Gender Divergence in Sectors of Work*

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Abstract

We document an increasing divergence in the sector of employment between men and women from 1980 to 2020. While *occupational* sorting of men and women converged, the sectoral composition of employment between by gender has diverged. The divergence is present in both the U.S. time series as well as in the cross-section of E.U. countries. The paper provides a structural decomposition of rising sectoral segregation into three constituent drivers: preferences, discrimination, and technology. Changing preferences of married women, particularly for the Education and Health sector, explain around half of the increase in segregation. However, we rule out changing preferences as an explanation for the persistence of the gender earnings gap.

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1 Introduction

Over the past 50 years, women's occupational choices, hours, and wages have converged substantially towards men's (Goldin 2014; Hsieh et al. 2019; Albanesi 2024). We document that over the same period in the U.S., the sectors where men and women work have actually *diverged*, leading to *more* gender segregation by sector. This makes the incidence of sector specific shocks more unequal across genders, which matters for the depth and persistence of future recessions (Alon et al. 2020b). It also raises a host of interesting questions on the persistence of gender differences in labor market outcomes and what might be driving them, and the extent to which job amenities are determined by sector of work.

The rise in gender segregation by sector is entirely driven by married women; segregation for single women has not changed. In contrast, the decline in *occupational* segregation over the same period has been roughly the same for single and married women (Figure 1). Explanations for rising gender segregation should account for these differences, which suggest that single and married women may value employment in different sectors quite differently.

Structural transformation plays a role: around 40% of the aggregate rise in segregation is due to the growing employment share of gender segregated sectors like Information (which is male dominated) and Education and Health (which is female dominated). However, the other 60% is due to within-sector changes in gender composition. Our findings are also consistent with cross country evidence from Europe. Across Europe, countries with the smallest hours gap between men and women, which we take as a measure of gender convergence on other dimensions, have the highest levels of gender segregation by sector, consistent with the time series pattern for the U.S.

Our new stylized fact is robust to using various levels of sector disaggregation. It also does not seem to be driven by a change in the distribution of occupations across sectors. Changes in women's employment shares across sectors over time drive most of the change in segregation (hold men's employment shares fixed at the 1980s shows a similar rise in segregation as allowing them to vary), so we focus most of our discussion on the determinants of women's sectoral choices.

Hsieh et al. (2019) attribute the decline in occupational segregation to changing occupation-specific discrimination, and to a much lesser extent changing preferences for occupations. We apply their framework to decompose the forces driving sectoral rather than occupational choices. Married women's changing preferences for sectors explain about 60% of the rise in gender segregation, while changes in technology and discrimination each explain around fifteen percent. Finally, we ask whether these preferences contribute to the persistence of the gender earnings gap. In fact, women increasingly prefer high paid sectors. Absent the changes in preferences we estimate, the gender earnings gap would be ten percent larger today.

We provide suggestive evidence about the sector characteristics that married women value. Married women's preferences are positively correlated with the sector's share of part time workers, suggesting hours flexibility is potentially an important amenity. Their preferences are also positively correlated with the average number of children workers in that sector have, suggesting a role for "child-friendliness." Homophily, measured by the share of workers who are female, does not seem to play a role in shaping sector amenities for married women, nor does riskiness, measured by correlation with the business cycle.

Related Literature In addition to the literature on gender convergence, this paper is related to work on fixed gender differences in occupational and sectoral choice, for example due to the brains vs. brawn content of tasks (Olivetti 2014; Olivetti and Petrongolo 2016; Ngai and Petrongolo 2017; Cortés and Pan 2018; Lordan and Pischke 2022) and the relationship of gender differences in sectoral choice to structural transformation (Kuhn, Manovskii, and Qiu 2024; Coskun and Sengul 2024). Little has been done to document or understand *changes* in sectoral choice by gender over time.

Trends in sectoral segregation are driven by changing preferences, consistent with a growing literature on the importance of job amenities like workplace flexibility in employment choice (Mas and Pallais 2017). Wiswall and Zafar (2017) attribute around a quarter of the gender wage gap in the U.S. to non-wage amenities, and Morchio and Moser (2024) provide additional evidence for Brazil as well as a model of amenity offerings and worker search. In the tradition of Sorkin (2018), Corradini, Lagos, and Sharma (2024) use revealed preferences of job movers to infer male and female preferences for a variety of amenities negotiated by unions in Brazil. Women value family-friendly amenities like maternity leave, hours flexibility, and childcare payments, while men tend to value higher pay. Maestas et al. (2023) and Boar and Lashkari (2021) find large variation in amenities across occupations that matter for welfare and inequality. Maideu-Morera (2024) finds only minor differences between men and women in the overall rise in occupational amenities over time, though this is not the focus of his paper. Our contribution is to point out that *sectors* seem to also differ in amenities, highlighting the need for systematic measures of amenities across sectors and a theory of why they differ.

Another related literature studies the persistence of the gender earnings gap (Blau and Kahn 2000) due to greedy occupations (Goldin 2014; Goldin 2015; Wasserman 2022), motherhood penalties (Kleven, Landais, and Søgaard 2019), bargaining differences (Biasi and Sarsons 2021; Coskun, Gartner, and Taskin 2025), job search behavior (Cortés et al. 2023), local norms (Ashraf et al. 2024), and the age structure (Arellano-Bover et al. 2024). We rule out changing preferences for sectors as an explanation for the persistence of the gender earnings gap.

Finally, our findings on gender segregation will be of interest to macroeconomists studying sector specific shocks, and are related to the literature on the macroeconomic consequences of household labor supply (Doepke and Tertilt 2016; Albanesi and Olivetti 2016; Alon et al. 2020a; Alon, Coskun, and Doepke 2020; Alon et al. 2022; Coskun and Dalgic 2024; Ellieroth 2023; Ellieroth and Michaud 2024; Balleer, Merz, and Papp 2025).

2 Stylized Facts

The primary data source is the IPUMS Current Population Survey (IPUMS-CPS) data. The analysis focuses on changes in segregation for five cohorts of young people (ages 25-35) between 1975 and 2019. The 1980 cohort covers 1975-1984, the 1990 cohort 1985-1994, and so on. International data comes form the European Union Labor force Survey (EU-LFS). See Appendix A.1 for additional details on the data sources, sample populations, and variable construction.

2.1 Rising Gender Segregation in the United States

We measure gender segregation at time t using the Blau and Hendricks (1979) definition

$$S_t = \frac{\Sigma_{i \in I} |p_{igt} - p_{imt}|}{2},$$

where i indexes either sector or occupation, g indexes the group of interest (single or married women), and m is the reference group (men). p_{igt} is the share of all employed members of group g working in sector or occupation i, so that $\Sigma_{i \in I} \, p_{igt} = 1$.

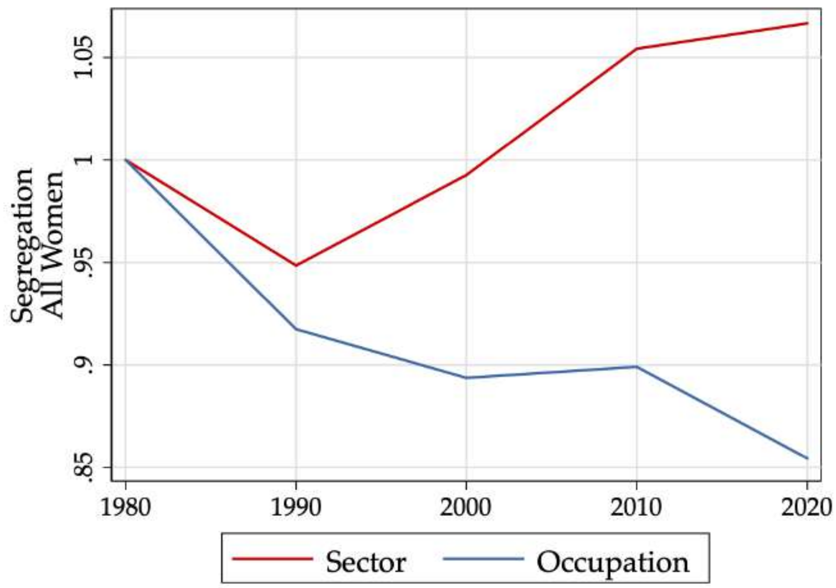


Figure 1: Occupational convergence and sectoral divergence.

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019. Sectors are defined by BLS's (Bureau of Labor Statistics) main sectors and occupations as 2-digit occupations from SOC codes (Standard Occupational Classification). See Appendix A.1.1 for details.

The index provides a measure of the total divergence in the employment composition across groups. For example, if men and women are equally distributed across sectors, $S_t = 0$. If instead every sector is either totally male- or female-dominated, $S_t = 1$. Intermediate cases produce index values strictly between 0 and 1. The metric is also naturally weighted, with larger sectors contributing more to measured segregation.[1]

Figure 1 displays the evolution of gender segregation in the United States across occupations and sectors of work between 1980–2020. It confirms the well-known fact in the literature that there has been a large decrease in the gender segregation of occupations, which decreased by 15% since 1980. At the same time, however, the data also show that there has been a large concurrent *increase* in the gender segregation across sectors of employment, which increased by 7% over the same period. Occupations remain more segregated than sectors in level terms, though the gap narrowed considerably over this period (Figure A.1).

[1] If a large sector has 30% of all employed married women and 20% of all employed men, this sector contributes $\frac{|0.3-0.2|}{2} = 0.05$ to total segregation. A sector one tenth the size with 3% of married women and 2% of men (same gender ratio as the larger sector) contributes $\frac{|0.03-0.02|}{2} = 0.005$.

The diverging trends in occupational and sectoral segregation raise questions about the extent to which labor market outcomes for men and women are truly converging during this period. The timing is also significant. Most of decrease in occupational segregation occurred alongside the rise in female labor market participation, while the increase in sectoral segregation is concentrated after 2000, when women's labor force participation plateaued (Albanesi 2024). The difference in timing suggests that sectoral effects may play a greater role in explaining persistent gender differences in labor markets outcomes in recent years, while occupation effects and rising participation rates played a more central role during the earlier period.

Role of Specific Industries and Structural Transformation. Figure 2 decomposes the change in segregation into the contributions of each sector. The three sectors that contributed the most to the rise in segregation are Construction, Information, and Education and Health Services. Construction and Information were male-dominated in the 1980s (93% and 56% male, respectively), whereas Education and Health Services was female-dominated (70% female). The male-dominated sectors became even more male-dominated (91% and 62% male, respectively) and the education and health services sector became even more female-dominated (77% female).

Even without changes in gender composition, segregated sectors can contribute to rising segregation by simply experiencing faster employment growth than other sectors because the segregation measure is weighted by size. In general services sectors tend to be female dominated and have grown substantially in the last half century (Ngai and Petrongolo 2017). Figure A.3 plots the counterfactual path for segregation if sectoral employment shares are held fixed at their 1980 values. Changing gender composition within sectors explains 59% of the rise in segregation and the remaining 41% is due to structural transformation.

Marital Status and Presence of Children. Gender gaps in labor market outcomes may also be the result of family labor supply decisions or the differential impact of childcare on male and female work prospects (Doepke and Tertilt 2016; Doepke and Kindermann 2019; Coskun, Dalgic, and Ozdemir 2023). Figure 3 investigates this possibility by comparing trends in sectoral segregation for married and single women, and women with and without children, with all men as the comparison group throughout.

The disaggregated segregation series suggest a prominent *family channel* effect: married women account for the entire rise in sectoral segregation. Between 1980–2020, the sec-

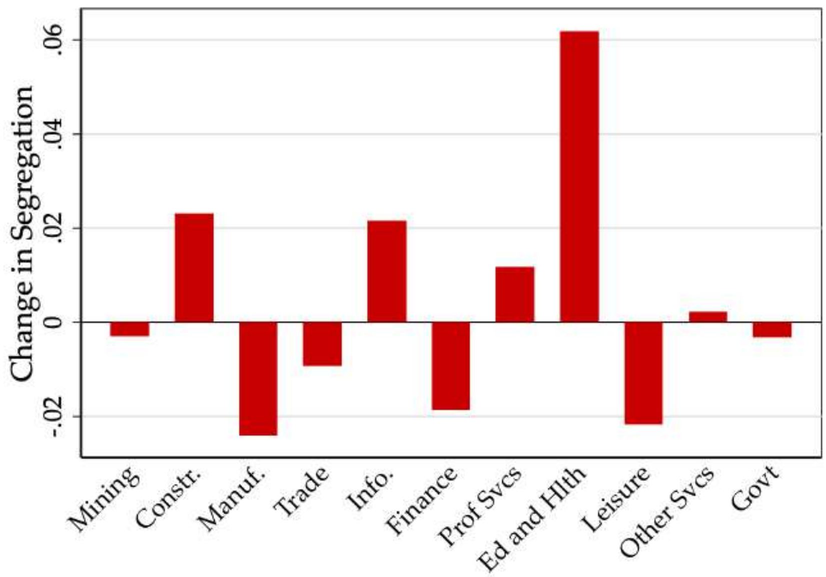


Figure 2: Sector Contributions to Changes in Aggregate Segregation, 1980–2020

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019. Bars report the change in absolute difference between the fraction of women working in sector s among all working women and the fraction of men working in sector s among all working men from year 1980 to 2020. See Appendix A.1.1 for details.

toral segregation of married women increased by 17%, while segregation was -1% lower for single women.[2] Figure A.4 similarly shows that married women also drive the sectoral contributions to segregation in Figure 2. The divergence between married and single women is likely the result of both the effect of household specialization as well as the impact of childcare. The two channels cannot be readily discriminated in the data as marriage is often a precursor to the arrival of children and most children are raised in married couples. The dashed lines in Figure 3 show that the divergence in sectoral segregation across households with and without children was similar to those broken down by marital status.

Cross-Country Evidence. The evolution of gender equality and female labor force participation has followed systematic patterns across many different countries (Olivetti 2014; Olivetti and Petrongolo 2016). Changes in technology and gender norms led to

[2]Figure A.2 plots the rise in segregation for single and married women compared to single and married men, respectively. Single women have a much lower level of segregation compared to single men and show an increase over time. The rise in segregation for married women compared to married men is roughly the same as when the reference group is all men.

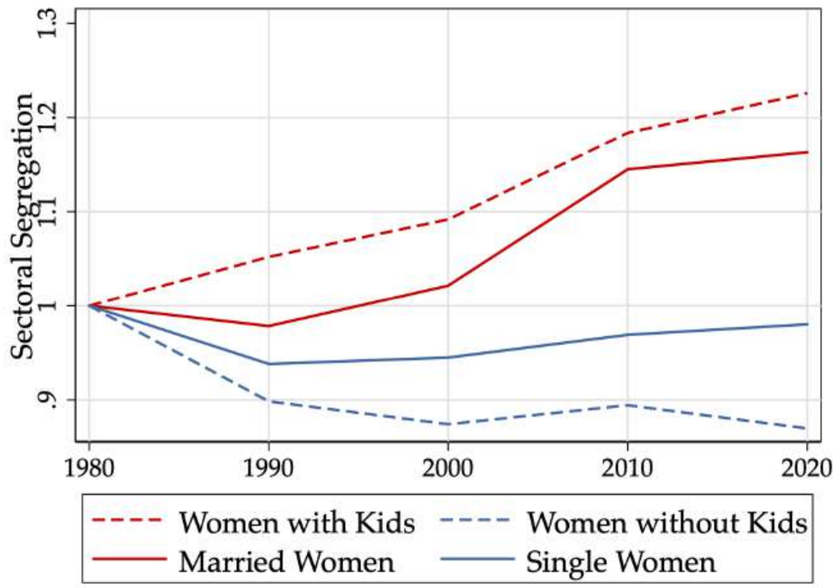


Figure 3: Sectoral Segregation: Role of Children

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019. Motherhood is defined as the existence of children younger than age 18. Solid lines represent the segregation when the sample is divided into 3 groups as men, single women, married women, whereas in dashed lines, the division is as men, women with kids, women without kids. See Appendix A.1.1 for details.

large increases in female labor force participation and reductions in occupational segregation and earnings gaps. Figure 4 shows that the rise in sectoral gender segregation also appears to be more than just a United States phenomenon. It employs data from the European Union Labour Force Survey (EU-LFS) covering 16 developed economies from 2008-2019, when consistent sector codes are available. The data show a strong positive correlation between a country's sectoral segregation and its gender gap in hours worked per capita, a measure of overall labor market convergence.

As a means of comparison, Figure 4 super-imposes the evolution of sectoral segregation and the gender hours gap in the United States since 1980. Both the time series in the United States and European cross-country data paint a similar picture: in economies where women work more, sectoral gender segregation is higher. As in the United States, the cross-country correlation is also driven primarily by married rather than single women (Figure A.7). Similarly, adjusting for cross-country differences in the sectoral composition of work preserves the positive correlation, indicating that it depends on within sector effects that are not the results of structural transformation or differences in

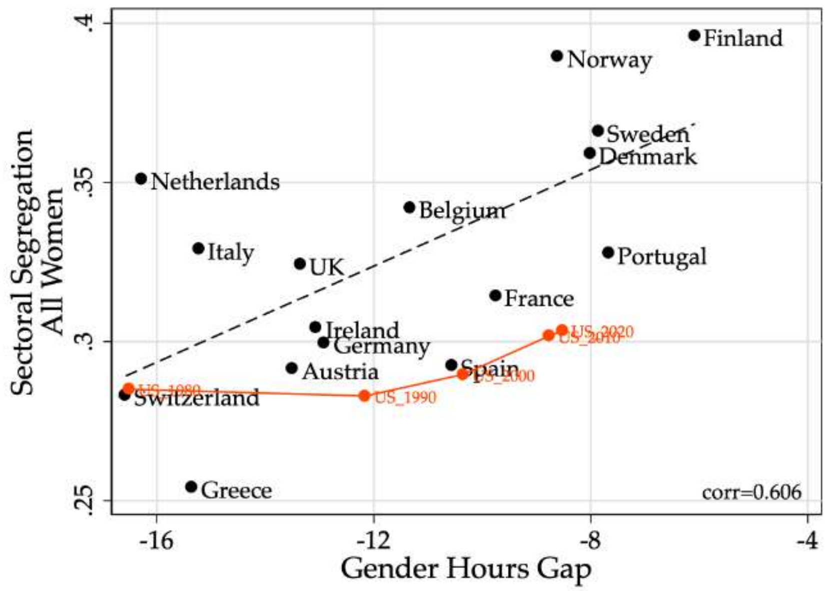


Figure 4: Sectoral Segregation in Europe

Note: Data source is EU-LFS for European countries. Average sectoral segregation for 25-54 age group and for the year 2008-2019 is reported. Gender hours gap is the average of 2005-2009. See Appendix A.1.2 for details. Data points for the US are exactly the same as in Figure 1.

the services share across EU countries (Figure A.8).

2.2 Robustness

The appendix contains a number of additional robustness exercises. Section A.2.2 examines how trends compare when computed using finer industry classifications at the 2- or 3-digit NAICS level. Consistent with the above, the more disaggregated measures continue to show rising segregation for married women, with trends that are flat or decreasing for single women.

Another possibility is that the rise in sectoral segregation merely reflects a sectoral reshuffling of occupations–which remain more segregated than sectors despite recent convergence. Many occupations have become more concentrated within certain sectors due to the rise of domestic outsourcing (Katz and Krueger 2019). For example, increasing sectoral segregation may reflect the fact that the female-dominated clerical services occupation, which used to be distributed across many sectors, is now concentrated in the professional services sector.

To assess these compositional effects, section A.2.1 recomputes sectoral segregation by aggregating over the two dimensional sector by occupation space. The disaggregated computation enables us to account for the contribution of within-sector changes in occupational composition to overall sectoral segregation. The rise in sectoral segregation is robust to holding fixed changes in the occupational composition of sectors (the blue line with fixed occupation shares in Figure A.3 closely tracks the actual change, suggesting that changing occupational composition within sectors played no role).

While the aggregate pattern is unchanged, the compositional changes do influence the relative contribution of particular sectors to overall segregation. We consider two examples, the Management occupation and the Education and Health sector to make this point. First, when neglecting sectors, there appears to be substantial occupational convergence in Management (the dashed line in Figure A.9c). However, once we account for the distribution of managers across sectors, we find that segregation declined much less (that is, more women became managers, but in sectors that were female dominated like Leisure and Hospitality). By contrast, in the Education and Health sector, the rise in segregation is substantial, even accounting for the distribution of occupations within the sector (i.e., women moved into Education and Health but moved roughly equally into healthcare assistant roles and practitioner roles.)

Finally, section A.2.3 examines the extent to which segregation trends are driven by changes in the employment composition of men, women, or both groups. As an assessment, Figure A.11 computes two alternative paths for segregation holding either the composition of male or female employment fixed at their 1980 level, respectively. Changes in women's employment composition are what drive the rise in sectoral segregation: when only female employment shares change, the rise in sectoral segregation between 1980–2020 is 30% higher than in Figure 1. When only male employment shares change, sectoral segregation actually *decreases*, falling by 11% by 2020.

3 A Model-Based Decomposition of Sectoral Segregation

The preceding section documents a rise in sectoral segregation, driven predominantly by changes in the employment composition of married women. This section exploits the heterogeneity among women to learn about the underlying drivers of the aggregate fact. It adapts the model of Hsieh et al. (2019) to explain the changing employment choices of married and single women relative to men between 1980–2020. In the model, sectoral segregation can be explained by either changes in preferences, changes in gender discrimination, or changes in technology. Under suitable assumptions the three channels can be separately identified with data on sectoral earnings and employment shares.

The model population consists of heterogeneous individuals making consumption, education, and job sector choices. The lifetime utility U of an individual from group g in cohort c who chooses to work in sector i is given by

$$\log U = \beta \left[\sum_{t=c}^{c+2} \log C_{ig}(c,t) \right] + \log[1 - s_i(c)] + \log z_{ig}(c)$$

where C is consumption, s denotes pre-period time investment in human capital, and z is a sector specific utility term common to all members of a group g. Households live for three periods (young, middle age, and old) with c indexing their cohort and t indexing the time period. Coefficient β captures the utility value of consumption relative to leisure in the pre-period. Consumption is given by household earnings net of educational expenditures e,

$$C_{ig}(c,t) = [1 - \tau^w_{ig}(t)] w_i(t) h_{ig}(c,t) \epsilon - e_{ig}(c,t)[1 + \tau^h_{ig}(c)]$$

where ϵ is the individual's sector-specific ability and $w_i(t)$ is the sector's efficiency wage rate. Parameters $\tau^w_{ig}(t)$ and $\tau^h_{ig}(c)$ capture sector-group specific discrimination in labor markets and sector-group specific barriers to human capital accumulation. Individual human capital $h_{ig}(c,t)$ depends on their pre-period investment of time s and educational expenditures, such that

$$h_{ig}(c,t) = \gamma(t-c) s_i(c)^{\phi_i(c)} e_{ig}(c,t)^{\eta}$$

where $\phi_i(c)$ captures the sector-specific returns to education, which may vary across cohorts and sectors. Parameter η is the elasticity of human capital with respect to educational expenditure and function $\gamma(t-c)$ captures returns to experience.

The model economy has I distinct sectors. If each individual's sector-specific abilities are drawn from a multivariate Fréchet distribution, $F(\epsilon_1, ..., \epsilon_I) = \exp\left(-\sum_{i=1}^{I} \epsilon_i^{-\theta}\right)$, the model gives rise to tractable expressions for earnings and sector choice probabilities. With additional normalizations, the model identifies differences in group-specific preferences and discrimination from data on group-specific sector shares and earnings gaps. Two group-specific normalizations are required to address the two degrees of freedom lost to the fact that sector shares must sum to one and the fact that sector wages are not observed in the home sector (i.e. the non-participating population).

Following Hsieh et al. (2019), we achieve identification by normalizing the home sector so that preferences equal one and no group faces discrimination in home production. Under this normalization, earnings and employment shares of any group g relative to the benchmark group (men) can be expressed,

$$\frac{\text{wage}_{i,g}}{\text{wage}_{i,m}} = \left(\frac{\tau_{i,g}}{\tau_{i,m}}\right)^{-\frac{1}{1-\eta}} \times \left(\frac{\text{share}_{i,g}}{\text{share}_{i,m}}\right)^{-\frac{1}{\theta(1-\eta)}} \tag{1}$$

$$\frac{\text{share}_{i,g}}{\text{share}_{i,m}} = \left(\frac{1-\text{LFP}_g}{1-\text{LFP}_m}\right) \times \left(\frac{\tau_{i,g}}{\tau_{i,m}}\right)^{-\theta} \times \left(\frac{z_{i,g}}{z_{i,m}}\right)^{-\frac{\theta(1-\eta)}{3\beta}} \tag{2}$$

where wage_{ig} is the geometric average of earnings and share_{ig} is the share of group g employed in sector i. LFP_g is the labor force participation rate of group g. The equations provide intuition for how the model identifies discrimination and preferences from the data. The first equation says that conditional on selection – proxied by relative employment shares – the within sector wage gaps between groups identify relative levels of discrimination τ_g/τ_m. The second equation says that conditional on participation and discrimination, differences in sector employment shares reflect relative preferences z_g/z_m.

The final channel that can drive changes in sector employment shares by group are technological factors. These include sectoral efficiency wages (productivity) $w_i(t)$ and the returns to education $\phi_i(c)$. While these technological factors are common to all groups within a time period or cohort, they may still contribute to changes in segregation and earnings gaps by interacting with prevailing differences in the composition of employment across groups. Identifying these factors requires an additional assumption that the benchmark group (men) face no discrimination in education and labor markets.[3] In this case, sectoral wages $w_i(t)$ (and preferences $z_{i,m}$) can be recovered directly from male earnings and employment data. Returns to education $\phi_i(c)$ can be retrieved by inverting the optimal human capital investment policy, $s_i^*(c)$, and using data on male years of schooling across sectors.

The remaining structural parameters $\eta, \theta, \beta,$ and $\gamma(t-c)$ are fit following the approach in Hsieh et al. (2019). Given these, changes in preferences, discrimination, and technology can be retrieved from sectoral data on earnings, employment shares, and years of

[3] In some sense, this is without loss of generality if we interpret the discrimination parameters τ as capturing *relative* discrimination across groups, with men as the normalized benchmark.

schooling across groups. By construction, the procedure *exactly matches* the aggregate trends in sectoral segregation (through the employment shares) and the gender earnings gap (through earnings). Changes in these aggregates over time are therefore driven by the interaction of the model's three channels: the evolution of group specific preferences for different types of jobs z_{ig}; changes in the degree of gender discrimination in labor and education markets τ_{ig}; and technological shifts affecting relative wages w_i and the returns to education ϕ_i across sectors. Appendix A.3 contains additional details on the model and computational algorithm.

4 Quantitative Results

Estimating the model on the IPUMS-CPS data yields preferences and discrimination for men, single women, and married women in five different cohorts from 1976-2019 across eleven sectors, including the home sector. Before turning to the main exercise we summarize these estimates, which have intuitive properties.

Consistent with Hsieh et al. (2019)'s findings for occupations, average discrimination across sectors declined substantially from 1980 to 2020. Dispersion in discrimination across sectors also declined. Discrimination against single and married women is highly but not perfectly correlated (around 90%) and married women face discrimination that is 23% higher than single women on average, possibly reflecting motherhood penalties, though this difference declines from 65% on average in 1980 to just 1% in 2020. For both married and single women the largest decline in discrimination was in Other Services.

In terms of technology, returns to education ϕ_i increased across cohorts and there was no significant change in the dispersion of returns to education across sectors. Reflecting productivity growth, efficiency wages w_i grew on average, with a decline in the dispersion of wages across the broad sectors. Real wages grew fastest in the Leisure and Hospitality sector (105%), followed by Information (87%). Wages in Construction grew by 32% and wages in Education and Health grew by 15%.

Finally, preferences for sectors are more correlated across cohorts of married women (80%) than between single and married women within a cohort (70%), validating our approach of considering them separately. Men's preferences for sectors are the most stable over time (96%). Dispersion in preferences across sectors was roughly stable over time for both single and married women. Men increased their preferences for Trade, Manufacturing and Government. Single women's relative preferences increased the most

		Actual	Prefs. (z)	Disc. (τ)	Tech. (w, ϕ)
Segregation	Married	0.049	0.029	0.006	0.008
	Single	-0.006	-0.015	-0.032	0.016
Gender Earnings Gap	Married	-0.347	-0.080	-0.214	-0.077
	Single	-0.097	-0.023	-0.004	-0.060

Table 1: Decomposition of the role of preferences (z), discrimination (τ), and technology factors (efficiency wages w and returns to schooling ϕ) for changes in segregation and the gender wage gap between 1980 and 2010. Each entry shows the model-predicted change in each row variable that can be attributed to the column variable using a leave-one-out decomposition. See text for additional details.

for services: Information, Finance, Education and Health, and Professional Services. The pattern for married women was similar: Information, Government, Education and Health, and Finance. Women's preferences are weakly negatively correlated with discrimination against them (-0.29 for married women and -0.58 for single women).

4.1 Drivers of Sectoral Segregation

Table 1 reports the main quantitative results decomposing the rise in segregation into its constituent drivers: preferences, discrimination, and technology. The model matches the data on segregation and earnings from 1980–2020 by construction. Since the three channels interact non-linearly in the model, the table reports a leave-one-out decomposition of aggregate trends. Each entry reports the resulting change in the row variable that can be attributed to changes in the column variable. For example, the column titled "Prefs." shows how much of the change in segregation or the gender earnings gap remains *unexplained* when only discrimination and technology vary, attributing this gap to the omission of the preference channel.

The results show that changes in the preferences of married women were the most important driver of rising segregation from 1980 to 2020. Changing preferences can account for 59% ($\frac{0.029}{0.049}$) of the increase in married women's sectoral segregation, while changes in discrimination and technology each explain around 15%. In contrast, changes in the preferences of single women actually *reduced* sectoral segregation between 1980 and 2020. The results also indicate that discrimination in male dominated sectors increased for married women while decreasing for single women, pointing to the possibility of caregiving penalties. Finally, single women are increasingly concentrated in sectors with faster wage growth and higher returns to education. As these sectors are typically male dominated, the technology channel explains why overall segregation barely changed for single women since 1980.

4.2 Implications for the Gender Earnings Gap

The second panel of Table 1 reports the impact of each channel on the evolution of the overall gender earnings gap from 1980 to 2020. As with the employment shares underlying segregation, the quantitative exercise matches the changes in earnings by group, and hence the gender earnings gap, by construction. The table shows that most of the fall in the aggregate gender earnings gap since 1980 was due to married (-0.347) rather than single (-0.097) women. However the youngest cohort of married women in 2020 still face a gender earnings gap of 15% compared to men.

The decomposition results show that both single and married women shifted their preferences toward higher paying sectors. The contribution of these preference shifts was virtually equal across the two groups, explaining 23% ($\frac{0.080}{0.347}$) of the reduction in the earnings gap for married women and 24% for single women. Instead, technology and discrimination appear to be driving the different trends in earnings gaps for single and married women. For single women, changes in technology appear to be the dominant factor, accounting for 62% of the decline in their gender earnings gap, while discrimination only account for just over 4%. The situation is reversed for married women. Reductions in discrimination account for 62% of the declining earnings gap for married women, while technology changes only account for 22%. In an absolute sense, the largest overall factor behind the declining gender earnings gap since 1980 is the reduction in labor market discrimination against married women.

4.3 The Impact on Specific Sectors

Figure 5 further decomposes the results by showing how each of the model's channels shapes the within sector contributions to aggregate segregation. Formally, it decomposes the sectoral components displayed in Figure 2 into contributions from preferences, discrimination, technology, and their interaction.[4]

The results shows that the effect of each of the model's channels was far from uniform across sectors. Some sectoral contributions are dominated by a single channel. For in-

[4]The within decomposition follows the same leave-one-out procedure used to decompose the aggregate trends in Table 1.

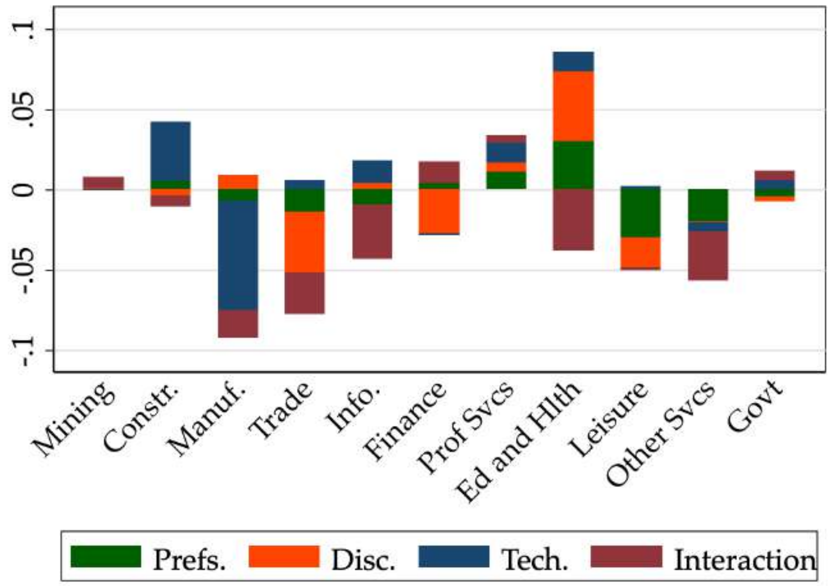


Figure 5: Segregation Changes by Sector, 1980-2020: Model Counterfactuals

Contribution of each channel: preferences, discrimination, or technology, in explaining the actual change in segregation in each sector between 1980 and 2020 by holding that driver fixed and attributing the unexplained change in segregation under that counterfactual to that driver.

stance, the contributions of the finance sectoral are nearly entirely explained by changes in discrimination, while the construction sector is driven almost entirely by changes in wages. Other sectors exhibit more balanced effects. For instance, the rise in sectoral segregation in the professional services is due in roughly equal parts to all three channels.

The figure also highlights the sectoral anatomy underlying each of the channel's aggregate contributions. It shows that both preferences and discrimination made big contributions to segregation by further concentrating women in the female-dominated education and healthcare sectors. However, outside these sectors the two channels operated very differently. Preferences affected mostly the service sectors, reducing segregation in leisure and other low skills service sectors. In contrast, the effects of discrimination are largely concentrated in the Trade and Finance sectors, where segregation fell thanks mostly due to reductions in discrimination against women. Finally, the impact of technological factors was concentrated in the male dominated Construction and Manufacturing sectors. In particular, the results show that changes in relative wages appear to mostly have moved women between these two male-dominated sectors. This observation explains in part the muted contribution of the technology channel to aggregate trends in sectoral segregation.

4.4 Potential Mechanisms Behind the Preferences Channel

The decomposition results show that the changing job preferences of married women are a primary driver of rising sectoral segregation in the United States. These preferences, $z_{i,g}$, capture all non-wage utility benefits that each group gets from working in a particular sector. This section relates these estimated preferences to observable sector-level non-wage amenities to shed light on the type of work characteristics behind them.

Four categories of amenities are considered: work arrangements, measured by hours worked per week and the share of part time workers; child-friendliness, measured by the average number of children of workers in that sector; homophily, measured by the female share within that sector; business cycle risk, measured by the correlation of the sector's employment with the business cycle.[5] To mitigate potential endogeneity of workplace characteristics, we measure sector amenities using male employees only whenever possible. The regression model is:

$$\frac{z_{i,g,t}}{z_{i,m,t}} \;=\; \beta_0 \;+\; \boldsymbol{\beta}\mathbf{X}_{i,t} \;+\; \epsilon_{i,t},$$

where $\frac{z_{i,g,t}}{z_{i,m,t}}$ are married or single women's preferences for sector i at time t measured relative to men, in order to account for "gender neutral" amenities that attract both genders equally. $\mathbf{X}_{i,t}$ is the vector of sector-level amenities and controls for sector wages.

Table 2 presents the results separately for married and single women. The third column reports the F-statistic corresponding to the test that the estimated coefficients are the same across the two groups of women. The parenthetical values report p-values. The results suggest that sectors with a higher share of part time workers are more attractive to married women. Interestingly, conditional on the part time share, married women also prefer sectors with longer hours per week. Women also appear to favor sectors with higher number of working parents with children. In contrast, homophily and business cycle risk appear not to play a significant role for either single or married women.

Taken together, one way to interpret the regression results is that married women prefer flexible work arrangements that are compatible with childcare considerations.[6] The interpretation is also consistent with a growing body of work on the examining the

[5] Most of the variation in amenities is across sectors rather than within sectors over time. See Appendix Table A.11.

[6] In principle, the estimated preferences may capture several different dimensions of sectoral amenities. First, sector amenities could be constant over time and the way married women value them has changed. Second, amenities themselves may have changed over time. Third, the composition of married women

	Married	Single	Diff.
Part time share, men only	0.961	-0.581	1.542
	[0.091]	[0.209]	[0.032]
Hours, men only	0.036	-0.012	0.048
	[0.009]	[0.305]	[0.007]
Num. children, men only	0.176	-0.005	0.181
	[0.075]	[0.959]	[0.191]
Female share	-0.041	-0.042	0.001
	[0.740]	[0.767]	[0.994]
Business cycle risk	0.016	-0.012	0.028
	[0.605]	[0.742]	[0.555]
Log wage	-0.047	-0.006	-0.0410
	[0.168]	[0.837]	[0.352]
R^2	0.431	0.059	
Observations	55	55	

Table 2: Preferences and Amenities at the Sector Level. Correlation of women's relative preferences $\tilde{z}_{igt}/\tilde{z}_{imt}$ with sector-level amenities. Weighted by group employment shares. p-values in parentheses. Source: CPS and model output, see text for details.

non-wage occupational preferences of women in other contexts (Mas and Pallais 2017; Wiswall and Zafar 2017). While the results here are indicative, they should be interpreted with caution given the small sample size (five cohorts times eleven market sectors) and concern over potential reverse causality.[7] While comprehensively measuring the role of non-wage amenities across sectors over time is beyond the scope of this paper, we believe it would be a fruitful area for future research.

5 Conclusion

Despite substantial gender convergence in many labor market outcomes since the 1970s, sector of work has diverged: sectors are now more segregated by gender than they were 50 years ago. Given that this divergence is entirely driven by married women, we conclude that sectoral choices are made in the context of household characteristics,

could change over time due to changing selection into marriage. Figure A.6 reports the share of each group in the population over time, labor force participation rates, hours, and education levels for each group over time.

[7]For instance, do married women prefer a sector because it has a particular characteristic, or does a sector have a characteristic because it has a high share of married women?

including the presence of children, in ways that may distort output by affecting the allocation of talent across sectors, not just occupations (Hsieh et al. 2019).

While in the U.S. most of the rise in segregation occurred after female labor force participation had mostly stopped growing, in Europe countries with larger differences in male and female hours worked are less segregated than countries with small gender gaps. Women on the margin of participating in market work may have different preferences over sectors than women who are firmly attached to the labor force.

Several areas merit further research. First, married women's preferences for sectors are systematically correlated with characteristics like the share of part time workers and the number of children per worker, which strongly suggests that sectors differ in terms of amenities, while most work on amenities has focused on occupations or individual firms. The composition of workers within a sector may itself shape the provision of amenities in that sector as in (Corradini, Lagos, and Sharma 2024), and developing theories of the amenity menus sectors offer is also an interesting area for future research, and may include the task content of production, the degree of labor market power, the expected length of employment relationships, and so on.

References

Albanesi, Stefania. 2024. "Changing Business Cycles: The Role of Women's Employment." Conditionally accepted, American Economic Journal: Macroeconomics.

Albanesi, Stefania, and Claudia Olivetti. 2016. "Gender Roles and Medical Progress." *Journal of Political Economy* 124 (3): 650–95.

Alon, Titan, Sena Coskun, and Matthias Doepke. 2020. "Trends in Work and Leisure: It's a Family Affair." Unpublished Manuscript, Northwestern University.

Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt. 2022. "From mancession to shecession: Women's employment in regular and pandemic recessions." *NBER Macroeconomics Annual* 36 (1): 83–151.

Alon, Titan, Matthias Doepke, Jane Olmstead-Rumsey, and Michèle Tertilt. 2020a. "The Impact of COVID-19 on Gender Equality." *Covid Economics: Vetted and Real-Time Papers* Issue 4:62–85.

———. 2020b. "This Time It's Different: The Role of Women's Employment in a Pandemic Recession." NBER Working Paper 27660.

Arellano-Bover, Jaime, Nicola Bianchi, Salvatore Lattanzio, and Matteo Paradisi. 2024, June. "One Cohort at a Time: A New Perspective on the Declining Gender Pay Gap." Working paper 32612, National Bureau of Economic Research.

Ashraf, Nava, Oriana Bandiera, Virginia Minni, and Vıctor Quintas-Martınez. 2024. "Gender Gaps across the Spectrum of Development: Local Talent and Firm Productivity."

Balleer, Almut, Monika Merz, and Tamás K. Papp. 2025. "Heterogeneous Preferences, Spousal Interaction, and Couples' Time-Use."

Biasi, Barbara, and Heather Sarsons. 2021. "Flexible Wages, Bargaining, and the Gender Gap*." *The Quarterly Journal of Economics* 137 (1): 215–266 (08).

Bick, Alexander, Bettina Brüggemann, and Nicola Fuchs-Schündeln. 2019. "Hours Worked in Europe and the United States: New Data, New Answers." *Scandinavian Journal of Economics* 121 (4): 1381–1416.

Blau, Francine D., and Lawrence M. Kahn. 2000. "Gender Differences in Pay." *Journal of Economic Perspectives* 14 (4): 75–99.

Blau, Francine D, and Wallace E Hendricks. 1979. "Occupational segregation by sex: Trends and prospects." *Journal of Human Resources*, pp. 197–210.

Boar, Corina, and Danial Lashkari. 2021, October. "Occupational Choice and the Intergenerational Mobility of Welfare." Working paper 29381, National Bureau of Economic Research.

Corradini, Viola, Lorenzo Lagos, and Garima Sharma. 2024. "Collective Bargaining for Women: How Unions Can Create Female-Friendly Jobs."

Cortés, Patricia, and Jessica Pan. 2018. "Occupation and Gender." In *The Oxford Handbook of Women and the Economy*. Oxford University Press.

Cortés, Patricia, Jessica Pan, Laura Pilossoph, Ernesto Reuben, and Basit Zafar. 2023. "Gender Differences in Job Search and the Earnings Gap: Evidence from the Field and Lab." *The Quarterly Journal of Economics* 138 (4): 2069–2126 (05).

Coskun, Sena, Husnu Dalgic, and Yasemin Ozdemir. 2023. "Child Penalties and Fertility across Sectors." *Working Paper*.

Coskun, Sena, and Husnu C Dalgic. 2024. "The emergence of procyclical fertility: The role of breadwinner women." *Journal of Monetary Economics* 142:103523.

Coskun, Sena, Hermann Gartner, and Ahmet Ali Taskin. 2025. "Rent Sharing and the Gender Bargaining Gap: Evidence from the Banking Sector." *Working Paper*.

Coskun, Sena, and Gonul Sengul. 2024. "Bundling Services with Female Employment: Unpacking the Link Across Countries." *Working Paper*.

Doepke, Matthias, and Fabian Kindermann. 2019. "Bargaining over Babies: Theory, Evidence, and Policy Implications." *American Economic Review* 109 (9): 3264–3306.

Doepke, Matthias, and Michèle Tertilt. 2016. "Families in Macroeconomics." Chapter 23 of *Handbook of Macroeconomics, Vol. 2*. North Holland.

Ellieroth, Kathrin. 2023. "Spousal Insurance, Precautionary Labor Supply, and the Business Cycle."

Ellieroth, Katrin, and Amanda Michaud. 2024. "Quits, Layoffs, and Labor Supply."

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

———. 2015. "Hours flexibility and the gender gap in pay." *Center for American Progress*, vol. 31.

Hsieh, Chang-Tai, Erik Hurst, Charles I Jones, and Peter J Klenow. 2019. "The allocation of talent and U.S. economic growth." *Econometrica* 87 (5): 1439–1474.

Katz, Lawrence F., and Alan B. Krueger. 2019. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995-2015." *ILR Review* 72 (2): 382–416 (2016).

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.

Kuhn, Moritz, Iourii Manovskii, and Xincheng Qiu. 2024. "Female Employment and Structural Transformation." IZA Discussion Paper 17118.

Lordan, Grace, and Jörn-Steffen Pischke. 2022. "Does Rosie Like Riveting? Male and Female Occupational Choices." *Economica* 89 (353): 110–130.

Maestas, Nicole, Kathleen J. Mullen, David Powell, Till von Wachter, and Jeffrey B. Wenger. 2023. "The Value of Working Conditions in the United States and the Implications for the Structure of Wages." *American Economic Review* 113 (7): 2007–47 (July).

Maideu-Morera, Gerard. 2024. "Amenity-Biased Technical Change."

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." *American Economic Review* 107 (12): 3722–59 (December).

Morchio, Iacopo, and Christian Moser. 2024. "The gender pay gap: Micro sources and macro consequences." Technical Report, National Bureau of Economic Research.

Ngai, L. Rachel, and Barbara Petrongolo. 2017. "Gender Gaps and the Rise of the Service Economy." *American Economic Journal: Macroeconomics* 9 (4): 1–44 (October).

Olivetti, Claudia. 2014. "The Female Labor Force and Long-run Development: The American Experience in Comparative Perspective." In *Human Capital in History: The American Record*, edited by L. Platt Boustan, C. Frydman, and R.A. Margo. University of Chicago Press.

Olivetti, Claudia, and Barbara Petrongolo. 2016. "The Evolution of Gender Gaps in Industrialized Countries." *Annual Review of Economics* 8:405–434.

Sorkin, Isaac. 2018. "Ranking Firms Using Revealed Preference." *The Quarterly Journal of Economics* 133 (3): 1331–1393 (01).

Wasserman, Melanie. 2022. "Hours Constraints, Occupational Choice, and Gender: Evidence from Medical Residents." *The Review of Economic Studies* 90 (3): 1535–1568 (07).

Wiswall, Matthew, and Basit Zafar. 2017. "Preference for the Workplace, Investment in Human Capital, and Gender." *The Quarterly Journal of Economics* 133 (1): 457–507 (08).

A Online Appendix

A.1 Data Appendix

A.1.1 Data Description: United States

We use IPUMS-CPS data from 1975 to 2019. We apply the crosswalk procedure provided by the Census Bureau to map 1990 Census industry codes to NAICS (North American Industry Classification System) codes, which are then aggregated into main sectors by the Bureau of Labor Statistics. Similarly, we use a crosswalk from the 2010 occupation codes to SOC (Standard Occupational Classification) codes, which can be used at the two-digit level. We exclude individuals working in agriculture or the military from our analysis. Our sample consists of individuals aged 25 to 55.

Individuals working fewer than 10 hours per week are categorized as non-employed, while those working between 10 and 30 hours per week are assigned a 50% weight to the home sector (non-employed) and a 50% weight to the employed group, following Hsieh et al. (2019).

A.1.2 Data Description: Europe

We use the harmonized European Labour Force Survey from 1995 to 2019 for individuals aged 25 to 54. The measure of working hours is constructed using the methodology described in Bick, Brüggemann, and Fuchs-Schündeln (2019). The European-wide NACE (Nomenclature of Economic Activities) harmonized industry classification is only available for the years 2008–2019; therefore, we restrict our segregation analysis to this period. We convert NACE codes to align them with the U.S. sector classification, following the approach in Alon et al. (2022). The following aggregations are applied: Trade, Transportation, Electricity, and Water are grouped under "Trade"; Professional and Administrative Services under "Prof Svcs"; Education and Health under "Ed and Hlth"; Finance and Real Estate under "Finance"; and Accommodation and Arts under "Leisure." The remaining sectors are labeled as follows: Public Administration as "Govt," Construction as "Constr.," Other Services as "Other Svcs," Information as "Info," Manufacturing as "Manuf.," and Mining as "Mining." Agriculture is excluded from the analysis.

A.2 Additional Figures and Tables

Figure A.1 illustrates the segregation of sectors and occupations for married and single women relative to all men.

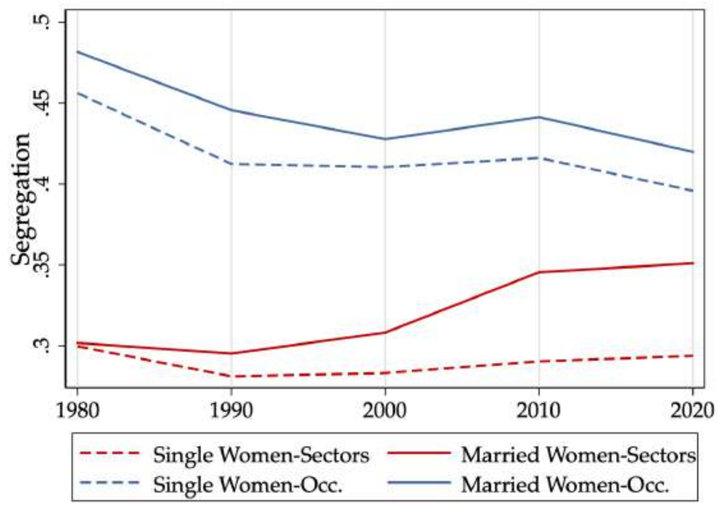
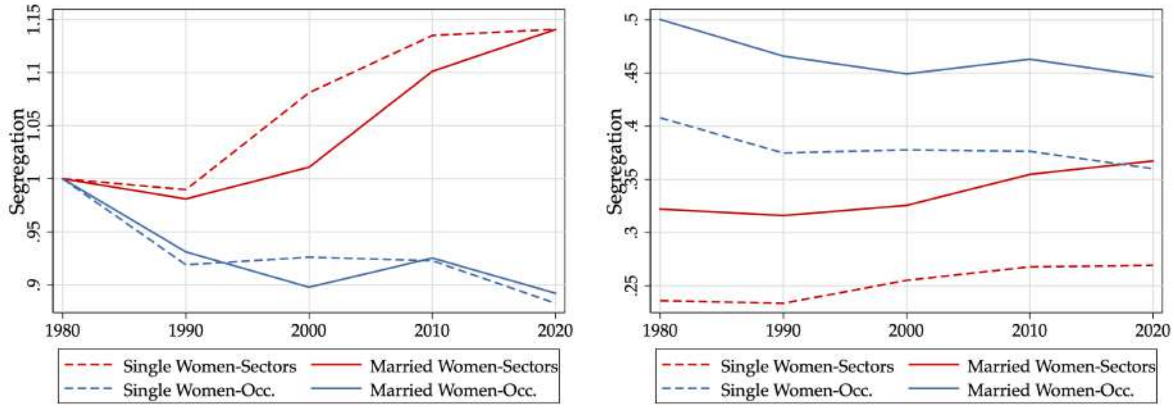


Figure A.1: Occupational convergence and sectoral divergence wrt Marital Status.

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019.

Figure A.2 presents both sectoral and occupational gender segregation for single and married individuals, where the comparison group consists of men with the same marital status. We find that, regardless of whether women are compared to all men or only to men with the same marital status, sectoral segregation increases, while occupational convergence also rises.

Figure A.3 shows the actual sectoral segregation of women alongside a counterfactual segregation measure, which holds sectoral shares within the overall labor force fixed at their 1980s levels. The purpose of this counterfactual is to assess the impact of the expansion of the female-dominated service sector, which may have amplified segregation. However, even with fixed sector sizes, segregation would have increased significantly. Therefore, we conclude that changes in sectoral composition account for only 25% of the rise in sectoral segregation among married women (Figure A.5) and 41% among all women (Figure A.3).



(a) Normalized to 1980s

(b) Levels

Figure A.2: Gender Segregation within Marital Status

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019.

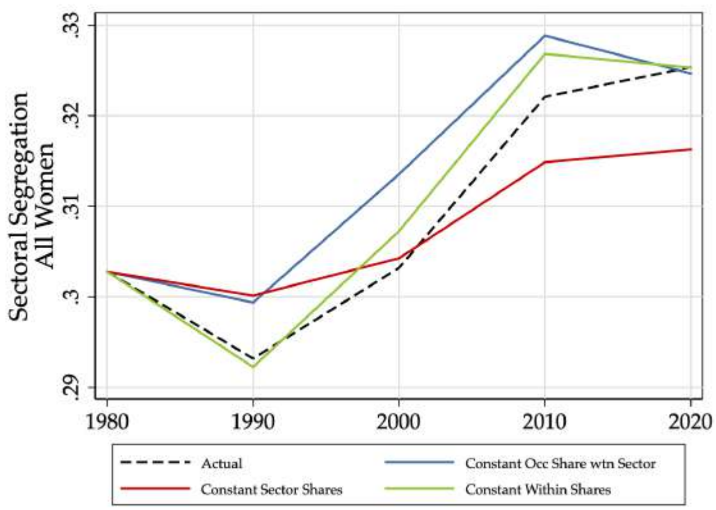


Figure A.3: Fixed Sector Sizes

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019. Hypothetical "constant sector size" assumes the 1980's overall sectoral distribution.

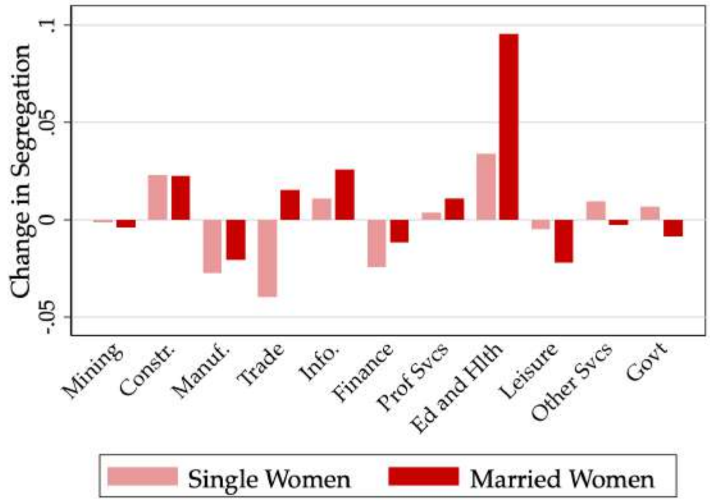


Figure A.4: Changes in Segregation 1980-2020

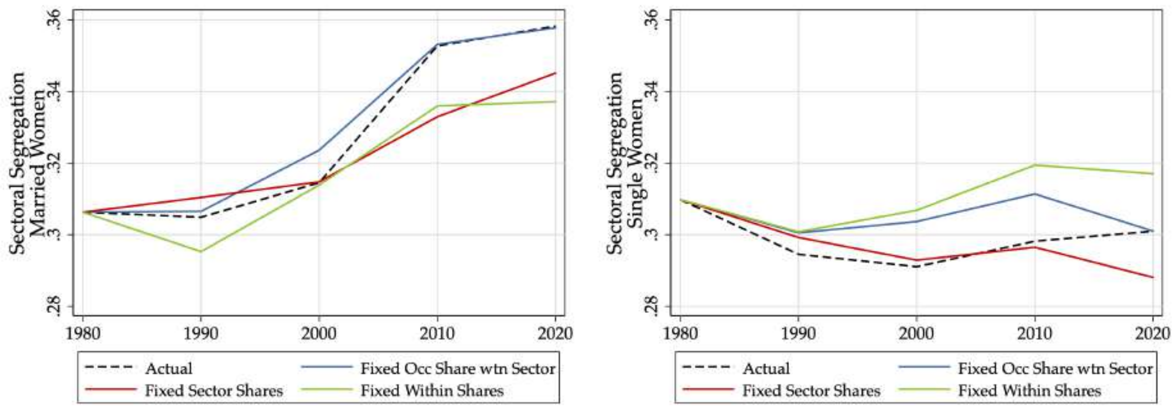
Notes: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019.

In Figure A.5, we calculate segregation under several counterfactual scenarios. It is important to note that in each scenario, we exogenously hold one factor constant without accounting for its impact on other measures. To ensure comparability, we normalize the sum of employment shares across sectors to 1 in each counterfactual scenario. Consider the measure employment share of sector s and occupations o for gender f, represented as $\frac{p^f_{so}}{\sum_s \sum_o p^f_{so}}$ which serves as the key variable in constructing the segregation measure. This can be expressed as follows:

$$\frac{p^f_{so}}{\sum_s \sum_o p^f_{so}} = \underbrace{\frac{p^f_{so}+p^m_{so}}{\sum_o p^f_{so}+p^m_{so}}}_{\text{Occupation share wtn Sector}} \underbrace{\frac{p^f_{so}}{p^f_{so}+p^m_{so}}}_{\text{Wtn female share}} \underbrace{\frac{\sum_o p^f_{so}+p^m_{so}}{\sum_s \sum_o p^f_{so}+p^m_{so}}}_{\text{Sector Share}} \underbrace{\frac{\sum_s \sum_o p^f_{so}+p^m_{so}}{\sum_s \sum_o p^f_{so}}}_{\text{1/Female Share}}$$

By holding one component of the above equation constant at its 1980s level, we calculate the hypothetical employment share of sector s and occupation o for all groups (married women, single women, and men) across all sector-occupation pairs. We then normalize the sum of employment shares for each group to 1.

Figure A.5a shows that if sectoral composition remained unchanged (i.e., sector shares were held constant), the segregation of married women would be lower. Similarly, if women's representation within each sector-occupation pair had remained constant (i.e., within-sector shares did not change), segregation would also be lower. This suggests that the increase in female representation within jobs contributed to amplifying segregation. Finally, if occupational composition within each sector had remained unchanged (i.e., occupation shares within sectors were held constant), segregation would be slightly higher.

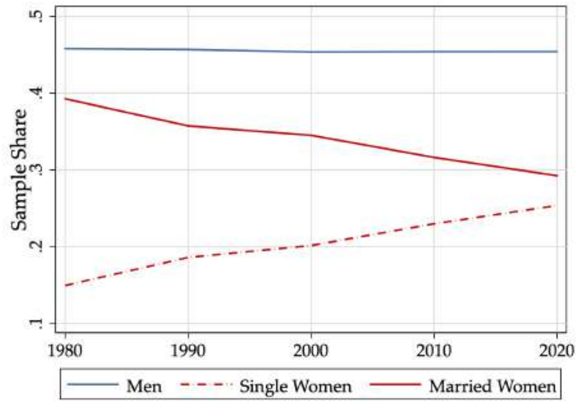


(a) Married Women

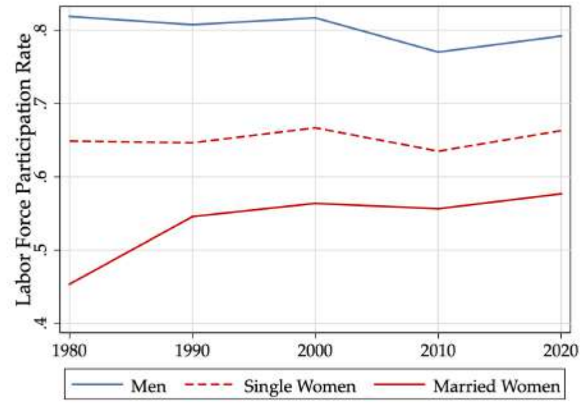
(b) Single Women

Figure A.5: Counterfactual Segregation

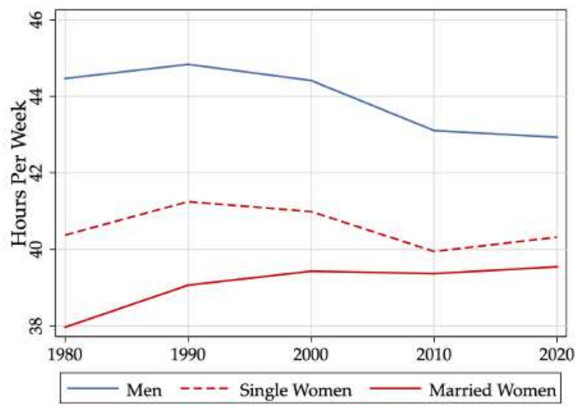
Notes: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019.



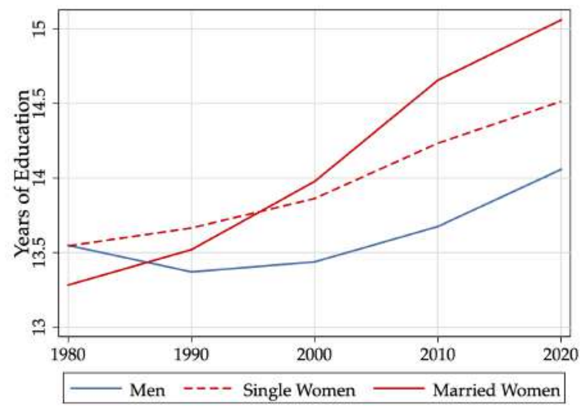
(a) Sample Share



(b) Labor Force Participation



(c) Hours



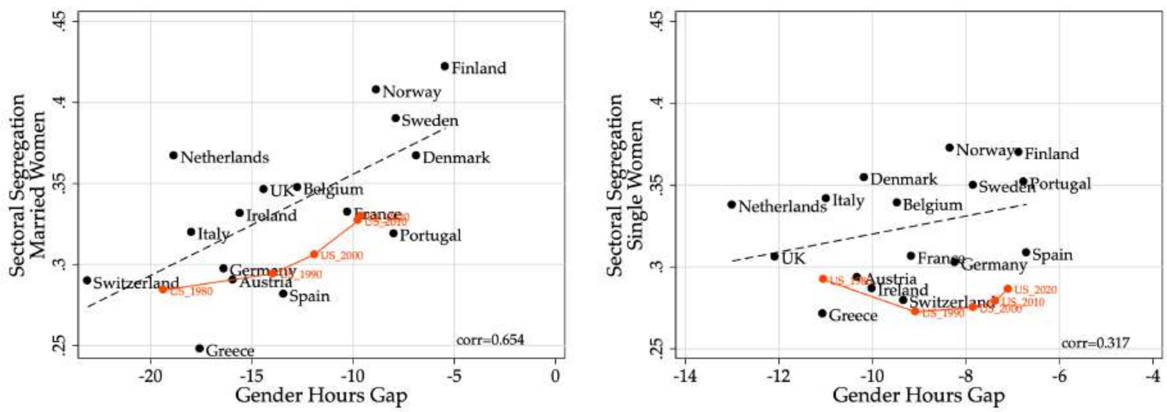
(d) Education

Figure A.6: Characteristics of Each Group

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019.

Figure A.7 breaks down the analysis presented in Figure 4 by marital status. The left panel (Figure A.7a) shows that sectoral segregation is highly correlated with the observed gender hours gap per capita for married women. In contrast, Figure A.7b shows that this correlation is not significant for single women.

To examine the impact of different sectoral compositions on segregation across European countries, we calculate a counterfactual segregation measure by holding all sector sizes fixed at the EU average while allowing female shares within each sector to vary across countries as observed in the data. This exercise aims to rule out the influence of large government and education-health sectors in some countries, which tend to be female-dominated. Figure A.8 demonstrates that the counterfactual segregation measure also strongly correlates with the gender hours gap. This suggests that the results are not merely driven by more gender-equal countries having larger female-dominated sectors but rather by the fact that female shares within sectors are also higher in these countries.



(a) Married Women

(b) Single Women

Figure A.7: Segregation in Europe

Note: Data source is EU-LFS for European countries. Average sectoral segregation for 25-54 age group for 2008-2019 is reported. Gender hours gap is the average of 2005-2009 for the respective group of single and married women relative to all men. See Appendix A.1.2 for details. Data points for the US are exactly the same as in Figure A.1.

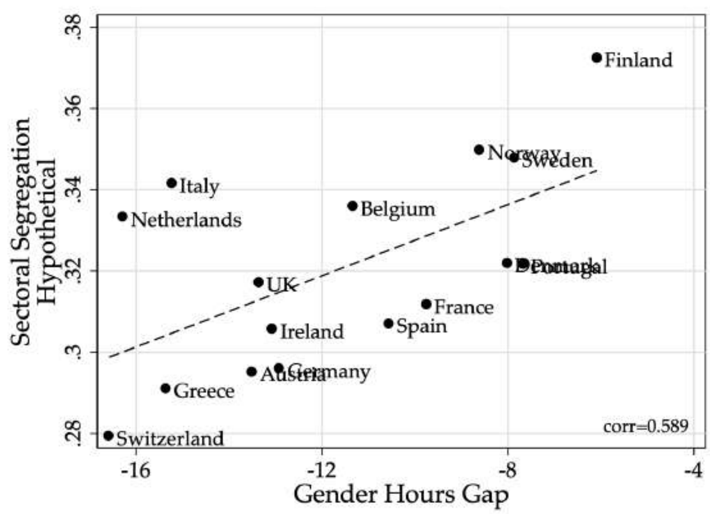


Figure A.8: EU-average Sector Sizes

Note: Data source is EU-LFS for European countries. Average sectoral segregation for 25-54 age group and for the year 2008-2019 is reported. Gender hours gap is the average of 2005-2009. Hypothetical sectoral segregation assumes the EU-average overall sectoral distribution to rule out the effect of sector sizes in segregation.

A.2.1 Segregation Measure

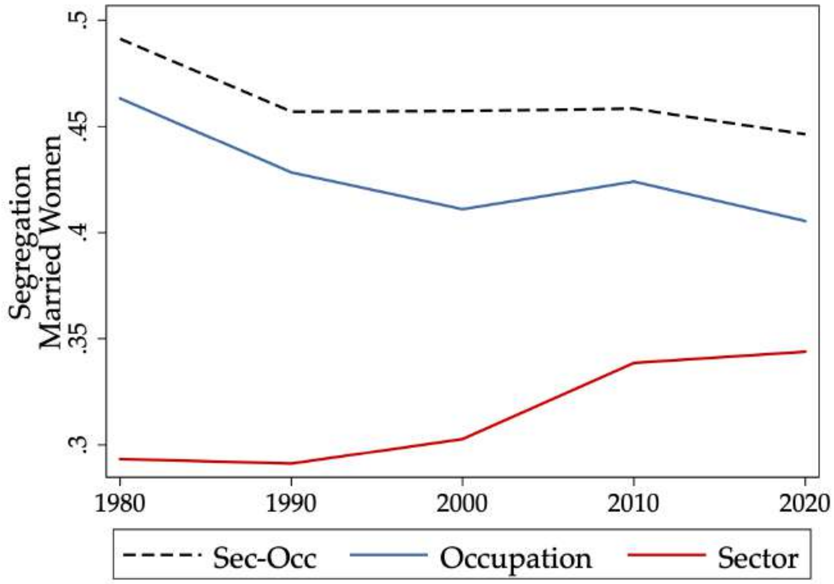
Segregation is defined as $\frac{\Sigma_s |p_{sf} - p_{sm}|}{2}$ where s is sectors p_{sf} and p_{sm} are employment shares of women and men in a given sector. For robustness, we also compute employment shares for sector and occupation pairs, across 11 sectors (BLS sectors) and 22 occupations (SOC-2 digit). We exclude sector-occupation pairs with fewer than 50 observations, resulting in a total of 110 sector-occupation pairs for further analysis of segregation.

An alternative segregation measure is given by $\frac{\Sigma_{so} |p_{sof} - p_{som}|}{2}$ where so is sector-occupation pairs, p_{sof} and p_{som} are employment shares of women and men in a given sector-occupation pair.

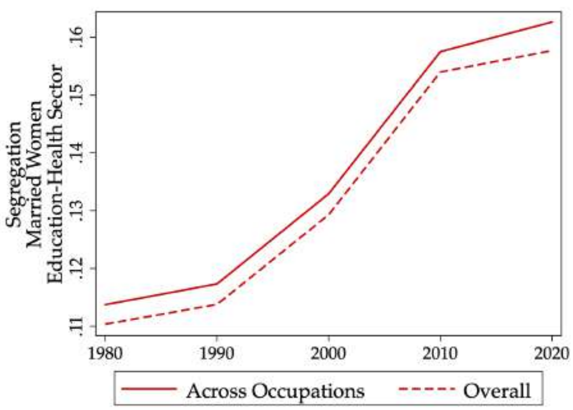
We further define two versions of segregation for a single sector or occupation; 1) overall segregation: $\frac{|\Sigma_s p_{sof} - \Sigma_s p_{som}|}{2}$, 2) segregation which takes into account either sectoral or occupational variation; $\frac{\Sigma_s |p_{sof} - p_{som}|}{2}$. The second measure is larger than the first if an additional imbalance exists in the second dimension, which may be masked in the first measure. Figure A.9a presents different segregation measures for married women. When segregation is calculated at the occupational level, we observe convergence. When calculated at the sectoral level, we observe divergence. However, when measured across sector-occupation pairs, the pattern appears more stable. By construction, the segregation level is highest for sector-occupation pairs: even slight gender imbalances in sectoral distribution for a single occupation result in a larger value for formula (2) than for formula (1).

Repeating this analysis for specific sectors and occupations provides useful insights. Figure A.9b reports sectoral gender segregation for the education and health sector. Even when occupational variation within the sector is considered (blue line), the overall trend remains largely unchanged apart from a slightly higher value. This suggests that gender imbalance in the education and health sector is not primarily driven by sorting into different occupations within the sector.

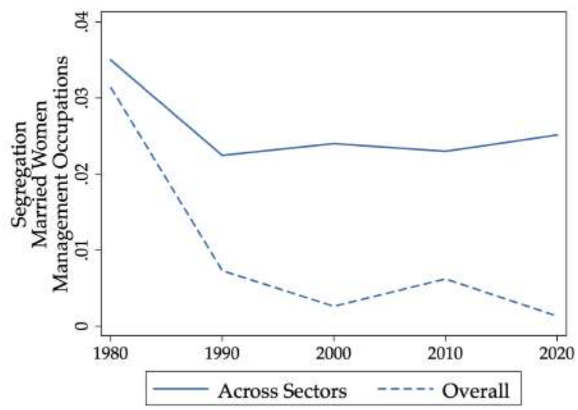
In contrast, Figure A.9c illustrates segregation trends for management occupations. A decline in segregation over time (red line) indicates gender convergence in management occupations. However, when accounting for sectoral variation (blue line), we see that gender convergence in management did not occur uniformly across sectors, leading to a more stable pattern after the 1990s.



(a) Overall



(b) Education and Health Sector



(c) Management Occupations

Figure A.9: Sector-Occupation Segregation of Married Women

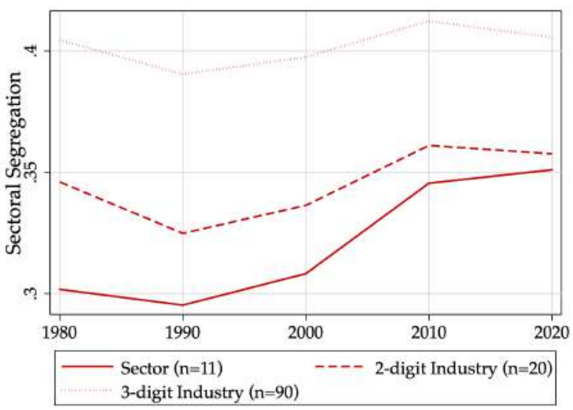
Notes: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019. Dashed lines in panel b and c refer to the segregation measure only with respect to occupations or sectors, whereas solid lines considers sectoral (or occupational) variation within occupations (or sectors) as well.

A.2.2 Sector Disaggregation

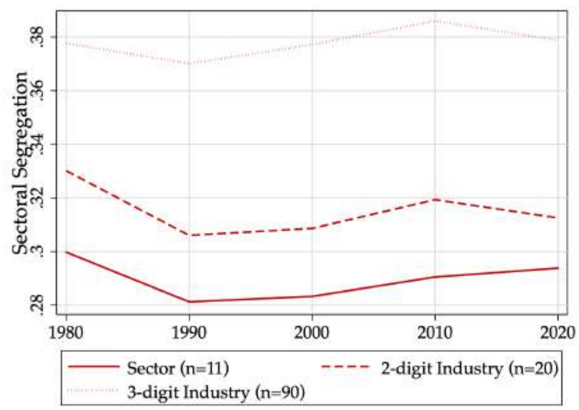
The conversion of 1990 industry codes into NAICS codes may introduce some inconsistencies, as certain industries in the 1990 codes might only match to NAICS at the 2-digit level. Consequently, the segregation measure could be affected by these inconsistencies when higher NAICS digits are considered. For robustness, we also report sectoral segregation for higher-digit classifications in Figure A.10.

We observe a stable segregation pattern for single women across different levels of aggregation in Figure A.10b. In contrast, Figure A.10a shows that segregation rises over time for married women at all levels of aggregation, although the gradient is lower for higher digits.

Kuhn, Manovskii, and Qiu (2024) find the constant gender shares in manufacturing and services to be quite unexpected, given the well-documented changes in gender composition over time in more finely defined sectors or occupations. This highlights the importance of developing a theory of aggregation for these classifications.



(a) Married Women



(b) Single Women

Figure A.10: Sector Segregation at higher digits

Notes: Sector is defined as BLS sectors, 2-digit and 3-digit NAICS classification is based on crosswalk from 1990 industry codes to NAICS provided by Census Bureau.

A.2.3 Men, Women, Or Both?

Figure A.11 decomposes the segregation of all women relative to all men into its components: one representing the distribution of employment across sectors for women, and the other for men. When we hold men's sectoral distribution constant at its 1980s level and only allow women's (both married and single) sectoral distribution to vary as it did in the data, we observe that segregation would have increased even more compared to the actual segregation if the only change had come from women's sectoral composition. This suggests that the change in men's sectoral distribution has mitigated segregation, as men are working in female-dominated sectors to a greater extent, consistent with the growth of the service sector.

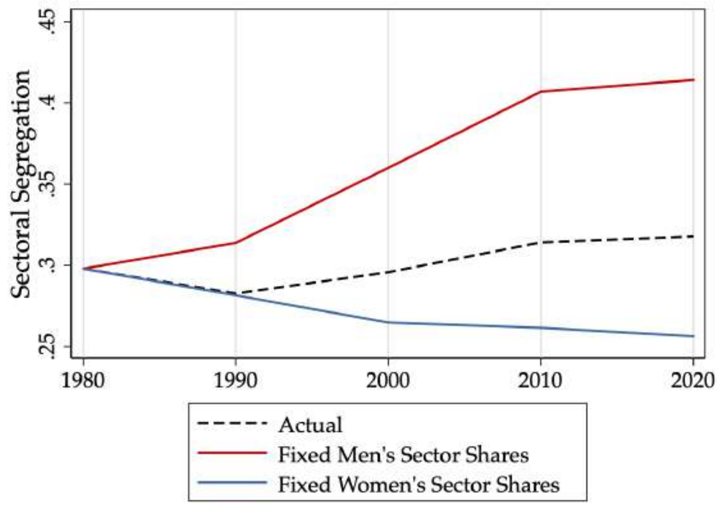


Figure A.11: Gender Decomposition of Segregation

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. Years are pooled for every 10 years such that 1980 refers to 1975-1984 etc..., 2020 refers to 2015-2019. Hypothetical scenarios assume 1980's sectoral distribution within men(women) by only varying women(men)'s sectoral distribution.

A.2.4 Potential Mechanisms

Table A.11: Fraction of Variance in Amenities: Permanent Cross-Sector Differences

PT share (men)	Hours (men)	Num. kids (men)	Fem. share	Risk	Log earnings
0.874	0.722	0.718	0.979	0.643	0.872

Note: Data source is IPUMS-CPS between 1975-2019, age group is 25-35. The values are the share of the total variance in each amenity explained by the sector fixed effect. "PT share (men)" is the share of men who work part time, "Hours (men)" is average hours per week for male employees, "Num. kids (men)" is the average number of children male employees have, "Fem. share" is the female share of total employment, "Risk" is the correlation of the sector's employment with the business cycle, "Log earnings" is average log earnings of all employees.

A.3 Computational Appendix

The computational algorithm follows the approach in Hsieh et al. (2019). Parameters θ, η, β are set in the same manner as in their work. Returns to education, ϕ_i, are also estimated following their approach by computing,

$$s_i = \frac{\text{years of schooling}}{25}$$

for each cohort $\times$ year $\times$ occupation and then inverting the optimal schooling policy, so

$$\phi_i = \frac{s_i}{1-s_i} \times \frac{1-\eta}{3\beta}.$$

Given these parameters, the model identifies group discrimination τ, preferences z, and occupational wages w using data on earnings and employment. Identification requires assuming that men face no discrimination in market work; no group faces discrimination in home production; and normalizing preferences for the home sector to one for all groups. With these assumptions, the following algorithm reveals the unknowns,

1. Using earnings and employment shares of the youngest cohort of men in each time period, compute male preferences, $z_{i,m}$ and wages w_i for each occupation and year. With K market occupations and the home sector, this involves solving a system of $2K+1$ non-linear structural equations.[8]

2. Given baseline group (men) preferences $z_{i,m}$, combine formulas 1 and 2 to recover preferences for all groups using earnings gaps and participation rates,

$$\tilde{z}_{i,g} = \left(\frac{\overline{\text{wage}}_{i,g}}{\overline{\text{wage}}_{i,m}}\right)^{-\frac{1}{1-\eta}} \times \left(\frac{1-LFP_g}{1-LFP_m}\right)^{-\frac{1}{\theta}} \times \tilde{z}_{i,m},$$

   where true preferences are recovered by $z_{i,g} = (\tilde{z}_{i,g})^{\frac{3\beta}{1-\eta}}$.

3. Given the normalizations, recover discrimination τ by combining equation 1 with

[8]Since we observe home sector employment share, but not earnings. Note that this initial step differs slightly from the implementation of Hsieh et al. (2019) who additionally impute home sector wages are on parity with that of secretaries, avoiding the non-linearity in solving the system by pinning down $m_m(c)$.

earnings and employment data,

$$\tau_{i,g} \;=\; \frac{\tau_{i,g}}{\tau_{i,m}} = \left(\frac{\text{share}_{i,g}}{\text{share}_{i,m}}\right)^{-\frac{1}{\theta}} \times \left(\frac{\overline{\text{wage}}_{i,g}}{\overline{\text{wage}}_{i,m}}\right)^{-(1-\eta)} \qquad .$$

Some of the computational exercises will also rely on estimates of the returns-to-experience, $\gamma(t-c)$. Given estimated wages, these can be recovered using within cohort lifecycle earnings growth,

$$\frac{\overline{\text{wage}}_{i,m}(c,t)}{\overline{\text{wage}}_{i,m}(c,c)} = \frac{w_i(t)\gamma_i(t-c)s_i^{\phi}(t)}{w_i(c)s_i^{\phi}(c)}$$

which implies

$$\gamma_i(t-c) = \left(\frac{\overline{\text{wage}}_{i,m}(c,t)}{\overline{\text{wage}}_{i,m}(c,c)}\right) \times \left(\frac{w_i(t)s_i^{\phi(t)}}{w_i(c)s_i^{\phi(c)}}\right)^{-1}$$

where $\gamma(0) \equiv 1$. Finally, Hsieh et al. (2019) shows how the composite group discrimination τ can be further decomposed with additional assumptions on initial conditions. Additional decompositions of this type are not pursued here.