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ORIGINAL ARTICLE

Earnings inequality and the expansion of care services in the United States, 1985–2019

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Abstract

Earnings in care services are lower than in other industries, particularly among professional and managerial employees, and are more compressed than in other industries. The growth of primarily female employment in care services since the 1980s has buffered overall increases in wage inequality while slowing convergence in the gender wage differential.

1 | INTRODUCTION

The industries that make up the service sector are heterogeneous in many respects. Health, education, and social services, labelled here as 'care industries' or 'care services', are often publicly financed and employ a far larger percentage of women than business services or other services. Most care occupations are located in care industries, and these occupations typically pay less than others, controlling for differences in gender, education and other covariates (Barron & West, 2013; Budig et al., 2019; England et al., 2002; Hirsch & Manzella, 2015). Employment in care services, even in professional and managerial occupations, is also associated with pay penalties, while employment in business services (especially financial services) is associated with pay premia (Bivens & Mishel, 2013; Folbre et al., 2023; Philippon & Reshef, 2012).

Since employment in both care and business services has expanded significantly in recent years, the differences between these two key components of the service sector bear on trends in wage inequality, which began rising in the United States since 1980. Disparities between workers at the middle and the top of the wage distribution have grown particularly sharply (Aeppli & Wilmers, 2022; Autor et al., 2008). Research points to the influence of job characteristics on wages, independent of shifting demands for human capital that might result from skill-biased technical change (Acemoglu & Autor, 2011). Much of this literature focuses on occupation-specific tasks (Autor & Handel, 2013; Firpo et al., 2011). The distributional effects of public sector employment have also been noted (Borjas, 2002).

Following early work by Krueger and Summers (1988) that documented the existence of interindustry wage differentials net of controls for human capital and job characteristics, an expanding literature highlights the important role of establishments and firms in wage-setting and in shaping wage inequality (Card et al., 2018). It finds, for instance, that much of the increase in wage inequality in the United States between the 1970s and 2010s can be attributed to increased dispersion of earnings among establishments, driven largely by industry differences (Barth et al., 2016; Haltiwanger & Spletzer, 2020).

Research suggests that the polarisation of earnings in the United States has been largely driven by increased earnings within financial services (Philippon & Reshef, 2012). Earnings inequality has also increased somewhat among the predominantly female workers in care occupations, who are mostly in care industries (Dwyer, 2013). However, both median earnings and the overall dispersion of earnings remain lower in care services than business services (Folbre et al., 2023). This pattern suggests that the increased employment in care services that took place among women may have buffered overall increases in wage inequality even as it reinforced the gender wage differential.

We test these hypotheses by applying unconditional quantile regression analysis (Firpo et al., 2009) to cross-sectional data from the U.S. Current Population Survey. We consider two periods of time, 1985–1988 and 2016–2019, that span a 30-year window of rising wage inequality and converging gender wage differentials in the United States. Our choice of quantile regressions—rather than simple mean regressions—is motivated by our interest in factors influencing wage inequality, and gender wage gaps across the distribution, rather than just at the mean. Both questions require us to estimate the effect of covariates on particular distributional statistics (such as differences in log wage across percentiles). The approach developed by Firpo et al. (2009) offers a flexible and simple method for estimating these effects.

We first investigate the effect of care and business service employment on wage inequality (as measured by log wage differentials between the 90th and 10th percentiles, 50th and 10th percentiles, and 90th and 50th percentiles), in each time period. We then decompose the *change* in these measures over both periods (decomposing, e.g., the change in the 90–10 log wage differential between 1985–1988 and 2016–2019). We also estimate the effect of women's overrepresentation in care services, decomposing gender wage differentials (and changes in these differentials over time) at the 10th, 50th and 90th percentiles. We make no causal inferences but demonstrate that the distinction between care services and business services helps explain trends in wage inequality.

2 | WAGES IN CARE SERVICES AND BUSINESS SERVICES

A broad institutionalist tradition looks beyond individual worker characteristics to link wage inequality to aspects of economic structure (Blau & Kahn, 1992; Rowthorn, 1992; Rubery et al., 2005). These include shifts in the demand for skill, task specificity, offshoreability, vulnerability to technological change and potential for rent capture (Acemoglu & Autor, 2011; Baumol, 2012; Firpo et al., 2011; Manning, 2010). Services in general are less conducive to outsourcing and automation than other industries because they entail more personal contact. However, care services, consisting of three major industries, health, education and social services, have several distinctive characteristics. They are far more female-dominated than other service industries (see Table 1), a factor that has been shown to reduce relative earnings on the occupational level (England et al., 2007). Care services often generate positive externalities and are more likely to include public sector provision or third-party payment than either business services (such as finance, insurance and real estate) or other services, (such as transport, communication, retail and hospitality services). Industry-specific effects on earnings are significant for professionals and managers in care services, and research shows lower rates of return to human capital in care occupations (Budig et al., 2019; Folbre et al., 2023). While many activities within business and other services require social skills and emotional labour, they do not require empathy or genuine concern for the well-being of students, patients or clients (Folbre, 2012; Folbre et al., 2023).

Care, business, and other services each claim roughly similar shares of total private full-time full-year (FTFY) employment in the United States, together representing almost three-fourths of all private FTFY employment (see Table 1). Supporting Information S1: Appendix A specifies the 1990 industry codes utilized to define these industry categories and discusses alternative classifications and nomenclatures.

Private employment in these three industry categories expanded significantly in the period of growing wage inequality between 1980 and 2019 (Figure 1). Disaggregated employment patterns reveal a distinctly gendered dynamic: employment growth in care services was more important for women than for men, while the reverse holds true for business services. By 2019, almost a third of private FTFY women were employed in care services, compared to 20% in 1980, and 20% of private FTFY men were employed in business services, compared to 11% in 1980.

Both care services and business services are more human capital-intensive than other industry groups. In 2016–2019, about half the employees in both of these sectors had a college degree or higher, compared to about a quarter of those in other services and nonservices (Table 1). These two sectors also had a relatively high percentage of top-level occupations (professionals, managers, and business and financial occupations): about 63% for both care services and business services, compared to 19% and 28% for other services and nonservices.

Cross-sectional estimates controlling for education, age, and other covariates find penalties for working in both care industries and care occupations (Barron & West, 2013; Budig et al., 2019; England et al., 2002; Folbre et al., 2023; Hirsch & Manzella, 2015). Earnings in care services are particularly compressed at the top of the earnings distribution (Folbre et al., 2023). Figure 2A shows weekly wages by percentile for workers in each industry group, using data from the Current Population Survey. Despite similarities in educational qualifications, workers in care services at nearly every percentile earn less than workers in business services, and this gap in wages is much larger in the upper than in the lower half of the wage distribution. Figure 2B compares average wages across four relatively well-represented occupational groups in each industry: while wages across industries are similar among 'office and administrative' workers, we see far sharper differences across the top three occupations: managers, business and financial occupations, and professionals in care services (and also in other

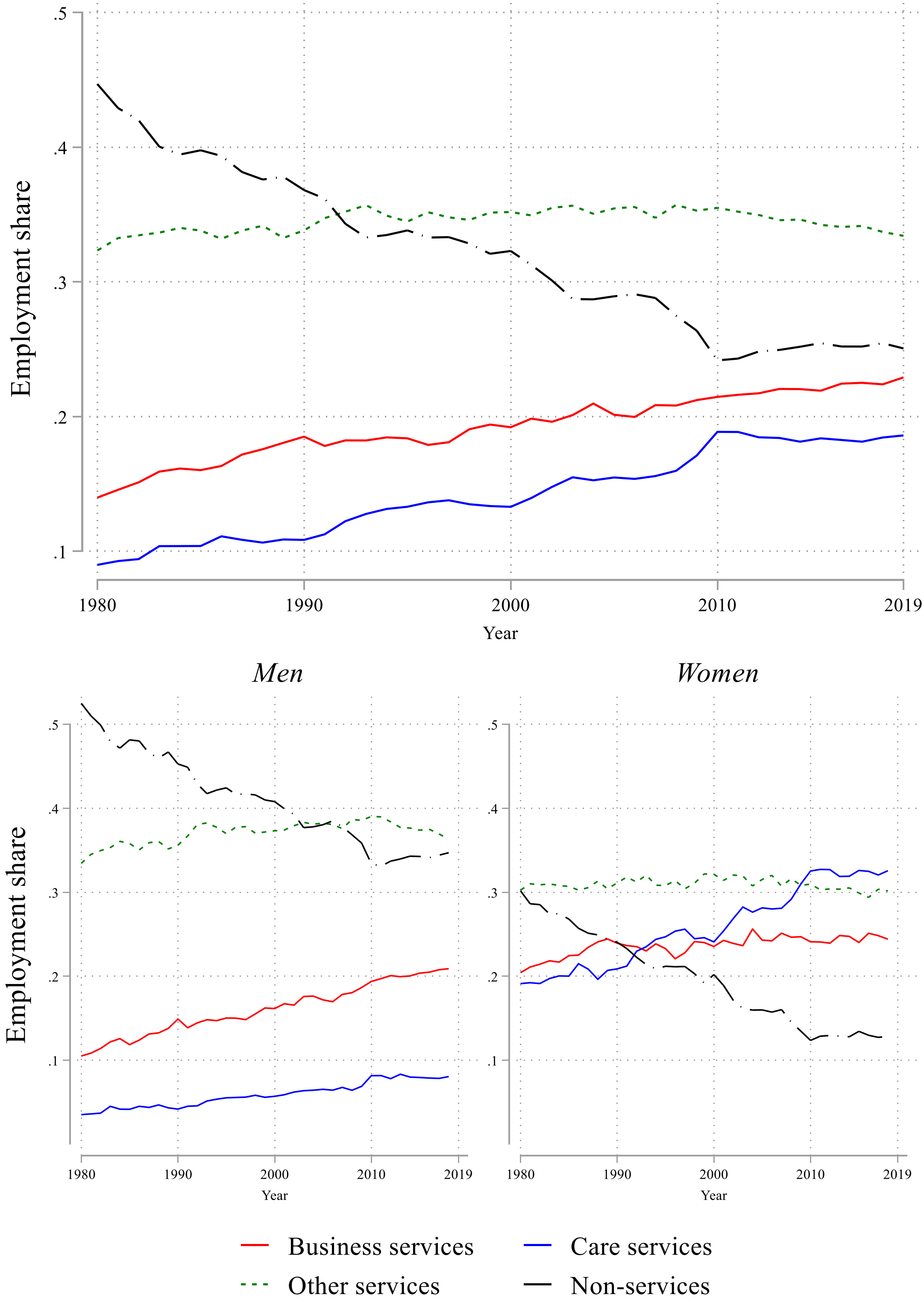
TABLE 1 Worker characteristics and wages by broad industry group, 2016–2019.

	Care services	Business services	Other services	Nonservices
Employment share	0.183	0.223	0.340	0.253
Women	0.750	0.467	0.373	0.217
Education				
Less than high school	0.026	0.028	0.086	0.133
High school degree	0.173	0.155	0.355	0.365
Some college	0.317	0.241	0.314	0.254
College degree	0.271	0.380	0.196	0.177
Advanced degree	0.213	0.195	0.048	0.071
Occupation				
Managers	0.099	0.191	0.102	0.126
Business & Financial	0.025	0.164	0.026	0.035
Professionals	0.501	0.279	0.066	0.119
Service	0.222	0.071	0.187	0.035
Sales	0.004	0.084	0.231	0.027
Office & Administrative	0.126	0.164	0.126	0.070
Farming	0.000	0.000	0.001	0.028
Maintenance	0.008	0.017	0.073	0.052
Production	0.005	0.013	0.037	0.247
Transport	0.007	0.012	0.143	0.062
Weekly wages (2019 dollars)				
Average	1155	1567	1002	1199
Standard deviation	1294	1749	1168	1239
10th percentile	408	497	353	431
Median	866	1135	731	896
90th percentile	1963	2885	1841	2188
90–10 ratio	4.808	5.804	5.209	5.077
90–50 ratio	2.268	2.542	2.518	2.441
50–10 ratio	2.120	2.283	2.069	2.080
Observations	34,047	39,790	62,173	47,231

Source: CPS ASEC. 1980–2019, private sector wage and salary workers ages 18–64. Excludes part-time or part-year workers and workers with missing or allocated earnings. Detailed industry codes for broad groups in Supporting Information S1: Appendix A. ASEC sampling weights used.

services) earn much less, on average, than their counterparts in business services and nonservices.

In one of the few studies to explore earnings inequality in care occupations over time in the United States, Dwyer (2013) emphasises a process of polarisation that paralleled larger trends,


Employment share
.5
.4
.3
.2
.1
1980
1990
2000
2010
2019
Year
Men
Women
Employment share
Business services
Care services
Other services
Non-services

emphasising growing inequalities between relatively low status 'reproductive' work and more heavily credentialed work in 'nurturant' care. Polarisation among care occupations, however, remained lower than among other occupations, and could largely reflect the impact of increased inequality in educational credentials.

We analyze the effect of growing employment in private care services on wage inequality, controlling for differences in education and other covariates, building on other studies of the impact of sectoral change on earnings inequality. Grimshaw (2000) decomposes the Theil index of wage inequality to argue that public sector employment has had a moderating effect in the United Kingdom. Similarly, Borjas (2002) finds that relative wage compression in public employment in the United States increased significantly after 1970. To avoid any confounding overlap between care services and the public sector—to identify the effects of care services on inequality distinct from the equalising effects of public provision—we focus on private sector employment. (Even though a substantial portion of care services are provided by public institutions, care provision has shifted towards the private sector in recent decades, and the share of public employment within care services has decreased.) We expect that care services exert an equalising effect on the wage distribution of private sector workers, and the expansion of care services (partially) counteracts the increase in wage inequality since the 1980s.

We are also interested in the falling gap in pay between women and men in the United States after 1980. Reductions in the gender wage gap have been much slower after the 1990s (England et al., 2020). Blau and Kahn (2017) argue that despite women's occupational upgrading over this period, occupation and industry continue to explain a major portion of the current gender gap in pay. We expect that women's disproportionate employment in care services lowers their wages relative to men, and that their growing employment in care services has slowed reductions in the gender wage gap.

Our main hypotheses are therefore as follows:

H1: The shift toward greater employment in care services had an equalising effect on the overall distribution of wages, net of changes in education and other covariates (in the relevant counterfactual this employment remained in nonservices).

H2: Women's increased representation in care services slowed improvements in the overall gender wage differential.

3 | DATA AND METHODS

We apply quantile regression decompositions to data from the Current Population Survey (CPS), developing counterfactuals that illustrate the implications of sectoral shifts over the 1980–2019 period. We use the nationally representative Annual Social and Economic Supplement (ASEC) of the CPS, obtaining extracts prepared by the Integrated Public Use Microdata Series database from 1980 to 2019 (corresponding to wages and employment in 1979

FIGURE 1 Employment shares by industry group, 1980–2019. *Source*: Current Population Survey Annual Social and Economic Supplement. 1980–2019, private sector wage and salary workers ages 18–64. Excludes part-time or part-year workers and workers with missing or allocated earnings. Detailed industry codes for broad groups in Supporting Information S1: Appendix A. ASEC sampling weights used.

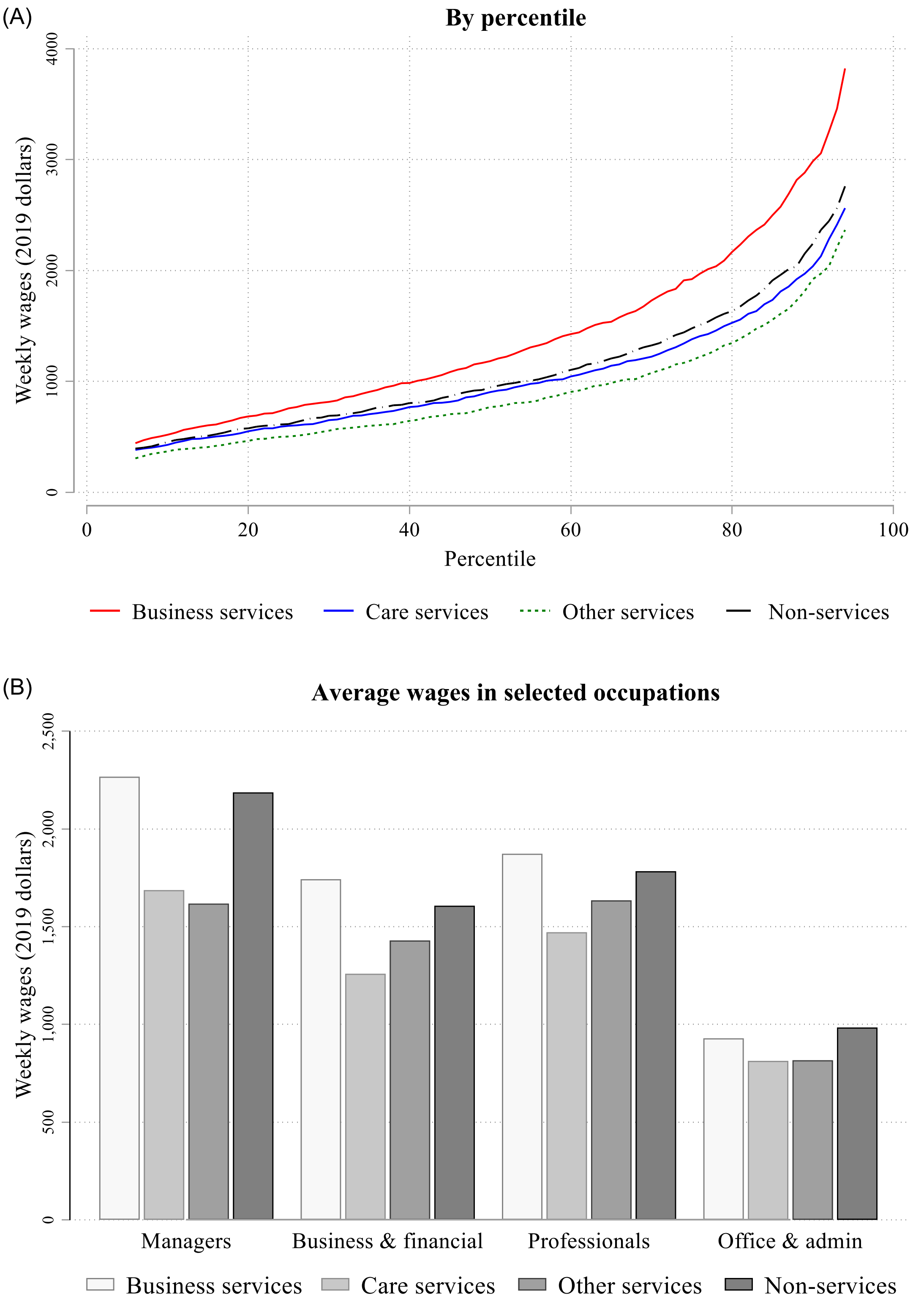


FIGURE 2 Weekly wages by industry group, 2016–2019. (A) By percentile. (B) Average wages in selected occupations. *Source*: Same as Figure 1.

to 2018) (Flood et al., 2020).[1] For much of our analysis we restrict our comparisons to two time periods: 1985–1988 and 2016–2019, that span the 30-year window covering the rise in wage inequality in the United States, and the fall in the gender wage gap.[2]

We include private sector workers aged 18–64, excluding self-employed workers, unpaid workers, and members of the armed forces. In our primary analysis we exclude workers who report usual hours worked in a week to be less than 35 h or who report weeks worked to be less than 50 weeks. This enhances the comparability of our analysis to prior research on wage inequality in the United States, which usually focuses on full-time, full-year workers. Supporting Information S1: Appendix D presents key results for the full set of workers, including part-time or part-year workers, as well as public sector workers.

Our dependent variable is the log of weekly wages, constructed by dividing total wage earnings by total weeks worked (both in the previous year). We use weekly instead of hourly wages because the measure of total hours worked in a week is noisy (Lemieux, 2006). We use data files provided by the Bureau of Labour Statistics to harmonise top-coding methods across time and drop observations with allocated earnings. We focus on the wage distribution between the 10th and the 90th percentiles, which renders our analysis robust to any remaining top-coding inconsistencies. We use the CPI-U index to express all wages in 2019 dollars. We follow the precedent of dropping observations with weekly wages less than half the 1982 minimum wage or $67/week in 1982 dollars (Autor et al., 2008).[3]

An alternative source of earnings data is the Outgoing Rotation Group (ORG) supplement, which is administered to CPS households in their fourth and eighth month in the CPS rotation, with work and income questions pertaining to current employment. While the annual reference period in the ASEC yields noisier estimates than the ORG, we prefer the ASEC as it has a higher top-code threshold for wages and 'swaps' incomes rather than censoring them at the top-code threshold. Top-coding for workers not paid by the hour (the top-code threshold for weekly earnings is $2884.61) is substantial in the ORG, making it less suited (than the ASEC) to study earnings inequality across industries.

We construct four industry categories: splitting service industries into care services (health, education and social services), business services (finance, insurance, real estate, business and professional services) and other services, (transport, communication, wholesale, retail, personal and hospitality services). The fourth category is nonservices (agriculture, mining, construction and manufacturing). A discussion of the rationale for this categorization, as well as empirical support for our aggregation decisions, are found in Supporting Information S1: Appendices A and B.

The main covariates controlled for fall into four categories: human capital consisting of potential experience and its square and education (less than high school, completed high

[1]The ASEC is conducted by the U.S. Census Bureau in March of each year and serves as the source of official federal statistics on income, poverty and health insurance coverage (U.S. Census Bureau, 2019). It has been the workhorse data set for research on earnings inequality in the United States.

[2]We terminate our analysis at 2019, to avoid complications involved with the impact of the COVID pandemic on labour markets, and set 1985 as our starting point to avoid the recession of the early 1980s and the subsequent fallout. We use 3-year intervals to provide an adequate sample size for quantile regressions and to make our analysis less sensitive to annual variation. In our robustness checks, we assess whether our conclusions are robust to this choice of time period.

[3]Of the roughly 0.5 million wage and salary workers, aged 18–64 and with unallocated earnings in our two time periods (1985–1988 and 2016–2019), we retain 56% (or 298,747 workers) who are full-time, full-year and work in private sector establishments for our core analysis. After dropping those with weekly wages below this threshold, we have a final sample of 298,581 workers.

school, some college, college graduate and advanced degree); occupation (11 major occupational groups); demographics (marital status, children, race and ethnicity); and region (dummy variables for south, mid-west, west, and north-east and for metropolitan residence).[4] We follow Jaeger (1997) in harmonising changes in the definition of educational variables over time. Years of potential experience are based on age minus 6 minus years of education. A union membership variable is not available for the entire ASEC sample: as a robustness check, we present results in Supporting Information S1: Appendix E including this as an explanatory variable for the subsample for which it is available. Our analysis applies individual-level ASEC weights provided by the CPS to adjust for the stratified sampling scheme, normalised to sum to 1 for each year.

To explore implications of employment in care services for various quantiles of the unconditional wage distribution we use recentered influence function (RIF) regressions, termed unconditional quantile regressions in this context. Firpo et al. (2009) show that the conditional expectation of the RIF of a particular quantile q_τ (defined as $RIF\left(Y;q_\tau\right) = q_\tau + \left(\tau\text{-}1\left\{Y \leq q_\tau\right\}\right)/f_Y\left(q_\tau\right)$ where $f_Y(.)$ is the marginal density function of Y), makes the variable of interest the quantile itself. Modelling this conditional expectation as a linear function of explanatory variables,

$$E\left[RIF\left(Y;q_\tau\right)|\boldsymbol{X}\right] = \boldsymbol{X\beta} + \varepsilon,$$

we can estimate the parameter $\boldsymbol{\beta}$ (sometimes called the RIF regression coefficient) through an OLS regression of the *RIF* on $\boldsymbol{X}$. These regressions allow us to estimate the effect of a small change in the mean value of a covariate on a particular quantile of the unconditional wage distribution (Firpo et al., 2009). The RIF regression coefficient for care services at the 10th percentile, divided by 100, for example, conveys the effect of a 1 percentage point increase in the employment share of care services on wages at the 10th percentile of the (unconditional) wage distribution. The dependent variable is log weekly wages, and regressors include industry group (care services, business services and other services) and the controls outlined earlier. Nonservices are the omitted category for industry group because this corresponds to the scenario of shifting employment from nonservices towards care services (or business services, or other services)—the empirical trend that we observe over the last three decades. The industry-specific contributions of our decompositions, as we explain later, can be interpreted as the possible impact on wage inequality of shifts in employment from nonservices towards particular service industry categories.

We first estimate the effect associated with care service employment within each period on three summary measures on wage inequality: the difference in log weekly wages at the 90th and 10th percentiles, 50th and 10th percentiles and 90th and 50th percentiles. We then decompose the *change* in these three measures between 1985–1988 and 2016–2019 to test our first hypothesis regarding the implications of growing care service employment for the growth of wage inequality. We do this by applying Kitagawa–Oaxaca–Blinder style decompositions to changes in the three summary measures. Assuming that the conditional expectation of the RIF

[4]We use harmonised occupation codes based on the 2010 Census Bureau occupational classification system provided by IPUMS and create 11 categories based on Census headings: managerial occupations, business and financial operations, professionals, service occupations, sales occupations, office and administrative support, farming, construction, maintenance, production and transportation occupations.

is linear in $\boldsymbol{X}$, the wage differential at the τth quantile between the time period 2016–2019 ($t = 1$) and 1985–1988 ($t = 0$), $\Delta(\tau)$, can be decomposed as

$$\Delta(\tau) = E(\boldsymbol{X}_1)'\boldsymbol{\beta}_1(\tau) - E(\boldsymbol{X}_0)'\boldsymbol{\beta}_0(\tau)$$

$$= \Big[E(\boldsymbol{X}_1) - E(\boldsymbol{X}_0)\Big]'\boldsymbol{\beta}^*(\tau) + E(\boldsymbol{X}_1)'\Big[\boldsymbol{\beta}_1(\tau) - \boldsymbol{\beta}^*(\tau)\Big] + E(\boldsymbol{X}_0)'\Big[\boldsymbol{\beta}^*(\tau) - \boldsymbol{\beta}_0(\tau)\Big],$$

where the subscripts denote the time period, $\boldsymbol{\beta}_1(\tau)$ and $\boldsymbol{\beta}_0(\tau)$ are RIF regression coefficients at the τth quantile, and $\boldsymbol{\beta}^*(\tau)$ is the reference vector used to weight the composition effects. The first term in the equation represents the composition effect, the last two terms, wage structure effects.

To address our second hypothesis regarding the effect of care service expansion on the gender gap we decompose the gender wage gap at the 10th, 50th and 90th percentiles of the wage distribution separately for the two periods. The wage differential at the τth quantile between women ($g = f$) and men ($g = m$), $D(\tau)$, can be decomposed as

$$D(\tau) = E(\boldsymbol{X}_f)'\boldsymbol{\beta}_f(\tau) - E(\boldsymbol{X}_m)'\boldsymbol{\beta}_m(\tau)$$

$$= \Big[E(\boldsymbol{X}_f) - E(\boldsymbol{X}_m)\Big]'\boldsymbol{\beta}^*(\tau) + E(\boldsymbol{X}_f)'\Big[\boldsymbol{\beta}_f(\tau) - \boldsymbol{\beta}^*(\tau)\Big] + E(\boldsymbol{X}_m)'\Big[\boldsymbol{\beta}^*(\tau) - \boldsymbol{\beta}_m(\tau)\Big],$$

where $\boldsymbol{\beta}_f(\tau)$ and $\boldsymbol{\beta}_m(\tau)$ are the RIF regression coefficients for women and men respectively at the τth quantile, and $\boldsymbol{\beta}^*(\tau)$ is the reference vector. We group the detailed composition effects into the contributions of occupation, human capital, region, and demographics, and show the contribution of each industry group separately. We then decompose the *change* in the gender wage gap between 1985–1988 and 2016–2019.

3.1 | Methodological issues

The Kitagawa–Oaxaca–Blinder decomposition is sensitive to the choice of the reference vector of coefficients used to weight the composition effects. Rather than using coefficients from a particular period (either 1985–1988 or 2016–2019), we use pooled coefficients, obtained by RIF regressions for the pooled sample (both periods), to weight composition effects. We present detailed decomposition results only for composition effects, because the scaling of continuous variables can affect the portion of the gap attributable to wage structure effects (Kassenboehmer & Sinning, 2014).

We test the sensitivity of our estimates to the choice of nonservices as the omitted category. Grouping composition effects for sector and occupation, human capital and so on, ensures that the reported estimates are not affected by the specific choice of omitted category for categorical variables within these groups. The total wage structure effect is also unaffected by choice of categorical variable. However, industry composition effects *are* affected, because the pooled coefficients that are used to weight the changes in employment shares are estimated with reference to the omitted industry group. For example, the contribution of care services to the change in wages (between 1985–1988 and 2016–2019) at a particular quantile is calculated by weighting the change in care service employment by the coefficient for care services from the pooled regression of the quantile-specific RIF for log weekly wages in which nonservices is the omitted category. If, instead, business services were the omitted category, the coefficient for care services would change, altering the estimated contribution of care services in the decomposition. We present results from three alternate regressions, where we switch from nonservices as the reference to each of the other three industry groups. This represents an important robustness check because our hypotheses center on industry coefficients.

4 | RESULTS

Differences in wage patterns across industry groups in the 2016–2019 period are presented in Table 1. Average weekly wages, as well as wages at the 10th, 50th and 90th percentiles, for workers in care services are lower than their counterparts in business services and nonservices. Wages in other services are generally lower than wages in care services, but these comparisons do not account for levels of education and professional employment, which are significantly higher in care services. Pay compression in care services is high relative to the three other sectors: the standard deviation of log wages in care services is lower than in business services, and similar to that in other services and nonservices; the 90–10 wage ratio is lower in care services than in others (4.81, compared to 5.80 in business services, 5.20 in other services and 5.10 in nonservices). While the 50–10 ratio differs little across industry groups, care services have a particularly low 90–50 wage ratio, reinforcing the patterns highlighted earlier in the discussion of Figure 2.

4.1 | Industry wages differentials across the distribution

To illustrate the effects of wage compression within care services, we estimate unconditional quantile regressions for each decile of the wage distribution in 2016–2019 and plot the coefficients for each industry group. As shown in Figure 3, unconditional quantile coefficients for care services decline monotonically across deciles. Coefficients for business services decline slightly until the 50th percentile and then begin to increase. Other services do not exhibit a trend. Care service employment is associated with a decline in overall wage inequality in 2016–2019, and this effect is particularly pronounced at the upper half of the wage distribution.

Table 2 presents coefficients for the full set of regressors for unconditional quantile regressions at the 10th, 50th and 90th percentiles. A 1 percentage point increase in the share of care service employment (at the expense of nonservices) increases wages at the 10th percentile by 0.000246 log points (0.025%), reducing wages by 0.001440 log points (0.155%) at the 50th percentile, and by 0.002964 log points (0.345%) at the 90th percentile. Consistent with Figure 3, the effect of care services on wages grows increasingly negative along the wage distribution. Business services have the strongest effects (in this case, least negative effects) relative to the other industry groups at the 50th and 90th percentile of the wage distributions. Other coefficients have the expected signs: a higher share for managerial occupations increases wage inequality by increasing wages disproportionately at the top of the wage distribution (professional employment is the relevant omitted category), as do the educational variables, while the share of women workers decreases wage inequality.

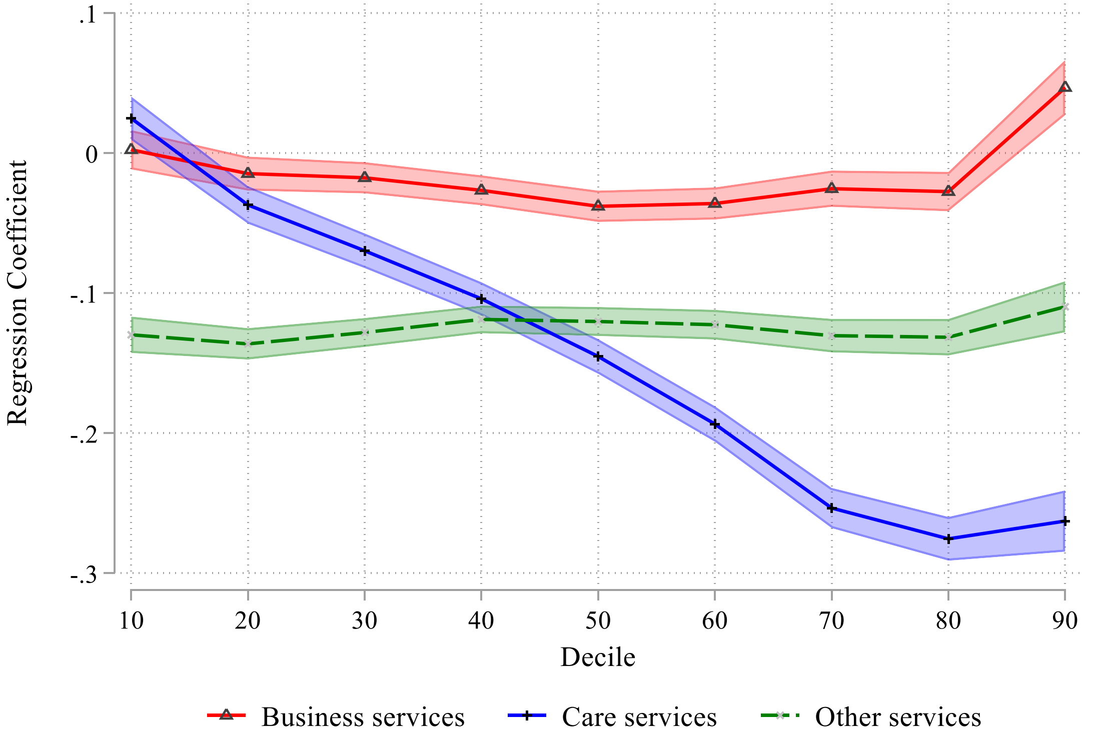


FIGURE 3 Unconditional quantile regression coefficients, 2016–2019. *Source*: Same as Figure 1. Bands represent 95% confidence intervals based on bootstrapped standard errors (100 replications). Reference industry group is nonservices.

4.2 | Care services expansion and wage inequality growth

Our results from 2016 to 2019 suggest that care services have an equalising effect on the wage distribution. We now move to the dynamic aspect of the question, examining the effect of care service expansion on changes in wage inequality over time. First, we first decompose the gap in log wages between the 90th and 10th percentile (the 90–10 gap), the 50th and 10th percentile (the 50–10 gap), and the 90th and 50th percentile (the 90–50 gap) in each of the two periods, 1985–1988 (Table 3, panel A) and 2016–2019 (panel B). Confirming our expectations, care services have a negative effect on overall inequality, as measured by the 90–10 gap, in both periods, with the negative effect growing stronger in the 2016–2019 period.[5] Much of this change comes from the equalising effect of care services on the top half of the wage distribution, as measured by the 90–50 gap: the RIF coefficient of care services on the 90–50 gap goes from negative 0.05 log points in 1985–1988 to negative 0.15 log points in 2016–2019. On the other hand, business services are associated with increases in the 90–50 gap in both 1985–1988 and 2016–2019.

[5] A 1 percentage point increase in the share of care service employment is associated with 0.002753 log point (or 0.24%) decrease in the 90–10 gap in 1985–1988; this changes to 0.003212 log points (or 0.27%) in the 2016–2019 period.

TABLE 2 Recentered influence function regressions for 10th, 50th and 90th percentiles of log weekly wages, 2016–2019.

	10th Percentile	50th Percentile	90th Percentile
Industry			
Care services	0.0246***	−0.1440***	−0.2964***
	(0.0067)	(0.0081)	(0.0134)
Business services	0.0021	−0.0428***	0.0228
	(0.0054)	(0.0082)	(0.0167)
Other services	−0.1114***	−0.1227***	−0.1252***
	(0.0066)	(0.0066)	(0.0123)
Occupation			
Managers	0.0195***	0.0603***	0.4200***
	(0.0052)	(0.0063)	(0.0193)
Business & Financial	0.0555***	0.0085	−0.0751***
	(0.0054)	(0.0095)	(0.0215)
Service	−0.4158***	−0.6250***	−0.1812***
	(0.0148)	(0.0090)	(0.0119)
Sales	−0.1180***	−0.2573***	−0.0046
	(0.0087)	(0.0073)	(0.0188)
Office & Administrative	−0.0244***	−0.4421***	−0.2406***
	(0.0092)	(0.0080)	(0.0130)
Farming	−0.2507***	−0.6575***	−0.3995***
	(0.0330)	(0.0196)	(0.0195)
Construction	−0.0404***	−0.3112***	−0.3724***
	(0.0118)	(0.0117)	(0.0200)
Maintenance	0.0473***	−0.1926***	−0.3853***
	(0.0095)	(0.0117)	(0.0190)
Production	−0.0532***	−0.3970***	−0.3529***
	(0.0139)	(0.0102)	(0.0148)
Transport	−0.0568***	−0.3535***	−0.3316***
	(0.0107)	(0.0088)	(0.0160)
Female	−0.1386***	−0.2534***	−0.3383***
	(0.0059)	(0.0050)	(0.0102)
Years of experience	0.0228***	0.0272***	0.0295***
	(0.0011)	(0.0008)	(0.0011)
Years of experience (squared)	−0.0004***	−0.0004***	−0.0004***
	(0.0000)	(0.0000)	(0.0000)

(Continues)

TABLE 2 (Continued)

	10th Percentile	50th Percentile	90th Percentile
Education			
Less than high school	−0.5046***	−0.7028***	−0.5560***
	(0.0252)	(0.0090)	(0.0143)
High school degree	−0.2263***	−0.4809***	−0.5002***
	(0.0093)	(0.0067)	(0.0104)
Some college	−0.1179***	−0.3251***	−0.4202***
	(0.0071)	(0.0060)	(0.0107)
Advanced degree	−0.0127***	0.1701***	0.7561***
	(0.0043)	(0.0061)	(0.0234)
Region			
South	−0.0271***	−0.0530***	−0.0578***
	(0.0051)	(0.0068)	(0.0112)
Midwest	−0.0029	−0.0512***	−0.1073***
	(0.0062)	(0.0071)	(0.0102)
West	0.0134**	−0.0012	0.0511***
	(0.0059)	(0.0075)	(0.0122)
Metropolitan area	0.0374***	0.1191***	0.1112***
	(0.0076)	(0.0059)	(0.0092)
Married	0.0751***	0.1251***	0.1094***
	(0.0051)	(0.0055)	(0.0079)
Children	−0.0153***	0.0297***	0.0997***
	(0.0052)	(0.0046)	(0.0077)
Race and ethnicity			
Black not Hispanic	−0.0876***	−0.1567***	−0.1284***
	(0.0086)	(0.0072)	(0.0100)
Other not Hispanic	−0.0389***	−0.0708***	−0.0438***
	(0.0076)	(0.0071)	(0.0130)
Hispanic	−0.1134***	−0.1853***	−0.1445***
	(0.0096)	(0.0066)	(0.0092)
Constant	6.0042***	6.9858***	7.7210***
	(0.0137)	(0.0115)	(0.0290)

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

TABLE 3 Recentered influence function regressions for inequality measures, 1985–1988 and 2016–2019.

	90–10 gap	50–10 gap	90–50 gap
A. 1985–1988			
Care services	−0.2753***	−0.2295***	−0.0458***
	(0.0151)	(0.0120)	(0.0127)
Business services	−0.0297**	−0.1129***	0.0832***
	(0.0140)	(0.0108)	(0.0118)
Other services	0.0550***	0.0313***	0.0237***
	(0.0098)	(0.0077)	(0.0088)
B. 2016–2019			
Care services	−0.3212***	−0.1689***	−0.1523***
	(0.0174)	(0.0068)	(0.0180)
Business services	0.0207	−0.0446***	0.0653***
	(0.0171)	(0.0080)	(0.0163)
Other services	−0.0139	−0.0112	−0.0027
	(0.0121)	(0.0088)	(0.0139)

Source: Current Population Survey Annual Social and Economic Supplement. 1985–1988 ($N = 115{,}340$) and 2016–2019 ($N = 183{,}241$). Sample restrictions same as Table 1. Reference industry group is nonservices. Bootstrapped standard errors (100 replications) in parentheses. $p < 0.10$.

**$p < 0.05$; ***$p < 0.01$

Table 4 decomposes the growth in wage inequality *between* 1985–1988 and 2016–2019, disaggregating the composition effect into the contributions of each industry group, occupation, human capital, region, and demographics. Supporting Information S1: Table C.1 presents sample means and standard deviations for all regressors disaggregated by period. All three gaps (90–10, 50–10 and 90-50) have increased over time, but the increase in the 90–50 gap dominates: much of the increase in the 90–10 gap comes from growing inequality at the top half of the wage distribution. The composition effects for industry in this table capture the contribution of the employment trends emphasised earlier: our decomposition estimates suggest that the expansion of care services was associated with 0.0215 log point reduction in the 90–10 gap that grew by 0.2351 log points over the entire period). To put it differently, in the counterfactual where care employment did not rise at the expense of nonservices, 90–10 inequality would have been higher by about 9%. On the other hand, the expansion of both business services and other services was associated with small positive contributions to 90–10 wage inequality.

The contrast between care services and business services in their contribution to the growth of inequality in the top half of the wage distribution is particularly striking: the expansion of care services was associated with a 0.0075 reduction in the 90–50 gap, while the expansion of business services was associated with a positive and significant 0.0045 *increase* in the 90–50 gap. As the 90–50 gap increased by 0.2048 log points over this period, the impact of the expansion of care services amounts to a dampening of inequality at the top by 4%, while the expansion of business services is associated with a 2% increase.

TABLE 4 Decomposition of changes in wage inequality between 1985–1988 and 2016–2019.

	90–10 gap	% total	50–10 gap	% total	90–50 gap	% total
Total change	0.2351***		0.0303***		0.2048***	
	(0.0090)		(0.0109)		(0.0066)	
Total composition	0.0844***	[35.9]	0.0584***	[192.7]	0.0260***	[12.7]
	(0.0030)		(0.0024)		(0.0023)	
Care services	−0.0215***	[−9.1]	−0.0140***	[−46.2]	−0.0075***	[−3.7]
	(0.0009)		(0.0007)		(0.0007)	
Business services	0.0008	[0.3]	−0.0037***	[−12.2]	0.0045***	[2.2]
	(0.0006)		(0.0004)		(0.0005)	
Other services	0.0001	[0.0]	0.0001	[0.3]	0.0001	[0.0]
	(0.0001)		(0.0000)		(0.0000)	
Occupation	0.0526***	[22.4]	0.0405***	[133.7]	0.0121***	[5.9]
	(0.0020)		(0.0012)		(0.0014)	
Human capital	0.0536***	[22.8]	0.0455***	[150.2]	0.0081***	[4.0]
	(0.0028)		(0.0023)		(0.0019)	
Region	0.0030***	[1.3]	0.0048***	[15.8]	−0.0018***	[−0.9]
	(0.0008)		(0.0006)		(0.0006)	
Demographic factors	−0.0043***	[−1.8]	−0.0147***	[−48.5]	0.0105***	[5.1]
	(0.0016)		(0.0014)		(0.0012)	
Total wage structure	0.1507***	[64.1]	−0.0281**	[−92.7]	0.1788***	[87.3]
	(0.0101)		(0.0115)		(0.0069)	

Source: Same as Table 3. Reference industry group is nonservices. Numbers in square brackets represent percentage contribution to change in a particular inequality measure between 1985–1988 and 2016–2019. Coefficients from pooled model used as the reference for computing composition effects. Bootstrapped standard errors (100 replications) in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

4.3 | Care services expansion and gender wage inequality

Women's greater employment in care services reduces their wages relative to men; this effect is magnified at the upper end of the wage distribution. Table 5 decomposes the gender wage gap separately for each period at the 10th, 50th and 90th percentiles. Women's overrepresentation in care services has had a negative effect on their wages relative to men: in 1985–1988, for example, gender differences in care sector employment contributed to 0.0337 log points (or 7%) of the 0.4644 gender wage gap at the median. This contribution has remained relatively stable (at 0.0333 log points) in 2016–2019; given the decline in the gender gap at the median between 1985 and 2019, the contribution of care services has *doubled* to account for 14% of the median gap.

The negative impact of care service employment on the wages of women relative to men is larger at the top than it is at the bottom: in 1985–1988, this effect was more than 10 times as large for the gender gap at the 90th percentile compared to the 10th percentile (0.0345 log

TABLE 5 Decomposition of the gender wage gap, 1985–1988 and 2016–2019.

	10th percentile	% total	50th percentile	% total	90th percentile	% total
A. 1985–1988						
Raw gap	−0.2704***		−0.4644***		−0.4907***	
	(0.0112)		(0.0054)		(0.0064)	
Total composition	−0.0282***	[10.4]	−0.0947***	[20.4]	−0.1245***	[25.4]
	(0.0034)		(0.0026)		(0.0038)	
Care services	−0.0030*	[1.1]	−0.0337***	[7.3]	−0.0345***	[7.0]
	(0.0016)		(0.0010)		(0.0025)	
Business services	−0.0059***	[2.2]	−0.0134***	[2.9]	−0.0041***	[0.8]
	(0.0011)		(0.0011)		(0.0014)	
Other services	0.0077***	[−2.8]	0.0063***	[−1.4]	0.0042***	[−0.9]
	(0.0006)		(0.0004)		(0.0006)	
Occupation	0.0046	[−1.7]	−0.0155***	[3.3]	−0.0381***	[7.8]
	(0.0035)		(0.0023)		(0.0027)	
Human capital	−0.0069***	[2.6]	−0.0233***	[5.0]	−0.0484***	[9.9]
	(0.0013)		(0.0017)		(0.0025)	
Region	0.0028***	[−1.0]	0.0032***	[−0.7]	0.0027***	[−0.6]
	(0.0007)		(0.0009)		(0.0006)	
Demographic factors	−0.0275***	[10.2]	−0.0182***	[3.9]	−0.0062***	[1.3]
	(0.0016)		(0.0008)		(0.0010)	
Total wage structure	−0.2422***	[89.6]	−0.3697***	[79.6]	−0.3662***	[74.6]
	(0.0105)		(0.0057)		(0.0067)	
B. 2016–2019						
Raw gap	−0.1321***		−0.2391***		−0.3036***	
	(0.0115)		(0.0039)		(0.0125)	
Total composition	0.0052*	[−3.9]	0.0020	[−0.8]	−0.0092***	[3.0]
	(0.0029)		(0.0018)		(0.0035)	
Care services	0.0010	[−0.8]	−0.0333***	[13.9]	−0.0576***	[19.0]
	(0.0020)		(0.0019)		(0.0034)	
Business services	−0.0001	[0.1]	−0.0013***	[0.5]	0.0011**	[−0.4]
	(0.0002)		(0.0001)		(0.0004)	
Other services	0.0094***	[−7.1]	0.0083***	[−3.5]	0.0067***	[−2.2]
	(0.0007)		(0.0005)		(0.0008)	
Occupation	−0.0243***	[18.4]	0.0065***	[−2.7]	0.0220***	[−7.2]
	(0.0030)		(0.0014)		(0.0029)	

(Continues)

TABLE 5 (Continued)

	10th percentile	% total	50th percentile	% total	90th percentile	% total
Human capital	0.0258***	[−19.5]	0.0297***	[−12.4]	0.0255***	[−8.4]
	(0.0008)		(0.0008)		(0.0016)	
Region	−0.0005***	[0.4]	−0.0006**	[0.3]	−0.0015***	[0.5]
	(0.0001)		(0.0002)		(0.0004)	
Demographic factors	−0.0061***	[4.6]	−0.0074***	[3.1]	−0.0053***	[1.7]
	(0.0007)		(0.0003)		(0.0005)	
Total wage structure	−0.1374***	[104.0]	−0.2411***	[100.8]	−0.2944***	[97.0]
	(0.0112)		(0.0039)		(0.0138)	

Source: Same as Table 3. The reference industry group is nonservices. Numbers in square brackets represent percentage contribution to overall gender gap in the specific period. Coefficients from the pooled model used as the reference for computing composition effects. Number of observations in 1985–1988: 45,863 (women) and 69,477 (men) and in 2016–2019: 78,441 (women) and 104,800 (men). Bootstrapped standard errors (100 replications) in parentheses.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

points vs. 0.003 log points, or 7% compared to 1% of the respective gaps). This striking differential in the way care services lower the earnings of women at the top compared to women at the bottom has only grown larger in the recent period: in 2016–2019, the contribution of care service employment to the gender gap at the 90th percentile had increased to 0.0576 log points (or 19% of the gap at the 90th percentile).

Table 6 brings together the top and bottom panels of Table 5, presenting estimates of the contribution of the regressors to the *change* in the gender wage gap between 1985–1988 and 2016–2019. While the gender wage gap declined across all percentiles, the factors underlying the change are heterogenous. In particular, women's improved educational characteristics contributed to a reduction in gender wage differentials; on the other hand, their increased concentration in care services held back convergence at the top. Care services contributed a *negative* 0.0230 log point effect on the change in the gender wage gap at the 90th percentile, which improved by 0.187 log points. To put it differently, had women's employment in care services not increased between 1985 and 2019, the gender gap at the 90th percentile would have been 2 percentage points (or 12%) smaller than it is now. The expansion of care services had negligible effects on the reduction in the gap at the 50th percentiles and 10th percentiles.

At both the 50th and the 90th percentiles, occupational shifts have boosted women's wages; however, their concomitant movement into care services appears to have cancelled out some of these gains for women at the top, suggesting that the concentration of relatively highly educated women in care services helps explain the recent lack of progress toward gender parity in earnings. This finding complements previous research finding that industrial segregation is an important factor in explaining the continued gender wage gap (Blau & Kahn, 2017).

4.4 | Robustness checks

We assess the robustness of our results to the choice of time period. Specifically, we estimate the equalising effect of care services on overall inequality for each year in the entire 1980 to

TABLE 6 Decomposing change in gender wage gap between 1985–1988 and 2016–2019.

	10th percentile	% total	50th percentile	% total	90th percentile	% total
Change in						
Raw gap	0.1383***		0.2252***		0.1871***	
	(0.0184)		(0.0073)		(0.0134)	
Total composition	0.0334***	[24.2]	0.0967***	[42.9]	0.1153***	[61.6]
	(0.0053)		(0.0055)		(0.0076)	
Care services	0.0041**	[3.0]	0.0004	[0.2]	−0.0230***	[−12.3]
	(0.0018)		(0.0011)		(0.0040)	
Business services	0.0059***	[4.3]	0.0121***	[5.4]	0.0051***	[2.7]
	(0.0009)		(0.0006)		(0.0013)	
Other services	0.0017**	[1.2]	0.0020***	[0.9]	0.0025**	[1.3]
	(0.0008)		(0.0007)		(0.0012)	
Occupation	−0.0290***	[−21.0]	0.0220***	[9.8]	0.0601***	[32.1]
	(0.0043)		(0.0031)		(0.0047)	
Human capital	0.0327***	[23.6]	0.0530***	[23.5]	0.0739***	[39.5]
	(0.0019)		(0.0020)		(0.0034)	
Region	−0.0033***	[−2.4]	−0.0038***	[−1.7]	−0.0042***	[−2.2]
	(0.0005)		(0.0004)		(0.0006)	
Demographic factors	0.0214***	[15.5]	0.0108***	[4.8]	0.0010	[0.5]
	(0.0016)		(0.0013)		(0.0016)	
Total wage structure	0.1049***	[75.8]	0.1286***	[57.1]	0.0718***	[38.4]
	(0.0176)		(0.0060)		(0.0109)	

Source: Same as Table 3. Reference industry group is nonservices. Numbers in square brackets represent percentage contribution to change in overall gender gap at the specified percentile over 1985–1988 and 2016–2019. Coefficients from pooled model used as the reference for computing composition effects. Bootstrapped standard errors (100 replications) in parentheses.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

2019 period (Supporting Information S1: Appendix Figure C.1). Care services exhibit a consistently negative effect on inequality. We find similar results for the negative effect of women's overrepresentation in care services on their wages relative to men (Supporting Information S1: Appendix Figure C.2). Supporting Information S1: Table C.2 reassures us that our results are not sensitive to the choice of nonservices as the omitted category: the negative effects on care services on all three measures of wage inequality are similar when we use business services or other services as the reference group.

The simple Kitagawa–Oaxaca–Blinder decompositions of the unconditional wage quantiles assume that the conditional expectation of the RIF is linear and may produce biased results if this assumption does not hold (Barsky et al., 2002). We present reweighted estimates of our main results, using methods developed by Firpo et al. (2009, 2018). Supporting Information S1: Appendix C offers further justification and explanation for the reweighting, and estimates of our main results with reweighting in Supporting Information S1: Tables C.3, C.4 and C.5. The reweighted estimates are not substantially different to our main results.

Appendix D replicates the core set of results (for both overall wage inequality and gender wage inequality) for the sample inclusive of public sector and part-time part-year workers. Supporting Information S1: Appendix E restricts the sample to a subset of the ASEC and reproduces the analysis controlling for union coverage. All robustness checks confirm the results found in the main analysis.

5 | CONCLUSION

Research on rising inequality and the growth of service sector employment should devote more attention to the heterogeneity of service industries. Care services have distinctive characteristics that make it difficult for both firms and workers to capture the full benefits of the services they provide. Precisely because they generate positive social benefits, health, education and social welfare services are likely to be produced or subsidised by the public sector. Yet even when these services are provided through private sector employment, they entail pay penalties that are particularly prominent at the top of the occupational distribution. These pay penalties suggest that changes in the industrial composition of employment have implications for the shape of the earnings distribution.

Our analysis of pooled data from the CPS ASEC between 1985–1988 and 2016–2019 performs a thought experiment based on counterfactuals. Overall service employment expanded significantly over this period. What if, all else equal, substantially fewer women had moved into care services between 1985–1988 and 2016–2019, and substantially more women had moved into business services? Our decomposition of trends based on unconditional quantile regressions that control for trends in human capital and other important covariates suggests that we would have greater overall polarisation of earnings but also greater improvements in gender wage inequality.

All else is not equal. Many important worker characteristics (including actual labour force experience and job tenure) remain unobserved, and the causal linkages between earnings and employment in specific industries are difficult to identify. Still, our findings make a strong case for greater attention to the specific—and highly gendered—implications of employment in care services.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

We use publicly available data from the Current Population Survey's Annual Social and Economic Supplement and provide code (in STATA) that reproduces our results.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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