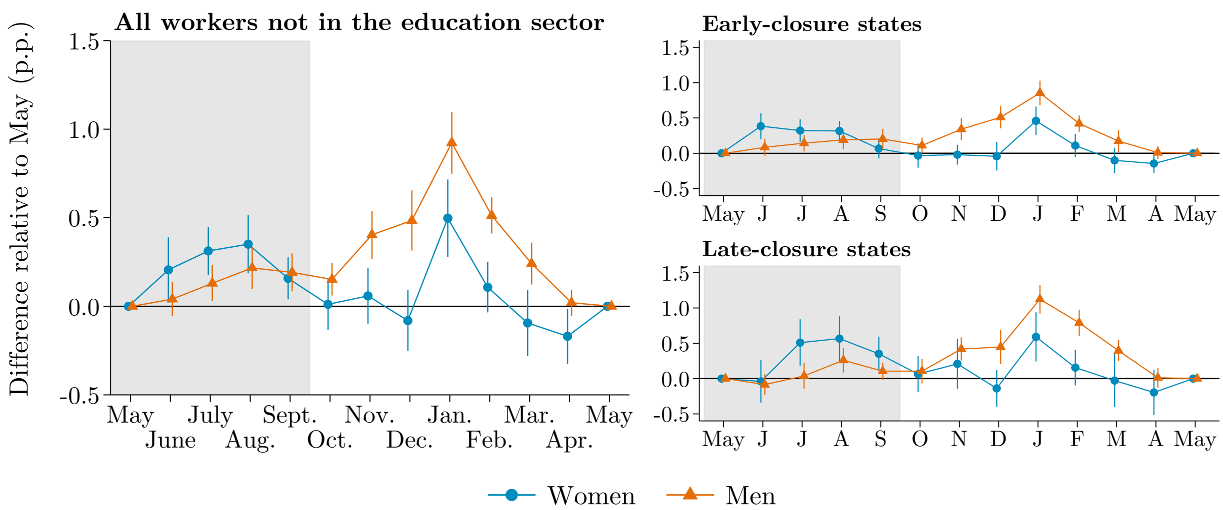
Source: American Time Use Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating an individual-level version of Equation (1) on 2004–2019 ATUS respondents aged 25–49 who reside with a youngest child aged 6–12. The specification controls for a linear spline in calendar time and for day-of-week fixed effects. See Appendix B.3 for definitions of each childcare category.

Figure 9: Separations from employment among education and non-education workers

(a) Exits from the education sector

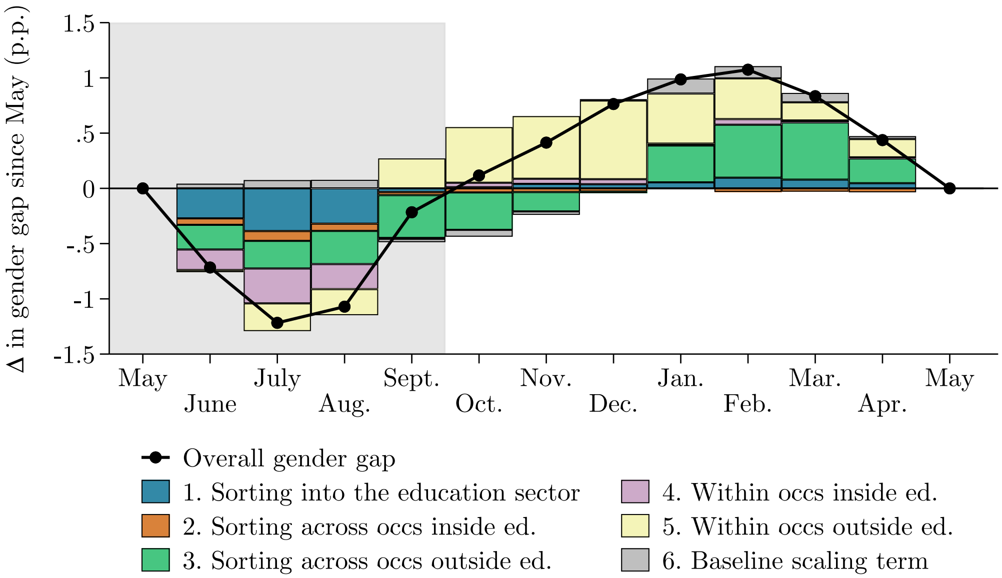


(b) Exits from other sectors



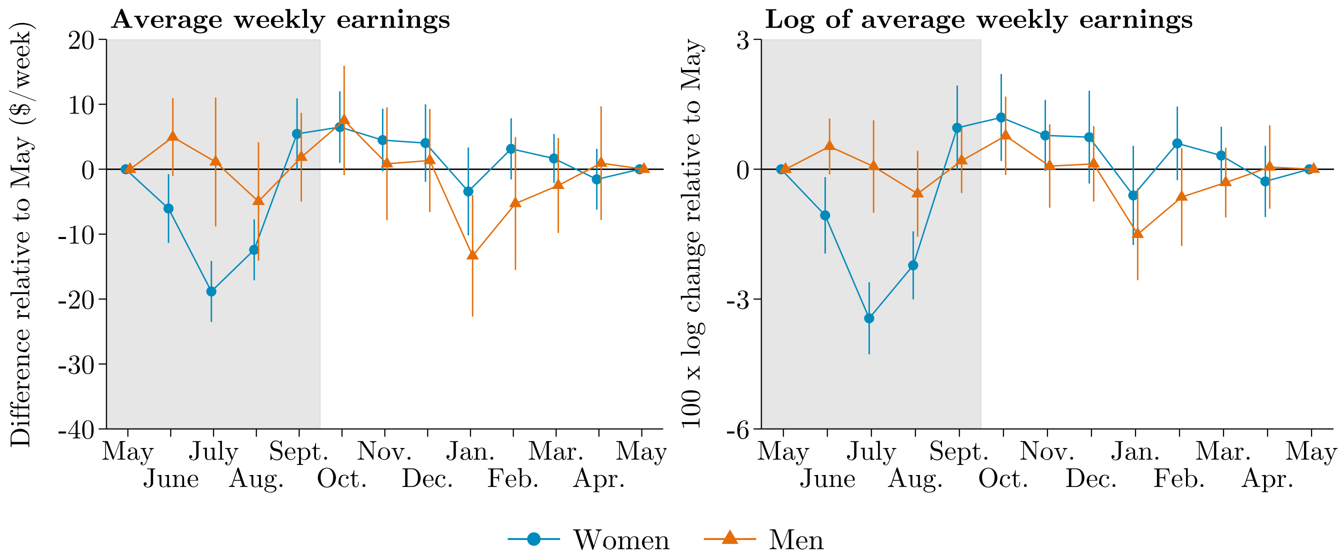
Source: Current Population Survey.
Notes: Coefficients $\widehat{\delta}_m$ from estimating Equation (2) among respondents employed in a given sector in the previous month; where indicated, the sample is further restricted to individuals in a given occupation or in states with early versus late school closures. The outcome is the percentage of individuals who separated into non-employment in the current month. For occupations within the education sector, coefficients for October–April are estimated but not shown. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Figure 10: Decomposition of female–male differences in the seasonality of employment



Source: Current Population Survey.
Notes: Additive decomposition of the gender gap in cumulative changes in EPOP between May and the indicated month into gender differences in sectoral/occupational sorting and gender differences in employment conditional on job type. See text and Appendix C for details on the decomposition methodology. See Appendix Table A.5 for point estimates and standard errors.

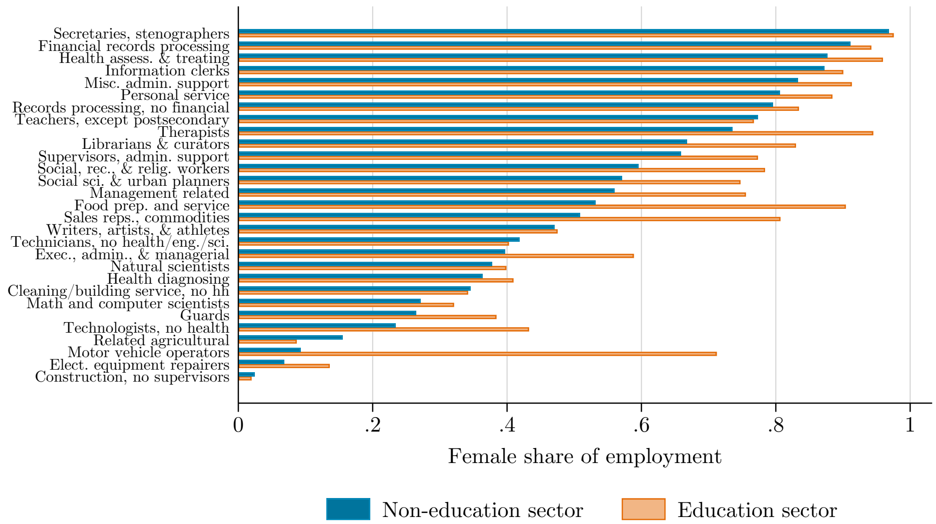
Figure 11: Seasonal changes in weekly earnings



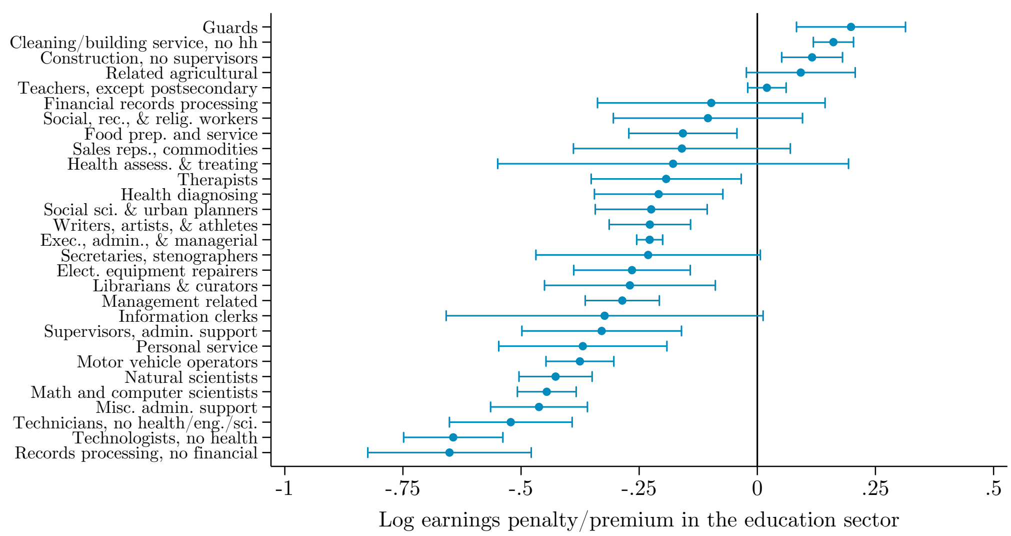
Source: Current Population Survey, Outgoing Rotation Groups.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for average weekly earnings and the log of average weekly earnings. The survey years are limited to 1994–2019 as paid and unpaid absences from work are not distinguished before 1994. Individuals with zero weekly earnings are included in group averages, so that the measure reflects both intensive and extensive margins of weekly earnings. See text for details on construction of the earnings measure. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Figure 12: Gender composition and relative earnings in occupations present both within and outside the education sector

(a) Female share of employment



(b) Education-sector earnings penalty/premium

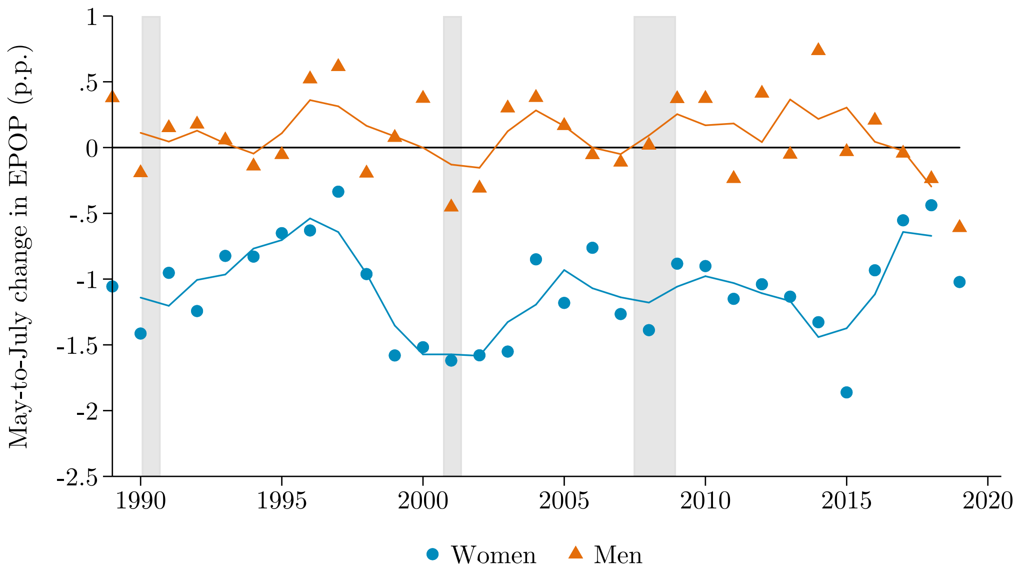


Source: Current Population Survey, Annual Social and Economic Supplements.
Notes: The 29 listed occupations, drawn from a set of 74 two-digit Census occupations, are those for which average monthly employment exceeds 20,000 in both the education and non-education sectors. (a) Female employment as a share of each occupation, computed separately for each sector. (b) Coefficients on the interaction of occupation fixed effects with an education-sector dummy from an individual-level regression of log annual male earnings controlling for occupation main effects, educational attainment, a quadratic in age, and calendar year. Bars show 95 percent confidence intervals, with standard errors clustered by household.

Price and Wasserman (2024): Online Appendix

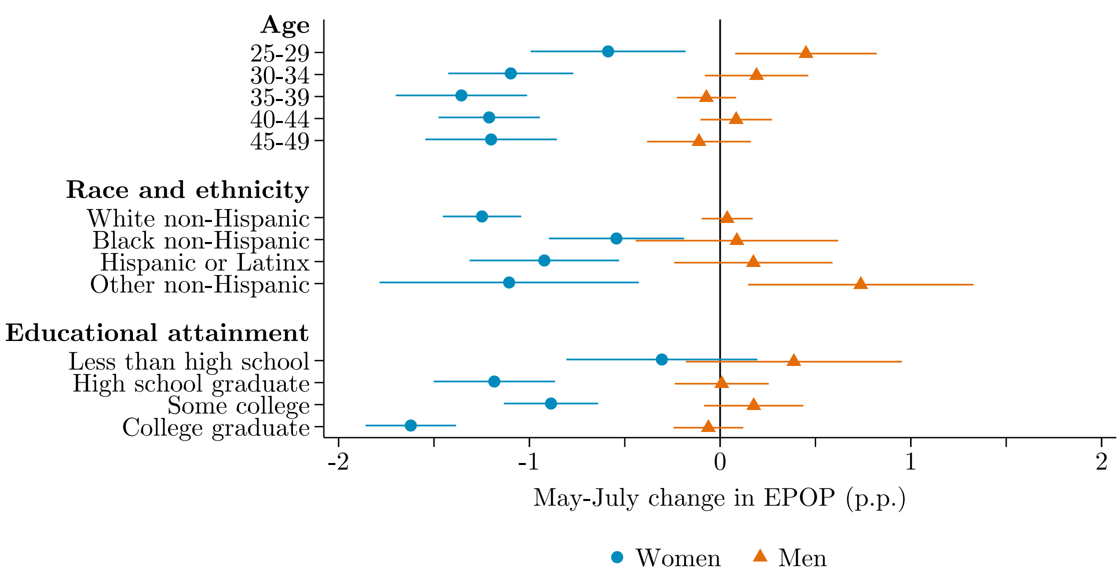
A Additional Figures and Tables

Appendix Figure A.1: May–July changes in employment-to-population ratios, 1989–2019



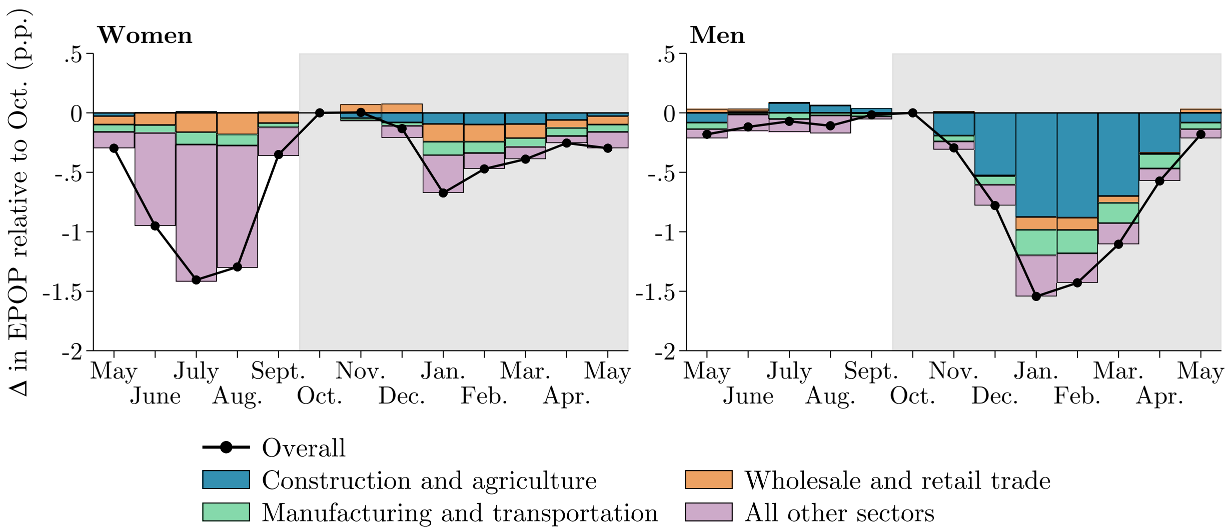
Source: Current Population Survey.
Notes: Plotted points show non–seasonally adjusted May–July changes in EPOP for respondents aged 25–49. Smoothed curves show three-year centered moving averages. Shading denotes recessions, as dated by the National Bureau of Economic Research.

Appendix Figure A.2: Demographic heterogeneity in May–July changes in employment



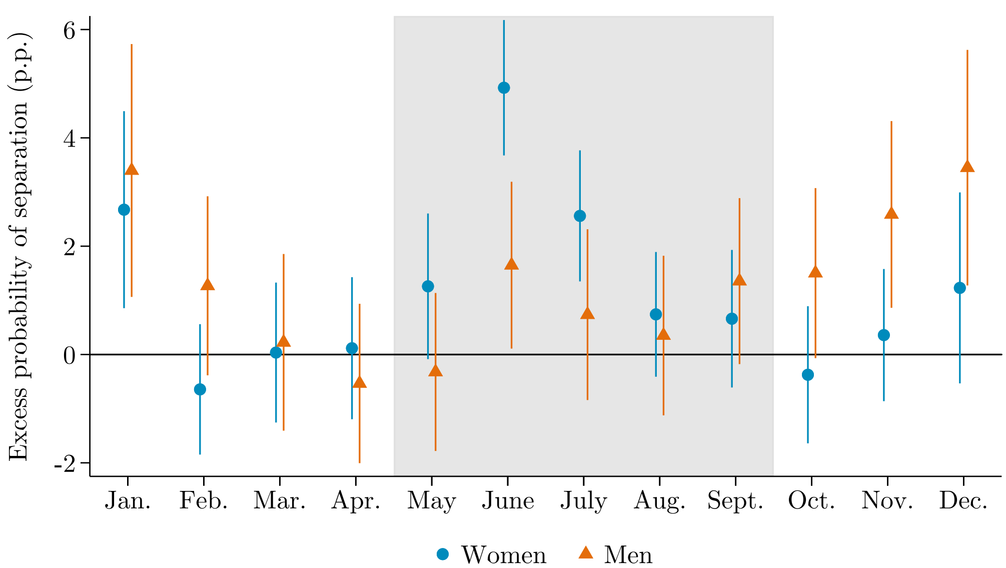
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_7$ (representing May–July changes) from estimating Equation (1) separately by sex × the indicated characteristic. See Appendix B.1 for details on our coding of race, ethnicity, and educational attainment. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.3: Sectoral composition of the winter drop in employment



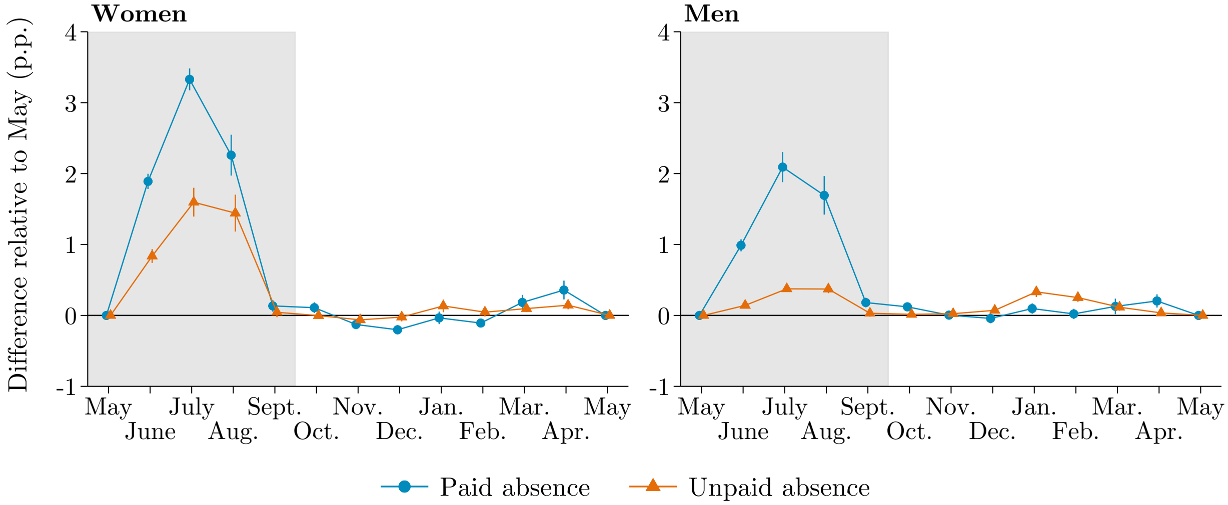
Source: Current Population Survey.
Notes: Additive decomposition of cumulative changes in EPOP between October and the indicated month into contributions from net flows between the indicated sectors and non-employment. Net flows are transformations of the coefficients $\widehat{\delta}_m$ obtained by estimating Equation (2) using gross monthly transitions (see Appendix C).

Appendix Figure A.4: Excess recurrence of separations 12 months after an initial one



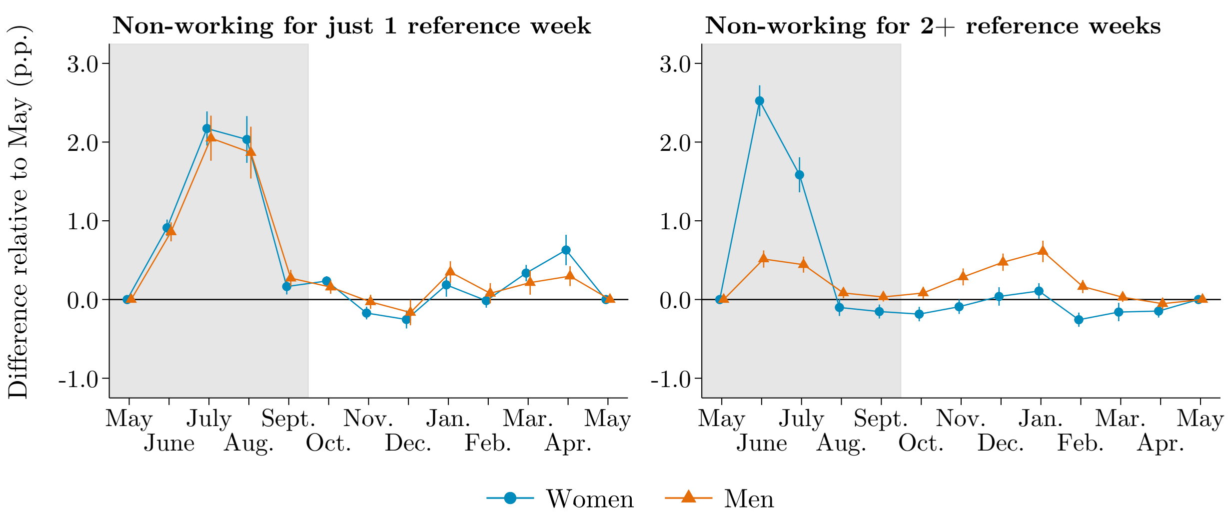
Source: Current Population Survey.
Notes: Excess recurrence of separations from employment into non-employment at annual intervals, obtained by estimating $\widehat{\rho}_{12} - \frac{1}{2}(\widehat{\rho}_{11} + \widehat{\rho}_{13})$ in Equation (20) as in Coglianese and Price (2020) (see Appendix E.1). Bars show 95 percent confidence intervals, with standard errors clustered by household.

Appendix Figure A.5: Seasonal changes in paid and unpaid absences from work



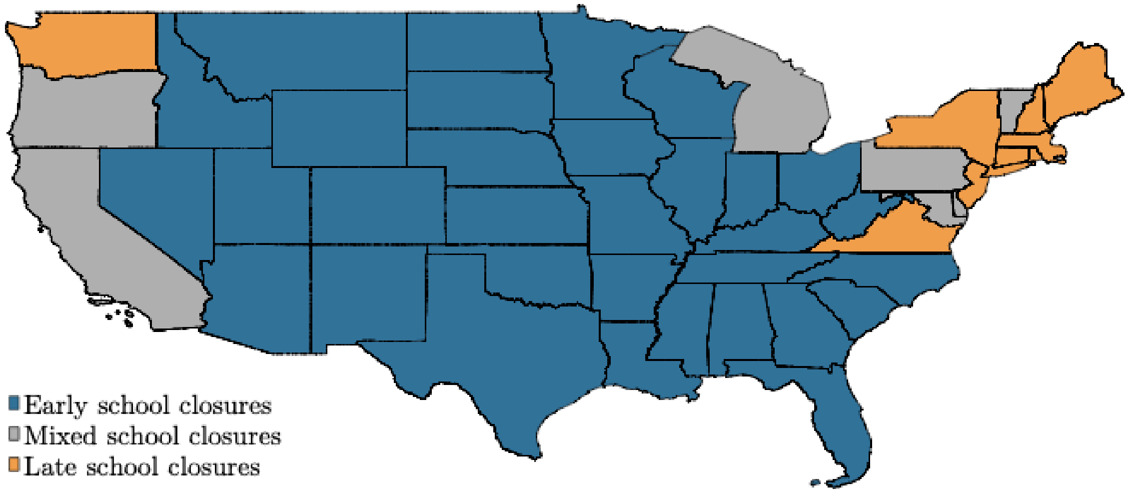
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for paid and unpaid absences from work during the reference week. The survey years are limited to 1994–2019 as absence types are not distinguished before 1994. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.6: Seasonal changes in the prevalence of briefer versus longer work interruptions



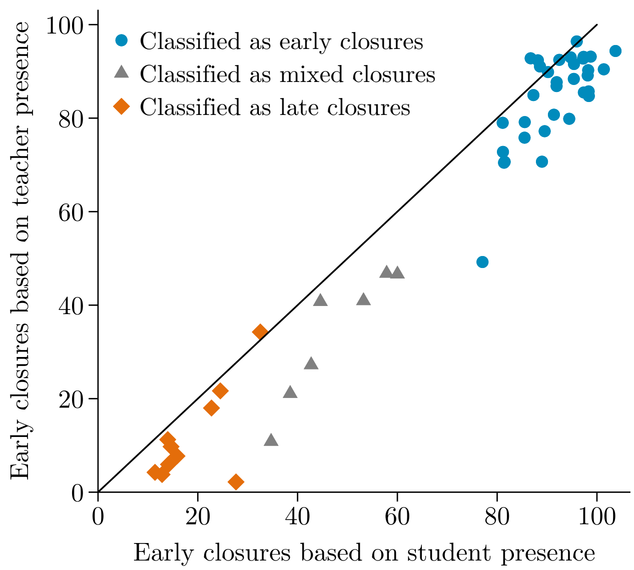
Source: Current Population Survey.
Notes: Coefficients $\widehat{\delta}_m$ from estimating Equation (2) in a sample of respondents observed for at least three consecutive monthly reference weeks. Let W denote "employed and at work" during a given month's reference week and NW denote "non-employed or absent" in that week. In the left panel, the dependent variable is an indicator for a $W \to NW \to W$ spell, with non-work occurring in the indicated month. In the right panel, the dependent variable is an indicator for having a $W \to NW \to NW$ spell with non-work beginning in that month. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.7: Classification of US states by the timing of K–12 school closures



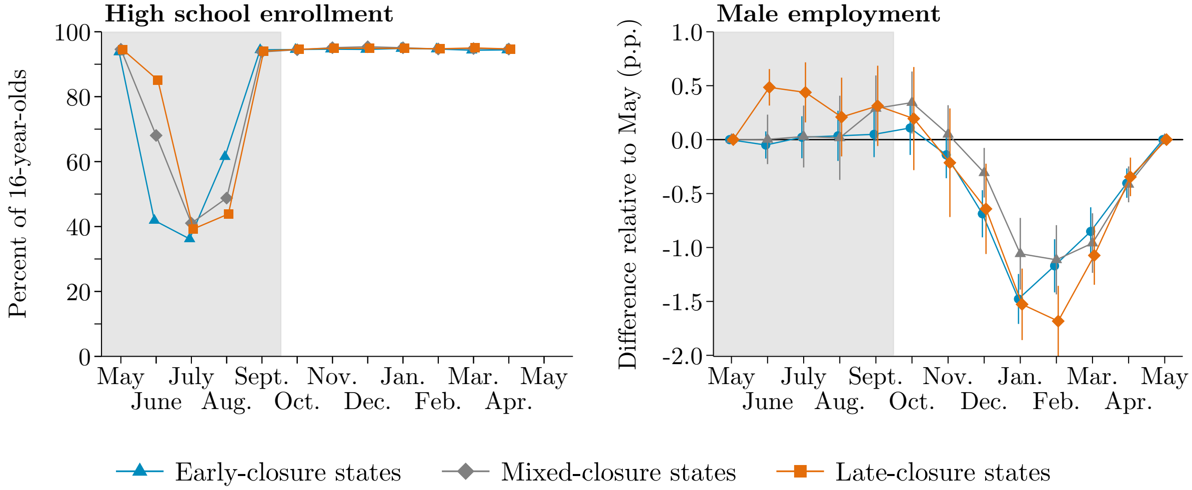
Source: Current Population Survey; US Census Bureau shapefiles.
Notes: States are classified based on the share of the total May–July drop in high school enrollment among 16-year-olds that occurs by the June CPS reference week. "Early-closure" states are those in which this statistic exceeds two thirds; "late-closure" states are those in which it is below one third. The remaining states are "mixed-closure" states. Alaska and Hawaii (not shown) are early-closure states.

Appendix Figure A.8: Comparing alternative measures of school closure timing



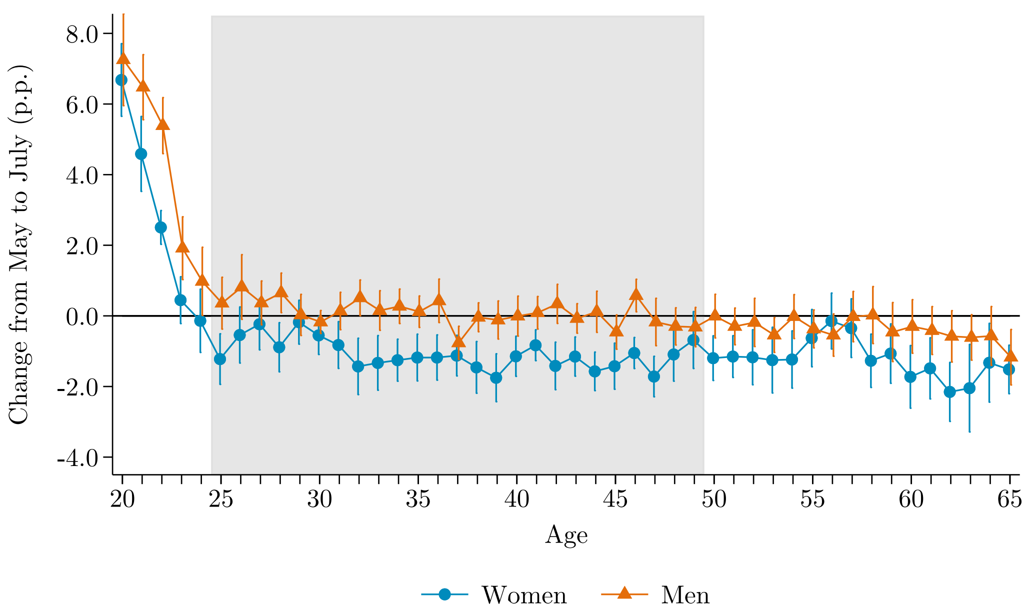
Source: Current Population Survey.
Notes: For the student-based measure, we compute the average May–July decline in high school enrollment among 16-year-olds, then show the share of this decline that occurs by the June reference week. For the teacher-based measure, we instead use the May–July decline in the number of teachers present at work during the reference week. Marker colors and symbols reflect the student-based classification.

Appendix Figure A.9: Cross-state synchronization of school closures with male employment



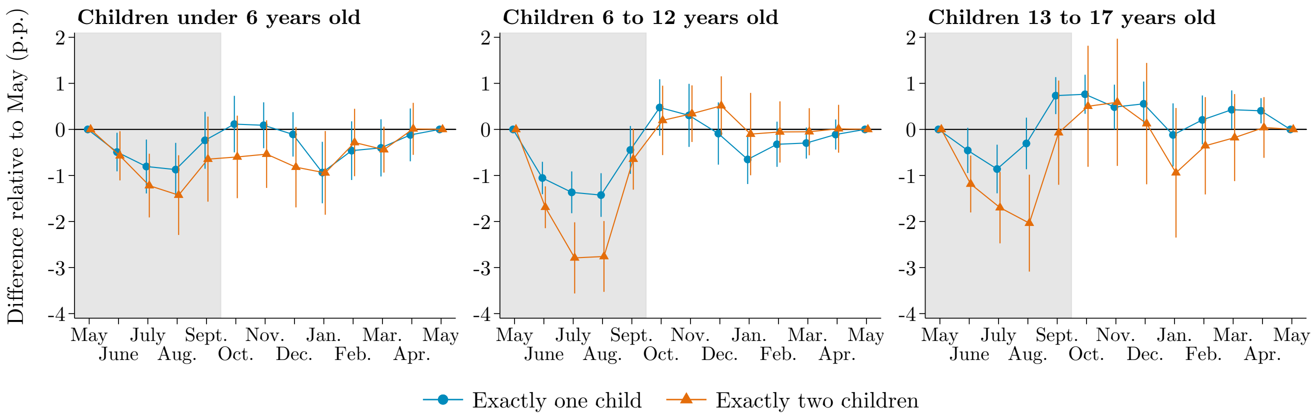
Source: Current Population Survey.
Notes: Left panel shows the percentage of 16-year-olds who report being enrolled in high school in the indicated month in states with early school closures (mostly in effect by the June reference week), late school closures (mostly in effect only as of July), or mixed school closures (in between). Right panel shows coefficients $\widehat{\beta}_m$ from estimating Equation (1) for male EPOP separately in each group of states. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.10: Evolution of May–July employment changes over the life cycle



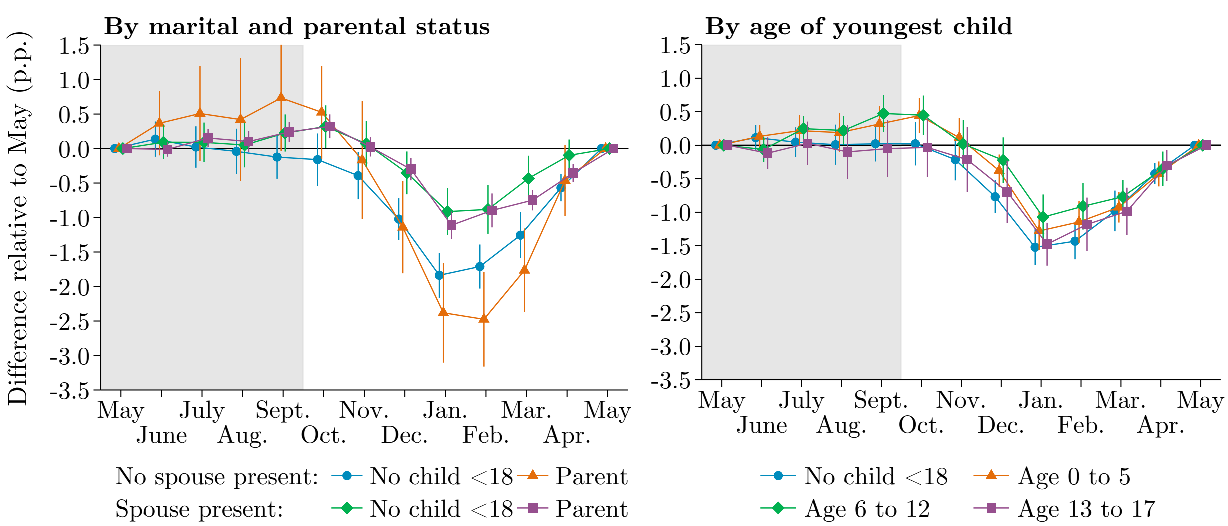
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_7$ (representing May–July changes) from estimating Equation (1) separately by sex × one-year age bins. The shaded region denotes the age range used in our main estimation sample. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.11: Seasonal changes in female employment by number of children



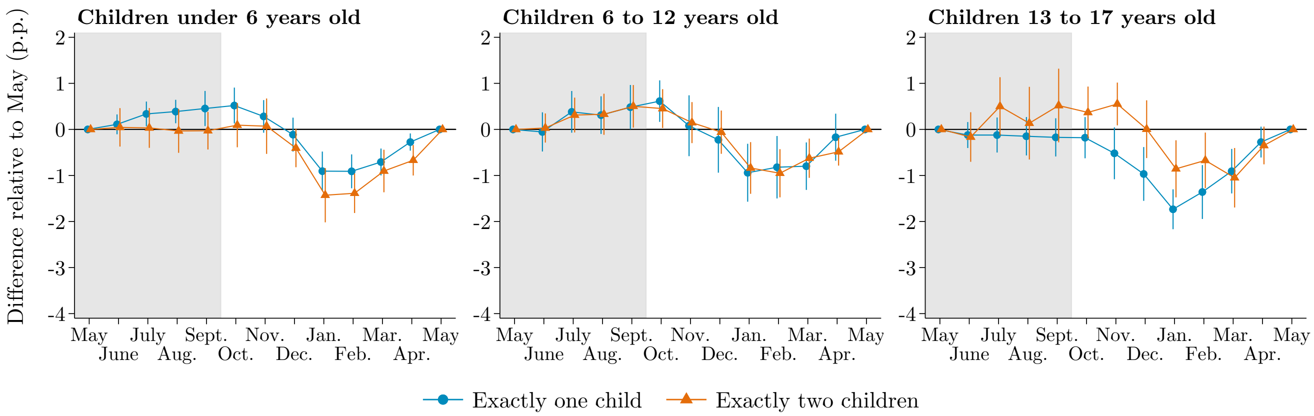
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for female EPOP separately among mothers with exactly one child versus exactly two children in the indicated age range (and no other children). Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.12: Seasonal changes in male employment by marital and parental status



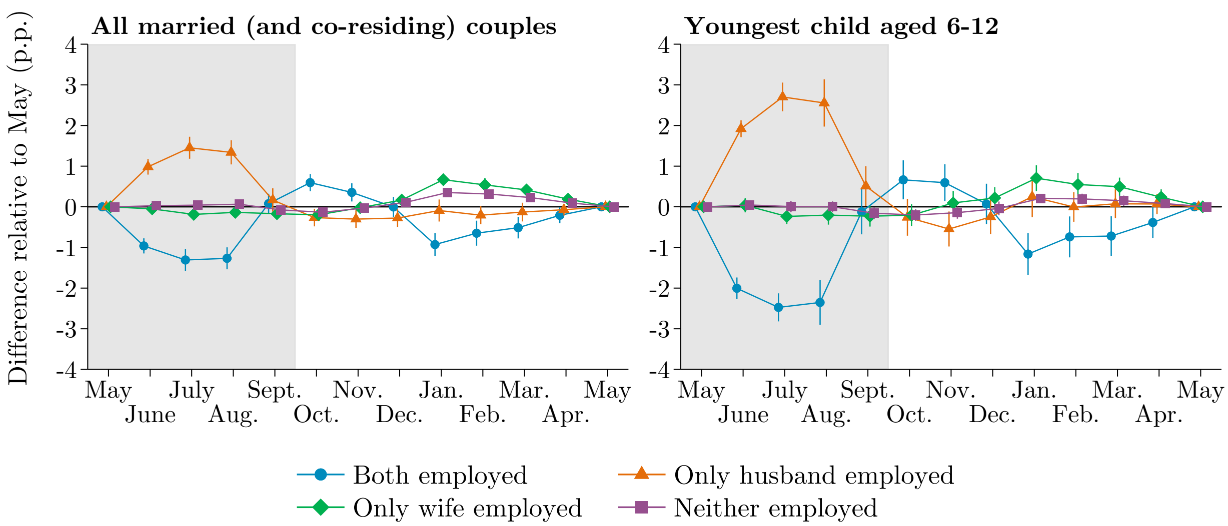
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for male EPOP separately by marital and parental status. "Spouse present" refers to married individuals residing in the same household as their spouse; parental status is defined relative to an individual's own children, including adoptees and step-children. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.13: Seasonal changes in male employment by number of children



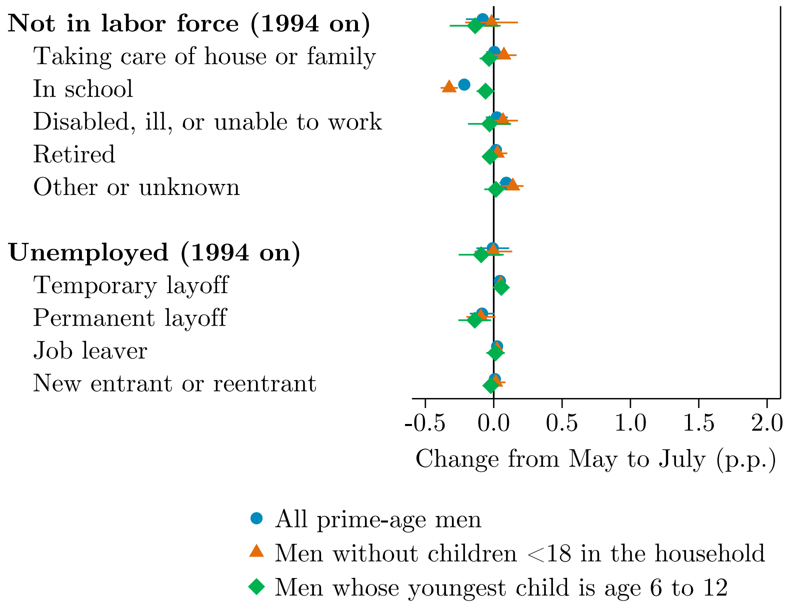
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for male EPOP separately among fathers with exactly one child versus exactly two children in the indicated age range (and no other children). Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.14: Joint employment patterns within married households



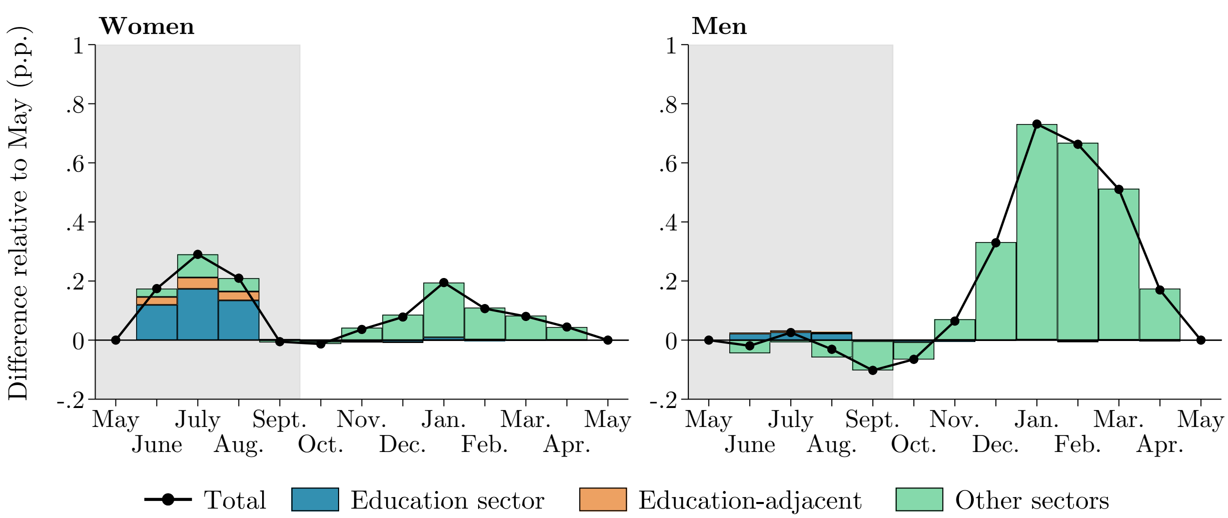
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) at the household level among opposite-sex married couples residing together and with no other prime-age adults. Households are weighted by the mean of the spouses' sampling weights. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.15: Decomposition of May–July changes in male non-employment



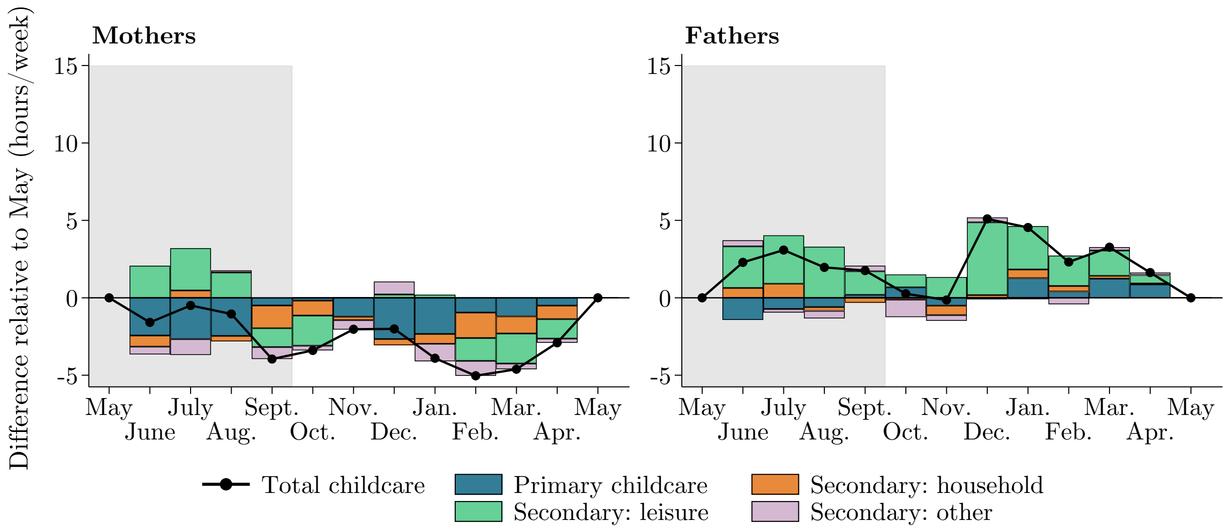
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_7$ (representing May–July changes) from estimating Equation (1) for subcategories of non-participation and unemployment. The survey years are limited to 1994–2019 as types of non-participants are not distinguished before 1994. Non-participation status denotes a respondent's major activity during the reference week. Unemployment status denotes a respondent's reason for being unemployed. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.16: Sectoral composition of seasonality in temporary layoffs



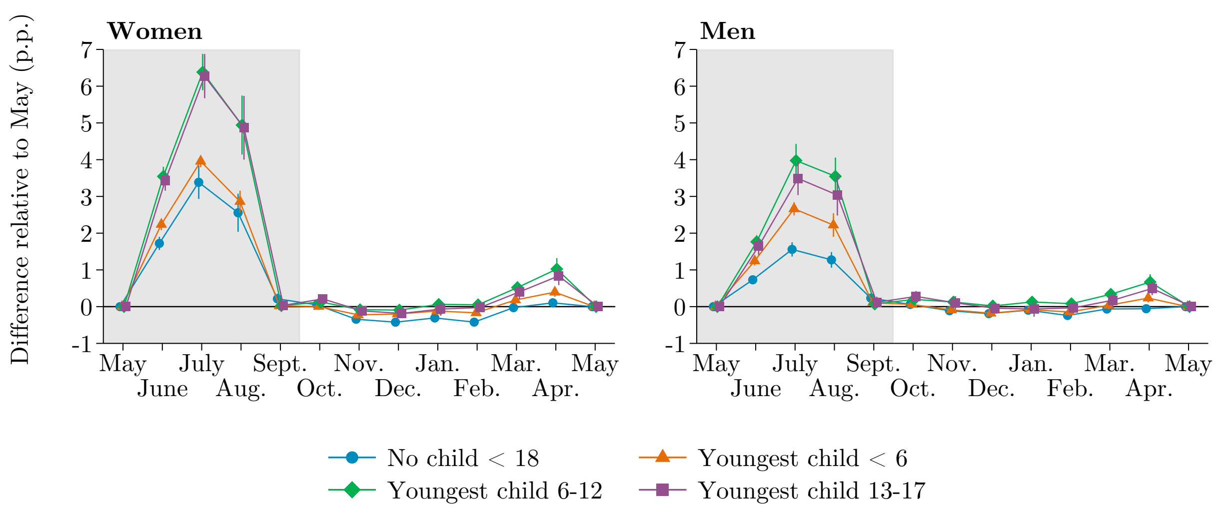
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) using the share of each group that is unemployed on temporary layoff from the indicated sector. Education-adjacent industries are child day care services and bus service and urban transit.

Appendix Figure A.17: Decomposition of total childcare time among parents of children under 6



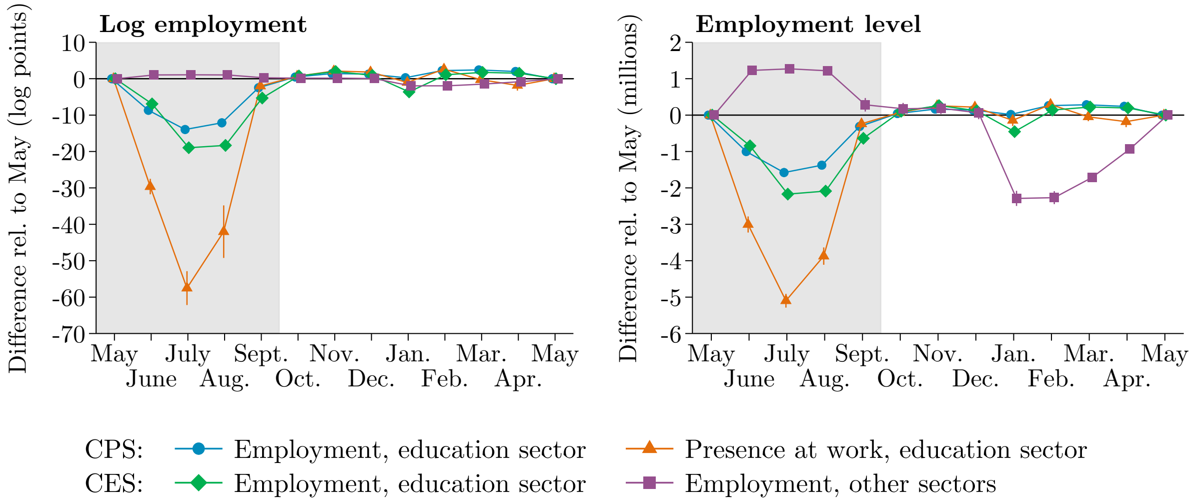
Source: American Time Use Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating an individual-level version of Equation (1) on 2004–2019 ATUS respondents aged 25–49 who reside with a youngest child under 6 years old. We control for a linear spline in calendar time and for day-of-week fixed effects. See Appendix B.3 for definitions of each childcare category.

Appendix Figure A.18: Vacation-related absence from work by sex and parental status



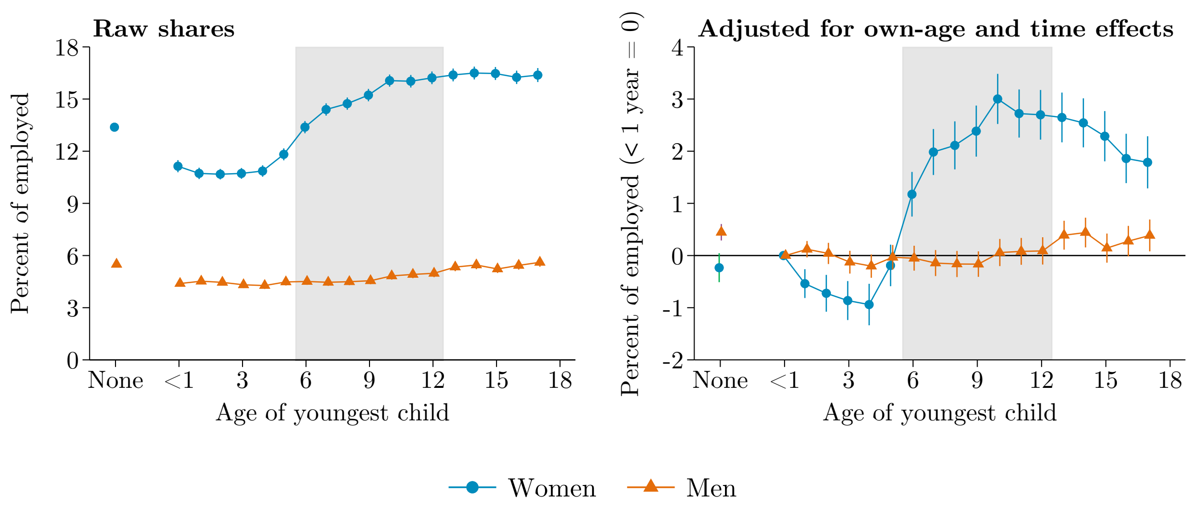
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for vacation-related absence from work during the reference week, separately by sex and parental status. The survey years are limited to 1994–2019 due to a break in the coding of reasons for absence. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.19: Seasonal changes in employment in education and other sectors



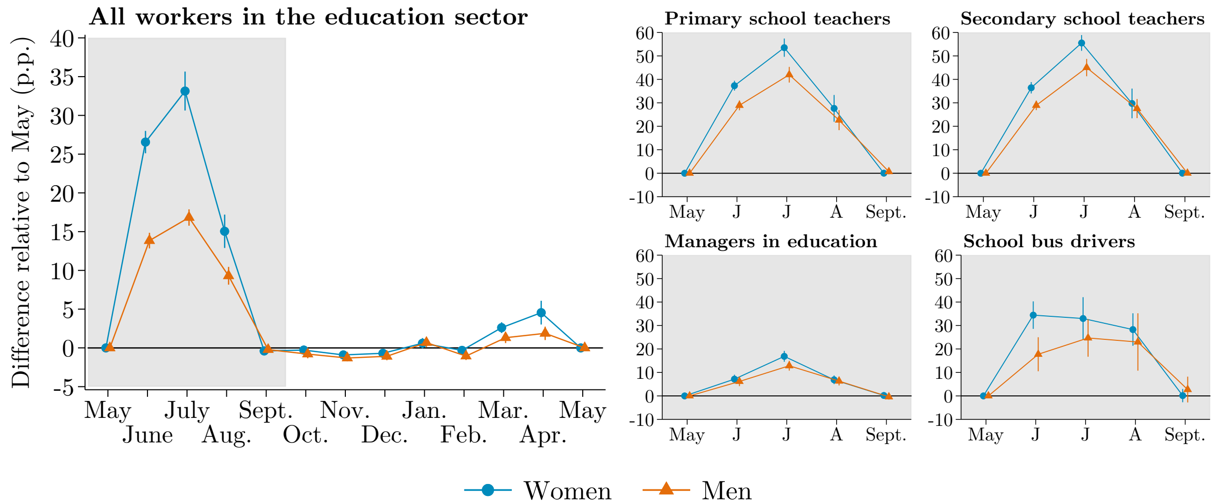
Source: Current Population Survey and Current Employment Statistics.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) for (i) CPS workers in the education sector, (ii) the subset of these workers present at work, (iii) CES employment in the education sector, and (iv) CES employment in other non-farm sectors. (iii) and (iv) use the non–seasonally adjusted BLS series PAYNSA, CEU6561000001, CEU9092161101, and CEU9093161101. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.20: Propensity to work in education as a function of child age



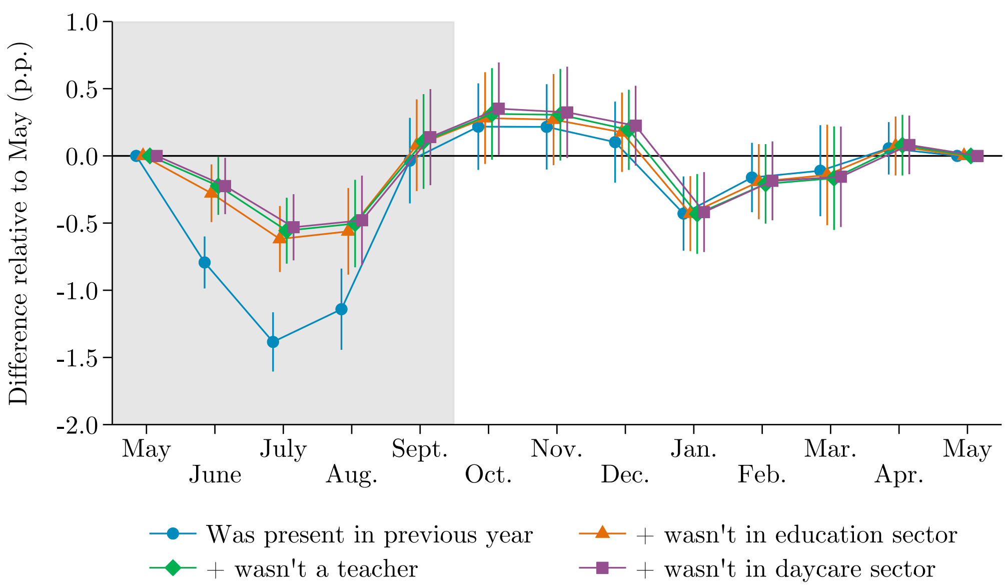
Source: Current Population Survey.
Notes: Left panel reports raw shares employed in the education sector in a sample of employed individuals aged 20–64 and observed during the non-summer months. Right panel reports child-age effects from sex-specific individual-level regressions of an indicator for working in education on a full set of one-year age-of-youngest-child effects, an indicator for having no child under 18 in the household, a full set of one-year own-age effects, and a linear spline in calendar time. The coefficient for parents with a newborn is normalized to zero. Bars show 95 percent confidence intervals, with standard errors two-way clustered on individual and year-month.

Appendix Figure A.21: Education workers' probability of switching to zero hours worked



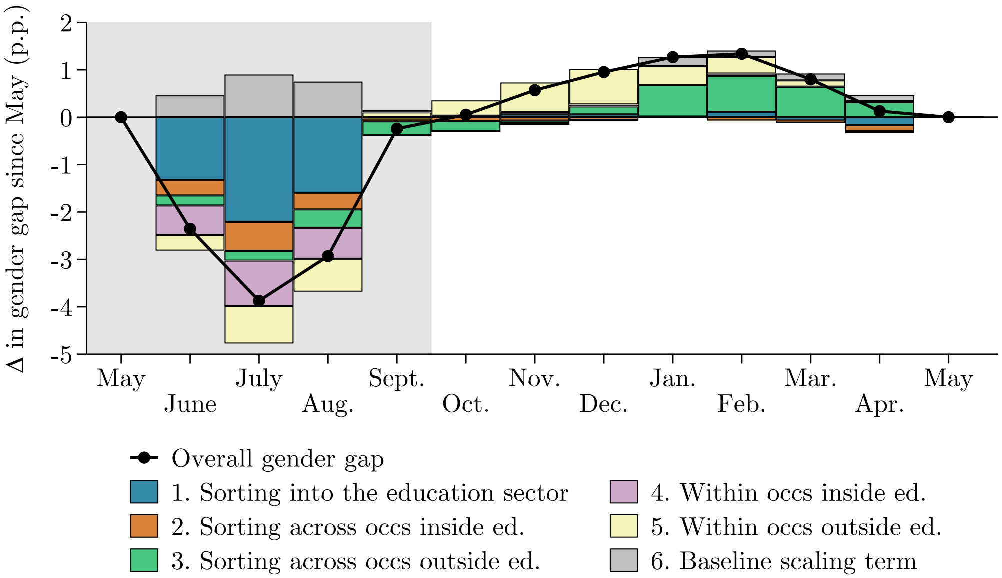
Source: Current Population Survey.
Notes: Coefficients $\widehat{\delta}_m$ from estimating Equation (2) among respondents who worked positive hours in the education sector during the previous month's reference week, either in any occupation (left panel) or in the indicated occupation (right panel); the outcome is the percentage of these individuals who worked zero hours in the current month's reference week. Bars show 95 percent confidence intervals based on Newey-West standard errors. In the right panel, coefficients for October–April are estimated but not shown.

Appendix Figure A.22: Seasonal changes in employment among women unconnected to education-related jobs during their first four months in the CPS



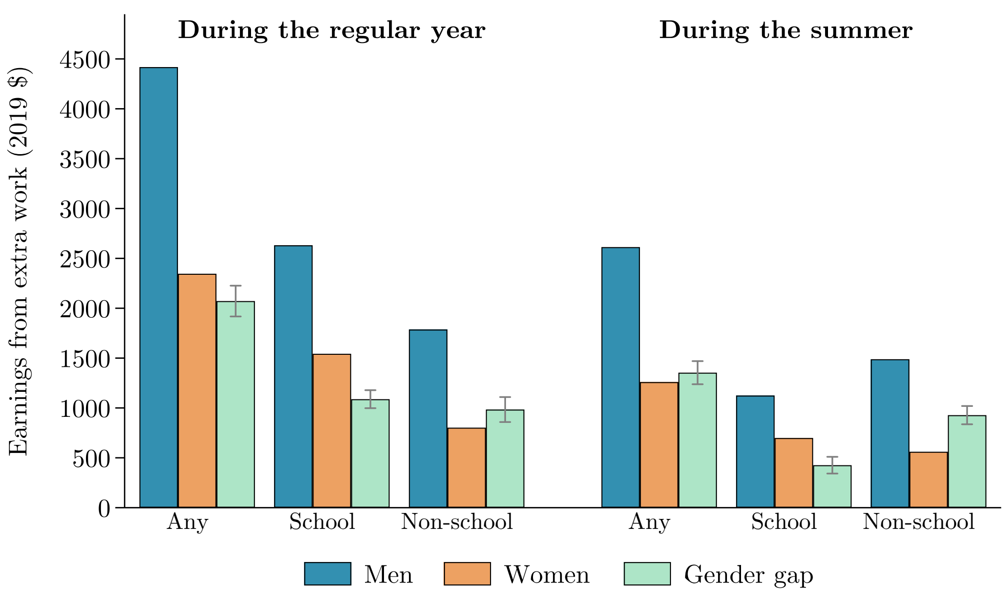
Source: Current Population Survey.
Notes: Coefficients $\widehat{\beta}_m$ from estimating Equation (1) among women who were present throughout rotation groups 1–4 and are now being observed in rotation groups 5–8. Successive series exclude respondents who report their industry (if employed) or previous industry (if non-employed) as the education sector in any of rotation groups 1–4, then additionally exclude individuals who were previously teachers or affiliated with child day care services. Bars show 95 percent confidence intervals based on Newey-West standard errors.

Appendix Figure A.23: Decomposition of female–male differences in presence at work



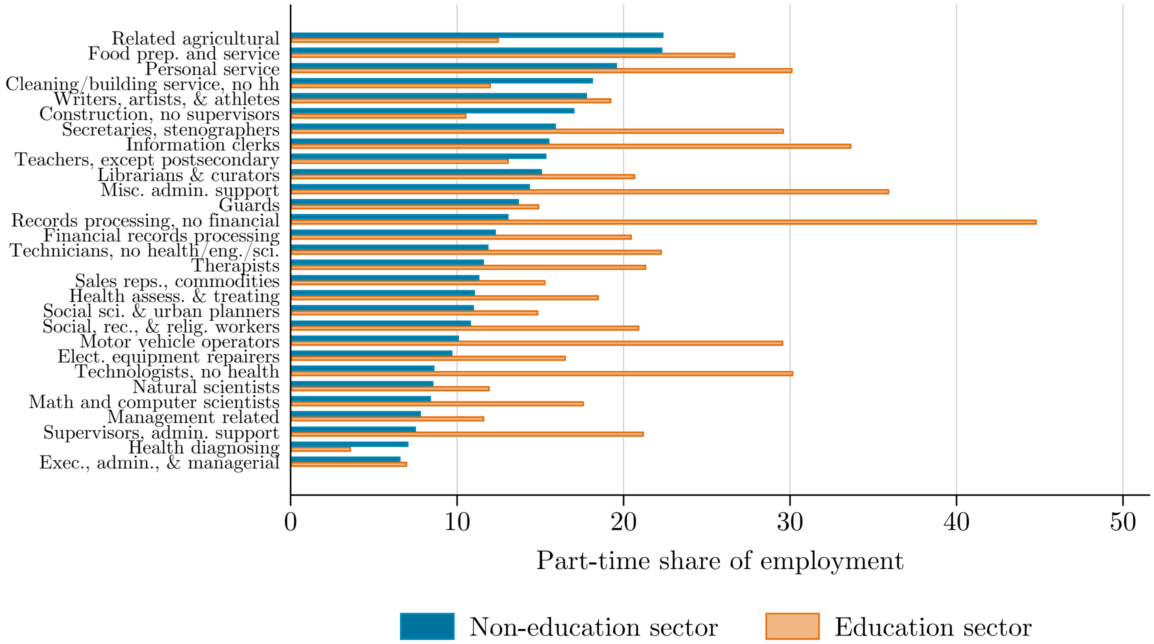
Source: Current Population Survey.
Notes: Additive decomposition of the gender gap in cumulative changes in presence at work between May and the indicated month into gender differences in sectoral/occupational sorting and gender differences in presence conditional on job type. See text and Appendix C for details on the decomposition methodology.

Appendix Figure A.24: Gender gaps in supplemental earnings among teachers



Source: Schools and Staffing Survey.
Notes: Supplemental earnings of full-time teachers during the regular school year and the summer months in 2019 dollars. School-based work entails participation in extracurricular activities, coaching, or summer/evening teaching. The regression-adjusted gender gaps control for age categories, teaching experience, race/ethnicity, master's degree, school type (primary or secondary), subject taught, urban status of school, and Census region.

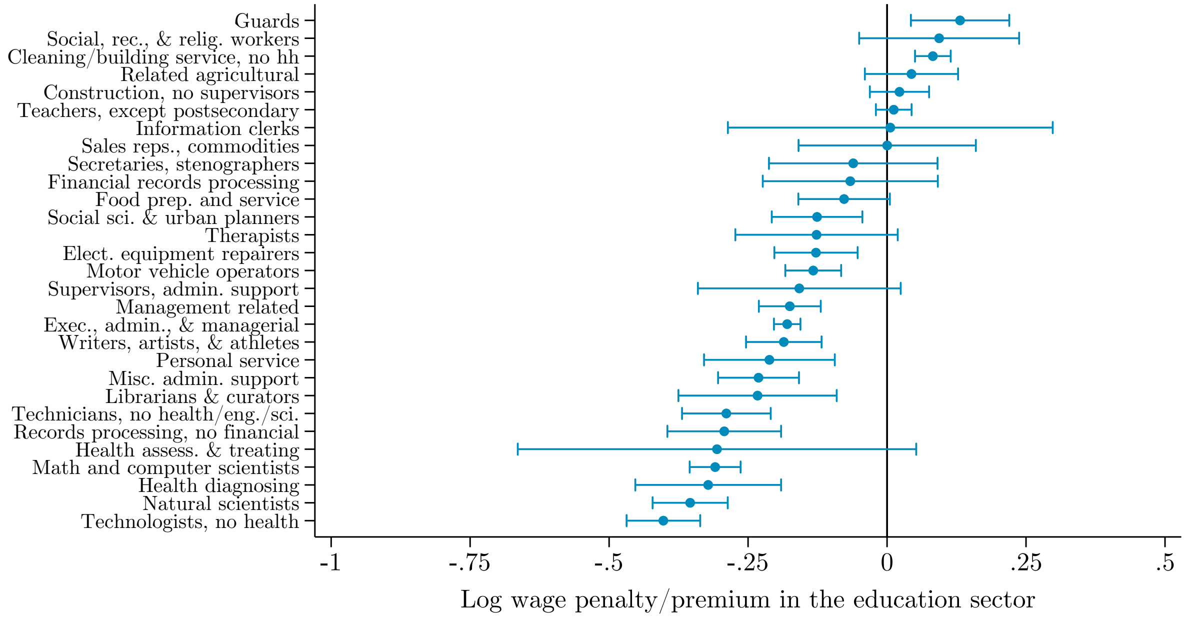
Appendix Figure A.25: Male part-time employment in occupations present both within and outside of the education sector (non-summer months)



Source: Current Population Survey.

Notes: Share of men employed in each occupation who worked part-time during the reference week, computed separately for the education and non-education sectors. The 29 listed occupations, drawn from a set of 74 two-digit Census occupations, are those for which average monthly employment exceeds 20,000 in each of the two sectors.

Appendix Figure A.26: Education-sector hourly wage penalties/premia within occupations present both within and outside of the education sector



Source: Current Population Survey, Annual Social and Economic Supplements.
Notes: Coefficients on the interaction of occupation fixed effects with an education-sector dummy, from an individual-level regression of log hourly wage controlling for occupation main effects, educational attainment, a quadratic in age, and calendar year. Log hourly wage equals log annual earnings minus log weeks worked and log hours per week. The 29 listed occupations, drawn from a set of 74 two-digit Census occupations, are those for which average monthly employment exceeds 20,000 in both the education and non-education sectors. Bars show 95 percent confidence intervals, with standard errors clustered by household.

Appendix Table A.1: Summary statistics for the main estimation sample

	All prime-age		Parents (child 6–12)	
	Women	**Men**	**Mothers**	**Fathers**
	(1)	(2)	(3)	(4)
Demographics				
Age	37.0	36.9	38.2	39.9
	(7.1)	(7.1)	(5.7)	(5.5)
Married, spouse present	60.6	59.6	69.7	88.2
Own child < 18 in household	59.6	49.0	100.0	100.0
Youngest < 6 years old	26.2	24.2	0.0	0.0
Youngest 6–12 years old	22.0	16.9	100.0	100.0
Youngest 13–17 years old	11.3	7.9	0.0	0.0
Labor market activity				
Employed	71.9	86.8	71.9	91.3
At work during reference week	68.4	84.2	68.6	88.6
Absent during reference week	3.5	2.6	3.4	2.7
Unemployed	3.8	4.6	4.1	3.7
Temporary layoff	0.4	0.8	0.5	0.8
Other reason unemployed	3.4	3.8	3.6	2.9
Not in labor force	24.3	8.6	24.0	5.0
Not in labor force (1994 or later)	24.2	9.0	23.7	5.2
Taking care of house or family	16.5	1.3	18.2	1.2
Other major activity	7.7	7.7	5.5	4.0
Hours worked in reference week	25.6	36.6	24.7	39.4
	(20.0)	(19.4)	(19.5)	(18.2)
Observations	9,033,776	8,351,163	2,005,503	1,443,127

Source: Current Population Survey.
Notes: The sample consists of civilians aged 25–49 spanning 1989–2019. All statistics are sample means, with standard deviations reported in parentheses for non-binary variables. All statistics other than age and hours worked are expressed as percentages. Non-employed and absent individuals are coded as working zero hours. Columns (3) and (4) restrict to parents whose youngest child residing in the household is aged 6–12. Observations are weighted to obtain representative estimates.

Appendix Table A.2: Decomposition of May–July changes in hours along extensive and intensive margins

Change in hours worked during reference week	**Women** Δ	**Women** $\%\Delta$	**Men** Δ	**Men** $\%\Delta$
Total change from May to July:				
(1)	-3.0	-11.2	-2.0	-5.3
Contribution from extensive margin:				
(2) Employed, at work $\longleftrightarrow$ not employed	-0.4	-1.3	-0.0	-0.1
Contribution from intensive margin:				
(3) Employed, at work $\longleftrightarrow$ employed, absent	-2.1	-8.0	-1.3	-3.5
(4) Δ among those employed, at work	-0.5	-1.9	-0.7	-1.7

Source: Current Population Survey.
Notes: Row (1) reports the change in average hours worked from May to July among respondents observed in May, June, and July. Rows (2)–(4) decompose this change by tabulating net hours changes among workers in the indicated categories. "Employed, at work" are employed individuals with positive hours worked during the reference week; "employed, absent" are employed individuals who worked zero hours during the reference week; and "not employed" are those unemployed or out of the labor force. "Δ among those employed, at work" is the change in hours worked among those employed with positive hours in both the May and July reference weeks. Percent changes are relative to average May hours. The overall May–July changes reported in this table differ slightly from Figure 4 because we restrict the sample to individuals linkable over time and because we report raw changes rather than regression estimates.

Appendix Table A.3: Demographic heterogeneity in May–July changes in employment (p.p.; negative numbers indicate larger declines)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age							
25–29 (omitted)	–	–	–	–	–	–	–
	–	–	–	–	–	–	–
30–34	-0.41	-0.18	-0.45	-0.30	-0.34	-0.26	-0.21
	(0.24)	(0.24)	(0.46)	(0.46)	(0.45)	(0.49)	(0.48)
35–39	-0.69	-0.21	-0.63	-0.16	-0.27	-0.28	-0.10
	(0.24)	(0.24)	(0.44)	(0.45)	(0.45)	(0.47)	(0.48)
40–44	-0.55	-0.12	-0.56	-0.20	-0.19	-0.06	-0.02
	(0.24)	(0.25)	(0.43)	(0.45)	(0.45)	(0.47)	(0.48)
45–49	-0.57	-0.32	-0.73	-0.57	-0.50	-0.01	-0.04
	(0.24)	(0.25)	(0.43)	(0.45)	(0.45)	(0.46)	(0.48)
Race and ethnicity							
White non-Hispanic (omitted)	–	–	–	–	–	–	–
	–	–	–	–	–	–	–
Black non-Hispanic	0.57	0.41	0.81	0.68	0.72	0.74	0.67
	(0.24)	(0.24)	(0.40)	(0.41)	(0.41)	(0.43)	(0.44)
Hispanic or Latinx	0.03	0.15	0.02	0.17	0.24	0.24	0.33
	(0.29)	(0.28)	(0.47)	(0.47)	(0.47)	(0.50)	(0.50)
Other non-Hispanic	0.44	0.52	0.92	1.00	0.51	0.27	0.37
	(0.33)	(0.32)	(0.53)	(0.53)	(0.53)	(0.57)	(0.56)
Educational attainment							
Less than high school	1.00	0.96	1.97	1.92	1.75	1.84	1.77
	(0.32)	(0.32)	(0.56)	(0.55)	(0.55)	(0.56)	(0.56)
High school graduate (omitted)	–	–	–	–	–	–	–
	–	–	–	–	–	–	–
Some college	0.35	0.34	0.28	0.31	0.43	0.39	0.39
	(0.20)	(0.20)	(0.33)	(0.32)	(0.32)	(0.34)	(0.33)
College graduate	-0.34	-0.38	-0.19	-0.15	1.06	0.67	0.68
	(0.19)	(0.19)	(0.31)	(0.30)	(0.31)	(0.34)	(0.33)
Sample restrictions:							
Observed throughout first year			X	X	X	X	X
Unconnected to ed. in first year						X	X
Controls for:							
Household structure		X		X	X		X
Connection to ed. in first year					X		
Number of observations	1,503,595	1,503,595	418,971	418,971	418,971	369,262	369,262
R^2	0.051	0.074	0.049	0.071	0.078	0.043	0.067

Source: Current Population Survey.
Notes: Coefficients on covariate × July interactions in individual-level regressions of an employment indicator on main effects and July interactions of the indicated characteristics in a sample of prime-age women observed in either May or July. Columns (3)–(7) restrict the sample to women who were present throughout rotation groups 1–4 and are now being observed in rotation groups 5–8. Columns (6)–(7) further restrict to women who were not affiliated with the education sector in any of rotation groups 1–4. Controls for household structure are main effects and two- and three-way interactions of indicators for the presence of a spouse, the presence/youngest age of own children in the household, and July. Controls for education connection are main and interaction effects of an indicator for affiliation with the education sector in any of rotation groups 1–4. Standard errors in parentheses are clustered by individual.

Appendix Table A.4: Gender differences in sectoral and occupational sorting

		% in sector/occ Women	Men	Pr(E → N)
Sector:				
(1)	Education	13.3	4.7	7.6
(2)	Non-education	86.7	95.3	4.0
	Total	100.0	100.0	4.4
Occupation in education sector:				
(3)	Primary school teacher	27.9	15.4	9.1
(4)	Secondary school teacher	9.0	16.9	7.4
(5)	Other non-college teacher	17.7	8.3	9.3
(6)	College teacher	5.3	14.6	7.8
(7)	Administrative staff	13.5	2.8	8.3
(8)	Managers	8.0	11.2	2.7
(9)	Food/trans./cleaning services	7.1	9.4	9.9
(10)	Other	11.5	21.4	6.0
	Total education	100.0	100.0	7.6

Source: Current Population Survey.
Notes: Employment shares and separation rates among respondents observed in May, June, and July of the same year and employed as of May. The first two columns measure respondents' sector and occupation in May. The last column reports the percentage of these individuals who were non-employed as of July (computed as the average of the female and male shares non-employed, to avoid conflating differences in occupations' separation rates with differences in their gender composition).

Appendix Table A.5: Decomposition of female–male differences in the seasonality of employment

Component	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May
Overall change in gender gap	0.000	-0.716	-1.217	-1.071	-0.216	0.117	0.414	0.764	0.987	1.074	0.834	0.437	0.000
	(0.000)	(0.087)	(0.098)	(0.135)	(0.151)	(0.140)	(0.105)	(0.104)	(0.114)	(0.107)	(0.132)	(0.091)	(0.000)
Sorting into the education sector	0.000	-0.272	-0.386	-0.320	-0.034	0.010	0.041	0.038	0.055	0.097	0.079	0.047	0.000
	(0.000)	(0.014)	(0.016)	(0.016)	(0.014)	(0.010)	(0.011)	(0.011)	(0.014)	(0.013)	(0.008)	(0.007)	(0.000)
Sorting across occupations inside ed.	0.000	-0.058	-0.089	-0.066	-0.028	-0.037	-0.034	-0.029	-0.008	-0.032	-0.029	-0.035	0.000
	(0.000)	(0.006)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.000)
Sorting across occupations outside ed.	0.000	-0.224	-0.250	-0.300	-0.387	-0.339	-0.175	-0.014	0.333	0.479	0.517	0.223	0.000
	(0.000)	(0.058)	(0.079)	(0.084)	(0.088)	(0.061)	(0.071)	(0.101)	(0.098)	(0.097)	(0.082)	(0.068)	(0.000)
Within occupations inside ed.	0.000	-0.186	-0.316	-0.227	-0.009	0.041	0.047	0.045	0.017	0.051	0.019	0.011	0.000
	(0.000)	(0.020)	(0.021)	(0.032)	(0.028)	(0.024)	(0.025)	(0.024)	(0.025)	(0.022)	(0.020)	(0.017)	(0.000)
Within occupations outside ed	0.000	-0.019	-0.251	-0.236	0.271	0.503	0.567	0.712	0.453	0.369	0.164	0.165	0.000
	(0.000)	(0.119)	(0.142)	(0.184)	(0.181)	(0.139)	(0.124)	(0.163)	(0.133)	(0.129)	(0.158)	(0.112)	(0.000)
Baseline scaling component	0.000	0.042	0.075	0.077	-0.029	-0.062	-0.032	0.012	0.136	0.110	0.085	0.026	0.000
	(0.000)	(0.010)	(0.013)	(0.015)	(0.015)	(0.015)	(0.012)	(0.013)	(0.016)	(0.016)	(0.014)	(0.011)	(0.000)

Source: Current Population Survey.
Notes: Point estimates and standard errors for the decomposition presented in Figure 10. Decomposition components are derived from a set of job-specific flow specifications (as in Equation (2)) estimated separately by sex. See Appendix C.2 for details on the decomposition procedure, which employs Kitagawa-Oaxaca-Blinder techniques, and calculation of standard errors, which we obtain by stacking regression models in the manner of seemingly unrelated regression.

B Details on Data Preparation

This section provides further details on our preparation of data from the Current Population Survey and American Time Use Survey, as well as our procedure for constructing the linear spline used as a regression control throughout our analysis.

B.1 Current Population Survey

Our analysis draws mainly on basic monthly CPS extracts provided by IPUMS (Flood et al., 2023a). We also use the Earner Study, administered to Outgoing Rotation Groups, and the Annual Social and Economic Supplement (ASEC), which accompanies the March CPS.

Sample restrictions. We limit our analysis to individuals aged 25–49. We further exclude members of the armed forces, who are not counted towards the official unemployment rate and for whom we do not observe key labor market variables (such as hours worked).

Longitudinal linkages. We link CPS observations across individuals over time and across individuals in the same household using the IPUMS variables `cpsidp` and `cpsid`, respectively. We lack reliable linkages in mid-1995, owing to changes in the CPS household identifiers.

IPUMS cautions that `cpsidp` sometimes yields erroneous links stemming from errors in data collection and advises researchers to validate individual linkages using sex, age, and race. We do so as in Madrian and Lefgren (2000). For month-to-month analyses, we exclude individuals whose observed sex, race, or ethnicity differs between consecutive months, as well as those whose age differs by more than two years.[1] For analyses tracking respondents over three months (Appendix Figure A.6, Appendix Table A.2, and Appendix Table A.4), we exclude individuals with any inconsistencies within these months. For analyses tracking respondents in consecutive years (Appendix Figure A.4, Appendix Figure A.22, and Appendix Table A.3), we exclude individuals for whom we observe inconsistencies in any of these variables at any point in their tenure in the survey.

Sampling weights. For cross-sectional analyses, we weight observations using the variables `wtfinl` (for analyses using basic monthly CPS extracts), `earnwt` (for analysis using weekly earnings), and `asecwt` (for analyses using the March ASEC). For longitudinal analyses, we weight observations using raked weights we compute ourselves. Although IPUMS provides a set of raked longitudinal weights that align gross labor market flows with stocks in the full set of adult CPS respondents, this equivalence holds only in the aggregate and breaks down once we restrict to prime-age individuals. Adapting replication files supplied by IPUMS, we construct raked weights via iterative proportional fitting, separately by sex and separately for each pair of consecutive months (Frazis et al., 2005). Applying these

[1]Although gender and racial identity can evolve over time, changes in these variables in the brief periods between CPS survey rounds are more likely to reflect distinct respondents than changes in self-identification. We allow for slight inconsistencies in the reporting of age because, among observations exhibiting logically impossible combinations of lagged and current age, very slight discrepancies are disproportionately common, suggesting that in many cases the same individual is in fact being observed on both occasions.

raked weights to the set of longitudinally linkable individuals in our sample yields gross flows among employment, unemployment, and non-participation consistent with observed changes in the stock of individuals in each status in our full cross-sectional sample.

Demographic characteristics.

- **Marital status:** We identify respondents who are married with a spouse present using the variable `marst`. We distinguish them from those who are married with an absent spouse, separated, divorced, widowed, or never married. To analyze joint employment patterns among married couples, we identify spouses using the variable `sploc`.
- **Parental status:** We link children in each household to their (biological, adoptive, or step-) parents using the variables `momloc`, `poploc`, `momloc2`, and `poploc2`, which encompass both same- and opposite-sex couples. We take particular note of the age of each adult respondent's youngest child in the household and bin parents into four groups: youngest child is under 6 years old, youngest child is 6–12 years old, youngest child is 13–17 years old, or the adult has no own child under 18 in the household. These age cutoffs mirror groupings used by IPUMS in its preparation of the ATUS data.
- **Educational attainment:** We classify individuals into four educational categories—"less than a high school degree", "high school degree", "some college", and "college degree or higher"—using the variable `educ`, which is populated both before and after changes to the underlying CPS questions in 1992.
- **Race/ethnicity:** We code individuals as "white non-Hispanic", "Black non-Hispanic", "Hispanic or Latinx", or "other non-Hispanic" using the variables `race` and `hispan`.

Sectors. We define the education sector using the variable `ind1990`, which bridges changes over time in the CPS industry codes. The education sector encompasses five industry codes: elementary and secondary schools, colleges and universities, vocational schools, libraries, and educational services not elsewhere classified.

Occupations and job types. We classify occupations using the variable `occ1990`, which harmonizes CPS occupation codes in concordance with the 1990 decennial Census. We aggregate these detailed codes into two coarser levels of aggregation.

First, for the analysis in Section 7.3, we obtain 74 two-digit occupations by grouping detailed occupations listed under the same headers in the IPUMS codebook.

Second, for analyses in Section 6.2 and Section 6.3, we partition jobs into 28 job types on the basis of both sector and occupation. Within the education sector, we distinguish five job types: (i) pre-K, kindergarten, and primary school teachers; (ii) secondary school teachers; (iii) postsecondary teachers; (iv) other staff in elementary and secondary schools; and (v) other staff in the education sector. Outside of education, we construct the following 23 job types by combining related two-digit occupations:

> executive, administrative, and managerial; management-related; engineers and scientists; health care professionals; teachers (outside the education sector); lawyers

and social scientists; other professionals; technologists and technicians; sales supervisors; sales; secretaries and records clerks; other administrative support; cleaning services; protective services; food services; health services; personal services; farming, forestry, and fishing; mechanics and repairers; construction trades; extractive and precision production; machine operators, assemblers, and inspectors; and transportation and material moving.

Our classification strikes a balance between pooling similar jobs—so as to yield more reliable estimates of each occupation's seasonal patterns—and distinguishing between jobs with dissimilar skill requirements and characteristics. For example, we combine "health diagnosing occupations", "health assessment and treating occupations", and "therapists" into "health care professionals", but we keep these groups separate from the lower-wage occupations that constitute "health services".

Earnings. As described in Section 7.2, we compute weekly earnings using the variables `earnweek` (usual weekly earnings), `paidhour` (paid on an hourly basis), `hourwage` (hourly wage), `ahrsworkt` (actual hours worked during the reference week), and `uh_payabs_b2` (paid for time off during the reference week). We multiply top-coded values for usual weekly earnings and hourly wages by a constant factor of 1.5, then deflate earnings to December 2019 dollars using the Personal Consumption Expenditures price index.

Reference week timing. The CPS reference week usually, but not always, includes the 12th day of the month. We calculate the number of weeks elapsed between successive CPS reference weeks by following BLS guidance:

1. Define the reference week as the 7-day calendar week (Sunday to Saturday) that includes the 12th day of the month.

2. Shift the December reference week one week earlier if the calendar week that includes December 5 would otherwise be contained entirely within the month of December.

3. Shift the November reference week one week earlier if Thanksgiving falls during the week containing November 19.[2]

In our CPS sample, reference weeks are spaced four weeks apart in 63.7 percent of year-month periods, five weeks apart in 33.9 percent of these periods, and three or six weeks apart in the remainder.

Annual Social and Economic Supplement (ASEC). For the analysis of the education sector earnings premium/penalty, we use the CPS Annual Social and Economic Supplement (ASEC), 1989–2019, which is administered in March of each year. The supplement includes respondents' annual income derived from wages and salaries (variable `incwage`). We trim

[2]According to the BLS, the Census Bureau sometimes advances the November reference week by one week in other years as well, when it determines that there is not enough time to process the data before December interviews begin. We do not observe these judgmental deviations and thus do not adjust for them.

extremely low values of annual income, equivalent to earning less than the nadir of the minimum wage over our sample period, working 10 hours per week, and working 20 weeks per year. For the years 1989–1995, we multiply top-coded earnings by a constant factor of 1.5; from 1996 onward, the Census Bureau replaces top-coded earnings with replacement values that obviate the need for further adjustment. We then deflate earnings to December 2019 dollars using the Personal Consumption Expenditures price index.

We use this income information alongside the respondent's industry and occupation during the previous year to compute the regression-adjusted education-sector earnings premium or penalty in each occupation. The regression controls for educational attainment, a quadratic in age, and calendar-year fixed effects, in addition to occupation fixed effects and their interactions with the education sector. To estimate the wage premium/penalty, we compute log hourly wages as log annual earnings minus the sum of weeks worked last year (`wkswork1`) and usual hours worked per week last year (`uhrsworkly`).

B.2 Choosing knots for the linear spline

Our workhorse specifications in Equations (1) and (2) control for a linear spline in calendar time. To motivate this approach, suppose first that a given outcome variable (such as female EPOP) contains a linear time trend. Because our analysis period runs from January 1989 through December 2019, later months in the year tend to occur slightly later in calendar time, so that a naïve regression on month dummies alone would be biased in proportion to the degree of secular drift. In addition, one might worry that turning points in the business cycle happen to occur at particular points in the calendar year. To address these potential biases, and to improve the precision of our estimates, we use a flexible spline function with knots at key turning points in the business cycle.

Our choice of knots is inspired by recent research on the cyclical properties of unemployment and labor force participation. Dupraz, Nakamura, and Steinsson (2019) note that turning points in the unemployment rate do not align perfectly with official business cycle dates from the National Bureau of Economic Research, while Cajner, Coglianese, and Montes (2021) and Hobijn and Şahin (2021) document the sluggish response of the labor force participation rate (LFPR) to cyclical conditions, especially in the wake of the Great Recession. Motivated by these observations, we adopt a data-driven approach that locates knots tailored to prime-age EPOP and LFPR:

1. We start with an algorithm from Dupraz, Nakamura, and Steinsson (2019, hereafter DNS) that locates turning points in the US unemployment rate by searching for local extrema while ignoring small fluctuations within a tolerance band. Adapting their replication code, we locate turning points in seasonally adjusted EPOP for ages 25–54, as published by the Bureau of Labor Statistics (Labor Force Statistics series LNS12300060).[3]

2. The DNS procedure yields six turning points that fall within our 1989–2019 analysis

[3]The DNS algorithm deals with the possibility of "ties" by selecting the earliest peak or trough within a given expansion or contraction. We depart slightly from their procedure by instead taking the midpoint between the earliest and latest candidate inflection points (rounding up to the nearest month when needed).

period: January 1990, February 1993, April 2000, October 2003, January 2007, and June 2010. We discard the January 1990 turning point since it falls near the edge of our period.

3. Although a linear spline with these knots can effectively capture broad movements in prime-age EPOP, it imposes a linear trend for the last decade of our analysis period, and it misses an important turning point in prime-age participation during the mid-2010s. To remedy these defects, we rerun the DNS algorithm using the seasonally adjusted LFPR for ages 25–54 (Labor Force Statistics series LNS11300060) and retain the turning point in October 2014.

We end up with six knots: February 1993, April 2000, October 2003, January 2007, June 2010, and October 2014. Besides corresponding to notable inflection points in prime-age labor market conditions, these knots are situated roughly five years apart and hence serve as a flexible means to model trend movements in other outcomes we examine as well.

B.3 American Time Use Survey (ATUS)

Launched in 2003, the ATUS (another BLS product) surveys a random subset of outgoing CPS respondents a few months after their final CPS interview (Hamermesh, Frazis, and Stewart, 2005; Guryan, Hurst, and Kearney, 2008). One randomly selected adult member of the household is asked to provide a detailed, minute-by-minute accounting of their activities throughout the previous day. Paralleling our CPS sample, we assemble IPUMS ATUS data on individuals aged 25–49 over the period 2004–2019 (Flood et al., 2023b); we discard 2003 because of issues with data completeness. We multiply minutes spent on each activity by $^7/_{60}$, so our measures are expressed in terms of hours per week.

We examine both narrow and broad measures of time allocated to childcare activities. First, we follow Guryan, Hurst, and Kearney (2008) in constructing a measure of "primary" childcare, defined as intervals of time in which the respondent was mainly engaged in childcare activities. Second, we compute "total" childcare by adding in the ATUS measure of secondary childcare, defined as time spent engaging in childcare concurrently with some other primary activity. We exploit the granular structure of the ATUS to decompose secondary childcare according to whether it accompanies household activities, leisure activities, or other activities.

The ATUS diary dates are distributed evenly throughout the year, but weekends are deliberately oversampled. We employ IPUMS sampling weights that adjust for both cross-household and day-to-day differences in sampling probability, so that our estimates are representative of prime-age adults' time allocation throughout the week as well as the year.

Primary childcare time. Our definition of primary childcare time follows Guryan, Hurst, and Kearney (2008), who write:

> *We define "total childcare" as the sum of four primary time use components. "Basic" childcare is time spent on the basic needs of children, including breast-feeding, rocking a child to sleep, general feeding, changing diapers, providing medical care (either directly or indirectly), grooming, and so on. However, time spent*

preparing a child's meal is included in general "meal preparation," a component of nonmarket production. "Educational" childcare is time spent reading to children, teaching children, helping children with homework, attending meetings at a child's school, and similar activities. "Recreational" childcare involves playing games with children, playing outdoors with children, attending a child's sporting event or dance recital, going to the zoo with children, and taking walks with children. "Travel" childcare is any travel related to any of the three other categories of childcare. For example, driving a child to school, to a doctor, or to dance practice are all included in "travel" childcare.

We identify the ATUS activities matching these verbal descriptions and use them to construct measures of basic, educational, recreational, and travel childcare, then sum these measures to obtain primary childcare.

Secondary childcare time. Alongside each person $\times$ primary activity observation, the ATUS reports whether the respondent had a child under age 13 in their care while engaging in that activity. Following our definition of parental status, we use a measure of secondary childcare that counts only instances when the child under an adult's care is the parent's own child. We define total childcare as the sum of primary and secondary childcare. To shed additional light on seasonal changes in time use, we also partition time spent on secondary childcare according to the primary activity it accompanies:

1. Household activities, a category reported directly in the ATUS;
2. Leisure activities, which we define as the union of the ATUS categories "socializing, relaxing, and leisure", "sports, exercise, and recreation", and "traveling"; and
3. All other activities.

Data quality and completeness. We exclude observations with data quality flags (which note, for example, cases in which a respondent intentionally provided a wrong answer or could not remember their activities), as well as those with incomplete time diaries (cases in which total time usage sums to less than 24 hours).

C Decomposition Details

In this appendix, we derive two key decompositions used in the main text. First, we show how seasonal changes in employment rates can be decomposed into contributions from inflows versus outflows (Figure 3). Second, we show how gender differences in employment seasonality can be decomposed into gender differences in job sorting as well as gender differences conditional on job type (Figure 10).

Notation. We begin by introducing notation common to both decompositions.

- Let $g \in \{♀ \text{ (female)}, ♂ \text{ (male)}\}$ index gender.

- Let $m \in \{0, 1, \ldots, 12\}$ index calendar months relative to the base month 0, which we take to be May. We sometimes use $m = 12$ as an alternative label for the base month.
- Let e_{gm} denote group g's EPOP in month m. Let f_{gm} and s_{gm} denote the shares of each population *finding* or *separating from* employment in month m, and let $n_{gm} \equiv f_{gm} - s_{gm}$.

  We refer to f_{gm} as *inflows*, s_{gm} as *outflows*, and n_{gm} as *net inflows*. Since our empirical implementation implicitly averages across years after netting out low-frequency time trends, monthly changes in (e, f, s, n) represent the typical seasonal pattern in each outcome.
- For any variable x, we define the operators

$$\begin{aligned}
\Delta_g(x) &\equiv x_{♀} - x_{♂} && \text{(female–male gap)} \\
\Delta_m(x) &\equiv x_m - x_{m-1} && \text{(month-to-month change)} \\
\mathbb{E}_g(x) &\equiv \frac{1}{2}(x_{♀} + x_{♂}) && \text{(cross-gender average)} \\
\mathbb{E}_y(x) &\equiv \frac{1}{12}\sum_{m=1}^{12} x_m && \text{(within-year average)}
\end{aligned}$$

  These operators may be nested: for example, the gender gap in the month-to-month change is written as: $\Delta_g(\Delta_m(x)) = (x_{♀m} - x_{♀,m-1}) - (x_{♂m} - x_{♂,m-1})$.

C.1 Stock-flow decomposition

We begin with the decomposition shown in Figure 3, which expresses changes in each group's EPOP between months $m-1$ and m as the sum of an inflow component and an outflow component.

Stock-flow identity. Since month-to-month changes in EPOP equal net inflows, we have the law of motion

$$e_{gm} = e_{g,m-1} + f_{gm} - s_{gm} \qquad \text{for } m > 0, \tag{6}$$

where $m = 0$ and $m = 12$ both denote May. By recursive substitution, $e_{g12} = e_{g0} + \sum_{m=1}^{12}(f_{gm} - s_{gm})$. But since e_{gm} represents a seasonal cycle, we know that $e_{g0} = e_{g12}$: net of low-frequency trends and idiosyncratic shocks, EPOP evolves from May through April and then returns to its May level. It follows that

$$\sum_{m=1}^{12} f_{gm} = \sum_{m=1}^{12} s_{gm} \tag{7}$$

Intuitively, EPOP can remain stable over a 12-month cycle only if total inflows exactly counterbalance total outflows over that period.

Dividing Equation (7) by 12 yields $\mathbb{E}_y(f_g) = \mathbb{E}_y(s_g)$: average inflows equal average outflows over the seasonal cycle. Adding and subtracting these (equal) terms to Equation (6), we obtain

$$\Delta_m(e_{gm}) \equiv \underbrace{(f_{gm} - \mathbb{E}_y(f_g))}_{\text{excess inflows}} - \underbrace{(s_{gm} - \mathbb{E}_y(s_g))}_{\text{excess outflows}} \tag{8}$$

Intuitively, EPOP rises between two consecutive months to the extent that inflows exceed their average monthly rate and/or outflows fall short of their average monthly rate.

Estimation. Equation (8) is estimable. Let β^f_{gm} and β^s_{gm} denote the parameters of interest in our inflow and outflow specification, respectively. Start with inflows. Since these parameters represent differences in flows between month m and the base month, we have $f_{gm} = f_{g0} + \beta^f_{gm}$, so that

$$\mathbb{E}_y(f_g) = \frac{1}{12}\sum_{m=1}^{12} f_{gm} = \frac{1}{12}\sum_{m=1}^{12}(f_{g0} + \beta^f_{gm}) = f_{g0} + \mathbb{E}_y(\beta^f_g) \tag{9}$$

We can then rewrite excess inflows as

$$f_{gm} - \mathbb{E}_y(f_g) = (f_{g0} + \beta^f_{gm}) - (f_{g0} + \mathbb{E}_y(\beta^f_g)) = \beta^f_{gm} - \mathbb{E}_y(\beta^f_g) \tag{10}$$

Rewriting excess outflows in the same fashion, and replacing each parameter with its empirical estimate, we obtain our stock-flow decomposition:

$$\Delta_m(e_{gm}) \equiv \underbrace{(\widehat{\beta}^f_{gm} - \mathbb{E}_y(\widehat{\beta}^f_g))}_{\text{excess inflows}} - \underbrace{(\widehat{\beta}^s_{gm} - \mathbb{E}_y(\widehat{\beta}^s_g))}_{\text{excess outflows}} \tag{11}$$

Although Figure 3 is expressed in terms of one-month changes, one could cumulate these decomposition terms across months to estimate the contributions of inflows versus outflows to changes in EPOP between any pair of months m and m'. In addition, confidence intervals can be readily constructed via the delta method.

C.2 Job decomposition

We now turn to the decomposition shown in Figure 10. Our goal is to decompose $\Delta_g(\Delta_m(e_g))$, which represents gender differences in the evolution of EPOP between months $m-1$ and m, into a set of terms representing gender differences in sorting across job types and gender differences in seasonality conditional on job type. Having done so, we can then cumulate the decomposition terms across months to characterize gender differences over the full seasonal cycle.

Step 1: Partition employment into jobs and sectors. We partition employment into a set of job types $\mathbb{J}$, indexed by j, which we call "jobs" for brevity. These jobs are nested within the education and non-education sectors, $S \in \{E, \not{E}\}$, so that $\mathbb{J} = J_E \cup J_{\not{E}}$. In our empirical implementation, we distinguish five job types within education and 23 job types outside of education.

Step 2: Express seasonal changes in EPOP in shift-share form. To leverage standard decomposition techniques, we first write $\Delta_m(e_g)$ as a share-weighted average of job-level flow rates.

Let e_{gjm} denote the share of population g employed in job j in month m, so that $e_{gm} = \sum_{j \in \mathbb{J}} e_{gjm}$. Let f_{gjm} denote the share of population g moving from non-employment into job j, and let s_{gjm} denote the share moving from job j into non-employment. We define $n_{gjm} \equiv f_{gjm} - s_{gjm}$ as net inflows from non-employment into job j. Note that these flows exclude job-to-job transitions, which cancel out in the aggregate and hence leave no imprint on overall EPOP.

Next, we express seasonal changes in EPOP as the sum of net inflows across job types:

$$\Delta_m(e_g) = n_{gm} = \sum_{j \in \mathbb{J}} n_{gjm} \tag{12}$$

As in the aggregate case, these seasonal movements must cumulate to zero over a full 12-month cycle, so that $\mathbb{E}_y(f_{gj}) = \mathbb{E}_y(s_{gj})$ and hence $\mathbb{E}_y(n_{gj}) = 0$. Subtracting this expression, we obtain

$$\Delta_m(e_g) = \sum_{j \in \mathbb{J}} (n_{gjm} - \mathbb{E}_y(n_{gj})) \tag{13}$$

Now, multiply and divide the summand by e_{gj0}, the share of population g employed in job j in the base month:

$$\Delta_m(e_g) = \sum_{j \in \mathbb{J}} e_{gj0} \underbrace{\left(\frac{n_{gjm}}{e_{gj0}} - \frac{\mathbb{E}_y(n_{gj})}{e_{gj0}} \right)}_{\equiv \lambda_{gjm}} = \sum_{j \in \mathbb{J}} e_{gj0} \lambda_{gjm}, \tag{14}$$

where the newly defined term λ_{gjm} represents *group g's excess net flows from non-employment into job j in month m as a share of baseline employment.*

Step 3: Decompose the gender gap between and within job types. With the shift-share formulation in hand, we can express the gender gap in employment seasonality as

$$\Delta_g(\Delta_m(e_g)) = \Delta_g \left(\sum_{j \in \mathbb{J}} e_{gj0} \lambda_{gjm} \right) \tag{15}$$

We are now in the realm of familiar decomposition techniques. Using the standard trick of adding and subtracting cross-terms, we can decompose the righthand side as[4]

$$\Delta_g \left(\sum_{j \in \mathbb{J}} e_{gj0} \lambda_{gjm} \right) = \underbrace{\sum_{j \in \mathbb{J}} \Delta_g(e_{gj0}) \mathbb{E}_g(\lambda_{gjm})}_{\text{between jobs}} + \underbrace{\sum_{j \in \mathbb{J}} \mathbb{E}_g(e_{gj0}) \Delta_g(\lambda_{gjm})}_{\text{within jobs}} \tag{16}$$

[4] As with any Kitagawa-Oaxaca-Blinder-style decomposition, we face the question of which gender to use as the base group in each term. Equation (16) uses cross-gender averages in each term to avoid making an arbitrary choice.

Intuitively, the *between-job* component captures gender differences in seasonality arising from differences in the share of each group employed at various jobs that differ in their propensity to generate employment inflows/outflows throughout the year. The *within-job* component captures gender differences in employment flows conditional on a given allocation across job types.

Step 4: Separate the job-sorting and baseline EPOP effects. While the within-job component in Equation (16) has a straightforward economic interpretation, the between-job component does not, as it confounds gender differences in sorting with gender differences in employment rates. With a little more algebra, however, we can separate these effects:

$$\sum_{j\in\mathbb{J}} \Delta_g(e_{gj0})\mathbb{E}_g(\lambda_{gjm}) = \underbrace{\sum_{j\in\mathbb{J}} \Delta_g\left(\frac{e_{gj0}}{e_{g0}}\right)\mathbb{E}_g(e_{g0})\mathbb{E}_g(\lambda_{gjm})}_{\text{job-sorting effect}} + \underbrace{\Delta_g(e_{g0})\sum_{j\in\mathbb{J}} \mathbb{E}_g\left(\frac{e_{gj0}}{e_{g0}}\right)\mathbb{E}_g(\lambda_{gjm})}_{\text{baseline EPOP effect}} \tag{17}$$

The *job-sorting effect* captures the extent to which—conditional on being employed—male and female workers differ in their propensity to work in jobs with different seasonal patterns. The *baseline EPOP effect* is a scaling term that accounts for gender differences in employment rates: because male EPOP exceeds female EPOP, a seasonal shift that has the same *proportional* impact on male and female employment rates will have a bigger *absolute* impact on men than on women. By splitting out the baseline EPOP effect (which we regard as a nuisance term), we can better assess how job sorting contributes to the gender gap in summer work interruptions.

Step 5: Distinguish sorting across sectors from sorting within sectors. We can further unpack the job-sorting effect to distinguish sectoral sorting from sorting across jobs within a given sector. To condense notation:

- Let $\phi_{gj} \equiv \frac{e_{gj0}}{e_{g0}}$ denote group g's employment in job j as a fraction of its total employment.
- Let $\widetilde{\lambda}_{jm} \equiv \mathbb{E}_g(e_{g0})\mathbb{E}_g(\lambda_{gjm})$ denote excess net flows in job j, averaged across genders and then scaled by aggregate EPOP.
- Sum these within sector $k \in \{E, \not{E}\}$: $\Phi_{gk} \equiv \sum_{j\in J_k} \phi_{gj}$ and $\Lambda_{km} \equiv \sum_{j\in J_k} \mathbb{E}_g\left(\frac{\phi_{gj}}{\Phi_{gk}}\right)\widetilde{\lambda}_{jm}$.

The job-sorting effect then becomes simply $\sum_j \Delta_g(\phi_{gj})\widetilde{\lambda}_{jm}$, which we subdecompose as follows:

$$\begin{aligned}\sum_{j\in\mathbb{J}} \Delta_g(\phi_{gj})\widetilde{\lambda}_{jm} = &\underbrace{\Delta_g\left(\Phi_{gE}\Lambda_{Em} + \Phi_{g\not{E}}\Lambda_{\not{E}m}\right)}_{\text{sorting into the education sector}} \\ &+ \underbrace{\sum_{j\in J_E} \Delta_g(\phi_{gj})(\widetilde{\lambda}_{jm} - \Lambda_{Em})}_{\text{sorting across ed.-sector jobs}} + \underbrace{\sum_{j\in J_{\not{E}}} \Delta_g(\phi_{gj})(\widetilde{\lambda}_{jm} - \Lambda_{\not{E}m})}_{\text{sorting across non-ed. jobs}}\end{aligned} \tag{18}$$

Intuitively:

- The first term captures gender differences in sorting into the education sector, "priced" using average seasonal patterns in education versus non-education as a whole.
- The second and third terms capture gender differences in sorting into jobs with different seasonal patterns, both within education (such as primary versus secondary school teachers) and outside education (such as construction trades versus health care professionals).

Step 6: Isolate gender differences within jobs in each sector. In a similar (but simpler) fashion, we can also subdecompose the within-job component from Equation (16) into two terms:

$$\sum_{j \in \mathbb{J}} \mathbb{E}_g(e_{gj0})\Delta_g(\lambda_{gjm}) = \underbrace{\sum_{j \in J_E} \mathbb{E}_g(e_{gj0})\Delta_g(\lambda_{gjm})}_{\text{within education-sector jobs}} + \underbrace{\sum_{j \in J_{\not E}} \mathbb{E}_g(e_{gj0})\Delta_g(\lambda_{gjm})}_{\text{within non-education jobs}} \tag{19}$$

Note that, in Equation (19), each subcomponent can be viewed as a single entity representing the sector as a whole, or one could subdivide it further to examine the contributions made by gender differences within specific jobs, such as differences among primary school teachers or differences among health care professionals.

Empirical implementation. Equations (16) and (17) give us a three-way decomposition of the gender gap in employment seasonality into within-job, job-sorting, and baseline EPOP components. Equations (17) to (19) unpack these further into the six-way decompositions shown in Figure 10, Appendix Figure A.23, and Appendix Table A.5.

To implement these decompositions, we need (1) a partition $\mathbb{J}$ of sector-occupation pairings into job types, (2) estimates of the share of women/men employed in aggregate and in each job, and (3) estimates of the λ terms capturing net excess flows. As detailed in Appendix B.1, we distinguish 28 job types by defining 5 broad occupations within education and 23 broad occupations outside of education. We then compute baseline employment shares as simple average employment shares across all May observations in our analysis period. We estimate the λ terms by estimating our standard seasonal specification on grouped data, with one observation per sex $\times$ job type.

Confidence intervals. Each term in our decomposition combines parameter estimates from a subset of 2 $\times$ J notionally independent regressions. To construct confidence intervals for each decomposition term, we stack a copy of the group-level data for each constituent regression, then estimate a single stacked model in the manner of seemingly unrelated regression. We cluster errors at the year $\times$ month level, so that the error terms can be arbitrarily correlated across outcomes in each stack. Using the stacked covariance matrix, we can then construct confidence intervals via the delta method.[5]

[5]As a check on this procedure, we compared the confidence intervals for the overall gender gap in EPOP obtained via this method with those obtained from a direct regression using aggregate flows. These match

D A Model of Labor Supply with Summer School Closures

We use a two-period model to illustrate how schools' summer closures may contribute to gender differences in employment over both the seasonal cycle and the life cycle. In our model, period 1 represents a typical year during the early part of an agent's working life, before she (or he) has children. Period 2 represents years later in life when children are old enough to attend school but young enough to require supervision during the summer months, when schools are not in session. We abstract from other portions of the life cycle so as to focus attention on the most pertinent theoretical issues.

We proceed in four steps. In step I, we develop a static variant of the model that is isomorphic to period 2 in the full dynamic model. In step II, we determine which of the available strategies are "admissible" in the sense of being optimal for some possible parameter values. In step III, we perform comparative statics showing how optimal behavior responds to parents' increased disutility from working during the summer months. We interpret these comparative statics as a reduced-form representation of comparisons between agents who differ in parental status, child age, the availability of spousal childcare, or access to market-provided childcare. In step IV, we extend the static model into a two-period dynamic model and derive additional implications about life-cycle career choices.

Step I: static setup

We consider a single agent deciding whether and in which sector to work at different points throughout the year. Here and throughout, the model is in partial equilibrium in the sense that we do not endogenize employment opportunities or wages. We also abstract from fertility decisions and take the presence or absence of children as exogenous.

Time periods. Each period, or "year", is divided into two subperiods, which we call "seasons" and index by $\tau \in \{A, B\}$. Season A, which we sometimes call "winter" for concreteness, represents the school year, whereas season B represents the summer.[6] Since our initial focus is on a single year, we omit year subscripts until step IV.

Work status. The agent chooses whether to supply one unit of labor and, if so, in which sector to work. In a given season, the agent's work status ("job") is $j \in \{E, N, O\}$, where:

- E represents being employed (and at work) in the *education* sector;
- N represents being employed (and at work) in the *non-education* sector; and
- O represents being non-employed (or employed but absent).

We abstract from both job search and leave-taking. First, we assume that the agent can obtain a job in either sector at zero cost and at any time. As a result, there is no meaningful

up to the slight numerical errors one would expect from repeated application of the delta method.

[6] Although (for simplicity) we model the two seasons as being of equal length, it would be straightforward to modify the model to allow for "winter" to be three times as long as "summer".

distinction between unemployment and non-participation in our model.[7] Second, as detailed below, there is also no meaningful distinction between non-employment and vacation. Under these assumptions, the single status O suffices to capture all forms of non-work during a given season.

Strategies. A *strategy*, denoted by s, is an ordered pair (j_A, j_B) representing the agent's employment status during both winter and summer. Since each status can assume three different values, there are nine available strategies. For brevity, we often write $s = EE$ or $s = NO$ in place of $s = (E, E)$ or $s = (N, O)$. We write $s^*(\theta)$ for the optimal strategy under parameter vector θ, which we define explicitly below.

Utility. Utility $u(s|\theta)$ from choosing strategy s given parameters θ equals earnings net of distaste for labor and childcare costs, with each component summed across seasons.

Earnings. Let $w_{j\tau}$ denote base wages from working in job j during season τ. Let b_j be a bonus awarded for working year-round in job j. We make four assumptions about earnings in each sector:

Assumption A1. $w_{OA} = w_{OB} = 0$.

Non-work yields zero earnings. This assumption abstracts from unemployment benefits, cash welfare, or any other forms of non-labor income.

Assumption A2. $w_{EA} > w_{EB} > 0$.

Education jobs pay less over the summer. This assumption captures the idea that the demand for education workers is greater during the school year but remains positive during the summer.

Assumption A3. $w_{NA} = w_{NB} \equiv w_N > 0$.

Non-education jobs pay the same base wage in each season. This assumption abstracts from seasonal differences in labor demand in sectors like agriculture, construction, and retail.

Assumption A4. $b_N > 0$, $b_E = b_O = 0$.

Non-education jobs offer a within-year continuity bonus, whereas education jobs do not. This assumption captures the idea that, in many jobs, full-year employment offers premium earnings (or, equivalently, interrupted employment carries an earnings penalty).

These assumptions amount to a parsimonious way of modeling the key idea that education-sector jobs are more flexible than non-education jobs, especially as pertains to

[7] Although unemployment is a first-order consideration at high frequencies, it is of secondary importance relative to participation decisions over longer time horizons. We focus on a single year for purposes of exposition, but we interpret our model as capturing employment dynamics over longer periods each lasting for at least several years.

summer work. Although many of our theoretical results would obtain under weaker assumptions, the sharp parameter restrictions assumed above simplify the exposition and streamline the proofs.

Distaste for labor and childcare costs. Working in sector j in season τ entails flow disutility $\Phi_{j\tau} \equiv \phi_j + D_{j\tau}(\Delta^R + \Delta^C)$, where ϕ_j is a sector effect, $D_{j\tau} \equiv \mathbb{1}\{j \neq O, \tau = B\}$ is an indicator for summer employment, and Δ^R and Δ^C capture preferences over the seasonal timing of work related to recreational opportunities or childcare considerations, respectively.[8] We assume:

Assumption B1. $\phi_O = 0$.

We normalize the intrinsic distaste for non-employment to zero. With this normalization, ϕ_E and ϕ_N absorb any overall labor-leisure preferences—including those related to childcare considerations operative year-round—as well as relative preferences for one sector over the other.

Assumption B2. $\Delta^R > 0$.

All else equal, agents have at least a slight preference for taking leisure in summer relative to winter, reflecting the greater recreational opportunities available in the summer. This assumption simplifies the exposition by ruling out the possibility that some agents choose to work exclusively during summer, but it is immaterial for the model's main results.

Assumption B3. $\Delta^C \geq 0$.

When the inequality is strict, parental considerations make summer employment especially costly for two possible reasons, which are not mutually exclusive. The first is *childcare constraints*: while schools provide implicit childcare during the school year, working parents must arrange costly childcare arrangements when schools are closed for the summer. The second is *leisure complementarities*: parents who choose to work over the summer may forgo utility they would otherwise have received from spending time with their children while they are not in school. Although Δ^C admits both interpretations, for ease of exposition we refer to Δ^C as a measure of childcare costs.

As with our assumptions about the earnings process, our main results would continue to obtain under weaker assumptions about leisure preferences and childcare costs.

Parameters. Let $\theta \equiv (w_{EA}, w_{EB}, w_N, b_N, \phi_E, \phi_N, \Delta^R, \Delta^C)$ be a vector of exogenous parameters. Apart from the restrictions made above, these parameters may vary freely across agents with different productivities, comparative advantages, leisure preferences, and household structures.

[8] Our notation ϕ_j abstracts from the possibility that some jobs are more pleasant or unpleasant to perform at certain times of year: for example, workers may particularly dislike working in outdoor occupations in the winter. Relaxing this assumption would have no bearing on our comparative statics.

We will be chiefly interested in comparative statics with respect to Δ^C, which captures summer childcare costs. Since these exercises hold recreational preferences Δ^R fixed, we define $\Delta \equiv \Delta^R + \Delta^C$ and focus on comparative statics with respect to Δ.

Step II: admissible strategies

We can write out the utility associated with each available strategy as follows:

Strategy	Earnings	Distaste	Childcare	Utility
OO	0	0	0	0
EO	w_{EA}	ϕ_E	0	$w_{EA} - \phi_E$
OE	w_{EB}	ϕ_E	Δ	$w_{EB} - \phi_E - \Delta$
EE	$w_{EA} + w_{EB}$	$2\phi_E$	Δ	$w_{EA} + w_{EB} - 2\phi_E - \Delta$
NO	w_N	ϕ_N	0	$w_N - \phi_N$
ON	w_N	ϕ_N	Δ	$w_N - \phi_N - \Delta$
NN	$2w_N + b_N$	$2\phi_N$	Δ	$2w_N + b_N - 2\phi_N - \Delta$
EN	$w_{EA} + w_N$	$\phi_E + \phi_N$	Δ	$w_{EA} + w_N - \phi_E - \phi_N - \Delta$
NE	$w_N + w_{EB}$	$\phi_N + \phi_E$	Δ	$w_{EB} + w_N - \phi_E - \phi_N - \Delta$

By inspection, three strategies can be immediately ruled out:

- OE is strictly dominated by EO since $w_{EA} > w_{EB}$ and $\Delta > 0$.
- ON is strictly dominated by NO since $\Delta > 0$.
- NE is strictly dominated by EN since $w_{EA} > w_{EB}$.

The dominated strategies represent work configurations that, though of course present to some extent in the real world, are of secondary importance for our analysis.[9] Each of the remaining six strategies is *admissible* in the sense of being the optimal strategy for some parameter vector θ.

Lemma 1. *For each strategy $s_k \in \{OO, EO, EE, NO, NN, EN\}$, there exists a parameter vector θ_k such that $s^*(\theta_k) = s_k$. Moreover, θ_k can be chosen such that s_k is the unique optimum.*

Proof: Fix an initial vector θ_0 satisfying the assumptions stated previously. By taking certain parameter values to the limit while keeping all other parameters fixed, we can make each of the six strategies uniquely optimal:

- OO: take $\phi_E \to \infty$ and $\phi_N \to \infty$.
- EO: take $w_{EA} \to \infty$ and $\Delta \to \infty$.
- EE: take $w_{EA} \to \infty$ and $w_{EB} \to \infty$.

[9] Pure summer employment (OE or ON) is common among young adults but less common among prime-age adults. Although employment rates among prime-age men are significantly higher in summer than in winter, seasonal patterns among men primarily track the timing of adverse winter weather rather than the timing of summer break.

- NO: take $w_N \to \infty$ and $\Delta \to \infty$, with $\Delta > w_N + b_N - \phi_N$.
- NN: take $w_N \to \infty$.
- EN: take $w_{EA} \to \infty$ and $w_N \to \infty$, with $w_{EA} - \phi_E > w_N + b_N - \phi_N$.

The surviving strategies mirror employment patterns that commonly arise in the data.

Step III: comparative statics

We now consider comparative statics as Δ increases to $\Delta' = \Delta + \delta$, with all other parameters held fixed. To illustrate how summer childcare costs may shape employment decisions, we show how agents pursuing each admissible strategy under the original parameter vector θ reoptimize under the new vector θ'. Under each admissible strategy, utility changes as follows:

Strategy (s)	$u(s\|\theta)$	$u(s\|\theta') - u(s\|\theta)$
OO	0	0
EO	$w_{EA} - \phi_E$	0
EE	$w_{EA} + w_{EB} - 2\phi_E - \Delta$	$-\delta$
NO	$w_N - \phi_N$	0
NN	$2w_N + b_N - 2\phi_N - \Delta$	$-\delta$
EN	$w_{EA} + w_N - \phi_E - \phi_N - \Delta$	$-\delta$

To streamline the exposition, we ignore the edge cases where the agent is initially indifferent between two or more strategies.

Theorem 1. *Consider agents whose optimal strategy $s^*(\theta)$ is initially inframarginal, so that for $\delta \approx 0$ the new optimum $s^*(\theta')$ coincides with the original one. For sufficiently large values of δ, we observe the following changes in optimal behavior:*

(i) If $s^*(\theta) \in \{OO, EO, NO\}$, then $s^*(\theta') = s^*(\theta)$.

(ii) If $s^*(\theta) \in \{EE, EN\}$, then $s^*(\theta') = EO$.

(iii) If $s^*(\theta) = NN$, then each of $s^*(\theta') \in \{NO, EO, OO\}$ is potentially optimal.

Proof: Strategies EE, NN, and EN are clearly subobtimal when δ is large, so it suffices to consider whether OO, EO, or NO yields the most utility in each case.

(i) If $s^*(\theta) \in \{OO, EO, NO\}$, then $u(s^*(\theta)|\theta') = u(s^*(\theta)|\theta)$, whereas $u(s|\theta') \leq u(s|\theta)$ for all $s \neq s^*(\theta)$. It follows that $s^*(\theta)$ remains optimal under θ'.

(ii) By revealed preference, it must be that $w_{EA} - \phi_E > 0$, since otherwise the agent could have profitably deviated to strategy OE (in the case $s^*(\theta) = EE$) or ON (if $s^*(\theta) = EN$). Therefore $u(EO|\theta') > u(OO|\theta')$, so that EO is preferred to OO.

Likewise, it must be that $w_{EA} - \phi_E > w_N - \phi_N$ (in the case $s^*(\theta) = EE$) or $w_{EA} - \phi_E > w_N + b_N - \phi_N$ (in the case $s^* = EN$), since otherwise the agent could have profitably deviated to NE or NN, respectively. Thus EO is preferred to NO, as well.

(iii) Let θ_{-b} denote all parameters other than b. For any given choice of θ_{-b}, there exists some threshold b^* such that strategy *NN* is optimal for $b > b^*$. Fix such a value of b, then take $\delta \to \infty$, so that strategy *NN* is dominated and the new optimum is either *NO*, *EO*, or *OO*. Among these possibilities:
   - *NO* dominates if $w_N - \phi_N > \max\{0, w_{EA} - \phi_E\}$.
   - *EO* dominates if $w_{EA} - \phi_E > \max\{0, w_N - \phi_N\}$.
   - *OO* dominates if $0 > \max\{w_{EA} - \phi_E, w_N - \phi_N\}$.

Intuitively, as summer childcare costs rise, (i) agents who counterfactually would have been non-employed over the summer are simply reinforced in their original decisions; (ii) agents whose primary job is in education choose to be non-employed over the summer; and (iii) agents who would otherwise have worked year-round outside of education either take the summer off, switch to education, or withdraw from employment altogether.

Step IV: two-period model

Now suppose the agent lives for two periods, indexed by $t \in \{1, 2\}$, each with seasons $\tau \in \{A, B\}$, and chooses a strategy s_t in each period to maximize lifetime utility.

Parameter vectors. Let $\theta \equiv (\theta_1, \theta_2, \beta)$, where θ_t is defined as in the static model and β is defined below. Let $\theta_{-\Delta,t}$ be a list of all period t parameters other than Δ. We maintain assumptions *A1–A4* and *B1–B3* from the static model and additionally assume:

Assumption C1. $\theta_{-\Delta,1} \equiv \theta_{-\Delta,2}, \quad \Delta_2 \geq \Delta_1.$

The earnings and distaste parameters are identical across periods, so we omit t subscripts. Agents' distaste for summer employment potentially rises in period 2, when they may have school-aged children.

Career premium. Potential earnings are linked across periods because of returns to career continuity. If the agent is employed in job $j \in \{E, N\}$ during the *winter* (season A) of period 1, we assume she receives supplemental income β_j in the event she remains employed in that same job during the winter of period 2. For simplicity, we assume that this supplemental income—which we call the *career premium*—is the same across sectors, though this assumption is inessential.

Assumption C2. $\beta_E = \beta_N \equiv \beta > 0, \quad \beta_O = 0.$

We regard β as a reduced-form representation of sector-specific human capital, seniority provisions, defined-benefit pensions, and other mechanisms that reward agents who remain in the same line of work throughout their careers. Because (in the real world) the school year lasts much longer than the summer, we assume that receipt or non-receipt of the career premium depends only on employment status in the winter season.

Utility. We assume that utility is additively separable across periods and can be written as

$$v(s_1, s_2|\theta) = u(s_1|\theta_1) + u(s_2|\theta_2) + \beta(s_1, s_2)$$

where $u(\cdot)$ is defined as in the static model. The function $\beta(s_1, s_2)$ equals β if the agent receives a career premium and zero otherwise. The bonus for year-round work, if received, is embedded in $u(\cdot)$. Since we consider only two periods, we ignore discounting to avoid cluttering the notation.

Strategies. The full strategy space consists of $9 \times 9 = 81$ ordered pairs $s \equiv (s_1, s_2)$ corresponding to actions taken in each of the two years, but—as in the static model—strategies OE, ON, and NE are dominated within each year, leaving $6 \times 6 = 36$ remaining possibilities.

Of these, only 11 strategies are admissible (potentially optimal) under our assumptions. Although a full characterization of the model solution would proceed by backward induction, we can establish the results of interest more directly by exploiting the fact that only the career premium links choices across years: decisions are otherwise separable between the two periods.

Lemma 2. *In the first period, each of the strategies $s_1^*(\theta) \in \{OO, EO, EE, NO, NN, EN\}$ is optimal for some set of parameter values. In the second period:*

(i) If $s_1^*(\theta) \in \{OO, EO, NO\}$, then $s_2^*(\theta) = s_1^*(\theta)$.

(ii) If $s_1^*(\theta) = EE$, then each of $s_2^*(\theta) \in \{EE, EO\}$ is potentially optimal.

(iii) If $s_1^*(\theta) = EN$, then each of $s_2^*(\theta) \in \{EN, EO\}$ is potentially optimal.

(iv) If $s_1^*(\theta) = NN$, then each of $s_2^*(\theta) \in \{NN, NO, EO, OO\}$ is potentially optimal.

Proof: To show that all six strategies may be optimal in the first period, it suffices to consider the case $\beta \approx 0$ and appeal to the corresponding arguments in the static setup of step II. Next:

(i) Suppose $s_1^*(\theta) \in \{OO, EO, NO\}$. Since the increment to utility from summer work is lower in period 2 than in period 1 (reflecting increased childcare costs), revealed preference ensures that the agent won't work in the summer of period 2, or equivalently $s_2^*(\theta) \in \{OO, EO, NO\}$. Furthermore, revealed preference—reinforced by the career premium, which discourages sectoral switching across years—ensures that these agents will make the *same* choice in both years. It follows that $s_2^*(\theta) = s_1^*(\theta)$.

(ii) If $s_1^*(\theta) = EE$, then revealed preference—again reinforced by the career premium—ensures that the agent will continue to work in the education sector in the winter of period 2. Revealed preference also ensures that, in the summer of period 2, the agent will either work in education (if $\Delta_2 - \Delta_1$ is small) or refrain from working (if $\Delta_2 - \Delta_1$ is large), so that $s_2^*(\theta) \in \{EE, EO\}$.

(iii) If $s_1^*(\theta) = EN$, the argument is analogous to that for $s_1^*(\theta) = EE$.

(iv) Suppose that $s_1^*(\theta) = NN$, and consider the limiting case $\beta \to 0$ so that the problem becomes separable across periods. Then, since the two periods are identical except that $\Delta_2 \geq \Delta_1$, the same arguments used in the proof of Theorem 1 establish the potential optimality of NN (if $\Delta_2 \approx \Delta_1$) and NO, EO, OO (if $\Delta_2 \gg \Delta_1$).

The lemma characterizes the distinct kinds of life-cycle career patterns that arise in our model. First, many agents make the same labor supply decisions throughout their working lives. Second, some agents work in the education sector, engage in summer work early in their careers, and then refrain from summer work once they have school-aged children. Third, some agents work in the non-education sector early in their careers, then switch to the more flexible education sector once they face summer childcare costs. Finally, some agents work in non-education early in their careers, then withdraw from the labor force altogether when raising children.[10]

Our final result extends Theorem 1 from our static model to the two-period setting.

Theorem 2. *Consider comparative statics as Δ_2 increases to $\Delta_2' = \Delta_2 + \delta$, with all other parameters held fixed; let θ and θ' describe the original and perturbed parameter vectors. Conditional on choices made in period 1 (s_1^*), choices made in period 2 (s_2^*) respond as in the static model. Additionally, however, some agents for whom $s^*(\theta) = (NN, NN)$ will instead choose $s^*(\theta') = (EE, EO)$ or $s^*(\theta') = (EO, EO)$ when summer childcare costs rise. All other choices made in period 1 are unaffected by changes in Δ_2.*

Proof: By backward induction, period 2 in our two-period model is isomorphic to the single period considered in our static model, with potential earnings modified where appropriate for agents eligible for a career premium. As a result, all of our earlier comparative statics pass through unaltered in the second period of our dynamic setup.

We now show that some agents switch from NN to EE or EO in period 1 in response to *future* summer childcare costs. To see how this can arise, consider the special case in which $w_{EA} > 0$, $w_{EB} = 0$, $w_N = 0$, $\phi_E = \phi_N = 0$, $\Delta_1 \approx 0$, $\Delta_2 \approx 0$, and $b > w_{EA}$. In this special case, the agent initially chooses (NN, NN) under baseline parameters θ because earnings from doing so—which come exclusively in the form of the year-round continuity bonus b—exceed earnings available in the education sector.

Now increase summer childcare costs ($\delta \to \infty$) to the point that the agent no longer finds it optimal to work in the summer of period 2. Because the agent's earnings from non-education employment were predicated on year-round employment, the agent will switch from $s_2^*(\theta) = NN$ to $s_2^*(\theta') = EO$, thereby taking advantage of the more flexible earnings opportunities afforded by education employment. But if, in addition, $b < w_{EA} + \beta$, the agent will also switch from $s_1^*(\theta) = NN$ to $s_1^*(\theta') = EO$ because doing so secures receipt of the education sector's career premium in period 2.

[10]As modeled here, decisions to quit the labor force in period 2 are driven solely by parents' incremental disutility from *summer* employment. If childcare considerations impose positive costs on working parents during the school year as well, those costs would provide additional incentives for agents to leave employment in period 2.

If we modify this example so that $w_{EB} = \varepsilon > 0$, the agent will instead switch to (EE, EO).

With this last result, we can see that the model generates two kinds of sectoral sorting in response to summer childcare constraints. First, there is *contemporaneous sorting*: some agents switch from non-education into education upon experiencing summer childcare costs. Second, there is *anticipatory sorting*: some agents switch from non-education into education earlier in their careers. Intuitively, agents who know they will eventually want to make such a change may seek education employment from the beginning because of the returns to career continuity.

Our model also formalizes two distinct ways in which agents may be penalized for interrupted employment: agents who refrain from summer work miss out on the returns to continuous *year-round* employment, while those who switch sectors mid-career upon encountering summer childcare costs miss out on the returns to continuous *life-cycle* employment.

E Supplemental analyses

We close this appendix with two additional analyses: first, an examination of the tendency for a given individual to experience summer work interruptions in back-to-back years; second, a look at supplemental earnings among teachers during the summer versus the school year.

E.1 Recurrent summer work interruptions in consecutive years

Coglianese and Price (2020) introduce a method for identifying seasonal work interruptions at the individual level on the basis of patterns of recurrent transitions from employment into non-employment spaced exactly 12 months apart. Exploiting the limited longitudinal dimension of the CPS, we apply that method to determine the extent to which individuals experiencing summer work interruptions tend to do so in back-to-back years.

Let y_{it} be an indicator variable equal to 1 if individual i was employed in period $t-1$ but not in period t. Using our sample of prime-age CPS respondents, we first identify all such work interruptions that occur during an individual's first four months in the sample, such that—barring attrition—we can observe that individual's employment status one year later. Letting t_0 denote the period in which the base separation occurred, we stack all available observations 10–14 months after baseline and estimate regressions of the form

$$y_{it} = \sum_{\tau=10}^{14} \rho_\tau \mathbb{1}\{t - t_0 = \tau\} + \beta weeks_t + \varepsilon_{it} \tag{20}$$

Thus $\rho_{10}, \ldots, \rho_{14}$ capture the relative probability of a recurrent work interruption occurring 10, 11, 12, 13, or 14 months after the initial one, adjusting for the fact that more separations tend to be observed when successive reference weeks are further apart. We cluster standard errors at the household level to allow for within-person serial correlation in the outcome variable as well as cross-sectional dependence among members of the same household.

Following Coglianese and Price (2020), we define the *excess recurrence* of work interruptions at annual intervals as $\rho_{12} - \frac{1}{2}(\rho_{11} + \rho_{13})$. Intuitively, excess recurrence tells us to what extent a given group of workers exhibit repeated exits from employment spaced exactly 12 months apart, net of the background rate of exit observed at similarly distant (but non-annual) horizons. Coglianese and Price demonstrate that excess recurrence aligns well with the demographic, sectoral, and temporal hallmarks of seasonal fluctuations in US employment.

Appendix Figure A.4 plots estimates of excess recurrence obtained by stratifying our CPS sample by sex and by the calendar month in which the base separation occurred. For women, work interruptions occurring between the May and June reference weeks are 4.9 percentage points more likely to be repeated 12 months later than 11 or 13 months later. Excess recurrence is also elevated in July—echoing the continued outflows of women from employment we see in that month (Figure 3)—as well as in January, when many businesses are trimming payrolls after the holiday shopping season. As a point of comparison, Coglianese and Price (2020) estimate an excess recurrence of 1.4 p.p. among all prime-age CPS respondents. By this measure, then, women show a pronounced tendency not only to exit employment at the start of summer, but to do so in (at least) two consecutive years.[11]

E.2 Schools and Staffing Survey (SASS)

The 1999–2000 Schools and Staffing Survey (SASS) from the National Center for Education Statistics provides a nationally representative snapshot of US public school teachers (Tourkin et al., 2004).

Variable definitions: The survey asks teachers about their supplemental earnings—i.e., earnings in addition to their base salary—during the summer months and, separately, during the regular school year. The survey additionally distinguishes school-based and non–school-based supplemental work, where school-based work entails participation in extracurricular activities, coaching, and summer/evening teaching. From these earnings variables, we create indicator variables for supplemental work (school- or non–school-based) during the regular school year and summer months. We use these variables in our analysis of gender differences in the propensity to engage in supplemental work and earnings from supplemental work during the school year and summer months. SASS provides earnings categories for each type of supplemental work. To construct numeric earnings, we take the midpoint of each category. We multiply the top-coded earnings category by a constant factor of 1.5. We assign zero earnings when the individual does not engage in that type of supplemental work. We then deflate earnings to December 2019 dollars using the Personal Consumption Expenditures price index.

We also define the following regression controls:

- Teacher total experience: total years of teaching experience, in years
- Teacher age category: <30 years, 30–39 years, 40–49 years, 50+ years

[11] Although annually recurrent separations are quite common among those employed in the education sector (consistent with patterns reported elsewhere in the paper), we observe qualitatively similar patterns if we exclude baseline departures from educational employment into non-employment.

- Teacher race/ethnicity: white non-Hispanic, Black non-Hispanic, Hispanic, other non-Hispanic
- Teacher educational attainment: indicator for whether the teacher has a master's degree
- School urban/rural status: large/mid-size city, urban fringe, small town/rural
- School region: Northeast, Midwest, South, West
- School level: elementary, secondary, combined
- Teacher field of assignment: pre-K, kindergarten, general elementary; math/science; English/language arts; social science; special education; foreign languages; bilingual/ESL; vocational/technical education; all others

Sample restrictions: We limit our sample to regular full-time teachers.

Regression-adjusted gender gaps: We regress the earnings from each type of supplemental work on a female indicator, age categories, teaching experience, race/ethnicity, master's degree, school type (primary, secondary), subject taught, urban status of school, and Census region. Each regression is weighted by the SASS sampling weights.

Appendix Figure A.24 plots the regression-adjusted gender gaps in earnings from supplemental work among full-time public school teachers, throughout the summer months and the regular school year, controlling for demographic, job, and school characteristics. Supplemental earnings over the summer months are $1,350 lower for female teachers than for observationally similar male teachers.

We also explored gender differences in the propensity to engage in each type of supplemental work. Conditional on observables, female teachers are 18.8 percentage points less likely than male teachers to engage in any type of paid summer work. Furthermore, the gender gap in supplemental work is 3.8 percentage points larger during the summer months than during the regular school year, with the growth stemming from a differential uptick in men working outside of schools during summer. Overall, these results echo our above findings that, within granular educational occupations, women's work hours fall during the summer months, relative to men's and relative to the regular school year.

Appendix References

Cajner, Tomaz, John Coglianese, and Joshua Montes. 2021. "The Long-Lived Cyclicality of the Labor Force Participation Rate." Federal Reserve Board Finance and Economics Discussion Series No. 2021-047.

Coglianese, John and Brendan M. Price. 2020. "Income in the Off Season: Household Adaptation to Yearly Work Interruptions." Federal Reserve Board Finance and Economics Discussion Series No. 2020-084.

Dupraz, Stéphane, Emi Nakamura, and Jón Steinsson. 2019. "A Plucking Model of Business Cycles." NBER Working Paper No. 26351.

Flood, Sarah M., Liana C. Sayer, Daniel Backman, and Annie Chen. 2023b. "American Time Use Survey Data Extract Builder: Version 3.2 [dataset]." College Park, MD: University of Maryland and Minneapolis, MN: IPUMS. https://doi.org/10.18128/D060.V3.2.

Frazis, Harley J., Edwin L. Robison, Thomas D. Evans, and Martha A. Duff. 2005. "Estimating Gross Flows Consistent with Stocks in the CPS." *Monthly Labor Review*, 128: 3–9.

Guryan, Jonathan, Erik Hurst, and Melissa Kearney. 2008. "Parental Education and Parental Time with Children." *Journal of Economic Perspectives*, 22(3): 23–46.

Hamermesh, Daniel S., Harley Frazis, and Jay Stewart. 2005. "Data Watch: The American Time Use Survey." *Journal of Economic Perspectives*, 19(1): 221–232.

Hobijn, Bart and Ayşegül Şahin. 2021. "Maximum Employment and the Participation Cycle." NBER Working Paper No. 29222.

Madrian, Brigitte C. and Lars John Lefgren. 2000. "An Approach to Longitudinally Matching Current Population Survey (CPS) Respondents." *Journal of Economic and Social Measurement*, 26(1): 31–62.