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The Changing Value of Employment and Its Implications

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Abstract

We characterize the employment value of different worker-occupation matches and estimate the substitutability of match-specific inputs in production. In an equilibrium model of the U.S. labor market, we examine the responses of employment and wages to shifts in technology and match values. Earnings are mainly driven by technology while match value heterogeneity influences the distribution of workers across occupations. The model delivers measures of rents and compensating differentials. After 1980, employment rents increased for educated workers but stagnated for others. Compensating differentials have risen on average, particularly in occupations where worker mobility has grown.

JEL Codes: D51, D58, J2, J3, J62.

Keywords: employment; wages; equilibrium; technological change; heterogeneity; occupations.

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1 Introduction

Significant changes in employment and wages have been documented in the U.S. labor market over the past five decades.[1] The uneven nature of these changes across occupations and workers suggests that shifts in production arrangements and in workers' heterogeneous preferences for job attributes may both be contributing factors. While a growing body of research examines the labor market impacts of technological change and automation (e.g. Autor and Dorn, 2013; Autor and Salomons, 2018; Acemoglu and Restrepo, 2022) we have a limited understanding of how non-wage compensation and job amenities offset, or reinforce, technological change. This is despite evidence that non-wage attributes shape workers' valuations of employment opportunities. For example, data on job injuries suggest that earnings dispersion is an imperfect measure of compensation inequality in the US in the 1990s (Hamermesh, 1999). Maestas et al. (2018) and Dube et al. (2022) document that employment conditions contribute to job choice, employee retention, and overall compensation. They also show that tastes for non-wage rewards vary systematically with gender, age, and education. In a model of human capital accumulation featuring search frictions and occupational choice, Taber and Vejlin (2020) find that about $\frac{1}{3}$ of observed choices would be different if workers only cared about pecuniary rewards. Lamadon et al. (2022) estimate that workers are, on average, willing to pay over $\frac{1}{10}$ of their wages to stay in their current jobs. Lehmann (2022) argues that a positive correlation between wages and non-wage amenities exacerbated inequality in the Austrian labor market between 1996 and 2011.

In this study, we examine the combined influence of technological change and workers' heterogeneity in job valuations on occupation-level employment and returns. Focusing on the US labor market between 1980 and 2018, we begin by estimating, through a revealed preferences approach, distinct components of worker-occupation match values. To characterize the changing distributions of worker-occupation match values, we combine information on headcounts, earnings, and hours worked in all job matches, including matches observed so infrequently that realized wage distributions are uninformative in isolation. That is, we use information about the relative scarcity of matches as well as the pecuniary returns and hours worked in each match.

The approach does not restrict attention to subsets of workers and jobs; rather, we elicit match values conditional on gender, education, age, and occupation. This flexibility accommodates empirically relevant dimensions of heterogeneity (for example, Wiswall and Zafar, 2018 suggest that women may value work schedules and job stability more than men).

[1] Well-documented shifts include the increasing employment and wages of skilled workers (Katz and Murphy, 1992; Katz and Autor, 1999; Beaudry et al., 2016; Valletta, 2017), the declining share of middle-paying occupations (Acemoglu and Autor, 2011), the emergence of IT-intensive jobs (Gallipoli and Makridis, 2018), the growing presence of women in high-pay occupations (Cortes et al., 2018), the rising rewards to soft non-cognitive skills (Deming, 2017), the shrinking labor supply of young men (Aguiar et al., 2017), the convergence of the occupational distributions across demographic groups (Hsieh et al., 2019).

The analysis is carried out in a discrete choice setting that distinguishes between observable and latent (unobserved) components of match values. Estimates of observable components convey information about the value of earnings and hours worked.[2] The latent components reflect non-pecuniary returns as well as possible heterogeneity in deferred, or other, compensation. For this reason, we avoid referring to latent components as non-pecuniary attributes even though such attributes are captured by latent components. The analysis imposes few restrictions apart from the low-level requirements of a Roy model in which relative returns drive job selection (Willis, 1986).

We estimate the empirical counterpart of the model using cross-sectional data (Census, ACS) on earnings, hours worked and employment headcounts across occupations. We find that match values are poorly approximated by wages and hours alone. Similar jobs carry different returns to different workers (Autor et al., 2014; Cortes et al., 2017) and the latent components are more dispersed than the observable ones across worker-occupation matches.

Since employers cannot make wage offers fully contingent on idiosyncratic job valuations, due to imperfect information about workers' preferences, the components of match value bundled within a job cannot be easily traded against each other. This implies that workers earn rents from ongoing employment, reflecting their unobserved idiosyncratic job values.

We illustrate how to quantify the magnitudes of rents, alongside compensating differentials, using model estimates of worker-occupation match values. Rents and compensating differentials are connected: by definition, compensating differentials capture the trade-offs faced by workers whose rents are close to zero and who are marginal in their occupation choice. Such workers would take a different job if relative wages and non-wage compensation were slightly different, and their trade-offs can be interpreted as marginal rates of substitution. Compensating differentials are, therefore, conceptually distinct from the empirical covariation between wage and non-wage job attributes, which is occasionally examined in the applied literature. We discuss these differences in Appendix H, where we consider alternative measures of compensating differentials.

Our estimates suggest that both rents and compensating differentials have changed significantly over time, especially when we condition on gender and education. After 1980, employment rents have grown among educated workers but not others. In particular, rents have fallen for non-college male workers while they have expanded among educated women (Cortes et al., 2018). The average rent has risen from about \$14,500 in 1980 to just below \$16,000 in 2018 (all values in year 2000 dollars). Over the same period, we document a growing divide between cognitive and manual jobs, with rents in routine manual occupations exhibiting the largest declines.

[2] Occupations vary in their time demands (Erosa et al., 2022a). Heterogeneous preferences for leisure may contribute to occupational choice, for example, if wages are a convex function of time (Aaronson and French, 2004; Erosa et al., 2022b).

An increasing share of the rents enjoyed by college workers in skilled jobs is derived from latent components of match values. Depending on the occupation, latent components account for between 1/3 and 1/2 of rent gaps between workers in 2018.

Rents appear to reflect occupation characteristics: for example, workers in riskier jobs retain higher rents on average. If we measure risk by the dispersion of wages within a worker-occupation cell, a 10-dollar increase in the standard deviation of wages is associated with a 4.5% increase in rents. Moreover, the same 10-dollar increase in the standard deviation of wages is associated with a positive change of up to 0.7 standard deviations in the latent match value. That is, occupations that exhibit higher wage dispersion have, on average, proportionally larger latent employment values (see Appendix J).

Furthermore, we find evidence that, since 1980, compensating differentials in the US labor market have grown in many worker-occupation pairs, although this growth slowed down after 2000. Variation of compensating differentials in the cross-section of worker occupation-pairs is closely associated with occupational mobility. One interpretation of this finding is that occupational mobility may help workers trade off different job attributes as they switch jobs (Section 4 and Appendix I). This is not surprising if worker flows induce equilibrium adjustments that affect compensation. By the same token, less mobility would be associated with lower estimates of compensating differentials as latent returns are not systematically priced in terms of wage differences.

Our findings suggest that the U.S. workforce changed significantly between 1980 and 2018, both in composition and in latent valuations of employment. At the same time, large shifts have occurred on the demand side of the labor market due to technological change. In the last part of the paper, we bring together the demand and supply of match-specific inputs and assess the intensity of equilibrium responses to technology and workforce changes. The endogenous responses are mediated by a production technology that aggregates worker-occupation inputs supplied by intermediate firms (Appendix B).

In Section 3 we discuss the identification and estimation of the aggregate production function. Then, given a parametric form for technology, we perform counterfactual exercises and quantify the relative contribution of shifts in the demand for, and in the supply of, different worker-occupation inputs. To account for heterogeneity in labor supply elasticities, we break them down into an intensive and an extensive margin. The extensive margin is important to control for differences in employment responses to wages across worker-occupation pairs. Moreover, we use the estimates of aggregate labor supply elasticities to validate the model as they can be compared to existing measures in the literature.

Results indicate that the evolution of wages is broadly explained by technological change and that price responses due to shifts in aggregate labor supply are less prominent than those induced by technological transformation.

Shifts in latent values have asymmetric effects on the employment patterns of different worker types. For example, had latent returns stayed at their 1980 levels, the labor market participation of men would be much higher in 2018.

Technological change has offset the negative impact of latent returns on the labor force participation of college-educated men but it has reinforced the drop in the participation of non-college men.

In contrast, women have experienced a double lift from latent returns and technology, which have bolstered their labor force participation and earnings. Among non-college women, latent returns and technological change have contributed similarly to increased participation. For college-educated women, the main push has come from technological change.

The rest of the paper is organized as follows. In Section 2 we describe the model. Section 3 overviews the identification of model parameters and shows baseline estimates. In Section 4 we characterize employment rents and compensating differential, and present estimates of their values for different occupations and workers. Section 5 overviews counterfactual experiments designed to assess how technological progress and a changing workforce have contributed to historical patterns of employment and earnings. Extensions and robustness checks are presented in Section 6. Section 7 concludes.

2 Model

We study a competitive labor market with two-sided heterogeneity (workers and jobs). The sorting of workers in equilibrium reflects the distribution of relative returns. The wage component of labor market returns is determined in equilibrium.

Markets. Time is discrete and a period (year) is indexed by t. There are a finite number $M > 1$ of separate labor markets, indexed by m. Each (m, t) pair is an independent labor market with its own supply of, and demand for, workers.

Workers. A continuum set of workers of size S_{mt} populates each (m, t) market. Each worker in market (m, t) is indexed by $\iota \in S_{mt}$ and belongs to a distinct demographic group $i \in I$. We let μ_{imt} denote the mass of workers of type i, so that $\sum_i \mu_{imt} = S_{mt}$. Workers choose whether to work and, if so, their occupation $j = 1, ..., J$. If they do not work, they are in the idle state indexed as $j = 0$.

The utility that a worker derives from each possible state $j = 0, ..., J$ consists of two elements: (i) a systematic utility component (U_{ijmt}) that depends on their type i, occupation j, and current labor market (m, t); (ii) an idiosyncratic component which reflects unobserved individual preferences for an occupation (θ_j^ι).

Workers of type i supply h_{ijmt} hours of labor paid at the hourly rate $\tilde{w}_{ijmt}$. Workers consume their income in each period. Income is the sum of labor income and non-labor income $\tilde{y}_{imt}$. Finally, letting P_{mt} be the price of the consumption good in each separate market (m, t), we define as $w_{ijmt} = \tilde{w}_{ijmt}/P_{mt}$ and $y_{ijmt} = \tilde{y}_{ijmt}/P_{mt}$ the real wage and real non-labor income, respectively.

The worker's problem. The problem of a worker of type i can be characterized in two steps. First, conditional on being matched to occupation j, the systematic utility component is maximized by solving

$$U_{ijmt}(w_{ijmt}, y_{imt}) = \max_{h_{ijmt}} \quad u_c\left(c_{ijmt}\right) - u_h^i\left(h_{ijmt}\right) + b_{ijt} \qquad \text{s.t.} \quad c_{ijmt} = w_{ijmt}h_{ijmt} + y_{imt}, \tag{1}$$

where $u_c(\cdot)$ is consumption utility, $u_h^i(\cdot)$ captures the disutility from working and can differ across types; b_{ijt} denotes latent benefits accruing to a type i worker in occupation j and period t. The systematic component of utility can vary across markets since observable wages and non-labor income depend on the specific (m, t) pair. The latent component of utility varies with occupation, demographic group, and time.[3]

The latent value of not working is set to zero so that the systematic utility of non-employment $(j = 0)$ is $U_{i0t}(0, y_{imt}) = u_c(y_{imt}) - u_h(0)$. The normalization $b_{i0t} = 0$ for all t and all i implies no loss of generality and is necessary because b_{i0t} is not separately identified from all other b_{ijt}. Given the normalization of b_{i0t} and additive separability of match value, all the b_{ijt} terms include the value of home production. That is, differences between employment and non-employment reflect the value of home production. Therefore, estimated variation in b_{ijt} conveys also information about changes in productivity at home.

Workers in occupation j receive an additional return from the individual unobserved component θ_j^ι, which captures idiosyncratic values of occupations. We assume that θ_j^ι is randomly distributed as Type I Extreme Value with a zero location parameter and scale parameter equal to σ_θ. The distribution of these idiosyncratic values is independent of time and market.

The second step in the problem of the worker is the occupation choice. Given a set of idiosyncratic preference shocks $\{\theta_j^\iota\}_{j=1}^J$, the worker ι solves

$$\max_{j=0,1,..,J} U_{ijmt}(w_{ijmt}, y_{imt}) + \theta_j^\iota \tag{2}$$

By the properties of the Extreme Value distribution, the fraction of workers of type i supplying

[3] Latent components in the model do not vary across markets since local amenities are enjoyed by all workers regardless of occupation and market-specific latent components cancel out in the definition of surplus. In the empirical analysis, we perform robustness checks (Appendix K) by estimating a model in which latent returns can change across labor markets.

labor to occupation j in market m is

$$\frac{\mu_{ijmt}}{\mu_{imt}} = \frac{\exp\left(U_{ijmt}(w_{ijmt}, y_{imt})/\sigma_\theta\right)}{\sum_{j'=0}^{J} \exp\left(U_{ij'mt}(w_{ij'mt}, y_{imt})/\sigma_\theta\right)} \tag{3}$$

Firms. Within each market and period, a representative final good producer uses a continuum of size one of intermediate goods to produce its output. Each intermediate is produced by a different firm, indexed by v. Intermediate goods producers employ one occupation j and, therefore, intermediate goods can be thought of as the output of an individual occupation. Since each intermediate firm produces a differentiated good, they have market power in the intermediate goods' market, and non-zero profits are made. Labor markets are competitive. For convenience we partition intermediate firms into subsets $\{V_{jt}\}_{j=1,\ldots,J}$ such that, for any pair of firms $v, v' \in V_{jt}$, their production technologies differ only up to an idiosyncratic productivity (TFP) shock. The V_{jt} partition splits the continuum of intermediate producers into a finite number of subsets containing producers that employ the same input j. In Appendix C we generalize the model to a setting where intermediate producers employ both capital and labor.[4]

Final good production. The final good producer solves:

$$\begin{aligned} \max_{\{\lambda_{jmtv}\}} \quad & P_{mt} Y_{mt} - \int_v p_{jmtv} \lambda_{jmtv} dv \\ \text{s.t.} \quad & Y_{mt} = \left(\int_v \lambda_{jmtv}^{\rho} dv \right)^{\frac{1}{\rho}}, \end{aligned} \tag{4}$$

where λ_{jmtv} are demanded quantities of the intermediate goods. The final good price P_{mt} in market (m, t) is a function of intermediate prices p_{jmtv},

$$P_{mt} = \left(\int_v p_{jmtv}^{\frac{-\rho}{1-\rho}} dv \right)^{\frac{-(1-\rho)}{\rho}}$$

Optimality for this production problem implies

$$p_{jmtv} = \left[\frac{\lambda_{jmtv}}{Y_{mt}} \right]^{-(1-\rho)} P_{mt}$$

[4] The key empirical relationships are unchanged and we show that in the baseline model without capital, estimates of substitutability between different worker-occupation labor inputs are a lower bound.

Producers of intermediate goods. The profit maximization of an intermediate producer $v \in V_{jt}$ is:

$$\begin{aligned}
\max_{p_{jmtv},\lambda_{jmtv},L_{ijmtv}} \quad & p_{jmtv}\lambda_{jmtv} - \sum_i \tilde{w}_{ijmt} L_{ijmtv} \\
\text{s.t.} \quad & \lambda_{jmtv} = z_{jmtv} \sum_i \beta_{ij} L_{ijmtv} \\
& p_{jmtv} = \left[\frac{\lambda_{jmtv}}{Y_{mt}}\right]^{-(1-\rho)} P_{mt},
\end{aligned} \tag{5}$$

where z_{jtv} is an idiosyncratic shock drawn from an occupation-specific distribution ($z_{jtv} \sim F_{jt}(v)$). Optimality implies the following expression for profits,

$$\pi_{jmtv} = \frac{1-\rho}{\rho} \sum_i \tilde{w}_{ijmt} L_{ijmtv}$$

The aggregate production function, derived analytically in Appendix B, is:

$$Y_{mt} = A_t \left[\sum_j \alpha_{jt} \left(\sum_i \beta_{ijt} L_{ijmt}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{6}$$

where $\alpha_{jt} = \frac{\tilde{\alpha}_{jt}}{\sum_{j'} \tilde{\alpha}_{j't}}$ and $A_t = \left(\sum_{j'} \tilde{\alpha}_{j't}\right)^{\frac{1}{\rho}}$ with $\tilde{\alpha}_{jt} = \left(\int_{v \in V_{jt}} z_{jmtv}^{\frac{\rho}{1-\rho}} dv\right)^{1-\rho}$. In the appendix, we also show that the wage function for match (i,j) in market (m,t) is

$$w_{ijmt} = \rho A_t^{\rho} \alpha_{jt} \beta_{ijt} \left(\frac{Y_{mt}}{\sum_{i'} \beta_{i'jt} L_{i'jmt}}\right)^{(1-\rho)}. \tag{7}$$

Equilibrium. A competitive equilibrium in period t is a set of prices ($\tilde{w}_{ijmt}$, p_{ijmtv}, P_{mt}, occupational choices μ_{ijmt}, labor supply choices h_{ijmt} and labor demands L_{ijmtv} such that:

1. given wages and preference shocks, each worker solves the problems described in equations (1) and (2);
2. final good producer and intermediate firms behave optimally and solve (4) and (5), respectively;
3. all markets clear. In particular, labor market clearing implies that for all matches (i,j) and markets (m,t), it is the case that $L_{ijmt} = \mu_{ijmt} h_{ijmt}$ where $L_{ijmt} = \sum_{v \in V_{jt}} L_{ijmtv}$.

3 Identification and Estimation of Model Parameters

To estimate the empirical counterpart of the model we need data on the cross-sectional distributions of employment and earnings for different worker types. In what follows we overview the identification of utility and production parameters and describe data sources and estimation. More details are in Appendix A.

3.1 Data

We use decennial Census data from 1980, 1990, and 2000; in addition, we pool together three years of the American Community Survey (King et al., 2010) to get samples of comparable size for 2010 (2009-2011) and 2018 (2017-2019). We consider individuals aged between 25 and 54 and exclude those still in education, as well as workers in farming, forestry, and fishing. We define worker-side heterogeneity as a combination of gender, age (three groups: 25-34, 35-44, 45-54), and education (college graduates and above, and less than college). This results in 12 distinct worker groups, indexed by $i \in I$. On the demand side, we consider a set of 13 occupations in addition to the non-employment state. The occupation states are indexed by $j \in J$ and are reported in Table 1 along with their aggregation into four broad task clusters (see Acemoglu and Autor, 2011; Cortes and Gallipoli, 2018). We consider four geographical markets, indexed by $m \in M$, corresponding to U.S. Census regions (Northwest, Midwest, South, and West).

For each cell, consisting of a match (i, j) and a market (m, t), we compute total employment, average hours worked, average wages, and average non-labor income. To account for differences in the cost of living across regions we adjust the income measures by a local CPI based on the cost of housing (Moretti, 2013). To measure total employment we use population weights and count a worker as employed if they report working at least 15 hours per week. Non-labor income consists of the sum of incomes from businesses and farms.

3.2 Identification

Model parameters are identified by variations in employment shares across occupations and by differences in labor supply and wages across workers.

Preferences. The employment equation (3) links the employment in each occupation to the observed pecuniary value in those jobs. The occupation value is scaled by the parameter σ_θ, which reflects the dispersion of idiosyncratic preferences. The relationship in (3) is helpful to quantify the value of each (i, j) match relative to a different employment state. We define

Table 1: Occupation categories used for estimation.

Managerial, Professional Specialty and Technical (Non-Routine Cognitive)	
1	Executive, Administrative, and Managerial
2	Management Related
3	Professional Specialty
4	Technicians and Related Support
Sales and Administrative Support (Routine Cognitive)	
5	Sales
6	Administrative Support
Service (Non-Routine Manual)	
7	Protective Service
8	Other Service
Precision Production, Craft, Repair, Operators, Fabricators, and Laborers (Routine Manual)	
9	Mechanics and Repairers
10	Construction Trades
11	Precision Production
12	Machine Operators, Assemblers, and Inspectors
13	Transportation and Material Moving

the surplus relative to non-employment as

$$\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right) = \frac{U_{ijt}(w_{ijmt}, y_{imt}) - U_{i0t}(0, y_{imt})}{\sigma_\theta}. \tag{8}$$

Assuming isoelastic utility for consumption and leisure, we use the functional forms:

$$u_c(c) = \frac{c^{1-\sigma} - 1}{1-\sigma} \qquad u_h^i(h) = \psi_i \frac{h^{1-\gamma}}{1-\gamma}$$

Under these parametric restrictions, equation (8) shows that we can use cross-sectional variation in employment, hours worked and wages to estimate: (i) the latent return b_{ijt} for occupation-worker pair (i, j) in period t, and (ii) the scaling parameter σ_θ, which dictates the dispersion of idiosyncratic preferences. Optimality of labor supply in the worker's problem (1) implies

$$(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma} w_{ijmt} = \psi_i h_{ijmt}^{-\gamma} \tag{9}$$

If $\gamma \leq 0$, the disutility from work is a convex function and (9) has a unique solution. We do not restrict γ but show that its estimated value satisfies the condition for uniqueness.

Technology parameters. The wage equations in (7) and labor market equilibrium imply

$$\frac{w_{ijmt}}{w_{ij'mt}} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\widetilde{L}_{j'mt}}{\widetilde{L}_{jmt}}\right)^{1-\rho}$$

where $\widetilde{L}_{jmt} = \sum_{i'} \beta_{i'jt}L_{i'jmt}$. The β parameters are identified up to a normalization by within-occupation ratios of wages between worker groups (proof in Appendix A). Normalizing $\beta_{1jt} = 1$, for all $j = 1, ..., J$ and all t, we estimate the remaining β shares by averaging the within-occupation wages in the M markets and obtain $\hat{\beta}_{ijt} = \frac{1}{M}\sum_{m=1}^{M} \frac{w_{ijmt}}{w_{1jmt}}$. The remaining parameters are estimated using wage ratios (see Appendix A) like

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho - 1)\log\left(\frac{\sum_{i'} \beta_{i'jt}L_{i'jmt}}{\sum_{i'} \beta_{i'1t}L_{i'1mt}}\right) \tag{10}$$

To estimate the equation above we measure the second term on its right-hand side using $\hat{B}_{ijt} = \log\left(\frac{\hat{\beta}_{ijt}}{\hat{\beta}_{i1t}}\right)$; this term should have a coefficient equal to one, a restriction that we can test. The empirical counterpart of the third term on the right-hand side of (10) is $\hat{\Lambda}_{jmt} = \log\left(\frac{\sum_{i'} \hat{\beta}_{i'jt}\mu_{i'jmt}h_{i'jmt}}{\sum_{i'} \hat{\beta}_{i'1t}\mu_{i'1mt}h_{i'1mt}}\right)$, which measures the supply of labor efficiency units to occupation j. Then, the relationship in (10) is estimated as

$$W_{ijmt} = \gamma_{jt} + \psi\hat{B}_{ijt} + \phi\hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{11}$$

where $W_{ijmt} = \log\left(\frac{w_{ijmt}}{w_{i1mt}}\right)$ and $\phi = \rho - 1$.

3.3 Estimation of preference parameters

We estimate the model in two steps. First, we recover the parameters dictating utility and labor supply choices. Next, conditional on estimates from the first step, we estimate production technology parameters (shares and elasticity of substitution between different labor inputs).

Curvature parameters and disutility of labor. We use the optimality condition in (9) to express hours worked as a function of wages and non-labor income. That is,

$$\log\left(h_{ijmt}\right) = f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) + \epsilon^1_{ijmt}$$

where $\boldsymbol{X}_{ijmt} = [w_{ijmt};\ y_{imt}]$, $\tilde{\boldsymbol{\Omega}}_i = [\sigma;\ \gamma;\ \psi_i]$, and $f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) = \log(\hat{h}_{ijmt})$ is the logarithm of hours worked as predicted by the model which will be numerically computed. This delivers two sets of moments for the GMM estimation of labor supply parameters. Namely,

$$E\left[\log\left(h_{ijmt}\right) - f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) |i\right] = 0 \tag{12}$$

$$E\left[\left(\log\left(h_{ijmt}\right) - f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)\right) \boldsymbol{Z}^1_{ijmt}\right] = 0 \tag{13}$$

To account for potential endogeneity bias, the second set of moments posits orthogonality with respect to a vector of instruments $\boldsymbol{Z}^1_{ijmt}$.

Extensive margin of labor supply. The definition in (8) implies that we can cast the occupation choice as a function $g\left(\boldsymbol{X}_{ijmt}; \boldsymbol{\Omega}_i\right)$ such as

$$\begin{aligned} g\left(\boldsymbol{X}_{ijmt}; \boldsymbol{\Omega}_i\right) &= \frac{U_{ijt}(w_{ijmt}, y_{imt}) - U_{i0t}(y_{imt})}{\sigma_\theta} \\ &= \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt} + y_{imt}\right) - u^i_h\left(\hat{h}_{ijmt}\right) + b_{ijt} - u_c\left(y_{imt}\right)}{\sigma_\theta} \end{aligned}$$

where $\boldsymbol{\Omega}_{ijt} = \tilde{\boldsymbol{\Omega}}_i \bigcup [\sigma_\theta;\ b_{ijt}]$. Letting $\Upsilon_{ijmt} = \log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right)$, and using the estimates $\hat{h}_{ijmt} = \exp\left(f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)\right)$, we can recover the parameters dictating the extensive margin of labor supply from the empirical relationship:

$$\Upsilon_{ijmt} = g\left(\boldsymbol{X}_{ijmt}; \boldsymbol{\Omega}_{ijt}\right) + \epsilon^2_{ijmt}.$$

In practice, we use the following moment conditions:

$$E\left[\Upsilon_{ijmt} - g\left(\boldsymbol{X}_{ijmt}, \boldsymbol{\Omega}_{ijt}\right)|i,j,t\right] = 0 \tag{14}$$

$$E\left[\left(\Upsilon_{ijmt} - g\left(\boldsymbol{X}_{ijmt}, \boldsymbol{\Omega}_{ijt}\right)\right)\boldsymbol{Z}^2_{ijmt}\right] = 0 \tag{15}$$

where $\boldsymbol{Z}^2_{ijmt}$ is a vector of instruments.

Simulated method of moments. We denote as $\boldsymbol{X}$ the data vector of wages and hours worked. To calculate the cell averages we consider only people reporting at least 15 hours of work per week and positive earnings. Given the parameter matrix $\boldsymbol{\Omega} = \{\boldsymbol{\Omega_{ijt}}\}$, where $\boldsymbol{\Omega}_{ijt} = [\sigma;\ \gamma;\ \psi_i] \bigcup [\sigma_\theta;\ b_{ijt}]$, we want to solve the estimation problem

$$\hat{\boldsymbol{\Omega}} = \arg\min_{\boldsymbol{\Omega}} \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}\right)^T \boldsymbol{W}\boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}\right) \tag{16}$$

where $\boldsymbol{W}$ is a positive definite weighting matrix[5], $\boldsymbol{Z}$ is the vector of instruments, and $\boldsymbol{M}$ is the set of target moments described in (12), (13), (14) and (15).

The problem in (16) is computationally demanding as it requires solving the labor supply first order conditions in (9) for all the (i, j) and (m, t) pairs. Therefore we reformulate the problem by specifying the first order conditions as constraints (Su and Judd, 2012). We let $\boldsymbol{\Omega}^+$ be the union of the parameter matrix $\boldsymbol{\Omega}$ and $\{\hat{h}_{ijmt}\}_{\forall i,j,m,t}$, where the latter is the set of model-generated labor supplies. The estimation problem becomes

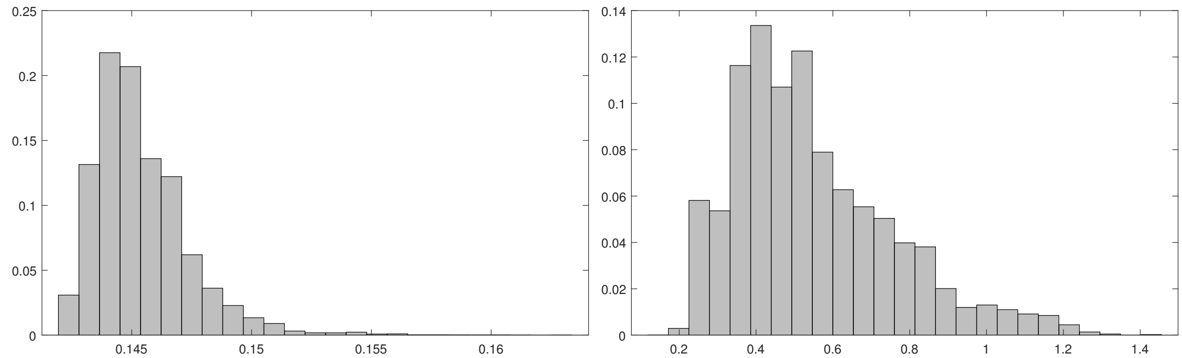
$$\hat{\boldsymbol{\Omega}} = \arg\min_{\boldsymbol{\Omega}^+} \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}^+\right)^T \boldsymbol{W}\boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}^+\right) \tag{17}$$

$$\text{s.t.} \quad -\sigma \log(w_{ijmt}\hat{h}_{ijmt} + y_{imt}) + \log(w_{ijmt}) = \log(\psi_i) - \gamma \log(\hat{h}_{ijmt}) \quad \forall i, j, m, t$$

where the constraints represent the FONC with respect to the intensive margin of labor supply. The presence of these constraints ensures that at the optimum labor supply satisfies the first order conditions (i.e. that the function $f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)$ is numerically approximated). Using this technique we avoid having to solve for optimal hours in each iteration of the optimization algorithm, substantially reducing the computation time.

We report estimates of the parameter matrix $\boldsymbol{\Omega}$ in Appendix L; specifically, Table 8 shows estimates of the curvature of the consumption utility and of the scaling factor of the extreme value preference shocks (respectively, σ and σ_θ). In estimation, we use 10 and 20-year lagged wages as instruments for current wages. Table 17 shows estimates of both weight and curvature of dis-utility from labor (ψ, γ). Tables 10-14 report all estimates of latent match-specific values (b_{ijt}) for different years.

[5]To reduce small sample biases (Altonji and Segal, 1996) the weights matrix W is an identity matrix.



(a) Intensive margin (b) Extensive margin

Figure 1: Distribution of labor supply elasticities in the sample population.

3.4 Labor supply elasticities

The preference parameter estimates imply a distribution of labor supply elasticities, which is of interest for various reasons. First, it can be used to validate preference estimates. Second, elasticities can be broken down into intensive and extensive margin components, thereby providing insights into the relative contribution of the two margins to aggregate changes in labor supply. Lastly, by considering the distribution of extensive margin elasticities across (i, j) worker-occupation pairs, in the equilibrium analysis we can account for the occupation-specific employment responses of different demographic groups.

Intensive margin. To compute the uncompensated elasticity of labor supply, we take the total differential of the optimality condition for the intensive margin of labor supply in (9). After rearranging it, we get

$$\frac{dh_{ijmt}}{dw_{ijmt}} = \frac{-\sigma(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma-1}w_{ijmt}h_{ijmt} + (w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma}}{\sigma(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma-1}w_{ijmt}^2 - \gamma h_{ijmt}^{-\gamma-1}\psi}$$

The uncompensated elasticity of labor supply at the intensive margin is defined as

$$\epsilon_{ijmt}^{int} = \frac{dh_{ijmt}}{dw_{ijmt}}\frac{w_{ijmt}}{h_{ijmt}}$$

Figure (1a) shows the distribution of estimated intensive margin labor supply elasticities in the population, obtained by plotting preference parameter estimates across (i, j, m, t) cells. The average elasticity is 0.15 in every sample year we consider, which is well within the range of existing estimates of uncompensated labor supply elasticities (see, for example, Blundell and MaCurdy, 1999; Chetty et al., 2011; Keane, 2011; Keane and Rogerson, 2012, 2015; Attanasio et al., 2018).

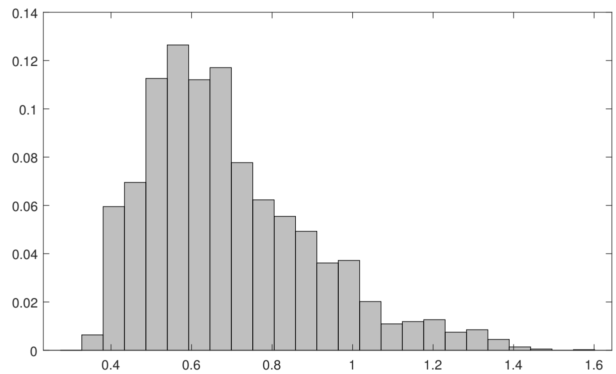


Figure 2: Distribution of cumulative elasticities of labor supply (extensive plus intensive).

Extensive margin. Next, we define the extensive margin elasticity of labor supply as the ratio of the percentage change in workers choosing a particular occupation and the percentage change in the wage rate paid in that occupation. That is,

$$\epsilon_{ijmt}^{ext} = \frac{d\mu_{ijmt}}{dw_{ijmt}} \frac{w_{ijmt}}{\mu_{ijmt}}.$$

From the utility maximization problem in (2), we obtain

$$\frac{d\mu_{ijmt}}{dw_{ijmt}} = \mu_{imt} \frac{e^{U_{ijmt}/\sigma_\theta} \frac{1}{\theta} \left[u_c'(c_{ijmt}) \left(h_{ijmt} + \frac{dh_{ijmt}}{dw_{ijmt}} w_{ijmt} \right) - u^{i'}(h_{ijmt}) \frac{h_{ijmt}}{dw_{ijmt}} \right]}{\left[\sum_{j'=0}^{J} \exp\left(U_{ij'mt}/\sigma_\theta \right) \right]^2} \sum_{j'=0, j' \neq j}^{J} \exp\left(U_{ij'mt}/\sigma_\theta \right)$$

Figure (1b) shows the distribution of estimates of the extensive margin elasticities. The average elasticity varies little from year to year, ranging between 0.55 and 0.60.

Combined elasticity. We define the total labor supply within each ($ijmt$)-cell as the aggregate hours worked in that cell and denote it as $L_{ijmt} = \mu_{ijmt} h_{ijmt}$. By combining the intensive and extensive margins, we can compute the cumulative elasticity of labor supply to changes in the own wage rate within each cell, which is:

$$\epsilon_{ijmt}^{tot} = \frac{L_{ijmt}}{dw_{ijmt}} \frac{w_{ijmt}}{L_{ijmt}} = \left(\frac{d\mu_{ijmt}}{dw_{ijmt}} h_{ijmt} + \frac{dh_{ijmt}}{dw_{ijmt}} \mu_{ijmt} \right) \frac{w_{ijmt}}{L_{ijmt}} \tag{18}$$

Figure 2 shows the distribution of estimated cumulative elasticities of labor supply. The average cumulative elasticity varies between 0.70 and 0.74, depending on the year.

Equation (18) separates the relative contribution of the extensive margin (first term) and the intensive margin (second term) to the cumulative elasticity. On average, the extensive margin accounts for almost $\frac{4}{5}$ of the cumulative elasticity.

Aggregate labor supply responses. Finally, we define the aggregate labor supply in period t as $L_t = \sum_{i,j,m} L_{ijmt}$. The elasticity of the aggregate labor supply is the percentage change in the aggregate supply in response to a percentage change in the average wage, assuming that the change in the average wage is obtained by a homogeneous change across the distribution of wages. That is,

$$\epsilon_t^{agg} = \frac{dL_t}{d\bar{w}_t}\frac{\bar{w}_t}{L_t}$$

where $\bar{w}_t$ is the average wage and

$$\frac{dL_t}{d\bar{w}_t} = \sum_{ijm}\left(\frac{L_{ijmt}}{dw_{ijmt}} + \sum_{j'}\frac{L_{ijmt}}{dw_{ij'mt}}\right).$$

The second summation in the latter equation captures the fact that a change in the wage rate in one occupation affects labor supply in all other occupations. Estimates of the aggregate elasticity range between 0.72 and 0.78, depending on the year.

3.5 Estimation of technology parameters

The worker-occupation shares β_{ijt} are estimated using within-occupation wage ratios. With those in hand, the α_{jt} and ρ are recovered using a first-difference specification of the wage conditions in (11). This specification flexibly allows for the use of instrumental variables to account for endogeneity in input demands.

To illustrate all the estimation steps, note that $\hat{\rho} = \hat{\phi} + 1$, and $\hat{\phi}$ can be estimated from (11). Next, one can recover the $\gamma_{jt} = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right)$ in (11) by projecting the residuals $\tilde{W}_{ijmt} = W_{ijmt} - \hat{B}_{ijt} - \hat{\phi}\hat{\Lambda}_{jmt}$ on occupation-year fixed effects. Then, the value of each occupation weight α_{jt} in the production technology (6) is obtained from the restriction $\sum_j \alpha_{jt} = 1$ for all t. The full set of estimated β_{ijt} shares, alongside plots of the combined $\alpha_{jt} \times \beta_{ijt}$ weights, are reported in Appendix D.

Endogenous production inputs. We use two different approaches to account for potential endogeneity of labor inputs. Each strategy instruments the changes in labor input log-ratios $\Delta\hat{\Lambda}_{jmt}$ in (11) with predicted log-ratios of headcounts.

The model suggests that differences in the labor participation (headcount) in each occupation over time are the by-product of worker match values, conditional on their demographic group, or due to shifts in the overall demographic composition of the labor force. For example, participation in manual construction jobs may change if a young non-college men value work in construction less, or if the overall number young non-college men changes over time.

The first identification strategy leverages aggregate demographic shifts that exogenously impact local labor markets, holding constant the occupation shares of workers within a market and demographic group. We let s_{ijmt} be the share of type i workers in market m choosing to work in occupation j. The predicted labor supply to occupation j is $\hat{L}^h_{jmt} = \sum_i s_{ijmt-10}\mu_{imt}$, where h denotes the headcount and $s_{ijmt-10}$ are the employment shares in the previous decade. We use the latter measure to construct the predicted relative supply $\hat{\Lambda}^h_{jmt} = \log\left(\frac{\hat{L}^h_{jmt}}{\hat{L}^h_{1mt}}\right)$ in period t. The instrument is defined as

$$\text{IV1}_{jmt} = \Delta\hat{\Lambda}^h_{jmt} = \hat{\Lambda}^h_{jmt} - \log\left(\frac{L^h_{jmt-10}}{L^h_{1mt-10}}\right) \tag{19}$$

where L^h_{jmt-10} is the actual number of workers in occupation j in market m at time $t-10$. Given exogeneity of aggregate shifts in the demographic structure of the labor force, this is a valid instrument as it is correlated with the regressor but is uncorrelated with the error term.

The second identification strategy relies more on theoretical restrictions as we build on the observation that, by definition, shifts in latent returns affect occupation-specific employment given observed wages. One can therefore develop a set of instruments by using changes in occupation shares due to variation in latent returns b_{ijt}. Equation (8) implies

$$\varrho_{ijmt} = \log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right) = \frac{b_{ijt} + \Pi_{ijmt}}{\sigma_\theta} \quad \Longrightarrow \quad \Delta\varrho_{ijmt} = \frac{\Delta b_{ijt} + \Delta\Pi_{ijmt}}{\sigma_\theta}$$

where $\Pi_{ijmt} = U_{ijmt} - U_{i0mt}$ is the observed pecuniary component of the returns. If we set $\Delta\Pi_{ijmt} = 0$ in the equation above, we obtain a counterfactual $\hat{\varrho}_{ijmt}$:

$$\hat{\varrho}_{ijmt} = \Delta\hat{\varrho}_{ijmt} + \varrho_{ijmt-10} = \frac{b_{ijt} - b_{ijt-10}}{\sigma_\theta} + \varrho_{ijmt-10}.$$

We estimate a set of counterfactual shares as $\hat{s}_{ijmt} = \frac{\exp(\hat{\varrho}_{ijmt})}{1+\sum_{j'=1,\ldots,J}\exp(\hat{\varrho}_{ij'mt})}$, which can be used to predict labor inputs as $\hat{L}^h_{jmt} = \sum_i \hat{s}_{ijmt}\mu_{imt}$. These fitted values can be employed, in turn, to construct a set of instruments (IV2_{jmt}), as described in equation (19).

Substitution among worker-occupation inputs. Table 2 shows estimates of the coefficients on $\Delta\hat{\Lambda}_{jmt}$ and $\Delta\hat{B}_{ijt}$ in equation in (11).Endogeneity introduces a positive bias in the estimates of ϕ. Columns 2 and 3 report estimates obtained after instrumenting $\Delta\hat{\Lambda}_{ijmt}$ with either of the two instrument sets. Estimates of ρ suggest that the elasticity of substitution between worker-occupation inputs is larger than one and within the range $1.65 - 1.76$.

We consider the values in column 4 as our baseline estimate, implying an elasticity of substitution of 1.64. When using multiple instruments together, one can compute a p-value for the over-identification test (Sargan, 1958). We find that the validity of the instruments cannot be rejected. Moreover, in all cases, the estimated coefficient on $\Delta\hat{B}_{ijt}$ is not significantly different from one, which is consistent with the theoretical restrictions of the model.

	OLS	IV		
	(1)	(2)	(3)	(4)
$\hat{\phi}$	-0.0834	-0.6041***	-0.5681***	-0.6100***
	(0.0610)	(0.1212)	(0.1348)	(0.1256)
$\hat{\psi}$	0.9771***	0.9771***	0.9771***	0.9771***
	(0.0413)	(0.0414)	(0.0414)	(0.0414)
Observations	2,496	2,496	2,496	2,496
Instrument set		IV1	IV2	IV1-IV2
Test $\hat{\psi} = 1$ (p-val)	0.5796	0.5812	0.5810	0.5812
OverId p-val				0.4152
Implied ρ	0.9166***	0.3959***	0.4319***	0.3900***
	(0.0610)	(0.1212)	(0.1348)	(0.1256)
Implied elast. of sub.	11.9974	1.6554***	1.7604***	1.6394***
	(58.5230)	(0.3740)	(0.4802)	(0.4036)

Bootstrapped standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2: Estimation results for equation (11) in first differences.

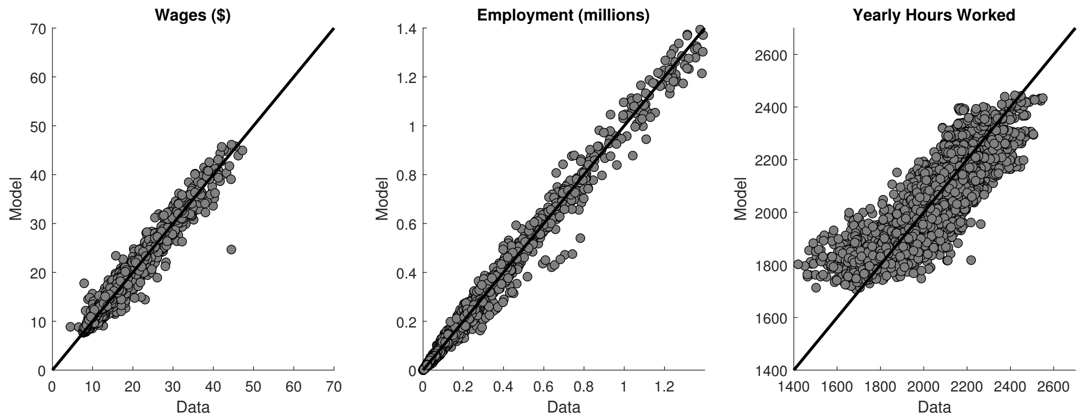


Figure 3: Goodness of fit. Left: model implied wages vs. data. Center: model implied employment vs. data. Right: model implied hours worked vs. data.

Prices and quantities in model and data. Figure 3 compares data on average wages and employment in each worker-occupation cell (i, j) with their model counterparts obtained by solving for the equilibrium in each market and year. Simulated prices and quantities match data observations closely. The model accounts for, respectively, 99%, 95%, and 72% of total variation in employment, wages, and hours worked.

3.6 Production shares

Changes in current wages depend on productivity. In turn, the productivity of each worker-job pair responds, in equilibrium, to shifts in the supply of labor aggregates that are induced by latent returns. In what follows we separately characterize the changes in technology and in the distributions of observable and latent match values.

We begin by documenting the evolution of technology parameters, which suggests productivity divergence among worker-occupation inputs.

Technology shares by occupation category. The marginal product of a type-i worker in occupation j at time t is increasing in the technology shares $\alpha_{jt}\beta_{ijt}$. Figure 4 plots the employment-weighted loadings $\alpha_{jt}\beta_{ijt}$ of four broad occupation categories (levels in the left panel, growth rates after 1980 in the right one). Production shares in some occupation categories have stagnated after 1980. Routine manual jobs have experienced a mild but steady decline and estimates of $\alpha_{jt}\beta_{ijt}$ are 26% lower in 2018 relative to 1980.

The remaining occupation categories exhibit production share growth of 10-16% in the 1980s but their productivity paths diverged in the 1990s. After the mid-1990s, non-routine cognitive jobs show faster growth in their shares, adding up to a change of roughly 70% by 2018. In contrast, growth in non-routine manual and routine cognitive occupations was less vigorous (with cumulative changes of 42% and 24% over the sample period). The fanning out

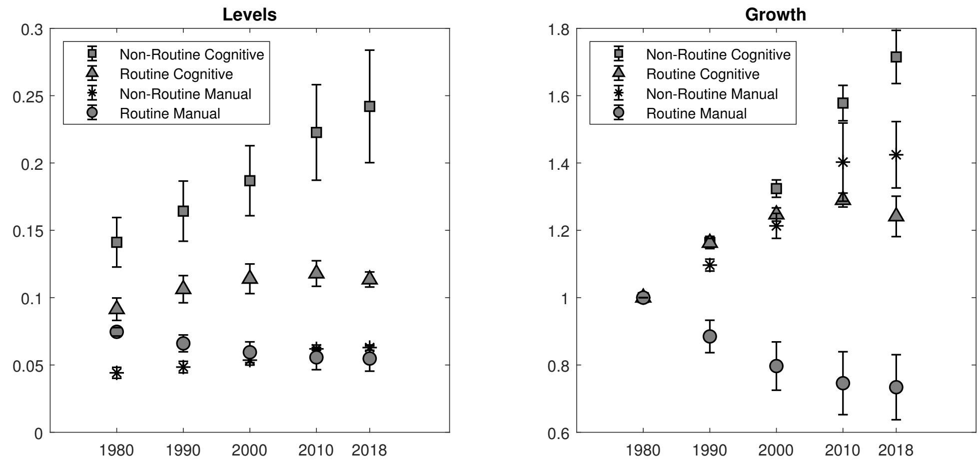


Figure 4: Average production shares of four major occupation categories (based on estimates of $\alpha_{jt}\beta_{ijt}$). Left panel: levels. Right panel: growth relative to 1980.

of production shares underlies changes in observable wages and employment.

Technology shares by worker group. Figure 5 breaks down changes in production shares by worker type. First, we note that the share of routine manual occupations drops or stagnates for all gender and education groups. Workers in college-level jobs exhibit large gains in all but routine manual occupations. Their gains in cognitive occupations are the largest, consistent with the notion of growing match-specific returns. However, a college degree does not significantly improve productivity in manual occupations. For non-college workers, only the production shares of non-routine jobs exhibit positive changes.

3.7 Latent heterogeneity in returns

Data on quantities (employment) and prices (wages) allow to distinguish between observable and latent components of match-specific values. We examine changes in match values by separately considering shifts in the distributions of these components.

Figure 6 plots the density of cumulative match values and of its three components, expressed in utility terms. Specifically, it plots the distribution of the observable wage component, the dis-utility from hours worked, and the latent component net of hours worked. It is apparent that (i) the dis-utility from work is very concentrated;[6] (ii) the latent component has the most dispersed distribution.

[6]This finding refers to the total amount of hours worked in a year. Goldin (2014) shows that the way hours are distributed in a week and schedule flexibility may be important. The value of such flexibility is captured in the model by the latent returns.

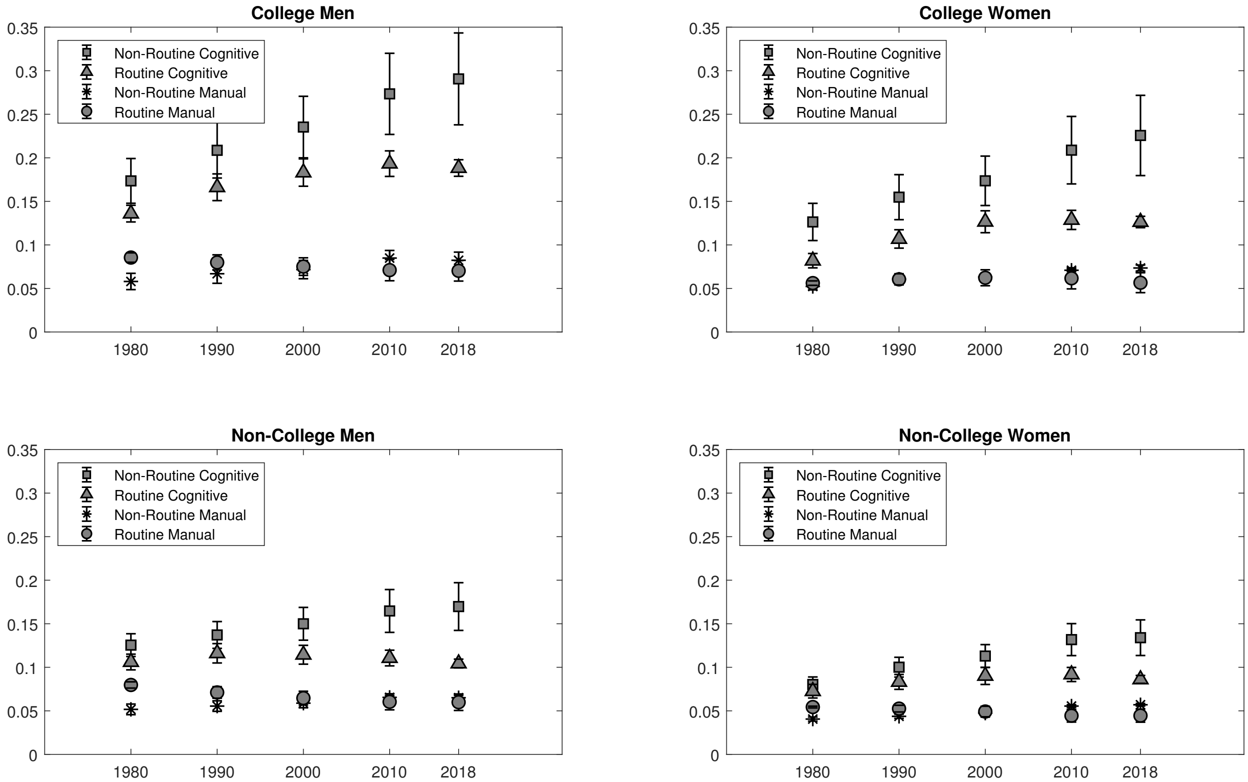


Figure 5: Average production shares of four broad occupation categories by worker demographic group (based on estimates of $\alpha_{jt}\beta_{ijt}$). Brackets are 95-percent confidence intervals around point estimates.

Location and latent heterogeneity. To examine the nature of latent returns, we project estimates of b_{ijt} on location-specific measures that capture how frequent certain occupations are in urban settings. As the distribution of job opportunities is not homogeneous across locations, some occupations may occur more frequently in urban and densely populated areas. To the extent that urban settings offer different amenities, it is possible that the latent value of an occupation may be related to its prevalence in those settings. That is, the latent value of a worker-occupation pair may depend on the location where it is found. Occupations that are concentrated in urban areas may exhibit higher b_{ijt} if the latter components capture the value of urban amenities. To explore this conjecture we project estimates of latent returns on measures that capture differences across occupations in their location (e.g., urban or rural, population density). For each occupation we compute: (i) the fraction of workers living in urban areas; (ii) the fraction of workers in a central city, defined as the central city of a metropolitan area, as well as the fraction of workers in urban areas excluding central cities; (iii) the average local population in the place where the job is done. To account for heterogeneity by gender, we perform this analysis separately for men and women.

Table 20 in Appendix F shows that, for men, urban and central city effects are not pre-

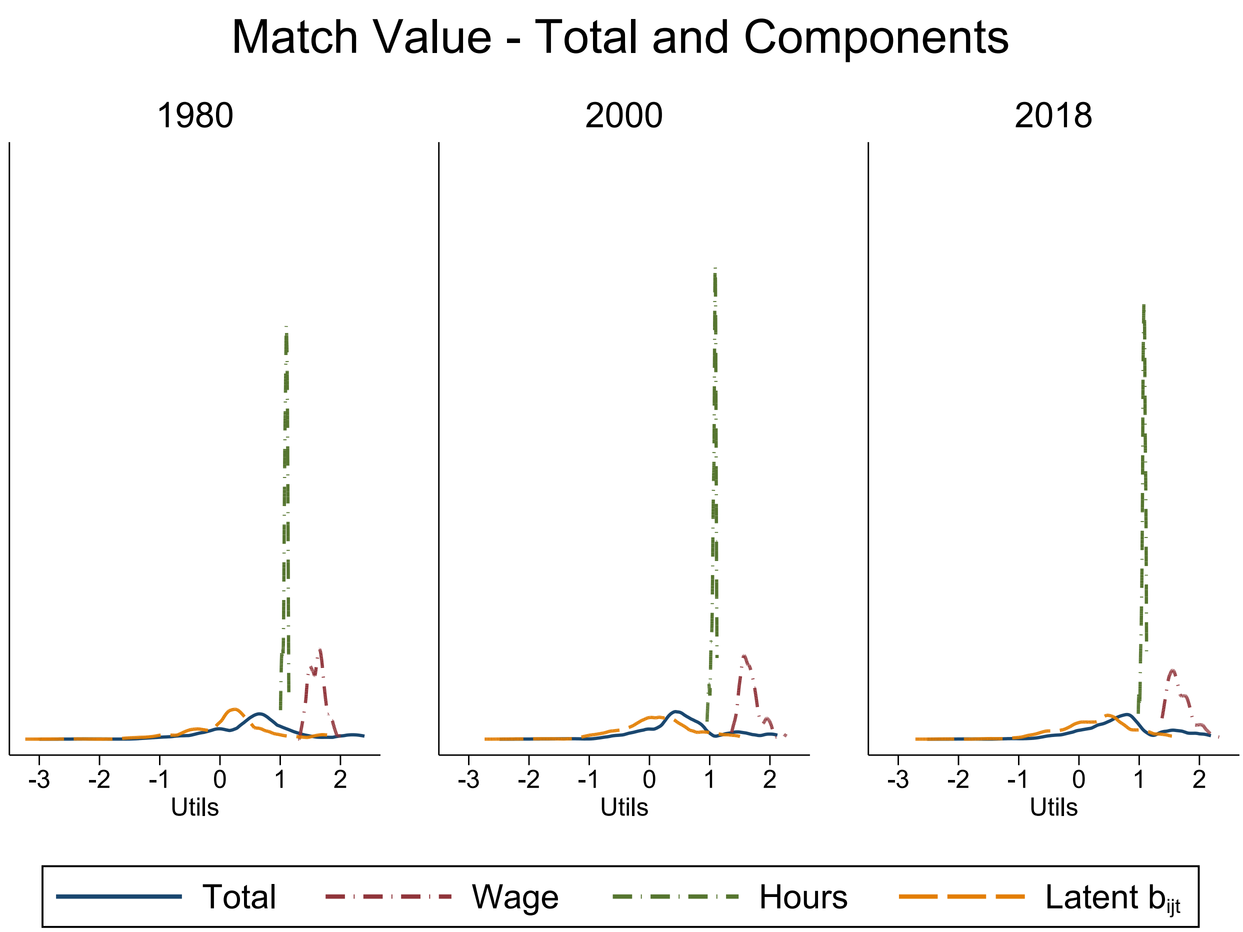


Figure 6: The figure shows, for different years, the cross-sectional distributions (densities) of: (1) total match values (total of all systematic, non random components); (2) observable wage components of match values; (3) dis-utility from hours worked; (4) latent components b_{ijt}. The unit of observation is the worker-occupation pair. Distributions are employment-weighted.

Average Rents (year 2000 $)

Year	All	College Men	College Women	Non-College Men	Non-College Women
	(1)	(2)	(3)	(4)	(5)
1980	14,520	22,678	14,165	15,839	9,013
1990	14,766	24,349	16,021	14,860	9,677
2000	16,056	27,390	18,199	14,884	10,500
2010	14,983	26,470	17,981	12,701	9,392
2018	15,989	27,458	18,864	12,909	9,460

Table 3: Estimated average rents by year and gender-education group.

cisely estimated while there is a positive and highly significant correlation between latent components and population density. Estimates for women, in contrast, are highly significant and larger. This suggests that location attributes may be relatively more important in determining the occupational choices of women. In all cases, the coefficients are positive: jobs in urban, dense areas have higher latent returns. Additional controls for age and education (columns 2, 5, and 6 in Table 20) make the estimated effects larger and more significant for both men and women. A detailed description of these findings is in Appendix F.

4 Rents from Employment and Compensating Differentials

We characterize jobs as bundles of observable and latent components that cannot be separately acquired once employed. For this reason, employed workers are inframarginal in their occupation choice and enjoy returns whose combined value is higher than their outside option (that is, higher than the second best job they have access to).

We define the employment rent as the pecuniary value that makes a worker indifferent between their current occupation and their outside option. This definition includes the idiosyncratic latent components (θ_j^ι) that influence worker ι's choices above and beyond systematic match quality.

4.1 Estimating rents

Consider worker ι in demographic group i, and let j be their current occupation and j' their second best option. We define $\tilde{R}^\iota_{ijj'mt}$ as the change in worker ι's wage that would make them indifferent between current and second-best occupation. The wage gap $\tilde{R}^\iota_{ijj'mt}$ must be such that:

$$\tilde{U}_i(w_{ijmt} - \tilde{R}^\iota_{ijj'mt}, y_{imt}) + b_{ijt} + \theta^\iota_j = \tilde{U}_i(w_{ij'mt}, y_{imt}) + b_{ij't} + \theta^\iota_{j'} \tag{20}$$

where $\tilde{U}_i(w, y) = u_c(wh_i(w, y) + y) - u^i_h(h_i(w, y))$. It follows that the total employment rent

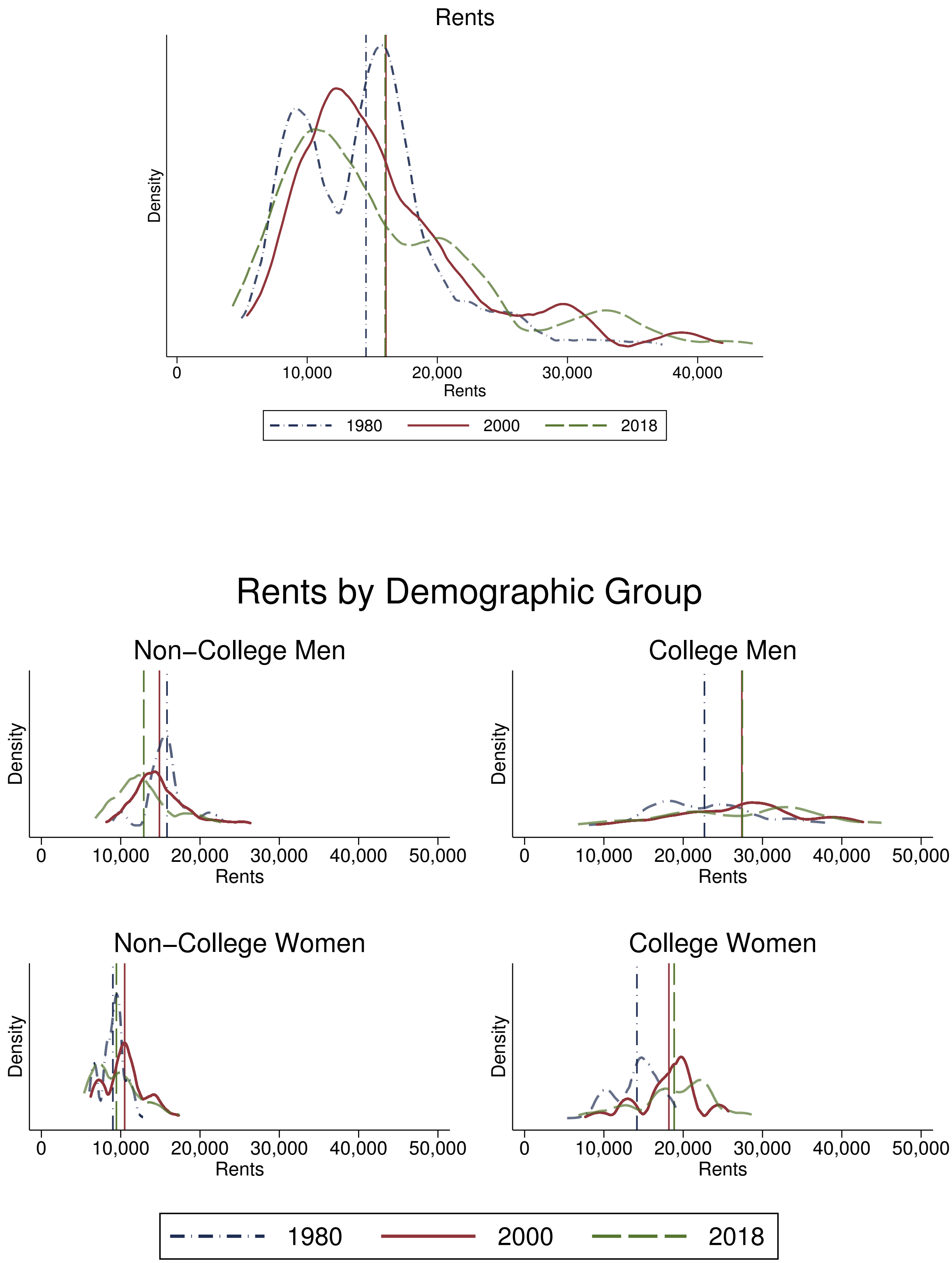


Figure 7: Distribution of job rents (employment-weighted): pooled (top panel) and disaggregated (bottom four panels). All values are in year 2000 dollar-equivalents. Vertical lines show averages in different years.

of worker ι, accounting for labour supply, is

$$R^{\iota}_{ijj'mt} = w_{ijmt}h_{ijmt} - (w_{ijmt} - \tilde{R}^{\iota}_{ijj'mt})h_i(w_{ijmt} - \tilde{R}^{\iota}_{ijj'mt}, y_{imt}),$$

which is the difference between the earnings in the current occupation and the earnings the worker would receive if the wage is changed to the point of indifference (derivations are in Appendix G.) We compute the average rent for each (i, j, m, t) cell and denote the cell-specific averages as R_{ijmt}.

4.2 The distribution of employment rents

Table 3 shows estimates of rents by year, gender and education. The average across all worker-occupation pairs (first column) has grown over time, rising by roughly 10% from about $14,500 in 1980 to almost $16,000 in 2018.

Not all rents have risen over the sample period, and the gap between education groups has grown significantly. College-level rents have gone up but non-college rents have stagnated or fallen, like in the case of non-college men. This observation is consistent with the view that male workers in non-college jobs may have experienced a shrinking labor market surplus (see also Aguiar et al., 2017).

The mounting disparity in employment rents can be probed further by examining Figure 7, which displays employment-weighted kernel densities of rents in different years (expressed in year 2000 dollar equivalents). The top panel of the figure plots the cross-sectional distribution of all rents, while the bottom panels show rent densities conditional on gender and education. It is apparent that the distribution of rents among educated workers has shifted to the right, while that of non-college men shifted to the left (Cortes et al., 2018).

Growing dispersion is visible when we compare averages across occupation categories, as in Table 4. The main occupational divide is between cognitive and manual jobs, with the former experiencing growth and the latter showing sizable drops. Lower rents are especially conspicuous in routine manual occupations, where the 2018 rents are about 1/5 below the 1980 baseline values.

The role of systematic variation in latent match values. To assess the influence on rents of the systematic components of latent values, we design counterfactual experiments where all workers within a demographic group are assigned the same systematic latent component; that is, we set $b_{ijt} = b_{it}$ for all (i, j) pairs. The uniform value b_{it} within each group i is set to preserve the labor force participation of that group at the same level as in the baseline. This avoids confounding effects due to group-level labor supply responses in equilibrium.

To facilitate comparisons to rents in the baseline model, where b_{ijt} are allowed to vary across (i, j) pairs, we hold wages fixed at their baseline levels. Therefore, the exercise conveys

Average Rents (year 2000 $)

Year	Non-Routine Cognitive	Routine Cognitive	Non-Routine Manual	Routine Manual
	(1)	(2)	(3)	(4)
1980	18,728	12,137	9,142	14,316
1990	19,421	12,812	9,191	13,246
2000	22,009	13,840	9,812	13,167
2010	21,626	12,661	8,394	11,439
2018	22,625	13,169	8,834	11,752

Table 4: Estimated average rents by year and occupation category.

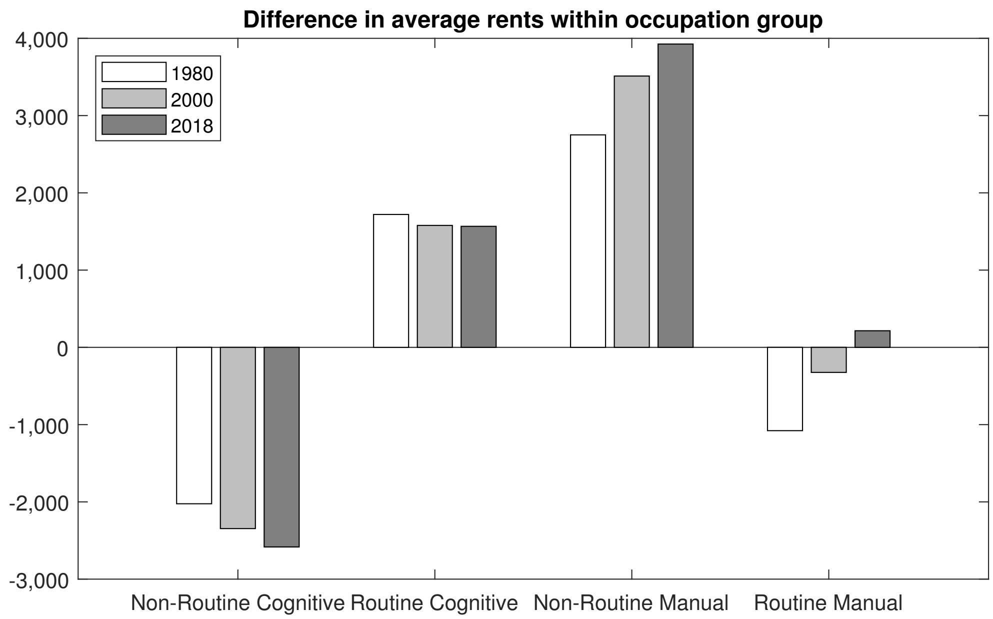


Figure 8: Counterfactual exercises: changes in employment rents (in year 2000 dollars, relative to baseline estimates) when latent employment values are set to be the same for all workers. Changes are reported by year and by broad occupation category.

information about the influence on rents of heterogeneity in systematic latent match values, holding constant both wages and group-level labor supplies.

Figure 8 shows differences in the average rent (in year 2000 $) by occupation category. Removing variation in systematic latent values induces a significant drop in rents in non-routine cognitive occupations with some of the changes reaching almost $3,000$ dollars per year, which is roughly 20% of the average NRC rent in 2018.

These losses are in stark contrast to the positive changes in other occupations. For example, removing heterogeneity of the b_{ijt} latent values in non-routine manual matches increases rents in those occupations up to $4,000$ dollars per year, or over 45% of the average NRM rent in 2018. This is evidence that a large share of estimated rents is driven by systematic components of latent match values. Workers in routine and manual jobs would be better off if systematic latent match values were equalized across occupations but workers in non-routine cognitive occupation would enjoy lower rents.

Wage dispersion and rents. It is conceivable that employment rents vary with job characteristics. For example, one might ask whether occupation-specific wage risk matters for workers' rents. In Appendix J we explore this question by examining the relationship between the dispersion of wages within each $ijmt$-cell and average rents. We find that more wage dispersion is associated with higher rents. A 10-dollar increase in the standard deviation of wages is associated with a 4.3% increase in monetary rents. Moreover, the same increase in risk is associated with a positive change of about 0.3 standard deviations in total match value. Both the observable and latent components of surplus contribute to the positive risk-return relationship; however, the latent value accounts for a larger share of total surplus in riskier occupations. This implies that latent employment values are proportionally larger, as a share of total surplus, in occupations that exhibit more wage dispersion.

4.3 Compensating differentials

Jobs combine different bundles of wages and latent returns and occupational choices entail a trade-off between them. Given the discrete nature of match value components and the fact they cannot be freely exchanged within a given job, assessing the trade-off is not trivial. In what follows we illustrate how one can estimate compensating differentials for different occupation-worker cells by considering workers at the margin of the occupation choice. By focusing on workers who are close to indifference between their current occupation j and their second best option j' (see Lamadon et al., 2022), it is possible to identify the marginal rate of substitution between observable and latent components within each worker-occupation pair.[7]

If we consider a marginal worker ι, the compensating differential between occupations j and j' is the difference between the utility worker ι would get in the second best occupation if it was paid at the same rate as their current occupation, and the utility they get from their current job. We denote the compensating differential between j and j' as $CD^{\iota}_{ijj'mt}$ and define it as:

$$CD^{\iota}_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'} - \tilde{U}_i(w_{ijmt}, y_{imt}) - b_{ijt} - \theta^{\iota}_{j}$$

In Appendix G we show that $CD^{\iota}_{ijj'mt}$ can be written as:

$$CD^{\iota}_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) - \tilde{U}_i(w_{ij'mt}, y_{imt}) = CD_{ijj'mt}.$$

The quantity $CD_{ijj'mt}$ does not depend on the identity of the individual worker ι but only on their observed characteristics. We can then define the compensating dollar value as the

[7] Empirical studies often define compensating differentials as the covariance between wage and non-wage components (see Lehmann, 2022). In Appendix H, we revisit our findings using this alternative definition.

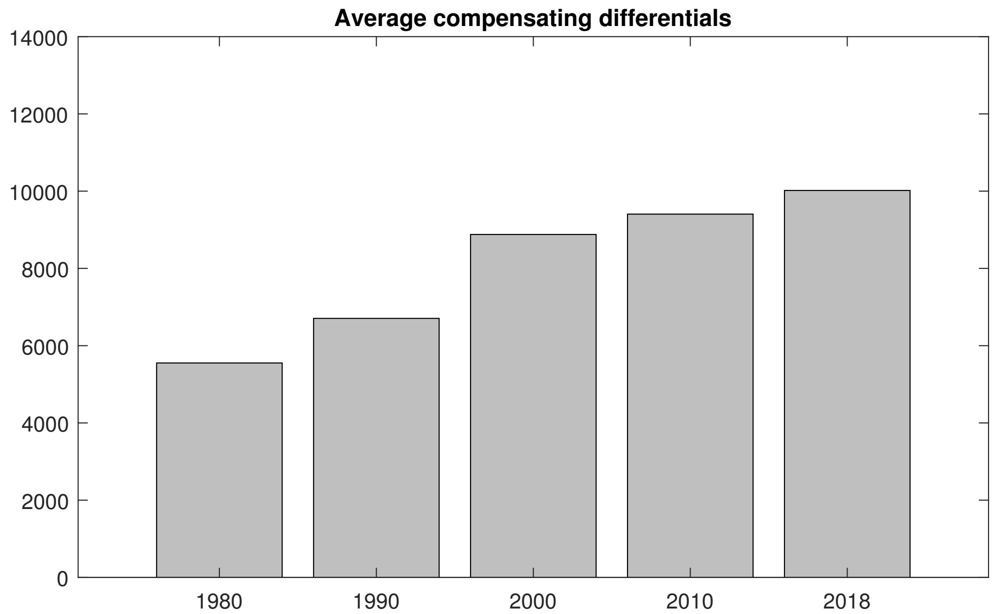


Figure 9: Average absolute compensating differentials by year. Values are in year 2000 dollar-equivalents.

reduction in labor income from the current occupation that makes $CD_{ijj'mt} = 0$,

$$u_c(w_{ijmt}h_{ijmt} + y_{imt} - CD^{\$}_{ijj'mt}) - u_h(h_{ijmt}) = u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}). \quad (21)$$

Estimates of compensating differentials. For each (i, j, m, t) cell, we compute the mean absolute compensating differential as:

$$\overline{CD}^{\$}_{ijmt} = \sum_{j'=1,..,J;j'\neq j} \omega_{ijj'mt} |CD^{\$}_{ijj'mt}|$$

where the weights are a function of employment shares $(\omega_{ijj'mt} = \frac{\mu_{ij'mt}}{\sum_{j''=1,..,J;j''\neq j'} \mu_{ij''mt}})$.

Figure 9 shows employment-weighted averages of $\overline{CD}^{\$}_{ijmt}$ by year, documenting an increasing pattern whereby their values approximately doubled between 1980 and 2018.

In Figure 10 and Table 5 we show averages of the mean absolute compensating differentials by year and occupation category. These measures are obtained by considering marginal workers who are indifferent between two jobs in the same occupation category. Compensating differentials are highest in non-routine jobs and we find evidence that they have grown in all occupation categories. Figure 11 and Table 6 report compensating differentials after conditioning on year and worker type. These estimates suggest that college men experienced the largest growth in mean absolute compensating differentials, from a value of less than $\$10,000$ to almost $\$18,000$ over the sample period.

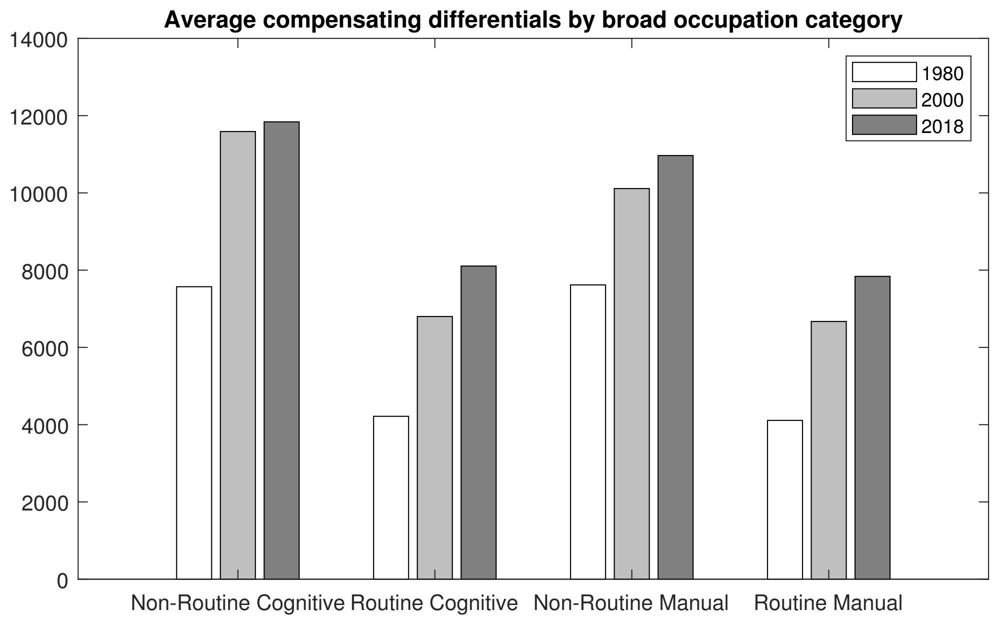


Figure 10: Averages of absolute compensating differentials by occupation category and year. All values are in year 2000 dollars.

Average Compensating Differentials (year 2000 $)

Year	Non-Routine Cognitive	Routine Cognitive	Non-Routine Manual	Routine Manual
	(1)	(2)	(3)	(4)
1980	7,571	4,216	7,618	4,111
1990	8,135	5,341	8,927	5,380
2000	11,588	6,800	10,113	6,672
2010	11,197	7,684	10,988	7,216
2018	11,840	8,106	10,967	7,839

Table 5: Averages of absolute compensating differentials ($\overline{CD}^{\$}_{ijmt}$) by year and occupation category.

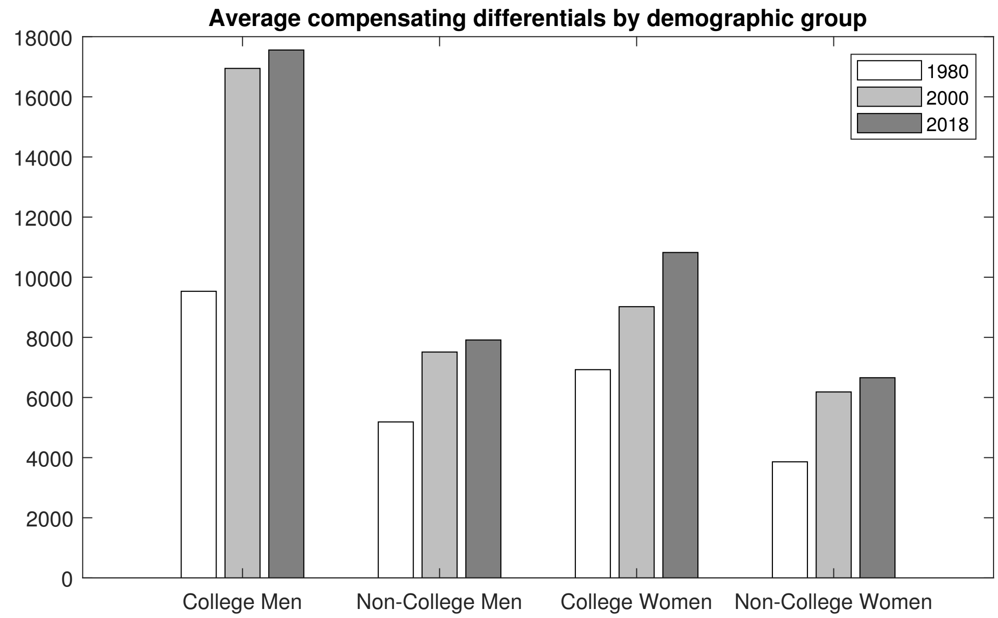


Figure 11: Averages of absolute compensating differentials by worker group and year. All values are in year 2000 dollars.

The large and growing magnitudes of compensating differentials across occupation and demographic categories indicate that latent components of job values are being exchanged at higher prices than before. As we discuss below, we find evidence that these shifts are strongly associated to mobility across occupation pairs.

Compensating differentials and occupational mobility. Compensating differentials allow workers to trade off differences between pecuniary and latent returns by switching occupations. To illustrate this trade off, consider two occupations, denoted as A and B, which offer the same wage rate; however, A offers more amenities than B. For simplicity, suppose that workers are homogeneous and value the latent aspects of each occupation in the same

Average Compensating Differentials (year 2000 $)

Year	All	College Men	College Women	Non-College Men	Non-College Women
	(1)	(2)	(3)	(4)	(5)
1980	5,552	9,532	6,925	5,186	3,861
1990	6,706	11,127	6,874	6,122	5,262
2000	8,878	16,945	9,020	7,512	6,184
2010	9,405	15,492	10,123	7,797	7,427
2018	10,018	17,556	10,823	7,912	6,657

Table 6: Averages of absolute compensating differentials ($\overline{CD}^{\$}_{ijmt}$) by year and worker group.

way. If workers can freely move across occupations, those in B would rationally switch to A. In equilibrium, this flow of workers would cause a change in relative wages up to the point where the total return in occupation A equals that in occupation B. When occupational mobility is not impeded, equilibrium forces result in systematic compensating differentials that equalize total returns. By the same token, higher switching costs and less mobility would imply that latent components are less accurately reflected in wage differences. For this reason, compensating trade-offs may appear lower when job mobility is limited and wages do not consistently respond to changes in the value of latent components.

In Appendix I we examine the relationship between compensating differentials and occupational mobility (Kambourov and Manovskii, 2008; vom Lehn et al., 2022) by using workers' gross flows across occupation pairs as a proxy for the cost of occupational mobility (see Cortes and Gallipoli, 2018). Appendix Table 23 shows that compensating differentials respond to changes in mobility across occupation pairs. A 1% increase in the flow of workers within an occupation pair is associated with an almost 10% increase in the monetary value of compensating differentials.

5 Technological Progress with a Changing Workforce

The distributions of pecuniary and latent components of surplus have experienced significant changes since 1980. To account for the interaction between these forces, and assess their contributions to long-term shifts in employment and wages, we use the equilibrium framework developed in Section 2.

We perform two sets of exercises to explore the quantitative impact of different sources of structural change. First, we ask how employment and wages would have changed if the distribution of latent employment returns had stayed at its 1980 levels. Second, we compute counterfactuals holding constant technology parameters at their 1980 levels.

To separately account for partial and general equilibrium effects, we consider two additional counterfactual experiments: in one, we compute employment changes in different years holding wages at their 1980 levels. This shows how employment responded to changes in latent employment values in the absence of general equilibrium price responses. In another counterfactual, we explore wage changes holding constant quantities (employment shares) at their 1980 levels. This illustrates the partial equilibrium effects of technological progress when employment responses are restricted.

We find evidence of an ongoing race between technological transformation and a changing workforce. Increases in the supply of educated workers and their productivity have resulted in a larger surplus for an expanding set of worker-job matches.

While changes in employment are largely explained by shifts in latent returns from employment, technology has the most prominent influence on the distribution of wages. The

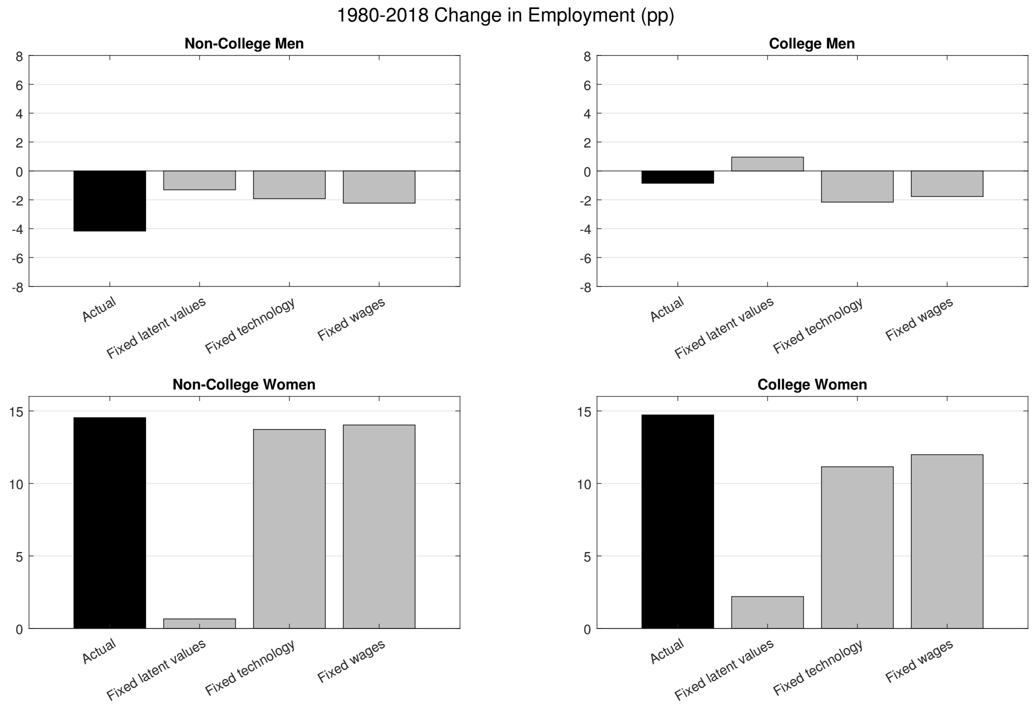


Figure 12: Changes in employment rates by demographic group. Comparisons of baseline and counterfactual scenarios between 1980 and 2018. Changes are in percentage points.

latter do respond to employment shifts but their responses are offset by technological change. Such patterns occur in most occupations but are especially salient in the cognitive ones, which are those where latent rents are highest. Workers in these occupations, especially educated women, have enjoyed a combination of higher employment, higher wages, and growing rents.

5.1 Counterfactual exercises: employment changes by worker type

Figure 12 plots the 1980-2018 cumulative employment changes in four demographic types defined by gender and education.[8] The black bars show the historical percentage change in employment.

Participation has declined for men since 1980: the drop was small for college-educated men (one percentage point) and more substantial for the less educated (-4 percentage points). Changes are more pronounced among women, with both high-education (+15) and low-education (+14) individuals experiencing higher employment.

The counterfactual experiments reveal that changes in labor force participation of both men and women respond to latent components of returns. In fact, holding latent values at their 1980 level has by far the largest impact on employment outcomes (as opposed to holding technology or wages fixed).

[8] Plots of the evolution of employment, alongside wages, are in Appendix L.

When we hold technology parameters at their 1980 level, we see that technological change has had an asymmetric effect on men depending on their education. For college males, technological change has offset the negative impact of latent returns on labor force participation. Employment rates for college men would be much lower if technology parameters were the same as in 1980. For non-college men, however, technology and latent values have both contributed to much lower employment rates.

The patterns are different among women: latent returns and technology have both lifted female labor force participation. For low-education women, latent returns explain most of the observed employment growth. For college-educated women, latent returns are the main driver of higher employment but technology accounts for a non-trivial part (about a quarter) of their employment growth.[9]

While gender patterns of employment are strikingly different over the sample period, it appears that technology has boosted employment among all educated workers while having a muted (or outright negative) impact on less educated ones.

The rightmost bar in each panel shows the partial equilibrium impacts of changes in latent components of returns. This is done by holding wages at their 1980 level so that the counterfactuals allow for changes in latent returns but shut down wage responses. In all four panels, the outcomes closely align with the bars corresponding to the fixed technology scenario, suggesting that price adjustments have little impact on employment. As we show below, however, equilibrium responses are stronger when we consider employment shares across occupation categories, which indicates that price responses do matter for the occupation composition.

5.2 Counterfactual exercises: employment changes by occupation category

In Figure 13, we summarize counterfactuals designed to assess how changes in technology and latent returns have influenced employment in four broad occupation categories (defined in Table 1).

The black bar in the top-left panel shows the well-documented increase in non-routine cognitive (NRC) employment. From 1980 to 2018 the NRC employment share climbed by 10 percentage points. How much did technological change contribute to this run-up? Holding technology parameters at their 1980 values, we can account for roughly three-quarters of the increase in NRC employment, while holding latent returns at their 1980 values we can explain about 85% of this increase. This implies a significant contribution from technology, considerably larger than the contribution of latent components. The rightmost bar in each panel shows partial equilibrium outcomes where wages are held at their 1980 levels.

It is interesting to compare the fixed wage experiments to the fixed technology ones because

[9] Technology shares subsume possible shifts in wage discrimination (see Hsieh et al., 2019).

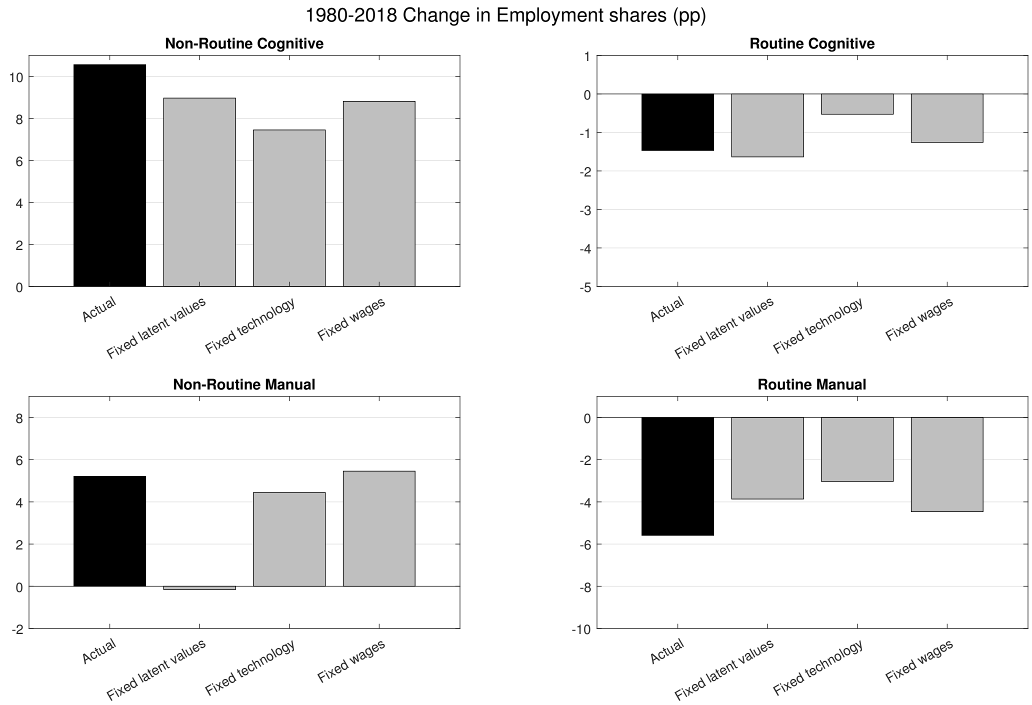


Figure 13: Changes in employment shares by occupation category. Comparison of baseline and counterfactual scenarios between 1980 and 2018. Changes in percentage points.

in both counterfactuals the effects of technological change are muted. The difference between the two counterfactuals is that the fixed-technology experiment allows for price responses to other exogenous labor supply changes (workforce composition), which seem to make a noticeable difference for NRC employment. What we learn is that technological and workforce composition changes have been comparatively more important drivers of NRC employment than latent employment values. The importance of workforce composition changes is also apparent from the observation that none of the counterfactuals implies employment changes close to zero.

The second fastest growing occupation category was non-routine manual jobs (NRM), which experienced employment growth of about 5 percentage points. Unlike NRC occupations, this increase was almost exclusively driven by latent return components (when we hold them to their 1980 level, NRM employment growth collapses). Technological change and equilibrium price adjustments contributed little to NRM employment patterns.

The top-right panel performs similar exercises for routine cognitive (RC) jobs, showing a slight decline in the employment share for such occupations (approximately, a 1.5 percentage points drop). Counterfactual experiments suggest that technology has contributed the most to this drop.

Lastly, the bottom-right panel shows outcomes for routine manual (RM) jobs. Technology

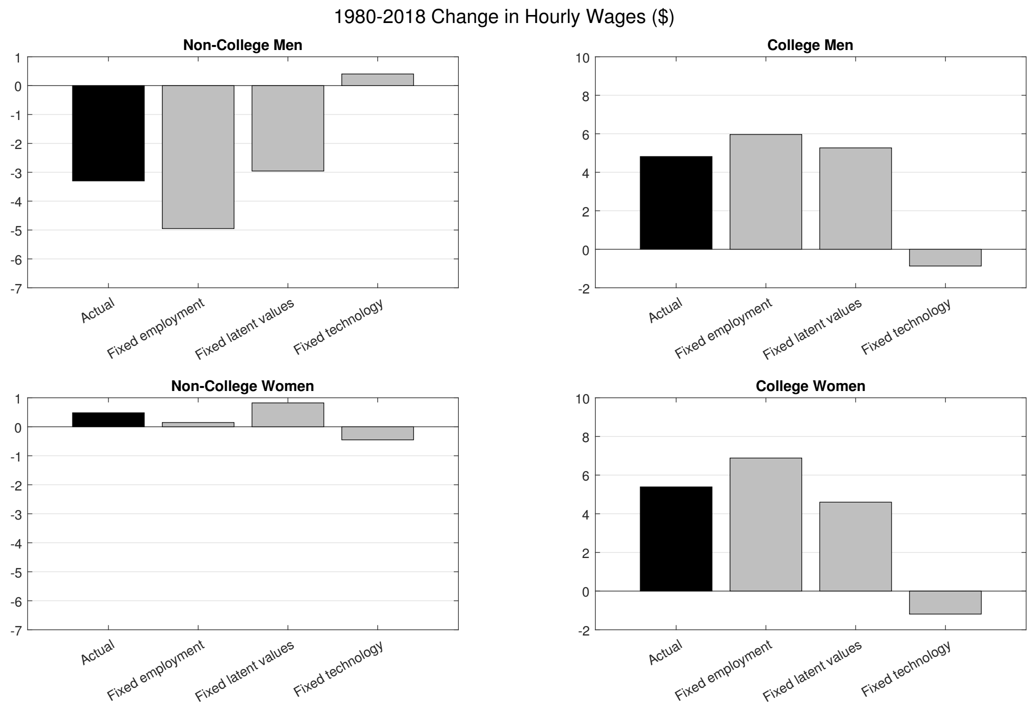


Figure 14: Changes in average hourly wage by demographic group. Actual versus counterfactual scenarios between 1980 and 2018.

and latent surplus both contributed to a 6 percentage point employment fall in these occupations, with technology having a stronger influence. The difference between partial equilibrium and fixed technology outcomes suggests that general equilibrium effects mitigated the negative impact of technological change on routine manual employment. As workers flew out of those jobs, marginal returns did increase and this, in turn, slowed the workers' outflow.

To sum up, technological change has been a key driver of run-ups in the share of cognitive and routine manual jobs. In NRM occupations the largest contribution has come from latent return components.

A comparison between Figure 12 and 13 (in particular, the counterfactual exercises in which we keep technology at its 1980 level) shows that, while technology has had a limited impact on the overall labor force participation of each demographic group, it did have a significant impact on the type of occupation workers chose. Figure 13 illustrates that technological change has contributed to the shift from routine occupations to non-routine ones, especially in cognitive jobs.

5.3 Counterfactual exercises: wages

We use a similar approach to examine the forces that underpin wage changes. Figure 14 shows actual and counterfactual wage changes for different worker types. Between 1980 and 2018

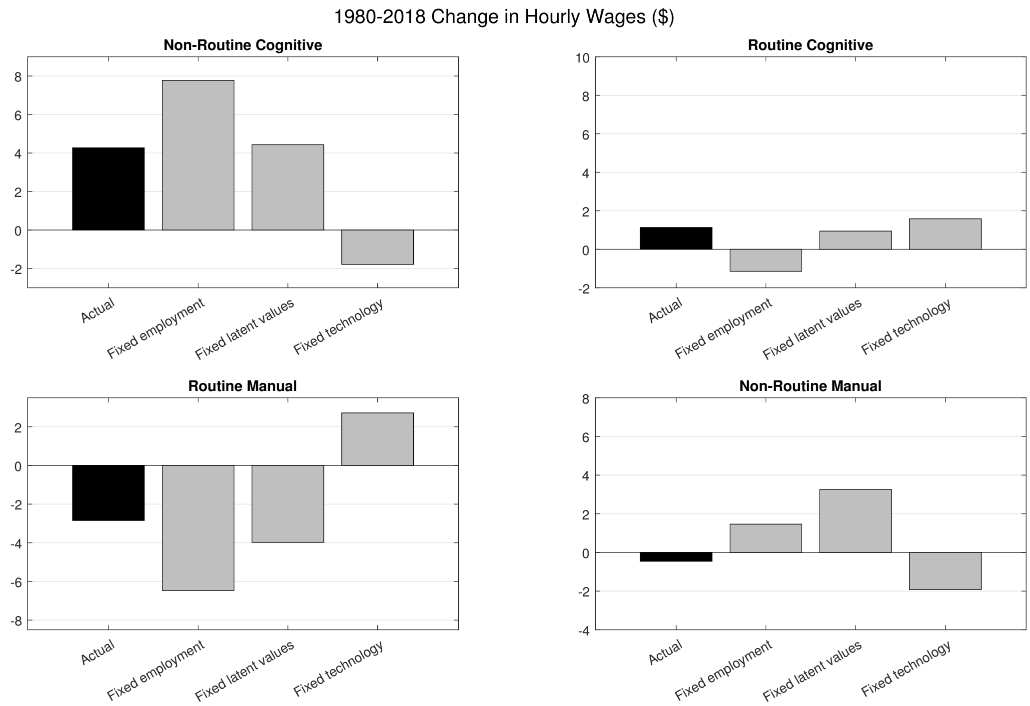


Figure 15: Changes in average hourly wage in four occupation categories. Actual versus counterfactual scenarios between 1980 and 2018.

hourly wages increased significantly for college graduates (right panels). This was mostly driven by technological change while the equilibrium effects originating from latent components were fairly small. Their low magnitude can be appreciated by looking at the small gaps between "fixed employment" and "fixed latent" experiments.

In contrast, wages for non-college men declined over the sample period. Also in this case technological change was the main contributor, with equilibrium effects mitigating the wage drops of non-college men.

The bottom left panel shows that low-education women experienced a small increase in wages, which contributed to the substantial reduction of their wage gap with men. Technology was again a key driver of these patterns.

Figure 15 illustrates the actual and counterfactual changes in hourly wages by occupation category. Striking changes are apparent in non-routine cognitive (NRC) and routine manual (RM) occupations. The wage changes in these two occupation categories mirror those observed among college graduates and non-college men in Figure 14. This is not surprising as NRC occupations are predominantly performed by college graduates (men and women) while RM occupations are largely populated by non-college men.

Counterfactual percentage differences relative to observed 2018 wages.

	Demographic group			
Holding fixed:	Collge Men	College Women	Non-College Men	Non-College Women
1980 Employment share	3.82%	6.68%	-11.30%	-2.85%
1980 Pop. composition and b_{ijt}	1.93%	-0.93%	-4.93%	-4.80%
1980 Pop. composition only	0.32%	1.39%	-6.79%	-5.74%
Wage/hour in 2018	29.9	22.3	14.6	11.8

Table 7: Counterfactual percentage differences relative to 2018 observed wages. Dollar values in the last row are expressed in year 2000 $.

Accounting for changes in workforce and technology. The evidence presented above suggests that, between 1980 and 2018, technological change played a pivotal role in shaping relative wages. At the same time, the workforce changed significantly in terms of its composition and latent valuations of employment. How did these changes interact with each other? We examine this question by breaking down wage changes into incremental responses following the initial partial equilibrium impact of technological change.

Table 7 shows wage deviations (in percentage terms) relative to the 2018 baseline wage values. Each row in the table (except the bottom row) reports the counterfactual wage deviation as we sequentially allow for different layers of employment responses. The bottom row shows the baseline dollar value of hourly wages in 2018. Each column identifies a demographic group (by gender and education). The first row shows the wage deviations when the distribution of total employment is the same as in 1980. This partial equilibrium counterfactual corresponds to the one described in Figure 15 and only reflects the direct effect of technological change on wages. The positive gaps for college workers, as opposed to the negative ones for non-college workers, confirm the asymmetric impact of technology across education groups.

In the second row, we allow for employment responses while holding latent values b_{ijt} as well as the population composition fixed at their 1980 levels. A comparison between the first row (1980 Employment) and the second (1980 Pop. Composition and b_{ijt}) illustrates how the equilibrium responses to technological change have depressed the wages of college graduates, especially those of women.

Growing returns to cognitive and non-routine manual occupations (see Figure 4) have attracted more workers partially offsetting the growth in the wages of college educated workers, who are initially more likely to be employed in these occupations, and the decline in the wages of non-college men who are over-represented in routine manual occupations in 1980.

As shown in Figure 12, technological change has contributed to an increase in the labor force participation of college women. This increase is reflected in the larger fall in their wages, relative to men, when we allow for employment responses. Finally, non-college women, who are initially more likely to be employed in non-routine manual occupations, suffered from increased competition from men entering these occupations.

In the third row, we allow for the historical changes in latent valuations of employment while holding the population composition fixed. Therefore, the deviations shown in the third row are due exclusively to changes in workforce demographic composition between 1980 and 2018.

This exercise illustrates how the shrinking share of non-college workers has lifted the wages in this group. When we hold the workforce composition fixed at its 1980 levels, the wages of non-college workers are $6-7\%$ lower than observed. As expected, the opposite occurs for college graduates, whose ranks have grown, although magnitudes are smaller.

The growing share of college graduates has increased the supply of labor in cognitive occupations which college graduates are more likely to populate, partially offsetting the direct effect of higher productivity. This effect is especially strong among women who, over time, have reversed the college gap with men. An inverse effect is apparent in the wages of non-college workers: the reduction in their number mitigates the negative impact of technological change on their wages.

These findings highlight the presence of significant equilibrium responses due to changes in workforce composition and latent employment valuations. If we contrast these responses to those shown in Figure 14, we further confirm the prominent quantitative impact of technological change on relative wages.

6 Extensions and Robustness

In what follows we consider some extensions and assess robustness to alternative assumptions. First, we estimate a version of the model where latent returns can vary across labor markets. Second, we compute alternative measures of compensating differentials. Third, we consider a model with endogenous capital in intermediate production and use it to check the robustness of the empirical relationships estimated in the baseline model.

6.1 Variation in latent values across locations

The systematic components of latent surplus could, in principle, vary systematically across locations. In Appendix K we study a model specification that allows for heterogeneity in latent returns over time and across markets. Identification requires that we impose restrictions on the structure of latent factors. To this purpose, we cast the component b_{ijmt} as the sum of a time-varying demographic-and-occupation component (like in the baseline model) and a term that can change across market-occupation pairs. The latter term reflects possible differences in the latent value of an occupation due to location-specific features. In practice, this amounts to redefining $b_{ijmt} = b_{ijt} + b_{jm}$ and identification requires that all values be estimated relative to a reference region-occupation b_{jm}.

Table 25 in Appendix K shows estimates of the b_{jm} for different census regions and occupations. While most estimates of local effects are significant, their values are rather small relative to the b_{ijt} components. A variance decomposition illustrates that the contribution of the local b_{jm} terms is less than one percent of the total variance of systematic latent returns b_{ijmt}. These magnitudes imply little or no influence of the variation in b_{jm} on baseline findings.

6.2 Alternative measures of compensating differentials

The baseline definition of compensating differentials emphasizes the trade-off between observed wages and latent employment values faced by workers who are marginal in their occupation choice. The compensating differential between occupations j and j' is the difference between the utility a worker would get in the second best occupation if it was paid at the same rate as their current occupation, and the utility they get from their current job. By definition, this measure includes the idiosyncratic valuations of the two marginal occupations. On the other hand, the empirical literature often resorts to an indirect measure of compensating differentials based on covariation between current wages and proxies of non-wage compensation.

To relate our findings to these alternative measures, in Appendix H we report two different measures of covariation between the value of observed wages and latent components of overall returns. The first measure is based on the value of $cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt})$, which we estimate for each year and demographic group. Panel A of Appendix Table 22 reports the results of this exercise, documenting a positive and increasing covariance for college graduates, with pronounced growth among men. For non-college workers we find negative covariations, with a trend towards lower covariances among men. The positive and increasing covariances for college men are in line with findings in Lehmann (2022), which estimates wage and non-wage compensation for a sample of male workers who experience job-to-job transitions.

The covariances reported in Panel A of Table 22 do not account for the idiosyncratic job valuations across workers in the same demographic group. We extend our analysis and, as shown in Panel B of Appendix Table 22, we report measures of covariation that include the average of the idiosyncratic workers' valuations within each cell. The cell-specific averages of idiosyncratic job values $\bar{\theta}_{ijmt}$ are obtained through model simulations and we use them to estimate the following covariances:

$$cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt} + \bar{\theta}_{ijmt}).$$

The resulting measures account for the idiosyncratic component of latent values and are different from estimates in Panel A. Specifically, Panel B shows negative and diminishing covariations for all demographic groups. This indicates the presence of positive and increasing compensating differentials and is consistent with estimates for the baseline definition of compensating differentials.

6.3 Capital inputs in intermediate production

In Appendix C we examine the robustness of the main empirical relationship to the introduction of capital inputs in production. Specifically, we generalize the intermediate production technology to account for endogenous capital choices. This analysis shows that, just like in the baseline model, the distribution of labor inputs in the cross-section of intermediate good producers can be expressed as a simple function of relative productivities (producer-level TFPs). Moreover, we find that the empirical relationship in equation (11), used to recover technology parameters, remains valid. Both shares and elasticities can be recovered using the baseline identification strategy. The one difference is that a correction must be applied to account for capital shares in the estimation of the elasticity of substitution between worker-occupation aggregates. This follows from the observation that, in the baseline model, the ϕ parameter in equation (11) gives a point estimate of $(\rho^{\text{base}} - 1)$, where ρ^{base} denotes the baseline estimate of the substitution parameter ρ. Solving a model with endogenous capital inputs, however, we show that ϕ delivers an estimate of $\frac{\rho-1}{1-\rho(1-\gamma)}$ and $1 - \rho^{\text{base}} = \frac{1-\rho}{1-\rho(1-\gamma)}$, where γ is the capital share in intermediates' production.

Assuming a positive value of γ means that the baseline estimate ρ^{base} is a lower bound of the curvature parameter ρ. This results in an upward rescaling of the elasticity of substitution. In turn, this suggests that estimates of price responses in the counterfactuals are an upper bound of the equilibrium effects. For example, given the baseline estimate of $\hat{\phi} = -0.61$ in (11), if we set $\gamma = 2/3$ we obtain $\rho = 0.49$ and an elasticity of substitution of 1.96 (as opposed to the 1.65 of the baseline elasticity estimate in Table 2).

7 Conclusions

Significant labor market shifts have occurred since the 1980s in both employment and wages. Such changes convey information about different components of worker-occupation match values. We suggest an approach to estimate these components by combining data on employment, earnings and hours worked within an equilibrium model of the labor market.

We model jobs as bundles of observable and latent characteristics that cannot be separately acquired. The analysis emphasizes that similar jobs have different values to different workers. Since employers cannot condition wages on latent returns, rents emerge in equilibrium. At the margin, compensating differential can be defined by considering workers whose employment rents are close to zero. We estimate average rents and compensating differentials for all worker-occupation pairs.

Our estimates indicate that employment rents have risen among educated workers while stagnating for others. At the same time, compensating differentials increased in most jobs. Compensating differentials are strongly associated with occupational mobility, which suggests that workers may use job mobility to trade off alternative occupation characteristics.

These findings suggest that the U.S. workforce has changed in composition and in latent valuations of employment since 1980. At the same time, large shifts in production arrangements and technology have reshaped the demand side of the labor market. To bring together demand and supply of match-specific inputs, we consider a technology that employs match-specific intermediate inputs, estimate its parameters and use it to gauge the intensity of equilibrium responses to technological change and to shifts in the distribution of latent match values. Endogenous wage responses, mediated by a production technology that aggregates worker-occupation inputs, make it possible to characterize both employment and earnings as equilibrium outcomes.

To quantify the contribution of demand and supply forces to observed labor market patterns, we design counterfactual exercises that compare the influences of technological progress and of changes in latent match values on the distribution of workers across jobs and their compensation. This analysis suggests that shifts in latent match values are important when accounting for employment patterns. For example, had latent returns stayed at their 1980 levels, the participation of both high and low education men would be much higher in 2018. Technological change has had asymmetric effects on the labor market participation of male workers: while it offset the negative impact of drops in latent returns among college-educated men, it further reduced the participation of non-college men.

The picture looks different among women, as changes in latent returns and technology reinforced each other to bolster female labor force participation. For non-college women, latent returns and technological change contributed similarly to increased participation. For college-educated women, the main contribution has come from technological change.

The equilibrium analysis indicates that the evolution of wages in worker-occupation matches is largely explained by technological change. Price responses due to shifts in occupation headcounts, while present, are less prominent than the price effects induced by technological transformation.

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A Identification and estimation

This section discusses the identification and estimation of model parameters and provides an overview of the empirical analysis.

Identification: utility and technology parameters

To show the identification of the structural parameters, we consider a simplified version of the model in which non-labor income is zero for all workers, and we show that we can identify all the parameters even without exploiting the empirical variation in this dimension. This assumption simplifies the problem by allowing us to derive a closed form solution to the first order condition. First consider the time-consumption problem described in equation (1). With the assumed functional forms, the problem becomes

$$\begin{aligned} U_{ijmt} = \max_{h_{ijmt}} \quad & \frac{c_{ijmt}^{1-\sigma} - 1}{1-\sigma} - \psi_i \frac{h_{ijmt}^{1-\gamma}}{1-\gamma} + b_{ijt} \\ \text{s.t.} \quad & c_{ijmt} = w_{ijmt} h_{ijmt} \end{aligned} \tag{22}$$

the associated first order condition in logarithmic form is

$$\log(h_{ijmt}) = -\frac{1}{\sigma-\gamma}\log(\psi_i) + \frac{1-\sigma}{\sigma-\gamma}\log(w_{ijmt}) \tag{23}$$

The empirical counterpart of this is

$$\log(h_{ijmt}) = \alpha_i + \beta\log(w_{ijmt}) + \epsilon_{ijmt}^1 \equiv f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) + \epsilon_{ijmt}^1 \tag{24}$$

with

$$\alpha_i = -\frac{1}{\sigma-\gamma}\log(\psi_i) \qquad \beta = \frac{1-\sigma}{\sigma-\gamma} \tag{25}$$

With the linear specification of $f(\cdot,\cdot)$, moments (12) and (13) describe an OLS estimator of (24). From the estimation of the latter equation we can obtain γ and ψ_i as a function of σ:

$$\gamma = \sigma - \frac{1-\sigma}{\beta} \qquad \psi_i = \exp\left(-\frac{1-\sigma}{\beta}\alpha_i\right) \tag{26}$$

We are now left with three sets of parameters to estimate, namely σ, σ_θ, and b_{ijt}, and at least three moments from equations (14) and (15), given that $\boldsymbol{Z}_{ijmt}^2$ has at least two elements

$Z^2_{1,ijmt}$ and $Z^2_{2,ijmt}$. From eq. (14) we have

$$\tilde{b}_{ijt} = E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u_h^i\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta}\middle| i,j,t\right] \tag{27}$$

where $\tilde{b}_{ijt} = \frac{b_{ijt}}{\sigma_\theta}$. Plugging this into (15) gives

$$E\left[\left(\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u_h^i\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta} - E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u_h^i\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta}\middle| i,j,t\right]\right)\boldsymbol{Z}^2_{ijmt}\right] = 0 \tag{28}$$

which is a system of at least two equations in two unknowns, σ and σ_θ, which drives the identification of the latter. Once σ and σ_θ are identified, eq. (27) identifies b_{ijt}.

Production function identification.

On the firm side, taking the ratio between the wages for two demographic groups within an occupation (eq. (7)),we have that

$$\frac{w_{ijmt}}{w_{i'jmt}} = \frac{\beta_{ijt}}{\beta_{i'jt}} \tag{29}$$

which shows that the β's are directly identifiable from wage data as long as we normalize the value of the β's for one demographic group (e.g. setting $\beta_{1jt} = 1$ for all j and t). Taking a similar ratio within demographic groups across occupations and using market clearing gives

$$\frac{w_{ijmt}}{w_{ij'mt}} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\widetilde{L}_{j'mt}}{\widetilde{L}_{jmt}}\right)^{1-\rho} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\sum_{i'}\beta_{i'j't}L_{i'j'mt}}{\sum_{i'}\beta_{i'jt}L_{i'jmt}}\right)^{1-\rho} \tag{30}$$

Once we know the β's, we can identify the $\alpha's$ (up to a normalization) and ρ's as follows. Taking the log of eq. (30) for $j' = 1$ gives

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho-1)\log\left(\frac{\sum_{i'}\beta_{i'jt}L_{i'jmt}}{\sum_{i'}\beta_{i'1t}L_{i'1mt}}\right) \tag{31}$$

Since, at this point, the β's are known, one can compute $\Lambda_{jmt} = \log\left(\frac{\sum_{i'}\beta_{i'jt}L_{i'jmt}}{\sum_{i'}\beta_{i'1t}L_{i'1mt}}\right)$, $B_{ijt} = \frac{\beta_{ijt}}{\beta_{i1t}}$ and $W_{ijmt} = \log\left(\frac{w_{ijmt}}{w_{i1mt}}\right)$ and regress the latter on Λ_{jmt} and a set of occupation dummies $\boldsymbol{\gamma}$, separately for each year:

$$W_{ijmt} = \gamma_{jt} + \psi B_{ijt} + \phi\Lambda_{jmt} + \epsilon_{ijmt} \tag{32}$$

Then the α's are identified by $\frac{\alpha_{jt}}{\alpha_{1t}} = e^{\hat{\gamma}_{jt}}$ imposing $\sum_j \alpha_{jt} = 1$ for each t, and ρ by $\rho = \left(1 + \hat{\phi}\right)$.

Once all these parameters are identified, the TFP parameters A's are identified as residuals using the fact that in our model, thanks to the constant returns to scale assumption, total production is $\Upsilon_{mt} = \sum_i \sum_j w_{ijmt} L_{ijmt}$.

B Production sector: derivations

In this appendix, we report all the derivations concerning the production function. To reduce notation cluttering we omit the time and market indexes in all the equations.

We begin by considering the intermediate firm's problem in eq. (5) that, plugging the constraints into the objective function, becomes

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} - \sum_i \tilde{w}_{ij} L_{ijv} \tag{33}$$

the associated first order condition is

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho} \rho \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho-1} \beta_{ij} \tag{34}$$

For any two firms $v, v' \in V_j$ the latter gives

$$z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho-1} = z_{jv'}^{\rho} \left(\sum_i \beta_{ij} L_{ijv'} \right)^{\rho-1} \tag{35}$$

$$\sum_i \beta_{ij} L_{ijv'} = \frac{z_{jv}^{\frac{\rho}{\rho-1}}}{z_{jv'}^{\frac{\rho}{\rho-1}}} \sum_i \beta_{ij} L_{ijv} \tag{36}$$

Integrating over $v' \in V_j$ we get

$$\sum_i \beta_{ij} L_{ij} = z_{jv}^{\frac{\rho}{\rho-1}} \int_{v' \in V_j} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \sum_i \beta_{ij} L_{ijv} \tag{37}$$

$$\sum_i \beta_{ij} L_{ijv} = z_{jv}^{\frac{-\rho}{\rho-1}} \left(\int_{v' \in V_j} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \right)^{-1} \sum_i \beta_{ij} L_{ij} \tag{38}$$

The aggregate production function is given by

$$Y = \left(\int_v \upsilon_{jv}^{\rho} dv \right)^{\frac{1}{\rho}} \tag{39}$$

$$= \left(\sum_j \int_{v \in V_j} \upsilon_{jv}^{\rho} dv \right)^{\frac{1}{\rho}} \tag{40}$$

$$= \left(\sum_j \int_{v \in V_j} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} dv \right)^{\frac{1}{\rho}} \tag{41}$$

Using (38) this gives

$$Y = \left[\sum_j \int_{v\in V_j} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv}\right)^{\rho} dv\right]^{\frac{1}{\rho}} \tag{42}$$

$$= \left[\sum_j \int_{v\in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \left(\int_{v'} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv'\right)^{-\rho} \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{43}$$

$$= \left[\sum_j \underbrace{\left(\int_{v\in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv\right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{44}$$

$$= \left[\sum_j \tilde{\alpha}_j \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{45}$$

$$= A\left[\sum_j \alpha_j \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{46}$$

where $\alpha_j = \frac{\tilde{\alpha}_j}{\sum_{j'} \tilde{\alpha}_{j'}}$ and $A = \left(\sum_{j'} \tilde{\alpha}_{j'}\right)^{\frac{1}{\rho}}$. Moreover, substituting (38) into (34) we have

$$\tilde{w}_{ij} = PY^{(1-\rho)}\rho \underbrace{\left(\int_{v\in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv\right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_{i'} \beta_{i'j} L_{i'j}\right)^{\rho-1} \beta_{ij} \tag{47}$$

$$\frac{\tilde{w}_{ij}}{P} = Y^{(1-\rho)}\rho\tilde{\alpha}_j \frac{\sum_{j'} \tilde{\alpha}_{j'}}{\sum_{j'} \tilde{\alpha}_{j'}} \left(\sum_{i'} \beta_{i'j} L_{i'j}\right)^{\rho-1} \beta_{ij} \tag{48}$$

$$w_{ij} = \rho A^{\rho} \alpha_j \beta_{ij} \left(\frac{Y}{\sum_{i'} \beta_{i'j} L_{i'j}}\right)^{(1-\rho)} \tag{49}$$

where $w_{ij} = \frac{\tilde{w}_{ij}}{P}$.

C Model with capital inputs

The setup is similar to the baseline model. Here, we assume that intermediate good producers also use capital in production. They solve

$$\max_{p_{jv},\lambda_{jv},L_{ijv}} \quad p_{jv}\lambda_{jv} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{50}$$

$$\text{s.t.} \quad \lambda_{jv} = z_{jv}\left(\sum_i \beta_{ij} L_{ijv}\right)^{\gamma} (\eta_j K_{jv})^{1-\gamma} \tag{51}$$

$$p_{jv} = \left[\frac{\lambda_{jv}}{Y}\right]^{-(1-\rho)} P \tag{52}$$

Equivalently

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho}\left(\sum_i \beta_{ij} L_{ijv}\right)^{\rho\gamma} (\eta_j K_{jv})^{\rho(1-\gamma)} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{53}$$

The associated first order conditions are

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho}\rho\gamma\left(\sum_{i'} \beta_{i'j} L_{i'jv}\right)^{\rho\gamma-1} (\eta_j K_{jv})^{\rho(1-\gamma)} \beta_{ij} \tag{54}$$

and

$$r = PY^{(1-\rho)} z_{jv}^{\rho}\rho(1-\gamma)\left(\sum_{i'} \beta_{i'j} L_{i'jv}\right)^{\rho\gamma} (\eta_j K_{jv})^{\rho(1-\gamma)-1} \eta_j \tag{55}$$

Dividing the two first order conditions by each other we get

$$\frac{\tilde{w}_{ij}}{r} = \beta_{ij}\frac{\gamma}{1-\gamma}\frac{K_{jv}}{\sum_{i'} \beta_{i'j} L_{i'jv}} \Rightarrow K_{jv} = \frac{w_{ij}(1-\gamma)}{r\gamma\beta_{ij}}\sum_{i'} \beta_{i'j} L_{i'jv} \tag{56}$$

Notice that this implies

$$\frac{K_{jv}}{\sum_{i'} \beta_{i'j} L_{i'jv}} = \frac{\tilde{w}_{ij}(1-\gamma)}{r\gamma\beta_{ij}} = \frac{K_j}{\sum_{i'} \beta_{i'j} L_{i'j}} \tag{57}$$

where $K_j = \int_{v' \in V_j} K_{jv} dv$ and $L_{ij} = \int_{v' \in V_j} L_{ijv} dv$.
Using (56) into (54) we get

$$\tilde{w}_{ij} = \left(\frac{\tilde{w}_{ij}}{r}\right)^{\rho(1-\gamma)} PY^{(1-\rho)} z_{jv}^{\rho}\rho\gamma^{1-\rho(1-\gamma)}(1-\gamma)^{\rho(1-\gamma)}\eta_j^{\rho(1-\gamma)}\left(\sum_{i'} \beta_{i'j} L_{i'jv}\right)^{\rho-1} \beta_{ij}^{1-\rho(1-\gamma)} \tag{58}$$

$$w_{ij} = \Xi \eta_j^{\frac{\rho(1-\gamma)}{1-\rho(1-\gamma)}} z_{jv}^{\frac{\rho}{1-\rho(1-\gamma)}} \beta_{ij} \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\frac{\rho-1}{1-\rho(1-\gamma)}} \tag{59}$$

where $\Xi = \left[Y^{(1-\rho)} \rho\gamma \left(\frac{1-\gamma}{r\gamma} \right)^{\rho(1-\gamma)} \right]^{\frac{1}{1-\rho(1-\gamma)}}$ and $w_{ij} = \frac{\tilde{w}_{ij}}{P}$ as before.
Notice that (59) implies the same relationship described in (36) and, thus, equation (38). Using (38) in (59) we get

$$w_{ij} = \Xi \Lambda_j \beta_{ij} \left(\sum_{i'} \beta_{i'j} L_{i'j} \right)^{\frac{\rho-1}{1-\rho(1-\gamma)}} \tag{60}$$

where $\Lambda_j = \eta_j^{\frac{\rho(1-\gamma)}{1-\rho(1-\gamma)}} \left(\int_{v \in V_j} \frac{1}{z_{jv}^{\frac{\rho}{\rho-1}}} dv \right)^{\frac{1-\rho}{1-\rho(1-\gamma)}}$. Dividing the latter by the same equation for $j = 1$ and taking logs

$$\log \left(\frac{w_{ij}}{w_{i2}} \right) = \log \left(\frac{\Lambda_j}{\Lambda_1} \right) + \log \left(\frac{\beta_{ij}}{\beta_{i1}} \right) + \frac{\rho - 1}{1 - \rho(1-\gamma)} \log \left(\frac{\sum_{i'} \beta_{i'j} L_{i'j}}{\sum_{i'} \beta_{i'1} L_{i'1}} \right) \tag{61}$$

The empirical counterpart of this equation is equivalent to that in the paper.

$$W_{ijmt} = \gamma_{jt} + \psi \hat{B}_{ijt} + \phi \hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{62}$$

However, it is not possible to recover the value of all the structural parameters from the estimated reduced form equation.

The elasticity of substitution in production. In the baseline model we have $\phi = \rho^{\text{base}} - 1$. In this generalized model, however, $\phi = \frac{\rho-1}{1-\rho(1-\gamma)}$. Thus

$$1 - \rho^{\text{base}} = \frac{1-\rho}{1-\rho(1-\gamma)} \tag{63}$$

If $\rho \in [0, 1]$, then $1 - \rho(1-\gamma) \in [0, 1]$ and $1 - \rho^{\text{base}} > 1 - \rho$, that is

$$\rho^{\text{base}} < \rho \tag{64}$$

This implies that if the baseline estimate ρ^{base} is a lower bound of the curvature parameter ρ. Assuming $\gamma = 2/3$, a common choice in the literature, the baseline estimate of $\hat{\phi} = -0.61$ delivers $\rho = 0.49$ which implies an elasticity of substitution of about 1.96.

	NON-IV	IV		
	(1)	(2)	(3)	(4)
$\hat{\sigma}$	0.3002***	0.2753***	0.2859***	0.2810***
	(0.0191)	(0.0736)	(0.0780)	(0.0649)
$\hat{\sigma}_\theta$	2.9685***	2.9685***	2.9685***	2.9685***
	(0.1448)	(0.4236)	(0.2022)	(0.2008)
Instrumental Variables				
$w_{ijmt-10}$	No	Yes	No	Yes
$w_{ijmt-20}$	No	No	Yes	Yes
y_{imt-10}	No	Yes	No	Yes
y_{imt-20}	No	No	Yes	Yes

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Results from the GMM estimator in equation (16). Prameters and standard errors for $\hat{\sigma}_\theta$ are scaled down by 1000.

D Method-of-moments estimates

D.1 Preference parameters and producction technology share

Table 8 shows estimates of the curvature of consumption utility (σ) and of the scale parameters of the extreme value preference shock (σ_θ). Column 1 reports estimates obtained without using instruments. That is, $\boldsymbol{Z}^1_{ijmt}$ includes the logarithm of contemporaneous wages and non-labor income, $\boldsymbol{Z}^2_{ijmt}$ are the logarithm of contemporaneous wages. In columns (2), (3), and (4) we instrument for wages and non-labor income using their 10-year and 20-year lagged values. We refer to column (2) as our baseline specification. Results are not sensitive to using the estimates in columns (3) or (4). Table 17 shows estimates of the remaining utility parameters: the weight and curvature of disutility from labor (ψ, γ). Estimates of the latent match-specific surplus for different (i, j) matches for different years (b_{ijt} are in Tables 10-14) As for the production function estimates, tables 15 to 19 show point estimates and standard errors (in parenthesis) for technology input shares in different years (1980, 1990, 2000, 2010, 2018). Share estimates are presented for all occupation-worker combinations.

			NON-IV	IV		
			(1)	(2)	(3)	(4)
		$\hat{\gamma}$	-4.1489	-4.8535	-3.8444	-3.8444
			(0.2197)	(0.6095)	(0.4497)	(0.4402)
ψ_i						
Age 25-34	Non-college	Men	0.9982	0.0058	11.9290	11.9290
			(0.1483)	(0.0032)	(6.9124)	(3.5599)
		Women	1.6933	0.0109	19.2453	19.2453
			(0.2274)	(0.0053)	(11.0030)	(5.8896)
	College	Men	1.0692	0.0062	12.9025	12.9025
			(0.1619)	(0.0035)	(7.7103)	(3.9269)
		Women	1.5900	0.0099	18.4665	18.4665
			(0.2234)	(0.0051)	(10.8629)	(5.6986)
Age 35-44	Non-college	Men	1.0102	0.0058	12.2070	12.2070
			(0.1536)	(0.0033)	(7.2603)	(3.6975)
		Women	1.6568	0.0106	18.9706	18.9706
			(0.2263)	(0.0053)	(10.9762)	(5.8275)
	College	Men	1.0841	0.0062	13.2802	13.2802
			(0.1692)	(0.0037)	(8.2564)	(4.1372)
		Women	1.9095	0.0122	22.0656	22.0656
			(0.2712)	(0.0065)	(13.2986)	(7.0254)
Age 44-54	Non-college	Men	1.0745	0.0063	12.9847	12.9847
			(0.1634)	(0.0035)	(7.8101)	(3.9694)
		Women	1.5534	0.0098	17.8936	17.8936
			(0.2137)	(0.0050)	(10.3727)	(5.4770)
	College	Men	1.1466	0.0066	14.0492	14.0492
			(0.1787)	(0.0039)	(8.8377)	(4.4114)
		Women	1.6911	0.0106	19.6681	19.6681
			(0.2508)	(0.0057)	(12.1845)	(6.3714)
		Instrumental Variables				
		$w_{ijmt-10}$	No	Yes	No	Yes
		$w_{ijmt-20}$	No	No	Yes	Yes
		y_{imt-10}	No	Yes	No	Yes
		y_{imt-20}	No	No	Yes	Yes

Bootstrapped standard errors in parentheses

Table 9: Estimates of the utility parameters realtive to the disutility of hours worked from the GMM estimator in equation (16). Parameter estimates and standard errors for ψ_i are scaled up by 10^{14}.

	Age 25-34				Age 35-44							
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	-1.4878	-3.2459	0.5533	-1.9191	-0.9283	-2.9402	1.0158	-2.1112	-1.1708	-3.0430	0.7779	-2.0613
	(0.4002)	(0.2834)	(0.5065)	(0.3654)	(0.5145)	(0.3005)	(0.7101)	(0.3953)	(0.5398)	(0.3026)	(0.7851)	(0.4106)
Manag. rel.	-3.0457	-3.8916	-0.0540	-2.3392	-2.5262	-3.8745	-0.1200	-3.0834	-2.6547	-4.0760	-0.4542	-3.2623
	(0.4148)	(0.3018)	(0.4597)	(0.3665)	(0.4901)	(0.3177)	(0.5911)	(0.3626)	(0.5031)	(0.3290)	(0.5814)	(0.3627)
Professional	-2.1282	-2.9672	1.4050	-0.0820	-1.8474	-2.8969	1.6284	-0.2299	-2.1441	-3.1352	1.3204	-0.1830
	(0.3926)	(0.3090)	(0.4406)	(0.3768)	(0.4850)	(0.3102)	(0.5793)	(0.4113)	(0.5109)	(0.3135)	(0.5984)	(0.4392)
Technicians	-2.1418	-3.4254	-0.6331	-2.4310	-2.1018	-3.6386	-0.8573	-3.0474	-2.5332	-3.9762	-1.5141	-3.3553
	(0.4195)	(0.2938)	(0.4387)	(0.3663)	(0.5418)	(0.3130)	(0.6495)	(0.3806)	(0.5572)	(0.2945)	(0.6696)	(0.3710)
Sales	-1.2888	-2.5622	0.3071	-2.2090	-0.9780	-2.3355	0.2614	-2.5170	-1.2049	-2.3942	0.0538	-2.4375
	(0.3608)	(0.2354)	(0.4471)	(0.3060)	(0.4241)	(0.2310)	(0.5822)	(0.2702)	(0.4017)	(0.2261)	(0.5678)	(0.2469)
Admin. Support	-1.4226	-1.1203	-0.3088	-1.2685	-1.2814	-1.1042	-0.5101	-1.7229	-1.3983	-1.3184	-0.8162	-1.5922
	(0.3860)	(0.2649)	(0.4068)	(0.2914)	(0.4440)	(0.2641)	(0.5156)	(0.2804)	(0.4512)	(0.2721)	(0.5453)	(0.2713)
Protective Services	-2.2812	-5.6506	-1.6216	-5.3055	-1.9927	-5.5749	-1.6705	-6.1484	-2.4167	-5.7086	-2.5099	-6.8945
	(0.3875)	(0.2768)	(0.4299)	(0.3470)	(0.4273)	(0.2784)	(0.4996)	(0.3929)	(0.4140)	(0.2490)	(0.4929)	(0.3255)
Other Services	-1.4189	-1.9590	-1.3480	-2.6414	-1.2927	-1.7488	-1.8979	-3.2308	-1.3685	-1.8570	-2.1774	-3.2322
	(0.2742)	(0.2058)	(0.2841)	(0.2612)	(0.2841)	(0.1971)	(0.3330)	(0.2602)	(0.2803)	(0.1955)	(0.3283)	(0.2309)
Mechanics	-1.0655	-5.4617	-1.8939	-5.8979	-0.9160	-5.6089	-2.1405	-6.4500	-1.2492	-5.8905	-2.6052	-6.6867
	(0.3891)	(0.3278)	(0.3707)	(0.3231)	(0.4188)	(0.2984)	(0.4134)	(0.2694)	(0.4055)	(0.3159)	(0.3765)	(0.1921)
Construction Traders	-0.9967	-6.1371	-1.1880	-6.1382	-0.8493	-6.2345	-1.4884	-6.3987	-1.1540	-6.6105	-2.0368	-6.5491
	(0.3800)	(0.2621)	(0.3364)	(0.2393)	(0.4235)	(0.2542)	(0.4095)	(0.1839)	(0.4144)	(0.2690)	(0.4723)	(0.2485)
Precision Prod.	-1.3714	-4.2160	-1.2276	-4.4759	-0.9943	-3.8627	-1.1694	-4.9059	-1.2015	-4.0056	-1.4966	-4.9390
	(0.4102)	(0.2571)	(0.4551)	(0.3094)	(0.4606)	(0.2609)	(0.5806)	(0.2817)	(0.4683)	(0.2494)	(0.6406)	(0.2526)
Machine Operators	-0.7317	-2.3996	-1.6471	-4.0508	-0.6779	-2.2181	-1.9854	-4.3922	-1.0166	-2.3813	-2.3786	-4.2907
	(0.3859)	(0.2399)	(0.3686)	(0.2528)	(0.4162)	(0.2482)	(0.3818)	(0.2378)	(0.4064)	(0.2435)	(0.3976)	(0.2103)
Transportation	-0.5010	-3.4999	-1.2953	-4.9676	-0.3948	-3.3063	-1.7199	-5.4342	-0.6971	-3.5889	-2.1900	-5.5532
	(0.3781)	(0.2496)	(0.3854)	(0.2989)	(0.4055)	(0.2497)	(0.3736)	(0.2564)	(0.3995)	(0.2501)	(0.3656)	(0.2429)

Bootstrapped standard errors in parentheses

Table 10: Estimates of the non-pecuniary component of surplus for 1980 normalized by $\hat{\sigma}_\theta$.

	Age 25-34				Age 35-44							
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	-1.5984	-2.5402	0.6403	-1.0464	-1.2153	-2.1813	0.9041	-1.2448	-1.2510	-2.3509	0.6639	-1.1770
	(0.3891)	(0.3038)	(0.5377)	(0.4124)	(0.5124)	(0.3524)	(0.7115)	(0.4738)	(0.5948)	(0.3538)	(0.8261)	(0.4870)
Manag. rel.	-3.0358	-3.0750	0.1944	-1.2005	-2.6806	-2.8315	0.0096	-1.8619	-2.6907	-3.1208	-0.3807	-2.0295
	(0.3743)	(0.3099)	(0.4814)	(0.4021)	(0.5148)	(0.3419)	(0.5833)	(0.4149)	(0.5030)	(0.3526)	(0.6418)	(0.4019)
Professional	-2.2010	-2.5496	1.4714	0.2085	-1.9133	-2.1300	1.4888	0.2293	-2.1209	-2.4500	1.2130	0.4026
	(0.4057)	(0.3426)	(0.4875)	(0.4125)	(0.4679)	(0.3475)	(0.6049)	(0.4432)	(0.5201)	(0.3422)	(0.6878)	(0.4641)
Technicians	-2.0524	-2.9513	-0.1161	-1.7561	-2.0683	-2.8193	-0.5438	-2.2732	-2.4309	-3.2900	-1.2170	-2.3922
	(0.4000)	(0.3161)	(0.4795)	(0.4038)	(0.4771)	(0.3336)	(0.5825)	(0.4091)	(0.5589)	(0.3286)	(0.7060)	(0.4201)
Sales	-1.1565	-1.9610	0.6286	-1.2800	-1.0240	-1.8018	0.5194	-1.7929	-1.0751	-1.9152	0.1190	-1.6225
	(0.3539)	(0.2451)	(0.5030)	(0.3861)	(0.4269)	(0.2551)	(0.5864)	(0.3696)	(0.4458)	(0.2439)	(0.6411)	(0.3217)
Admin. Support	-1.4380	-0.8756	-0.2115	-0.8727	-1.3788	-0.6756	-0.4081	-1.2167	-1.5105	-0.8701	-0.9257	-1.1171
	(0.3489)	(0.2707)	(0.3960)	(0.3138)	(0.4156)	(0.2817)	(0.4689)	(0.3058)	(0.4485)	(0.2838)	(0.5082)	(0.2986)
Protective Services	-2.2491	-4.7410	-1.4151	-4.2526	-2.1308	-4.6000	-1.3371	-4.7117	-2.2832	-4.9990	-1.9546	-5.1605
	(0.3858)	(0.3420)	(0.4205)	(0.4296)	(0.4441)	(0.3079)	(0.5013)	(0.4151)	(0.4436)	(0.2995)	(0.5318)	(0.4223)
Other Services	-1.1043	-1.4671	-1.0969	-2.1385	-1.2274	-1.3454	-1.3870	-2.5570	-1.3359	-1.4365	-1.9691	-2.5835
	(0.2583)	(0.1905)	(0.2918)	(0.2508)	(0.2816)	(0.1964)	(0.3256)	(0.2588)	(0.2780)	(0.2033)	(0.3597)	(0.2624)
Mechanics	-1.1171	-5.0191	-1.7714	-4.9158	-1.0740	-4.8149	-1.7492	-5.3473	-1.2654	-5.2478	-2.3696	-5.8572
	(0.3491)	(0.3008)	(0.3798)	(0.3481)	(0.4099)	(0.3732)	(0.4332)	(0.3720)	(0.4147)	(0.3330)	(0.4414)	(0.3575)
Construction Traders	-0.9227	-5.3975	-1.4421	-5.4696	-0.9494	-5.3798	-1.2847	-5.5651	-1.2448	-5.7305	-2.0625	-6.1859
	(0.3427)	(0.2606)	(0.3210)	(0.3216)	(0.3791)	(0.2555)	(0.3528)	(0.2700)	(0.4052)	(0.2789)	(0.4305)	(0.3155)
Precision Prod.	-1.5947	-3.8462	-1.7165	-4.1781	-1.4316	-3.6048	-1.5211	-4.3586	-1.4876	-3.7575	-1.9644	-4.4575
	(0.3778)	(0.2473)	(0.4548)	(0.3592)	(0.4480)	(0.2634)	(0.5224)	(0.3157)	(0.4705)	(0.2588)	(0.5772)	(0.2918)
Machine Operators	-0.9586	-2.3041	-1.6973	-3.6720	-0.9683	-2.0752	-1.7152	-3.8585	-1.1632	-2.2112	-2.2765	-3.9427
	(0.3427)	(0.2298)	(0.3340)	(0.2679)	(0.3954)	(0.2502)	(0.3976)	(0.2567)	(0.4050)	(0.2549)	(0.4017)	(0.2275)
Transportation	-0.5482	-3.1485	-1.2816	-4.4827	-0.5605	-2.9828	-1.3163	-4.6658	-0.7083	-3.1833	-1.9660	-4.6572
	(0.3268)	(0.2439)	(0.3472)	(0.2806)	(0.3689)	(0.2589)	(0.3687)	(0.2882)	(0.3788)	(0.2565)	(0.3578)	(0.2608)

Bootstrapped standard errors in parentheses

Table 11: Estimates of the non-pecuniary component of surplus for 1990 normalized by $\hat{\sigma}_\theta$.

	Age 25-34				Age 35-44							
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	-2.1277	-2.8237	0.2117	-1.1617	-1.7238	-2.5261	0.4905	-1.3698	-1.7714	-2.4949	0.2153	-1.1280
	(0.4206)	(0.3343)	(0.6157)	(0.4778)	(0.5553)	(0.3917)	(0.8621)	(0.5994)	(0.6228)	(0.4254)	(0.9077)	(0.5931)
Manag. rel.	-3.4008	-3.2233	-0.2453	-1.2973	-3.2462	-2.9562	-0.3816	-1.7058	-3.1166	-2.9359	-0.5978	-1.6956
	(0.4007)	(0.3314)	(0.5628)	(0.4530)	(0.4872)	(0.3663)	(0.7145)	(0.4996)	(0.5179)	(0.3851)	(0.6648)	(0.4858)
Professional	-2.3356	-2.6230	1.1069	0.1486	-2.2730	-2.2786	1.0787	-0.0777	-2.2977	-2.2517	0.8336	0.3918
	(0.4342)	(0.3345)	(0.5115)	(0.4303)	(0.4879)	(0.3764)	(0.6745)	(0.4818)	(0.5028)	(0.3894)	(0.7026)	(0.4843)
Technicians	-2.7371	-3.1442	-0.3301	-2.0728	-2.6555	-2.9136	-0.6092	-2.3071	-2.7846	-2.9685	-1.2850	-2.2859
	(0.4222)	(0.3437)	(0.6173)	(0.4818)	(0.5204)	(0.3717)	(0.7229)	(0.5067)	(0.5378)	(0.3835)	(0.7332)	(0.4713)
Sales	-1.5656	-1.9711	0.0449	-1.5840	-1.5069	-1.9050	-0.0077	-1.9765	-1.5361	-1.9044	-0.2875	-1.7882
	(0.3661)	(0.2685)	(0.5942)	(0.4484)	(0.4444)	(0.2850)	(0.7304)	(0.5003)	(0.4518)	(0.2772)	(0.6449)	(0.4266)
Admin. Support	-1.6309	-0.9731	-0.5196	-1.0214	-1.7035	-0.7859	-0.7055	-1.3107	-1.7134	-0.7251	-0.9052	-0.9931
	(0.3296)	(0.2747)	(0.4233)	(0.3479)	(0.3893)	(0.2941)	(0.4982)	(0.3500)	(0.4138)	(0.3074)	(0.4963)	(0.3420)
Protective Services	-2.4331	-4.3892	-1.4070	-3.9992	-2.5152	-4.3370	-1.6428	-4.3588	-2.6081	-4.5649	-1.9632	-4.4411
	(0.4057)	(0.3184)	(0.4647)	(0.4195)	(0.4731)	(0.3542)	(0.5280)	(0.4504)	(0.4599)	(0.3515)	(0.5503)	(0.4461)
Other Services	-1.3071	-1.3302	-1.3051	-2.0766	-1.4232	-1.2342	-1.5016	-2.4438	-1.5713	-1.3270	-1.8140	-2.2936
	(0.2624)	(0.2066)	(0.3142)	(0.2614)	(0.2900)	(0.2083)	(0.3524)	(0.2681)	(0.2869)	(0.2120)	(0.3257)	(0.2498)
Mechanics	-1.4842	-5.0774	-2.0529	-5.2386	-1.3326	-4.7844	-1.9936	-5.4540	-1.4515	-4.8941	-2.1875	-5.2940
	(0.3537)	(0.3126)	(0.3897)	(0.3742)	(0.3929)	(0.3482)	(0.4372)	(0.4090)	(0.4140)	(0.3744)	(0.4118)	(0.3959)
Construction Traders	-1.2819	-5.4469	-2.0119	-6.0982	-1.2023	-5.2740	-1.8496	-5.9131	-1.4708	-5.5482	-2.0037	-5.8089
	(0.3330)	(0.3517)	(0.3537)	(0.2992)	(0.3695)	(0.3044)	(0.3556)	(0.2872)	(0.3779)	(0.2624)	(0.3516)	(0.2395)
Precision Prod.	-2.0035	-3.5233	-2.2628	-4.0285	-1.7772	-3.2579	-2.0772	-4.2499	-1.8452	-3.3525	-2.2324	-3.9812
	(0.3625)	(0.2554)	(0.4173)	(0.3218)	(0.4063)	(0.2685)	(0.5145)	(0.3683)	(0.4337)	(0.2762)	(0.4885)	(0.3298)
Machine Operators	-1.5000	-2.6633	-2.2877	-4.1130	-1.5267	-2.4048	-2.2641	-4.1404	-1.6658	-2.4204	-2.4012	-3.8689
	(0.3315)	(0.2392)	(0.3754)	(0.2955)	(0.3784)	(0.2560)	(0.4073)	(0.3214)	(0.3907)	(0.2618)	(0.3869)	(0.3033)
Transportation	-0.9276	-3.3243	-1.8241	-4.9753	-0.8919	-3.0473	-1.7228	-4.9874	-1.0110	-3.2657	-1.9120	-4.7646
	(0.3158)	(0.2420)	(0.3446)	(0.3238)	(0.3476)	(0.2639)	(0.3748)	(0.3433)	(0.3603)	(0.2796)	(0.3676)	(0.2858)

Bootstrapped standard errors in parentheses

Table 12: Estimates of the non-pecuniary component of surplus for 2000 normalized by $\hat{\sigma}_\theta$.

	Age 25-34				Age 35-44							
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	-2.2186	-2.7587	0.1123	-1.0025	-1.7567	-2.4655	0.4908	-1.1919	-1.8187	-2.3916	0.1770	-1.0752
	(0.3551)	(0.2927)	(0.5424)	(0.4408)	(0.4727)	(0.3641)	(0.8055)	(0.5769)	(0.5376)	(0.4104)	(0.8888)	(0.6266)
Manag. rel.	-3.6461	-3.4225	-0.2617	-1.1183	-3.3894	-3.0928	-0.3851	-1.5252	-3.4818	-2.9576	-0.7505	-1.4374
	(0.3844)	(0.3120)	(0.5456)	(0.4459)	(0.4621)	(0.3646)	(0.7715)	(0.5198)	(0.4924)	(0.3939)	(0.7714)	(0.5388)
Professional	-2.4512	-2.4790	0.9848	0.3668	-2.2906	-2.3074	0.9932	-0.0293	-2.5076	-2.2659	0.5989	0.1080
	(0.3839)	(0.3214)	(0.4991)	(0.4246)	(0.4609)	(0.3651)	(0.6953)	(0.4929)	(0.4869)	(0.3944)	(0.7387)	(0.5002)
Technicians	-2.8982	-3.0013	-0.4008	-1.9597	-2.7943	-2.8474	-0.5682	-2.4914	-3.0158	-2.8572	-1.1509	-2.3495
	(0.3985)	(0.3396)	(0.5550)	(0.4393)	(0.4858)	(0.3636)	(0.6985)	(0.5160)	(0.5253)	(0.3867)	(0.7366)	(0.5327)
Sales	-1.5810	-1.7951	-0.0453	-1.3761	-1.5256	-1.8434	-0.0494	-1.8600	-1.6740	-1.8408	-0.3691	-1.7207
	(0.3018)	(0.2183)	(0.4906)	(0.3793)	(0.3788)	(0.2525)	(0.7127)	(0.4570)	(0.3897)	(0.2555)	(0.6682)	(0.4181)
Admin. Support	-1.6682	-1.0949	-0.5184	-0.8400	-1.7383	-0.8910	-0.8026	-1.3400	-1.9124	-0.7896	-1.1071	-1.0758
	(0.2818)	(0.2440)	(0.3685)	(0.3111)	(0.3398)	(0.2739)	(0.4989)	(0.3330)	(0.3685)	(0.2928)	(0.4980)	(0.3320)
Protective Services	-2.4747	-4.1756	-1.3884	-3.6344	-2.3320	-4.0389	-1.2842	-4.0885	-2.7119	-4.1809	-2.0115	-4.1504
	(0.3663)	(0.2924)	(0.4452)	(0.3947)	(0.4521)	(0.3422)	(0.5594)	(0.4544)	(0.4567)	(0.3458)	(0.5765)	(0.4811)
Other Services	-0.9724	-0.9108	-0.8845	-1.5698	-1.0754	-0.8851	-1.2361	-2.1866	-1.3831	-0.9949	-1.6209	-2.0095
	(0.2137)	(0.1800)	(0.2600)	(0.2322)	(0.2326)	(0.1784)	(0.3063)	(0.2189)	(0.2483)	(0.1855)	(0.2995)	(0.2191)
Mechanics	-1.7175	-5.3241	-2.1659	-5.3227	-1.5688	-5.1555	-2.0404	-5.5422	-1.6555	-5.1457	-2.3179	-5.3716
	(0.3216)	(0.2662)	(0.3640)	(0.3621)	(0.3638)	(0.3210)	(0.4207)	(0.3995)	(0.3784)	(0.3542)	(0.4136)	(0.3588)
Construction Traders	-1.4234	-5.8017	-2.0918	-6.2367	-1.3272	-5.5624	-1.9890	-6.1823	-1.5749	-5.4806	-2.2270	-5.8426
	(0.3057)	(0.2648)	(0.3281)	(0.2911)	(0.3410)	(0.2781)	(0.3682)	(0.3326)	(0.3527)	(0.2706)	(0.3561)	(0.2825)
Precision Prod.	-2.4780	-3.4816	-2.6028	-3.7893	-2.1638	-3.3984	-2.4471	-4.3877	-2.1913	-3.3783	-2.6252	-4.1828
	(0.3115)	(0.2392)	(0.3792)	(0.2944)	(0.3627)	(0.2515)	(0.4991)	(0.3555)	(0.3920)	(0.2615)	(0.5437)	(0.3938)
Machine Operators	-1.8768	-3.2023	-2.5290	-4.0819	-1.7220	-2.7726	-2.3968	-4.3855	-1.9295	-2.7414	-2.7162	-4.2185
	(0.2849)	(0.1962)	(0.3514)	(0.3314)	(0.3200)	(0.2158)	(0.3999)	(0.3320)	(0.3395)	(0.2317)	(0.4030)	(0.3175)
Transportation	-0.9500	-3.3467	-1.7402	-4.7734	-0.8023	-2.9559	-1.6190	-4.8135	-0.9963	-2.9622	-1.8614	-4.5848
	(0.2706)	(0.2012)	(0.2906)	(0.2548)	(0.3001)	(0.2201)	(0.3354)	(0.2800)	(0.3115)	(0.2368)	(0.3084)	(0.2591)

Bootstrapped standard errors in parentheses

Table 13: Estimates of the non-pecuniary component of surplus for 2010 normalized by $\hat{\sigma}_\theta$.

	Age 25-34				Age 35-44							
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	-1.9079	-2.4544	0.2732	-0.6640	-1.4431	-2.2892	0.6517	-0.8650	-1.5011	-2.2453	0.3613	-0.8235
	(0.3672)	(0.2953)	(0.5808)	(0.4470)	(0.4782)	(0.3681)	(0.8377)	(0.5926)	(0.5396)	(0.4258)	(0.9689)	(0.6617)
Manag. rel.	-3.2769	-3.2916	0.0574	-0.8362	-3.0347	-3.0052	-0.1335	-1.2510	-3.1665	-2.9152	-0.5748	-1.2192
	(0.3708)	(0.3027)	(0.5551)	(0.4711)	(0.4911)	(0.3742)	(0.7863)	(0.5553)	(0.5141)	(0.4234)	(0.8568)	(0.5866)
Professional	-2.1263	-2.2268	1.1860	0.6070	-1.9606	-2.1962	1.1712	0.2384	-2.1417	-2.2060	0.7347	0.2009
	(0.3789)	(0.3030)	(0.5171)	(0.4358)	(0.4529)	(0.3479)	(0.7184)	(0.5188)	(0.5047)	(0.3794)	(0.7856)	(0.5280)
Technicians	-2.5716	-2.7159	-0.0934	-1.6719	-2.4627	-2.6716	-0.2853	-2.2365	-2.6460	-2.6960	-0.9181	-2.3150
	(0.3996)	(0.3115)	(0.6272)	(0.4677)	(0.4861)	(0.3655)	(0.8217)	(0.5355)	(0.5241)	(0.3790)	(0.8583)	(0.5590)
Sales	-1.3777	-1.6212	-0.0551	-1.2701	-1.4103	-1.8176	-0.1083	-1.7769	-1.5635	-1.8723	-0.3725	-1.6742
	(0.3043)	(0.2186)	(0.5186)	(0.3934)	(0.3908)	(0.2623)	(0.7558)	(0.4882)	(0.4276)	(0.2860)	(0.7713)	(0.4770)
Admin. Support	-1.3532	-1.0081	-0.2406	-0.6378	-1.4873	-0.9769	-0.5589	-1.1116	-1.6985	-0.8576	-0.9581	-0.9613
	(0.2746)	(0.2386)	(0.3649)	(0.3128)	(0.3356)	(0.2718)	(0.4998)	(0.3403)	(0.3607)	(0.2990)	(0.5287)	(0.3456)
Protective Services	-2.2547	-3.8630	-1.1880	-3.3867	-2.2454	-4.0899	-1.1410	-3.8025	-2.4183	-4.0875	-1.5404	-3.9632
	(0.3477)	(0.2698)	(0.4236)	(0.3683)	(0.4408)	(0.3306)	(0.5475)	(0.4647)	(0.4823)	(0.3530)	(0.5790)	(0.4962)
Other Services	-0.7479	-0.6856	-0.6908	-1.2940	-0.7879	-0.7642	-0.9475	-1.8406	-1.0424	-0.8361	-1.3974	-1.8156
	(0.2292)	(0.1970)	(0.2795)	(0.2416)	(0.2409)	(0.1935)	(0.3153)	(0.2364)	(0.2526)	(0.1961)	(0.3031)	(0.2555)
Mechanics	-1.5176	-5.1918	-2.0397	-4.9555	-1.4215	-5.1793	-1.9161	-5.4069	-1.5266	-5.0979	-2.2877	-5.4589
	(0.3271)	(0.2560)	(0.3678)	(0.3100)	(0.3682)	(0.3262)	(0.4270)	(0.3862)	(0.3895)	(0.3200)	(0.4370)	(0.4108)
Construction Traders	-1.3274	-5.2759	-2.0910	-5.6555	-1.0327	-5.1307	-1.8415	-5.7494	-1.3257	-5.2892	-2.2869	-5.9787
	(0.3270)	(0.2238)	(0.3616)	(0.3313)	(0.3557)	(0.3010)	(0.3922)	(0.3525)	(0.3731)	(0.3173)	(0.4986)	(0.3864)
Precision Prod.	-2.2248	-3.0440	-2.2503	-3.1738	-2.0419	-3.2105	-2.2297	-3.8201	-2.0821	-3.2775	-2.4466	-4.0112
	(0.3171)	(0.2409)	(0.4155)	(0.2945)	(0.3635)	(0.2588)	(0.4904)	(0.3347)	(0.3868)	(0.2744)	(0.5002)	(0.3589)
Machine Operators	-1.5969	-2.9030	-1.9425	-3.7031	-1.5709	-2.8259	-2.0848	-4.1862	-1.6926	-2.7118	-2.5224	-3.9683
	(0.2962)	(0.2135)	(0.3407)	(0.3131)	(0.3221)	(0.2188)	(0.3878)	(0.3381)	(0.3378)	(0.2476)	(0.3845)	(0.3234)
Transportation	-0.6268	-2.8054	-1.2604	-3.8164	-0.5094	-2.7379	-1.1669	-4.1167	-0.6112	-2.7234	-1.4280	-4.0025
	(0.2731)	(0.2072)	(0.2958)	(0.2336)	(0.3058)	(0.2280)	(0.3156)	(0.2556)	(0.3153)	(0.2429)	(0.3187)	(0.2701)

Bootstrapped standard errors in parentheses

Table 14: Estimates of the non-pecuniary component of surplus for 2016 normalized by $\hat{\sigma}_\theta$.

	Age 25-34				Age 35-44				Age 45-54			
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	1.0000	0.7464	1.3278	0.9740	1.3304	0.8031	1.9680	1.1339	1.4423	0.8040	2.2515	1.1761
	(0.0000)	(0.0054)	(0.0091)	(0.0082)	(0.0092)	(0.0084)	(0.0139)	(0.0151)	(0.0100)	(0.0066)	(0.0138)	(0.0170)
Manag. rel.	1.0000	0.7673	1.1633	0.9446	1.2266	0.8226	1.5731	1.0029	1.2984	0.8512	1.6266	0.9991
	(0.0000)	(0.0104)	(0.0140)	(0.0117)	(0.0142)	(0.0117)	(0.0281)	(0.0226)	(0.0166)	(0.0138)	(0.0249)	(0.0301)
Professional	1.0000	0.8289	1.1780	1.0250	1.2768	0.8426	1.6418	1.1975	1.3880	0.8515	1.7680	1.2836
	(0.0000)	(0.0105)	(0.0130)	(0.0108)	(0.0137)	(0.0105)	(0.0184)	(0.0134)	(0.0166)	(0.0112)	(0.0198)	(0.0144)
Technicians	1.0000	0.7382	1.0935	0.9271	1.3368	0.7862	1.7160	1.0336	1.4141	0.7449	1.8461	1.0212
	(0.0000)	(0.0076)	(0.0104)	(0.0102)	(0.0148)	(0.0470)	(0.0215)	(0.0417)	(0.0190)	(0.0090)	(0.0373)	(0.0213)
Sales	1.0000	0.6843	1.3060	0.9092	1.2175	0.6812	1.7904	0.8568	1.1947	0.6666	1.8341	0.7956
	(0.0000)	(0.0047)	(0.0106)	(0.0174)	(0.0090)	(0.0058)	(0.0301)	(0.0214)	(0.0113)	(0.0066)	(0.0207)	(0.0206)
Admin. Support	1.0000	0.7246	1.1091	0.8060	1.1945	0.7316	1.4951	0.8330	1.2555	0.7538	1.6459	0.8087
	(0.0000)	(0.0044)	(0.0102)	(0.0072)	(0.0089)	(0.0045)	(0.0147)	(0.0093)	(0.0108)	(0.0050)	(0.0168)	(0.0104)
Protective Services	1.0000	0.7608	1.1673	0.9604	1.1390	0.7628	1.4408	1.1173	1.1425	0.6831	1.4841	0.9428
	(0.0000)	(0.0212)	(0.0294)	(0.0256)	(0.0110)	(0.0417)	(0.0201)	(0.0887)	(0.0128)	(0.0142)	(0.0281)	(0.1405)
Other Services	1.0000	0.7880	1.0952	1.0118	1.0800	0.7640	1.3400	1.1006	1.1002	0.7590	1.4290	0.9769
	(0.0000)	(0.0098)	(0.0188)	(0.0195)	(0.0097)	(0.0077)	(0.0477)	(0.0835)	(0.0112)	(0.0072)	(0.0752)	(0.0405)
Mechanics	1.0000	0.8832	0.9998	0.8912	1.1152	0.8224	1.1905	0.7778	1.1178	0.8600	1.1757	0.5456
	(0.0000)	(0.0249)	(0.0163)	(0.0608)	(0.0067)	(0.0183)	(0.0254)	(0.1044)	(0.0083)	(0.0271)	(0.0339)	(0.0813)
Construction Traders	1.0000	0.7237	0.9358	0.6693	1.1542	0.7195	1.2173	0.5747	1.1668	0.7582	1.4389	0.7476
	(0.0000)	(0.0321)	(0.0132)	(0.0446)	(0.0087)	(0.0294)	(0.0271)	(0.0755)	(0.0072)	(0.0364)	(0.0402)	(0.1283)
Precision Prod.	1.0000	0.6551	1.1594	0.8005	1.1610	0.6659	1.5745	0.7818	1.2183	0.6501	1.7908	0.7051
	(0.0000)	(0.0137)	(0.0121)	(0.0192)	(0.0079)	(0.0165)	(0.0286)	(0.0419)	(0.0109)	(0.0100)	(0.0294)	(0.0435)
Machine Operators	1.0000	0.6511	1.0018	0.6975	1.1158	0.6835	1.1191	0.7082	1.1274	0.6685	1.2246	0.6247
	(0.0000)	(0.0040)	(0.0301)	(0.0176)	(0.0072)	(0.0057)	(0.0244)	(0.0425)	(0.0069)	(0.0047)	(0.0478)	(0.0241)
Transportation	1.0000	0.6945	1.0757	0.8322	1.1124	0.7041	1.1247	0.7754	1.1317	0.7033	1.1537	0.7339
	(0.0000)	(0.0073)	(0.0190)	(0.0458)	(0.0064)	(0.0067)	(0.0213)	(0.0367)	(0.0070)	(0.0071)	(0.0325)	(0.0760)

Bootstrapped standard errors in parentheses

Table 15: Estimates of β_{ijt} for 1980.

	Age 25-34				Age 35-44				Age 45-54			
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	1.0000	0.8344	1.4565	1.1600	1.3641	0.9797	2.0399	1.4305	1.6299	0.9853	2.4371	1.4637
	(0.0000)	(0.0086)	(0.0184)	(0.0118)	(0.0111)	(0.0095)	(0.0177)	(0.0131)	(0.0155)	(0.0104)	(0.0193)	(0.0229)
Manag. rel.	1.0000	0.8825	1.3574	1.1683	1.3755	0.9893	1.7463	1.2961	1.4335	1.0149	1.9859	1.2491
	(0.0000)	(0.0113)	(0.0177)	(0.0141)	(0.0562)	(0.0130)	(0.0222)	(0.0175)	(0.0179)	(0.0134)	(0.0334)	(0.0241)
Professional	1.0000	0.9025	1.2693	1.1083	1.1942	0.9293	1.6731	1.2799	1.3648	0.9090	1.9547	1.3366
	(0.0000)	(0.0140)	(0.0178)	(0.0160)	(0.0176)	(0.0146)	(0.0245)	(0.0183)	(0.0231)	(0.0147)	(0.0312)	(0.0182)
Technicians	1.0000	0.8450	1.2700	1.1018	1.2271	0.9037	1.6272	1.1948	1.4890	0.8895	2.0371	1.2116
	(0.0000)	(0.0080)	(0.0233)	(0.0136)	(0.0119)	(0.0109)	(0.0278)	(0.0146)	(0.0213)	(0.0109)	(0.0365)	(0.0281)
Sales	1.0000	0.7349	1.4969	1.1878	1.2421	0.7782	1.8542	1.2235	1.3374	0.7399	2.1010	1.0655
	(0.0000)	(0.0063)	(0.0152)	(0.0131)	(0.0110)	(0.0082)	(0.0158)	(0.0188)	(0.0137)	(0.0066)	(0.0252)	(0.0249)
Admin. Support	1.0000	0.8258	1.1922	0.9745	1.2319	0.8741	1.5052	1.0334	1.3709	0.8787	1.6922	1.0046
	(0.0000)	(0.0064)	(0.0198)	(0.0110)	(0.0106)	(0.0065)	(0.0140)	(0.0137)	(0.0164)	(0.0070)	(0.0247)	(0.0152)
Protective Services	1.0000	0.9493	1.1437	1.2066	1.1832	0.8638	1.4649	1.2580	1.2190	0.8412	1.6000	1.2533
	(0.0000)	(0.0331)	(0.0189)	(0.0835)	(0.0160)	(0.0133)	(0.0226)	(0.0301)	(0.0178)	(0.0328)	(0.0267)	(0.0615)
Other Services	1.0000	0.7793	1.2052	1.0650	1.1296	0.8198	1.4365	1.2008	1.1531	0.8466	1.6238	1.1990
	(0.0000)	(0.0089)	(0.0247)	(0.0166)	(0.0140)	(0.0094)	(0.0312)	(0.0504)	(0.0139)	(0.0138)	(0.0680)	(0.0487)
Mechanics	1.0000	0.9184	1.1479	1.1008	1.2119	1.1596	1.4110	1.2452	1.2659	1.0268	1.4716	1.1459
	(0.0000)	(0.0173)	(0.0197)	(0.0347)	(0.0097)	(0.0348)	(0.0823)	(0.0463)	(0.0117)	(0.0193)	(0.0589)	(0.1130)
Construction Traders	1.0000	0.8154	0.9895	1.0033	1.1430	0.7926	1.1671	0.8988	1.2599	0.8541	1.4666	1.0667
	(0.0000)	(0.0226)	(0.0216)	(0.0757)	(0.0082)	(0.0373)	(0.0258)	(0.0686)	(0.0150)	(0.0529)	(0.0584)	(0.2296)
Precision Prod.	1.0000	0.6929	1.2836	1.0450	1.2255	0.7480	1.5590	0.9848	1.3268	0.7399	1.7650	0.9153
	(0.0000)	(0.0107)	(0.0508)	(0.0366)	(0.0126)	(0.0117)	(0.0351)	(0.0334)	(0.0149)	(0.0117)	(0.0331)	(0.0598)
Machine Operators	1.0000	0.7109	1.0292	0.8496	1.1894	0.7848	1.3004	0.8872	1.2539	0.8004	1.3534	0.7747
	(0.0000)	(0.0077)	(0.0139)	(0.0252)	(0.0086)	(0.0085)	(0.0349)	(0.0307)	(0.0097)	(0.0083)	(0.0356)	(0.0306)
Transportation	1.0000	0.7999	1.1162	0.9468	1.1695	0.8566	1.2860	1.0332	1.2381	0.8452	1.3027	0.9487
	(0.0000)	(0.0140)	(0.0291)	(0.0260)	(0.0082)	(0.0139)	(0.0216)	(0.0495)	(0.0121)	(0.0197)	(0.0305)	(0.0448)

Bootstrapped standard errors in parentheses

Table 16: Estimates of β_{ijt} for 1990.

	Age 25-34				Age 35-44				Age 45-54			
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	1.0000	0.8590	1.5340	1.2444	1.3680	1.0221	2.2791	1.6886	1.5627	1.1050	2.4794	1.6560
	(0.0000)	(0.0133)	(0.0189)	(0.0159)	(0.0162)	(0.0144)	(0.0279)	(0.0235)	(0.0193)	(0.0147)	(0.0317)	(0.0188)
Manag. rel.	1.0000	0.8984	1.4689	1.2296	1.2482	0.9985	1.9810	1.4645	1.3627	1.0490	1.9193	1.4142
	(0.0000)	(0.0279)	(0.0415)	(0.0311)	(0.0378)	(0.0248)	(0.0534)	(0.0397)	(0.0450)	(0.0265)	(0.0535)	(0.0364)
Professional	1.0000	0.8378	1.2423	1.0836	1.1666	0.9549	1.7358	1.3075	1.2253	0.9848	1.8737	1.3134
	(0.0000)	(0.0138)	(0.0160)	(0.0140)	(0.0170)	(0.0134)	(0.0219)	(0.0181)	(0.0177)	(0.0135)	(0.0244)	(0.0173)
Technicians	1.0000	0.8808	1.5442	1.2557	1.2738	0.9662	1.9146	1.4210	1.3530	0.9985	2.0148	1.3142
	(0.0000)	(0.0143)	(0.0226)	(0.0266)	(0.0196)	(0.0144)	(0.0287)	(0.0239)	(0.0223)	(0.0163)	(0.0392)	(0.0230)
Sales	1.0000	0.7855	1.7078	1.3506	1.2550	0.8539	2.2270	1.6122	1.3118	0.8266	2.0494	1.3678
	(0.0000)	(0.0157)	(0.0284)	(0.0282)	(0.0173)	(0.0148)	(0.0336)	(0.0300)	(0.0225)	(0.0118)	(0.0348)	(0.0390)
Admin. Support	1.0000	0.8976	1.3390	1.1419	1.2163	0.9760	1.7012	1.2619	1.3298	1.0159	1.7629	1.2287
	(0.0000)	(0.0105)	(0.0256)	(0.0153)	(0.0155)	(0.0090)	(0.0249)	(0.0270)	(0.0168)	(0.0099)	(0.0236)	(0.0193)
Protective Services	1.0000	0.8492	1.2078	1.1283	1.2081	0.9623	1.4612	1.3162	1.2037	0.9585	1.5904	1.3177
	(0.0000)	(0.0150)	(0.0344)	(0.0355)	(0.0197)	(0.0181)	(0.0218)	(0.0255)	(0.0166)	(0.0228)	(0.0205)	(0.0316)
Other Services	1.0000	0.8519	1.2755	1.0868	1.1455	0.8708	1.5302	1.2233	1.1704	0.8827	1.4904	1.1383
	(0.0000)	(0.0130)	(0.0357)	(0.0236)	(0.0203)	(0.0118)	(0.0509)	(0.0328)	(0.0165)	(0.0118)	(0.0356)	(0.0285)
Mechanics	1.0000	0.9500	1.1537	1.1245	1.1492	1.0850	1.3894	1.3558	1.2405	1.1560	1.3770	1.3324
	(0.0000)	(0.0408)	(0.0221)	(0.0531)	(0.0114)	(0.0215)	(0.0311)	(0.0641)	(0.0137)	(0.0211)	(0.0290)	(0.0597)
Construction Traders	1.0000	1.0633	1.1088	0.9920	1.1435	0.9964	1.2209	1.0003	1.2058	0.8579	1.2662	0.8656
	(0.0000)	(0.1267)	(0.0452)	(0.0660)	(0.0121)	(0.0549)	(0.0316)	(0.0661)	(0.0104)	(0.0259)	(0.0324)	(0.0810)
Precision Prod.	1.0000	0.7574	1.2190	0.9670	1.1557	0.8173	1.5871	1.1917	1.2671	0.8286	1.6046	1.0658
	(0.0000)	(0.0150)	(0.0338)	(0.0281)	(0.0212)	(0.0166)	(0.0475)	(0.0522)	(0.0206)	(0.0163)	(0.0407)	(0.0424)
Machine Operators	1.0000	0.7713	1.2037	0.9651	1.1736	0.8411	1.3961	1.1424	1.2459	0.8574	1.3783	1.0716
	(0.0000)	(0.0139)	(0.0399)	(0.0244)	(0.0140)	(0.0131)	(0.0336)	(0.0400)	(0.0138)	(0.0123)	(0.0243)	(0.0482)
Transportation	1.0000	0.8235	1.1526	1.1032	1.1383	0.9128	1.3554	1.2404	1.2149	0.9662	1.3940	1.0725
	(0.0000)	(0.0142)	(0.0321)	(0.0758)	(0.0099)	(0.0115)	(0.0455)	(0.0725)	(0.0118)	(0.0197)	(0.0359)	(0.0455)

Bootstrapped standard errors in parentheses

Table 17: Estimates of β_{ijt} for 2000.

	Age 25-34				Age 35-44				Age 45-54			
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	1.0000	0.8923	1.5912	1.3556	1.3682	1.1323	2.4822	1.9160	1.5997	1.2668	2.8439	2.0677
	(0.0000)	(0.0127)	(0.0172)	(0.0148)	(0.0164)	(0.0130)	(0.0256)	(0.0187)	(0.0153)	(0.0144)	(0.0294)	(0.0215)
Manag. rel.	1.0000	0.8801	1.4755	1.2688	1.2473	1.0499	2.1714	1.5927	1.3510	1.1293	2.2711	1.6328
	(0.0000)	(0.0183)	(0.0279)	(0.0212)	(0.0303)	(0.0181)	(0.0413)	(0.0276)	(0.0273)	(0.0202)	(0.0440)	(0.0293)
Professional	1.0000	0.9130	1.3497	1.2096	1.2435	1.0548	1.9777	1.5153	1.3413	1.1292	2.1857	1.5236
	(0.0000)	(0.0114)	(0.0132)	(0.0127)	(0.0151)	(0.0130)	(0.0213)	(0.0152)	(0.0150)	(0.0125)	(0.0205)	(0.0148)
Technicians	1.0000	0.9250	1.4469	1.1992	1.2534	1.0092	1.9010	1.5145	1.3987	1.0625	2.0876	1.5545
	(0.0000)	(0.0168)	(0.0253)	(0.0217)	(0.0232)	(0.0172)	(0.0306)	(0.0277)	(0.0332)	(0.0185)	(0.0356)	(0.0267)
Sales	1.0000	0.7799	1.6942	1.3693	1.2894	0.9182	2.5664	1.7725	1.3641	0.9253	2.5212	1.6225
	(0.0000)	(0.0075)	(0.0236)	(0.0154)	(0.0140)	(0.0112)	(0.0312)	(0.0236)	(0.0140)	(0.0093)	(0.0299)	(0.0266)
Admin. Support	1.0000	0.9419	1.3612	1.2021	1.2473	1.0761	1.9344	1.3892	1.3889	1.1427	2.0221	1.3828
	(0.0000)	(0.0059)	(0.0189)	(0.0103)	(0.0093)	(0.0064)	(0.0279)	(0.0113)	(0.0107)	(0.0064)	(0.0231)	(0.0115)
Protective Services	1.0000	0.8729	1.2643	1.1630	1.2669	1.0288	1.6517	1.4505	1.3116	1.0251	1.7872	1.5308
	(0.0000)	(0.0188)	(0.0168)	(0.0254)	(0.0118)	(0.0153)	(0.0178)	(0.0295)	(0.0140)	(0.0166)	(0.0199)	(0.0322)
Other Services	1.0000	0.9131	1.2613	1.1712	1.1248	0.9208	1.5830	1.2049	1.2380	0.9496	1.6257	1.2153
	(0.0000)	(0.0054)	(0.0171)	(0.0159)	(0.0097)	(0.0064)	(0.0312)	(0.0192)	(0.0094)	(0.0069)	(0.0363)	(0.0187)
Mechanics	1.0000	0.8949	1.1665	1.2181	1.1656	1.1027	1.4271	1.4705	1.2437	1.2083	1.4597	1.3200
	(0.0000)	(0.0222)	(0.0214)	(0.0824)	(0.0095)	(0.0255)	(0.0293)	(0.0629)	(0.0109)	(0.0349)	(0.0242)	(0.0723)
Construction Traders	1.0000	0.9559	1.1181	1.0005	1.1512	1.0183	1.3201	1.2699	1.2264	0.9724	1.3549	1.0932
	(0.0000)	(0.0591)	(0.0288)	(0.0914)	(0.0106)	(0.0490)	(0.0330)	(0.0865)	(0.0108)	(0.0364)	(0.0397)	(0.0883)
Precision Prod.	1.0000	0.8324	1.2683	1.0244	1.2023	0.8848	1.7306	1.3262	1.3315	0.9193	1.9683	1.4324
	(0.0000)	(0.0123)	(0.0280)	(0.0228)	(0.0116)	(0.0132)	(0.0380)	(0.0443)	(0.0135)	(0.0137)	(0.0527)	(0.0662)
Machine Operators	1.0000	0.7405	1.2762	1.2721	1.1571	0.8305	1.5304	1.3896	1.2560	0.8857	1.6389	1.3147
	(0.0000)	(0.0096)	(0.0269)	(0.0441)	(0.0106)	(0.0090)	(0.0422)	(0.0845)	(0.0118)	(0.0086)	(0.0375)	(0.0420)
Transportation	1.0000	0.8050	1.1002	1.0389	1.1442	0.8970	1.3514	1.2161	1.2177	0.9600	1.3287	1.1254
	(0.0000)	(0.0126)	(0.0219)	(0.0518)	(0.0080)	(0.0114)	(0.0377)	(0.0594)	(0.0090)	(0.0090)	(0.0286)	(0.0489)

Bootstrapped standard errors in parentheses

Table 18: Estimates of β_{ijt} for 2010.

	Age 25-34				Age 35-44				Age 45-54			
	Non-college		College		Non-college		College		Non-college		College	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	1.0000	0.8774	1.6526	1.3424	1.3559	1.1120	2.4998	1.9082	1.5652	1.2806	2.9920	2.1235
	(0.0000)	(0.0178)	(0.0325)	(0.0217)	(0.0221)	(0.0186)	(0.0373)	(0.0295)	(0.0260)	(0.0199)	(0.0525)	(0.0343)
Manag. rel.	1.0000	0.8869	1.5580	1.3974	1.3621	1.1130	2.3207	1.7725	1.4704	1.2455	2.6294	1.8614
	(0.0000)	(0.0162)	(0.0302)	(0.0279)	(0.0311)	(0.0274)	(0.0426)	(0.0319)	(0.0297)	(0.0371)	(0.0524)	(0.0357)
Professional	1.0000	0.8700	1.4250	1.2638	1.2411	1.0158	2.0715	1.6116	1.4122	1.0982	2.3532	1.6352
	(0.0000)	(0.0137)	(0.0203)	(0.0182)	(0.0195)	(0.0143)	(0.0286)	(0.0229)	(0.0197)	(0.0167)	(0.0347)	(0.0234)
Technicians	1.0000	0.8405	1.6202	1.2710	1.2525	1.0092	2.2318	1.5687	1.3838	1.0323	2.4252	1.6247
	(0.0000)	(0.0158)	(0.0280)	(0.0240)	(0.0208)	(0.0287)	(0.0384)	(0.0309)	(0.0247)	(0.0198)	(0.0426)	(0.0322)
Sales	1.0000	0.7773	1.7689	1.4110	1.3301	0.9496	2.7224	1.8942	1.4862	1.0263	2.8695	1.8404
	(0.0000)	(0.0146)	(0.0441)	(0.0312)	(0.0270)	(0.0206)	(0.0609)	(0.0484)	(0.0325)	(0.0219)	(0.0592)	(0.0377)
Admin. Support	1.0000	0.9452	1.3859	1.2441	1.2613	1.0946	1.9903	1.4629	1.3937	1.1982	2.1923	1.4803
	(0.0000)	(0.0123)	(0.0177)	(0.0167)	(0.0159)	(0.0123)	(0.0328)	(0.0199)	(0.0166)	(0.0137)	(0.0400)	(0.0202)
Protective Services	1.0000	0.8382	1.2596	1.1457	1.3075	1.0387	1.7075	1.5664	1.4682	1.1217	1.8915	1.6792
	(0.0000)	(0.0177)	(0.0171)	(0.0238)	(0.0171)	(0.0206)	(0.0229)	(0.0424)	(0.0189)	(0.0227)	(0.0255)	(0.0494)
Other Services	1.0000	0.9290	1.2542	1.1425	1.0843	0.9202	1.5011	1.2099	1.1637	0.9377	1.5197	1.3146
	(0.0000)	(0.0162)	(0.0267)	(0.0211)	(0.0132)	(0.0121)	(0.0302)	(0.0252)	(0.0152)	(0.0131)	(0.0372)	(0.0944)
Mechanics	1.0000	0.8518	1.1574	1.0399	1.1652	1.0645	1.4053	1.3919	1.2564	1.0681	1.5206	1.4952
	(0.0000)	(0.0334)	(0.0291)	(0.0430)	(0.0091)	(0.0738)	(0.0341)	(0.0829)	(0.0116)	(0.0322)	(0.0404)	(0.0882)
Construction Traders	1.0000	0.7359	1.1529	1.1047	1.1180	0.9964	1.2826	1.3119	1.2101	1.0229	1.7883	1.3713
	(0.0000)	(0.0318)	(0.0538)	(0.1035)	(0.0163)	(0.0717)	(0.0444)	(0.1238)	(0.0271)	(0.0502)	(0.3659)	(0.1642)
Precision Prod.	1.0000	0.8216	1.3489	1.0238	1.1831	0.9026	1.6746	1.2476	1.2905	0.9411	1.7757	1.3449
	(0.0000)	(0.0124)	(0.0343)	(0.0534)	(0.0146)	(0.0126)	(0.0394)	(0.0392)	(0.0141)	(0.0219)	(0.0578)	(0.0533)
Machine Operators	1.0000	0.7788	1.1918	1.1365	1.1192	0.8028	1.4298	1.3253	1.2035	0.9034	1.4893	1.2668
	(0.0000)	(0.0151)	(0.0271)	(0.0380)	(0.0129)	(0.0117)	(0.0446)	(0.0760)	(0.0153)	(0.0171)	(0.0459)	(0.0536)
Transportation	1.0000	0.8202	1.1226	0.9395	1.1582	0.9158	1.2684	1.1021	1.2222	0.9720	1.3456	1.1713
	(0.0000)	(0.0145)	(0.0258)	(0.0321)	(0.0126)	(0.0158)	(0.0267)	(0.0688)	(0.0121)	(0.0155)	(0.0350)	(0.0431)

Bootstrapped standard errors in parentheses

Table 19: Estimates of β_{ijt} for 2016.

E Elasticity of labor supply

The elasticity of labor supply can be defined at the level of different worker-occupation (i, j) cells. In what follows we overview how we estimate the distributions of different labor supply elasticities. Next we relate these estimates to aggregate labor supply.

E.1 Uncompensated elasticity: intensive margin

To compute the uncompensated elasticity of labor supply we start from the equation that defines the MRS between hours and wages for the intensive labor supply choice:

$$(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma} = \psi_i h_{ijmt}^{-\gamma}.$$

The total differential of the MRS is:

$$\left[-\sigma(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma-1}w_{ijmt}h_{ijmt} + (w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma}\right] dw_{ijmt}+ \\ \left[-\sigma(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma-1}w_{ijmt}^2\right] dh_{ijmt} = -\gamma h_{ijmt}^{-\gamma-1}\psi dh_{ijmt}$$

After rearranging:

$$\frac{dh_{ijmt}}{dw_{ijmt}} = \frac{-\sigma(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma-1}w_{ijmt}h_{ijmt} + (w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma}}{\sigma(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma-1}w_{ijmt}^2 - \gamma h_{ijmt}^{-\gamma-1}\psi}$$

The uncompensated elasticity at the intensive margin is,

$$\epsilon_{ijmt}^{int} = \frac{dh_{ijmt}}{dw_{ijmt}}\frac{w_{ijmt}}{h_{ijmt}}$$

Figure (1a) in the main body of the paper shows the distribution of the intensive margin elasticity of labor supply in the population based on model estimates. The average elasticity is 0.15.

E.2 Uncompensated elasticity: extensive margin

The extensive margin elasticity of labor supply is defined as the ratio of the percentage change in the number of workers choosing a particular occupation and the percentage change in the wage rate paid in that occupation. That is,

$$\epsilon_{ijmt}^{ext} = \frac{d\mu_{ijmt}}{dw_{ijmt}}\frac{w_{ijmt}}{\mu_{ijmt}}.$$

From equation (2) we get:

$$\frac{d\mu_{ijmt}}{dw_{ijmt}} = \mu_{imt}\frac{e^{U_{ijmt}/\sigma_\theta}\frac{1}{\theta}\left[u_c'(c_{ijmt})\left(h_{ijmt}+\frac{dh_{ijmt}}{dw_{ijmt}}w_{ijmt}\right)-u^{i'}(h_{ijmt})\frac{h_{ijmt}}{dw_{ijmt}}\right]}{\left[\sum_{j'=0}^{J}\exp\left(U_{ij'mt}/\sigma_\theta\right)\right]^2}\sum_{j'=0,j'\neq j}^{J}\exp\left(U_{ij'mt}/\sigma_\theta\right)$$

Figure (1b) shows the distribution of extensive margin elasticities in the population, obtained from the model estimates. The average elasticity is between 0.55 and 0.60 across all years.

E.3 Uncompensated elasticity: total response

The total labor supply (hours) within each (i, j, m, t) cell is denoted as $L_{ijmt} = \mu_{ijmt}h_{ijmt}$. We can compute the total elasticity of labor supply to changes in the wage rate within each cell as

$$\epsilon_{ijmt}^{tot} = \frac{L_{ijmt}}{dw_{ijmt}}\frac{w_{ijmt}}{L_{ijmt}} = \left(\frac{d\mu_{ijmt}}{dw_{ijmt}}h_{ijmt} + \frac{dh_{ijmt}}{dw_{ijmt}}\mu_{ijmt}\right)\frac{w_{ijmt}}{L_{ijmt}} \tag{65}$$

Figure 2 shows the distribution of total elasticity estimates in the population. The average is 0.72. Equation (65) allows one to compute the relative contribution of the extensive margin (first term in the summation) and the intensive margin (second term) to total elasticity. On average the extensive margin accounts for about 78% of the total elasticity.

E.4 Aggregate elasticity

Aggregate labor supply is defined as $L_t = \sum_{i,j,m} L_{ijmt}$. We define the aggregate elasticity of labor supply as the percent change in aggregate supply corresponding to a percent change in the average wage assuming that the change in the average wage is obtained by a homogeneous change across the distribution of wages (all wages change by the same amount), namely

$$\epsilon_t^{agg} = \frac{dL_t}{d\bar{w}_t}\frac{\bar{w}_t}{L_t}$$

where $\bar{w}_t$ is the average wage and

$$\frac{dL_t}{d\bar{w}_t} = \sum_{ijm}\left(\frac{L_{ijmt}}{dw_{ijmt}} + \sum_{j'}\frac{L_{ijmt}}{dw_{ij'mt}}\right).$$

The second summation in the latter equation captures the fact that a change in the wage rate in one occupation affects labor supply in all the other occupations. This spill-over effect can be further broken down into different components,

$$\frac{L_{ijmt}}{dw_{ij'mt}} = \frac{d(\mu_{ijmt}h_{ijmt})}{dw_{ij'mt}} = \frac{d\mu_{ijmt}}{dw_{ij'mt}}$$
$$= -\mu_{imt}e^{U_{ijmt}/\sigma_\theta} \frac{e^{U_{ij'mt}/\sigma_\theta} \frac{1}{\sigma_\theta} \left[u'_c(c_{ij'mt}) \left(h_{ij'mt} + \frac{dh_{ij'mt}}{dw_{ij'mt}w_{ij'mt}}\right) - u_h^{i'} \frac{dh_{ij'mt}}{dw_{ij'mt}}\right]}{\left[\sum_{j'=0}^{J} \exp\left(U_{ij'mt}/\sigma_\theta\right)\right]^2}.$$

The aggregate elasticity is between 0.72 and 0.78, depending on the year.

F Projecting latent returns on observables

In this appendix, we investigate the determinants of latent returns by projecting their estimates on observable variables. Given data constraints, we focus on the role of geographic amenities and of gender discrimination.

F.1 Geography and urban amenities

The distribution of job opportunities is not homogeneous across geography. Some occupations are more concentrated in urban, densely populated areas while others are in rural, less-dense areas. Different geographic areas are also characterized by different levels of local amenities. As a consequence, the location of an occupation can also affect its attractiveness.

Arguably, urban areas tend to offer more and better amenities making occupations that are concentrated in urban areas more attractive. To explore this relationship we regress our estimates of latent returns on several measures of the geographic location of occupations.[10] For each occupation we compute: (i) the fraction of workers living in urban areas, (ii) the fraction of workers in a central city, defined as the central city of a metropolitan area, and the fraction of workers in urban areas excluding central cities (this measure is not available for 1990), (iii) average local population (available after the year 2000). We project our estimates of latent returns on these three measures separately for men and women.

Table 20 show the estimation results. Columns 1, 3, and 5 report the results from regressing b_{ijt} on the geographic variables without any other control. For men the coefficients are often not significant and the R2 is always very low (low explanatory power). For women we have always significant coefficients and relatively high R2, which suggests that geography is more important in determining the occupational choices of women than those of men. In all cases, the coefficients are positive: jobs in urban, dense areas are preferred. Adding controls

[10] A caveat is in order. We must proxy job location with workers' residence. Given this data limitation, a more flexible interpretation is that the local-amenity value of an occupation is determined by the local amenities that a worker can access given the geographic constraints imposed by the chosen occupation.

for age and education (columns 2, 5, and 6) makes the estimated coefficient bigger and more significant for both men and women.

F.2 Gender-specific frictions

Besides capturing the value of amenities associated with each occupation, our estimates of latent returns reflect the effects of gender-specific frictions in access to some occupations. Larger frictions for a particular demographic group cause fewer workers from this group to enter an occupation which, in our estimates, translates into a lower estimate of the corresponding b_{ijt}. In this section, we explore this hypothesis by projecting the difference of our estimates in latent returns between women and men on a proxy for gender-specific frictions.

As a proxy for gender frictions we use differences in the occupation-specific unemployment rate between women and men. The underlying assumption is that under competitive markets if there is no gender-specific friction in access to an occupation, the unemployment rate should be the same for men and women.[11] Intuitively, we expect a higher difference in unemployment rates (e.g. women's unemployment relatively larger than men's) to reflect larger gender-specific frictions.

Table 21 shows the results of these projections. In Column 1, we see that the gap in unemployment rates can explain alone 13.6% of the variation in the gender gap of latent returns. The estimated coefficient is sizable in magnitude and of the expected sign (all variables are standardized). An increase of one standard deviation in the unemployment gap corresponds to a fall of 0.37 standard deviations in b_{ijt}. In Column 2 we include year fixed effects, age and education fixed effects to control for differences in preferences of men and women that arise with age (e.g. women of childbearing age might be less keen on working in certain occupations), as well as education fixed effects. Results are not affected by these additional controls.

To account for differences in productivity between men ad women, in Column 3 we include gender gaps in estimated productivity β_{ijt}. This additional control does not affect the results and, interestingly, the estimated coefficient on the productivity gap is negative suggesting that women tend to be relatively more productive in occupations in which they get relatively lower latent returns.

A possible concern is that, in occupations where the unemployment gap is largest, women search for longer and are pickier about work conditions (e.g. flexibility in hours). Several things can be said in this respect: (i) if the concern is about total hours worked, this shouldn't matter as hours are not part of the b_{ijt} as we account for them through a type-specific "disu-

[11] In markets where workers are paid their marginal product, differences in productivity should be reflected in wages and not in unemployment rates. In our model, systematic differences in productivity across demographic groups are captured by the production parameters β_{ijt}. As a robustness check, we control for the β_{ijt} parameters in the regressions estimated below.

	Men					
	(1)	(2)	(3)	(4)	(5)	(6)
	b_{ijt}	b_{ijt}	b_{ijt}	b_{ijt}	b_{ijt}	b_{ijt}
Frac. in urban area	0.660	2.989**				
	(0.728)	(0.963)				
Frac. in central city			4.659	5.095*		
			(2.368)	(2.342)		
Frac. in urban area (non central)			0.424	2.547		
			(1.235)	(1.424)		
Population density					1.276***	1.319***
					(0.335)	(0.309)
Constant	-2.356***	-4.240***	-3.618***	-4.720***	-12.58***	-13.25***
	(0.603)	(0.781)	(0.821)	(0.978)	(2.801)	(2.597)
Observations	390	390	312	312	234	234
R^2	0.002	0.191	0.016	0.186	0.059	0.230
Age and Education FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

	Women					
	(1)	(2)	(3)	(4)	(5)	(6)
	b_{ijt}	b_{ijt}	b_{ijt}	b_{ijt}	b_{ijt}	b_{ijt}
Frac. in urban area	10.57***	18.99***				
	(1.164)	(1.576)				
Frac. in central city			36.58***	44.90***		
			(3.465)	(3.516)		
Frac. in urban area (non central)			4.220*	9.527***		
			(1.808)	(2.138)		
Population density					5.856***	6.017***
					(0.460)	(0.460)
Constant	-12.13***	-19.06***	-17.69***	-22.96***	-52.12***	-53.69***
	(0.965)	(1.279)	(1.202)	(1.468)	(3.839)	(3.863)
Observations	390	390	312	312	234	234
R^2	0.175	0.300	0.330	0.416	0.411	0.433
Age and Education FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Results for job location.

	(1)	(2)	(3)	(4)	(5)
	Gap in b_{ijt}	Gap in b_{ijt}	Gap in b_{ijt}	Gap in b_{ijt}	Gap in b_{ijt}
Gap in unemp. rate	-0.368***	-0.371***	-0.411***	-0.241***	-0.0767***
	(0.0472)	(0.0458)	(0.0421)	(0.0343)	(0.0162)
Gap in productivity			-0.481***	-0.151**	0.0624**
			(0.0546)	(0.0488)	(0.0230)
Non-Routine Cognitive				-0.289**	
				(0.102)	
Routine Cognitive				-0.608***	
				(0.120)	
Routine Manual				0.838***	
				(0.0937)	
Constant	-0.00422	0.102	-0.111	-0.0302	-0.0388
	(0.0471)	(0.126)	(0.118)	(0.121)	(0.0547)
Observations	389	389	389	389	389
R^2	0.136	0.262	0.387	0.644	0.946
Age and Education FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Results for gender frictions.

tility of hours" term; (ii) if the concern is about work schedule flexibility, this might introduce a bias. If women prefer jobs that allow for more flexibility and, conditional on choosing an occupation, they search for longer to find the most flexible employer, the coefficient on the unemployment gap would become more negative (that is, the coefficient would not only reflect frictions but also longer search times due to preferences). For this reason, the coefficient we estimate is a lower bound and, to get an upper bound, we add controls for occupation type (Column 4) or occupation fixed effects (Column 5). These controls should also capture some of the frictions' impacts (averaged over time) and reduce the predictive power of the difference in unemployment. That is indeed what we observe in Columns 4 and 5.

G Analytical derivations of rents and of compensating differentials

Employment rents. Average rents can be computed by solving the following integral (Lamadon et al., 2022):

$$R_{ijmt} = E[R^{\iota}_{ijmt}] \tag{66}$$

$$= \int_0^{w_{ijmt}} (w_{ijmt}h_{ijmt} - wh_i(w, y_{imt})) \frac{1}{\mu_{ijmt}(w_{ijmt})} \frac{\partial \mu_{ijmt}(w)}{\partial w} dw \tag{67}$$

where $\mu_{ijmt}(w_{ijmt})$ is our conditional labor supply function (eq. (3) in the paper). The term

$$f_{ijmt}(w) = \frac{1}{\mu_{ijmt}(w_{ijmt})} \frac{\partial \mu_{ijmt}(w)}{\partial w} \tag{68}$$

is the conditional density function of the distribution of the reservation wage of workers of type i choosing to work in j. In other words $f_{ijmt}(w)$ gives the mass of workers of type i in market j and time t who optimally chose occupation j and who are indifferent between their chosen occupation and their second best option. Notice that the distribution of reservation wages has a mass at $w = 0$ since certain workers would always choose occupation j even if the wage rate was equal to zero.

We do not have a formed close solution for this integral but we can solve it numerically. To do so, we notice that

$$\frac{\partial \mu_{ijmt}(w)}{\partial w} = B_{ijmt}(w)C_{ijmt}(w) \frac{A_{imt}(w) - C_{ijmt}(w)}{A^2_{ijmt}(w)} \mu_{imt} \tag{69}$$

where

$$A_{ijmt}(w) = \exp\left(\frac{u_c(y_{imt})}{\sigma_\theta}\right) + \exp\left(\frac{u_c(wh_i(w, y_{imt}) + y_{imt}) - u^i_h(h_i(w, y_{imt})) + b_{ijt}}{\sigma_\theta}\right) + \tag{70}$$

$$+ \sum_{j' \neq j} \exp\left(\frac{u_c(w_{ij'mt}h_i(w_{ij'mt}) + y_{imt}) - u^i_h(h_i(w_{ij'mt})) + b_{ij'mt}}{\sigma_\theta}\right) \tag{71}$$

$$B_{ijmt}(w) = \frac{1}{\sigma_\theta} \left[(wh_i(w, y_{imt}) + y_{imt})^{-\sigma} - h_i(w, y_{imt})^{-\gamma} \frac{\partial h_i(w, y_{imt})}{\partial w}\right] \tag{72}$$

$$C_{ijmt}(w) = \exp\left(\frac{u_c(wh_i(w, y_{imt}) + y_{imt}) - u^i_h(h_i(w, y_{imt})) + b_{ijt}}{\sigma_\theta}\right) \tag{73}$$

Where the function $h_i(w, y)$ can be solved numerically and the derivative $\frac{\partial h_i(w,y)}{\partial w}$ can be computed using the envelope theorem on the FOC for hours. Dropping the subscripts for clarity we have

$$\begin{aligned}
&(wh+y)^{-\sigma} w = \psi h^{-\gamma} \qquad (74)\\
&\left[(wh+y)^{-\sigma} - \sigma(wh+y)^{-\sigma-1}wh\right] dw + \left[-\sigma(wh+y)^{-\sigma-1}w^2\right] dh = -\gamma\psi h^{-\gamma-1}dh\\
&\frac{\partial h}{\partial w} = \frac{(wh+y)^{-\sigma} - \sigma(wh+y)^{-\sigma-1}wh}{\sigma(wh+y)^{-\sigma-1}w^2 - \gamma\psi h^{-\gamma-1}}
\end{aligned}$$

In the numerical implementation, we approximate the integral with a sum by dividing the support $[0, w_{ijmt}]$ into 999 equal intervals. To approximate the function $h_i(w, y_{imt})$ we solve the first order equation in (9) for 500 equally spaced points over a grid of wages and we use linear interpolation to compute the function for values of the wage rate that are off-grid.

Compensating Differentials. Consider a worker ι who is marginal at the current occupation j and whose next best occupation is j'. If a worker is marginal, i.e. indifferent between the first choice and the second choice, then $\tilde{R}^{\iota}_{ijj'mt} = 0$ and eq. (20) becomes

$$\begin{aligned}
\tilde{U}_i(w_{ijmt} - \tilde{R}^{\iota}_{ijj'mt}, y_{imt}) + b_{ijt} + \theta^{\iota}_j &= \tilde{U}_i(w_{ij'mt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'}\\
b_{ijt} + \theta^{\iota}_j - b_{ij't} - \theta^{\iota}_{j'} &= \tilde{U}_i(w_{ij'mt}, y_{imt}) - \tilde{U}_i(w_{ijmt}, y_{imt})
\end{aligned} \qquad (75)$$

The compensating differential between occupations j and j' is defined as the difference between the utility worker ι would get by choosing its second best occupation if it was paid at the same rate as their preferred occupation, and the utility they get from their actual choice. Notice that if paid at the same rate workers would work the same amount of time, thus total income would be the same).

$$\begin{aligned}
CD^{\iota}_{ijj'mt} &= \tilde{U}_i(w_{ijmt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'} - \tilde{U}_i(w_{ijmt}, y_{imt}) - b_{ijt} - \theta^{\iota}_j\\
&= b_{ij't} + \theta^{\iota}_{j'} - b_{ijt} - \theta^{\iota}_j
\end{aligned} \qquad (76)$$

Substituting eq. (75) into (76), we have that

$$CD^{\iota}_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) - \tilde{U}_i(w_{ij'mt}, y_{imt}) = CD_{ijj'mt} \qquad (77)$$

As discussed in the body of this paper, we define the dollar value of compensating differentials as

$$u_c(w_{ijmt}h_{ijmt} + y_{imt} - CD^{\$}_{ijj'mt}) - u_h(h_{ijmt}) = u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}) \qquad (78)$$

where $h_{ij'mt} = h_i(w_{ijmt})$. The latter equation has a closed form solution given by

$$CD^{\$}_{ijj'mt} = w_{ijmt}h_{ijmt} + y_{imt} - u_c^{-1}\left(u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}) + u_h(h_{ijmt})\right) \qquad (79)$$

H Alternative measures of compensating differentials

In this appendix, we relate our estimates of compensating differentials to the covariation between wage and latent components of compensation. The baseline definition of compensating differentials focuses on the trade-offs faced by workers who are marginal in the occupation choice. This measure fully accounts for unobserved idiosyncratic components of each marginal worker's valuation. The applied literature often gauges the magnitude of compensating differentials from estimates of the covariance between wage and non-wage components of job values (Lehmann, 2022). While informative these measures are based on a sample that includes both marginal and inframarginal workers and do not include the idiosyncratic components of the workers' valuations. Through the lens of our model, the closest quantity to these measures is the covariation between the value of observed wages and latent components of overall returns; that is,

$$cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt}).$$

We compute this covariance separately for each year and demographic group and we show the results in Panel A of Table 22. We find a positive and increasing covariance for college graduates, with the growth being particularly pronounced among men. For non-college workers we find negative covariations and a trend towards lower covariances among men. The positive and increasing covariances for college men are in line with the findings of Lehmann (2022), which restricts attention to male workers who experience job-to-job transitions. Transitions that bypass unemployment tend to over-sample educated men, which is consistent with our findings.

To extend our analysis, in Panel B of Table 22 we report similar measures of covariation after including the average idiosyncratic workers' valuations within each cell. The average idiosyncratic job values $\bar{\theta}_{ijmt}$ are obtained by simulating the model. Specifically, we compute the following covariances

$$cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt} + \bar{\theta}_{ijmt}).$$

Results are sensitive to accounting for the idiosyncratic component of the non-wage values. For all demographic groups, we find negative and diminishing covariances, which suggests the presence of positive and increasing compensating differentials. This finding is in line with results based on our baseline definition of compensating differentials, as discussed in the main body of the paper.

Panel A: $cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt})$

Year	College Men	College Women	Non-College Men	Non-College Women
1980	0.076	0.102	-0.031	-0.038
1990	0.090	0.085	-0.045	-0.035
2000	0.139	0.140	-0.058	-0.039
2010	0.129	0.130	-0.078	-0.039
2018	0.119	0.113	-0.074	-0.036

Panel B: $cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt} + \bar{\theta}_{ijmt})$

Year	College Men	College Women	Non-College Men	Non-College Women
1980	-0.046	-0.022	-0.011	-0.005
1990	-0.065	-0.016	-0.016	-0.007
2000	-0.076	-0.033	-0.016	-0.007
2010	-0.091	-0.041	-0.017	-0.010
2018	-0.115	-0.045	-0.017	-0.011

Table 22: Covariances between observable and latent components of employment surplus, by year and demographic group. All covariances are normalized by the variance of idiosyncratic values, σ_θ^2.

I Occupational mobility and compensating differentials

To the extent that workers can more freely trade off the observable and latent returns within a job bundle, the relative value of the latent component should be better reflected in wage gaps between jobs with higher worker mobility. This is because low occupational mobility restricts these implicit transactions, possibly preventing some workers from moving to job bundles that better suit their preferences.

Pairwise compensating differentials and job flows. We examine the relationship between job mobility and compensating differentials by using workers' gross flows across occupations as a proxy for the cost of occupational mobility (see Cortes and Gallipoli, 2018). We use retrospective data to measure annual occupational mobility from the March CPS (vom Lehn et al., 2022) and obtain weighted flow data from the CPS. We match each model year with the corresponding year in the CPS and the two adjacent years, to increase sample sizes.

Letting $\xi_{imt,j\to j'}$ be the mass of people who flow from occupation j to j', the baseline measure of gross flows between two occupations is

$$\Xi_{ijj'mt} = \frac{\xi_{imt,j\to j'} + \xi_{imt,j'\to j}}{\mu_{ijmt} + \mu_{ij'mt}} \tag{80}$$

Next, we project changes in compensating differentials between two occupations on changes in the gross flow of workers between the same occupations,

$$\Delta \log(CD_{ijj'mt}) = \beta_0 + \beta_1 \Delta \log(\Xi_{ijj'mt}) + \epsilon_{ijj'mt} \tag{81}$$

If more intense job flows facilitate the emergence of systematic compensating differentials, the estimated value of β_1 should be positive. Table 23 illustrates our findings. Panel A (top panel) reports estimates including all the years in the sample. Panel B (bottom panel) reports results for the three decades after 2000.

Column (1) shows result for the full sample where all job pairs are considered, including rarely observed job flows. Column (2) includes only (j, j') occupation pairs in which both occupations belong to the same occupation category. These are the occupation pairs where most of the worker flows occur. The β_1 coefficient are precisely estimated in the sub-sample featuring common transitions, which suggests that considering all transitions adds more noise than signal. Estimated elasticities are larger for the later years 2000-2018 (as opposed to the full sample 1980-2018); on average, an increment of 1% in the gross flow of workers within an occupation pair is associated with an increase of 8.7% (19.7% after the year 2000) in the compensating differential between those occupations. Columns (3) to (6) lend similar evidence but they consider each broad occupation category separately. The stronger significance for non-routine cognitive (NRC) and routine-manual (RM) jobs is likely due to the much larger sample sizes in those occupation categories. Columns (7) and (8) split the sample of Column (2) by gender and show that the effects are larger and more precisely identified for men. This latter observation is consistent with the finding that compensating differentials tend to be lower among women (see Figure 11).

J Occupation-specific wage dispersion and rents

Some occupations may carry higher wage risk than others. For example, if there are differences in the performance-based component of wages across jobs, one might observe differences in the dispersion of ex-post pay. In this section, we examine whether workers in riskier occupations are compensated for higher wage uncertainty. To answer this question we compute the standard deviation of wage rates within each $ijmt$-cell and use it as a reference measure of wage risk for each $ijmt$ worker-occupation-market triplet. Then, within a $ijmt$ cell, we compute four distinct outcomes (that is, four measures of occupation returns) and separately project each return measure on the corresponding standard deviation of wages. The four measures of returns are: (i) rents; (ii) total surplus; (iii) observable current wage in a job; and (iv) occupation latent value. One should note that the latter two measures are the fundamental components that add up to total surplus. To facilitate comparisons, we normalize total surplus and its components by the standard deviation of total surplus so that the estimated coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Within-group	NRC	RC	NRM	RM	Men	Women
	$\Delta\log(CD_{ijj'mt})$							
Panel A: 1980-2018								
$\Delta\log(\Xi_{ijj'mt})$	-0.348	8.729***	14.05***	-17.69	-8.689	13.60***	12.79***	0.602
	(1.718)	(3.375)	(5.272)	(11.73)	(16.37)	(4.730)	(4.480)	(4.891)
Observations	5647	1536	701	174	52	609	968	568
Panel B: 2000-2018								
$\Delta\log(\Xi_{ijj'mt})$	4.038*	19.68***	27.25***	-0.382	-12.43	19.47**	24.11***	10.36*
	(2.195)	(4.776)	(6.885)	(12.73)	(20.88)	(8.192)	(6.692)	(5.836)
Observations	2902	800	382	90	26	302	495	305

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Projection of compensating differentials on job flows: Estimates of Equation (81). The unit of observation is the occupation pair. Column (1) refers to a sample where all job pairs are considered, including rarely observed job flows. Column (2) includes only (j, j') occupation pairs in which both occupations belong to the same broad occupation category. These are the occupation pairs where most of the worker flows occur. Columns (3) to (6) consider each broad occupation category separately. Columns (7) and (8) split the sample in column (2) by gender.

convey information about the way total surplus components change with occupation-level wage risk.

Table 24 reports the main findings of this exercise. For every dependent variable we first run a regression with no controls; then we run a regression including demographic controls (education, age, and gender fixed effects), occupation fixed effects, and year fixed effects. The results indicate that higher wage risk is associated with higher returns. Estimates in Columns 1 and 2 are semi-elasticities. Column 2, in particular, shows that a 10-dollar increase in the standard deviation of wages is associated with a 4.5% increase in rents. Moreover, Column 4 shows that the same increase in risk is associated with an increase of about 0.3 standard deviations in total match surplus. Comparing this estimate to those in Columns 6 and 8 suggests that both the pecuniary and latent components of surplus contribute to the positive risk-return relationship. In addition, they highlight that latent values are proportionally larger, as a share of total surplus, in occupations characterized by higher wage risk.

K Robustness: market variation in latent returns

In what follows we perform a robustness check by estimating an alternative version of the model where latent returns can vary across markets. To identify this specification we must impose additional structure on latent returns

$$b_{ijmt} = b_{ijt} + b_{jm},$$

This implies that we cast latent returns as the sum of a demographic-and-occupation component that can change over time (like in the baseline model) plus an additional term that varies across market-occupation pairs. The latter reflects differences in the latent value of an occupation that may depend on region-specific features such as climate, population density or cultural and social aspects.

Table 25 shows estimates of the market-occupation component b_{jm}. Identification requires that all values must be estimated relative to a reference region-occupation. The table shows that many coefficients are statistically significant. However, their values are not economically significant as the magnitudes of the b_{jm} terms are much smaller than the b_{ijt} components. Through a variance decomposition, we show that the b_{jm} contribution is less than one percent of the total variation across the overall latent returns b_{ijmt}. We have verified that such magnitudes are not sufficient to affect the subsequent estimation and results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Rents	Log Rents	Total surplus	Total surplus	Pecuniary Value	Pecuniary Value	Latent Value	Latent Value
Wage st.d.	0.0148***	0.00429***	0.0520***	0.0165***	0.00608***	0.00323***	0.0254***	0.00676***
	(0.000487)	(0.000248)	(0.00236)	(0.00181)	(0.000166)	(0.000111)	(0.00137)	(0.00108)
Observations	3120	3120	3120	3120	3120	3120	3120	3120
R^2	0.228	0.866	0.135	0.658	0.302	0.792	0.099	0.629
Demographic FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: Projection of rents, surplus, and components of surplus on measures of wage risk (standard deviations of wages). For each dependent variables we report the simple projection and a projection with controls for demographics, occupation, and time. Columns (1) and (2) report the results for log-rents. The coefficients can be interpreted as semi-elasticities. Columns (3) and (4) show the results for total surplus. The dependent variable is standardized. Columns (5) and (6) show the results for the pecuniary component of surplus. To ensure comparability with the coefficients of the previous two columns, the dependent variable has been normalized by the standard deviation of total surplus. The same normalization is applied to the latent value of surplus in columns (7) and (8).

	Market (Census Region)			
Occupation	Northeast	Midwest	South	West
Exec., Admin., Manag.	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Manag. rel.	0.0000	0.0889***	-0.0142	-0.0124
	(0.0000)	(0.0185)	(0.0315)	(0.0560)
Professional	0.0000	0.0858***	-0.0325**	-0.0925***
	(0.0000)	(0.0038)	(0.0144)	(0.0260)
Technicians	0.0000	0.1078***	0.0586***	0.0205***
	(0.0000)	(0.0096)	(0.0059)	(0.0066)
Sales	0.0000	0.1494***	0.0495	-0.0015
	(0.0000)	(0.0227)	(0.0406)	(0.0521)
Admin. Support	0.0000	0.0746***	-0.0558***	-0.0999***
	(0.0000)	(0.0043)	(0.0084)	(0.0304)
Protective Services	0.0000	-0.0996***	-0.0303	-0.1199***
	(0.0000)	(0.0374)	(0.0624)	(0.0415)
Other Services	0.0000	0.0084	-0.0755***	0.0454**
	(0.0000)	(0.0069)	(0.0060)	(0.0182)
Mechanics	0.0000	0.1751***	0.2289***	0.1179***
	(0.0000)	(0.0303)	(0.0230)	(0.0307)
Construction Traders	0.0000	0.0881***	0.2391***	0.1435***
	(0.0000)	(0.0269)	(0.0296)	(0.0247)
Precision Prod.	0.0000	0.3965***	0.0535***	-0.0976***
	(0.0000)	(0.0203)	(0.0108)	(0.0203)
Machine Operators	0.0000	0.4452***	0.0693***	-0.0775***
	(0.0000)	(0.0284)	(0.0107)	(0.0138)
Transportation	0.0000	0.2612***	0.0897***	-0.0200
	(0.0000)	(0.0278)	(0.0126)	(0.0144)

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Estimates of the market and occupation specific component of non-pecuniary returns.

L Additional tables and graphs

L.1 Counterfactual exercises: additional plots

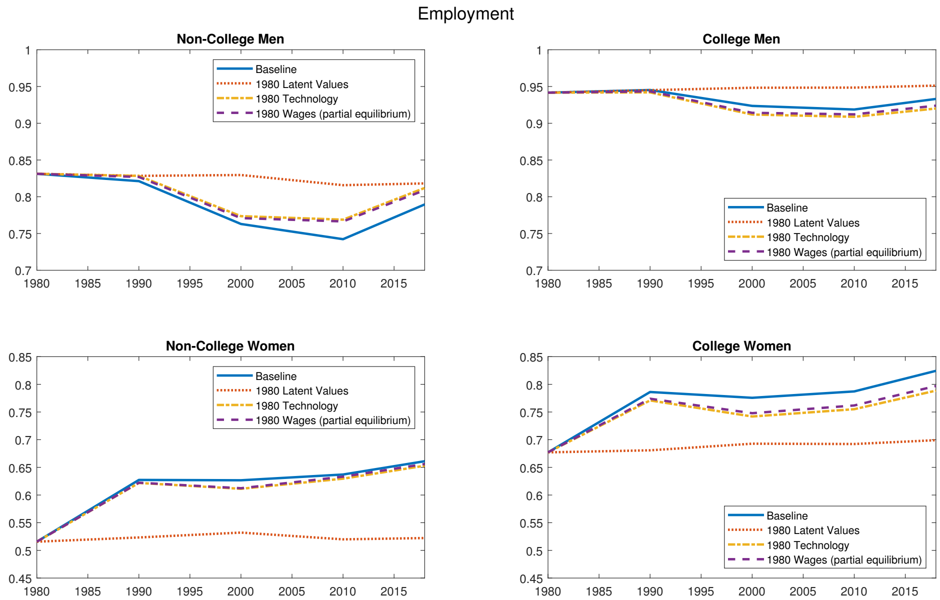

Figure 16: Evolution of the labor force participation of demographic groups in the baseline model (which replicates the data) and in the counterfactual scenarios.

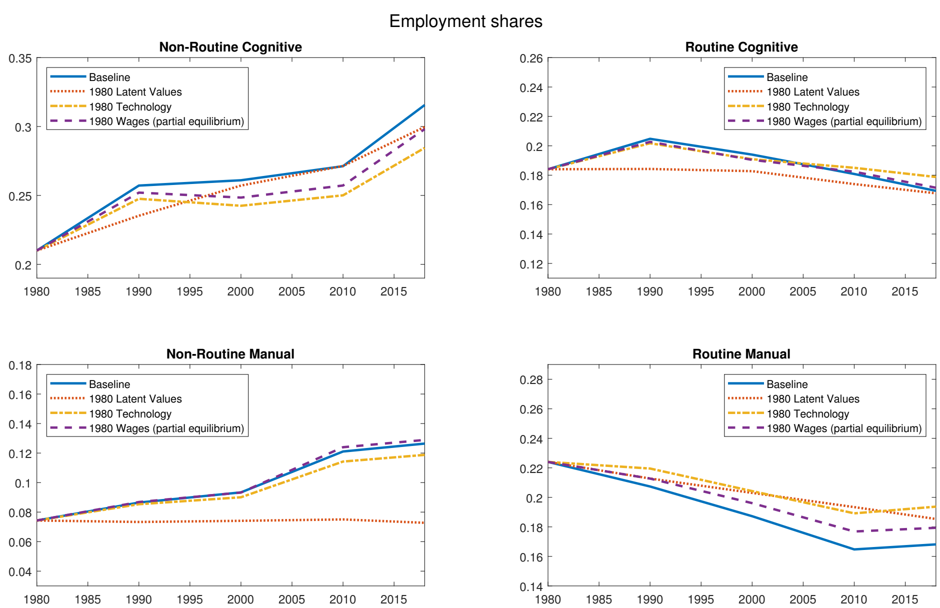

Figure 17: Evolution of the shares of the population employed in four major occupation groups in the baseline model (which replicates the data) and in the counterfactual scenarios.

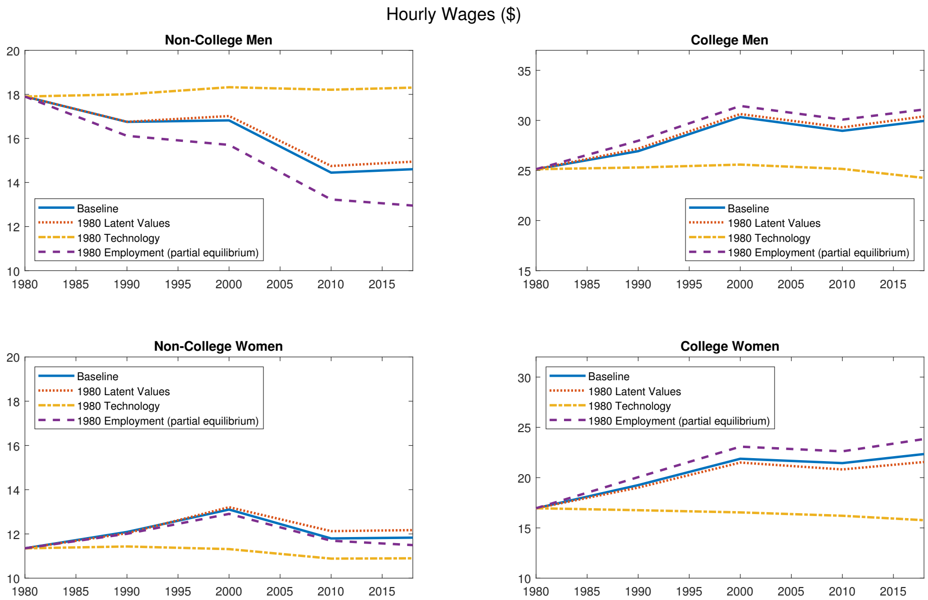

Figure 18: Evolution of the average hourly wage received by the different demographic groups in the baseline model (which replicates the data) and in the counterfactual scenarios.

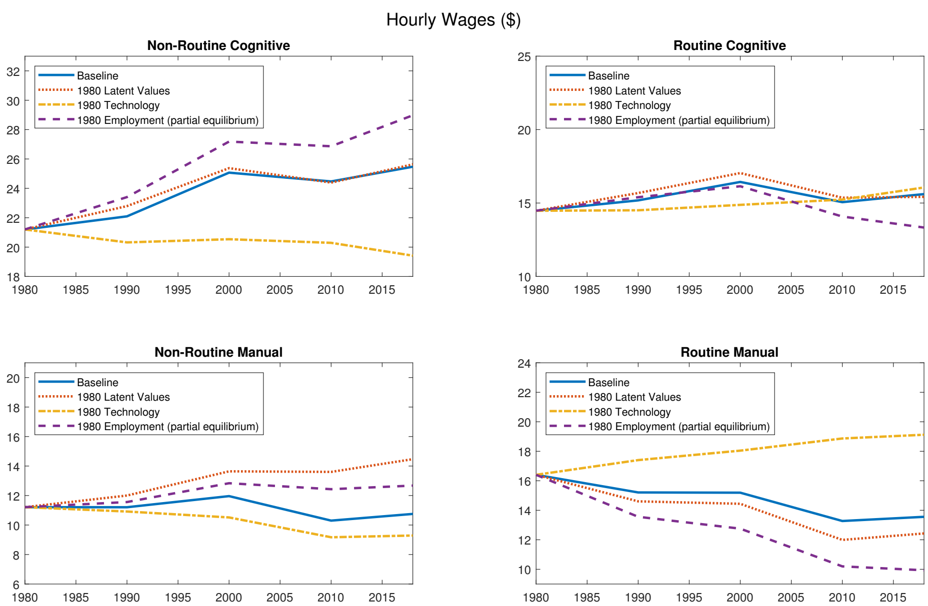

Figure 19: Evolution of the average hourly wage paid to the four major occupational groups in the baseline model (which replicates the data) and in the counterfactual scenarios.

L.2 Compensating differentials: additional plots

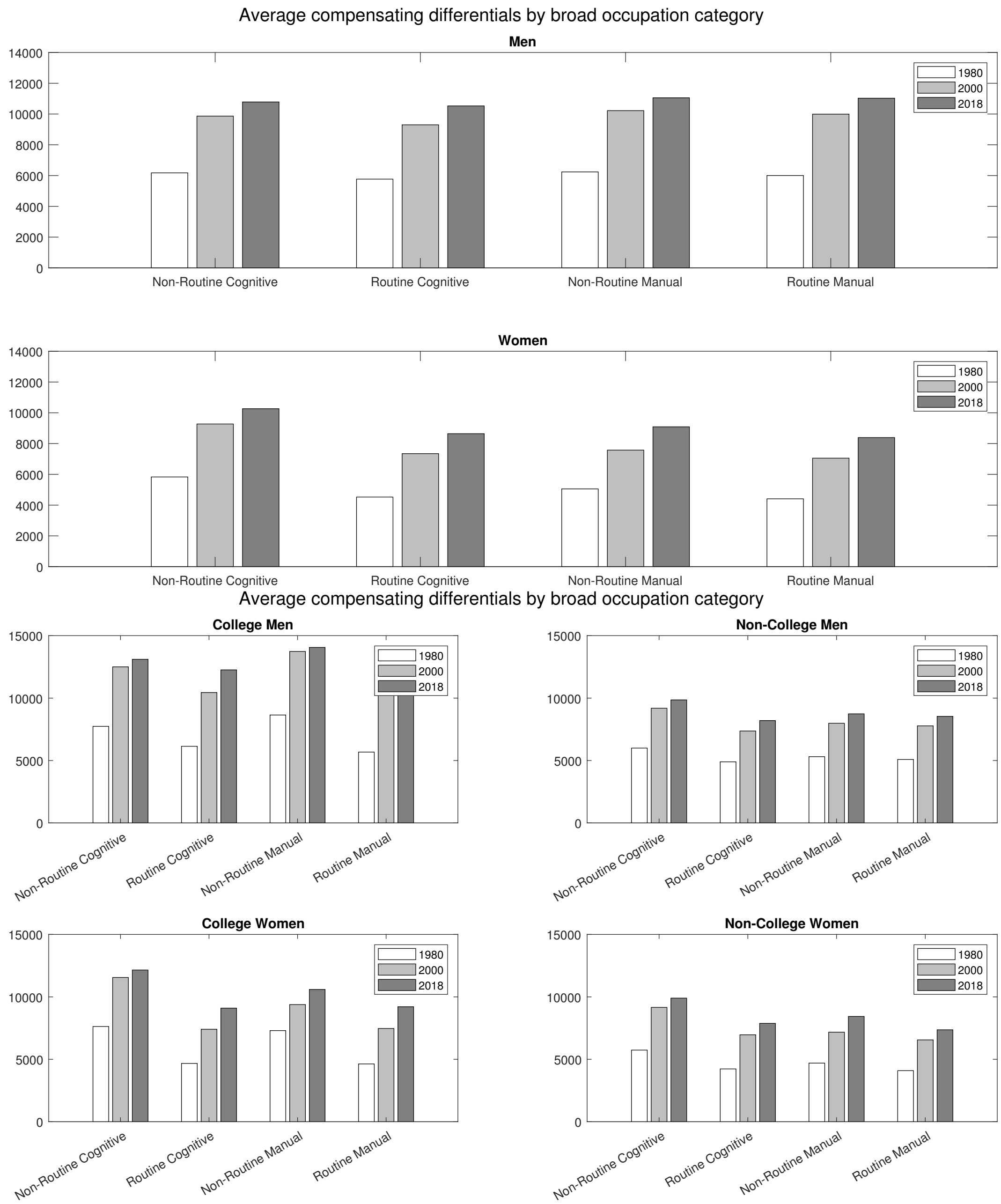

Figure 20: Averages of absolute compensating differentials by worker and occupation category, 1980-2018. All values are in year 2000 dollars.