More Women, Narrower Gaps: Gender Norms and Wages Within Occupations

Sophie Brochet*
Universitat Autònoma de Barcelona & Barcelona School of Economics

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Abstract

This paper examines how managers' and workers' gender-role attitudes shape gender wage inequality. I document smaller wage gaps between women and men with similar observable characteristics in occupations with higher female employment shares. Workers in these occupations, including men, hold more progressive gender-role attitudes. To explain these patterns, I develop a structural equilibrium model of dynamic occupational choice and firm wage setting. Workers' attitudes shape participation, sorting, and human capital accumulation, while managers' attitudes influence wages through their expectations of women's productivity. Managerial attitudes are central to explaining occupational wage-gap variation, while workers' attitudes affect female employment and aggregate production.

Keywords: gender wage gap, occupational choice, gender norms, managers, labor market power.
JEL Classification: J16, J24, J31, J42, J71.

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1 Introduction

Gender wage inequality in the United States has declined substantially over recent decades, yet significant differences in wages between women and men remain (Blau and Kahn, 2017). An important feature of this remaining inequality is that the magnitude of gender wage gaps varies considerably across occupations. In some occupations, women earn wages relatively close to those of men with similar observable characteristics, while in others the gap is much larger. Although the sources of gender wage gaps have been extensively studied, comparatively less attention has been devoted to understanding why these gaps differ so markedly across occupations. Explaining this variation can provide important insights into the forces sustaining gender wage inequality. It can also inform the design and evaluation of policies aimed at reducing it.

In this paper, I document a striking pattern: occupations employing more women tend to exhibit smaller gender wage gaps, conditional on observable worker characteristics. I also find that workers in these occupations tend to hold more progressive views about gender roles, including men. Gender norms prescribe the roles considered appropriate for women and men at work and in the family, and have been shown to shape labor market decisions and outcomes (Akerlof and Kranton, 2000; Fortin, 2005; Cortes, Hwang, Pan and Schönberg, 2026). This paper seeks to explain these facts by answering three questions: Can gender norms explain why gender wage gaps are smaller in occupations employing more women? How do workers' and managers' attitudes toward gender roles, alongside other worker preferences, shape gender wage inequality? What are the equilibrium effects of requiring firms to pay equally productive women and men the same wages within occupations?

To address these questions, I develop and estimate a structural equilibrium model of dynamic occupational choice and firm wage setting. Workers' gender-role attitudes and family circumstances influence their participation and occupational choices, shaping employment histories and human capital accumulation. In equilibrium, these choices endogenously determine occupational female shares and prevailing gender norms, which in turn influence workers' decisions. On the firm side, wages reflect both employer labor market power and managers' assessments of women's productivity, which may be shaped by their gender-role attitudes independently of workers' actual productivity. I find that managerial attitudes, proxied by those of senior male workers in each occupation, play a central role in the relationship between occupational female representation and gender wage gaps between comparable workers. Workers' attitudes toward gender roles are also a major determinant of female employment and occupational sorting, with substantial consequences for aggregate production.

In the empirical analysis, I examine the links between occupational female representation, gender-role attitudes, and wage inequality. Using the Current Population Survey (CPS), I show that the negative relationship between female representation and gender wage gaps is robust across alternative specifications. It also persists after accounting for workers' quantitative, technical, verbal, and social skills using the National Longitudinal Surveys of Youth 1979 and 1997 (NLSY79 and

NLSY97). These results suggest that differences in measured skills are unlikely to explain the pattern. Turning to gender-role attitudes, I combine data from the General Social Survey (GSS) with CPS wages. I find larger wage gaps in occupations where workers hold more traditional views, including when attitudes are measured exclusively among senior men. I then investigate whether occupational gender norms are associated with individual wage trajectories using NLSY employment histories. Women moving to occupations where senior men hold more traditional views than in their occupation of origin experience lower wage growth than women moving toward less traditional environments. No comparable pattern emerges among men. This asymmetry suggests that occupational norms are particularly associated with women's wages, rather than differences in pay affecting both genders similarly. However, this evidence cannot fully distinguish the effects of workers' choices from those of employers' wage setting, motivating the structural analysis that follows.

In the model, individuals choose each year whether to work and, if so, their occupation, working hours, and employer. These decisions depend on wages, family circumstances, and preferences over occupations and employers. Gender-role attitudes also influence the attractiveness of different career paths and workers' alignment with the norms prevailing in each occupation. Individuals make these decisions throughout their working lives, anticipating changes in family circumstances and facing costs of switching occupations or returning to employment after inactivity. Their career choices determine employment histories and thus human capital accumulation, while occupational sorting shapes female employment shares and prevailing gender norms. Sorting also determines the average attitudes of senior male workers within each occupation, which serve as a proxy for managers' attitudes.

On the firm side, workers' preferences over occupations and employers, together with frictions in changing career paths, make labor supply to individual firms imperfectly elastic. Firms consequently have wage-setting power, with markdowns that may differ across genders and occupations. Wages also depend on firms' expectations of worker productivity. Although actual productivity is determined by workers' productive characteristics under a common technology for women and men, managers' gender-role attitudes may influence their assessments of female workers' productivity. Wage offers therefore reflect both expected productivity and employer labor market power. These offers, in turn, influence workers' participation and occupational choices, affecting the composition of employment, human capital accumulation, occupational norms, and the labor supply facing firms.

The estimation draws on longitudinal histories of participation, broad occupational choices, and family transitions from the NLSY79 and NLSY97, wages and detailed occupational and hours choices from the CPS, and gender-role attitudes from the GSS. On the supply side, I estimate a dynamic discrete-choice model in the tradition of Keane and Wolpin (1997) by maximum likelihood, separately by gender. A nested logit structure (McFadden, 1978) captures substitution across broad occupational groups and, within each group, across detailed occupations and working-hour arrangements. NLSY histories primarily identify occupational switching and re-entry costs and

family transitions, while CPS choices and wages inform wage sensitivity and substitution across occupational and working-hour alternatives. Individual attitudes combine a component predicted from the GSS based on gender, education, and birth cohort with permanent unobserved heterogeneity informed by labor market choices. The estimated supply model provides labor supply elasticities facing representative firms within occupations, which determine wage markdowns. Male wages, adjusted for these markdowns, identify the parameters of a production technology common to women and men, including the returns to education and accumulated human capital and the depreciation of experience. Holding this technology fixed, female wages identify the additional influence of managerial attitudes on expected productivity, conditional on expected human capital and gender-specific wage markdowns.

The results reveal how worker preferences and employer wage setting jointly shape gender wage inequality. Workers tend to sort toward occupations whose norms are closer to their own attitudes, influencing occupational gender composition and prevailing norms. This preference is stronger among men. Preferences over work and family also shape participation and employment histories, affecting human capital accumulation and, consequently, wages and production. On the employer side, labor supply elasticities vary across occupations and are lower for women than for men on average (3.38 versus 4.69), partly reflecting women's lower sensitivity to wages. This implies larger wage markdowns for women, who receive on average 77% of their expected marginal revenue product, compared with 82% for men. While several mechanisms contribute to gender wage inequality, managerial attitudes play a particularly important role in explaining why conditional gender wage gaps tend to be smaller in occupations employing more women. Their influence on wage setting also affects the distribution of surplus between firms and female workers. Finally, I examine a policy restricting gender wage differences among workers in the same three-digit Census occupation, education group, accumulated human capital interval, and hours arrangement, while leaving the underlying sources of wage inequality in place.[1] I impose this restriction from 1980 onward and report its effects in 2019, the final year of the sample, allowing changes in career trajectories and human capital to accumulate over time. By 2019, the restriction reduces the conditional gender wage gap by 57% and raises women's wage-equivalent welfare by 3.5%, but lowers men's welfare by 3.3%. Aggregate output increases slightly, while firms' profits decline by only 0.6%, as the increase in women's wage bill is offset in roughly equal parts by additional revenue and lower total wage payments to men. These findings illustrate how a reduction in gender wage inequality can affect workers, firms, and aggregate production differently.

This paper contributes to the literature on gender norms and labor market outcomes by integrating workers' and managers' gender-role attitudes into a dynamic structural equilibrium model. More specifically, the model links their roles in occupational choices and wage setting, while allowing sorting to endogenously determine both prevailing occupational norms and the average attitudes of

[1]The constraint goes beyond existing equal-pay requirements, as these categories encompass narrower job titles and responsibilities through which gender wage differences may arise, including from job assignment and promotion decisions.

senior male workers used to proxy managers' views. This approach builds on Akerlof and Kranton (2000), who incorporate social prescriptions into individual preferences, and on evidence linking gender-role attitudes to women's labor market outcomes and occupational segregation (Fortin, 2005; Pan, 2015). While Broso, Gallice and Muratori (2024) examine how gender norms discourage women from entering higher-paying, male-dominated occupations, recent evidence highlights the importance of managers' attitudes for women's relative earnings and employment (Ronchi and Smith, 2026; Minni, Nguyen, Sarsons and Srebot, 2026). Bringing these dimensions into an equilibrium framework allows me to examine how workers' and managers' attitudes jointly shape occupational sorting and within-occupation wage inequality.

Second, this paper contributes to the literature on gender wage inequality by examining why gender wage gaps vary systematically with occupational female representation. While Macpherson and Hirsch (1995) study the lower average wages of female-dominated occupations, de Ruijter and Huffman (2003) and Brynin and Perales (2016) document smaller within-occupation gender wage gaps where more women work in European labor markets. I establish this relationship in the United States and use an estimated structural equilibrium model to investigate its determinants. Hsieh, Hurst, Jones and Klenow (2019) use a general equilibrium model to quantify the aggregate consequences of barriers to occupational choice, while Gayle and Golan (2012) examine gender earnings inequality through a dynamic structural model of occupational choice, human capital accumulation, and statistical discrimination. My analysis examines how workers' and managers' gender-role attitudes contribute to wage inequality within occupations through occupational sorting, human capital accumulation, and firms' wage setting. The framework also allows me to evaluate the equilibrium effects of requiring equal pay for equally productive women and men within occupations, while gender norms and employer labor market power remain in place.

Finally, this paper contributes to the literature on employer labor market power and gender wage inequality by allowing wage markdowns to differ across genders and occupations. I derive the labor supply elasticities facing representative firms from workers' estimated choices, accounting for occupational preferences, mobility frictions, and preferences over employers. This approach builds on models of wage-setting power arising from heterogeneous preferences over employers (Card, Cardoso, Heining and Kline, 2018; Azar, Berry and Marinescu, 2022; Lamadon, Mogstad and Setzler, 2022), and on evidence that gender differences in labor supply elasticities contribute to wage inequality (Ransom and Oaxaca, 2010; Barth and Dale-Olsen, 2009; Hirsch, Schank and Schnabel, 2010; Webber, 2016). While Fanfani (2022) combines employer labor market power with employer preferences and gender differences in compensating wage differentials, my framework incorporates managers' gender-role attitudes as an additional determinant of expected female productivity. The model thus distinguishes the roles of employer labor market power, managers' attitudes, and accumulated human capital in shaping within-occupation gender wage gaps.

The remainder of the paper is organized as follows. Section 2 presents descriptive evidence on occupational gender composition, norms, and wage gaps. Section 3 develops the equilibrium model;

Section 4 describes data, identification, and estimation; and Section 5 presents model estimates, fit, and the wage-gap decomposition. Section 6 analyzes the counterfactuals, and Section 7 concludes.

2 Motivational evidence

This section documents the empirical patterns motivating the analysis. I first characterize occupational gender composition and its relationship with conditional gender wage gaps. I then examine how gender-role attitudes vary across workers and occupations, and how occupational norms and senior male workers' attitudes, used as a proxy for managers' attitudes, relate to wage inequality, including evidence from occupational switches.

2.1 Occupations, female shares and gender wage gaps

Occupational classification and trends To study occupational sorting, I group three-digit Census occupations into eight broad categories based on their skill requirements. While standard Census major occupation groups are organized primarily around occupational fields, this classification distinguishes occupations according to their combinations of technical, quantitative, and verbal/social requirements. It therefore brings together occupations with similar broad skill profiles, even when they belong to different professional fields. This approach is particularly relevant for studying gender differences in occupational choice, as occupational skill requirements are closely associated with the sorting of women and men across jobs.

The classification is based on three dimensions of occupational requirements measured using O*NET data[2]: technical (T), quantitative (Q), and verbal/social (VS). Each three-digit Census occupation is assigned to one of eight mutually exclusive groups according to whether its requirements lie above or below the median across occupations in each dimension. Appendix Section A.1.1 provides details on the construction of these measures and the occupational classification. The resulting groups range from N, with below-median requirements in all three dimensions, to T–Q–VS, with above-median requirements in all three. These dimensions are also closely associated with occupational gender composition. Appendix Figure A.2 shows that, in 1980, female-dominated occupations had substantially higher verbal/social and lower technical requirements than male-dominated occupations, while differences in quantitative requirements were less pronounced.

The eight groups correspond to distinct profiles of occupational requirements. N includes food services, cleaning, and basic production work; T covers predominantly manual and technical occupations, while T–Q includes skilled trades such as electricians, plumbers, and machinists. Q comprises retail sales and routine accounting work, whereas VS includes personal services, communication, and administrative support. T–VS consists largely of nursing and related healthcare occupations, and

[2]National Center for O*NET Development (2007)

Q–VS includes management, finance, business services, and administrative occupations. Finally, T–Q–VS brings together engineering, computing, medicine, teaching, and other professional and technical occupations. The complete classification is reported in Appendix Table A.2.

The relative importance of these groups changed substantially between 1980 and 2019. Appendix Figure A.1 shows that T–VS experienced the strongest relative expansion, nearly tripling its share of total employment, while Q–VS and T–Q–VS also grew considerably. As reported in Appendix Table A.1, Q–VS increased from 20.3% to 27.9% of total employment and T–Q–VS from 10.0% to 15.0%, while the shares of N, T, Q, and T–Q declined. These changes were accompanied by substantial shifts in gender composition. The female share increased by 14.0 percentage points in Q–VS and 15.6 points in T–Q–VS, whereas T–VS remained heavily female despite its expansion. Occupational segregation nevertheless remained pronounced in 2019: women represented 79.5% of employment in VS and 83.3% in T–VS, compared with 14.4% in T and 10.7% in T–Q.

Female employment shares and unexplained wage gaps The relationship between occupational gender composition and wage inequality is examined further in Table 1. Column (1) documents a substantial gender wage gap after accounting for individual characteristics and occupation, year, and state fixed effects. Column (2) introduces the female employment share of each broad occupation and its interaction with the female indicator. The positive interaction coefficient (0.162) indicates that a 10 percentage point increase in the female employment share is associated with a 1.62 log point smaller conditional gender wage gap.

This relationship is not specific to the aggregation into eight broad occupations. Appendix Figure A.3 shows a similar negative relationship between female employment shares and unexplained gender wage gaps across three-digit occupations in both 1980 and 2019. Appendix Table A.3 confirms this pattern in individual-level regressions with three-digit occupation fixed effects, including in a specification further conditioning on industry. Together, these results establish a systematic association between occupational gender composition and within-occupation wage inequality.

Table 1: Female employment shares and gender wage gaps

	Baseline	With female share
Female	-0.264***	-0.342***
	(0.001)	(0.004)
Female × Female share		0.162***
		(0.007)
Female share		0.581***
		(0.017)
Observations	1,131,891	1,131,891

Notes: The table reports the results from the following weighted regression using CPS data:

$\log(\text{hourly wage}_{it}) = \beta_0 + \beta_1 \text{female}_i + \beta_2 \text{age}_{it} + \beta_3 \text{age}_{it}^2 + \beta_4 \text{part}_{it} + \text{educ. FE} + \text{race FE} + \text{year FE} + \text{occ FE} + \text{state FE} + \epsilon_{it}$

where part_{it} indicates part-time employment and occupation fixed effects are defined for the broad occupations presented in this section. Column (2) additionally includes the female employment share at the broad occupation-year level and its interaction with the female indicator. Regressions use CPS ASEC sampling weights. Heteroskedasticity-robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Because the occupational classification is based on skill requirements, differences in the skills of women and men sorting into these occupations could potentially contribute to the observed relationship. To investigate this possibility, I use the NLSY79 and NLSY97, which provide individual measures of quantitative, technical, and verbal/social skills corresponding to the dimensions used to construct the occupational groups. Appendix Section A.2.2 presents this analysis. Figure A.4 shows broadly similar distributions of skill match among women and men employed within the same occupations. Table A.4 reproduces the relationship between female employment shares and conditional gender wage gaps in the NLSY, with an interaction coefficient of 0.156, close to the CPS estimate of 0.162. This coefficient remains unchanged when conditioning on occupational skill match and increases slightly to 0.169 when conditioning directly on individual skill endowments. These findings suggest that differences in observed skills along the dimensions defining the occupational groups are unlikely to account for the relationship.

The following sections examine attitudes toward gender norms as a potential explanation for the differences in wage inequality across occupations.

2.2 Attitudes towards gender norms and occupational choice

Data The General Social Survey[3] (GSS), conducted by NORC at the University of Chicago, is a repeated nationally representative survey of U.S. adults and one of the main sources of long-run information on social attitudes in the United States. In addition to detailed demographic and socioeconomic characteristics, the GSS repeatedly asks respondents about family, work, politics,

[3]Davern, Bautista, Freese, Herd and Morgan (2026)

and the roles of women and men in society.

I use survey waves from 1977 to 2024 and restrict the sample to respondents aged 18 to 59. I focus on four questions that are repeatedly available over this period and that speak directly to traditional gender roles. Respondents are asked whether they agree that: (i) it is better for everyone involved if the man is the achiever outside the home while the woman takes care of the home and family; (ii) most men are better suited emotionally for politics than most women; (iii) a working mother can establish as warm and secure a relationship with her children as a mother who does not work; and (iv) a preschool child is likely to suffer if his or her mother works.

To construct the individual attitudes index, I recode all responses so that higher values correspond to more traditional gender-role attitudes. The question on women's suitability for politics is binary, while the remaining three questions are originally reported on four-point scales and are converted into binary indicators. I then average the four indicators at the individual level. The resulting index ranges from zero to one, with higher values indicating stronger adherence to traditional gender roles. Appendix Table B.1 reports summary statistics for the GSS sample, the index, and its individual components.

Correlates of individual attitudes Individual attitudes towards gender roles vary systematically with demographic characteristics and occupational choice. Appendix Table A.5 reports regressions of the individual attitudes index on gender, education, occupation, a time trend, and birth-cohort fixed effects, for the full sample and separately by gender. Women hold significantly less traditional attitudes than men, with an estimated difference of 0.086 on an index ranging from zero to one. College-educated individuals also exhibit more progressive attitudes, with similar coefficients for men and women.

Attitudes also differ substantially across occupations. Relative to N, workers in VS, T–VS, Q, Q–VS, and T–Q–VS hold significantly more progressive attitudes. Importantly, these differences persist when estimating the regressions separately for men and women, suggesting that occupational heterogeneity is not simply driven by differences in gender composition. The patterns also differ across genders. Men working in VS exhibit particularly progressive attitudes, while the associations for Q–VS and T–Q–VS are substantially stronger among women. These differences are consistent with gender-specific selection into occupations, whereby individuals with less traditional attitudes are more likely to pursue careers that depart from conventional gender roles. Conversely, remaining at home is associated with more traditional attitudes among women, but not significantly so among men.

Finally, attitudes exhibit pronounced differences across birth cohorts. More recent cohorts hold systematically less traditional views, with differences reaching over 0.4 points between the earliest and latest cohorts. In contrast, the estimated time trend is small, particularly for women, for whom it is not statistically significant. Although repeated cross-sectional data do not identify the evolution of individual attitudes over the life cycle, these findings suggest that generational differences are an

important feature of the evolution of individual attitudes. They motivate the assumption in the structural model that individual attitudes remain fixed throughout adulthood.

Occupational gender norms over time To construct the occupational gender norms index, I regress individual attitudes in the GSS on college education, birth-cohort fixed effects, and a time trend, separately by gender and broad occupation. I then use these estimates to predict attitudes for CPS workers based on their characteristics and compute the weighted average within each occupation-year. This procedure captures changes in workforce composition while allowing attitudes to evolve differently across occupations and genders.

Appendix Figure A.5 shows that gender norms became progressively less traditional across all occupations between 1980 and 2019, although substantial differences persist. These differences are closely related to occupational gender composition: the correlation between the female employment share and the occupational norms index is -0.63. Importantly, this relationship is not driven solely by the greater presence of women, who tend to hold more progressive attitudes. The correlation remains negative when the index is constructed separately for men (-0.51) and women (-0.33), consistent with sorting across occupations according to individual attitudes.

2.3 Gender norms and wages

2.3.1 Relationship between occupational gender norms and the gender wage gap

Table 2 examines the relationship between occupational gender norms and conditional gender wage gaps. Column (1) documents a gender wage gap of 0.218 log points after conditioning on individual characteristics and three-digit occupation, year, and state fixed effects. Column (2) introduces the occupational gender norms index and its interaction with the female indicator. The interaction coefficient is large and negative (-0.627): a 0.1 increase in the index, indicating more traditional gender norms, is associated with a 6.27 log point larger gender wage gap. Strikingly, the coefficient on the female indicator falls from -0.218 to -0.032. The estimated conditional gender wage gap is therefore closely related to the strength of traditional gender norms, with only a small intercept remaining when the index is set to zero. Although this value lies outside the range typically observed in the data, the result reveals a remarkably strong association between occupational norms and residual gender wage inequality.

Column (3) focuses on the attitudes of men aged 40 and above as a proxy for managers' attitudes, given their influence on employers' hiring, compensation, and promotion decisions. Older workers tend to have greater professional seniority, while men have historically been overrepresented in managerial positions. Although age and gender do not directly identify managers, this measure provides an indirect proxy for the occupational norms prevailing among those likely to influence these decisions. The relationship is equally striking: a 0.1 increase in the senior male norms index is

associated with a 5.14 log point larger gender wage gap, while the coefficient on the female indicator falls further to -0.017. The estimated wage gap thus varies almost proportionally with the intensity of traditional gender norms, even when these norms are measured exclusively among senior men.

This last result is particularly informative about the potential mechanisms underlying the relationship. Women's own gender-role attitudes may influence their occupational choices, career investments, and labor supply, thereby contributing to wage differences. The strong association with senior men's attitudes is also consistent with a role for managers' attitudes in wage setting, although it does not rule out contributions from women's own career choices or other correlated occupational characteristics. While these results remain descriptive and cannot distinguish managers' attitudes from other correlated occupational characteristics, they motivate examining whether changes in the normative environment faced by individual workers are associated with changes in their wages.

Table 2: Relationship between occupational gender norms and the gender wage gap

	Baseline	With GN (all)	With GN (senior male)
Female	-0.218***	-0.032***	-0.017***
	(0.001)	(0.006)	(0.005)
Female × GN index		-0.627***	
		(0.017)	
GN index		0.678***	
		(0.048)	
Female × Senior male GN index			-0.514***
			(0.011)
Senior male GN index			0.767***
			(0.015)
Observations	1,131,891	1,131,891	1,131,891
R^2	0.437	0.438	0.439

Notes: The baseline model in column (1) consists in the weighted regression (with CPS data):

$\log(\text{hourly wage}_{it}) = \beta_0 + \beta_1 \text{female}_i + \beta_2 \text{age}_{it} + \beta_3 \text{age}_{it}^2 + \beta_4 \text{part}_{it}$ +education FE+race FE+year FE+3-d.occ FE+state FE+ϵ_{it}

Columns (2) and (3) further include the gender norm index at the broad occupation-by-year level, computed using all workers and senior male workers only, respectively, as well as an interaction with the female indicator. Heteroskedasticity-robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.3.2 Wage dynamics around occupational switches

To complement the relationship between senior male workers' attitudes and conditional gender wage gaps documented above, I examine wage trajectories around occupational switches to destinations where senior men hold more or less traditional attitudes than in workers' occupations of origin. This descriptive analysis exploits within-worker variation in occupations and allows me to assess whether

the patterns are primarily associated with women's wages, men's wages, or both.

I use data from the National Longitudinal Survey of Youth 1979 (NLSY79) and the National Longitudinal Survey of Youth 1997 (NLSY97), two longitudinal surveys tracking individuals' employment and earnings histories. From the sample used for the structural estimation, I identify each worker's first eligible switch between the eight broad occupational groups, requiring a stable origin occupation before the switch and a stable destination afterward. I retain workers observed with valid hourly wages and working hours in six consecutive years, from two years before the switch to three years after. The resulting sample consists of 1,162 movers (539 women and 623 men). The distribution of occupational transitions is reported in Appendix Figure C.1 and Table C.1.

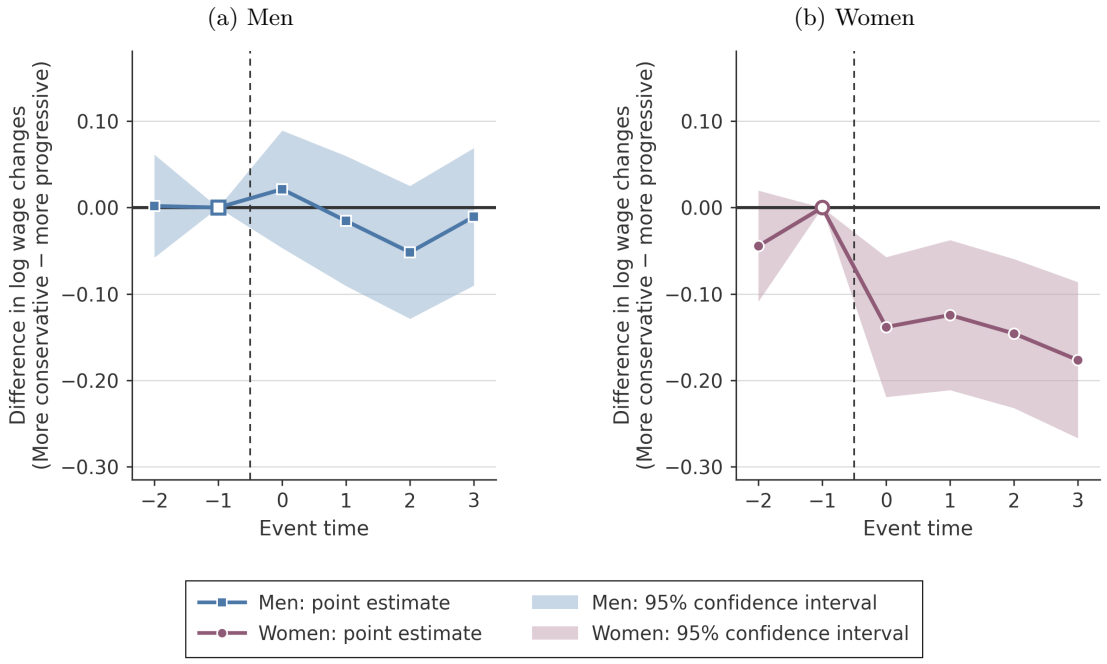
For each mover, I compute the change in occupational gender norms between the destination and origin occupations, evaluated in the year of the switch using the predicted attitudes of senior male workers. I define $D_i = \mathbf{1}\{\Delta N_i > 0\}$, where ΔN_i is the change in the norm index, so that $D_i = 1$ denotes a move toward more conservative norms and $D_i = 0$ a move toward more progressive norms. I estimate separately for women and men:

$$\log w_{ist} = \alpha_{is} + \delta_{st} + \rho_{\text{age}_{it}s} + \theta_s PT_{it} + \sum_{r \neq -1} \gamma_{sr} \mathbf{1}\{\tau_{it} = r\} + \sum_{r \neq -1} \beta_{sr} D_i \mathbf{1}\{\tau_{it} = r\} + \varepsilon_{ist}$$

Here, τ_{it} denotes event time, with the year preceding the switch ($r = -1$) as the reference period. The specification includes individual, calendar-year, and age fixed effects, together with a time-varying part-time employment indicator. The event-time indicators account for wage dynamics common to both groups, while β_{sr} measures the difference in wage changes between moves toward more conservative and more progressive attitudes of senior male workers, relative to the pre-switch year. Standard errors are clustered at the individual level.

Figure 1 reveals a marked difference between women's and men's wage trajectories around occupational switches. Among women, moves to occupations where senior male workers hold more traditional attitudes than in their occupation of origin are associated with significantly lower wage growth than moves to occupations where their attitudes are less traditional. The difference emerges at the time of the switch, reaching approximately 0.14 log points, and persists over the following three years, reaching 0.18 log points. In contrast, men's wage trajectories exhibit no systematic relationship with changes in senior men's attitudes, with coefficients close to zero and statistically insignificant throughout the event window. The corresponding estimates are reported in Table C.2. The pre-switch difference is small and statistically insignificant in the main specification. Extending the window to three years before the switch (Appendix Figure C.2) reveals some differences in earlier wage trajectories, although the post-switch divergence remains substantially larger.

Figure 1: Wage trajectories following occupational switches: more conservative vs. more progressive gender norms



Notes: The figure compares changes in log hourly wages for workers moving toward more versus less conservative occupational gender norms, relative to the year before the switch ($r = -1$). Norms are measured using senior male workers' attitudes. Estimates use pooled NLSY79 and NLSY97 data, with individual, year, and age fixed effects, common event-time indicators, and a part-time indicator. Shaded areas show 95% confidence intervals, with standard errors clustered by individual.

These findings suggest that the relationship between senior male workers' attitudes and the gender wage gap is more closely associated with women's wage trajectories than with men's. In particular, the absence of a comparable pattern among men is difficult to reconcile with an explanation based solely on gender-neutral differences in occupational pay or higher wage premia for men in more progressive occupations. Nevertheless, women's own gender-role attitudes may also contribute to these patterns through their career choices and human capital accumulation. The structural model developed below allows me to distinguish these channels from the role of managers' attitudes in wage setting.

3 Model

The model combines dynamic worker sorting with employer wage setting. Workers differ in their attitudes toward gender roles, which affect participation and sorting across occupations. Employment dynamics arise from changes in household composition and from costs of re-entering employment and switching across broad occupations. Employers have wage-setting power because workers have

heterogeneous preferences over firms and occupations. Managers' gender-role attitudes additionally influence wage setting by shaping their expectations of women's productivity, with these attitudes varying across occupations and over time.

3.1 Individual attitudes, occupational norms, and managerial attitudes

Individual attitudes toward gender roles Gender norms are social prescriptions concerning the roles considered appropriate for women and men in society, at work, and within the family. Individuals differ in their attitudes toward these norms, holding more or less traditional views about gender roles.

Let n denote an individual's gender-role attitudes, with higher values corresponding to more traditional views. Attitudes are determined by a linear function of gender s, education e, and birth cohort c, together with a permanent component of unobserved heterogeneity ζ:

$$n = f(s, e, c) + \zeta, \qquad 0 \leq n \leq 1. \tag{1}$$

The observed component captures systematic differences across demographic groups and cohorts, while ζ allows otherwise observationally similar individuals to hold persistently different attitudes. Individual attitudes are assumed to remain fixed throughout adulthood, consistent with the pronounced cohort differences documented in the empirical analysis.

Occupational gender norms Let N_{jt} denote the prevailing gender norms in broad occupation j at time t, defined as the average gender-role attitudes of workers employed in that occupation.

Occupational norms are therefore endogenously determined by the composition of the workforce in equilibrium. Individuals with different attitudes may find different occupational environments more or less attractive. Sorting consequently occurs not only along observable characteristics such as gender, education, and cohort, but also along the unobserved component ζ. Through their occupational choices, workers collectively shape the normative environment prevailing in each occupation.

Managerial attitudes Beyond the norms prevailing among workers as a whole, the gender-role attitudes of managers and supervisors may influence firms' decisions. Acting on behalf of firms, managers may determine or influence hiring, job assignments, performance evaluations, promotions, and compensation. I define occupation-level managerial attitudes N^M_{jt} as the average gender-role attitudes of managers within occupation j at time t.

I proxy managerial attitudes using the average attitudes of senior male workers in the occupation. Senior workers are more likely to hold positions of authority and influence personnel decisions, while men have historically been overrepresented in managerial and supervisory roles. Their attitudes

thus provide a proxy for the normative environment among those influencing firms' decisions. The role of managerial attitudes in wage setting is developed in Section 3.3.

3.2 Career decisions and the labor supply

The supply side of the model describes workers' dynamic sorting across occupational environments and determines the labor-supply elasticity faced by employers. This elasticity depends on both employer availability and substitution across alternatives, so labor market power can vary across occupations and worker groups, generating gender wage differences independently of managerial attitudes.

Individual's problem Individuals enter the model after completing their education, at age 18 for non-college workers and age 22 for college workers. They make annual labor-market decisions until retirement at age 60, after which they receive zero utility.

Career alternatives follow a three-level nested structure. At the upper level, workers choose between non-employment, denoted by u, and eight broad occupational groups j, representing fields of career specialization with distinct skill requirements and prevailing gender norms. This specialization is relatively persistent, whereas choices within each field are more flexible. Conditional on j, workers choose a detailed occupation o, among 264 in total, and part- or full-time work h. Finally, they choose among the K_{jot} employers available in that occupation, which may offer both part- and full-time jobs.

Employers within a given (j, o, t) are assumed symmetric in technology and equilibrium wage policies, offering identical category-specific wage schedules. Nevertheless, workers have idiosyncratic preferences over workplaces, making employers imperfect substitutes and giving individual firms upward-sloping labor supply. Employer choice can therefore be integrated out, with each detailed-occupation and hours alternative incorporating an inclusive value that depends on the common wage offer and the number of available employers K_{jot}.

Substitution across employers within (j, o, h) is governed by the scale parameter ρ^I, while ρ_s^T governs substitution across detailed occupations and hours arrangements within broad occupation j. The upper-level scale is normalized to one, with $0 < \rho^I < \rho_s^T < 1$. This nesting reflects the correlation structure of idiosyncratic preferences rather than a literal sequence of decisions.

Individuals differ by gender s, age a, education e, birth cohort c, gender-role attitudes n, and family status l, which combines marital status with the presence and age of children. A permanent component ζ of attitudes captures unobserved heterogeneity. State variables also include the previous broad occupation, allowing for costs of changing career specialization and re-entering employment after a period at home. Detailed occupation, hours, and employer identity are not carried into the next-period state.

Let $z_t = (x_t, \zeta, \boldsymbol{\nu}_t)$ denote the individual's state, where $x_t \in \mathcal{X}$ collects the observable state variables, $\zeta \in \Xi$ is the permanent unobserved component of individual attitudes, and $\boldsymbol{\nu}_t$ is the vector of current idiosyncratic preference shocks. The individual's problem is:

$$V_t(z_t) = \max_{j,o,h} \{U_{joh,t}(z_t) + \beta \mathbb{E}\left[V_{t+1}(z_{t+1}) \mid z_t, j\right]\} \tag{2}$$

where o and h are relevant only when $j \neq u$. Because these choices do not enter the next-period state, the continuation value depends on the broad occupation j but not on the detailed occupation or hours arrangement. Under the nested extreme-value structure, their choices can therefore be summarized by an inclusive value when solving the dynamic problem over broad occupations and non-employment. Family status evolves stochastically, while the current broad occupation determines the corresponding state next period. Individuals cannot save, so current labor income is consumed within the period.

Preferences Utility from employment depends on wages, occupational gender norms, individual attitudes, family circumstances, working hours, previous employment and broad occupation, and idiosyncratic preferences. Wages enter through log weekly income with a gender-specific coefficient α_s. Workers value occupational environments partly according to the match between their own gender-role attitudes and prevailing norms N_{jt}. Beyond this norm-matching component, attitudes also shape preferences for different career paths, through γ_{sj} at the broad-occupation level and γ_{sjo} at the detailed-occupation level. Family circumstances affect the value of employment and preferences for part- versus full-time work. Employer availability K_{jot} enters through the employer-level inclusive value. Previous period non-employment generates a cost of re-entering the labor force, and switching broad occupation generates a disutility cost. Utility from non-employment is normalized to zero.

Expectations Individuals are forward-looking about the consequences of their own choices but hold the aggregate economic environment fixed when forming expectations. In calendar year t, they evaluate future choices using the wage schedules and occupational gender norms prevailing in t, while accounting for the effect of current broad-occupation choices on future switching and re-entry costs. Family status evolves according to transition probabilities that depend on individual characteristics and the current family state. Workers take these future family transitions into account when making current labor-market decisions.

Labor supply and elasticity The nested choice structure determines the elasticity of labor supply faced by an individual employer and therefore its wage-setting power.

Consider a continuum of individuals with total mass normalized to one. Let F_t denote the joint distribution of observable states $x_t \in \mathcal{X}$ and permanent unobserved heterogeneity $\zeta \in \Xi$ in the population at time t. In a symmetric equilibrium, employers within (j, o, t) offer the same category-specific wage vector $\mathbf{w}_{joht}$ for each hours arrangement h. Let $p_t(j, o, h, k \mid x_t, \zeta; \mathbf{w}_{joht})$ denote

the probability of choosing broad occupation j, detailed occupation o, hours arrangement h, and employer k, given these wage offers and those available elsewhere. Labor supply to employer k for hours arrangement h is:

$$S_{johkt}(\mathbf{w}_{joht}) = \int_{\mathcal{X}\times\Xi} p_t(j, o, h, k \mid x_t, \zeta; \mathbf{w}_{joht})\, dF_t(x_t, \zeta) \tag{3}$$

Employers set wages by gender s, education e, and age a.[4] Let $\mathcal{X}_{sea} \subseteq \mathcal{X}$ denote the subset of states corresponding to these characteristics. Labor supply from this worker category is:

$$S_{seajohkt}(\mathbf{w}_{joht}) = \int_{\mathcal{X}_{sea}\times\Xi} p_t(j, o, h, k \mid x_t, \zeta; \mathbf{w}_{joht})\, dF_t(x_t, \zeta) \tag{4}$$

so that $S_{johkt} = \sum_{s,e,a} S_{seajohkt}$.

Conditional on (x_t, ζ), symmetry implies:

$$p_t(k \mid j, o, h, x_t, \zeta; \mathbf{w}_{joht}) = \frac{1}{K_{jot}} \tag{5}$$

The relevant elasticity considers a unilateral change in employer k's wage offer, holding all other wage offers fixed. Conditional on (x_t, ζ), the elasticity of labor supply equals that of the corresponding choice probability:

$$\begin{aligned}
\varepsilon_{seajohkt}(x_t, \zeta) &= \frac{\partial \log p_t(j, o, h, k \mid x_t, \zeta; w_{seajoht})}{\partial \log w_{seajoht}} \\
&= \frac{\alpha_s}{K_{jot}} \left[\frac{K_{jot} - 1}{\rho^I} + \frac{1 - p_t(o, h \mid j, x_t, \zeta; w_{seajoht})}{\rho^T_s} \right. \\
&\quad \left. + p_t(o, h \mid j, x_t, \zeta; w_{seajoht}) \left[1 - p_t(j \mid x_t, \zeta; w_{seajoht})\right] \right]
\end{aligned} \tag{6}$$

The three terms capture substitution toward another employer within the same (j, o, h), toward another detailed occupation or hours arrangement within j, and toward another broad occupation or non-employment.

Employers offer a common wage to workers within each (s, e, a, j, o, h) category, without observing their permanent type ζ. For each type ζ_{sq}, the relevant elasticity first aggregates over the remaining individual states:

$$\varepsilon_{seajohkt|\zeta_{sq}} = \frac{\int_{\mathcal{X}_{sea}} p_t(j, o, h, k \mid x_t, \zeta_{sq}; w_{seajoht}) \varepsilon_{seajohkt}(x_t, \zeta_{sq})\, dF_t(x_t, \zeta_{sq})}{\int_{\mathcal{X}_{sea}} p_t(j, o, h, k \mid x_t, \zeta_{sq}; w_{seajoht})\, dF_t(x_t, \zeta_{sq})} \tag{7}$$

[4] Three-digit occupations encompass different job titles and responsibilities, while age does not uniquely determine accumulated work experience. Gender-specific wage schedules should therefore not be interpreted as unequal pay for substantially equal work. This distinction is discussed further in the labor demand section.

The elasticity faced by the employer further aggregates across the permanent types:

$$\begin{aligned}\varepsilon_{seajohkt} &= \frac{\partial S_{seajohkt}}{\partial w_{seajoht}} \times \frac{w_{seajoht}}{S_{seajohkt}} \\ &= \sum_q \frac{S^{(q)}_{seajohkt}}{S_{seajohkt}} \varepsilon_{seajohkt|\zeta_{sq}}\end{aligned} \tag{8}$$

where

$$S^{(q)}_{seajohkt} = \int_{\mathcal{X}_{sea}} p_t(j, o, h, k \mid x_t, \zeta_{sq}; w_{seajoht})\, dF_t(x_t, \zeta_{sq})$$

Here, $F_t(x_t, \zeta_{sq})$ denotes the population distribution restricted to type ζ_{sq}, without renormalization. Thus, the firm-facing elasticity is a labor-supply-weighted average across individual states and permanent types. Employer availability and the attractiveness of alternatives throughout the choice hierarchy determine the resulting wage-setting power, which may differ across worker categories and occupations. The demand side uses these elasticities to distinguish wage differences arising from imperfect competition from those associated with expected productivity, including managers' assessments of women's productivity.

3.3 Labor demand and wage setting

Aggregate production A single final good is produced by combining the outputs of detailed occupations. Let $\mathcal{O}_j$ denote the set of detailed occupations o within broad occupation group j. The final-good technology is:

$$Y_t = \left[\sum_j \sum_{o \in \mathcal{O}_j} y^{\sigma}_{jot} \right]^{1/\sigma}, \qquad -\infty < \sigma < 1 \tag{9}$$

where $1/(1-\sigma)$ is the elasticity of substitution across occupational outputs.

Each detailed occupation o contains K_{jot} firms. Their role in the model is to allow the degree of competition for workers to vary across occupations, rather than to capture heterogeneity among firms within an occupation. Accordingly, I abstract from within-occupation differences in technology and occupational environment and assume that firms within (j, o, t) are symmetric.

Firm k in detailed occupation o produces:

$$y_{jokt} = T_{jot} \sum_{h \in \{20,40\}} h \left(\omega_{seajoht}\right)'_{s,e,a} \mathbf{S}_{johkt}(\mathbf{w}_{johkt}) \tag{10}$$

where T_{jot} denotes occupation-specific productivity, $\omega_{seajoht}$ is the realized average productive efficiency of workers in category (s, e, a, j, o, h, t), and $\mathbf{S}_{johkt}$ is the corresponding vector of labor supplies. Hours equal 20 or 40 for part- and full-time work, respectively.

Output in detailed occupation o is then:

$$y_{jot} = \sum_{k=1}^{K_{jot}} y_{jokt} \tag{11}$$

Worker productivity Productive efficiency of a worker i depends on his accumulated human capital, current hours, education, occupation, and time:

$$\omega_{it} = \Omega\left(A_{it}, h_{it}, e_i; j, o, t\right) \tag{12}$$

where A_{it} is the stock of accumulated human capital available to worker i at time t, h_{it} is the current hours choice, and e_i is education. I allow part-time work to be less productive per hour than full-time work, and the productivity returns to accumulated human capital, hours, and education to vary across occupations and over time.

Let $\mathbf{g}_{it} = (g_{i\tau})_{\tau<t}$ denote the individual's employment history from the end of education through period $t-1$, with one element for each year, equal to one if the individual worked during that year and zero otherwise. Following the work-history approach of Light and Ureta (1995), the timing of experience matters because previously accumulated human capital depreciates. Thus,

$$A_{it} = \sum_{\tau<t} \delta^{\,t-1-\tau} g_{i\tau}, \qquad 0 < \delta \leq 1 \tag{13}$$

where the sum runs over years since the individual completed education.

I assume that firms do not perfectly observe individual employment histories. Instead, they form expectations about past participation conditional on workers' gender, age, education, current broad occupation, and year. Expected accumulated human capital is therefore:

$$\mathbb{E}(A_{it} \mid s_i, a_{it}, e_i, j, t) = \sum_{\tau<t} \delta^{\,t-1-\tau} \mathbb{E}(g_{i\tau} \mid s_i, a_{it}, e_i, j, t) \tag{14}$$

Groups with more frequent career interruptions consequently have lower expected accumulated human capital, particularly when these interruptions are recent, since recent experience receives greater weight when $\delta < 1$.

I further assume that the productive-efficiency function Ω is identical for women and men. Conditional on accumulated human capital, education, current hours, occupation, and time, workers have the same productive efficiency regardless of gender. Gender differences in productivity can therefore arise through differences in accumulated human capital, but not through gender-specific differences in the production technology.

Managerial attitudes and expected productivity Managers' attitudes toward gender roles may influence their expectations about workers' productivity. Managers holding more traditional

views, according to which men should primarily provide for their families while women should take responsibility for caregiving, may expect women to prioritize family obligations over professional commitments. They may consequently anticipate lower work effort, more frequent absences, or more limited availability, leading them to underestimate women's productive contributions. These expectations need not reflect actual differences in productivity.

I assume that managers' expectations depend on both the broader normative environment and the attitudes prevailing within their occupation. Let N_{jt}^M denote occupation-level managerial attitudes, and $\bar{N}_t^M$ their aggregate average:

$$\bar{N}_t^M = \sum_j \text{share}_{jt}^M N_{jt}^M, \tag{15}$$

where share_{jt}^M denotes occupation j's share of all managers at time t.

I allow the influence of managerial attitudes on expected female productivity to differ between the general level of traditional attitudes and occupational deviations from that level. More traditional attitudes in the broader managerial environment may reinforce expectations that women devote less effort and availability to their careers. Within this environment, managers in occupations with relatively more traditional attitudes may hold particularly unfavorable expectations about women's productive contributions. I therefore specify the adjustment to expected female productivity as:

$$\mathcal{D}(\bar{N}_t^M, N_{jt}^M) = D_L \bar{N}_t^M + D_R(N_{jt}^M - \bar{N}_t^M). \tag{16}$$

The parameters D_L and D_R allow the broader normative environment and occupation-specific differences in managerial attitudes to have distinct effects on expected female productivity.

Using workers' observable characteristics to infer their accumulated human capital, managers form expectations about their productive efficiency. These expectations also depend on managerial attitudes toward gender roles:

$$\mathbb{E}\left(\omega_{it} \mid s_i, a_{it}, e_i, j, o, h, t, \bar{N}_t^M, N_{jt}^M\right) = \underbrace{\mathbb{E}\left(\omega_{it} \mid s_i, a_{it}, e_i, j, o, h, t\right)}_{\substack{\text{Expected productivity given} \\ \text{observable worker characteristics}}} \times \underbrace{\frac{1}{1 + \mathbf{1}\{s_i = \text{female}\}\mathcal{D}(\bar{N}_t^M, N_{jt}^M)}}_{\substack{\text{Effect of managerial attitudes} \\ \text{on expected productivity}}}$$

Managerial attitudes thus influence the productivity managers expect women to contribute, beyond differences in accumulated human capital and other productive characteristics. This influence applies only to expectations: actual productive efficiency remains determined by the common productivity technology Ω.

Imperfect competition and wage-setting power Following Card et al. (2018), heterogeneous preferences over firms' work environments give employers wage-setting power. As established on the supply side, workers respond to wage changes by substituting across employers, occupations, hours arrangements, and non-employment, with the resulting elasticities varying across worker categories

and occupations.

Firms within (j, o, t) are symmetric in technology and occupational environment and offer identical wage schedules in equilibrium. They set wages by gender s, education e, age a, and hours arrangement h, rather than for individual workers. The relevant firm-level labor-supply elasticity, $\varepsilon_{seajohkt}$, is derived in the supply section by integrating individual choice responses over observable states and permanent unobserved heterogeneity. When setting wages, each firm considers a unilateral deviation from the symmetric equilibrium, taking competitors' wage schedules as given. I additionally treat part- and full-time positions within the same employer as separate wage-setting units.[5]

Employer problem and wage setting Let $\bar{y}_{jokt}$ denote the firm's optimal output level. Conditional on this quantity, firm k chooses the wage vector $\mathbf{w}_{jokt}$ to minimize labor costs, using its expectations of workers' productivity to evaluate the production constraint:

$$\min_{\mathbf{w}_{jokt}} \sum_{h \in \{20,40\}} h \, \mathbf{w}'_{johkt} \mathbf{S}_{johkt}(\mathbf{w}_{johkt}) \tag{17}$$

subject to the production expected from the workers it employs:

$$T_{jot} \sum_{h \in \{20,40\}} h \left(\mathbb{E}\left[\omega_t \mid s, e, a, j, o, h, t, \bar{N}_t^M, N_{jt}^M \right] \right)'_{s,e,a} \mathbf{S}_{johkt}(\mathbf{w}_{johkt}) \geq \bar{y}_{jokt} \tag{18}$$

where $\mathbf{w}_{jokt}$ collects the wage vectors $\mathbf{w}_{johkt}$ offered for part- and full-time positions. Each $\mathbf{w}_{johkt}$ contains the wages offered to workers by gender s, education e, and age a, while $\mathbf{S}_{johkt}(\mathbf{w}_{johkt})$ is the corresponding vector of category-specific labor supply functions $S_{seajohkt}$ defined in the labor supply section. The vector $\left(\mathbb{E}[\omega_t \mid s, e, a, j, o, h, t, \bar{N}_t^M, N_{jt}^M] \right)_{s,e,a}$ contains the productive efficiency expected by managers for each worker category, with entries ordered consistently with the wage and labor supply vectors. Individuals in the same category receive the same wage, while the firm's expected production reflects the productive contributions anticipated from each category. Importantly, the production constraint is based on managers' expectations, which may underestimate women's productivity. Actual output remains determined by the production technology in equation (10).

The firm's wage-setting decision internalizes the response of labor supply to wages. Using the category-level labor-supply elasticity $\varepsilon_{seajohkt}$ defined above, let

$$\phi_{seajohkt} = \frac{\varepsilon_{seajohkt}}{1 + \varepsilon_{seajohkt}} \tag{19}$$

This term determines the fraction of the marginal revenue product assessed by managers that the firm offers in wages, given its labor market power. The associated oligopsony markdown is $1 - \phi_{seajohkt} = 1/(1 + \varepsilon_{seajohkt})$.

[5]Worker choices remain jointly determined across part- and full-time alternatives, but the employer does not internalize the cross-hours employment effect when setting the wage of a given hours arrangement.

The marginal revenue product per hour for category (s, e, a, j, o, h) is

$$MRP_{seajoht} = \frac{\partial Y_t}{\partial y_{jot}} \mu_t T_{jot} \omega_{seajoht} \tag{20}$$

Here, μ_t denotes the common marginal cost of production, corresponding to the Lagrange multiplier in the firm's cost-minimization problem. The marginal revenue product combines this value with occupation-specific technology T_{jot} and worker productive efficiency $\omega_{seajoht}$.

Using the expected productivity specified above, the first-order condition for wage setting gives:

$$w_{seajohkt} = \phi_{seajohkt} \underbrace{\frac{\mathbb{E}\left(MRP_{seajoht}\right)}{1 + \mathbf{1}\{s = \text{female}\}\mathcal{D}(\bar{N}_t^M, N_{jt}^M)}}_{\substack{\text{Marginal revenue product} \\ \text{expected by managers}}} \tag{21}$$

Wages thus depend on three distinct factors: workers' expected productive efficiency based on their characteristics and predicted accumulated human capital, the firm's wage-setting power, and the influence of managerial attitudes on expected female productivity. The latter reduces the marginal revenue product managers anticipate from employing women, leading to lower wage offers without any corresponding reduction in actual productive efficiency.

Gender-specific wage schedules should not, however, be interpreted as otherwise identical men and women performing exactly the same narrowly defined job receiving different wages. Detailed occupations encompass heterogeneous positions and job titles, so gender differences may also reflect assignment across positions and productive characteristics imperfectly observed in the data.

Wages are set before production takes place and cannot be adjusted retrospectively to realized output. Although actual productive contributions may exceed managers' expectations, individual performance is imperfectly observed. Moreover, realized firm output is subject to substantial idiosyncratic fluctuations, which managers cannot distinguish from individual contributions or compare with the unobserved shocks experienced by competing firms. I assume that these fluctuations are sufficiently large to prevent realized output from providing informative signals about the accuracy of managers' expectations.[6] As a result, productive contributions exceeding those anticipated by managers generate additional realized revenue without affecting previously determined wages, and the resulting gains accrue to firms as profits.

Managerial attitudes and labor market power can also interact through workers' occupational choices. Lower wages in occupations with more traditional managerial attitudes reduce the attractiveness of these alternatives, affecting labor supply and employers' wage-setting power elsewhere. Because workers have heterogeneous preferences over occupations and firms, they cannot costlessly reallocate toward environments with more favorable expectations of women's productivity. These interactions are captured by the equilibrium determination of wages and occupational choices.

[6] Firm-specific output fluctuations motivate the persistence of managers' expectations but are not explicitly introduced into the production technology or wage-setting equations.

3.4 Equilibrium

Definition At each date t, an equilibrium is a collection of worker decision rules, wage schedules, labor allocations, occupational outputs, and occupational gender norms such that workers optimally solve their dynamic career problem given wages, norms, and employer availability; firms optimally set wages given the resulting labor-supply schedules and the expected marginal value of occupational output; labor allocations are consistent with workers' choice probabilities and firm symmetry; outputs satisfy equations (10) and (9); and occupational gender norms and managerial attitudes are consistent with the composition of workers and managers, respectively, sorting into each occupation.[7]

Relative wages Consider a woman and a man of the same age and education, working the same hours in the same detailed occupation (j, o) at date t. Their relative hourly wage can be written as:

$$\frac{w^f}{w^m} = \underbrace{\frac{\mathbb{E}(MRP^f)}{\mathbb{E}(MRP^m)}}_{\text{productivity}} \times \underbrace{\frac{\phi^f}{\phi^m}}_{\text{oligopsony}} \times \underbrace{\frac{1}{1 + \mathcal{D}(\bar{N}_t^M, N_{jt}^M)}}_{\text{managerial attitudes}} \tag{22}$$

The first term captures differences in expected marginal revenue products arising from human capital accumulation. Since employers do not observe workers' complete employment histories, they infer accumulated human capital from observable characteristics. Women and men may therefore have different expected human capital because of differences in their past employment histories. The second term captures differences in wage-setting power: if labor supply from the female worker category is less elastic, then $\phi^f < \phi^m$, implying a larger wage markdown for women. The final term captures the additional influence of managers' attitudes on their expectations of women's productivity, independently of differences in actual productive efficiency.

4 Identification, estimation and data

I estimate the model by combining information on workers' career choices with wages and employment patterns across occupations. The supply side is estimated separately by gender, jointly using longitudinal career histories from the NLSY and cross-sectional information from the CPS. These estimates recover workers' dynamic choice behavior and the labor-supply elasticities faced by firms. On the demand side, I combine these elasticities with CPS wage data and the model's production structure to estimate worker productivity and the influence of managerial attitudes on wage setting. Together, the two sides of the model allow me to distinguish three sources of gender wage differences: expected productivity differences arising from human capital accumulation, wage

[7] The number of firms K_{jot} in each detailed occupation and year is taken as given. Wages, employment, output, and occupational gender norms are jointly determined in equilibrium, but firm entry and exit are not modeled.

markdowns associated with employer labor market power, and the influence of managerial attitudes on employers' expectations of women's productivity.

4.1 Labor supply: identification and estimation

I estimate the supply side separately by gender by maximum likelihood. The framework combines a finite-horizon dynamic discrete-choice model of participation and broad occupational choice, in the spirit of Keane and Wolpin (1997), with a nested GEV structure for detailed occupation, hours, and employer choice (McFadden, 1978). The combination of longitudinal career histories with cross-sectional information on occupational choices is also close in spirit to Llull (2018). In my setting, I jointly use NLSY career histories and cross-sectional information from the CPS, imposing the same structural parameters across both samples and allowing for a common distribution of permanent unobserved heterogeneity. For each candidate parameter vector, the dynamic problem is solved by backward induction and the two likelihood contributions are evaluated jointly.

State variables At age a, the individual state contains gender s, education e, family status l, previous broad occupation j_{t-1}, and individual attitudes. Education and the observed component of attitudes are fixed, age evolves deterministically, and family status evolves stochastically. Previous broad occupation is endogenous and generates costs of re-entering employment and switching broad occupations. Detailed occupation, hours, and employer identity affect current utility but are not carried into the next-period state.

Permanent unobserved heterogeneity Individual attitudes are written as:

$$n_{iq} = \bar{n}_i + \zeta_{sq} \tag{23}$$

where $\bar{n}_i$ is the observed component of attitudes and ζ_{sq} is a permanent component known to the individual but unobserved by the econometrician. I approximate its distribution separately by gender using three ordered mass points and impose a mean-zero normalization. To address the initial-conditions problem, I initialize all individuals at age 15 as single, with no child in the household and no previous employment attachment, and propagate demographic transitions forward from this common state. Labor-market choices begin at age 18 for non-college workers and age 22 for college workers.

Demographic transitions Family status combines marital status with three child states: no child in the household, a youngest child aged 4–18, and a youngest child aged 0–3. Annual transitions in marital status and the presence of children are modeled jointly, while a separate conditional transition determines whether a child is young. Transition probabilities depend on current family

status, age, education, calendar time, and individual attitudes. When forming expectations in year t, workers let age and family status evolve but evaluate future demographic transitions under the calendar environment prevailing in t, consistently with the static-expectations assumption described above.

Flow utility The flow utility from choosing broad occupation j and lower-nest alternative (o, h) can be decomposed into a component that is common to all detailed alternatives within j, denoted u^T_{isjt}, and a component governing detailed occupation and hours choices within the broad occupation, denoted u^I_{isjoht}:

$$\begin{aligned} u_{isjoht} = & \underbrace{\gamma_s \left(n_{iq} - N_{jt}\right)^2 + \gamma_{sj} n_{iq} + \mu^A_s \mathbf{1}\{\text{married}_{it}\} + \mu^Y_s \mathbf{1}\{\text{young child}_{it}\} - \kappa^R_s R_{it} - \kappa^J_s S_{ijt}}_{u^T_{isjt}} \\ & + \underbrace{\alpha_s \left[\log w_{seajoht} + \log h\right] + \rho^I \log K_{jot} + \gamma_{sjo} n_{iq} + \chi_{sl_{it}} \mathbf{1}\{h = \text{PT}\}}_{u^I_{isjoht}} + \upsilon_{isjoht} \end{aligned} \tag{24}$$

At the broad-occupation level, $\gamma_s(n_{iq} - N_{jt})^2$ captures the value of the match between the worker's attitudes and the gender norms prevailing in occupation j, while $\gamma_{sj} n_{iq}$ allows workers with different attitudes to sort differently across broad occupations beyond this norm-matching channel. The terms μ^A_s and μ^Y_s allow marriage and the presence of a young child to affect the attractiveness of working, while κ^R_s and κ^J_s capture the costs of re-entering employment and switching broad occupations. Utility from home is normalized to zero.

Conditional on j, α_s governs the value of earnings, $\rho^I \log K_{jot}$ captures the additional choice value generated by access to more employers, and $\gamma_{sjo} n_{iq}$ allows attitudes to affect sorting across detailed occupations. The part-time utility shifter $\chi_{sl_{it}}$ varies with the worker's current family status. Finally, υ_{isjoht} denotes the idiosyncratic taste shock associated with alternative (j, o, h). The vector of taste shocks across alternatives follows a generalized extreme-value distribution consistent with the nested choice structure, allowing shocks to be correlated within nests.

Employers within a given (j, o, t) are symmetric and offer the same category-specific wage schedule, although workers have idiosyncratic preferences over them. Employer choice can therefore be integrated out. Under symmetry, the number of available employers contributes the term $\rho^I \log K_{jot}$ to the value of the (o, h) alternative. I calibrate $\rho^I = 0.145$ using the mean detailed nesting parameter in Azar et al. (2022).

Choice probabilities Let x_{it} denote the observed state variables relevant for the current decision, and let q denote the worker's permanent latent type, which determines the latent component of

attitudes. Conditional on broad occupation j, detailed occupation and hours have probability:

$$P^I_{isoht|j}(x_{it}, q) = \frac{\exp\Big(u^I_{isjoht}(x_{it}, q)/\rho^T_s\Big)}{\sum_{o',h' \in j} \exp\Big(u^I_{isjo'h't}(x_{it}, q)/\rho^T_s\Big)} \tag{25}$$

with inclusive value:

$$IV_{isjt}(x_{it}, q) = \rho^T_s \log\left[\sum_{o,h \in j} \exp\Big(u^I_{isjoht}(x_{it}, q)/\rho^T_s\Big)\right] \tag{26}$$

Because detailed occupation and hours do not affect next period's state, they do not need to be carried as dynamic state variables. Their contribution to the value of broad occupation j is summarized by the inclusive value.

For broad occupation j, the choice-specific value is:

$$v_{isjt}(x_{it}, q) = u^T_{isjt}(x_{it}, q) + IV_{isjt}(x_{it}, q) + \beta \mathbb{E}\left[V_{i,t+1}(x_{i,t+1}, q) \mid x_{it}, j, q\right]. \tag{27}$$

The upper-level extreme-value scale is normalized to one and I set $\beta = 0.95$.

Likelihood The NLSY and CPS contributions are estimated jointly using the same structural parameters and distribution of permanent types. Let π_{sq} denote the probability of belonging to permanent type q for an individual of gender s, with $\sum_q \pi_{sq} = 1$. For an NLSY individual i, let $L^{NLSY}_{iq}(\theta_s)$ denote the probability of the complete observed history conditional on type q. It includes the observed sequence of broad labor-market choices and family-status transitions, while unobserved choices and states between interviews are summed over.

For a CPS individual, the detailed occupation and hours choice is observed conditional on the broad occupation j. Since the permanent type also affects broad occupational choices and the evolution of the observed state x_{it}, the conditional probability of (o, h) averages $P^I_{ioht|j}(x_{it}, q)$ over the model-implied distribution of q conditional on x_{it} and the observed broad occupation:

$$P_{ioht|j}(x_{it}) = \sum_q \Pr(q \mid x_{it}, j)\, P^I_{ioht|j}(x_{it}, q). \tag{28}$$

These conditional type probabilities depend on the population shares π_{sq} and the model-implied sorting of permanent types across states and occupations.

The joint log-likelihood is therefore:

$$\ell_s(\theta_s) = \sum_{i \in NLSY_s} \log\left[\sum_q \pi_{sq} L^{NLSY}_{iq}(\theta_s)\right] + \sum_{i \in CPS_s} \log P_{ioht|j}(x_{it}) \tag{29}$$

At each candidate parameter vector, the finite-horizon problem is re-solved for each permanent type before evaluating the likelihood.

Identification Identification relies on the complementary information provided by the longitudinal NLSY histories and the much larger CPS cross-section. The NLSY primarily identifies the dynamic parameters: within-individual transitions between employment, home, and broad occupations identify re-entry and occupational switching costs, while observed family histories identify the demographic transition process. Variation in wages and choices across detailed occupations and hours alternatives in the CPS identifies preferences within broad occupations, including the sensitivity to earnings α_s and the nesting parameter ρ_s^T. The norm-matching parameter is identified from differences in sorting as the distance between individual attitudes and occupational norms varies across workers, occupations, and time. This variation also helps distinguish norm matching from the additional broad- and detailed-occupation terms, which capture sorting by attitudes that is not tied to the prevailing occupational norm. Finally, persistence in career choices among observationally similar workers in the NLSY, together with cross-sectional sorting patterns in both samples, identifies the distribution of permanent unobserved heterogeneity. The model is estimated jointly using both datasets, with common structural parameters and a common latent-type distribution.

Standard errors I compute standard errors using the asymptotic robust sandwich covariance matrix of the converged estimator, based on observed-data score contributions. For the NLSY, each individual's complete observed history constitutes one contribution, thereby preserving dependence across observations of the same individual; for the CPS, contributions are defined at the individual level, with collapsed cells weighted by their multiplicity. The scores integrate over permanent latent types and unobserved states in the same way as the likelihood. Reported standard errors are conditional on the wage schedules and other first-stage inputs entering the supply problem.

4.2 Labor demand: identification and estimation

Supply-side inputs and labor-market histories The demand estimation uses two objects recovered from the labor-supply model. First, the estimated firm-level labor-supply elasticity implies the oligopsony markdown factor:

$$\widehat{\phi}_{seajohkt} = \frac{\widehat{\varepsilon}_{seajohkt}}{1 + \widehat{\varepsilon}_{seajohkt}} \tag{30}$$

Second, consistent with the model's assumption that employers observe workers' past employment histories only imperfectly, I use the supply model to predict past participation for workers with the same observed characteristics. Current broad occupation does not directly enter past participation probabilities; instead, it provides information about the worker's permanent latent type and her

current participation status. For a candidate depreciation parameter δ, the implied expected human-capital stock is:

$$\widehat{A}_{it}(\delta) = \sum_{\tau<t} \delta^{t-1-\tau} \sum_{q} \widehat{\Pr}\left(g_{i\tau} = 1 \mid s_i, a_{it}, e_i, t, q, g_{it} = 1\right) \widehat{\Pr}\left(q \mid s_i, a_{it}, e_i, j_{it}, t\right) \tag{31}$$

I assume that men work continuously from labor-market entry, while women's predicted participation histories are obtained from the supply model and rescaled using the corresponding predicted male histories, so that the male benchmark corresponds to potential experience. I use the normalization $\widetilde{A}_{it} = \widehat{A}_{it}/10$ below.

Human capital and male wages I estimate the human-capital technology from male wages, so that the productivity component of the gender wage gap is not chosen to fit female wages. Since managerial attitudes affect expected productivity only for women, the male wage equation implies that the hourly wage adjusted for the oligopsony markdown identifies the log expected marginal revenue product. I parameterize this object as:

$$\begin{aligned} \log w_{it} - \log \widehat{\phi}_{s_i e_i a_i j_i o_i h_i k t} &= cons + \lambda_{jot} + b_{je_i} \widetilde{A}_{it}(\delta) + \chi_{jot} e_i + \kappa_j PT_{it} + \epsilon^m_{it}, \\ \lambda_{jot} = \lambda_{jt} + \lambda_{jo1} + \lambda_{jo2}\text{trend}_t, &\qquad \chi_{jot} = \chi_{jo1} + \chi_{jo2}\text{trend}_t \end{aligned} \tag{32}$$

The term λ_{jot} captures the component of marginal revenue product that is common to workers in detailed occupation o at date t. The coefficient b_{je_i} governs the return to accumulated human capital and is allowed to vary across broad occupations and education groups. The term $\chi_{jot} e_i$ allows the return to education to vary across detailed occupations and over time, while $\kappa_j PT_{it}$ captures differences in productivity associated with part-time work. Finally, the measurement error is denoted ϵ^m_{it}.

The productivity technology is assumed to be common to men and women. In particular, men and women with the same education, hours arrangement, and occupation have the same productive efficiency at labor-market entry, before their accumulated human capital can differ. Gender differences in productivity later in the career can therefore arise through differences in accumulated human capital, but not through a gender-specific productivity component.

The depreciation parameter δ is estimated by profile nonlinear least squares. For each candidate value of δ, I construct the male human-capital stock, re-estimate the remaining parameters of the male wage equation by OLS, and select the value of δ that minimizes the profiled residual sum of squares. Because men observed working are assumed to have worked continuously since completing education, δ is identified from the curvature of the male wage profile over potential experience.

Managerial attitudes and expected female productivity Holding the human-capital technology estimated from male wages fixed, I use female wages to estimate the effect of managerial attitudes on expected productivity. As discussed in the model, I proxy managerial attitudes N^M_{jt}

using the average gender-role attitudes of men aged 40–59 in each broad occupation. The aggregate index $\bar{N}_t^M$ is constructed as the employment-weighted average of these occupational measures.

Following equation (16), I estimate two parameters: D_L, which captures the effect of the general level of managerial attitudes, and D_R, which captures the effect of occupational deviations from that level. This distinction allows the relationship between managerial attitudes and expected female productivity to differ between changes in the broader normative environment over time and differences across occupations within a given year.

Given this specification, the employer wage-setting condition derived in the model implies the following equation for female log wages:

$$\log w_{it} = \log \widehat{MRP}_{s_i e_i a_i j_i o_i h_i t} + \log \widehat{\phi}_{s_i e_i a_i j_i o_i h_i k t} - \log\left(1 + \mathcal{D}(\bar{N}_t^M, N_{j_{it}t}^M)\right) + \epsilon_{it}^f \tag{33}$$

Here, $\log \widehat{MRP}_{s_i e_i a_i j_i o_i h_i t}$ denotes the predicted log expected marginal revenue product, $\widehat{\phi}_{s_i e_i a_i j_i o_i h_i k t}$ is the estimated oligopsony markdown factor corresponding to the worker's category, and the final term captures the effect of managerial attitudes on expected female productivity. The expected MRP is constructed using the productivity parameters estimated from male wages, under the assumption of a common production technology across genders. These parameters are combined with each woman's observed characteristics, current occupation, and expected accumulated human capital, inferred from her model-predicted employment history.

I estimate D_L and D_R jointly by nonlinear least squares on individual female wages. Conditional on expected productivity and oligopsony markdowns, D_L is identified from changes over time in female wage residuals associated with the aggregate level of managerial attitudes, while D_R is identified from differences in these residuals across occupations with different managerial attitudes relative to the contemporaneous aggregate.

Substitution across occupational outputs The male wage estimation also recovers the occupation price component $\widehat{\lambda}_{jot}$. Let F_{jot} denote total effective labor employed in detailed occupation o at time t, so that occupational output can be written as $y_{jot} = T_{jot} F_{jot}$. The CES first-order condition then implies:

$$\lambda_{jot} = \log \mu_t + \sigma \log T_{jot} + (\sigma - 1) \log\left(\frac{F_{jot}}{Y_t}\right) \tag{34}$$

Using the estimated productivity schedule, I construct the sample analogue of effective labor as:

$$\widehat{F}_{jot} = \sum_{i:\, o(i)=o,\, t(i)=t} \widehat{\omega}_{it} h_{it}^* \varpi_{it}^{CPS} \tag{35}$$

where ϖ_{it}^{CPS} denotes the CPS sampling weight and $h_{it}^* = 1$ for full-time and $1/2$ for part-time workers.

Because $\widehat{F}_{jot}$ is constructed from finite CPS samples, I correct sampling-error attenuation using repeated split-sample measurements and the ORIV estimator of Gillen, Snowberg and Yariv (2019). For each of 50 random household splits, effective labor is constructed independently in both halves of the sample; after removing a common time trend, detailed-occupation fixed effects, and occupation-specific linear trends, the two measurements instrument each other in the stacked ORIV estimator. If $\widehat{\beta}^{ORIV}$ denotes the estimated coefficient on log effective labor, the CES parameter is:

$$\widehat{\sigma} = 1 + \widehat{\beta}^{ORIV} \tag{36}$$

ORIV addresses sampling error in effective labor but not endogeneity of true occupational labor supply to unobserved demand shocks; identification of σ therefore additionally relies on residual variation in effective labor being orthogonal to such shocks.

Standard errors Standard errors are obtained from a household-level bootstrap of the demand estimation, treating the supply-side estimates as fixed inputs. In each replication, I re-estimate the male wage regression, the parameters on managers' attitudes D_L and D_R, and the CES parameter σ. For σ, I also report the analytical standard error from the stacked ORIV estimator, clustered at the detailed-occupation level. Thus, the bootstrap captures sampling uncertainty in the demand estimation conditional on the estimated supply-side objects.

4.3 Data

To estimate the model, I use the panels of two cohorts of the National Longitudinal Survey of Youth (NLSY79[8] and NLSY97[9]) for the individual's longitudinal histories of the supply side, which allow the estimation of the dynamic broad nest level, and the March supplement of the Current Population Survey (CPS) from IPUMS[10] for the finer occupation level nest and the demand part. For individuals in both datasets, the deterministic component of attitudes toward gender norms is predicted from a common GSS specification that regresses individual attitudes on gender, college education, and five-year birth-cohort fixed effects. This provides a comparable measure across the NLSY79, NLSY97, and CPS samples. For individuals born in 1934 or earlier, I use the fixed effect of the 1935–1939 cohort because the estimated fixed effects for the oldest birth cohorts are extreme and based on relatively limited support. This affects only about 5% of the CPS sample and produces historical work-experience profiles more consistent with available historical evidence.[11] Additionally,

[8] U.S. Bureau of Labor Statistics (2025)

[9] U.S. Bureau of Labor Statistics (2026)

[10] Flood, King, Rodgers, Ruggles, Warren, Backman, Breton, Cooper, Rivera Drew, Richards and Van Riper (2025)

[11] As a historical benchmark, I use evidence from the 1967 National Longitudinal Survey of Work Experience, Mature Women cohort, as reported in the U.S. Census Bureau (1976) *A Statistical Portrait of Women in the United States* (Tables 9-5 and 9-6). The survey followed women aged 30–44 and collected retrospective information on the number of years since leaving school in which they had worked at least six months. Table 9-5 reports the distribution of this work-experience share among women with income in 1966, while Table 9-6 reports averages by education and marital

I use the labor market concentration dataset of Choi and Marinescu (2023)[12] and the Business Dynamics Statistics[13] data to construct an estimate of the number of effective employers by detailed occupation and year faced by the individual.

National Longitudinal Survey of Youth For the dynamic component of labor supply, I use longitudinal histories from the nationally representative cross-sectional samples of the NLSY79 and NLSY97. The NLSY79 follows individuals born between 1957 and 1964, while the NLSY97 follows a younger cohort born between 1980 and 1984. The two cohorts are used to estimate dynamic broad-occupation choices and demographic transitions. I retain observations in which individuals are either employed in the private sector or voluntarily out of the labor force, corresponding to the home option in the model; unemployed observations are excluded. To address the initial-conditions problem in the demographic process, I assume that all individuals are single and childless at age 15 and let family status evolve from that common state. I therefore retain observed demographic histories from age 16 onward, while observations at younger ages are excluded.

For the NLSY79, I use survey waves from 1979 through 2012, when respondents are observed up to age 55. I stop in 2012 because retention of the cross-sectional sample falls below 70 percent in the subsequent wave. For the NLSY97, I use waves from 1997 through 2019, the end of the period covered by the analysis, when respondents are observed up to age 39. I do not impose the same age ceiling on the NLSY79: observations at older ages provide additional information on occupational and part- versus full-time choices later in the career. As both surveys become biennial in later years, choices in intervening years are treated as unobserved histories within the dynamic estimation. Descriptive statistics for both NLSY panels are reported in Appendix Table B.2.

Current Population Survey I complement the NLSY panels with matched observations from the March supplement of the Current Population Survey (CPS) over 1979–2019. The CPS is used on both the supply and demand sides of the model. Individuals are matched across two consecutive survey years, but only the second observation contributes directly to the likelihood. The first observation provides information on previous employment and occupation, which is used to construct lagged variables.

I retain only private-sector employees in the second year. For demand estimation, I use workers from labor-market entry—age 18 for non-college workers and 22 for college graduates—through age 59, restricting the sample to those working at least 20 weeks per year and trimming real hourly wages below \$1 and above \$250. For supply estimation, I further restrict the CPS to the birth cohorts represented in the NLSY panels. For women, predicted past participation from the supply model is rescaled relative to the corresponding predicted male participation profile, so that the male benchmark corresponds to continuous employment over potential experience while preserving the

status. These cohorts closely overlap with the oldest cohorts affected by the adjustment.

[12] See Choi and Marinescu (2024) for a complete description of the data construction.

[13] U.S. Census Bureau (n.d.)

model-implied female–male difference in past participation. Descriptive statistics are reported in Appendix Table B.3.

Because workers' choices depend on the wages available in alternatives they do not choose, the supply estimation requires wages for every occupation and hours alternative in the choice set. I construct these from a reduced-form wage schedule estimated on CPS log hourly wages as a flexible function of detailed occupation, year, part-time status, college education, potential experience, and gender, including occupation-specific time and experience profiles and selected interactions. To avoid overfitting sparsely populated cells, the most detailed interactions are partially shrunk toward broader wage profiles, with the degree of shrinkage selected by five-fold cross-validation. On occupation-gender cells observed in the data, the predicted schedule closely reproduces the level and dispersion of observed wages, as well as their ranking across occupations. Appendix Table B.4 reports corresponding moments for observed and predicted wages overall and by decade, together with the distribution of predicted wages over the full set of choice cells.

Other data To measure employer competition, I use the vacancy-based HHI data of Choi and Marinescu (2023), available by six-digit SOC occupation, commuting zone (CZ), and quarter from 2007Q1 to 2021Q2. Its inverse measures the effective number of equally sized recruiting employers. To extend the series back to 1979, I combine the Business Dynamics Statistics with CPS occupation–sector employment shares to construct local occupation-specific firm measures, and use their relationship with observed inverse HHI over the overlapping period to backcast earlier years. The predicted and observed measures have a correlation of 0.94 over this period.

Because the NLSY does not report geographic location, I average the measure across CZs within occupation-year. CZs are left unweighted: expressing employer availability relative to local population and weighting by the probability that an individual lives there offset the same population term. The resulting measure averages 5.27 effective employers (s.d. 7.28), compared with 6.25 (s.d. 7.93) for directly observed values. Since much of the early series is backcast, I calibrate the employer-nest parameter $\rho^I = 0.145$ from Azar et al. (2022), whose bottom nests are six-digit occupation-by-CZ markets.

5 Estimation results

This section presents the estimated parameters of the model and evaluates its fit to observed labor market outcomes. I then examine sorting on gender-role attitudes and decompose gender wage inequality into the contributions of expected productivity differences arising from human capital accumulation, wage markdowns associated with employer labor market power, and the influence of managerial attitudes on employers' expectations of women's productivity, distinguishing their roles in the evolution of wage gaps over time and their variation across occupations.

5.1 Parameter estimates

5.1.1 Supply-side parameter estimates

Table 3 reports the main supply-side parameter estimates, separately for men and women. Additional estimates for the demographic transition processes are reported in Appendix Table D.1. The estimates reveal substantial gender differences in labor-market attachment, preferences over occupational environments, and responses to wages.

Labor-market attachment and occupational mobility Family circumstances affect men's and women's labor-market decisions in opposite directions. Marriage and the presence of a young child increase the relative utility of employment for men, but reduce it for women, with a particularly large negative effect of young children among women. These differences are consistent with traditional patterns of household specialization, whereby women bear a greater share of family responsibilities while men maintain stronger labor-market attachment. Career choices also exhibit substantial persistence. The estimated costs of re-entering employment are 4.35 for men and 4.71 for women, while the costs of switching between broad occupations are 3.85 and 3.92, respectively. These costs capture frictions associated with resuming employment and changing occupational specialization, including the effort and investments required to pursue a different career path. Their magnitude suggests that workers do not readily adjust their participation and occupational choices in response to changes in current labor-market conditions.

Gender norms and occupational preferences The estimates indicate that workers value occupational environments whose gender norms are close to their own attitudes. The coefficient on the squared distance between individual attitudes and occupational norms is negative for both sexes, but substantially larger in magnitude for men (-3.47 versus -0.89). Thus, men exhibit a particularly strong preference for working among individuals whose views on gender roles resemble their own. This preference operates in both directions: traditional workers are less attracted to progressive occupational environments, while progressive workers are less attracted to traditional ones.

Beyond this preference for norm matching, individual attitudes shape the relative attractiveness of specific occupations. The estimates reveal patterns consistent with traditional gender roles. Among men, attitudes have relatively similar effects on preferences for N, T, Q, and VS, but more traditional views are associated with a markedly lower relative preference for T–VS, a predominantly female occupational group that includes nursing and related healthcare professions. Among women, the pattern is almost reversed: more traditional attitudes are associated with a substantially lower relative preference for T–Q, which comprises predominantly male technical and skilled-trade occupations, whereas T–VS is comparatively less sensitive to women's attitudes. These patterns suggest that workers with traditional views are particularly reluctant to pursue occupations strongly associated with the opposite sex.

Women's occupational preferences also exhibit a pronounced distinction between N and occupations involving greater specialization. Relative to N, more traditional attitudes are associated with lower preferences for T, Q, VS, and especially Q–VS and T–Q–VS. This is consistent with women holding more progressive views placing greater value on specialized career opportunities. Together with the norm-matching estimates, these differences illustrate two channels through which individual attitudes shape occupational sorting: preferences for working in a compatible normative environment and preferences for particular types of careers.

Wage sensitivity and substitution across jobs The estimated coefficient on log weekly earnings is 0.82 for men and 0.53 for women, indicating that men's occupational and labor-market choices respond more strongly to differences in earnings, holding other components of utility constant. The estimated nesting parameters are also well below one for both sexes (0.28 for men and 0.19 for women), indicating substantial correlation in unobserved preferences across detailed occupations and hours arrangements belonging to the same broad occupational group. This supports the distinction between broad career choices and substitution among more closely related employment alternatives. The employer-level nesting parameter is calibrated to 0.145 for both sexes.

Table 3: Main supply-side parameter estimates

Parameter	Men		Women	
	Estimate	SE	Estimate	SE
Top-level parameters				
Married, μ_s^A	.269***	.038	-.244***	.021
Young child, μ_s^Y	.231***	.053	-.458***	.021
Re-entry cost, κ_s^R	4.354***	.063	4.705***	.038
Broad-occupation switching cost, κ_s^J	3.852***	.023	3.918***	.021
Norm distance, γ_s	-3.470***	.285	-.885***	.224
Occupation-specific preferences by gender-role attitudes, γ_{sj}				
N, $\gamma_{s,N}$	-3.184***	.196	-2.697***	.099
T, $\gamma_{s,T}$	-3.151***	.197	-3.781***	.124
Q, $\gamma_{s,Q}$	-3.198***	.177	-3.626***	.107
VS, $\gamma_{s,VS}$	-3.157***	.190	-3.695***	.107
T-Q, $\gamma_{s,\mathrm{T-Q}}$	-3.270***	.209	-5.506***	.215
T-VS, $\gamma_{s,\mathrm{T-VS}}$	-5.883***	.325	-3.979***	.153
Q-VS, $\gamma_{s,\mathrm{Q-VS}}$	-4.774***	.185	-5.744***	.127
T-Q-VS, $\gamma_{s,\mathrm{T-Q-VS}}$	-4.345***	.239	-4.952***	.157
Intermediate-level parameters				
Log weekly wages, α_s	.816***	.029	.532***	.013
Within-broad-occupation dissimilarity parameter, ρ_s^T	.275***	.011	.186***	.004
Employer-level dissimilarity parameter, ρ^I	.145	–	.145	–
Part-time utility shifters, χ_{sl}				
No child in household, $\chi_{s,0}$	.103***	.012	.117***	.007
Youngest child 4–18, $\chi_{s,1}$	-.278***	.021	.162***	.008
Youngest child 0–3, $\chi_{s,2}$	-.184***	.020	.245***	.009
Permanent unobserved heterogeneity				
Support point $\zeta_{s,1}$	-.171***	.008	-.120***	.002
Support point $\zeta_{s,2}$	-.071***	.005	-.028***	.002
Support point $\zeta_{s,3}$	.242***	.012	.148***	.003

Notes: Robust sandwich standard errors are reported in the SE columns. Significance stars are based on the corresponding sandwich z-statistics: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The employer-level nesting parameter $\rho^I = 0.145$ is calibrated for both sexes and therefore has no standard error. The three support points ζ_{sq} are ordered and normalized to have mean zero, and are parameterized by two free parameters governing their relative spacing and scale.

Part-time employment and family responsibilities Preferences for part-time relative to full-time employment also differ substantially by gender and family circumstances. In the absence of children, the estimated part-time utility component is slightly positive for both men and women. With children, however, the patterns diverge: men exhibit a negative preference component for part-time work, while women's preference becomes more positive, particularly when their youngest child is under four years old. These estimates are consistent with gender differences in the allocation

of family responsibilities and the greater importance of flexible working arrangements for mothers.

Permanent preference heterogeneity Finally, the estimates indicate meaningful permanent unobserved heterogeneity in individual attitudes. The three support points exhibit greater dispersion among men than women, particularly at the upper end of the distribution, suggesting more heterogeneous persistent preferences related to gender roles among men. Together with the estimated occupation-specific preferences and norm-matching parameters, this heterogeneity contributes to persistent differences in occupational choices among otherwise observationally similar workers.

Implied labor supply elasticities and employer wage-setting power Table 4 reports the firm-level labor supply elasticities implied by the estimated worker preferences and the corresponding wage-setting factors. These objects are derived from the estimated choice probabilities across employers, detailed occupations, hours arrangements, and broad occupations. The reported values aggregate these elasticities within each broad occupation, weighting the underlying worker categories and employment alternatives by their model-implied employment shares. The corresponding oligopsony factors are averaged using the same weights. The estimated elasticities are consistently lower for women than for men, averaging 3.38 and 4.69, respectively. This difference partly reflects women's lower estimated sensitivity to wages and implies greater employer wage-setting power over female workers, independently of managerial attitudes. Accordingly, the oligopsony factors average 0.77 for women and 0.82 for men, implying larger wage markdowns for women relative to the marginal revenue product assessed by managers. These magnitudes are broadly consistent with estimates of firm-level labor supply elasticities in the monopsony literature, including Azar et al. (2022), whose framework also informs the calibration of the employer-level nesting parameter, and the gender differences documented by Ransom and Oaxaca (2010) and Barth and Dale-Olsen (2009). Elasticities also vary across occupations, reflecting differences in employer availability and workers' substitution opportunities. This variation is relatively moderate across broad occupational groups, although T–VS stands out as the occupation with the lowest female elasticity. These estimates establish a source of gender differences in employer wage-setting power distinct from the influence of managerial attitudes on expected productivity, which is quantified on the demand side.

Table 4: Implied labor supply elasticities and wage-setting factors

	Men		Women	
Broad occupation	$\hat{\varepsilon}$	$\hat{\phi}$	$\hat{\varepsilon}$	$\hat{\phi}$
N	4.57	0.82	3.34	0.77
T	4.63	0.82	3.33	0.77
Q	5.16	0.84	3.44	0.78
VS	4.78	0.83	3.47	0.78
T-Q	4.63	0.82	3.33	0.77
T-VS	4.81	0.83	3.14	0.76
Q-VS	5.07	0.83	3.46	0.78
T-Q-VS	4.68	0.82	3.41	0.77
All	4.69	0.82	3.38	0.77

Notes: Model-implied values are computed from the estimated labor supply side. ε denotes the firm-level labor supply elasticity, and $\phi = \varepsilon/(1+\varepsilon)$ is the associated oligopsony wage-setting factors entering firms' wage-setting condition. Both quantities vary across worker and job characteristics and are averaged using employment weights. The reported average of ϕ is obtained by averaging the underlying wage factors and therefore need not equal the transformation of the reported average elasticity. The *All* row pools the eight broad working occupations using the corresponding employment weights.

5.1.2 Demand-side parameter estimates

Table 5 reports the main demand-side parameter estimates. Additional estimates of occupation-specific returns to human capital, part-time productivity effects, and aggregate production parameters are reported in Appendix Table D.2, while Appendix Table D.3 summarizes the detailed-occupation and time-varying wage components.

Managerial attitudes and expected productivity Both parameters are positive and precisely estimated, indicating that more traditional managerial attitudes are associated with lower expected female productivity. The coefficient on the aggregate level of managerial attitudes, $D_L = 0.196$, captures how this relationship evolves with the broader normative environment. As gender-role attitudes become more progressive over time, this component declines, raising the productivity managers expect from female workers. The coefficient on occupational deviations from the contemporaneous average, $D_R = 0.435$, is substantially larger, indicating that managers in occupations with more traditional attitudes expect lower female productivity than those in more progressive occupational environments, holding actual productivity constant. Thus, the estimates capture both an aggregate evolution in managerial assessments of women's productivity and differences across occupational environments. The latter is particularly relevant for understanding the relationship between occupational gender norms and within-occupation gender wage gaps documented in the empirical analysis.

Human capital and productivity The estimated human-capital retention parameter is 0.890, implying that the contribution of past employment to current human capital depreciates at a rate of approximately 11% per year. Consequently, recent employment receives greater weight than more distant experience, making the timing of career interruptions relevant for workers' expected productivity. Appendix Table D.2 shows that returns to accumulated human capital vary substantially across occupations and education groups. They are particularly high in Q–VS and T–Q–VS, occupations encompassing many managerial, professional, and specialized careers. The estimated productivity adjustments for part-time employment are negative across all broad occupations, although their magnitude varies.

Table 5: Main demand-side parameter estimates

Parameter	Estimate	SE
Economy-wide managerial attitudes, D_L	.196***	.010
Differences in managerial attitudes across occupations, D_R	.435***	.058
Human-capital retention, δ	.890***	.001

Notes: Bootstrap standard errors based on 1,000 replications are reported in the SE column. Significance stars are based on the corresponding bootstrap distributions: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Additional demand-side parameter estimates are reported in Appendix Table D.2.

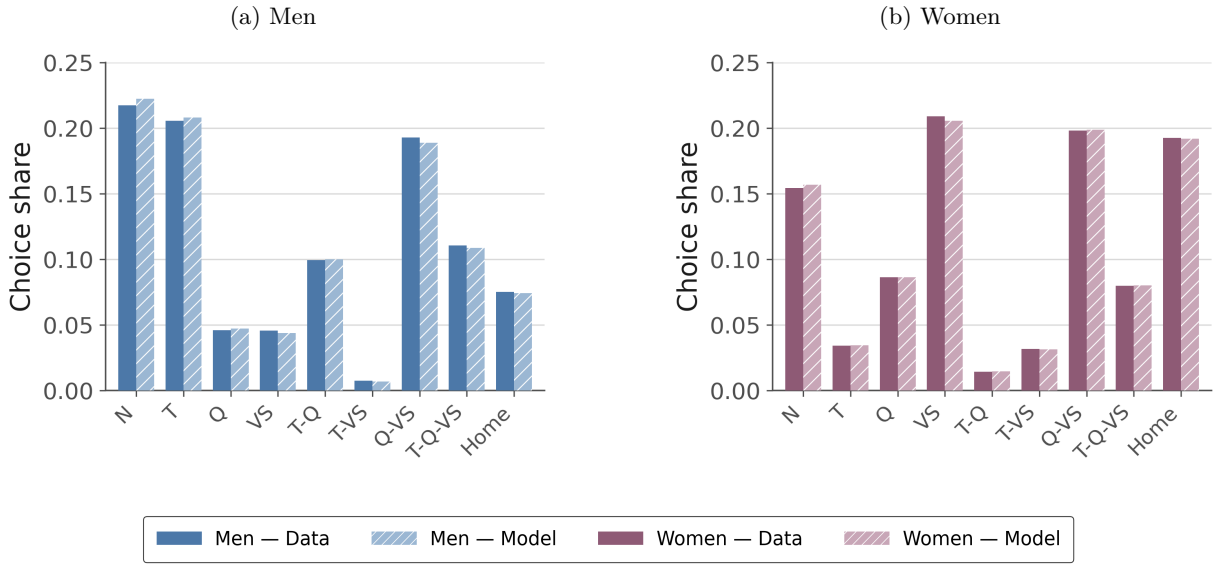
Together, these estimates allow the model to distinguish wage differences arising from expected human capital accumulation and employer labor market power from those associated with the influence of managerial attitudes on expected female productivity. The quantitative contributions of these mechanisms to observed gender wage inequality are examined in the following sections.

5.2 Model fit

Occupational choices Figure 2 compares the observed and model-predicted distributions of broad occupational choices and non-employment, separately for men and women of both NLSY cohorts. The model closely reproduces the observed employment shares across all eight occupational groups, as well as the substantially higher non-employment rate among women. In particular, it captures the pronounced gender differences in occupational sorting, including the greater concentration of men in T and women in VS. Appendix Figures D.1 and D.2 show that the model also reproduces the broad patterns of occupational choice separately for the NLSY79 and NLSY97 cohorts. At the individual-year level, the model achieves in-sample hit rates of 73.9% for women and 76.7% for men in predicting the choice between non-employment and the eight broad occupations, compared with 20.9% and 21.7%, respectively, for a simple benchmark that always predicts the most frequently observed alternative for each sex. Appendix Table D.4 provides additional fit statistics, including those for detailed occupational and hours choices. While the model closely matches aggregate

employment shares across detailed occupations, its ability to predict individual choices within broad occupational groups is more limited.

Figure 2: Observed vs predicted occupational choices



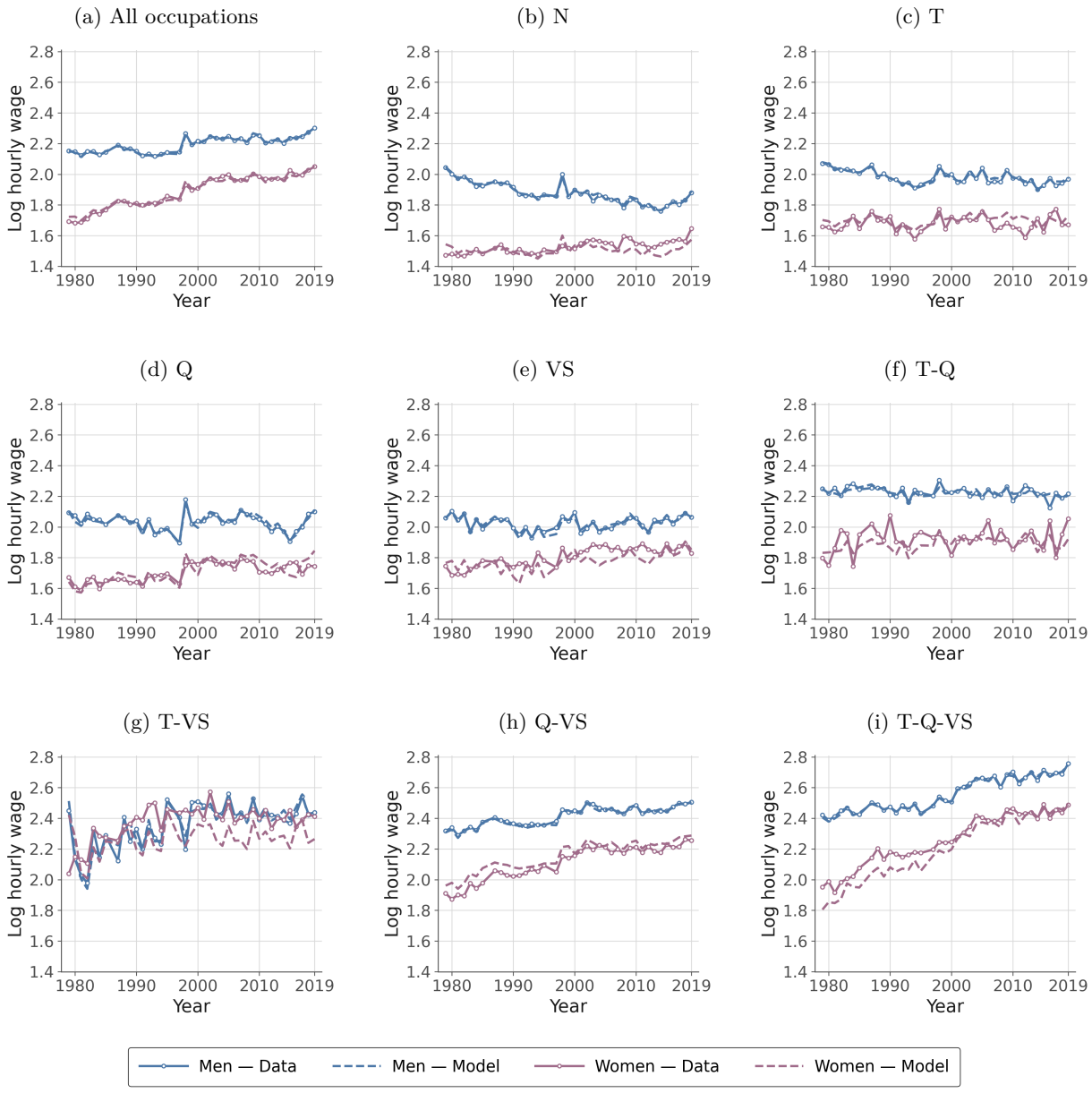
Notes: The figure compares observed and model-predicted broad occupational choices of individuals in the two NLSY panels.

Career dynamics and hours choices Appendix Table D.5 evaluates the model's ability to reproduce one-year labor-market transitions. The model closely matches transitions from employment into non-employment, but somewhat understates re-entry into employment, by approximately 5 percentage points for women and 4 percentage points for men. It also overpredicts persistence within broad occupations by about 6 percentage points for both sexes, indicating that the estimated model generates somewhat less occupational mobility than observed in the data. Finally, Appendix Table D.6 compares observed and predicted part-time employment shares. The model closely reproduces the aggregate incidence of part-time work for both sexes, predicting 19.6% for women and 6.8% for men, compared with 20.1% and 7.3% in the data. However, the fit is less precise across individual occupational groups, indicating that some heterogeneity in hours choices remains imperfectly captured.

Wage fit Figure 3 compares observed and predicted mean log hourly wages, both in the aggregate and across the eight broad occupations. The model closely reproduces wage levels and trends for both men and women, with a particularly close fit for men. Some discrepancies remain, notably in T–VS, a relatively small occupational group with more volatile observed wages, while predicted wage growth of women is somewhat steeper than observed in T–Q–VS. The fit for women is particularly informative given that productivity parameters are estimated exclusively from male wages. Female

wage predictions combine these common productivity parameters with gender-specific expected human capital and oligopsony markdowns, together with the effect of managerial attitudes on expected female productivity, captured by only two parameters estimated directly from female wages.

Figure 3: Observed and predicted log wages over time



Notes: The figure compares observed and model-predicted mean log hourly wages from 1979 to 2019, for women and men in the CPS sample, overall and by broad occupation group. Solid lines denote observed wages and dashed lines model predictions.

Additional evidence on wage fit is reported in Appendix Figures D.3 and D.4. The former compares

observed and predicted wage profiles over the life cycle, overall and across broad occupations. The model closely reproduces the evolution of wages with experience and, importantly, the widening of the gender wage gap over the career, including substantial heterogeneity across occupations. The latter examines gender wage gaps over calendar time. The model captures the overall decline in wage inequality between men and women, as well as differences in its evolution across occupations. Some discrepancies remain, with a somewhat steeper predicted decline in T–Q–VS and a slightly flatter one in Q–VS.

Additional model validation The appendix presents two additional validation exercises. First, Appendix Figure D.5 and Table D.7 compare the human capital reconstructed from observed NLSY79 employment histories with that implied by the model. The model reasonably reproduces the accumulation of human capital over the career, although it tends to overestimate gender differences in accumulated experience. This is informative given the role of predicted employment histories in determining expected productivity on the demand side.

Second, Appendix Figure D.6 examines whether the model reproduces the negative relationship between occupational female employment shares and conditional gender wage gaps documented in the empirical analysis. Focusing on differences in expected human capital, oligopsony markdowns, and the influence of managerial attitudes on expected female productivity, the model closely reproduces the observed gradient in 2019 (-0.121 compared with -0.133 in the data). [14] Appendix Table D.8 shows that the model reproduces this negative relationship in every year of the sample, although its magnitude is somewhat underestimated in later decades.

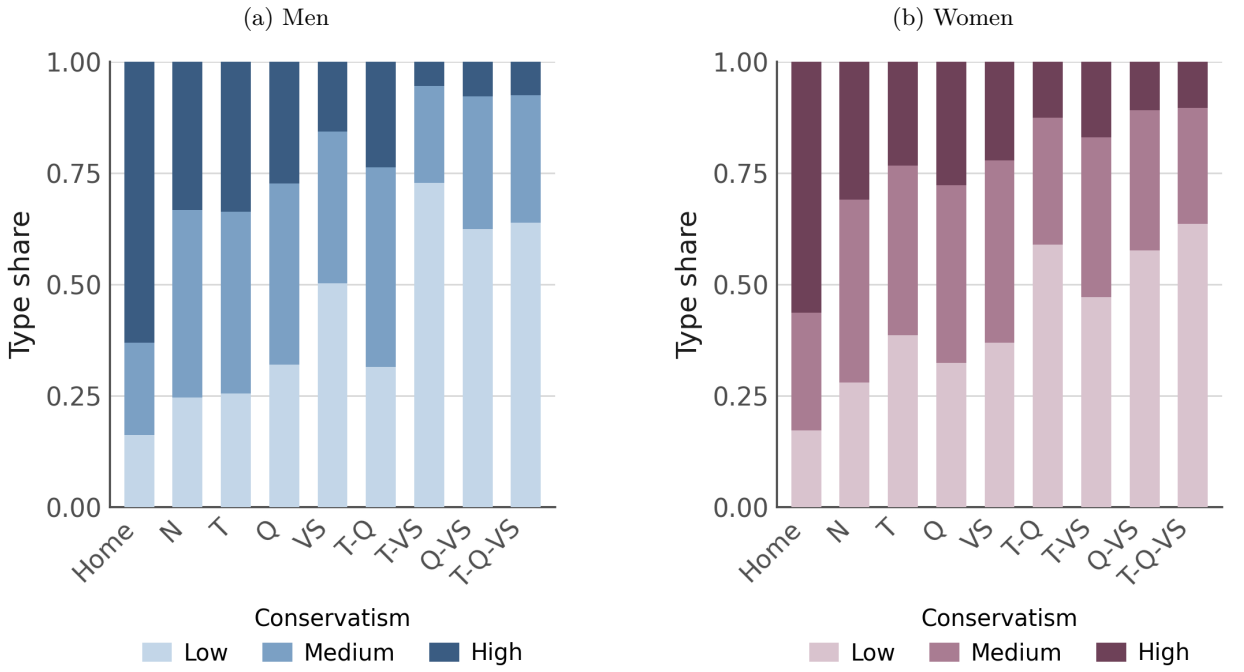
5.3 Main results

5.3.1 Gender attitudes and occupational sorting

Figure 4 illustrates how workers sort across career alternatives according to their attitudes towards gender roles. In the model, individual attitudes combine a deterministic component predicted from the GSS using gender, education, and birth cohort, and a permanent unobserved component estimated from labor-market choices. The latter is represented by three gender-specific latent types, whose estimated values are reported in Table 3. The figure shows the proportions of these types within each occupational group and non-employment, ordered from more progressive to more conservative. It therefore captures sorting along differences in attitudes beyond those explained by observable characteristics. While the figure reports type shares rather than their values, the estimates indicate greater dispersion in unobserved attitudes among men, particularly at the conservative end of the distribution.

[14] The full gender wage gap within broad occupations also includes differences arising from the sorting of men and women across detailed occupations. Because the paper focuses on wage differences conditional on occupation, this exercise isolates the three components operating within detailed occupations.

Figure 4: Latent type composition across career choices



Bars report average model-implied probabilities of belonging to each of the three permanent latent types, evaluated before the current choice and grouped by observed career choice. Types are ordered by the permanent attitude shifter ζ_{sq}, with higher values corresponding to more conservative gender attitudes. Home denotes the voluntary non-employment alternative.

The figure reveals substantial differences in latent-type composition across career choices, with distinct patterns for men and women. Among women, the most progressive type is particularly prevalent in T–Q, a predominantly male occupational group, as well as in Q–VS and T–Q–VS. Among men, progressive types are especially represented in T–VS, a predominantly female group, and in Q–VS and T–Q–VS. The contrast between T–Q and T–VS is particularly informative: progressive types are more strongly represented among women in the former and among men in the latter, consistent with the gender-specific occupational preference parameters discussed above. Non-employment, meanwhile, is associated with a relatively high proportion of conservative types for both sexes.

The interpretation of this latent heterogeneity as reflecting gender-role attitudes is motivated by the structure of the model and the patterns of occupational sorting it generates. The latent component augments an attitude index whose observed component is directly estimated from the GSS, and affects occupational choices through preferences for normative environments and occupation-specific preferences. Moreover, the gender-specific sorting patterns, particularly in occupations traditionally associated with the opposite sex, suggest a dimension of preference heterogeneity related to gender roles rather than simply to labor-market attachment.

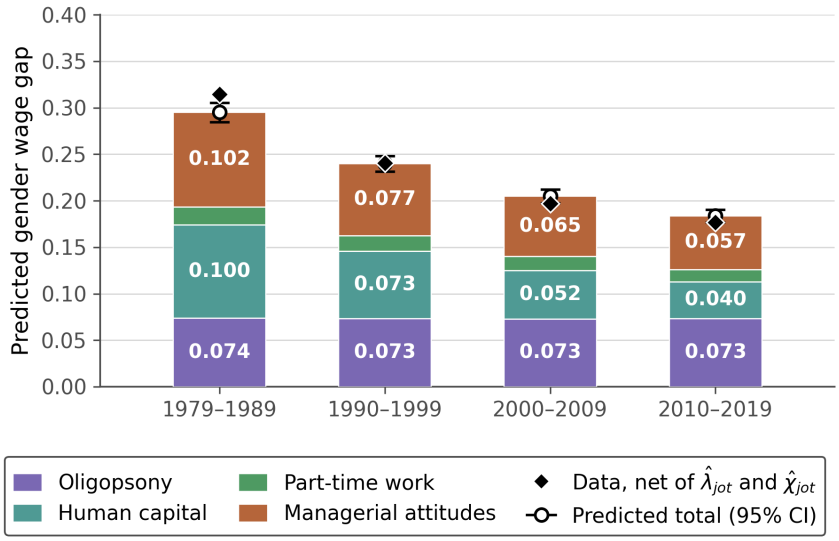
More generally, the results highlight the importance of permanent unobserved heterogeneity in shaping career choices. The estimated types are distributed very differently across employment alternatives, indicating that workers with otherwise similar observable characteristics can exhibit systematically different patterns of occupational sorting and labor-market participation. In the model, this heterogeneity contributes to the composition of occupational workforces and, through sorting, to the evolution of occupational norms. It therefore provides an important link between individual career decisions and the occupational environments that subsequently matter for wage setting.

5.3.2 Decomposition of the gender wage gap

Figure 5 decomposes the model-predicted gender wage gap into differences in expected human capital, part-time employment, oligopsony markdowns, and the influence of managerial attitudes on expected female productivity. By removing detailed-occupation wage components, the decomposition focuses on wage differences conditional on occupational specialization, rather than differences arising from the sorting of men and women across detailed occupations. The model closely reproduces the substantial decline in the conditional gender wage gap over time, from 29.4 log points in 1979–1989 to 18.3 log points in 2010–2019, compared with approximately 31 and 18 log points in the data, respectively.

Two mechanisms account for nearly all of this decline. The contribution of differences in expected human capital falls from 10.0 to 4.0 log points, consistent with the convergence in men's and women's employment histories. At the same time, the contribution of managerial attitudes declines from 10.2 to 5.7 log points, reflecting the evolution toward more progressive gender-role attitudes and their influence on employers' assessments of female productivity. Together, these two components account for approximately 10.5 log points of the 11.1 log point reduction in the predicted gap. By contrast, the contribution of oligopsony remains remarkably stable at around 7.3 log points throughout the sample. As the other components decline, differences in employer wage-setting power become the largest single contributor to the remaining gender wage gap in the most recent decade. Part-time employment contributes relatively little to either the level or the evolution of the gap.

Figure 5: Decomposition of the predicted gender wage gap over time



Notes: Bars report the model-predicted gender wage gap after removing detailed-occupation wage components. Within each decade, gaps are computed in broad-occupation × year × age × education cells and pooled across all occupations, using harmonic weights based on CPS-weighted male and female cell counts. The remaining predicted gap is decomposed into differences in expected human capital, part-time work, oligopsony markdowns, and the influence of managerial attitudes on expected female productivity. Diamonds report the corresponding observed gender wage gap after removing the same detailed-occupation wage components. Vertical lines report 95% percentile bootstrap confidence intervals for the model-predicted gap. Values are in log points.

Appendix Figure D.7 reveals substantial heterogeneity in the relative importance of these mechanisms across occupations. Managerial attitudes play a particularly important role in N, T, and T–Q, where their influence on expected female productivity contributes substantially to gender wage inequality. In Q–VS and T–Q–VS, differences in expected human capital contribute more substantially to wage inequality. This reflects the particularly high returns to accumulated experience in these occupations, where even relatively small differences in employment histories can translate into sizable wage gaps.

An interesting exception is T–VS, which includes nursing and other traditionally female healthcare occupations. In the earlier decades, women were already well established in these professions, while the relatively few men who entered them held particularly progressive gender-role attitudes compared with men in other occupations. This suggests an occupational environment in which women's employment and professional roles were especially accepted, and where managers may have assessed female workers more favorably than in traditionally male occupations. In the model, this unusually progressive normative environment raises managers' assessments of female productivity relative to those prevailing in other occupations, generating a negative contribution to the gender wage gap that partially offsets women's wage disadvantages arising from human capital and oligopsony. As managerial attitudes in T–VS become less distinctive relative to those in other occupations, this contribution turns positive.

5.3.3 Gender wage gap and female share

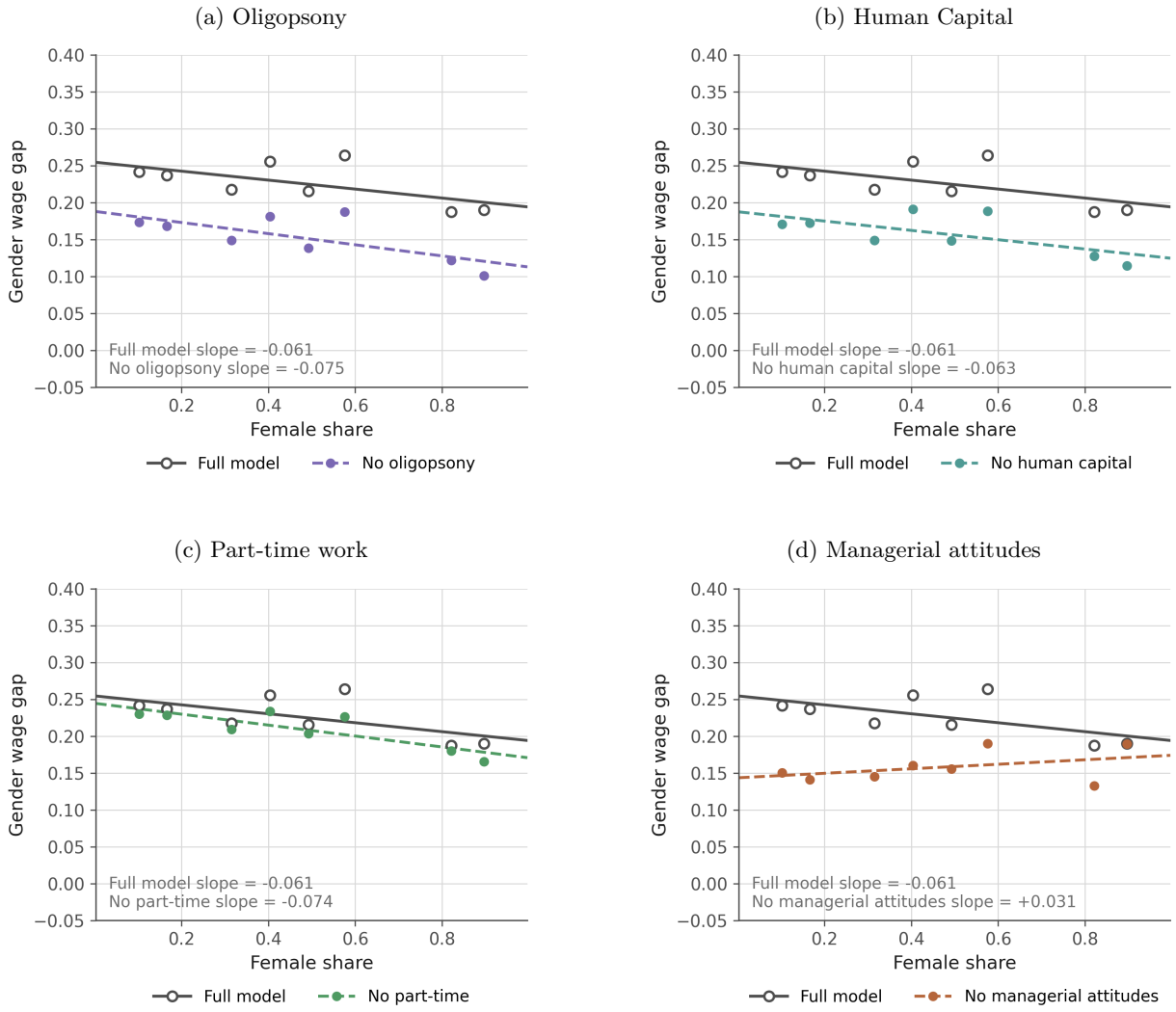
The preceding decomposition identifies the contributions of different mechanisms to the level and evolution of the conditional gender wage gap. However, these contributions need not explain why wage gaps systematically differ across occupations according to their female employment shares.

Figure 6 examines this relationship through an accounting decomposition of the model-predicted gender wage gap. The full-model gap is the difference between predicted male and female log wages, which can be decomposed into four contributions: expected human capital, part-time work, oligopsony markdowns, and the influence of managerial attitudes on expected female productivity. To assess the role of each mechanism, I recompute the gap by excluding its contribution from this sum, leaving the other three unchanged, rather than solving for a new equilibrium. Each point represents a broad occupation, averaging its predicted gender wage gap over the period 1979–2019. The fitted lines therefore summarize the relationship across the eight occupational groups over the full sample period. The full model generates a negative relationship between female employment shares and gender wage gaps, with a slope of -0.061.

Strikingly, removing the influence of managerial attitudes on expected female productivity reverses this relationship, producing a positive slope of 0.031. Managerial attitudes are therefore the central mechanism generating the negative occupational gradient in the estimated model. This reflects the relationship between occupational gender composition and managerial attitudes: occupations with fewer women tend to exhibit more traditional attitudes among senior male workers, which, in the model, translate into lower expected female productivity and consequently lower wage offers for women.

The other mechanisms play substantially different roles. Removing oligopsony makes the negative gradient slightly steeper, from -0.061 to -0.075, indicating that differences in employer wage-setting power modestly offset rather than generate the observed relationship. The contribution of part-time work operates in the same direction, with a slope of -0.074 when this component is removed. In contrast, removing differences in expected human capital leaves the gradient virtually unchanged (-0.063). Thus, although human capital and oligopsony account for substantial portions of the overall gender wage gap, their contributions do not systematically explain why wage inequality is greater in occupations with fewer women.

Figure 6: Role of model channels in the female share-gender wage gap relationship



Notes: Each panel compares the full model with predicted wage gaps after removing the indicated channel. Each point is the equal-year average for one broad occupation over the available years from 1979 to 2019, after removing detailed-occupation wage-price components. Lines show unweighted fits across the eight broad occupations.

Appendix Table D.9 confirms that these findings extend across the sample period. Removing the influence of managerial attitudes on expected female productivity makes the occupational gradient more positive in every year, with the largest effects in the earlier decades. This contribution declines over time as managerial attitudes become more progressive, but remains the principal source of the negative relationship throughout the period. Oligopsony consistently works in the opposite direction. Interestingly, the contribution of human capital changes over time: in the earlier decades, differences in expected human capital reinforce the negative relationship, indicating larger associated wage penalties in occupations with fewer women. By the 2010s, this pattern reverses, with human capital differences instead attenuating the negative gradient. This evolution is consistent with changing

gender differences in career histories and their occupational returns. Overall, the results identify the influence of managerial attitudes on expected female productivity as the principal mechanism explaining the relationship between occupational feminization and conditional gender wage inequality, while the contribution of workers' accumulated human capital has changed substantially over time.

6 Counterfactual exercises

I use the estimated model to assess the equilibrium consequences of three counterfactual changes: removing the influence of managerial attitudes on expected female productivity, shifting individual gender-role attitudes toward more progressive views, and restricting gender wage differentiation among comparable workers. These exercises examine how each change affects wages, employment, occupational choices, welfare, aggregate production, and the distribution of surplus.

6.1 Removing the influence of managerial attitudes on wage setting: equilibrium and distributional effects

The first counterfactual examines what the economy would look like if managerial attitudes no longer influenced employers' expectations of women's productivity. In the baseline model, this influence enters wage-setting decisions through:

$$\mathcal{D}(\bar{N}_t^M, N_{jt}^M) = D_L \bar{N}_t^M + D_R \left(N_{jt}^M - \bar{N}_t^M \right)$$

which affects the productivity managers expect from female workers, and consequently their wage offers, without affecting actual productivity. Starting in 1980, I set $D_L = D_R = 0$, eliminating this influence in all occupations. All other primitives remain at their estimated values, while wages, employment, occupational sorting, human capital, norms, output, and profits adjust endogenously over the transition for all CPS individuals.

This exercise quantifies how the influence of managerial attitudes on wage setting shapes labor allocation, aggregate production, and the distribution of surplus between workers and firm owners. By comparing the resulting equilibrium with the baseline, it assesses the economic consequences of this mechanism rather than the effects of a specific policy intervention.

Aggregate effects Table 6 reports the aggregate effects in 1980, 2000, and 2019. Removing the influence of managerial attitudes on expected female productivity substantially improves women's wages and narrows gender wage inequality. In 2019, women's mean log wage increases by 5.14 log points, compared with 0.30 log points for men, reducing the aggregate gender wage gap by 4.84 log points. The conditional gender wage gap falls by 36.33% relative to its baseline level. This measure compares men and women within detailed occupations, conditional on age, education, and hours,

and therefore abstracts from differences in employment composition across these characteristics. Its substantial decline indicates that the influence of managerial attitudes on wage setting accounts for an important part of wage differences between comparable workers. The remaining gap reflects other sources of inequality in the model, including differences in expected human capital and employers' wage-setting power.

The wage decomposition clarifies the source of these gains. In 2019, removing the effect of managerial attitudes on expected female productivity directly contributes 5.33 log points to the increase in women's mean wage, while changes in human capital add another 0.49 log points. Other demand-side adjustments are negligible, and changes in employment composition offset approximately 0.71 log points, as women are reallocated toward relatively lower-wage cells. Hence, the reduction in wage inequality primarily reflects changes in wage setting associated with the removal of this influence, rather than changes in the composition of employment.

To evaluate how workers are affected beyond their current earnings, I compute wage-equivalent variations (WEV), accounting for changes in employment choices and expected future opportunities. For each baseline individual state and latent type, the WEV is the permanent proportional increase in all baseline wage offers that would make the worker indifferent between the baseline and counterfactual environments. The adjustment applies to current and future wages, allowing workers to re-optimize over non-employment, occupations, and hours. Individual WEVs are then averaged using baseline population weights, separately by gender. In 2019, the mean WEV is +6.06% for women, and is positive for every woman in the baseline population. For men, the mean is slightly negative (−0.45%), despite a modest increase in their average wages. Changes in the non-wage value of occupational choices, particularly those associated with gender norms, more than offset their earnings gains on average. However, these effects vary considerably across men: the median WEV is approximately zero, and 48.5% experience a positive WEV.

The responses of aggregate employment and production are more modest than the wage and welfare effects. In 2019, female employment increases by 1.37 percentage points and male employment by 0.07 percentage points, while output rises by 1.00%. The increase in production reflects greater effective labor: approximately 80% of this increase comes from changes in employment and its allocation across jobs, and the remaining 20% from human capital accumulated through different employment histories since 1980. Despite higher output, aggregate profits fall by 8.26%, as higher female wages transfer part of the surplus from firms to workers. Thus, the main aggregate consequence of removing the influence of managerial attitudes on wage setting is a redistribution of surplus, accompanied by a relatively small improvement in production.

Table 6: Aggregate effects of removing the influence of managerial attitudes

Year	$\Delta \ln w_F$ (log pts)	$\Delta \ln w_M$ (log pts)	Δ GWG (log pts)	Δ CGWG (%)	WEV_F (%)	WEV_M (%)	ΔE_F (pp)	ΔE_M (pp)	ΔY (%)	$\Delta\Pi$ (%)
1980	+9.19	0.00	-9.19	-40.13	+10.59	0.00	+1.24	-0.01	+0.56	-10.35
2000	+5.86	+0.05	-5.81	-38.41	+7.41	-0.19	+2.06	-0.18	+0.96	-8.50
2019	+5.14	+0.30	-4.84	-36.33	+6.06	-0.45	+1.37	+0.07	+1.00	-8.26

Notes: The table reports counterfactual outcomes relative to the baseline economy when the influence of managers' attitudes is eliminated from 1980 onward. $\Delta \ln w_s$ denotes the change in mean log wages for sex $s \in \{F, M\}$. Δ GWG denotes the change in the aggregate gender wage gap, defined as the difference between men's and women's mean log wages among employed workers. Δ CGWG reports the percentage change in the conditional gender wage gap relative to its baseline value, with negative values indicating a narrowing of the gap. WEV_s denotes the mean wage-equivalent variation for sex s: for each baseline state and latent type, it is the permanent proportional change in all baseline wage offers that yields the same expected lifetime value as the counterfactual, allowing workers to re-optimize across home, occupations, and hours; the table reports its baseline-mass-weighted mean. ΔE_s denotes the change in the employment rate, ΔY the percentage change in aggregate output, and $\Delta\Pi$ the percentage change in aggregate profits.

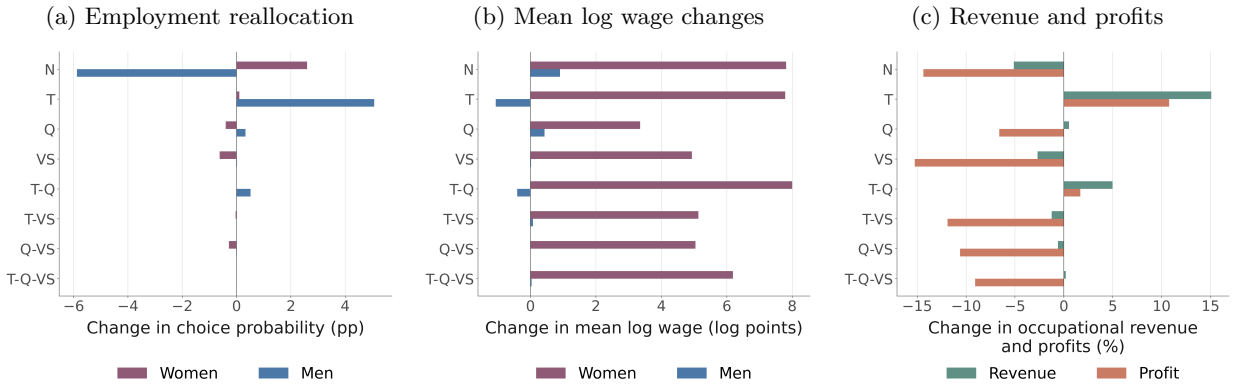
Occupational reallocation and occupation-level effects The relatively small aggregate employment responses conceal substantial reallocation across occupations. Figure 7 reports the effects in 2019, with the largest movements occurring in N and T. In N, women's probability of employment increases by 2.60 percentage points, while men's falls by 5.88 percentage points. Men's employment in T, by contrast, increases by 5.07 percentage points, with little change among women. These opposing movements largely offset one another in aggregate male employment. They also substantially change the gender composition of N, whose female employment share rises by 9.54 percentage points, driven in large part by declining male employment.

The mechanisms underlying these reallocations differ across women and men. For women, removing the influence of managerial attitudes on expected productivity improves wage opportunities throughout the economy, but the response is particularly strong in N, where occupational preferences are relatively favorable and gains in expected career value are especially pronounced. Initially, the expansion of female employment in N reflects both entry from non-employment and sorting from other occupations. These differences subsequently accumulate through employment histories and occupational persistence, as illustrated by the evolution of choice probabilities in Appendix Figure E.1. Men's choices respond differently. As women's employment increases in N, its prevailing norms become less traditional. This makes the occupation more attractive to men with relatively progressive attitudes, but less attractive to those with more traditional views, whose preferences are more sensitive to differences between their own attitudes and occupational norms. The latter become less likely to choose N and relatively more likely to choose T or non-employment. Through their effects on expected future opportunities and employment histories, these adjustments reinforce the initial responses, explaining why the substantial male reallocation develops gradually.

Changes in occupational employment and composition also affect wages and firms' outcomes. Women's mean log wages increase by 7.81 log points in N and 7.79 in T, primarily reflecting the

removal of the effect of managerial attitudes on wage setting. Men's wages respond indirectly, rising by 0.90 log points in N but falling by 1.06 in T, through changes in the marginal value of labor and the composition of employed workers. The consequences for firms differ substantially across occupations: revenue falls by 5.11% in N but rises by 15.08% in T, while profits change by −14.36% and +10.77%, respectively. Profits decline in six of the eight broad occupations (Appendix Table E.1), even though aggregate output increases. Removing the influence of managerial attitudes on wage setting therefore changes not only workers' earnings and occupational choices, but also how production and profits are distributed across occupations.

Figure 7: Occupational effects of removing the influence of managerial attitudes



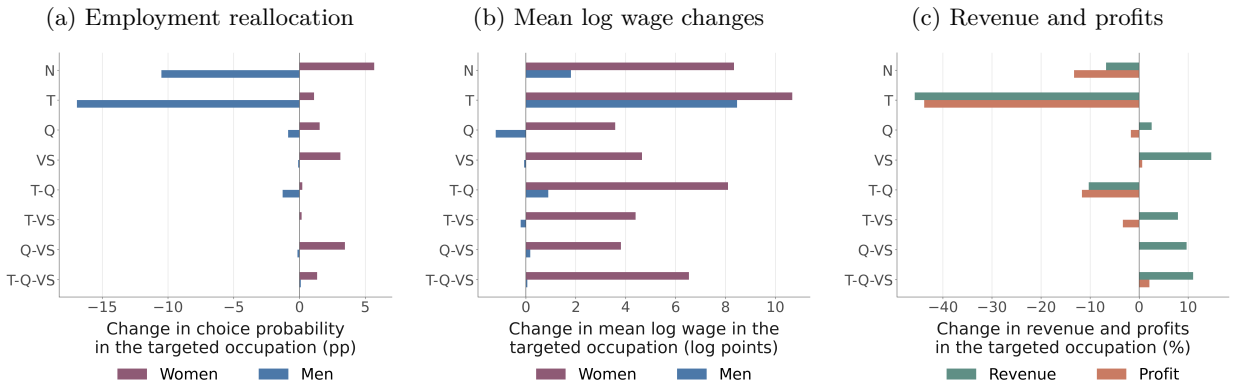
Notes: The figure reports the 2019 effects of removing the influence of managers' attitudes from 1980 onward. Panel (a) reports changes in the probability of working in each of the eight broad occupations, separately for women and men, expressed in percentage points of the respective gender's population. Panel (b) reports changes in mean log wages within each broad occupation, separately for women and men, expressed in log points. Panel (c) reports percentage changes in aggregate revenue and profits within each broad occupation. Occupational revenue is the total value of output produced in the occupation, summed across its detailed occupations and firms. Employment and wage changes are expressed as counterfactual minus baseline, while changes in revenue and profits are expressed as percentages of their respective baseline values.

Removing the influence of managerial attitudes in individual occupations The effects of removing the influence of managerial attitudes on expected female productivity may also depend on whether this influence persists elsewhere in the economy. To investigate this, I consider eight additional counterfactuals in which this effect is eliminated from one broad occupation at a time, while remaining unchanged in the other seven. Unlike economy-wide elimination, these changes improve women's wage opportunities in the targeted occupation relative to those available elsewhere. Appendix Table E.2 reports their aggregate effects. In 2019, removing this influence in N alone reduces the aggregate gender wage gap by 2.28 log points, compared with 4.84 log points under economy-wide elimination, and increases female employment by 0.88 percentage points. However, improvements in women's earnings do not necessarily translate into greater participation or production. When this influence is removed only in T, the aggregate gender wage gap falls by 1.33 log points, while

female employment decreases by 0.18 percentage points. These differences reflect the economy-wide adjustments induced by each counterfactual, which also mean that the effects of the eight exercises cannot be added together to reproduce those of eliminating this influence everywhere.

Figure E.1 shows how each counterfactual affects the occupation in which the influence of managerial attitudes on wage setting is removed. Women's employment increases in all eight targeted occupations, consistent with their improved wage opportunities relative to occupations where this influence persists. Yet these gains are accompanied by heterogeneous, and sometimes much larger, changes in male employment. In N, women's employment probability rises by 5.67 percentage points, while men's falls by 10.50 percentage points. The importance of conditions in other occupations is particularly evident in T. Under economy-wide elimination, male employment in T increases by 5.07 percentage points, whereas removing this influence only in T reduces it by 16.91 percentage points. The consequences for firms are similarly different: T's revenue and profits fall by 45.74% and 43.81%, respectively, when this influence is removed only there, compared with increases of 15.08% and 10.77% under economy-wide elimination. Thus, an occupation can attract more women after removing the influence of managerial attitudes on wage setting while experiencing a substantial contraction in employment and production. Whether it expands or contracts depends on the responses of both women and men, and on the opportunities they face in the rest of the economy.

Figure 8: Effects of removing the influence of managerial attitudes in one occupation at a time



Notes: The figure reports the 2019 effects of removing the influence of managerial attitudes on expected female productivity in one broad occupation at a time, starting in 1980. Each occupation corresponds to a separate counterfactual in which this influence is eliminated only in the indicated occupation, while remaining unchanged in all others. Panel (a) reports changes in the probability of working in the targeted occupation, separately for women and men, expressed in percentage points of the respective gender's population. Panel (b) reports changes in mean log wages within the targeted occupation, separately for women and men, expressed in log points. Panel (c) reports percentage changes in aggregate revenue and profits within the targeted occupation. Occupational revenue is the total value of output produced in the occupation, summed across its detailed occupations and firms. Employment and wage changes are expressed as counterfactual minus baseline, while changes in revenue and profits are expressed as percentages of their respective baseline values.

Overall, these counterfactuals show that the influence of managerial attitudes on expected female productivity is associated with higher profits for firm owners and lower wages and welfare for women, while its consequences for men vary with their preferences and occupational environments. Removing this influence improves women's wages and welfare and modestly increases aggregate production, but redistributes workers and profits across occupations in ways that depend crucially on whether it persists elsewhere in the economy.

6.2 The contribution of gender-role attitudes to labor market inequality

This set of counterfactuals examines how individual gender-role attitudes contribute to labor market inequality. Unlike occupational norms, which evolve endogenously with the composition of employment, individual attitudes are assumed to remain fixed throughout adulthood. This assumption reflects the idea that preferences concerning the appropriate roles of women and men are largely shaped earlier in life, through family, education, and the broader social environment. Although attitudes may continue to evolve during adulthood, changes are likely to be limited relative to differences across generations.

This distinction has important implications for policy. Individual preferences cannot be directly altered through conventional labor market interventions. However, policies that influence their formation at younger ages may contribute to longer-term cultural change. For example, Rivera-Garrido (2022) finds that additional schooling reduces traditional gender-role attitudes in adulthood, while school-based interventions explicitly targeting gender stereotypes have also been shown to influence children's attitudes (Spinner, Tenenbaum, Cameron and Wallinheimo, 2021; Gabrielli, Zava, Maricchiolo, Vecchio, Szpunar and Perucchini, 2026). Such interventions provide plausible channels through which attitudes may gradually evolve across generations, although the model does not explicitly describe their formation or the policies that influence them.

To assess their economic importance, I consider two counterfactuals in which individuals are assigned the gender-role attitudes of the youngest cohort within their education group, starting in 1980. In the first, this change applies only to women, allowing me to isolate the contribution of women's own preferences while holding men's attitudes fixed. In the second, attitudes change for both sexes, capturing the consequences of a broader cultural shift. Individual attitudes remain fixed throughout adulthood, as in the baseline model, while occupational choices, occupational norms, wages, and firm outcomes adjust endogenously. These experiments quantify the economic consequences of more progressive attitudes rather than the effects of a specific policy designed to change them.

Aggregate effects Table 7 reports the aggregate effects of changing individual gender-role attitudes. Both counterfactuals generate substantial increases in female employment, wages, and aggregate production. When only women's attitudes change, female employment rises by 8.90 percentage points in 2019, while mean log wages increase by 11.84 log points. Male employment also

increases slightly, although male wages decline by 3.01 log points. These adjustments reduce the aggregate gender wage gap by 14.85 log points, while output and profits both increase by 12.20%.

Allowing men's attitudes to change as well produces a broader expansion of economic activity. In 2019, female employment and wages increase by 8.41 percentage points and 12.53 log points, respectively, while male employment rises by 6.15 percentage points and male wages increase by 1.08 log points. Aggregate output expands by 17.78%, compared with 12.20% when only women's attitudes change. The reduction in the gender wage gap is nevertheless smaller, at 11.45 rather than 14.85 log points, primarily because men's wages also increase. Thus, a broader shift in attitudes generates larger aggregate gains without necessarily producing a greater reduction in relative wage inequality.

Despite these substantial wage gains, the conditional gender wage gap declines by only 27.29% in the first scenario and 24.30% in the second. Most of the increase in women's average wages reflects changes in employment composition rather than reductions in conditional wage differences. By 2019, improvements in women's relative human capital account for 2.68 and 2.31 log points of the reduction in the conditional gap, respectively, while changes in the contribution of managerial attitudes to expected female productivity account for another 1.89 and 1.75 log points. Although the counterfactuals leave the parameters governing managerial wage setting unchanged, changes in individual attitudes and occupational composition affect managerial attitudes and, consequently, employers' assessments of female productivity.

The effects also vary over time. Female employment gains are largest in the earlier decades, while the output response peaks around 2000 in both scenarios. Notably, the conditional gender wage gap initially increases in 1980, despite the reduction in the aggregate wage gap. This reflects a deterioration in women's relative human capital among comparable employed workers, which more than offsets the reduction in the contribution of managerial attitudes to expected female productivity. As employment histories and human capital adjust, this effect reverses, and the conditional wage gap declines in both scenarios by 2000 and 2019.

Table 7: Aggregate effects of changing workers' gender-role attitudes

Year	$\Delta \ln w_F$ (log pts)	$\Delta \ln w_M$ (log pts)	Δ GWG (log pts)	Δ CGWG (%)	ΔE_F (pp)	ΔE_M (pp)	ΔY (%)	$\Delta \Pi$ (%)
Panel A. Changing women's gender-role attitudes								
1980	+5.20	-0.04	-5.23	+20.55	+17.47	-0.66	+12.73	+17.48
2000	+15.28	-1.41	-16.69	-22.40	+17.37	+1.04	+19.56	+23.79
2019	+11.84	-3.01	-14.85	-27.29	+8.90	+1.79	+12.20	+12.20
Panel B. Changing gender-role attitudes for both sexes								
1980	+8.33	+3.98	-4.34	+8.79	+18.07	+6.05	+21.28	+20.12
2000	+16.87	+6.04	-10.83	-26.28	+17.06	+9.41	+30.64	+29.90
2019	+12.53	+1.08	-11.45	-24.30	+8.41	+6.15	+17.78	+14.86

Notes: The table reports counterfactual outcomes relative to the baseline economy when workers' gender-role attitudes are replaced, from 1980 onward, by those of the youngest cohort within the same education group. Panel A changes women's attitudes only, while Panel B changes the attitudes of both women and men. $\Delta \ln w_s$ denotes the change in mean log wages for sex $s \in \{F, M\}$. Δ GWG denotes the change in the aggregate gender wage gap, defined as the difference between men's and women's mean log wages among employed workers. Δ CGWG reports the percentage change in the conditional gender wage gap relative to its baseline value, with negative values indicating a narrowing of the gap. ΔE_s denotes the change in the employment rate, ΔY the percentage change in aggregate output, and $\Delta \Pi$ the percentage change in aggregate profits.

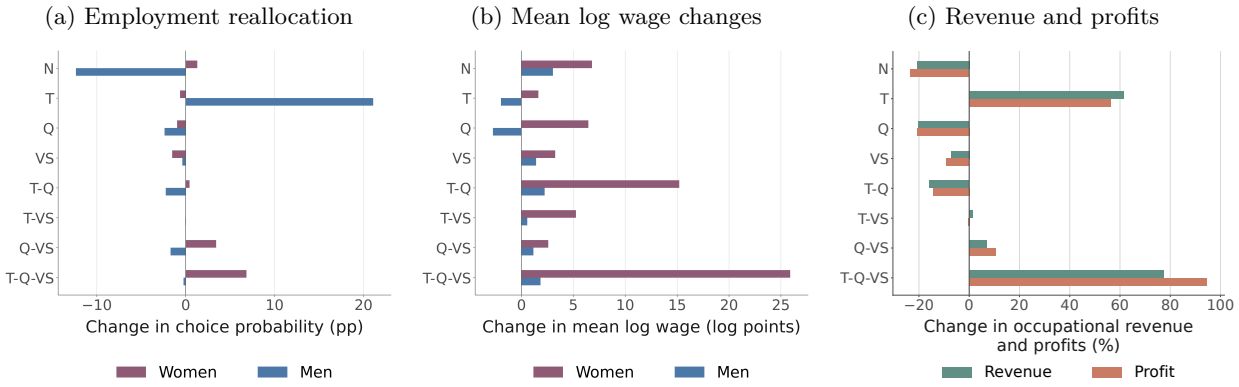
Occupational responses to changes in gender-role attitudes Figure 9 shows that changes in individual attitudes lead to substantial occupational reallocation, with markedly different patterns depending on whether men's attitudes also change. When only women's attitudes become more progressive (Panel A), female employment shifts primarily towards occupations requiring quantitative, verbal, and social skills. By 2019, women's employment probabilities increase by 6.84 percentage points in T–Q–VS and 3.42 points in Q–VS, while declining in VS, Q, and T. Male employment also undergoes substantial reallocation despite men's individual attitudes remaining unchanged: employment in N falls by 12.33 percentage points, while T gains 21.09 points. This illustrates how changes in women's preferences affect men's occupational choices through the resulting adjustments in wages, occupational norms, and future employment opportunities.

When attitudes change for both sexes (Panel B), the direction of male reallocation changes dramatically. Men's employment rises by 27.95 percentage points in N and falls by 19.97 points in T, reversing the pattern observed in Panel A. Women's employment also shifts away from N, while T–Q–VS and Q–VS remain the main destinations, gaining 7.44 and 4.63 percentage points, respectively. These differences reflect the interaction between individual attitudes and the occupational environment: changing men's own preferences alters their responses to prevailing norms, while the resulting changes in employment composition further affect those norms and employers' wage-setting decisions. The substantial reallocations also reflect accumulated employment histories. In the women-only scenario, for example, changes in inherited worker states account for 17.85 of the 21.09 percentage-point increase in men's employment probability in T.

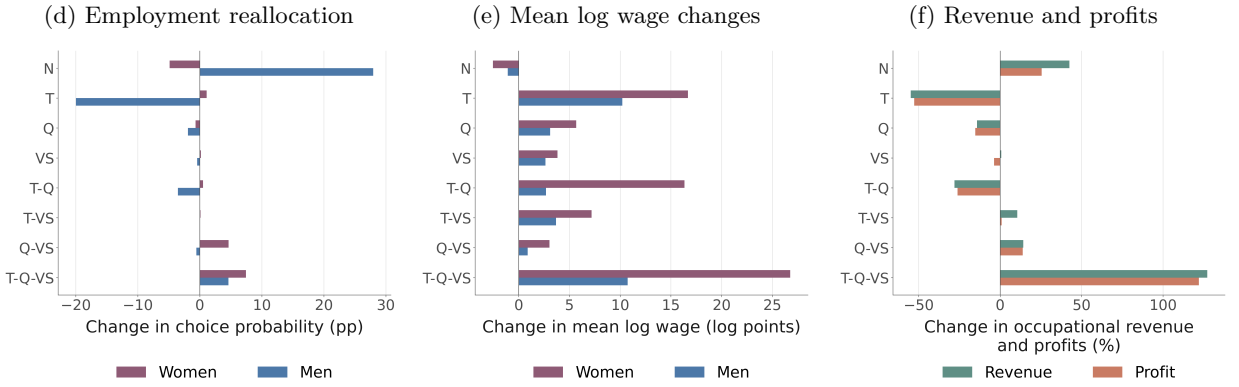
The consequences for wages and production are equally heterogeneous. In both scenarios, T–Q–VS experiences particularly large increases in women's mean log wages, of 25.9 and 26.8 log points, respectively. Its revenue increases by 77.57% when only women's attitudes change and by 127.14% when both sexes' attitudes change, accompanied by substantial increases in profits. Other occupations contract, notably N in the first scenario and T in the second, where revenue falls by 20.75% and 54.90%, respectively. Thus, the aggregate expansion in output and profits documented above conceals substantial redistribution of economic activity across occupations. Appendix Table E.3 reports the broad-occupation-level effects, while Appendix Figure E.2 traces the evolution of occupational employment over the counterfactual period.

Figure 9: Occupational effects of changes in gender-role attitudes

Panel A. Changing women's gender-role attitudes



Panel B. Changing gender-role attitudes for both sexes



Notes: The figure reports the 2019 effects of changes in gender-role attitudes relative to the baseline economy. Panel A considers changes in women's attitudes only, while Panel B allows attitudes to change for both women and men. In each panel, the three subfigures report, respectively, changes in the probability of working in each of the eight broad occupations, separately by sex (percentage points of the respective gender's population); changes in mean log wages within each occupation, separately by sex (log points); and percentage changes in occupational revenue and profits. Occupational revenue is the total value of output produced within the occupation, summed across detailed occupations and firms. Employment and wage changes are expressed as counterfactual minus baseline, while changes in revenue and profits are measured relative to their respective baseline values.

These findings highlight the importance of individual gender-role attitudes not only for occupational choices and wage inequality, but also for aggregate employment and production. Yet even substantial changes in attitudes leave considerable conditional wage inequality, suggesting that shifting individual preferences alone is insufficient to eliminate gender differences in pay.

6.3 Restricting gender wage differentiation

The final counterfactual examines the effects of restricting firms' ability to offer different wages to observationally equivalent men and women. Although gender-based pay differences for equal work are already prohibited, firms may assign men and women to differently paid positions within the same occupation. Evidence from U.S. matched employer–employee data documents substantial gender wage differences within establishments and occupations, conditional on observable worker characteristics (Bayard, Hellerstein, Neumark and Troske, 2003; King, Mendoza, Penner, Rainey and Tomaskovic-Devey, 2023). Ransom and Oaxaca (2010) illustrate how differences in job assignments can contribute to these disparities, including between positions involving relatively similar tasks.

Such differences may reflect variation in tasks, responsibilities, productivity, or workers' preferences, but also differences in firms' hiring, assignment, and promotion decisions. Benson, Li and Shue (2026), for example, show that women receive lower assessments of promotion potential despite higher performance ratings, and that marginally promoted women subsequently outperform marginally promoted men. Their findings point to biased assessments of potential and the resulting misallocation of promotion opportunities. This motivates policies combining pay audits, clearer job classifications, transparency in hiring and promotion criteria, and greater accountability for differences in job assignments and remuneration.

In the counterfactual, firms must offer the same wage to men and women within each year, detailed occupation, education group, human-capital interval, and working-hours category. They continue to set wages optimally under this constraint, accounting for gender-specific labor supply elasticities and the influence of managerial attitudes on expected female productivity. Both mechanisms therefore continue to influence the common wage, depending on the expected gender composition of employment, rather than generating separate wage offers. While the restriction is intended to operate within firms, the model assumes symmetric firms within detailed occupations. In practice, differences in firm productivity, job responsibilities, and unobserved worker characteristics would justify some wage variation, so the counterfactual represents a stronger restriction than a policy targeting only gender-based pay differences within firms.

Aggregate effects Table 8 reports the aggregate effects of the wage-setting constraint. By requiring common wage offers for comparable men and women, the policy substantially reduces gender wage inequality without eliminating either the influence of managerial attitudes on expected female productivity or employers' wage-setting power. In 2019, women's mean log wage increases by

3.13 log points, while men's falls by 0.30 log points, reducing the aggregate gender wage gap by 3.42 log points. The conditional gender wage gap declines by 57.15% relative to its baseline level. The wage-gap decomposition reveals an important distinction between the direct effect of the constraint and its equilibrium consequences. At unchanged employment composition, the change in wage offers would reduce the aggregate gap by 5.03 log points. However, the induced reallocation of workers, primarily across occupations, offsets 1.60 log points of this reduction. Equalizing wage offers within the groups covered by the policy therefore does not eliminate differences in average earnings, as workers continue to differ in where they work and in the wages associated with those choices.

The consequences extend beyond the redistribution of current wages. Women's mean wage-equivalent variation reaches +3.53% in 2019, whereas men's is −3.25%. The latter is particularly striking given the relatively small decline in men's average wages that year. It reflects the importance of changes in employment opportunities and expected future outcomes, which are not captured by average wages among employed workers. The restriction affects not only how workers are paid within a given employment category, but also their incentives to participate in the labor market and their allocation across occupations. These adjustments matter for the distribution of gains from the policy, even though the underlying mechanisms influencing wage setting remain present.

Perhaps the most distinctive result concerns the incidence of the policy. Female employment increases by 0.57 percentage points, while male employment falls by 1.05 percentage points in 2019. Despite this decline in male participation, aggregate output rises by 0.85%, indicating that changes in the allocation and effective supply of labor improve production. Aggregate profits, meanwhile, fall by only 0.59%. This limited response contrasts sharply with the 8.26% decline when the influence of managerial attitudes on expected female productivity is removed throughout the economy. The accounting decomposition helps explain why: relative to the increase in the female wage bill, the reduction in payments to men represents 43.8%, additional revenue 49.1%, and the decline in profits only 7.1%. Thus, firms accommodate the common-wage requirement largely through adjustments in employment, wages, and production, rather than absorbing most of the increase in women's earnings through lower profits. The policy substantially improves women's remuneration, but part of its cost is borne by men, whose employment and welfare decline. This illustrates a fundamental difference between restricting gender wage differentiation and removing the influence of managerial attitudes on wage setting.

Table 8: Aggregate effects of imposing common wages for comparable workers

Year	$\Delta \ln w_F$ (log pts)	$\Delta \ln w_M$ (log pts)	Δ GWG (log pts)	Δ CGWG (%)	WEV_F (%)	WEV_M (%)	ΔE_F (pp)	ΔE_M (pp)	ΔY (%)	$\Delta\Pi$ (%)
1980	+3.22	-1.28	-4.50	-31.03	+2.04	-0.73	+0.28	-0.14	+0.46	+0.07
2000	+2.78	-1.52	-4.30	-42.26	+2.78	-1.63	+0.59	-0.85	+0.19	-0.39
2019	+3.13	-0.30	-3.42	-57.15	+3.53	-3.25	+0.57	-1.05	+0.85	-0.59

Notes: The table reports counterfactual outcomes relative to the baseline economy when employers are required, from 1980 onward, to offer the same wage to workers within cells defined by detailed occupation, education, human capital (bins of 0.25), and part- or full-time status. $\Delta \ln w_s$ denotes the change in mean log wages for sex $s \in \{F, M\}$. Δ GWG denotes the change in the aggregate gender wage gap, defined as the difference between men's and women's mean log wages among employed workers. Δ CGWG reports the percentage change in the conditional gender wage gap relative to its baseline value, with negative values indicating a narrowing of the gap. WEV_s denotes the mean wage-equivalent variation for sex s: for each baseline state and latent type, it is the permanent proportional change in all baseline wage offers that yields the same expected lifetime value as the counterfactual, allowing workers to re-optimize across home, occupations, and hours; the table reports its baseline-mass-weighted mean. ΔE_s denotes the change in the employment rate, ΔY the percentage change in aggregate output, and $\Delta\Pi$ the percentage change in aggregate profits.

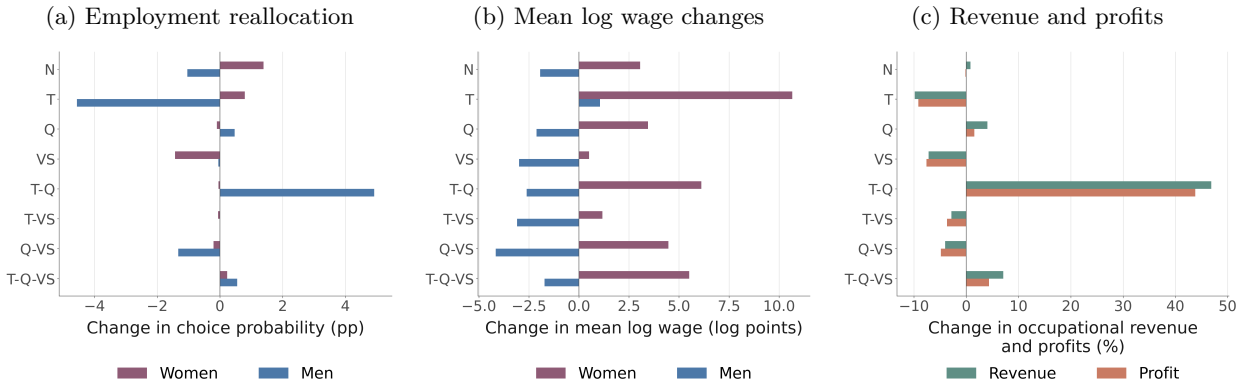
Occupational reallocation and occupation-level effects One of the most striking consequences of the common-wage constraint is the substantial reallocation of male employment across occupations. As shown in Figure 10, men's probability of working in T falls by 4.56 percentage points in 2019, while their probability of working in T–Q increases by 4.92 percentage points. Women's responses follow a different pattern: employment expands in N and T, by 1.39 and 0.79 percentage points, respectively, but contracts by 1.43 percentage points in VS. These movements also change occupational gender composition, increasing the female employment share in T by 4.41 percentage points and reducing it in T–Q by 3.84 percentage points.

The substantial reallocation of male employment reflects an important feature of the common-wage constraint: wages offered to men now depend on the labor supply of women within the same wage-setting group. Gender-specific labor supply elasticities and the influence of managerial attitudes on expected female productivity continue to affect wage setting, with their relative importance depending on the expected gender composition of employment. These adjustments change wage opportunities for both sexes and, through the resulting changes in occupational composition, also affect prevailing gender norms. Together, wages and norms shape the relative attractiveness of occupations and workers' expected future opportunities. For women, the changes in the current occupational environment favor N and T relative to VS, while for men they favor T–Q relative to T. These differences accumulate through employment histories and occupational persistence: by 2019, changes in inherited worker states account for most of the observed reallocation, as illustrated in Appendix Figure E.3.

The redistribution of employment is accompanied by substantial changes in wages and occupational activity. In T, women's mean log wages increase by 10.66 log points and men's by 1.05, even as male employment contracts sharply. In T–Q, women's wages rise by 6.12 log points while men's

fall by 2.61, alongside a large increase in male employment. These contrasting movements reflect changes in both wage offers and the composition of employed workers, so average wage changes need not follow employment in the same direction. The consequences for firms are equally pronounced. Revenue and profits fall by 9.85% and 9.16% in T, respectively, but increase by 46.86% and 43.81% in T–Q. Appendix Table E.4 shows that profits decline in five of the eight occupations, despite the relatively small aggregate reduction of 0.59%. Thus, rather than imposing a uniform cost on firms, the wage constraint substantially changes the distribution of employment, production, and profits across occupations.

Figure 10: Occupational effects of restricting gender wage differentiation



Notes: The figure reports the 2019 effects of imposing common wage offers for comparable men and women from 1980 onward, using human-capital intervals of width 0.25. Panel (a) reports changes in the probability of working in each of the eight broad occupations, separately for women and men, expressed in percentage points of the respective gender's population. Panel (b) reports changes in mean log wages within each broad occupation, separately for women and men, expressed in log points. Panel (c) reports percentage changes in aggregate revenue and profits within each broad occupation. Occupational revenue is the total value of output produced in the occupation, summed across its detailed occupations and firms. Employment and wage changes are expressed as counterfactual minus baseline, while changes in revenue and profits are expressed as percentages of their respective baseline values.

The common-wage constraint illustrates the trade-offs involved in reducing gender wage inequality without eliminating the underlying mechanisms that generate gender differences in wage offers. While women benefit from higher wages and improved welfare, the adjustment also reduces men's employment and welfare, with substantial reallocations of labor and production across occupations but relatively little change in aggregate profits.

7 Conclusion

This paper investigates why gender wage gaps, conditional on observable worker characteristics, are larger in occupations employing fewer women. Using four decades of U.S. data, I document

a negative relationship between occupational female representation and gender wage inequality. Occupations employing more women tend to have more progressive gender-role attitudes, and women moving toward more traditional occupational environments experience lower wage growth, unlike men. These findings suggest that understanding occupational differences in gender wage inequality requires considering not only workers' characteristics and sorting decisions, but also the environment in which wages are determined.

To investigate these mechanisms, I develop and estimate an equilibrium model of occupational choice and employer wage setting. Workers' individual gender-role attitudes influence their preferences for occupational environments, whose prevailing norms reflect the attitudes of their workforce. Managers' gender-role attitudes, in turn, influence their assessments of female productivity, without affecting workers' actual productive efficiency. Firms take these assessments into account when setting wages, alongside their labor market power. The results highlight the importance of managerial attitudes in explaining why gender wage gaps vary with occupational female representation. Differences in expected human capital and employer labor market power also contribute to wage inequality, particularly its overall level and persistence. These mechanisms are interconnected, as occupational choices shape employment histories, prevailing norms, and the wage opportunities available to workers.

The counterfactual analysis highlights the different economic implications of addressing these sources of inequality. Removing the influence of managerial attitudes on expected female productivity improves women's wages and welfare, with effects that are primarily distributional rather than driven by large increases in production. Changes in workers' own attitudes can instead generate substantial employment and output gains by reshaping occupational choices and career trajectories. This points to the potential longer-term importance of education and interventions targeting gender stereotypes. Policies aimed more directly at wage setting, such as pay transparency, clearer job classifications, and restrictions on gender wage differentiation, may also reduce wage inequality. However, the common-wage counterfactual illustrates that such restrictions can redistribute adjustment costs across women, men, and firms, with consequences for employment and welfare.

Overall, the findings emphasize that gender wage inequality reflects the interaction of human capital accumulation, employer labor market power, and gender-role attitudes operating through both workers' choices and managers' assessments of productivity. Addressing these different mechanisms can have very different consequences for labor allocation, aggregate production, and the distribution of surplus. While the counterfactuals are not predictions of specific policies, they provide a framework for understanding these trade-offs and the broader economic consequences of reducing gender wage inequality.

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A Additional descriptive evidence

A.1 Occupational classification and trends

A.1.1 Construction of occupational groups

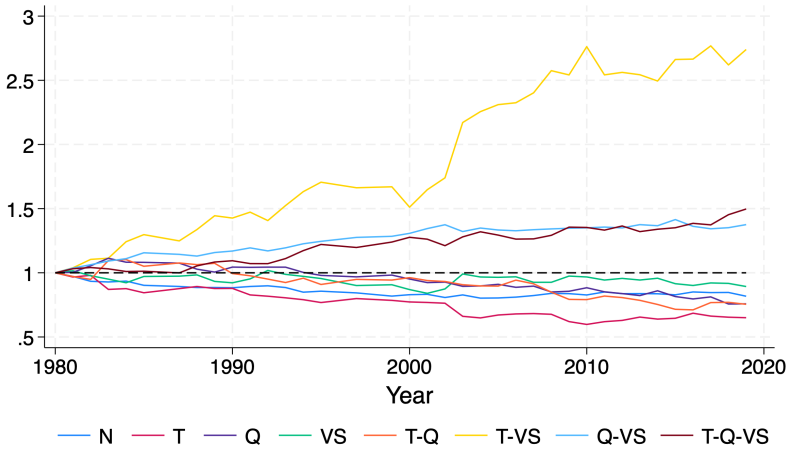
Occupational requirements are measured using O*NET version 12.0 (2007), which provides detailed information on the skills and knowledge required across occupations classified under the Standard Occupational Classification (SOC) system. I use this version throughout the sample period, assuming that relative occupational requirements remain stable over time. I map SOC occupations to the harmonized three-digit Census occupation codes developed by Dorn (2009), making minor adjustments to improve coverage. Occupational requirements are then aggregated at the three-digit Census occupation level, which serves as the basis for the classification into eight broad groups.

Four dimensions are initially constructed from O*NET descriptors. Quantitative requirements combine mathematical reasoning, number facility, and mathematics knowledge. Technical requirements combine biology, chemistry, physics, mechanical, and electronics knowledge, with greater weight assigned to mechanical skills. Verbal requirements combine reading comprehension and English language knowledge, while social requirements combine cooperation, social orientation, and leadership.

I combine verbal and social requirements into a single dimension (VS), leaving three dimensions: technical (T), quantitative (Q), and verbal/social (VS). Each three-digit Census occupation is classified according to whether its requirements exceed the median across occupations in each dimension, yielding eight mutually exclusive groups. The classification is fixed over time and does not use occupational gender composition. The complete list of occupations and their assigned groups is reported in Table A.2.

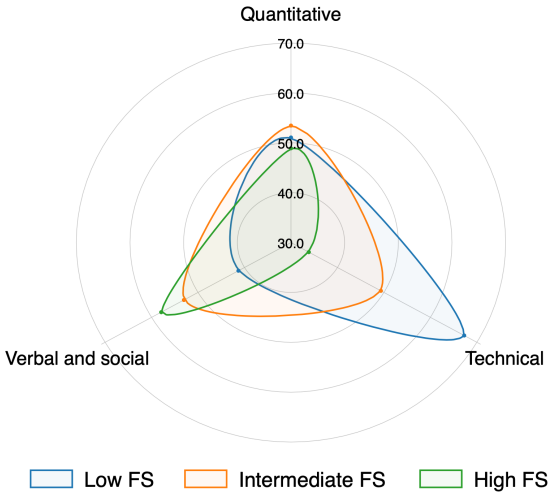
A.1.2 Descriptives

Figure A.1: Evolution of occupational employment shares, 1980–2019



Notes: The figure shows the evolution of each broad occupation's share of total employment relative to its 1980 level (1980 = 1). Employment shares are calculated using CPS sampling weights. Occupations are grouped into eight categories based on their technical (T), quantitative (Q), and verbal/social (VS) requirements. N denotes occupations with below-median requirements in all three dimensions.

Figure A.2: Occupational skill requirements by female representation in 1980



Notes: The figure reports average occupational skill requirements by tercile of the female employment share in 1980. Skill requirements are measured as percentiles across 3-digit occupations along three dimensions: quantitative, technical, and verbal/social skills. Low-FS occupations have a female share below 6 percent, intermediate-FS occupations between 6 and 44 percent, and high-FS occupations above 44 percent.

Table A.1: Occupational employment shares and female representation, 1980 and 2019

	1980	2019	Δ (pp)
Panel A. Share of total employment (%)			
N	22.5	18.4	-4.1
T	15.7	10.2	-5.5
Q	10.8	8.2	-2.6
VS	12.1	10.8	-1.3
T–Q	7.1	5.3	-1.7
T–VS	1.5	4.2	+2.7
Q–VS	20.3	27.9	+7.6
T–Q–VS	10.0	15.0	+5.0
Panel B. Female share within occupation (%)			
N	42.0	39.2	-2.8
T	16.8	14.4	-2.3
Q	61.7	54.3	-7.4
VS	85.3	79.5	-5.8
T–Q	7.5	10.7	+3.2
T–VS	94.6	83.3	-11.3
Q–VS	37.9	51.9	+14.0
T–Q–VS	20.3	35.9	+15.6

Notes: Panel A reports each broad occupation's share of total employment. Panel B reports the proportion of women employed within each broad occupation. Changes are measured between 1980 and 2019 in percentage points. Employment shares are computed from CPS-weighted counts. Occupation groups are defined using technical (T), quantitative (Q), and verbal/social (VS) requirements; N denotes occupations below the median in all three dimensions.

Table A.2: Broad occupation groups by skill requirements

Group N (no high skill requirements)
Athletes, sports instructors, and officials; Door-to-door sales, street sales, and news vendors; File clerks; Mail clerks, outside of post office; Messengers; Stock and inventory clerks; Meter readers; Housekeepers, maids, butlers, and cleaners; Laundry and dry cleaning workers; Bartenders; Waiters and waitresses; Cooks; Food preparation workers; Miscellaneous food preparation and serving workers; Janitors; Barbers; Hairdressers and cosmetologists; Recreation facility attendants; Animal caretakers, except farm; Graders and sorters of agricultural products; Masons, tilers, and carpet installers; Drywall installers; Painters, construction and maintenance; Concrete and cement workers; Glaziers; Roofers and slaters; Miscellaneous construction and related occupations; Furniture and wood finishers, other precision wood workers; Dressmakers, seamstresses, and tailors; Upholsterers; Shoemakers, other precision apparel and fabric workers; Hand molders and shapers, except jewelers; Bookbinders; Butchers and meat cutters; Batch food makers; Winding and twisting textile and apparel workers; Textile sewing machine operators; Clothing pressing machine operators; Miscellaneous textile machine operators; Cementing and gluing machine operators; Slicing, cutting, crushing, and grinding machine operators; Machine operators, n.e.c.; Production checkers, graders, and sorters; Truck, delivery, and tractor drivers; Bus drivers; Parking lot attendants; Railroad conductors and yardmasters; Production helpers; Packers and packagers by hand.
Group T (technical-intensive)
Painters, sculptors, craft-artists, and artist printmakers; Gardeners and groundskeepers; Farm workers, including nursery farming; Automobile mechanics and repairers; Bus, truck, and stationary engine mechanics; Small engine repairers; Auto body repairers; Heavy equipment and farm equipment mechanics; Repairers of industrial electrical equipment; Precision makers, repairers, and smiths; Repairers of mechanical controls and valves; Millwrights; Mechanics and repairers, n.e.c.; Electric power installers and repairers; Insulation workers; Structural metal workers; Drillers of earth; Miners; Other mining occupations; Plant and system operators, stationary; Metal and plastic processing machine operators; Sawing machine operators and sawyers; Metal and plastic processing machine operators, n.e.c.; Packers, fillers, and wrappers; Extruding and forming machine operators; Mixing and blending machine operators; Paper folding machine operators; Furnace, kiln, and oven operators, apart from food; Photographic process workers; Welders, solderers, and metal cutters; Assemblers of electrical equipment; Taxi cab drivers and chauffeurs; Operating engineers of construction equipment; Crane, derrick, winch, hoist, and longshore operators; Stevedores and miscellaneous material moving occupations; Helpers, construction; Helpers, surveyors; Construction laborers;

Table A.2 continued

Machine feeders and offbearers; Garage and service station related occupations; Vehicle washers and equipment cleaners; Laborers, freight, stock, and material movers.

Group Q (quantitative-intensive)

Retail salespersons and sales clerks; Cashiers; Transportation ticket and reservation agents; Records clerks; Bookkeepers and accounting and auditing clerks; Office machine operators, n.e.c.; Shipping and receiving clerks; Locksmiths and safe repairers.

Group VS (verbal/social-intensive)

Vocational and educational counselors; Social workers; Welfare service workers; Writers and authors; Technical writers; Designers; Musicians and composers; Photographers; Art/entertainment performers and related workers; Editors and reporters; Announcers; Health record technologists and technicians; Legal assistants and paralegals; Secretaries and stenographers; Typists; Receptionists and other information clerks; Library assistants; Telephone and other telecom operators; Dispatchers; Bill and account collectors; Administrative support jobs, n.e.c.; Guards and police, except public service; Health and nursing aides; Guides; Baggage porters, bellhops, and concierges; Recreation and fitness workers; Child care workers; Locomotive operators, engineers, and firemen.

Group T-Q (technical and quantitative)

Purchasing agents and buyers of farm products; Clinical laboratory technologists and technicians; Drafters; Programmers of numerically controlled machines; Supervisors of cleaning and building service workers; Pest control occupations; Farmers (owners and tenants); Timber, logging, and forestry workers; Aircraft mechanics; Industrial machinery repairers; Machinery maintenance occupations; Telecom and line installers and repairers; Repairers of electrical equipment, n.e.c.; Supervisors of construction work; Carpenters; Electricians; Plumbers, pipe fitters, and steamfitters; Explosives workers; Tool and die makers and die setters; Machinists; Other precision metal occupations; Cabinetmakers and bench carpenters; Bakers; Water and sewage treatment plant operators; Other plant and system operators; Lathe, milling, and turning machine operators; Punching and stamping press operatives; Grinding, abrading, buffing, and polishing machine operators; Nail, tacking, shaping, and joining machine operators; Separating, filtering, and clarifying machine operators; Ship crews and marine engineers.

Table A.2 continued

Group T-VS (technical and verbal/social)
Registered nurses; Occupational therapists; Physical therapists; Physicians' assistants; Broadcast equipment operators; Fire fighting, fire prevention, and fire inspectors; Protective service, n.e.c.; Dental laboratory and medical appliance technicians.
Group Q-VS (quantitative and verbal/social)
Financial managers; Human resources and labor relations managers; Managers and specialists in marketing, advertising, and public relations; Managers in education and related fields; Managers of properties and real estate; Managers and administrators, n.e.c.; Accountants and auditors; Insurance underwriters; Other financial specialists; Management analysts; Personnel, HR, training, and labor relations specialists; Buyers, wholesale and retail trade; Purchasing managers, agents, and buyers; Business and promotion agents; Actuaries; Mathematicians and statisticians; Librarians; Economists, market and survey researchers; Psychologists; Clergy and religious workers; Lawyers; Actors, directors, and producers; Sales supervisors and proprietors; Insurance sales occupations; Real estate sales occupations; Financial service sales occupations; Advertising and related sales jobs; Office supervisors; Interviewers, enumerators, and surveyors; Hotel clerks; Correspondence and order clerks; Human resources clerks, excluding payroll and timekeeping; Payroll and timekeeping clerks; Billing clerks and related financial records processing clerks; Weighers, measurers, and checkers; Material recording, scheduling, production, planning, and expediting clerks; Insurance adjusters, examiners, and investigators; Customer service representatives, investigators, and adjusters; General office clerks; Bank tellers; Data entry keyers; Statistical clerks; Police and detectives, public service; Optical goods workers.
Group T-Q-VS (high skill in all dimensions)
Chief executives, public administrators, and legislators; Managers of medicine and health occupations; Funeral directors; Inspectors and compliance officers, outside construction; Architects; Aerospace engineers; Metallurgical and materials engineers; Petroleum, mining, and geological engineers; Chemical engineers; Civil engineers; Electrical engineers; Industrial engineers; Mechanical engineers; Engineers and other professionals, n.e.c.; Computer systems analysts and computer scientists; Operations and systems researchers and analysts; Physicists and astronomers; Chemists; Geologists; Agricultural and food scientists; Biological scientists; Foresters and conservation scientists; Medical scientists; Physicians; Dentists; Veterinarians; Optometrists; Other health and therapy occupations; Pharmacists; Dieticians and nutritionists; Respiratory therapists; Therapists, n.e.c.; Primary school teachers; Secondary school teachers;

Table A.2 continued

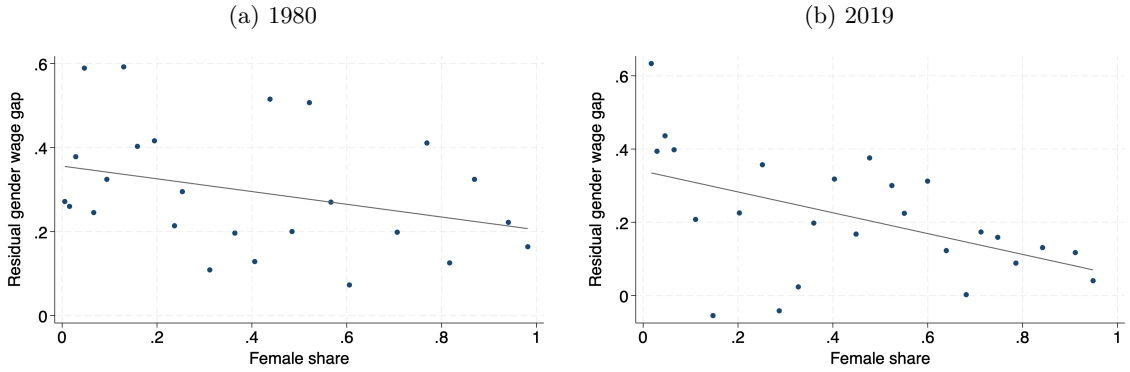
Archivists and curators; Social scientists and sociologists, n.e.c.; Radiologic technologists and technicians; Licensed practical nurses; Health technologists and technicians, n.e.c.; Engineering technicians; Surveyors, cartographers, and mapping scientists; Biological technicians; Science technicians; Airplane pilots and navigators; Computer software developers; Sales engineers; Supervisors of landscaping, lawn service, and groundskeeping workers; Supervisors of personal service jobs, n.e.c.; Public transportation attendants and inspectors; Supervisors of mechanics and repairers; Repairers of data processing equipment; Heating, air conditioning, and refrigeration mechanics; Production supervisors or foremen; Power plant operators.

Notes: Occupations are grouped based on whether their skill requirements in quantitative (Q), technical (T), and verbal/social (VS) dimensions are above the median, using O*NET measures. Each Census 3-digit occupation is assigned to one of eight mutually exclusive groups based on these three dimensions. Occupation codes are harmonized using Dorn (2009)'s mapping and matched to O*NET skill requirements.

A.2 Female employment shares and gender wage gaps

A.2.1 Robustness at the 3-digit occupation level

Figure A.3: Occupational gender wage gap and female share in disaggregated occupations



Notes: The figure shows a binscatter of the gender gap in wage residuals against the female employment share across 3-digit occupations in 1980 and 2019 (Current Population Survey). Wage residuals are obtained from the following weighted regression estimated over 1978–2020:

$$\log(\text{hourly wage}_{it}) = \beta_0 + \beta_1 \text{age}_{it} + \beta_2 \text{age}_{it}^2 + \text{education FE} + \text{race FE} + \text{year FE} + \text{state FE} + \epsilon_{it}$$

Table A.3: Female employment shares and gender wage gaps within three-digit occupations

	Baseline	With FS	With FS + industry FE
Female	-0.218***	-0.280***	-0.251***
	(0.001)	(0.003)	(0.003)
Female × Proportion of women		0.126***	0.111***
		(0.006)	(0.006)
Proportion of women		0.070***	0.059***
		(0.010)	(0.010)
Observations	1,131,891	1,131,891	1,131,859

Notes: The table reports the results from the following weighted regression using CPS data:

$$\log(\text{hourly wage}_{it}) = \beta_0 + \beta_1 \text{female}_i + \beta_2 \text{age}_{it} + \beta_3 \text{age}_{it}^2 + \beta_4 \text{part}_{it} + \text{educ. FE} + \text{race FE} + \text{year FE} + \text{3-d.occ FE} + \text{state FE} + \epsilon_{it}$$

where part_{it} denotes part-time work and occupation fixed effects are defined at the three-digit Census occupation level. Column (2) additionally includes the female employment share at the three-digit occupation-year level and its interaction with the female indicator. Column (3) further includes industry fixed effects. Heteroskedasticity-robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.2.2 Individual skills and the gender wage gap

The NLSY79 and NLSY97 provide individual measures of skills corresponding to the three dimensions used to classify occupations: quantitative, technical, and verbal/social. Quantitative, verbal, and technical skills are measured using the Armed Services Vocational Aptitude Battery (ASVAB), harmonized across cohorts following Arcidiacono, Aucejo, Maurel and Ransom (2025). Social skills are constructed from questions on extraversion and agreeableness in the Big Five personality inventory, adjusted for cohort and education differences and expressed as within-cohort percentiles. Verbal and social skills are combined into a single measure.

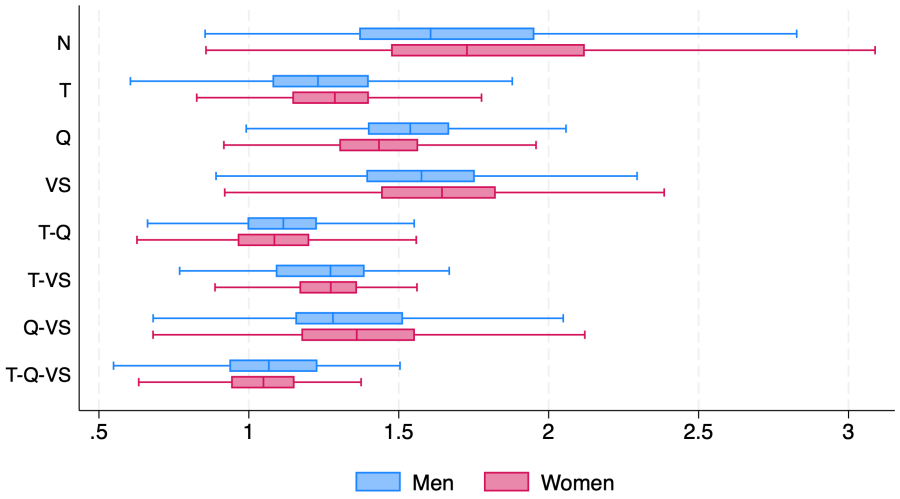
For each individual, I construct a measure of skill match between their endowments and the requirements of their current occupation:

$$M_{ij} = \sum_{k=1}^{3} \omega_{jk} \frac{s_{ik}}{r_{jk}},$$

where s_{ik} denotes individual i's endowment in skill dimension k, measured using the NLSY; r_{jk} denotes the corresponding level of skill required in occupation j, measured using O*NET; and ω_{jk} is the relative importance of that skill in occupation j, also measured using O*NET. The three dimensions are quantitative, technical, and verbal/social. Occupational requirements are rescaled to a common 0–100 scale before constructing the ratios.

Figure A.4 compares the distributions of skill match between women and men within the eight broad occupations. Table A.4 examines whether the relationship between occupational female shares and conditional gender wage gaps persists after accounting for skill match or individual skill endowments. The coefficient on the interaction between the female indicator and occupational female share remains unchanged when accounting for skill match (0.156), and increases slightly when accounting directly for individual skills (0.169), compared with 0.156 without these covariates. Together, these results suggest that differences in observed skills along the dimensions underlying the occupational classification are unlikely to explain the documented relationship.

Figure A.4: Distribution of occupational skill match by gender



Notes: The figure shows the distribution of individual skill-match scores by gender across the eight broad occupations, using NLSY79 and NLSY97 data. Skill match is measured using individual quantitative, technical, and verbal/social skills relative to the requirements of their three-digit Census occupation, weighted by the importance of each skill dimension in O*NET. Boxes indicate the interquartile range, horizontal lines the median, and whiskers extend to 1.5 times the interquartile range.

Table A.4: Female employment shares and gender wage gaps: Accounting for individual skills

	Baseline	With FS	With FS + skill match	With FS + skills
Female	-0.209***	-0.281***	-0.282***	-0.282***
	(0.010)	(0.021)	(0.021)	(0.021)
Female × Female share		0.156***	0.156***	0.169***
		(0.041)	(0.040)	(0.039)
Female share		0.655***	0.642***	0.646***
		(0.092)	(0.092)	(0.091)
Skill match			0.038***	
			(0.010)	
Quantitative skills				0.009***
				(0.001)
Technical skills				-0.000
				(0.001)
Verbal and social skills				0.003***
				(0.001)
Observations	65,532	65,532	65,532	65,532

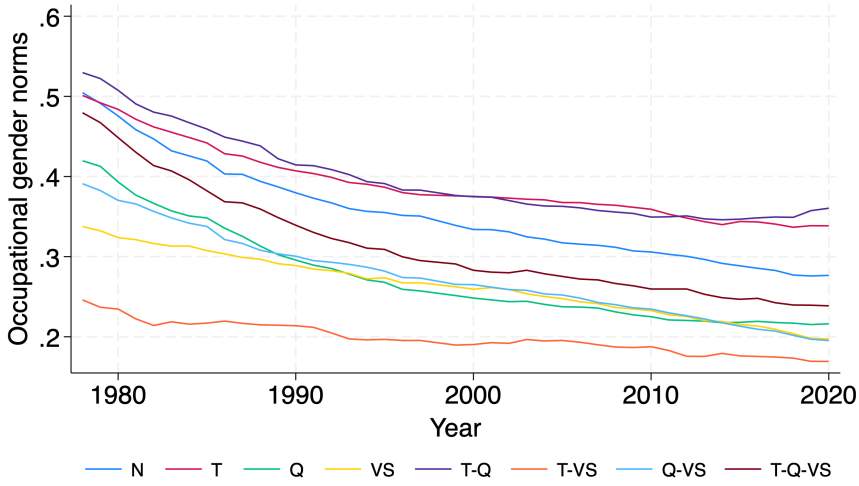
Notes: The table reports the results from the following weighted regression using NLSY79 and NLSY97 data:

$$\log(\text{hourly wage}_{it}) = \beta_0 + \beta_1 \text{female}_i + \beta_2 \text{experience}_{it} + \beta_3 \text{experience}_{it}^2 + \beta_4 \text{part}_{it} + \text{college FE} + \text{race FE} + \text{year FE} + \text{occ FE} + \epsilon_{it}$$

where part_{it} denotes part-time work and occupation fixed effects are defined at the broad occupation level. Column (2) additionally includes the female employment share at the broad occupation-year level and its interaction with the female indicator. Column (3) further accounts for individual skill match, while column (4) instead accounts for individual quantitative, technical, and verbal/social skill endowments. Regressions use NLSY sampling weights. Standard errors clustered at the individual level are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A.3 Gender norms across occupations

Figure A.5: Occupational gender norms over time



Notes: The figure plots the gender norm index by broad occupation and year. The index is constructed from GSS regressions of individual gender attitudes estimated separately by broad occupation and gender, using the same individual characteristics as in Table A.5. Predicted attitudes are then assigned to CPS workers and averaged within occupation-year using CPS sampling weights. Higher values indicate more conservative gender norms.

Table A.5: Correlates of individual attitudes towards gender norms

	All	Men	Women
Female	-0.086***		
	(0.005)		
College	-0.059***	-0.064***	-0.058***
	(0.006)	(0.010)	(0.008)
Home	0.032***	-0.014	0.059***
	(0.009)	(0.014)	(0.011)
T	0.020	0.019	0.009
	(0.012)	(0.015)	(0.024)
Q	-0.056***	-0.057**	-0.051**
	(0.013)	(0.021)	(0.017)
VS	-0.044***	-0.059**	-0.034**
	(0.010)	(0.018)	(0.012)
T-Q	0.015	0.010	0.004
	(0.014)	(0.016)	(0.034)
T-VS	-0.077***	-0.078*	-0.071***
	(0.014)	(0.031)	(0.016)
Q-VS	-0.048***	-0.031*	-0.062***
	(0.009)	(0.014)	(0.012)
T-Q-VS	-0.031**	-0.010	-0.060***
	(0.011)	(0.016)	(0.014)
Time trend	-0.001**	-0.002***	-0.000
	(0.000)	(0.000)	(0.000)
Birth cohort FE	$-0.012 \rightarrow -0.431^{***}$	$-0.075 \rightarrow -0.487^{***}$	$0.053 \rightarrow -0.368^{***}$
Observations	21,124	9,202	11,922
R^2	0.098	0.078	0.094

Notes: The table reports the results from regressions with survey weights:

$$attitudes_i = \beta_1 female_i + \beta_2 college_i + \sum_{j \neq N} \gamma_j occupation_{ijt} + \delta t + \eta_c + \varepsilon_{it}$$

where η_c denotes birth-cohort fixed effects and t is a time trend. The dependent variable is the index of individual attitudes towards gender norms, computed with the GSS data. Columns (1)–(3) report estimates for the full sample, men, and women, respectively. Occupational categories are defined relative to N, the omitted category. The regressions include a linear time trend and five-year birth-cohort fixed effects for cohorts born between 1918 and 1999. For birth-cohort fixed effects, the table reports the estimated coefficient for the earliest non-omitted cohort (1920–1924) and the latest cohort (1995-1999), respectively. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Descriptive statistics

Table B.1: Summary statistics: GSS sample

Variable	Mean (Std. dev.)		Min	Max	Observations
Individual characteristics					
	All				
Year	2001 (12.02)		1977	2024	21,124
Birth year	1962 (15.52)		1918	1999	21,124
Female	0.56 (0.50)		0	1	21,124
Age	38.55 (11.14)		18	59	21,124
	Women	*Men*			
College	0.26 (0.44)	0.29 (0.45)	0	1	11,922 / 9,202
Work-related variables					
	Women	*Men*			
Working	0.69 (0.46)	0.84 (0.37)	0	1	11,922 / 9,202
Supervisor	0.16 (0.37)	0.25 (0.43)	0	1	11,922 / 9,202
Occupation-related variables					
	Women	*Men*			
N	0.12 (0.33)	0.16 (0.37)	0	1	11,922 / 9,202
T	0.03 (0.16)	0.14 (0.35)	0	1	11,922 / 9,202
Q	0.06 (0.23)	0.03 (0.18)	0	1	11,922 / 9,202
VS	0.18 (0.38)	0.07 (0.25)	0	1	11,922 / 9,202
T–Q	0.01 (0.10)	0.09 (0.29)	0	1	11,922 / 9,202
T–VS	0.03 (0.18)	0.01 (0.11)	0	1	11,922 / 9,202
Q–VS	0.18 (0.39)	0.20 (0.40)	0	1	11,922 / 9,202
T–Q–VS	0.08 (0.28)	0.14 (0.35)	0	1	11,922 / 9,202
Gender attitudes					
	Women	*Men*			
Women in politics (*fepol*)	1.80 (0.40)	1.76 (0.43)	1	2	11,922 / 9,202
Working mother (*fechld*)	1.93 (0.86)	2.26 (0.84)	1	4	11,922 / 9,202
Preschool children (*fepresch*)	2.80 (0.81)	2.56 (0.77)	1	4	11,922 / 9,202
Family roles (*fefam*)	2.92 (0.86)	2.76 (0.80)	1	4	11,922 / 9,202
Gender attitudes index	0.26 (0.30)	0.35 (0.33)	0	1	11,922 / 9,202

Notes: The table reports descriptive statistics for the General Social Survey (GSS) sample used in the analysis. The gender attitudes measure is based on four GSS questions: (i) "Most men are better suited emotionally for politics than are most women" (*fepol*); (ii) "A working mother can establish just as warm and secure a relationship with her children as a mother who does not work" (*fechld*); (iii) "A preschool child is likely to suffer if his or her mother works" (*fepresch*); and (iv) "It is much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family" (*fefam*). For *fepol*, responses are coded 1 for agree and 2 for disagree; for the other three questions, responses range from 1 (strongly agree) to 4 (strongly disagree). I recode each item as a binary indicator equal to one for the more traditional response and define the gender norms index as the average of the four indicators. The index therefore ranges from 0 to 1, with higher values indicating more traditional gender norms. Supervisor equals one for respondents currently working in a supervisory position.

Table B.2: Summary statistics: NLSY79 and NLSY97 samples

Variable	Mean (Std. dev.)		Min	Max	Observations
Panel A. NLSY79					
Individual characteristics					
	All				
Year	1992 (9.43)		1979	2012	126,634
Birth year	1961 (2.20)		1957	1965	126,634
Female	0.52 (0.50)		0	1	126,634
Age	31.38 (9.66)		16	55	126,634
Any children	0.40 (0.49)		0	1	126,634
Child below age 4	0.16 (0.37)		0	1	126,551
Married	0.47 (0.50)		0	1	126,631
	Women	*Men*			
College	0.19 (0.39)	0.19 (0.39)	0	1	65,859 / 60,775
Predicted attitudes	0.25 (0.04)	0.34 (0.04)	0.18 / 0.27	0.29 / 0.38	65,859 / 60,775
Work-related variables					
	Women	*Men*			
Log hourly wage	1.81 (0.56)	2.06 (0.60)	0.00 / 0.00	5.45 / 5.50	43,428 / 44,083
Part-time	0.22 (0.41)	0.12 (0.32)	0	1	51,299 / 51,788
Working	0.87 (0.34)	0.97 (0.17)	0	1	65,859 / 60,775
Occupation-related variables					
	Women	*Men*			
N	0.16 (0.37)	0.23 (0.42)	0	1	53,799 / 47,655
T	0.04 (0.19)	0.22 (0.41)	0	1	53,799 / 47,655
Q	0.09 (0.28)	0.04 (0.20)	0	1	53,799 / 47,655
VS	0.23 (0.42)	0.06 (0.23)	0	1	53,799 / 47,655
T–Q	0.02 (0.13)	0.11 (0.31)	0	1	53,799 / 47,655
T–VS	0.04 (0.19)	0.01 (0.08)	0	1	53,799 / 47,655
Q–VS	0.19 (0.39)	0.19 (0.40)	0	1	53,799 / 47,655
T–Q–VS	0.08 (0.27)	0.11 (0.31)	0	1	53,799 / 47,655
Panel B. NLSY97					
Individual characteristics					
	All				
Year	2007 (6.03)		1997	2019	80,904
Birth year	1982 (1.38)		1980	1984	80,904
Female	0.50 (0.50)		0	1	80,904
Age	24.82 (6.05)		16	39	80,904
Any children	0.29 (0.45)		0	1	80,904
Child below age 4	0.19 (0.39)		0	1	80,900
Married	0.37 (0.48)		0	1	76,646
	Women	*Men*			
College	0.25 (0.43)	0.19 (0.39)	0	1	40,450 / 40,454
Predicted attitudes	0.20 (0.04)	0.30 (0.04)	0.15 / 0.24	0.24 / 0.33	40,450 / 40,454
Work-related variables					
	Women	*Men*			
Log hourly wage	1.83 (0.58)	1.98 (0.57)	0.00 / 0.00	5.20 / 5.51	17,866 / 19,722
Part-time	0.43 (0.50)	0.32 (0.47)	0	1	33,768 / 34,271
Working	0.86 (0.35)	0.92 (0.28)	0	1	40,450 / 40,454
Occupation-related variables					
	Women	*Men*			
N	0.13 (0.33)	0.19 (0.39)	0	1	24,280 / 23,962
T	0.02 (0.14)	0.17 (0.37)	0	1	24,280 / 23,962
Q	0.08 (0.27)	0.05 (0.22)	0	1	24,280 / 23,962
VS	0.21 (0.41)	0.08 (0.28)	0	1	24,280 / 23,962
T–Q	0.01 (0.09)	0.08 (0.27)	0	1	24,280 / 23,962
T–VS	0.04 (0.19)	0.01 (0.10)	0	1	24,280 / 23,962
Q–VS	0.20 (0.40)	0.18 (0.38)	0	1	24,280 / 23,962
T–Q–VS	0.08 (0.27)	0.10 (0.31)	0	1	24,280 / 23,962

Notes: The table reports descriptive statistics for the NLSY79 and NLSY97 samples. Their samples contain 5,750 and 5,336 distinct individuals, respectively.

Table B.3: Summary statistics: CPS sample

Variable	Mean (Std. dev.)		Min	Max	Observations
Panel A. Individual-level variables					
Individual characteristics					
	All				
Year	2000 (11.85)		1979	2019	536,205
Birth year	1961 (15.11)		1920	1999	536,205
Female	0.45 (0.50)		0	1	536,205
Age	39.09 (10.89)		18	59	536,205
Any children	0.57 (0.49)		0	1	536,205
Child below age 4	0.11 (0.31)		0	1	536,205
Married	0.65 (0.48)		0	1	536,205
	Women	*Men*			
College	0.24 (0.43)	0.26 (0.44)	0	1	243,073 / 293,132
Predicted attitudes	0.27 (0.08)	0.37 (0.09)	0.08 / 0.17	0.62 / 0.71	243,073 / 293,132
Work-related variables					
	Women	*Men*			
Log hourly wage	1.89 (0.60)	2.20 (0.64)	0.00 / 0.00	5.51 / 5.51	243,073 / 293,132
Part-time	0.22 (0.41)	0.07 (0.26)	0	1	243,073 / 293,132
Occupation-related variables					
	Women	*Men*			
N	0.18 (0.38)	0.21 (0.41)	0	1	243,073 / 293,132
T	0.04 (0.21)	0.18 (0.39)	0	1	243,073 / 293,132
Q	0.13 (0.33)	0.07 (0.26)	0	1	243,073 / 293,132
VS	0.21 (0.41)	0.04 (0.19)	0	1	243,073 / 293,132
T–Q	0.01 (0.12)	0.11 (0.31)	0	1	243,073 / 293,132
T–VS	0.06 (0.24)	0.01 (0.08)	0	1	243,073 / 293,132
Q–VS	0.29 (0.45)	0.23 (0.42)	0	1	243,073 / 293,132
T–Q–VS	0.09 (0.28)	0.15 (0.36)	0	1	243,073 / 293,132
Panel B. Occupation-level variables					
Female share by broad occupation group					
	All				
N	0.40 (0.03)		0.30	0.45	41
T	0.16 (0.02)		0.12	0.20	41
Q	0.58 (0.03)		0.44	0.62	41
VS	0.82 (0.03)		0.74	0.86	41
T–Q	0.10 (0.01)		0.06	0.13	41
T–VS	0.88 (0.04)		0.80	0.96	41
Q–VS	0.50 (0.06)		0.35	0.55	41
T–Q–VS	0.32 (0.05)		0.20	0.38	41

Notes: The table reports descriptive statistics for the CPS sample over 1979–2019. Individual-level statistics are based on the second of the two consecutive CPS observations available for each individual. The first observation is used in estimation to construct lagged variables, including transition probabilities and previous familiarity with the occupation. Occupation-level statistics report female employment shares by broad occupation group and year. These are constructed using observations from both CPS waves and CPS sampling weights, so as to capture the broader composition of each occupation.

Table B.4: Observed CPS wages and reduced-form estimated wage schedule (for supply estimation)

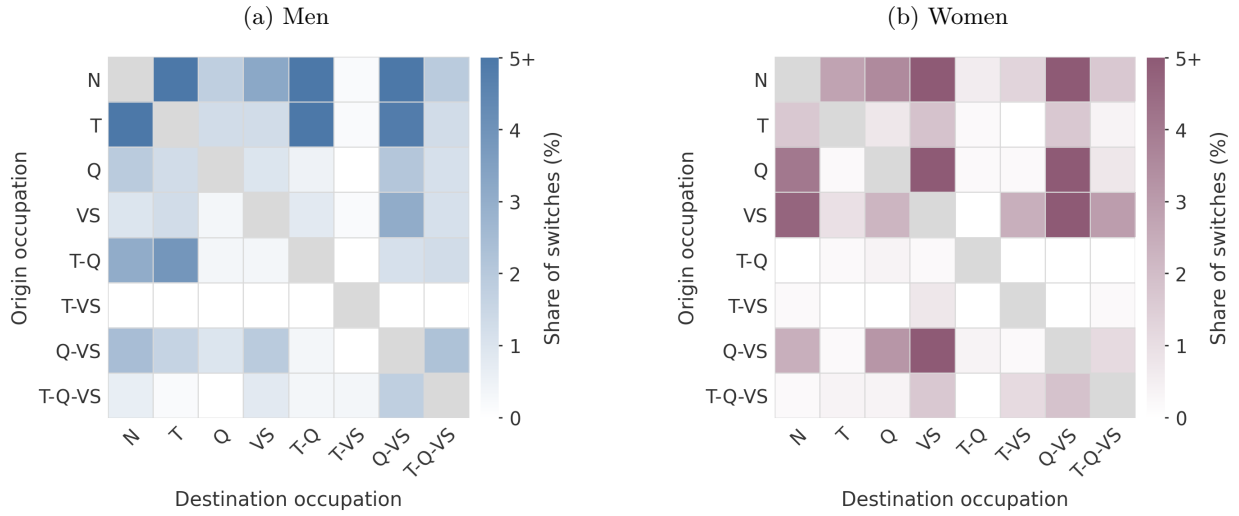
Variable	Mean (Std. dev.)				Observations
Panel A. Log of hourly wages by broad occupation group					
	Women		*Men*		
	Observed	*Predicted*	*Observed*	*Predicted*	
N	1.52 (0.49)	1.53 (0.18)	1.87 (0.54)	1.87 (0.28)	42,861 / 61,259
T	1.67 (0.48)	1.69 (0.17)	1.95 (0.55)	1.95 (0.29)	10,808 / 53,779
Q	1.67 (0.56)	1.68 (0.28)	2.09 (0.66)	2.09 (0.38)	30,747 / 21,895
VS	1.79 (0.50)	1.79 (0.24)	2.05 (0.60)	2.05 (0.34)	50,321 / 10,804
T–Q	1.96 (0.50)	1.96 (0.29)	2.21 (0.49)	2.22 (0.23)	3,608 / 31,542
T–VS	2.39 (0.47)	2.40 (0.24)	2.38 (0.56)	2.38 (0.35)	14,389 / 2,037
Q–VS	2.08 (0.56)	2.09 (0.32)	2.48 (0.63)	2.48 (0.36)	69,431 / 68,113
T–Q–VS	2.29 (0.60)	2.30 (0.38)	2.60 (0.56)	2.60 (0.36)	20,908 / 43,703
Total	1.89 (0.60)	1.89 (0.38)	2.20 (0.64)	2.20 (0.42)	243,073 / 293,132
Panel B. Log of hourly wages by decade					
	Women		*Men*		
	Observed	*Predicted*	*Observed*	*Predicted*	
1980–1989	1.74 (0.51)	1.75 (0.31)	2.19 (0.58)	2.18 (0.38)	49,163 / 66,118
1990–1999	1.83 (0.56)	1.84 (0.34)	2.15 (0.61)	2.19 (0.39)	49,889 / 59,949
2000–2009	1.95 (0.61)	1.93 (0.38)	2.22 (0.66)	2.21 (0.44)	71,758 / 81,725
2010–2018	1.98 (0.64)	2.00 (0.43)	2.21 (0.69)	2.21 (0.47)	61,692 / 70,875
Total	1.89 (0.60)	1.89 (0.38)	2.20 (0.64)	2.20 (0.42)	232,502 / 278,667
Panel C. Estimated wage schedule by broad occupation group					
	Women	*Men*	*Min*	*Max*	
N	1.71 (0.25)	1.89 (0.28)	0.60 / 0.80	2.77 / 2.94	294,276 / 354,027
T	1.81 (0.29)	1.99 (0.32)	0.66 / 0.79	2.69 / 2.89	268,254 / 299,895
Q	1.87 (0.27)	2.05 (0.32)	1.01 / 1.04	2.94 / 2.99	39,945 / 66,788
VS	1.89 (0.29)	2.06 (0.31)	0.84 / 0.81	2.74 / 2.97	160,096 / 185,351
T–Q	1.85 (0.33)	2.10 (0.34)	0.50 / 0.28	2.83 / 3.05	200,085 / 216,824
T–VS	2.06 (0.34)	2.18 (0.36)	0.95 / 0.95	2.81 / 3.04	46,027 / 52,705
Q–VS	2.03 (0.34)	2.27 (0.39)	0.55 / 0.68	3.41 / 3.64	248,346 / 327,675
T–Q–VS	2.24 (0.40)	2.39 (0.43)	0.45 / 0.31	3.82 / 3.91	338,046 / 371,864
Total	1.94 (0.37)	2.12 (0.40)	0.45 / 0.28	3.82 / 3.91	1,595,075 / 1,875,129
Goodness of fit					
	Women	*Men*			
Correlation observed vs. predicted	0.6399	0.6608			
Out-of-fold RMSE	0.4768				536,229

Notes: The table compares observed log hourly wages with the estimated wage schedule used in the labor supply estimation. Panels A and B report observed and predicted log hourly wages by broad occupation group and decade, respectively, separately for women and men. Panel C reports summary statistics for the estimated wage schedule by broad occupation group. In Panel C, minima, maxima, and numbers of observations are reported as women / men. Standard deviations are reported in parentheses. The goodness-of-fit statistics report the correlation between observed and predicted log hourly wages by sex and the out-of-fold root mean squared error (RMSE).

C Additional empirical results

C.1 Occupational mobility and gender norms

Figure C.1: Occupational transitions in the event-study sample



Notes: Each cell reports the share of occupational switches from the origin occupation (rows) to the destination occupation (columns), separately for women and men. Shares sum to one within sex. Both panels use the same linear color scale; cells representing 5% or more of switches are shown at the maximum intensity. The sample is the event-study sample.

Table C.1: Direction of the change in occupational gender norms

	Men		Women	
	More conservative	More progressive	More conservative	More progressive
Share of switches	39.5%	60.5%	36.4%	63.6%
Number of switches	246	377	196	343

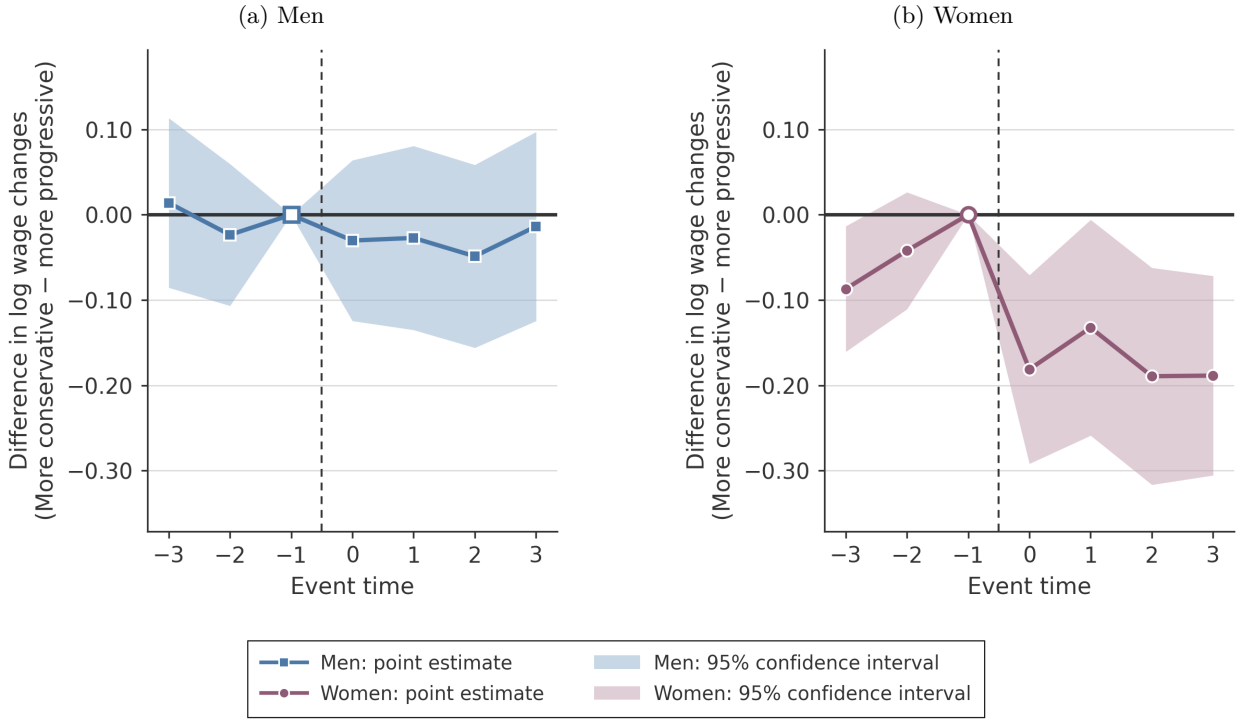
Notes: The table reports the direction of the change in occupational gender norms associated with the switch, separately by sex. A move is classified as more conservative when $\Delta N_i > 0$ and more progressive when $\Delta N_i < 0$, using gender norms among senior male workers. Shares are computed within sex. The sample is the event-study sample.

Table C.2: Event-study estimates around occupational switches

	Men	Women
More conservative move × event time (β_r)		
$r = -2$	0.002	-0.045
	(0.030)	(0.033)
$r = 0$	0.021	-0.138^{***}
	(0.035)	(0.041)
$r = 1$	-0.015	-0.124^{***}
	(0.038)	(0.044)
$r = 2$	-0.052	-0.146^{***}
	(0.039)	(0.044)
$r = 3$	-0.011	-0.177^{***}
	(0.041)	(0.046)
Event time (γ_r)		
$r = -2$	-0.010	-0.087^{*}
	(0.059)	(0.053)
$r = 0$	0.044	0.149^{***}
	(0.060)	(0.057)
$r = 1$	0.154	0.300^{***}
	(0.113)	(0.103)
$r = 2$	0.224	0.439^{***}
	(0.169)	(0.152)
$r = 3$	0.248	0.580^{***}
	(0.224)	(0.197)
Individual FE	Yes	Yes
Calendar-year FE	Yes	Yes
Age FE	Yes	Yes
Part-time FE	Yes	Yes
Observations	3,738	3,234
Individuals	623	539
Within R^2	0.146	0.122

Notes: The table reports event-study estimates separately for men and women using gender norms among senior male workers. The omitted period is ($r = -1$). Standard errors, clustered at the individual level, are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Figure C.2: Wage trajectories following occupational switches: more conservative vs. more progressive norms (extended pre-switch window)



Notes: The figure compares changes in log hourly wages following occupational switches toward more conservative versus more progressive gender norms, relative to the year before the switch ($r = -1$). Norms are measured using senior male workers' attitudes. The balanced sample includes 353 men and 275 women from pooled NLSY79 and NLSY97 data, observed from $r = -3$ to $r = 3$. Regressions include individual, year, and age fixed effects, common event-time indicators, and a part-time indicator. Shaded areas show 95% confidence intervals, with standard errors clustered by individual.

D Additional results from the model

D.1 Additional parameter estimates

Table D.1: Demographic transition parameters

Parameter	Men		Women	
	Estimate	SE	Estimate	SE
Being married				
Constant	-1.206***	.046	-1.153***	.034
Married$_t$	2.807***	.020	2.858***	.016
Youngest child 4–18$_t$	.295***	.021	-.030**	.015
Youngest child 0–3$_t$	.221***	.023	.037**	.016
Normalized age, z_a	-.102***	.013	-.067***	.011
Normalized age squared, z_a^2	-.200***	.007	-.149***	.006
College	.024	.017	.059***	.015
Attitude $\times G_{1s}$	-.007	.053	.586***	.073
Attitude $\times G_{2s}$	-.474***	.066	-.069	.080
Attitude $\times G_{3s}$	-.974***	.092	-.589***	.084
1980s	.274***	.030	.126***	.023
1990s	.127***	.030	.028	.023
2000s	.231***	.030	.073***	.022
2010s	.238***	.033	.043	.026
Having a child				
Constant	-1.897***	.051	-2.253***	.041
Married$_t$	.717***	.019	.644***	.016
Youngest child 4–18$_t$	3.062***	.022	3.599***	.021
Youngest child 0–3$_t$	2.819***	.023	3.579***	.030
Normalized age, z_a	-.439***	.017	-.617***	.017
Normalized age squared, z_a^2	-.299***	.010	-.271***	.009
College	-.101***	.018	-.100***	.016
Attitude $\times G_{1s}$	.367***	.061	1.634***	.096
Attitude $\times G_{2s}$	-.051	.065	.775***	.088
Attitude $\times G_{3s}$	-.382***	.078	-.033	.094
1980s	.137***	.037	.121***	.027
1990s	-.024	.039	.118***	.029
2000s	.030	.037	.029	.027
2010s	.127***	.040	.285***	.031
Having a young child conditional on having a child				
Constant	.007	.159	.445***	.095
Married$_t$	.436***	.037	.278***	.018
Youngest child 4–18$_t$	-2.534***	.041	-2.907***	.045
Youngest child 0–3$_t$	-.265***	.033	-.719***	.042
Normalized age, z_a	-.658***	.038	-.789***	.047

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Table D.1 – *continued*

Parameter	Men		Women	
	Estimate	SE	Estimate	SE
Normalized age squared, z_a^2	.118***	.028	.030	.028
College	.277***	.026	.295***	.020
Attitude $\times G_{1s}$	-.401***	.126	.029	.137
Attitude $\times G_{2s}$	-.363***	.097	-.142	.090
Attitude $\times G_{3s}$	.007	.100	.138	.097
1980s	-.029	.142	-.130*	.074
1990s	-.085	.145	-.112	.077
2000s	.014	.142	-.064	.073
2010s	.149	.144	.116	.077
Correlation in the joint marriage/any-child transition				
Correlation	.860***	.020	.296***	.015

Notes: Robust sandwich standard errors are reported. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The transition covariates are ordered as in the estimated demographic process. $z_a = (\text{age} - 40)/10$. 1979 is the omitted calendar-period category. The attitude age groups are sex-specific: for women, G_{1s} is age ≤ 23, G_{2s} is ages 24–28, and G_{3s} is age ≥ 29; for men, the corresponding groups are age ≤ 25, ages 26–29, and age ≥ 30.

Table D.2: Aggregate and broad occupation-level demand parameter estimates

Parameter	Estimate	SE	Estimate	SE
Occupation-specific parameters				
Human-capital returns by broad occupation, b_{je}				
	Non-college, b_{j0}		College, b_{j1}	
N	.655***	.013	.468***	.051
T	.696***	.015	.561***	.059
Q	.883***	.022	.802***	.043
VS	.773***	.033	.726***	.046
T-Q	.911***	.022	.540***	.061
T-VS	.908***	.098	.739***	.097
Q-VS	1.151***	.025	1.073***	.023
T-Q-VS	1.122***	.029	.950***	.023
Part-time productivity effects by broad occupation, κ_j^{PT}				
N	-.113***	.007		
T	-.135***	.009		
Q	-.195***	.015		
VS	-.073***	.021		
T-Q	-.114***	.016		
T-VS	-.118***	.043		
Q-VS	-.158***	.017		
T-Q-VS	-.072***	.020		
Aggregate parameters				
MRP intercept, *cons*	1.805***	.015		
CES parameter, σ	.969***	.004		

Notes: Bootstrap standard errors based on 1,000 replications are reported in the SE columns. Significance stars are based on the corresponding bootstrap distributions: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Human-capital returns b_{je} vary by broad occupation j and education group e. Part-time productivity effects κ_j^{PT} vary by broad occupation. The remaining demand-side parameters are reported in Table 5.

Table D.3: High-dimensional demand-side parameter estimates

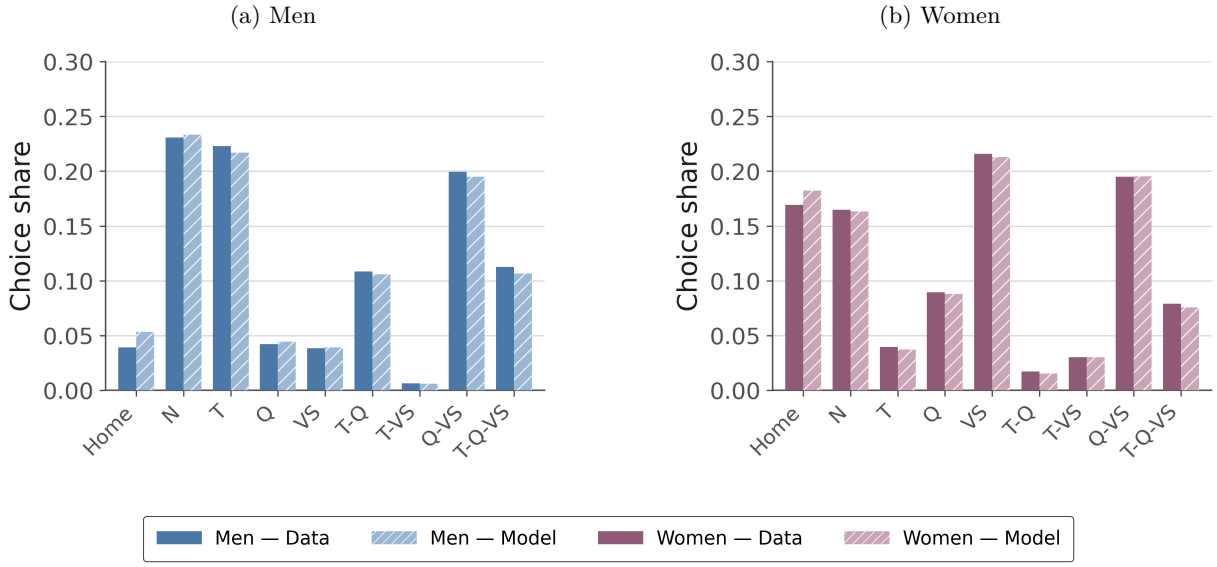
Broad occupation	# detailed occ.	Level		Trend	
		Mean	Range	Mean	Range
College premium					
Detailed-occupation coefficients, χ_{o1} and χ_{o2}					
N	49	.237	[−.119, .871]	.038	[−.121, .364]
T	42	.190	[−.219, .629]	.026	[−.132, .265]
VS	28	.141	[−.964, 1.011]	.058	[−.248, .414]
T-VS	8	.228	[.057, .896]	.090	[−.069, .194]
Q	8	.098	[−.398, .463]	.087	[−.069, .290]
T-Q	31	.391	[.042, 1.179]	.014	[−.228, .191]
Q-VS	44	.318	[−.191, .824]	.037	[−.212, .200]
T-Q-VS	54	.353	[−.174, .821]	.048	[−.133, .278]
Detailed-occupation price components					
Detailed-occupation coefficients, λ_{o1} and λ_{o2}					
N	49	-.073	[−.392, .492]	.008	[−.071, .118]
T	42	.188	[−.395, .559]	.031	[−.026, .127]
VS	28	.239	[−.215, .707]	-.016	[−.107, .149]
T-VS	8	-.279	[−.511, .000]	.043	[−.012, .160]
Q	8	-.057	[−.220, .071]	-.029	[−.131, .031]
T-Q	31	.098	[−.289, .379]	.025	[−.055, .176]
Q-VS	44	-.090	[−.572, .647]	.003	[−.152, .330]
T-Q-VS	54	.101	[−.318, .564]	.017	[−.194, .143]
Broad-occupation–year price components					
Broad-occupation–year coefficients, λ_{jt}					
N	39	-.130	[−.216, .000]		
T	39	-.262	[−.380, −.100]		
VS	39	-.411	[−.477, −.342]		
T-VS	39	.135	[−.139, .313]		
Q	39	-.193	[−.298, −.101]		
T-Q	39	-.260	[−.364, −.128]		
Q-VS	39	-.185	[−.247, −.110]		
T-Q-VS	39	-.228	[−.296, −.138]		

Notes: The table summarizes high-dimensional demand-side parameters that vary across detailed occupations or broad occupation–year cells. Reported means are unweighted. Ranges give the minimum and maximum coefficient within each broad occupation and are not confidence intervals. College-premium and detailed-occupation wage component levels are evaluated in 2000; trend coefficients are per decade, with $u_t = (t - 2000)/10$. For λ_{jt}, the second column denotes the number of years and the reported mean and range are across estimation years.

D.2 Additional model fit

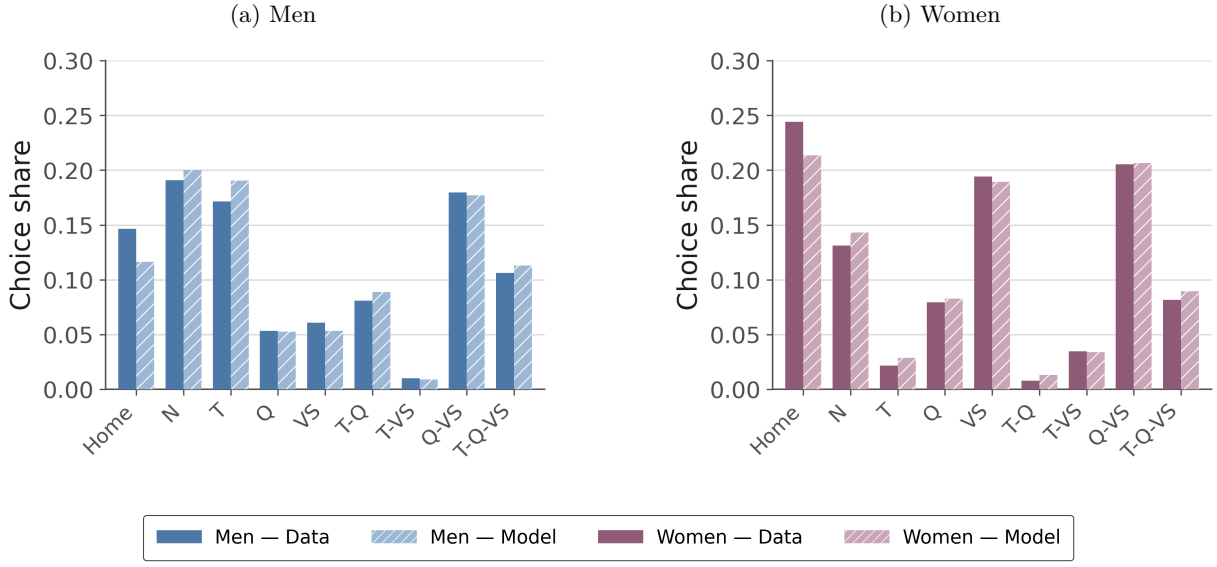
Career choices

Figure D.1: Observed vs predicted occupational choices (NLSY79)



Notes: The figure compares observed and model-predicted broad occupational choices of individuals in the NLSY79 panels.

Figure D.2: Observed vs predicted occupational choices (NLSY97)



Notes: The figure compares observed and model-predicted broad occupational choices of individuals in the NLSY97 panels.

Table D.4: In-sample choice fit, supply model

Choice margin	Sample	N	Hit rate	Benchmark	Mean P(chosen)	Brier skill	McFadden R^2	Agg. share TV
Women								
j	NLSY	74,756	73.9%	20.9%	0.589	0.501	0.486	–
$o \mid j$	CPS	62,834	26.6%	26.7%	0.161	0.002	0.010	0.020
$(o,h) \mid j$	CPS	62,834	20.8%	21.2%	0.106	-0.002	-0.006	0.097
Men								
j	NLSY	69,538	76.7%	21.7%	0.639	0.565	0.541	–
$o \mid j$	CPS	68,644	27.4%	27.6%	0.144	0.003	0.005	0.020
$(o,h) \mid j$	CPS	68,644	25.4%	25.6%	0.128	0.004	-0.003	0.058

Notes: j is the NLSY top-nest broad-occupation choice; $o \mid j$ and $(o,h) \mid j$ are CPS bottom-nest probabilities conditional on the observed broad occupation. The NLSY block is unweighted; CPS cases are collapsed cells and all CPS statistics use their `n_people` weights. N is the number of likelihood contributions. Hit rate takes the arg max over each observation's own feasible set, and the benchmark predicts the most frequent feasible alternative. Brier skill is $1 - BS_{\text{model}}/BS_{\text{benchmark}}$ with $BS_i = \sum_{a \in C_i} [P_i(a) - 1\{y_i = a\}]^2$ against that same benchmark. McFadden R^2 compares the model against a null with alternative-specific constants only, fitted by maximum likelihood on the same observations, feasible sets and weights. Aggregate share TV is the employment-weighted total variation between predicted and observed choice shares across the eight broad occupations: the share of probability mass that would have to be reallocated for the two to agree.

Table D.5: Fit of one-year career transitions

Transition	N	Data	Model	Diff. (pp)	Brier	Benchmark Brier
Panel A. Women						
Home → Work	7,497	28.6%	23.2%	-5.34	0.2022	0.2040
Work → Home	31,877	7.2%	7.6%	+0.43	0.0639	0.0665
Work → same j	31,877	77.6%	83.7%	+6.17	0.1751	0.1740
Panel B. Men						
Home → Work	2,333	43.4%	39.1%	-4.33	0.2353	0.2457
Work → Home	33,975	2.6%	3.3%	+0.77	0.0246	0.0250
Work → same j	33,975	81.4%	87.6%	+6.23	0.1554	0.1513

Notes: The table compares observed period-t transitions with one-step model predictions based on information available before the current career choice. The sample contains NLSY observations for which the lagged career state is observed. Because consecutive annual observations are required, the diagnostic covers ages 18–37. Work → same j is unconditional on remaining employed. Benchmark Brier is the score of a constant predictor equal to the empirical transition rate within the same sex and risk set.

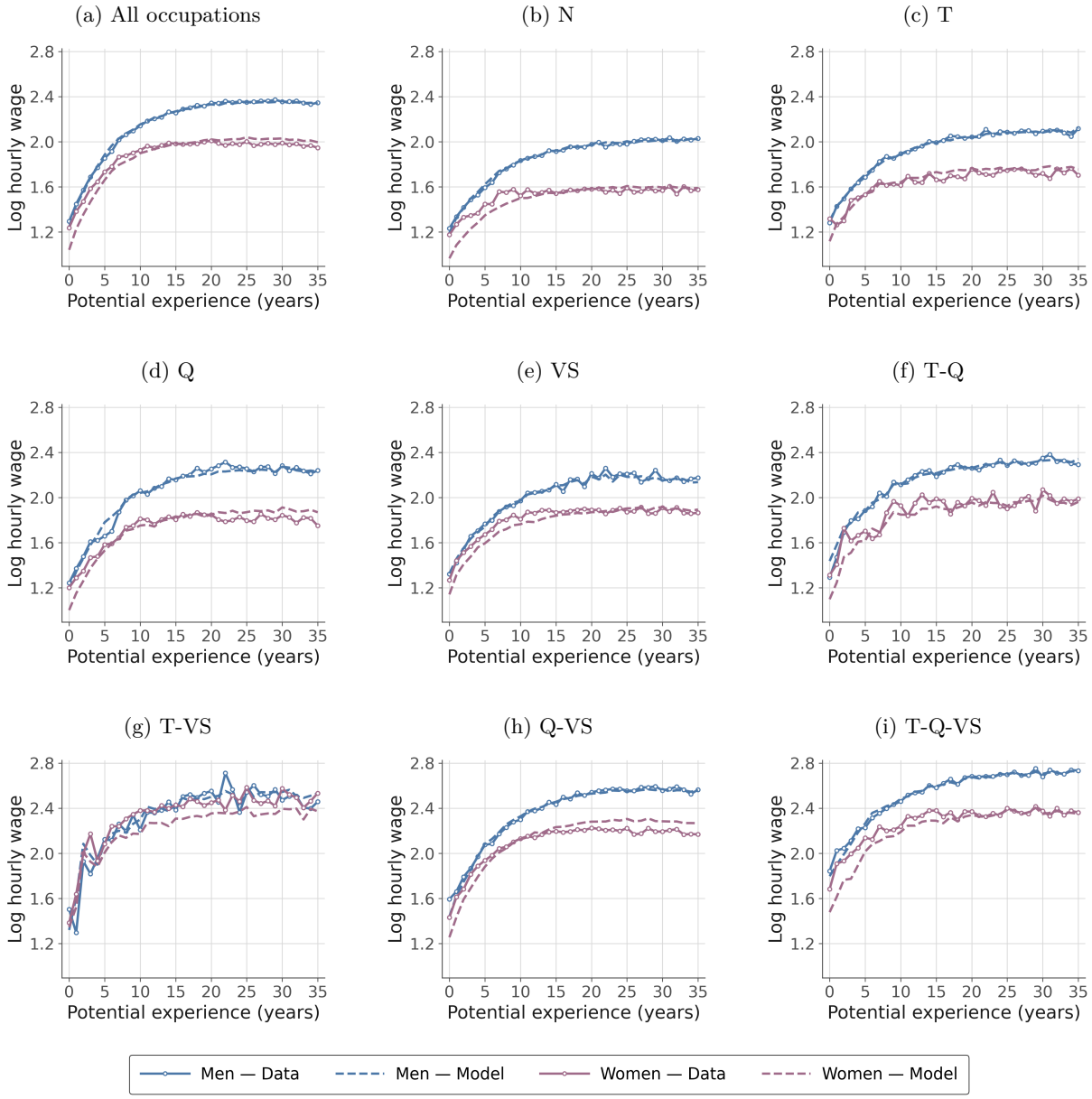
Table D.6: Observed and predicted part-time employment shares

	Women		Men	
Broad occupation	Data	Model	Data	Model
N	32.5%	21.1%	13.3%	7.6%
T	13.8%	19.1%	9.4%	7.2%
Q	32.6%	18.4%	11.6%	6.1%
VS	21.1%	18.7%	11.9%	9.0%
T-Q	17.0%	20.1%	4.0%	6.8%
T-VS	25.0%	27.2%	8.9%	8.4%
Q-VS	9.8%	17.2%	2.6%	5.7%
T-Q-VS	13.5%	23.4%	2.4%	6.5%
All	20.1%	19.6%	7.3%	6.8%

Notes: Observed and model-predicted CPS part-time shares. The occupation rows condition on the observed broad occupation j. All averages are weighted by CPS cell sizes.

Wages

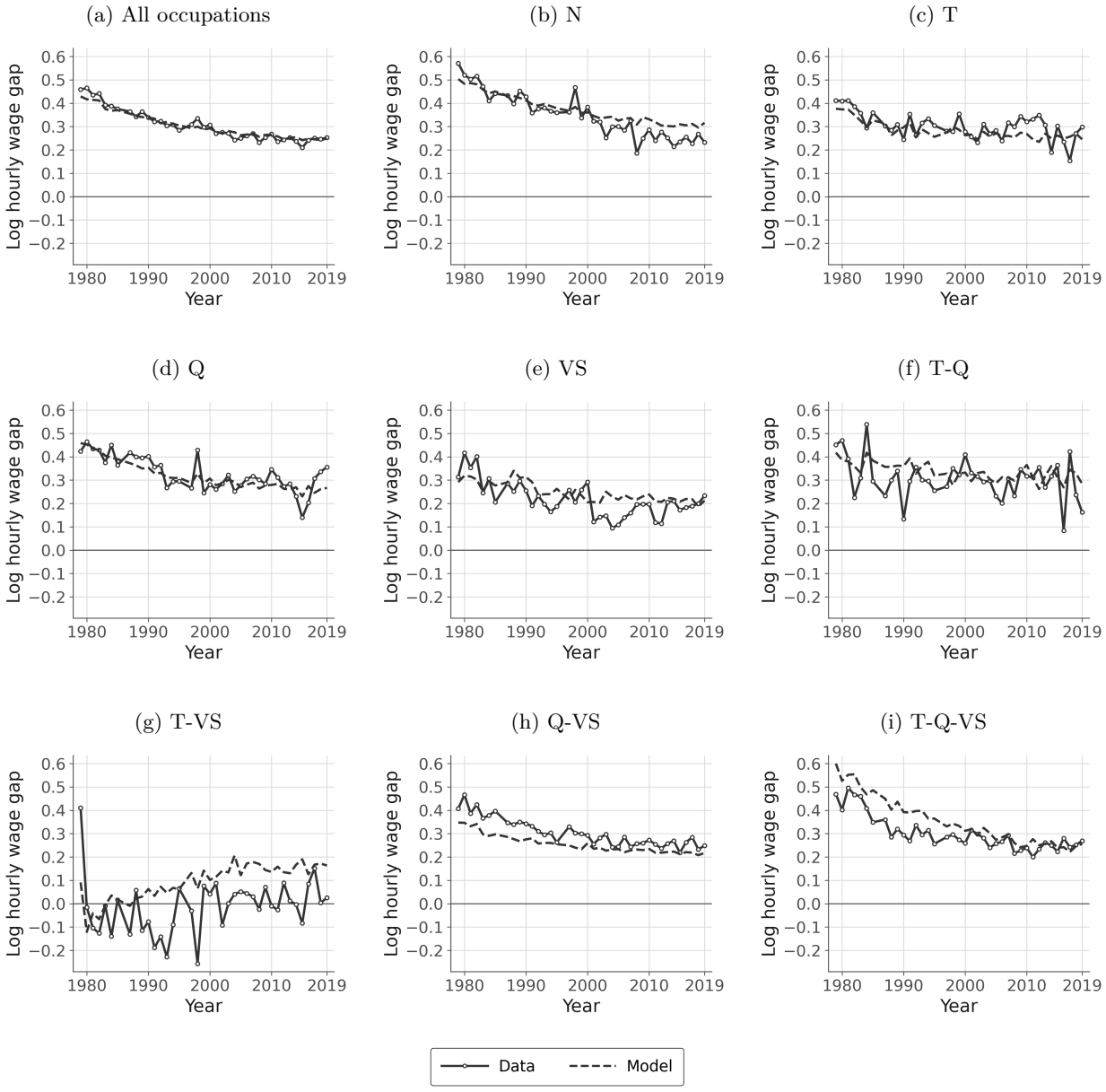
Figure D.3: Observed and predicted log wages over the life cycle



Notes: The figure compares observed and model-predicted mean log hourly wages over the life cycle, for women and men of the 1979-2019 CPS sample, overall and by broad occupation group. Solid lines denote observed wages and dashed lines model predictions.

Gender wage gaps

Figure D.4: Observed and predicted gender wage gaps over time

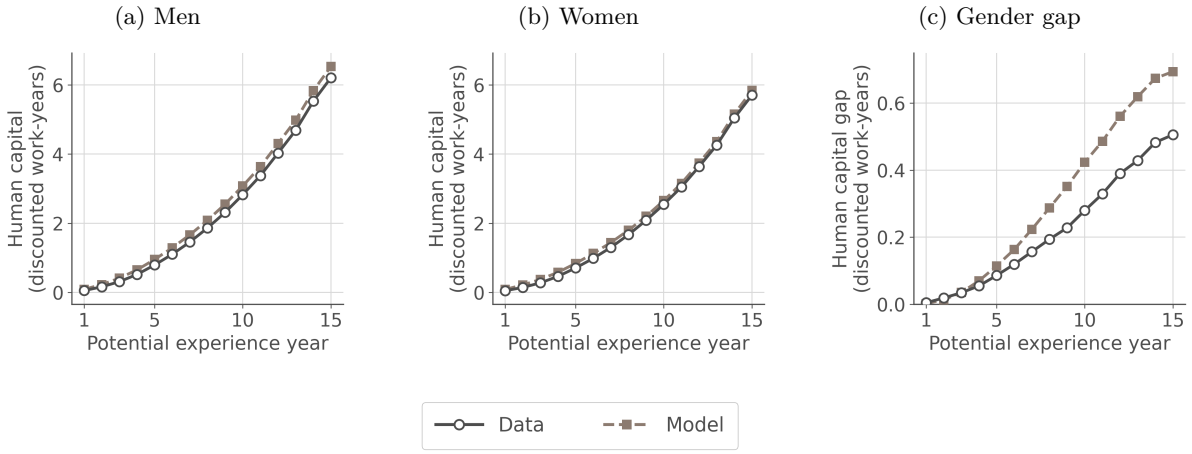


Notes: The figure compares observed and model-predicted differences in mean log hourly wages by gender over time, for women and men in the same age × education × year × broad occupation. Solid lines denote observed wages and dashed lines model predictions.

D.3 Model validation

Human capital reconstruction

Figure D.5: Validation of reconstructed human capital over the career



Notes: The figure fixes the sample of NLSY79 individuals observed at 15 years of potential experience and compares the cumulative contribution of their earlier career years to human capital in the data and in the model. Data use observed employment histories, while the model assumes continuous employment for men and uses model-implied past participation for women. Data and Model are evaluated on the same observed past-year support. Human capital is measured in discounted work-years. Potential experience is measured from labor-market entry, at age 18 for non-college workers and age 22 for college workers.

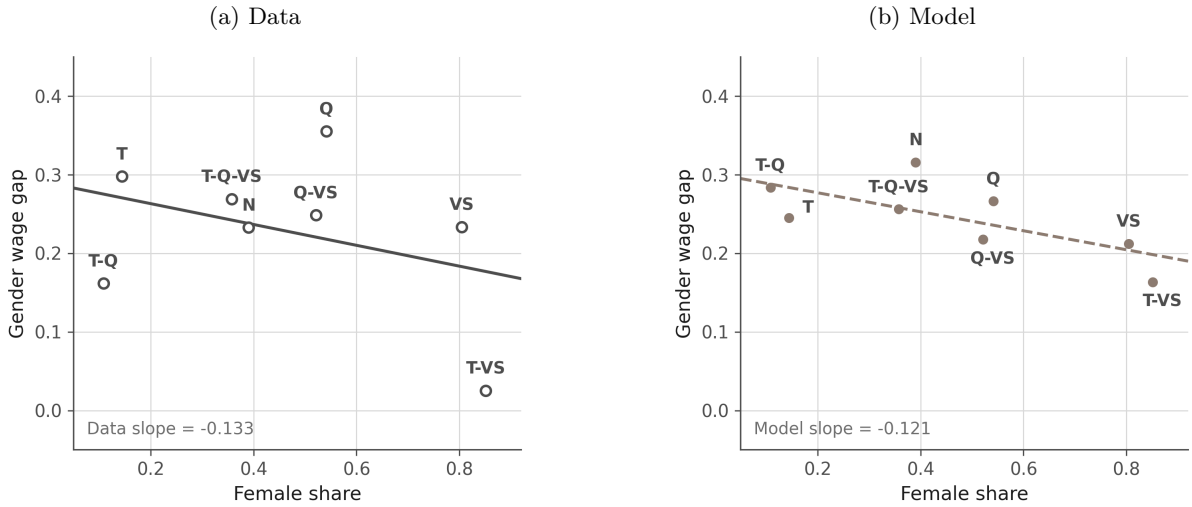
Table D.7: Validation of reconstructed human capital

Potential	Women		Men		Gender gap			Observations	
experience	Data	Model	Data	Model	Data	Model	Error	Women	Men
5	2.777	3.246	2.907	3.382	0.130	0.136	+0.006	1,866	1,966
10	4.916	5.186	5.235	5.669	0.319	0.483	+0.164	1,954	2,159
15	5.700	5.834	6.206	6.528	0.506	0.694	+0.188	1,397	1,460
20	4.917	4.973	5.338	5.570	0.421	0.597	+0.176	979	1,060
25	4.545	4.523	4.856	5.019	0.311	0.496	+0.185	940	900

Notes: The table compares observed and model-implied human capital, A_{it}, at selected levels of potential experience. Human capital accumulates past employment according to $A_{it} = \sum_{\tau<t} \delta^{t-1-\tau} g_{i\tau}$. Observed values use employment histories recorded in the NLSY79, while model values use the corresponding employment histories predicted by the model. Both are computed over the same observed-history support, without imputing missing NLSY79 years. The gender gap is the difference between male and female average human capital. Potential experience is measured from age 18 for non-college workers and age 22 for college workers.

Relationship between gender wage gap and female share

Figure D.6: Occupational gender wage gap and female share in 2019



Notes: Each point represents one broad occupation in 2019. Gender wage gaps compare men and women within age × education × broad-occupation cells and are aggregated giving greater weight to cells with substantial representation of both men and women. Lines show unweighted fits across the eight broad occupations. Female employment shares are observed in the CPS.

Table D.8: Occupational gender wage-gap gradient over time

Panel A. Gradient of the gap on the female share						
Period	N years	Data	Model	Difference	Data < 0	Model < 0
1979–1989	10	-0.298	-0.324	-0.026	10/10	10/10
1990–1999	9	-0.347	-0.241	+0.106	9/9	9/9
2000–2009	10	-0.274	-0.161	+0.113	10/10	10/10
2010–2019	10	-0.241	-0.150	+0.090	10/10	10/10
All years	39	-0.289	-0.219	+0.070	39/39	39/39
Panel B. Cross-sectional fit across the eight occupations						
Period	N years	Pearson	Spearman	MAE		
1979–1989	10	0.882	0.693	0.059		
1990–1999	9	0.872	0.624	0.067		
2000–2009	10	0.813	0.617	0.050		
2010–2019	10	0.690	0.555	0.059		
All years	39	0.813	0.622	0.059		
2019	1	0.512	0.143	0.069		

Notes: Panel A. The gender wage-gap gradient is estimated separately each year by regressing the gender wage gap on female share across the eight broad occupations. Data and Model report period averages of these annual slopes; Difference is Model minus Data. The last two columns report the number of years with a negative gradient. Panel B reports means of the annual cross-sectional statistics within each period, computed across the eight broad occupations on observed against predicted gaps; Spearman is the correlation of the ranks.

D.4 Additional analysis of the gender wage gap

Figure D.7: Decomposition of the predicted gender wage gap by broad occupation

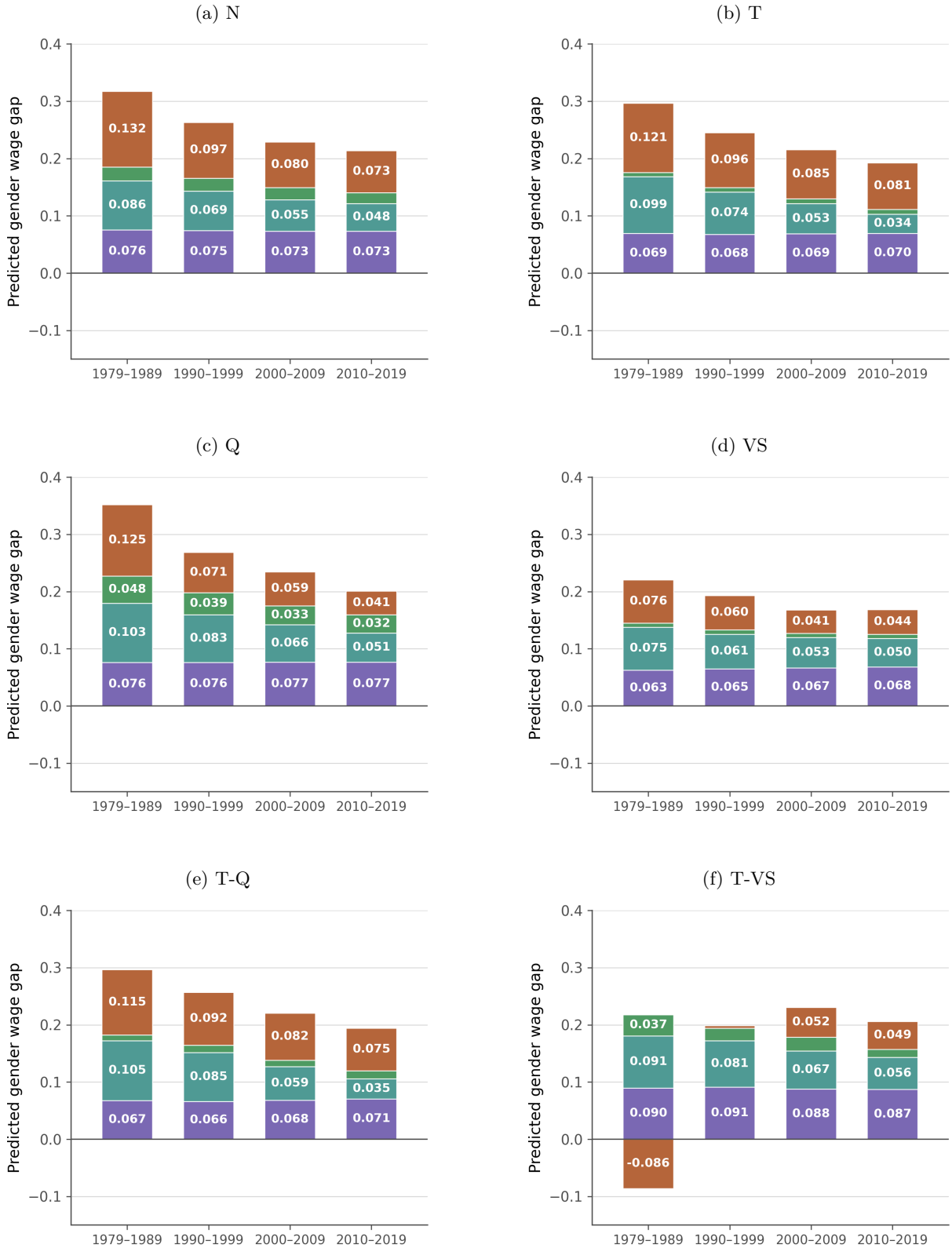
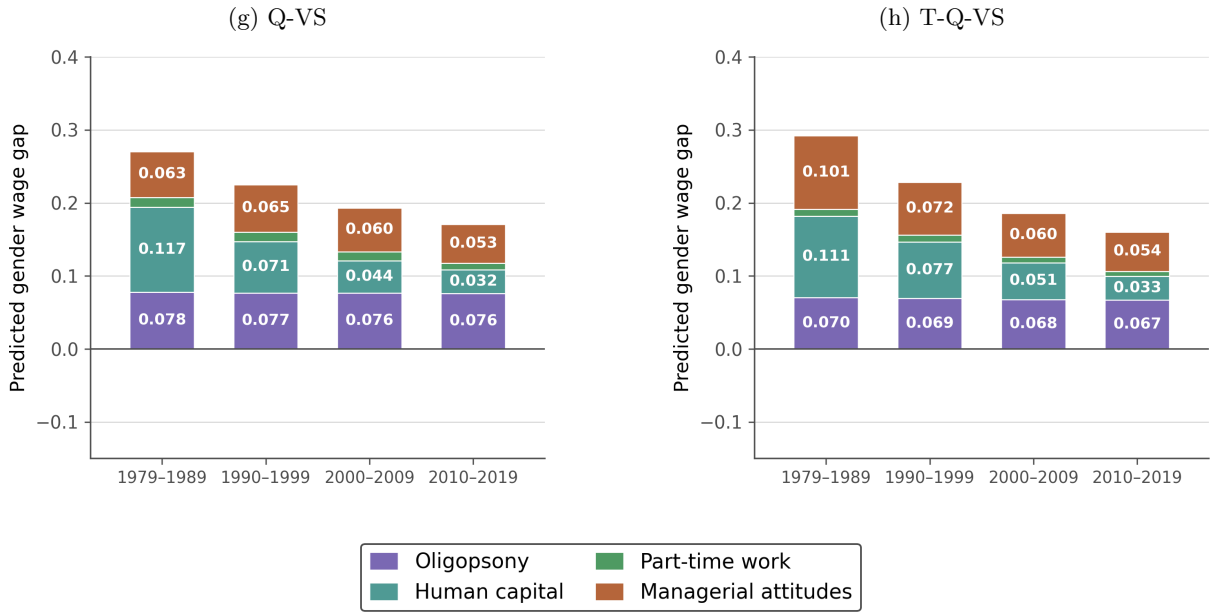


Figure D.7: Decomposition of the predicted gender wage gap by broad occupation *(continued)*



Notes: Each panel reports decade averages for one broad occupation after removing detailed-occupation wage components. Within each decade, gaps are computed in year × age × education cells and aggregated within each broad occupation, using harmonic weights based on CPS-weighted male and female cell counts. The remaining predicted gap is decomposed into human capital, part-time work, oligopsony, and managerial attitudes. Values are in log points.

Table D.9: Effect of model channels on the occupational gender wage-gap gradient

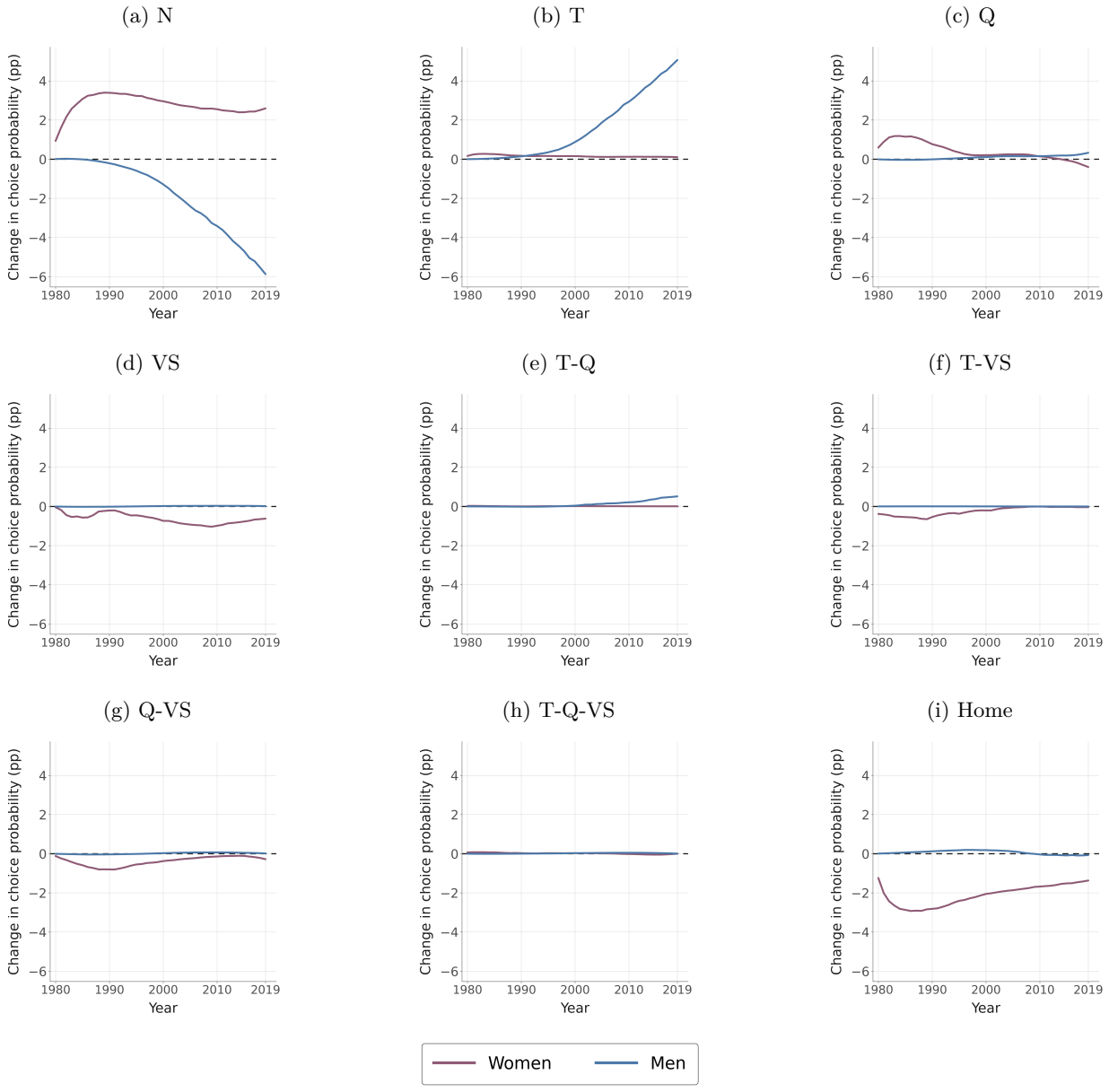
Period	N years	Full	No channel	Change	Range	Same sign
Panel A. Human capital						
1979–1989	10	-0.149	-0.124	+0.024	[+0.010, +0.035]	0/10
1990–1999	9	-0.069	-0.061	+0.008	[-0.006, +0.018]	1/9
2000–2009	10	-0.016	-0.025	-0.009	[-0.018, +0.002]	9/10
2010–2019	10	-0.003	-0.030	-0.027	[-0.037, -0.020]	10/10
All years	39	-0.059	-0.060	-0.001	[-0.037, +0.035]	20/39
Panel B. Part-time work						
1979–1989	10	-0.149	-0.175	-0.026	[-0.040, -0.018]	10/10
1990–1999	9	-0.069	-0.080	-0.011	[-0.020, +0.002]	8/9
2000–2009	10	-0.016	-0.028	-0.012	[-0.022, -0.004]	10/10
2010–2019	10	-0.003	-0.006	-0.003	[-0.013, +0.010]	6/10
All years	39	-0.059	-0.072	-0.013	[-0.040, +0.010]	34/39
Panel C. Oligopsony						
1979–1989	10	-0.149	-0.161	-0.012	[-0.017, -0.006]	10/10
1990–1999	9	-0.069	-0.087	-0.017	[-0.023, -0.015]	9/9
2000–2009	10	-0.016	-0.031	-0.015	[-0.020, -0.011]	10/10
2010–2019	10	-0.003	-0.016	-0.014	[-0.018, -0.010]	10/10
All years	39	-0.059	-0.073	-0.014	[-0.023, -0.006]	39/39
Panel D. Managerial attitudes						
1979–1989	10	-0.149	0.013	+0.162	[+0.130, +0.207]	10/10
1990–1999	9	-0.069	0.020	+0.089	[+0.067, +0.111]	9/9
2000–2009	10	-0.016	0.037	+0.053	[+0.040, +0.081]	10/10
2010–2019	10	-0.003	0.043	+0.046	[+0.042, +0.050]	10/10
All years	39	-0.059	0.029	+0.087	[+0.040, +0.207]	39/39

Notes: Each slope is estimated across the eight broad occupations separately by year after removing detailed-occupation wage-price components from model-predicted wages. Change is the no-channel slope minus the full model slope. *Same sign* reports the number of annual changes with the same sign as the channel's full-sample mean effect. 1986 and 1996 carry no matched panel in the source and are absent from every series.

E Additional counterfactual results

E.1 Removing the influence of managerial attitudes

Figure E.1: Occupational reallocation after removing the influence of managerial attitudes



Notes: The figure reports the evolution of employment reallocation after removing the influence of managerial attitudes from 1980 onward. Each panel shows the change in the probability of choosing the indicated broad occupation, or non-employment (Home), separately for women and men. Changes are computed as the difference between the counterfactual and baseline choice probabilities in each year, expressed in percentage points of the respective gender's CPS population. The counterfactual allows wages, occupational choices, and employment histories to adjust endogenously over time.

Table E.1: Occupation-level effects of eliminating the influence of managerial attitudes

Occupation	$\Delta \ln w_F$ (log pts)	$\Delta \ln w_M$ (log pts)	$\Delta P_F(j)$ (pp)	$\Delta P_M(j)$ (pp)	ΔFS_j (pp)	ΔR_j (%)	$\Delta \Pi_j$ (%)
N	+7.81	+0.90	+2.60	-5.88	+9.54	-5.11	-14.36
T	+7.79	-1.06	+0.10	+5.07	-1.16	+15.08	+10.77
Q	+3.35	+0.43	-0.40	+0.33	-2.09	+0.53	-6.60
VS	+4.94	+0.02	-0.62	+0.02	-0.46	-2.68	-15.24
T–Q	+8.00	-0.41	+0.01	+0.52	-0.46	+4.98	+1.69
T–VS	+5.13	+0.08	-0.03	0.00	-0.22	-1.24	-11.89
Q–VS	+5.04	-0.01	-0.28	+0.01	-0.36	-0.61	-10.61
T–Q–VS	+6.19	+0.03	0.00	0.00	-0.02	+0.21	-9.07

Notes: The table reports the 2019 effects by broad occupation of eliminating the influence of managerial attitudes from 1980 onward. $\Delta \ln w_s$ denotes the change in mean log wages among employed workers of sex $s \in \{F, M\}$ within each occupation. $\Delta P_s(j)$ denotes the change in the probability that a member of the sex-s population works in occupation j, while ΔFS_j denotes the change in the female share of employment in that occupation. ΔR_j and $\Delta \Pi_j$ denote percentage changes in total occupational revenue (the value of output) and profits, respectively. Wage changes are reported in log points, employment probabilities and female shares in percentage points, and revenue and profits as percentage changes relative to their baseline values.

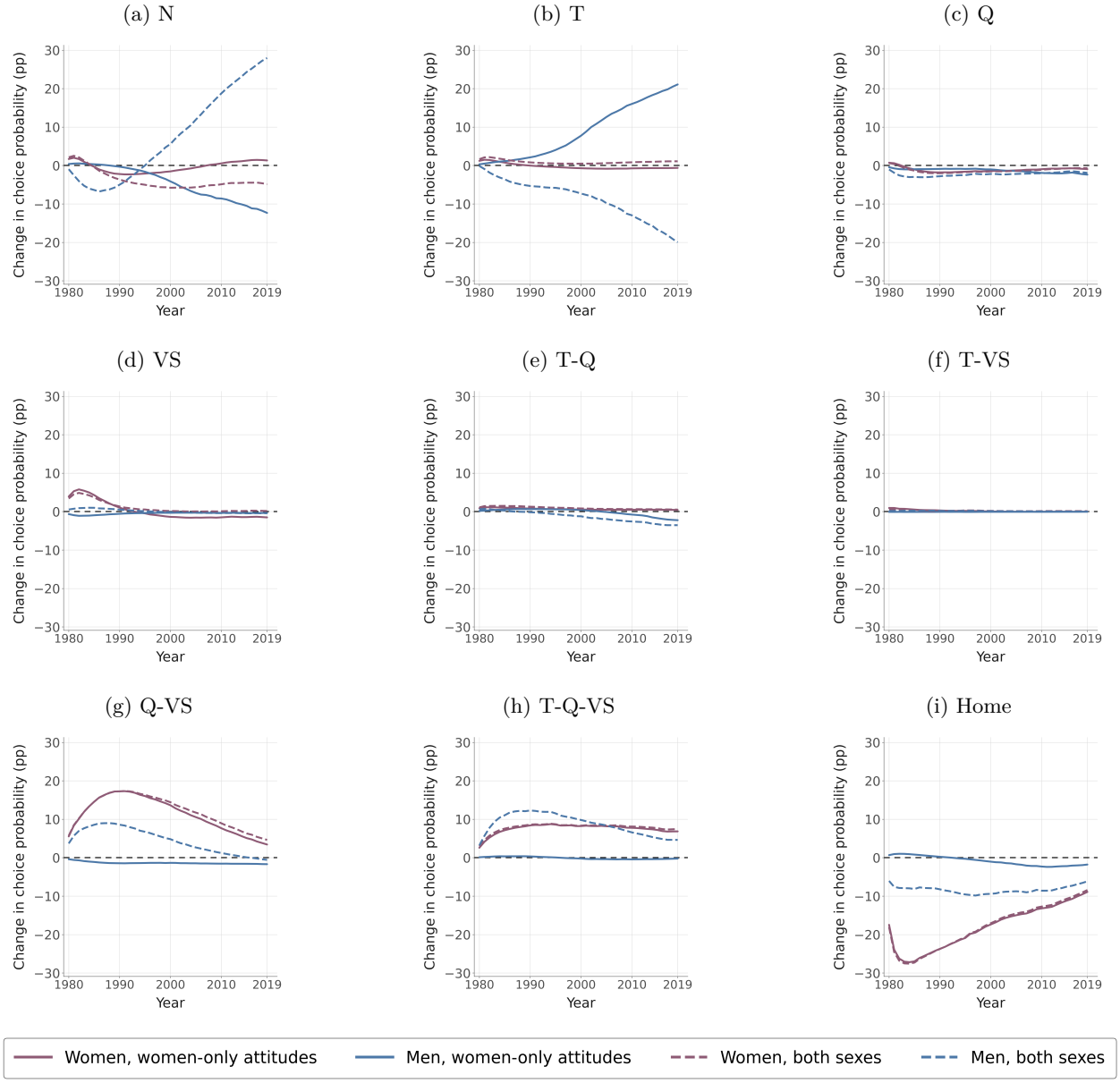
Table E.2: Aggregate effects of eliminating the influence of managerial attitudes in one occupation at a time

Occupation	Year	$\Delta \ln w_F$ (log pts)	$\Delta \ln w_M$ (log pts)	Δ GWG (log pts)	Δ CGWG (%)	ΔE_F (pp)	ΔE_M (pp)	ΔY (%)	$\Delta \Pi$ (%)
N	1980	+3.27	-0.01	-3.28	-16.15	+0.52	-0.01	+0.15	-3.62
	2000	+0.84	-0.18	-1.02	-17.30	+1.38	+0.10	+0.09	-2.96
	2019	+1.50	-0.78	-2.28	-14.92	+0.88	+0.86	+0.46	-2.79
T	1980	+0.97	0.00	-0.97	-6.90	+0.12	0.00	+0.07	-1.01
	2000	+0.30	+0.03	-0.26	-3.62	-0.05	-0.06	-0.07	-0.40
	2019	+0.57	-0.76	-1.33	-1.38	-0.18	+0.80	-0.12	-1.11
Q	1980	+2.46	0.00	-2.46	-9.21	+0.35	0.00	+0.18	-2.67
	2000	+1.09	-0.10	-1.19	-4.20	+0.30	+0.17	+0.27	-1.14
	2019	+0.48	-0.80	-1.28	-0.80	+0.02	+0.17	-0.29	-0.85
VS	1980	+2.09	+0.01	-2.08	-2.47	+0.22	0.00	+0.11	-2.44
	2000	+1.41	+0.02	-1.38	-1.86	+0.41	+0.21	+0.29	-1.78
	2019	+0.88	-0.61	-1.48	-0.29	+0.16	+0.19	-0.35	-2.02
T–Q	1980	+0.21	0.00	-0.21	-1.11	+0.02	0.00	+0.02	-0.23
	2000	+0.09	-0.05	-0.14	-0.78	-0.03	+0.06	-0.01	-0.14
	2019	0.00	-0.68	-0.68	-0.16	-0.05	+0.20	-0.25	-0.21
T–VS	1980	-0.81	0.00	+0.81	+0.64	-0.07	0.00	-0.09	+1.04
	2000	+0.09	0.00	-0.09	-0.14	+0.01	0.00	+0.02	-0.06
	2019	+0.15	-0.01	-0.15	-0.34	-0.01	+0.01	+0.01	-0.19
Q–VS	1980	+1.00	0.00	-0.99	-4.03	+0.08	0.00	+0.07	-1.26
	2000	+2.59	-0.01	-2.60	-8.38	+0.12	+0.17	+0.68	-2.58
	2019	+1.64	-0.35	-1.99	-5.04	-0.07	+0.14	+0.05	-2.67
T–Q–VS	1980	+0.59	0.00	-0.59	-2.66	+0.05	0.00	+0.05	-0.70
	2000	+0.49	0.00	-0.49	-1.85	-0.02	+0.04	+0.08	-0.57
	2019	+0.86	-0.03	-0.90	-2.97	-0.04	+0.03	+0.27	-0.91

Notes: The table reports aggregate effects of eliminating the influence of managerial attitudes in one broad occupation at a time, starting in 1980. Each occupation identifies a separate counterfactual in which the influence of the attitudes is eliminated only in that occupation and remains unchanged in all others. All outcomes refer to the entire economy, not only the targeted occupation. Changes are measured relative to the baseline in each year. $\Delta \ln w_F$ and $\Delta \ln w_M$ denote changes in mean log wages, and Δ GWG denotes the change in the aggregate gender wage gap, defined as the difference between men's and women's mean log wages. Δ CGWG denotes the percentage change in the conditional gender wage gap relative to its baseline value, conditioning on detailed occupation, age, education, and working hours. Negative values indicate a narrowing of the corresponding gap. ΔE_F and ΔE_M denote changes in employment rates, while ΔY and $\Delta \Pi$ denote percentage changes in aggregate output and profits. The counterfactuals represent separate equilibria, and their effects are not additive.

E.2 Changing individual attitudes counterfactual

Figure E.2: Occupational reallocation following changes in gender-role attitudes



Notes: The figure reports occupational reallocation under two counterfactual scenarios: changes in women's gender-role attitudes only, and changes in both women's and men's attitudes. Each panel shows the change in the probability of choosing the indicated broad occupation, or non-employment (home), separately by sex and scenario. Changes are measured relative to the baseline in percentage points of the respective gender's CPS population. Wages, occupational choices, and employment histories adjust endogenously over time.

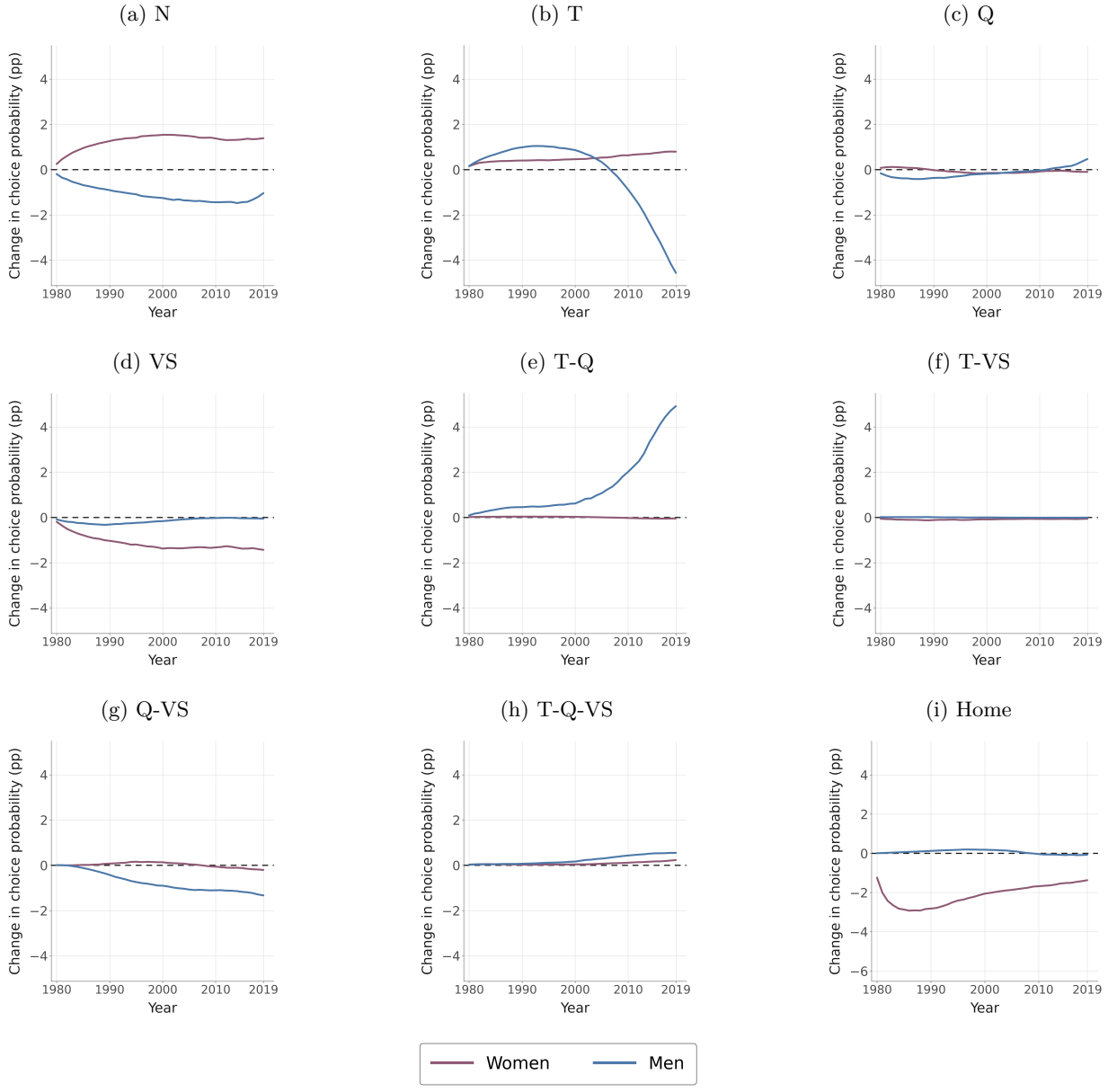
Table E.3: Occupation-level effects of changes in gender-role attitudes

Occupation	$\Delta \ln w_F$ (log pts)	$\Delta \ln w_M$ (log pts)	$\Delta P_F(j)$ (pp)	$\Delta P_M(j)$ (pp)	ΔFS_j (pp)	ΔR_j (%)	$\Delta \Pi_j$ (%)
Panel A: Women's attitudes only							
N	+6.80	+3.04	+1.31	-12.33	+18.02	-20.75	-23.29
T	+1.64	-1.98	-0.63	+21.09	-5.39	+61.33	+56.21
Q	+6.45	-2.74	-0.95	-2.38	+8.98	-20.18	-20.70
VS	+3.26	+1.41	-1.51	-0.37	+0.66	-7.16	-9.06
T–Q	+15.22	+2.25	+0.44	-2.24	+8.12	-15.72	-14.42
T–VS	+5.26	+0.57	-0.02	-0.05	+1.84	+1.38	-0.46
Q–VS	+2.59	+1.16	+3.42	-1.69	+6.98	+6.98	+10.39
T–Q–VS	+25.90	+1.84	+6.84	-0.24	+18.92	+77.57	+94.49
Panel B: Both sexes' attitudes							
N	-2.54	-1.09	-4.87	+27.95	-22.96	+42.52	+25.44
T	+16.67	+10.22	+1.10	-19.97	+23.91	-54.90	-52.77
Q	+5.66	+3.10	-0.68	-1.92	+7.07	-14.20	-15.28
VS	+3.82	+2.63	+0.17	-0.43	+1.88	+0.68	-3.78
T–Q	+16.34	+2.69	+0.52	-3.54	+12.71	-28.05	-26.16
T–VS	+7.18	+3.67	+0.11	0.00	+0.73	+10.47	+0.91
Q–VS	+3.03	+0.89	+4.63	-0.57	+5.79	+14.19	+13.84
T–Q–VS	+26.75	+10.73	+7.44	+4.62	+7.75	+127.14	+121.98

Notes: The table reports the 2019 effects by broad occupation of changes in gender-role attitudes from 1980 onward, considering changes in women's attitudes only (Panel A) and in both sexes' attitudes (Panel B). $\Delta \ln w_s$ denotes the change in mean log wages among employed workers of sex $s \in \{F, M\}$ within each occupation. $\Delta P_s(j)$ denotes the change in the probability of working in occupation j, and ΔFS_j the change in its female employment share. ΔR_j and $\Delta \Pi_j$ denote changes in occupational revenue and profits. Wage changes are expressed in log points, employment probabilities and female shares in percentage points, and revenue and profits as percentage changes relative to baseline.

E.3 Restricting gender wage differentiation counterfactual

Figure E.3: Occupational reallocation following restrictions on gender wage differentiation



Notes: The figure reports the evolution of employment reallocation following the introduction of a common-wage constraint for comparable men and women from 1980 onward, using human-capital intervals of width 0.25. Each panel shows the change in the probability of choosing the indicated broad occupation, or non-employment (home), separately for women and men. Changes are computed as the difference between the counterfactual and baseline choice probabilities in each year, expressed in percentage points of the respective gender's CPS population. The counterfactual allows wages, occupational choices, and employment histories to adjust endogenously over time.

Table E.4: Occupation-level effects of restricting gender wage differentiation

Occupation	$\Delta \ln w_F$ (log pts)	$\Delta \ln w_M$ (log pts)	$\Delta P_F(j)$ (pp)	$\Delta P_M(j)$ (pp)	ΔFS_j (pp)	ΔR_j (%)	$\Delta \Pi_j$ (%)
N	+3.06	-1.94	+1.39	-1.04	+2.63	+0.79	-0.15
T	+10.66	+1.05	+0.79	-4.56	+4.41	-9.85	-9.16
Q	+3.45	-2.12	-0.10	+0.47	-1.97	+4.03	+1.55
VS	+0.51	-2.99	-1.43	-0.05	-0.69	-7.20	-7.61
T–Q	+6.12	-2.61	-0.05	+4.92	-3.84	+46.86	+43.81
T–VS	+1.18	-3.09	-0.06	-0.01	-0.24	-2.83	-3.68
Q–VS	+4.47	-4.15	-0.21	-1.33	+2.55	-4.04	-4.85
T–Q–VS	+5.51	-1.72	+0.23	+0.55	-0.85	+7.07	+4.34

Notes: The table reports the 2019 effects by broad occupation of imposing common wage offers for comparable men and women from 1980 onward, using human-capital intervals of width 0.25. $\Delta \ln w_s$ denotes the change in mean log wages among employed workers of sex $s \in \{F, M\}$ within each occupation. $\Delta P_s(j)$ denotes the change in the probability that a member of the sex-s population works in occupation j, while ΔFS_j denotes the change in the female share of employment in that occupation. ΔR_j and $\Delta \Pi_j$ denote percentage changes in total occupational revenue (the value of output) and profits, respectively. Wage changes are reported in log points, employment probabilities and female shares in percentage points, and revenue and profits as percentage changes relative to their baseline values.