Gender Divergence in Sectors of Work*

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Abstract

The past half century has witnessed widespread gender convergence across many labor market outcomes, including hours worked, earnings, and occupations. This paper shows that, over the same period, men's and women's sectors of employment actually *diverged*. It structurally decomposes the rise in sectoral segregation into three underlying drivers representing changes in preferences, discrimination, and technologies. Changes in the employment preferences of married women are the most important factor, explaining 59% of the rise in segregation. These changes in preferences also reduce the gender earnings gap because the non-wage amenities women value are increasingly prevalent in higher paying sectors.

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I Introduction

Over the past fifty years, women's labor market outcomes have converged towards men's on many dimensions, including hours worked, earnings, and occupation choice (Goldin 2014; Olivetti and Petrongolo 2016; Hsieh et al. 2019). This paper documents that, over the same period, the sectors where men and women work have *diverged*, leading to *more* gender segregation by sector of employment. This makes the incidence of sector specific shocks more unequal across genders, which influences the depth and persistence of recessions (Bardóczy 2022; Alon et al. 2020; Patterson 2023; Fukui, Nakamura, and Steinsson 2023; Albanesi 2024). It also raises questions about the true extent of gender convergence in labor markets and the factors behind persistent differences.

The rise in sectoral segregation also relates to the *gender equality paradox* that some sociological differences between men and women seem to become more pronounced as societies become more egalitarian. The phenomenon is paradoxical in that one expects gender gaps to attenuate as barriers against women are removed. Instead, the literature documents the emergence of new forms of social differentiation between men and women as gender equality advances, including in values, personality, education and occupational preferences (Stoet and Geary 2018; Falk and Hermle 2018; Mac Giolla and Kajonius 2019; Breda et al. 2020; Cherney 2023; Schmader 2023; Herlitz et al. 2024). Understanding the root cause of these new forms of gender differentiation is critical to explaining the persistence of gender gaps in developed, egalitarian economies.

This paper documents a new instance of the gender equality paradox in the form of rising sectoral segregation in the United States from 1975 to 2019. It provides empirical and structural decompositions to identify the economic forces behind this trend and studies their implications. The stylized facts are robust to using various levels of sector disaggregation and to changes in the distribution of occupations across sectors. The findings are also consistent with cross-country evidence from other developed economies. In the European Union, countries with the smallest differences in hours worked between men and women—a broad measure of labor market convergence—are also those with the highest levels of gender segregation by sector.

The rise in sectoral segregation is entirely driven by the employment outcomes of married women, particularly those with children. This contrasts sharply with the decline in occupational segregation, which was similar for single and married women. Structural transformation of the economy's employment base also plays an important 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 bulk of the effect—the remaining 60%—is due to within-sector changes in the gender composition of employment.

Motivated by the empirical findings, we apply the structural decomposition approach of Hsieh et al. (2019) to understand the economic forces behind them. This framework—originally developed to study shifts in the *occupational* composition of employment—ascribes changes in the sectoral composition of employment to three fundamental factors: preferences, discrimination, and technology (encompassing both sectoral wages and the returns to education). Changes in the preferences of married women are the most important factor, accounting for 59% of the rise in sectoral segregation. Single women do not exhibit similar changes in preferences. Instead, shifts in the employment composition of single women are driven by changes in labor market discrimination.

The model also predicts how changes in each channel affect the evolution of the gender earnings gap. Changes in preferences reduced earnings inequality, explaining roughly one-quarter of the decline in the gender earnings gap during this period. The results reflect the fact that the non-wage amenities valued by women are increasingly provided by higher paying sectors.

At the sector level, there is considerable heterogeneity in the impact of each channel. Changes within some sectors are dominated by a single factor, while others exhibit more balanced contributions from each mechanism. For instance, reductions in segregation in the Finance sector are entirely due to declining discrimination, while the increase of segregation within the Education and Healthcare sector is equally explained by changes in preferences and discrimination.

The analysis concludes by relating the sectoral preferences from the model to observable sector-level amenities to shed light on the type of job attributes they may be capturing. Four categories of non-wage amenities are considered: work arrangements, measured by the share of part time workers and hours worked per week; child-friendliness, measured by the average number of children of workers in that sector; homophily, measured by the female share within that sector; and risk, measured by the correlation of the sector's employment with the business cycle. All groups appear to value flexible work arrangements in the form of the part time share, though the effect is most pronounced among married women. Married women are also the only group with preferences that are significantly correlated with a sector's child-friendliness.

Related Literature. The findings contribute to the literature studying the sources of gender inequality in labor markets and their implications. Existing research highlights many important channels, including motherhood penalties (Albanesi and Olivetti 2016; Kleven, Landais, and Søgaard 2019), occupation choice (Cortés and Pan 2018; Lordan and Pischke 2022; Wasserman 2022), bargaining differences (Biasi and Sarsons 2021; Coskun, Gartner, and Taskin 2025), job search behavior (Cortés et al. 2023), local norms (Ashraf et al. 2024), the demographic structure (Arellano-Bover et al. 2024), the impact of structural transformation (Olivetti and Petrongolo 2016; Ngai and Petrongolo 2017; Kuhn, Manovskii, and Qiu 2024; Peters et al. 2025), and more.

Methodologically, the structural decomposition follows the approach of Hsieh et al. (2019). Interestingly, while they find that declining discrimination explains most of the fall in occupational segregation, the results here suggest changes in preferences are driving the rise in sectoral segregation. The prominence of the model's preference channel is consistent with a growing body of research showing that men and women have different valuations of non-wage amenities like flexible work arrangements (Goldin 2015; Mas and Pallais 2017; Wiswall and Zafar 2017; Morchio and Moser 2024; Corradini, Lagos, and Sharma 2025). While many studies find that these gender-specific preferences increase the gender earnings gap, the results here suggest that compositional changes may be shrinking this effect over time, as the non-wage amenities valued by women are increasingly prevalent in higher paying sectors.

The findings also shed light on potential explanations of the gender equality paradox. While female labor force participation grew in response to reductions in discrimination, sectoral segregation increased due to the changing preferences of working women. The result is consistent with the *resource hypothesis* arguing that a more gender-equal distribution of resources, and the alleviation of subsistence constraints, enables men and women to express their preferences more independently from one another (Falk and Hermle 2018).[1] One subtlety is that in the model these aggregate effects reflect not only pre-existing differences, but also compositional changes due to selection. The results suggest that 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.

Finally, the results are pertinent to the macroeconomics literature on families and household decision making. Rising sectoral segregation can influence the division-of-labor

[1]The mechanism relates to the economics literature studying the dynamics of household bargaining (Doepke and Tertilt 2014; Doepke and Kindermann 2019) and studies of wealth effects on the valuation of non-wage amenities at work (Boar and Lashkari 2021; Luo and Mongey 2024).

across genders in other household tasks, such as childcare and home production (Doepke and Tertilt 2016; Alon, Coskun, and Doepke 2020; Coskun and Dalgic 2024). It also affects the extent of family insurance against sector-specific shocks, which can influence the depth and persistence of business cycle fluctuations (Bardóczy 2022; Alon et al. 2022; Fukui, Nakamura, and Steinsson 2023; Ellieroth 2023; Albanesi 2024).

II 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. Appendix A.1 contains additional details on the data sources, sample populations, and variable construction.

II.A Rising Gender Segregation in the United States

Gender segregation at time t is measured using the Blau and Hendricks (1979) definition

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

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

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.[2]

Figure 1 displays the evolution of gender segregation in the United States across sectors and occupations of work from 1980 to 2020. It confirms a well-known fact in the literature that there has been a large decrease in the gender segregation of occupations, which fell by 15% since 1980. At the same time, the data also show that there has been a large

[2] If a large sector employs 30% of all employed 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 the same gender ratio contributes $\frac{|0.03-0.02|}{2} = 0.005$.

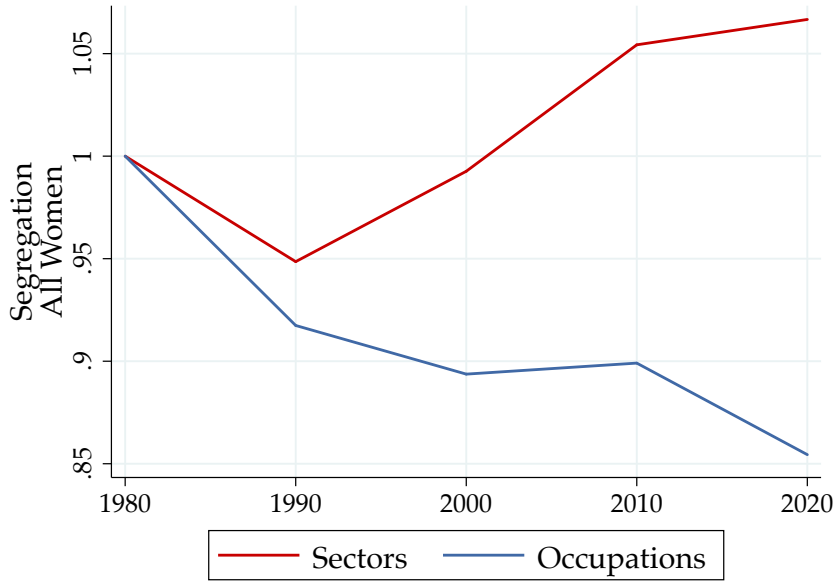


Figure 1: Sectoral Divergence and Occupational Convergence Between Men and Women

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). Segregation is indexed to 1 in 1980. See Appendix A.1.1 for details.

concurrent *increase* in the gender segregation of 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 (see figure A.1).

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 the 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 in earlier periods.

Role of Specific Industries and Structural Transformation. Figure 2 provides a heterogeneity analysis of the aggregate fact. Panel 2a decomposes the rise in aggregate sectoral segregation into the contributions of each sector. The three sectors that con-

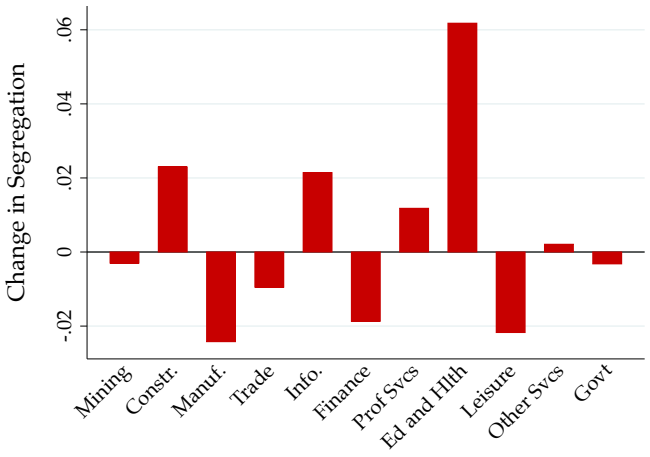
tribute the most to the rise in segregation are Construction, Information, and Education and Health. Construction and Information were male-dominated in the 1980s (93% and 56% male, respectively), whereas Education and Health were female-dominated (70% female). All three sectors increased their employment share relative to 1980, contributing to the rise in segregation through a size effect. However, in the Information and Education and Health sectors there was also a within-sector increase in segregation, with Information becoming more male-dominated (62%) and Education and Health becoming more female-dominated (77%).

These examples illustrate how segregated sectors can contribute to rising segregation by simply experiencing faster employment growth than less segregated sectors. A well studied example of this phenomenon is the Services sectors that tend to be female dominated and have grown substantially in the last half century (Ngai and Petrongolo 2017). To measure the extent to which structural transformation can explain rising segregation, Figure A.2 plots the counterfactual path for segregation if sectoral employment shares are held fixed at their 1980 values while the within-sector gender composition is allowed to vary as in the data. The shift-share exercise suggests that 40% of the rise in segregation is explained by structural transformation, while the remaining 60% reflects within sector compositional changes.

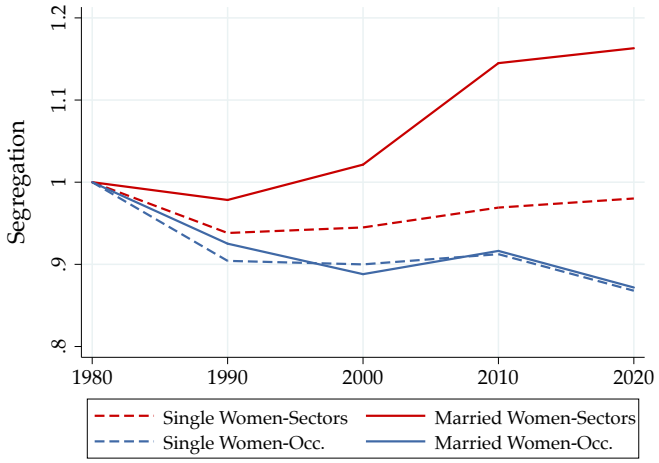
Marital Status and the Family Channel. Gender gaps in labor market outcomes may also be the result of joint household labor supply decisions and the spousal division-of-labor in home production and childcare (Doepke and Tertilt 2016; Doepke and Kindermann 2019; Kleven, Landais, and Søgaard 2019; Coskun, Dalgic, and Ozdemir 2023). Panel 2b investigates this possibility by comparing trends in sectoral segregation for married and single women separately, using all men as the common reference group.[3]

The disaggregated data suggest a prominent family channel effect. The figure shows that the rise in sectoral segregation is entirely due to married women. Between 1980 and 2020 the sectoral segregation of married women increased by 17%, while segregation fell by 1% for single women. This difference in trends is noteworthy since no comparable gap exists in occupational segregation. As the figure shows, the trend decline in occupational segregation was nearly identical across marital statuses. Figure A.5 shows that

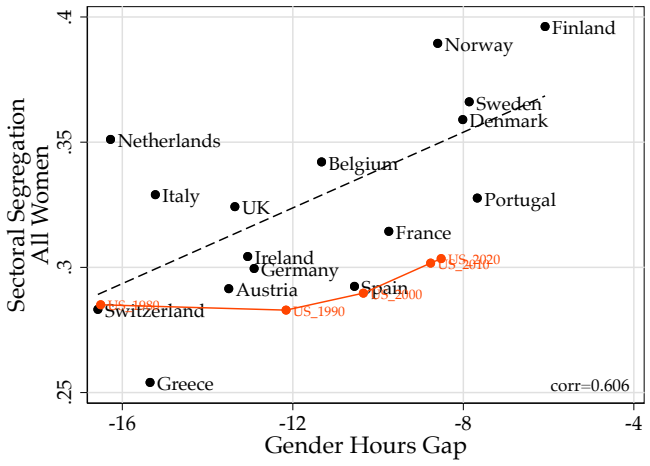
[3]For robustness, Figure A.4 plots the rise in segregation for single and married women using single and married men, respectively, as the reference group. Single women have a much lower level of segregation compared to single men and show an increase over time. The rise in segregation for married women compared to married men is roughly the same as when the reference group is all men.



(a) Contribution of Individual Sectors (United States)



(b) Sectoral Segregation by Marital Status (United States)



(c) Cross Country Evidence (Europe and United States)

Figure 2: Sectoral Segregation: Heterogeneity Analysis

Note: Data sources are IPUMS-CPS (1975-2019) and EU-LFS (2008-2019). The age group analyzed is 25-54 (Europe) and 25-35 (US). Gender hours gap is the average of 2005-2009. See Appendix A.1.1 and A.1.2 for details.

married women also drive the contributions of individual sectors to aggregate segregation displayed in the preceding panel 2a.

The diverging trends between married and single women may reflect selection into marriage or they may be the result of household specialization and the impact of childcare (or both). It is generally difficult to discriminate between these effects in the data. Nevertheless, the data do suggest that childcare considerations play an important role. Figure A.6 plots the change in sectoral segregation for women with and without children. It shows that women with children account for nearly all of the rise in segregation. The divergence between the two groups mirrors the one in marital statuses.[4] We maintain the focus on marital status rather than parental status to inform the literature on couples' joint labor supply decisions. Section IV.D investigates the relationship between the "child-friendliness" of different sectors and women's preferences, finding that child-friendliness matters for married women but not single women.

Cross-Country Evidence. The evolution of gender equality and female labor force participation has followed a systematic pattern across many different countries (Olivetti 2014; Olivetti and Petrongolo 2016). Changes in technology and gender norms led to large increases in female labor force participation and reductions in occupational segregation and earnings gaps. Panel 2c 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, panel 2c 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 cross-country European 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 employment preserves the positive correlation, indicating that it

[4]The specific impact of childcare is difficult to isolate since marriage is often a precursor to the arrival of children. Coskun, Dalgic, and Ozdemir (2023) also document that women often switch sectors prior to having children.

depends on within-sector effects that are not solely the result of structural transformation or differences in the services share across European economies (Figure A.8).

II.B Additional Robustness

The appendix contains a number of additional robustness exercises. Appendix A.2.1 examines how segregation trends compare when computed using finer industry classifications at the 2-digit NAICS level. The more disaggregated measures continue to show a rise in segregation for married women and modest decline 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. The rise in sectoral segregation is robust to holding fixed changes in the occupational composition of sectors (Figure A.2).

To assess these compositional effects in more detail, Appendix A.2.2 recomputes sectoral segregation by aggregating over the two dimensional sector by occupation space (Figure A.10a). While the aggregate pattern is unchanged, the compositional changes influence the relative contribution of particular sectors to aggregate segregation. The Management occupation and the Education and Health sector provide useful examples. First, when neglecting sectors, there appears to be substantial occupational convergence in Management (the dashed line in Figure A.10b). 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 (Figure A.10c). That is, women moved into Education and Health but moved roughly equally into healthcare assistant occupations and practitioner occupations.

Finally, Appendix 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 male or female employment shares across sectors fixed at their 1980 level. The results show that

it is women's employment composition that is driving the rise in sectoral segregation. When only female employment shares change, the rise in sectoral segregation between 1980–2020 is 30% higher than in the benchmark figure 1. When only male employment shares change, sectoral segregation actually *decreases*, falling by 11% by 2020.

III 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 adapts the structural model of Hsieh et al. (2019) to explain the changing employment choices of single and married women relative to men between 1980–2020. In the model, changes in the employment composition of any group can be explained by either changes in preferences, changes in discrimination, or changes in technology. Under suitable assumptions the three channels can be separately identified with data on sectoral earnings, education, and employment shares.

The model population consists of a unit mass of heterogeneous individuals making consumption, education, and sector of employment 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 time investment in human capital prior to entering the labor market, and z is a sector specific utility term capturing the value of all non-wage amenities in sector i to group g. Households live for three periods (young, middle age, and old) with c indexing their cohort and t indexing time. The coefficient β captures the utility value of lifetime consumption relative to leisure. 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. 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 both educational expenditures and the time spent in school,

as well as learning that takes place on the job, 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 sector-specific returns to education, which may vary across cohorts. Parameter η is the elasticity of human capital with respect to educational expenditure and the function $\gamma(t-c)$ captures returns to work 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 sectoral earnings and 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-working population).

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

$$\text{(1)} \qquad \frac{\text{earnings}_{igt}}{\text{earnings}_{imt}} = \left(\frac{\tau_{igt}}{\tau_{imt}}\right)^{-\frac{1}{1-\eta}} \times \left(\frac{\text{share}_{igt}}{\text{share}_{imt}}\right)^{-\frac{1}{\theta(1-\eta)}}$$

$$\text{(2)} \qquad \frac{\text{share}_{igt}}{\text{share}_{imt}} = \left(\frac{1-\text{LFP}_{gt}}{1-\text{LFP}_{mt}}\right) \times \left(\frac{\tau_{igt}}{\tau_{imt}}\right)^{-\theta} \times \left(\frac{z_{igt}}{z_{imt}}\right)^{-\frac{\theta(1-\eta)}{3\beta}}$$

where earnings_{igt} is the geometric average of earnings and share_{igt} is the share of group g employed in sector i at time t. LFP_{gt} is the labor force participation rate of group g.

These equations provide intuition for how the model identifies discrimination and preferences from the data. Equation 1 exploits the model's mapping from relative employment shares to relative ability levels in order to capture differences in selection across genders. If group g has a higher employment share in i than group m, g's average ability is expected to be lower (by a factor depending on θ and η). Conditional on this selection, the remainder of the gender earnings gap in sector i must be due to discrimination.

Equation 2 states that conditional on participation and discrimination, differences in employment shares reflect relative preferences z_{igt}/z_{imt}. That is, if a group is overrepresented in a sector relative to what their earnings would predict, it must be due to preferences.

The final channel that can drive changes in sectoral segregation are technological factors. These include sector-specific efficiency wages (productivities) $w_i(t)$ and 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 levels of discrimination and preferences of each group across sectors. Identifying these factors requires an additional assumption that the benchmark group (men) face no discrimination in education and labor markets.[5] In this case, sectoral wages $w_i(t)$ and men's preferences z_{imt} 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 over time.

The remaining structural parameters $\eta, \theta, \beta,$ and $\gamma(t-c)$ are fit following the approach in Hsieh et al. (2019).[6] Given these parameters, changes in preferences, discrimination, and technology can be estimated from sectoral data on earnings, employment shares, and years of schooling. 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_{igt}; changes in the degree of gender discrimination in labor and education markets τ_{igt}; and technological shifts affecting relative wages $w_i(t)$ and the returns to education $\phi_i(c)$ across sectors. Appendix A.3 contains additional details on the identifying assumptions and computational algorithm.

IV 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 1975-2019 across

[5] 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.

[6] Appendix Table A.3 reports the parameter values and identifying assumptions.

twelve sectors (including the home sector). The following paragraphs summarize these estimates–which have intuitive properties–before turning to the main counterfactuals.

Consistent with Hsieh et al. (2019)'s findings for occupations, the average sector's discrimination against women declined substantially. 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.

In terms of technology, the returns to education $\phi_i(c)$ increased across cohorts. Efficiency wages $w_i(t)$ also grew over time, reflecting productivity growth. Real wages grew fastest in the Leisure and Hospitality sector (105%), followed by Information (87%). Wages in Education and Health grew by 15%.

Using the relative preferences $\frac{z_{igt}}{z_{imt}}$ of women compared to men, sector preferences are more correlated across cohorts of married women (84%) than between single and married women within a cohort (68%), suggesting that single and married women have different valuations of certain non-wage amenities. Men's preferences are quite stable over time. Women's relative preferences increased the most for high-skilled services sectors: Information, Education and Health, and Finance. Single women also increased their relative preference for Professional Services, while married women increased their relative preference for Government.

Finally, women's preferences are negatively correlated with gender discrimination. The negative correlation suggests that reductions in discrimination against women not only raises their wages, but may also increase the provision of the non-wage amenities they most prefer. This type of endogenous increase in amenities is consistent with the findings of Corradini, Lagos, and Sharma (2025), who show that female-centric amenities increase when women have more representation in collective bargaining negotiations.

IV.A Drivers of Sectoral Segregation

Table 1 reports the main results decomposing the rise in sectoral 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

		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 Aggregate Changes in Segregation and Gender Earnings Gap

Note: Role of preferences (z), discrimination (τ), and technology (efficiency wages w and returns to schooling ϕ) for changes in segregation and the gender earnings gap, 1980-2020. 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 (Section IV.A.)

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.[7]

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 for married women, 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 effects of discrimination are quite different for single and married women. Changes in discrimination lead to an increase in the sectoral segregation of married women, but decreased it for single women. For married women, the greatest reductions in discrimination were in the more female dominated sectors, drawing in more women and increasing measured segregation. The opposite is true for single women: discrimination against single women fell more quickly in the more male-dominated sectors.

Technological change increased the sectoral segregation of both groups. Rapid wage growth in already highly segregated service sectors draws in both men and women, increasing the sector's employment share and contributing to a rise in aggregate segregation through a size effect (see Section II.A). Groups also respond differently to common technological changes in wages and returns to education because they interact with prevailing differences in discrimination and preferences.

[7] In the preferences counterfactual we fix preferences for men as well as women, and in the technology counterfactual we hold technology fixed for both genders. Since discrimination against men is normalized to one in each period, the discrimination counterfactual only varies discrimination for women.

IV.B Implications for the Gender Earnings Gap

The second panel of Table 1 reports the impact of each channel on the evolution of the aggregate gender earnings gap from 1980 to 2020. Most of the decline in the aggregate gender earnings gap since 1980 was due to married women rather than single 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 the preferences of both single and married women shifted 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. 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 accounts for just 4%. The situation is reversed for married women. Declining discrimination accounts for 62% of the reduction in the earnings gap for married women, while technology changes account for only 22%. In absolute terms, the largest factor behind the decline in the gender earnings gap since the 1980s is the reduction in labor market discrimination against married women.

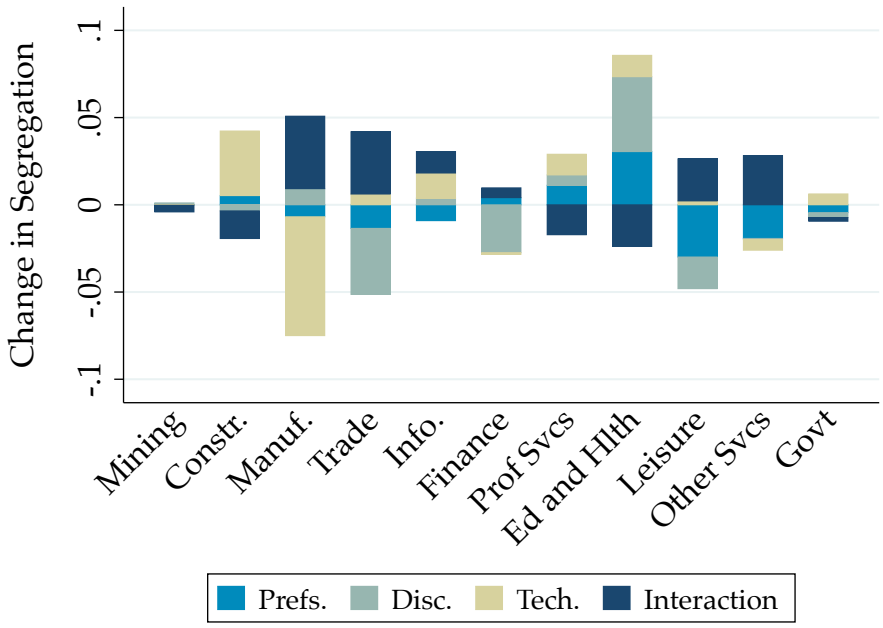
IV.C The Impact on Specific Sectors

Figure 3a further decomposes the results by showing how each of the model's channels shapes the contribution of individual sectors to aggregate segregation for all women. Formally, it decomposes the sectoral components in Figure 2a into contributions from preferences, discrimination, technology, and their interaction.[8]

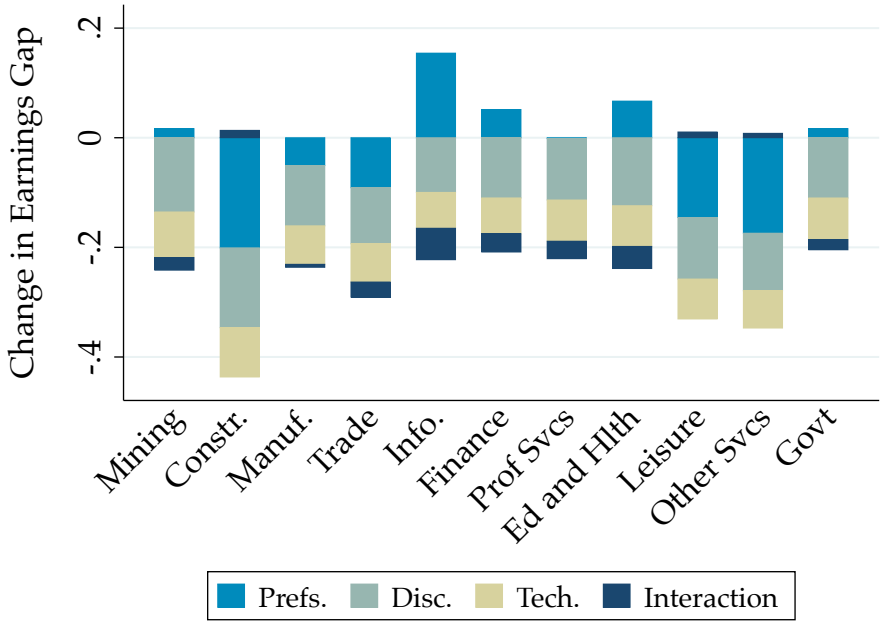
The impact of each of the model's channels is far from uniform across sectors. Some sectoral contributions are dominated by a single channel, while others exhibit more balanced effects. For instance, changes in segregation in the Finance sector are nearly entirely explained by a decline in discrimination, while changes in the Construction sector are driven almost entirely by changes in wages. In contrast, the rise in segregation in the Education and Healthcare sectors reflects more balanced contributions across the channels, depending substantially on changes in both preferences and discrimination.

Figure 3b provides the corresponding decomposition of changes in the aggregate gender earnings gap. The impact of each channel was more uniform for earnings gaps than

[8]The within decomposition uses the same leave-one-out procedure that is used to create Table 1.



(a) Change in Sectoral Segregation



(b) Change in Gender Earnings Gap

Figure 3: Decomposing Sectoral Changes in Segregation and Gender Earnings Gaps

Note: Contribution of preferences, discrimination, and technology to explaining the changes in sectoral gender segregation and the gender earnings gap in each sector between 1980 and 2020 in the United States. The decomposition holds each driver fixed one by one and attributes unexplained changes in each outcome to the omitted driver.

for segregation. Table 1 shows that falling discrimination is the largest driver of the decline in the gender earnings gap. It accounts for a steady 50% *within* nearly all sectors. Changes in technology generate a similarly uniform contribution, accounting for roughly 31% of the within effect for most sectors. Conversely, the contribution of preferences varies, accounting for most of the cross-sector heterogeneity in the evolution of the gender earnings gap.

IV.D Investigating 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_{igt}, capture all non-wage utility benefits that a group g gets from working in sector i. This section relates these estimated preferences to observable sector-level non-wage amenities to shed light on the type of job characteristics they may represent.

We measure four categories of amenities at the sector level: work arrangements, measured by the share of part time workers and the average hours worked per week; child-friendliness, measured by the average number of children workers have; homophily, measured by the female share of employment; business cycle risk, measured by the correlation of the sector's employment with the business cycle.[9] The regression model is

$$z_{igt} \;=\; \beta_{0g} \;+\; \boldsymbol{\beta}_g \mathbf{X}_{it} \;+\; \epsilon_{igt},$$

where z_{igt} is the estimated preferences of group g for sector i at time t. $\mathbf{X}_{i,t}$ is the corresponding vector of sector-level amenities, normalized by their standard deviation to facilitate interpretation. The coefficients $\boldsymbol{\beta}_g$ are estimated separately for each group to isolate the drivers of married women's preferences from "neutral" amenities that may equally attract both genders or marital groups.[10]

Table 2 presents the estimates for each group. Work arrangements and child-friendliness are the strongest correlates of the model derived preferences, while homophily and business cycle risk do not exhibit statistically significant relationships. All groups (married women, single women, and men) appear to have a preference for flexible work arrangements, proxied by the part-time share. The point estimates suggest this preference is

[9] Most of the variation in amenities is across sectors rather than within sectors over time. See Table A.1.

[10] Figure A.12 reports the share of each group in the population over time, as well as the evolution of their labor force participation rates, hours, and education levels.

	Married	Single	Men
Part time share	0.111	0.080	0.080
	[0.000]	[0.000]	[0.000]
Hours	0.032	-0.044	-0.028
	[0.055]	[0.014]	[0.004]
Num. children	0.019	0.001	-0.005
	[0.002]	[0.875]	[0.390]
Female share	-0.015	-0.023	-0.005
	[0.236]	[0.135]	[0.511]
Business cycle risk	0.002	-0.014	-0.008
	[0.748]	[0.108]	[0.159]
R^2	0.834	0.802	0.848
Observations	55	55	55

Table 2: Group Preferences For Sectoral Amenities

Note: Correlation of preferences z_{igt} with sector-level amenities, weighted by group employment shares. Row variables normalized by their standard deviation. p-values reported in parentheses. Source: IPUMS-CPS and model output.

stronger for married women than single women.[11] Interestingly, conditional on part-time share, married women also appear to favor sectors with longer work hours. However, the most pronounced difference across groups is for child-friendliness, which is highly correlated with married women's preferences but not those of the other groups.

Appendix Table A.2 attempts to partially address the endogeneity of workplace characteristics by re-estimating the model measuring sectoral amenities $\mathbf{X}_{it}$ using only male employees for work arrangements and child-friendliness.[12] While point estimates differ slightly, the qualitative differences between groups and their statistical significance remain unchanged.

Together, the results are consistent with the fact that women continue to be primary caregivers in the majority of households, even when both parents work (Alon et al. 2022). It is also consistent with a growing body of research measuring the non-wage occupational preferences of women in other contexts with much more precise data and empirical designs (Mas and Pallais 2017; Wiswall and Zafar 2017). While certainly indicative, the

[11] F-tests reject the null hypothesis that the married and single women's coefficients on part-time share are the same at the 10% significance level and the 5% level for married women versus men.

[12] For example, 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?

results here should of course be interpreted with caution given the small sample size (five cohorts times eleven market sectors) and absence of exogenous variation.

V Conclusion

There has been widespread gender convergence in labor market outcomes since the 1970s. At the same time, men's and women's sectors of employment diverged. Sectors are now more segregated by gender than they were 50 years ago. Similar patterns appear in cross-country data from Europe. In the United States, the trend is driven by the changing employment preferences of married women. The paper provides suggestive evidence that flexible work arrangements and childcare considerations are the main non-wage amenities underlying these preferences.

Changes in the preferences of married women have also decreased the gender earnings gap. Women increasingly value the non-wage amenities of higher paying sectors. One avenue for future research is to understand the extent to which these shifts represent increases in the provision of non-wage amenities in some sectors, or whether amenities are fixed and tastes are changing over time. Better measurement of the non-wage amenities offered by different sectors can provide insight; most of the existing literature focuses on the variation in amenities across firms or occupations. Developing theories to explain the amenity menus offered by different sectors—and how they may depend on considerations such as the task content of production, the degree of labor market power, the expected length of employment relationships, and so on—is also a fruitful direction for future research.

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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 level of segregation of sectors and occupations for married and single women relative to all men rather than the normalized series in the main text.

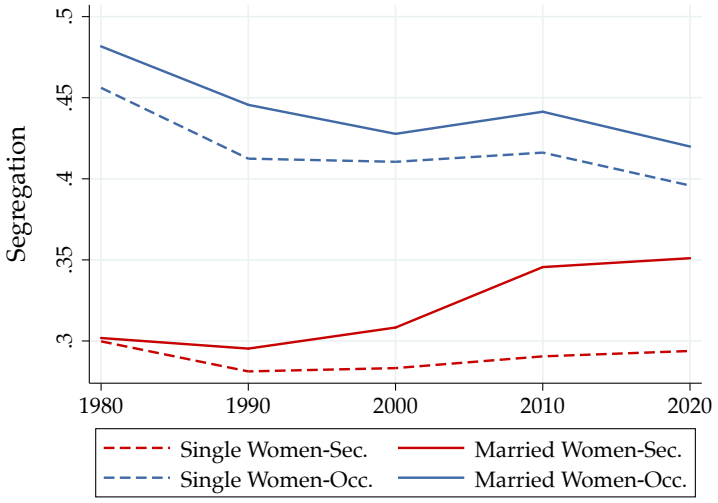


Figure A.1: Occupational convergence and sectoral divergence wrt Marital Status.

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 shows the actual sectoral segregation of women (the black dashed line) alongside a counterfactual segregation measure which holds sectoral employment shares of the overall labor force fixed at their 1980s levels (the red line). The formal decomposition is described in the next paragraph. The purpose of this counterfactual is to assess the impact of the expansion of (primarily female-dominated) service sectors, which may have amplified segregation. 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.3) and 41% among all women (Figure A.2).

In Figures A.2 and A.3, 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 measured employment share of sector s and occupations o for gender f, represented as $\frac{p^f_{so}}{\sum_s \sum_o p^f_{so}}$ (e.g. the share of women whose occupation is Manager in the

Education and Health sector) which serves as the key variable in constructing the segregation measure. This can be expressed as follows:

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

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.3a 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.

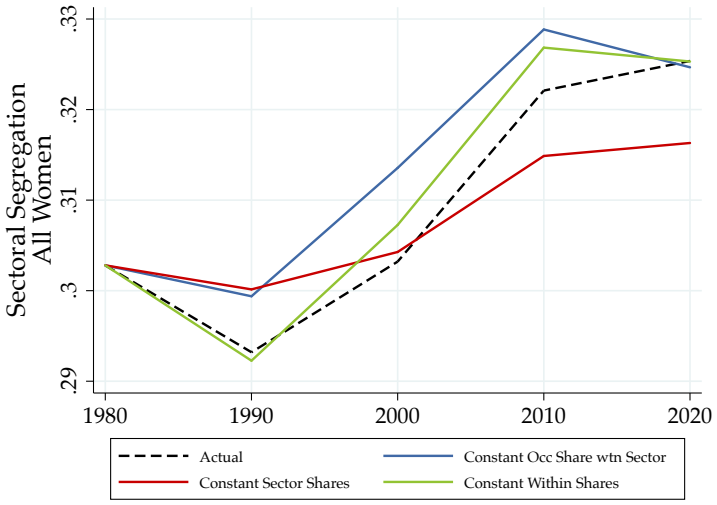
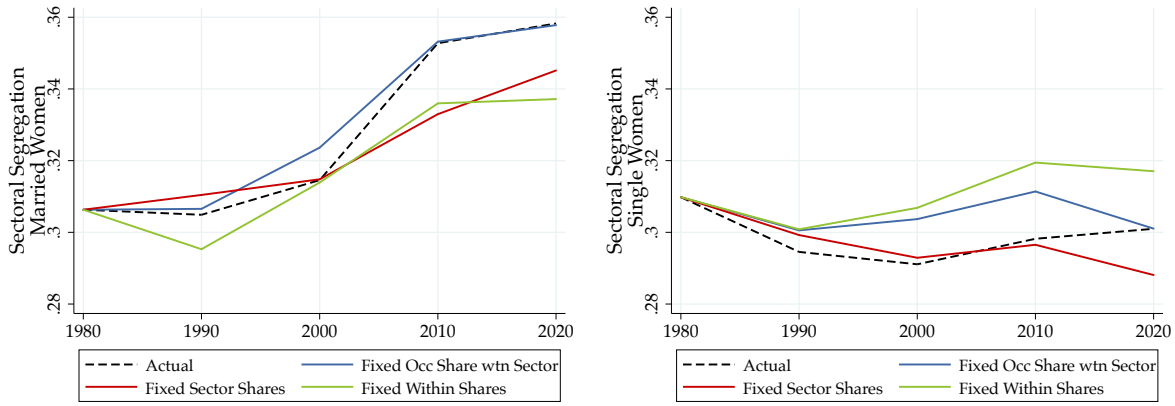


Figure A.2: Fixed Sector Sizes

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.

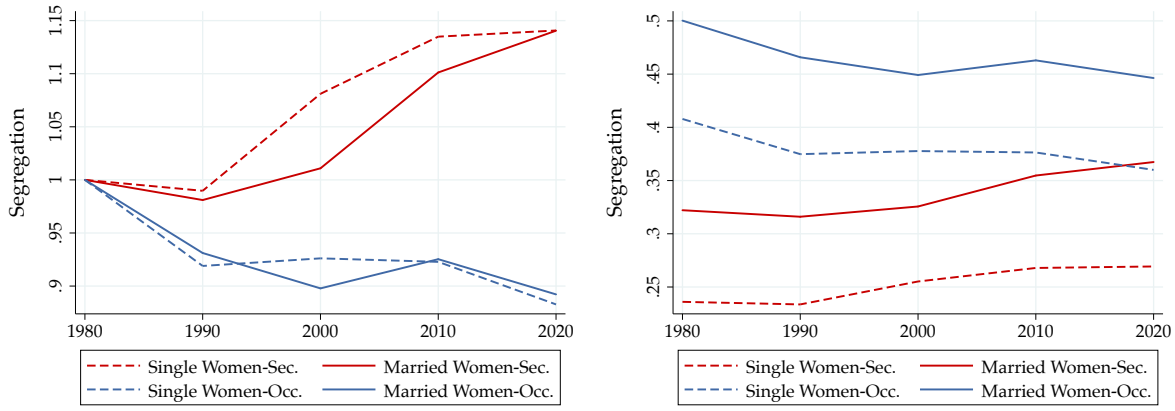


(a) Married Women (b) Single Women

Figure A.3: 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.

Figure A.4 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 segregation falls.



(a) Normalized to 1980s (b) Levels

Figure A.4: 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. Comparison group for single women is single men, and married men for married women.

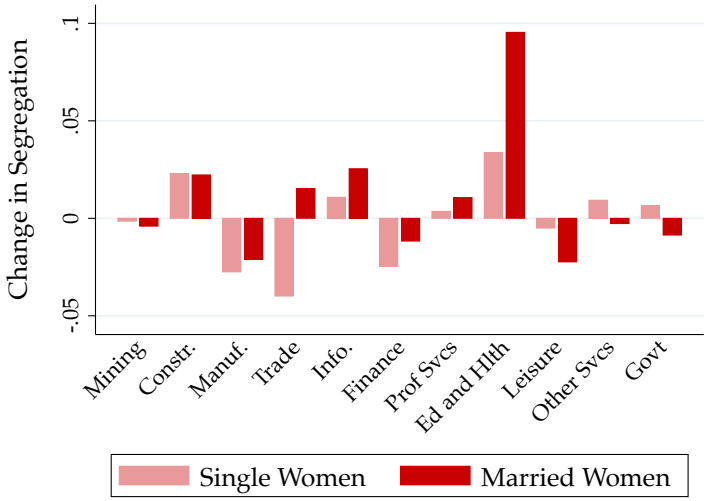


Figure A.5: Changes in Segregation 1980-2020

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.

Figure A.5 shows the contributions of each sector the rising segregation for single and married women separately. Education and Health contributed more to segregation for married than single women.

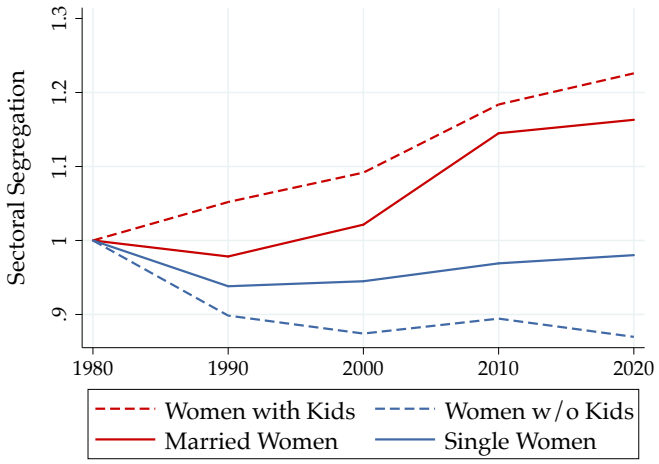


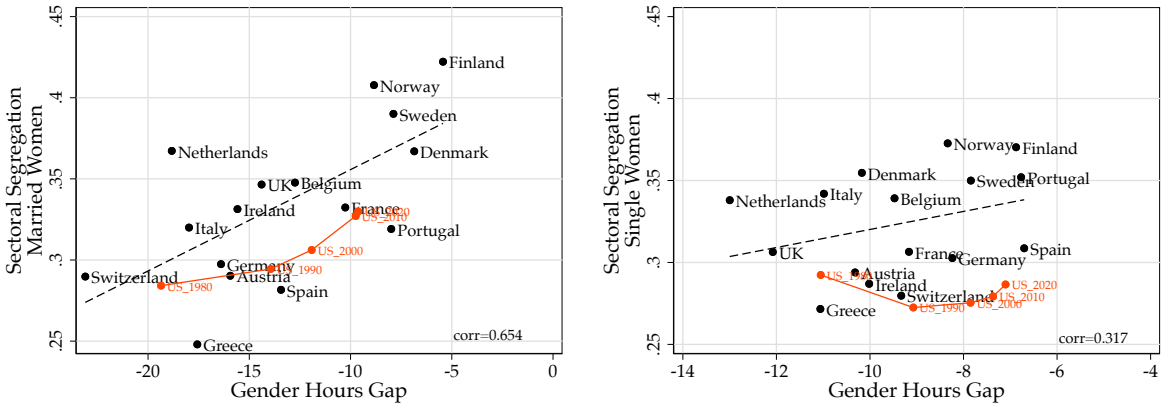
Figure A.6: Marital Status and Presence of Children (United States)

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.

Figure A.6 disaggregates the rise in sectoral segregation by presence of children and plots it in comparison to the decomposition based on marital status.

Figure A.7 breaks down the analysis presented in Figure 2c 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.

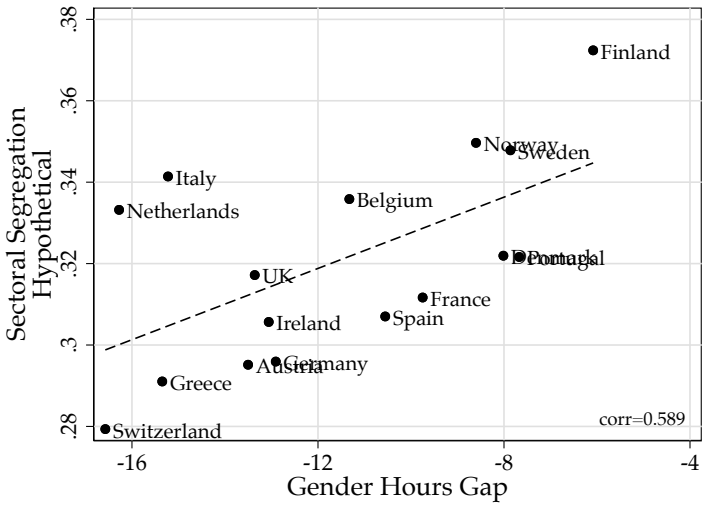


Figure A.8: EU-average Sector Sizes

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.

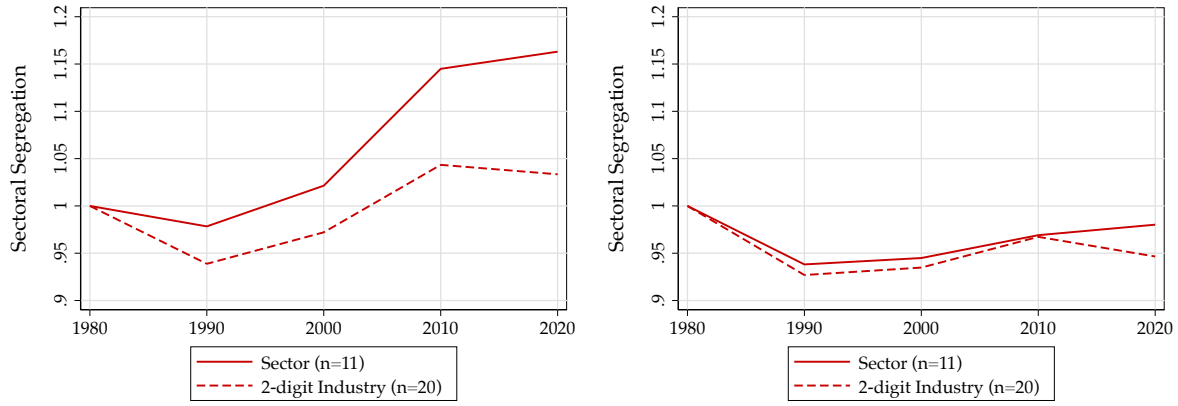
A.2.1 Sector Disaggregation

The conversion of 1990 industry codes into NAICS codes may introduce some inconsistencies, as certain industries in the 1990 codes 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. Therefore we report sectoral segregation at the 2-digit level in Figure A.9.

We observe a modest decline in segregation for single women at the 2-digit level in Figure A.9b. In contrast, Figure A.9a shows that segregation rises over time for married women, although the gradient is lower for at the 2-digit level. The discrepancy between broad sectors and the 2-digit industries in married women's segregation is mainly due to the Trade sector: most of the Trade sector is male-dominated throughout the sample period, except for retail stores, which began as female-dominated in 1980 and became less so over time. Taking all sub-sectors together, Trade overall became more male-dominated and thus contributed to married women's rising segregation, however the decline in segregation in retail trade at the 2-digit level makes the aggregate rise in segregation less dramatic at the 2-digit level.

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.9: Sector Segregation at the 2-digit level

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

A.2.2 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.10a 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

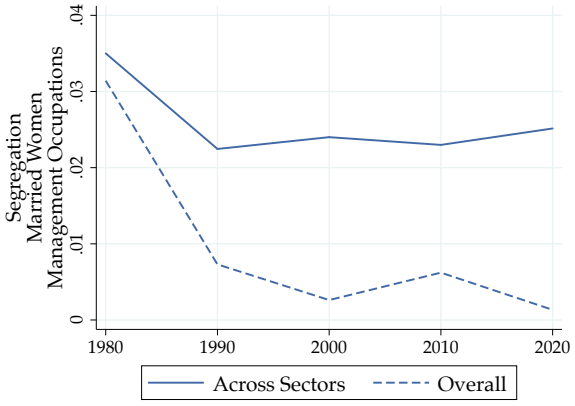
sector-occupation pairs, the pattern appears more stable. By construction, the segregation level is highest for sector-occupation pairs: even slight gender imbalances in sectoral distribution for a single occupation result in a larger value for formula (2) than for formula (1).

Repeating this analysis for specific sectors and occupations provides useful insights. Figure A.10c 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.

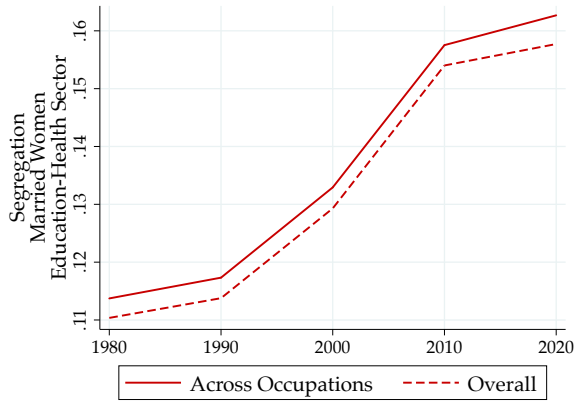
In contrast, Figure A.10b illustrates segregation trends for management occupations. A decline in segregation over time (red line) indicates gender convergence in management occupations. However, when accounting for sectoral variation (blue line), we see that gender convergence in management did not occur uniformly across sectors, leading to a more stable pattern after the 1990s.



(a) Overall



(b) Management Occupations



(c) Education and Health Sector

Figure A.10: 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.2.3 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.

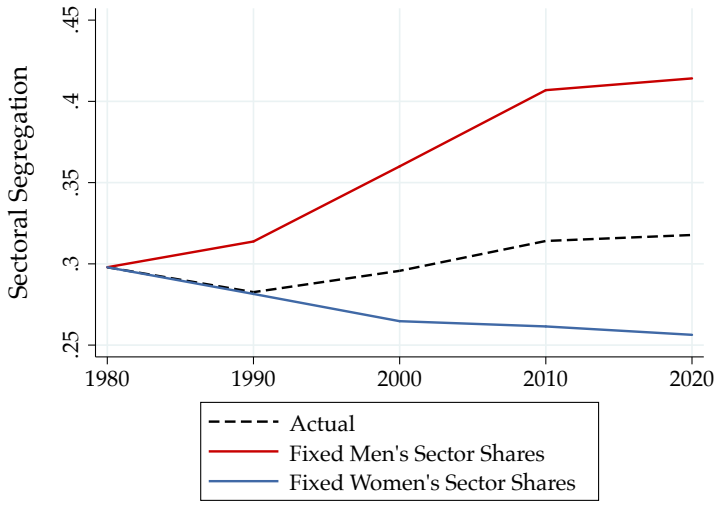
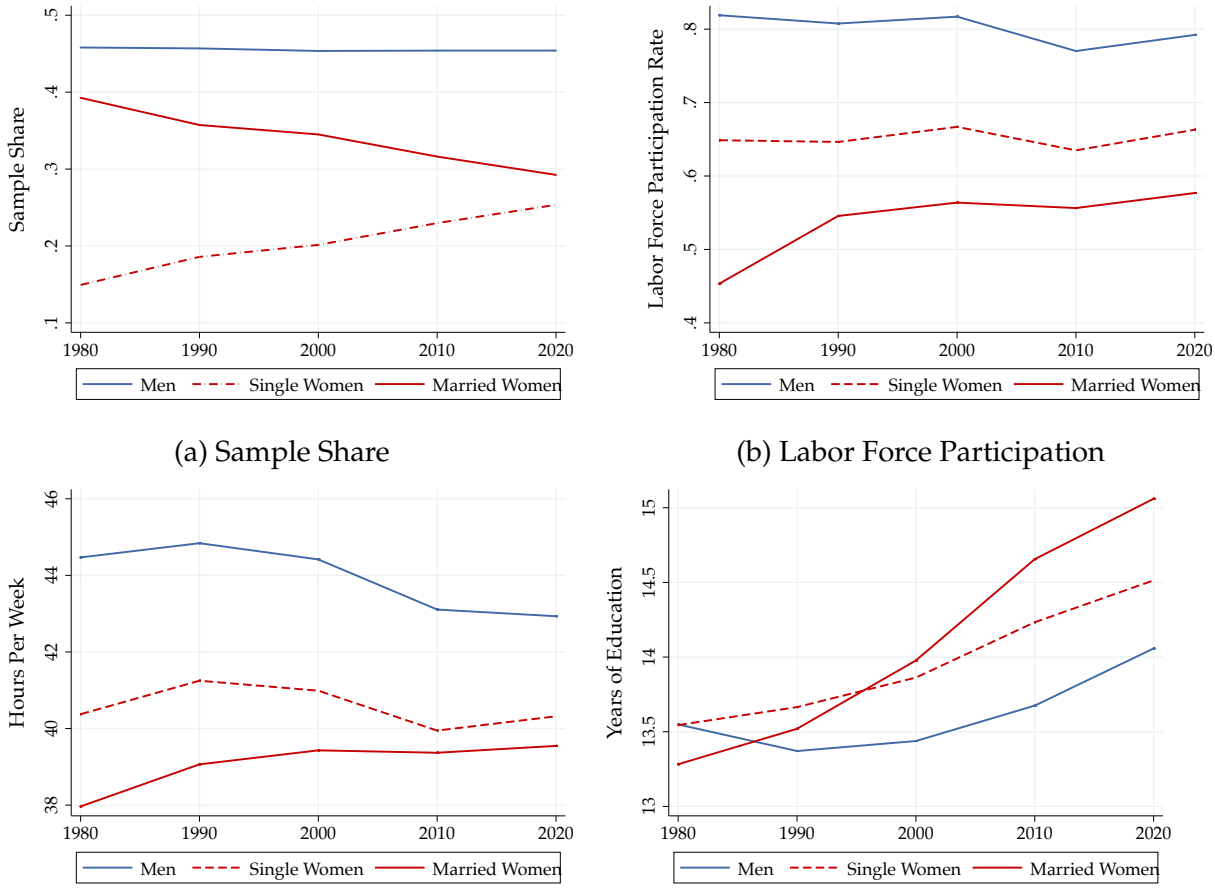


Figure A.11: Gender Decomposition of Segregation

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.

Finally Figure A.12 shows the sample share of each group (men, single women, and married women in each cohort, along with their characteristics (labor force participation rate, hours worked per week, and years of education).



(a) Sample Share

(b) Labor Force Participation

(c) Hours

(d) Education

Figure A.12: 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.

A.2.4 Potential Mechanisms

The riskiness measure is constructed using BLS Current Employment Statistics industry employment. The methodology by (Coskun and Dalgic 2024) is applied. Annual sectoral employment and GDP data are HP-filtered with a smoothing parameter of = 6.25 for the period 1975–2019. The 20-year centered correlation coefficients of the cyclical components of GDP and industry-level employment are used in the regression. The riskiness measure for the 1980s is based on the correlation coefficient from 1970 to 1989, for the 1990s, it is from 1980 to 1999, and so on. For the last decade, the 2020s, the correlation coefficient is calculated for the years 2010–2019.

Table A.1: Fraction of Variance in Amenities: Permanent Cross-Sector Differences

PT share	Hours	Num. kids	Fem. share	Risk
0.958	0.854	0.442	0.979	0.643

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" is the share of part time workers, "Hours" is average hours per week, "Num. kids" is the average number of children employees have, "Fem. share" is the female share of total employment, "Risk" is the correlation of the sector's employment with the business cycle.

	Married	Single	Men
Part time share, men only	0.123	0.084	0.082
	[0.000]	[0.000]	[0.000]
Hours, men only	0.098	0.022	0.007
	[0.000]	[0.404]	[0.528]
Num. children, men only	0.040	0.019	0.013
	[0.006]	[0.157]	[0.183]
Female share	0.010	0.014	0.026
	[0.478]	[0.420]	[0.029]
Business cycle risk	0.013	0.002	0.007
	[0.093]	[0.835]	[0.312]
R^2	0.670	0.675	0.824
Observations	55	55	55

Table A.2: Preferences and Amenities at the Sector Level.

Note: Correlation of preferences z_{igt} with sector-level amenities, weighted by group employment shares. Row variables normalized by their standard deviation. p-values reported in parentheses. Source: IPUMS-CPS and model output.

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 (see Table A.3). Returns to education, $\phi_i(c)$, are estimated by computing,

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

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

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

Given these parameters, the model identifies cohort-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. To identify the level of preferences for cross-year comparisons we need to also assume a home sector wage for each year. Hsieh et al. (2019) set this wage to be equal to the wage of the Secretary occupation, we set it to be the Leisure and Hospitality wage. The bottom panel of Table A.3 summarizes the model assumptions and normalizations. 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_{imt} and wages $w_i(t)$ 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.

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

$$\tilde{z}_{igt} = \left(\frac{\overline{\text{wage}}_{igt}}{\overline{\text{wage}}_{imt}}\right)^{-\frac{1}{1-\eta}} \times \left(\frac{1-LFP_{gt}}{1-LFP_{mt}}\right)^{-\frac{1}{\theta}} \times \tilde{z}_{imt},$$

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

3. Given the normalizations, recover discrimination τ by combining equation 1 with earnings and employment data,

$$\tau_{igt} \;=\; \frac{\tau_{igt}}{\tau_{imt}} = \left(\frac{\text{share}_{igt}}{\text{share}_{imt}}\right)^{-\frac{1}{\theta}} \times \left(\frac{\overline{\text{wage}}_{igt}}{\overline{\text{wage}}_{imt}}\right)^{-(1-\eta)}.$$

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.

Param.	Meaning	Value/Norm.
θ	Dispersion of idiosyncratic ability	1.46
η	Elasticity of human capital w.r.t education spending	0.106
β	Utility weight on pre-working life	0.231
$\tau_{i,men}$	Composite discrim. in all sectors for men	0
$\tau_{home,g}$	Composite discrim. in home sector, all groups	0
$\tilde{z}_{home,g}$	Pref. for home sector, all groups	1
$\overline{\text{wage}}_{home}$	Home sector wage for all groups	$\overline{\text{wage}}_{Leis.,m}$

Table A.3: Hsieh et al. (2019) estimate θ using dispersion of residuals from wage regressions on age, group, and education. η is estimated using education expenditure as a share of GDP. β estimated using Mincerian returns to schooling.