The Distribution of Labor Market Surplus

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Abstract

We characterize the distribution of worker-job surplus in the U.S. economy for different decades, and document extensive heterogeneity in the pecuniary and non-pecuniary rewards that workers derive from similar jobs. This heterogeneity is associated with compensating differentials, especially in non-college occupations and among women in college-level jobs. Estimates of worker-job match values are employed to recover technology parameters such as (i) the productivity of different occupation-demographic matches, and (ii) the substitutability of broad occupation groups in production. We use the latter to quantify the extent to which technological progress, as opposed to shifts in the heterogeneous valuations of jobs, accounts for structural change in the labor market. We find that, while employment patterns are the by-product of changes in both technology and preferences, the evolution of wages can almost entirely be explained by technological progress.

JEL Codes: J62, J24.

Keywords: occupations; workers; returns; heterogeneity, technology, equilibrium.

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1 Introduction

The structure of employment and wages has changed significantly over recent decades, and considerable labor market shifts have been documented in the literature. These include the increase in the employment and wages of skilled workers (Katz and Murphy, 1992; Katz and Autor, 1999; Beaudry et al., 2016; Valletta, 2017), the decline of middle-paying occupations (Acemoglu and Autor, 2011), the emergence of IT-intensive occupations (Gallipoli and Makridis, 2018), the growing presence of women in high paying occupations (Cortes et al., 2018), the growing reward to soft and non-cognitive skills in the labor market (Deming, 2017), the shrinking labor supply of young men (Aguiar et al., 2017) and the convergence of the occupational distributions of different demographic groups (Hsieh et al., 2019).

Observed changes in occupational sorting and job characteristics suggest that worker surplus from observationally identical matches (i.e. workers with certain characteristics matching to specific occupations) may have also changed.[1] While we recognize that the distribution of worker-job match values has experienced lasting shifts, we know less about the nature of these changes. Are they explained by productivity dynamics or by adjustments in the non-pecuniary value of different occupations? How do these different forces offset each other in equilibrium? This study characterizes the distribution of occupation-specific returns for different demographic groups in the US labor market, breaking them down into pecuniary and non-pecuniary components that have evolved over time. The latter estimates are used to quantify the extent to which different aspects of technological progress, as opposed to shifts in the non-pecuniary value of jobs, account for the rapidly changing structure of employment and wages.

We develop a model that delivers a simple measure of the heterogeneous values that different workers associate with identical occupations. The procedure is general enough to decompose each worker's surplus into different components, and further relate them to observable characteristics of both job and worker. We examine equilibrium outcomes in a competitive labor market with a heterogeneous supply side and a continuum of firms demanding labor in a set of heterogeneous occupations. Sorting is driven by the size of the match-specific surplus, which includes a systematic component (common to all matches of a particular worker-job type) and an individual random component. The systematic surplus comprises pecuniary and non-pecuniary returns, both of which vary over time. The model delivers a tractable empirical counterpart that can be estimated using observations from repeated cross-sections of the distribution of earnings, hours worked and employment across jobs. The selection of individual workers into specific occupations hinges on match-quality draws, as in classical models of random job selection described in Willis (1986). Unlike those models, systematic match

[1] For example, beyond wage changes, different occupations may experience changes in their time demands (Erosa et al., 2017; Cubas et al., 2019) and, therefore, their value to different types of workers that are not captured by standard pecuniary measures.

quality explicitly reflects measurable non-pecuniary components that drive total surplus from employment.

Our approach imposes minimal assumptions on the mechanics driving equilibrium outcomes, apart from the low-level requirements of a standard Roy model in which relative surplus comparisons drive sorting. Moreover, the approach is flexible enough to allow for the identification of changes in the distributions of heterogeneous rewards (pecuniary and non-pecuniary). Hence, the model can be used to characterize if, and how, these returns have changed for specific demographic subsets of the working-age population. That is, one can transparently draw inference about which types of workers have been positively (or negatively) impacted by the changes in the occupational structure of the labor market over recent decades, and the extent to which these impacts occur through changes in pecuniary or non-pecuniary returns.

Estimates reveal that large and persistent shifts have occurred in the distribution of job-specific worker surplus since the 1980s. Some of these changes are surprising, insofar they suggest that gender-specific surplus may be different from what wages alone may convey. Our findings are consistent with the view that the impact of changes in employment composition (due to technological change and globalization) has been very uneven across demographic groups (e.g. Autor et al., 2014; Cortes et al., 2017) and with the observation that certain groups may have suffered while others thrived.

In the second part of the paper, we nest our estimates of the distribution of worker surplus within a simple production structure and we draw inference about relative productivities and substitutability of heterogeneous worker-job inputs. To estimate production technology parameters we employ variation in our match-specific surplus estimates to instrument for changes in labor factors. In this way, we recover production technology parameters over different time intervals and, then, use them to perform counterfactual exercises that quantify the relative contribution of demand and supply shifts to the distribution of match-specific worker surplus and employment.

2 A Labor Market with Heterogeneous Workers and Jobs

We posit a competitive model of the labor market with two-sided heterogeneity (workers and jobs). Equilibrium sorting reflects the distribution of relative returns, both pecuniary and non-pecuniary.

Environment. There are T time periods indexed by t and $M > 1$ separate labor markets indexed by m. Each market each year is an independent labor market with its own labor supply and demand.

Workers. In each market m at time t, there is a continuum of workers, indexed by ι, of size S_{mt}. Each worker belongs to one of I demographic groups (types) indexed by i. Let μ_{imt} be the exogenous mass of workers of type i, such that $\sum_i \mu_{imt} = S_{mt}$. Workers choose their occupation $j = 1, ..., J$. They can also choose not to work, in which case $j = 0$.

The utility that the workers obtain from each possible choice $j = 0, ..., J$ is the sum of a systematic component that depends on their type, their occupational choice, and the labor market they belong to, U_{ijmt}, and an individual unobserved component θ_j^ι which captures the idiosyncratic preferences for different occupations.

Each worker supplies optimally supplies h_{ijmt} hours of labor paid at the hourly rate $\tilde{w}_{ijmt}$. Workers are hand-to-mouth and consume their income which is given by the sum of their labor income (if any) and their type-specific non-labor income $\tilde{y}_{imt}$ (exogenous). Let P_{mt} be the price of the consumption good, and $w_{ijmt} = \tilde{w}_{ijmt}/P_{mt}$ and $y_{ijmt} = \tilde{y}_{ijmt}/P_{mt}$ be real wage and real non-labor income respectively. The total systematic utility from working in occupation j is given by

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

where $u_c\left(\cdot\right)$ is a standard utility function, $u_h^i\left(\cdot\right)$ captures the disutility from working, which we allow to differ across types, and b_{ijt} captures non-pecuniary benefits accruing to a type i worker working in occupation j during period t. Conditioning on the specific match, the systematic component of utility from working varies across markets, and within each time period, only by the pecuniary payments (wage and non-labor income), while the non-pecuniary component of utility can change freely across occupations and demographic groups, and over time.

The systematic utility from not working ($j = 0$) is given by $U_{i0t}\left(0, y_{imt}\right) = u_c\left(y_{imt}\right) - u_h\left(0\right)$. Hence, there is no equivalent non-pecuniary systematic benefit from not working, namely there is no b_{i0t}. Such an element could not be separately identified from the other b_{ijt}'s. Not including it is equivalent to normalizing $b_{i0t} = 0$ for all t and all i, without loss of generality. Given this normalization, the value of non-employment does not explicitly account for the value of home production. This implies that the value of home production enters as a negative non-pecuniary benefit through b_{ijt}. That is, the additively separable b_{ijt} term subsumes, among other things, the value of home production. It is therefore possible to relate variation in estimated b_{ijt} with changes in home productivity.

In addition to the systematic component of utility, workers choosing occupation j receive an individual unobserved component θ_j^ι which captures the idiosyncratic preferences for different occupations. We assume that θ_j^ι is randomly distributed as a type I extreme value with zero location parameter and scale parameter σ_θ. Notice that the distribution of the preference shock is independent of time and market.

Given a sequence of realized preference shocks, each worker solves

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

By the properties of the extreme value distribution, the fraction of workers supplying labor to occupation j (including choosing not to work $j = 0$) is then given by

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

Firms. We assume that in each market and time period, a final good producer uses a continuum of size 1 of differentiated intermediate goods to produce the consumption good. Each one of these goods is produced by an intermediate firm according to one of J technologies, each using a different occupation as input (intermediates can be though of as occupational goods).[2] Since each intermediate firm produces a different good, they have some market power in the intermediate goods' market. Labor markets are competitive.

Let $\{V_{jt}\}_{j=1,...,J}$ describe a partition of the continuum of intermediate firms such that for each given couple of firms $v, v' \in V_{jt}$, they produce with the same production function (using the same input) up to an idiosyncratic TFP shock. The final good producer solves

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

where

$$P_{mt} = \left(\int_v p_{jmtv}^{\frac{-\rho}{1-\rho}} dv \right)^{\frac{-(1-\rho)}{\rho}} \tag{5}$$

The first order condition associated with this problem gives

$$p_{jmtv} = \left[\frac{\lambda_{jmtv}}{Y_{mt}} \right]^{-(1-\rho)} P_{mt} \tag{6}$$

The profit maximization problem of producer $v \in V_{jt}$ is

[2] In appendix C we discuss an extension of the model with capital.

$$
\begin{aligned}
\max_{p_{jmtv},\lambda_{jmtv},L_{ijmtv}} \quad & p_{jmtv}\lambda_{jmtv} - \sum_i \tilde{w}_{ijmt} L_{ijmtv} \\
\text{s.t.} \quad & \lambda_{jmtv} = z_{jmtv} \sum_i \beta_{ij} L_{ijmtv} \\
& p_{jmtv} = \left[\frac{\lambda_{jmtv}}{Y_{mt}}\right]^{-(1-\rho)} P_{mt}
\end{aligned} \tag{7}
$$

where z_{jtv} is an idiosyncratic shock drawn from an occupation specific distribution ($z_{jtv} \sim F_{jt}(v)$). The solution to the maximization problem delivers the following expression for profits

$$
\pi_{jmtv} = \frac{1-\rho}{\rho} \sum_i \tilde{w}_{ijmt} L_{ijmtv} \tag{8}
$$

Equilibrium. A competitive equilibrium in this economy consists of a sequence of prices ($\tilde{w}_{ijmt}$, p_{ijmtv}, P_{mt}, occupational choices (extensive margin labor supply) μ_{ijmt}, labor supply choices h_{ijmt} (intensive margin) and demanded labor L_{ijmtv} such that:

1. given the wages and the realization of the preference shocks each worker solves the maximization problems described in equations (1) and (2);

2. the final good producer and the intermediate firms behave optimally solving (4) and (7) respectively;

3. all labor markets clear, that is

$$
L_{ijmt} = \mu_{ijmt} h_{ijmt} \tag{9}
$$

for all i, j, m and t, where $L_{ijmt} = \sum_{v \in V_{jt}} L_{ijmtv}$

Aggregation In appendix B, we show that the aggregate production function can be expressed as

$$
Y_{mt} = A_t \left[\sum_j \alpha_{jt} \left(\sum_i \beta_{ijt} L_{ijmt} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{10}
$$

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 derive the following aggregate wage function

$$
w_{ijmt} = \rho A_t^{\rho} \alpha_{jt} \beta_{ijt} \left(\frac{Y_{mt}}{\sum_{i'} \beta_{i'jt} L_{i'jmt}} \right)^{(1-\rho)}. \tag{11}
$$

3 Data and Estimation

Our empirical implementation requires information about the cross-sectional distribution of labor supply and earnings across different demographic and occupation groups. Below we overview our data and estimation approach, after a very brief discussion of how utility and production parameters are identified. A more detailed discussion of identification can be found in Appendix A.1.

Identification of utility parameters. From equation (3), we obtain an expression linking relative employment in each occupation to the pecuniary surplus in that job. The latter is rescaled by the parameter σ_θ that captures the dispersion of idiosyncratic preferences for different occupations.

$$\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right) = \frac{U_{ijt}(w_{ijmt}, y_{imt}) - U_{i0t}(0, y_{imt})}{\sigma_\theta} \tag{12}$$

Equation (12) suggests that, under parametric assumptions about the pecuniary utility function, one may use cross sectional variation in employment, hours worked and wages for different job-worker matches to recover estimates of: (i) non-pecuniary returns b_{ijt} for all occupations j, workers i and time periods t; and (ii) the scaling parameter σ_θ, which measures the cross-sectional dispersion of idiosyncratic preferences for specific occupations.

Identification of technology parameters. Equation (11) delivers an expression linking observable wages to technology parameters. Taking the ratio of wage returns within demographic groups across occupations, and using market clearing conditions, delivers the expression

$$\frac{w_{ijmt}}{w_{ij'mt}} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\widetilde{L}_{j'mt}}{\widetilde{L}_{jmt}}\right)^{1-\rho} \tag{13}$$

where $\widetilde{L}_{jmt} = \sum_{i'} \beta_{i'jt} L_{i'jmt}$. As shown in Appendix A.1, worker-specific share parameters β_{ijt} are identified by within occupation wage ratios, while the α_{jt} and ρ can be recovered through estimation of the log linear approximation of equation (13).

3.1 Data

We use data from the 1980, 1990, and 2000 decennial Censuses and we pool together three years of the American Community Survey to get samples of comparable size for 2010 (2009-2011) and 2018 (2017-2019) (King et al., 2010).

We consider individuals aged between 25 and 54 and exclude those still in education, as well as workers in farming, forestry, and fishing occupations. We define the supply side heterogeneity, i, as a combination of gender, age (three groups: 25-34, 35-44, 45-54), and

Table 1: Occupational groupings used for the estimation of the model.

	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

education (college graduates and above, and less than college). This implies that we have 12 different demographic groups. On the demand side, we consider a set of 13 occupations (to which we add the non-employment status), indexed by j. The list of occupations is shown in Table 1, along with the aggregation to four broad task clusters as in Acemoglu and Autor (2011). We also consider four geographical markets, indexed by m, corresponding to the standard Census regions (Northwest, Midwest, South, and West).

For each (i, j, m, t) cell we compute total employment, mean hours worked, mean wage rate, and mean non-labor income. To account for differences in the cost of living across geographic regions we follow Moretti (2013) and adjust our income measures by computing a measure of local CPI based on the cost of housing. For total employment, we use the population weights. A worker is counted as employed if they report working at least 15 hours per week. Non-labor income is obtained as the sum of incomes from businesses and farms.

3.2 Estimation

Our estimation approach follows a two-step procedure. First, we recover the parameters affecting the labor supply choices of workers at the extensive and intensive margin using a GMM estimator. Secondly, we estimate production shares and elasticity of substitution between different labor inputs.

Estimation of utility parameters

For the implementation of our model we assume the following functional forms

$$u_c(c) = \frac{c^{1-\sigma}-1}{1-\sigma} \qquad u_h^i(h) = \psi_i \frac{h^{1-\gamma}}{1-\gamma} \tag{14}$$

Moments from the intensive margin of labor supply. By solving the maximization problem in equation (1), we obtain the first order condition describing the optimal supply of hours:

$$(w_{ijmt}h_{ijmt} + y_{imt})^{-\sigma} w_{ijmt} = \psi_i h_{ijmt}^{-\gamma} \tag{15}$$

If $\gamma \leq 0$, the function for the disutility from working is convex and the first order condition has a unique solution.[3] Despite not having a closed form solution the first order condition implicitly defines hours worked as a function of wages and non-labor income. The empirical counterpart of this implicit relation is a non-linear regression model of the following type

$$\log(h_{ijmt}) = f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) + \epsilon^1_{ijmt} \tag{16}$$

where $\boldsymbol{X}_{ijmt} = [w_{ijmt};\ y_{imt}]$ and $\tilde{\boldsymbol{\Omega}}_i = [\sigma;\ \gamma;\ \psi_i]$. From this non-linear regression, we derive the first set of moments to be used in our GMM estimator, namely

$$E\left[\log(h_{ijmt}) - f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) |i\right] = 0 \tag{17}$$

$$E\left[\left(\log(h_{ijmt}) - f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)\right) \boldsymbol{Z}^1_{ijmt}\right] = 0 \tag{18}$$

where $\boldsymbol{Z}^1_{ijmt}$ is a vector of instruments.

Moments from the extensive margin of labor supply. We derive the second set of moments from the empirical counterpart of equation (12). Let $\Upsilon_{ijmt} = \log\left(\mu_{ijmt}/\mu_{i0mt}\right)$,

[3] In the estimation process we do not need to and do not impose any restriction on γ. Nevertheless, the estimated value satisfies the condition for the uniqueness of the solution.

$\hat{h}_{ijmt} = \exp\left(f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)\right)$, and

$$g\left(\boldsymbol{X}_{ijmt}; \boldsymbol{\Omega}_i\right) = \frac{U_{ijt}(w_{ijmt}, y_{imt}) - U_{i0t}(y_{imt})}{\sigma_\theta}$$
$$= \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt} + y_{imt}\right) - u_h^i\left(\hat{h}_{ijmt}\right) + b_{ijt} - u_c\left(y_{imt}\right)}{\sigma_\theta} \tag{19}$$

where $\boldsymbol{\Omega}_{ijt} = \tilde{\boldsymbol{\Omega}}_i \bigcup [\sigma_\theta;\ b_{ijt}]$. The empirical counterpart of equation (12) is

$$\Upsilon_{ijmt} = g\left(\boldsymbol{X}_{ijmt}; \boldsymbol{\Omega}_{ijt}\right) + \epsilon^2_{ijmt} \tag{20}$$

From the latter we obtain the following moment conditions

$$E\left[\Upsilon_{ijmt} - g\left(\boldsymbol{X}_{ijmt}, \boldsymbol{\Omega}_{ijt}\right) | i, j, t\right] = 0 \tag{21}$$
$$E\left[\left(\Upsilon_{ijmt} - g\left(\boldsymbol{X}_{ijmt}, \boldsymbol{\Omega}_{ijt}\right)\right) \boldsymbol{Z}^2_{ijmt}\right] = 0 \tag{22}$$

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

Estimation of labor supply parameters. Let $\boldsymbol{X}$ a vector containing all the data (wages and labor supply at the intensive and extensive margin) and $\boldsymbol{\Omega} = \{\boldsymbol{\Omega_{ijt}}\}_{\forall i,j,t}$, the GMM estimator is defined as

$$\hat{\boldsymbol{\Omega}} = \arg\min_{\boldsymbol{\Omega}} \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}\right)^T \boldsymbol{W}\boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}\right) \tag{23}$$

where $\boldsymbol{W}$ is a positive definite weighting matrix[4], $\boldsymbol{Z}$ is the vector of instruments, and $\boldsymbol{M}$ is the set of target moments described in equations (17), (18), (21) and (22).

The optimization problem described in eq. (23) is computationally demanding as it requires to numerically solve equation (15) for all i, j, m and t. To reduce the computational, burden we reformulate the optimization problem by enforcing the validity of the first order conditions specifying them as constraints. Let $\boldsymbol{\Omega}^+$ be the union of $\boldsymbol{\Omega}$ and $\{\hat{h}_{ijmt}\}_{\forall i,j,m,t}$, where the latter is the set of model-implied labor supplies, the optimization problem becomes:

$$\hat{\boldsymbol{\Omega}} = \arg\min_{\boldsymbol{\Omega}^+} \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}^+\right)^T \boldsymbol{W}\boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}^+\right) \tag{24}$$
$$\text{s.t.} \quad \log\left(\hat{h}_{ijmt}\right) = f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) \quad \forall i, j, m, t$$

Table 2 shows the results from the GMM estimation with bootstrapped standard errors[5].

[4] In practice W is the identity matrix.

[5] Tables with the estimated values of the remaining parameters, b_{ijt}, γ, and ψ_i, can be found in Appendix D.

	NON-IV	IV		
	(1)	(2)	(3)	(4)
$\hat{\sigma}$	1.0019***	1.0028***	1.0015***	1.0017***
	(0.0149)	(0.0105)	(0.0066)	(0.0350)
$\hat{\sigma}_\theta$	1.4812*	1.4369**	1.5325**	1.5325**
	(0.8256)	(0.6110)	(0.7324)	(0.7223)
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 2: Results from the GMM estimator in equation (23).

Column 1 shows the results we obtain when estimating the labor supply parameters without using instruments, i.e. when $\boldsymbol{Z}^1_{ijmt}$ contains the logarithm of contemporaneous wages and non-labor income, and $\boldsymbol{Z}^2_{ijmt}$ contains the logarithm of contemporaneous wages. In columns (2), (3) and (4) we instrument for wages and non-labor income using their 10 and 20 years lagged-values. We chose column (2) as our baseline since it provides the most accurate estimate of σ_θ.

Estimation of production parameters

The estimation of the production function closely follows the identification procedure described in detail in Appendix A. In the appendix, we show that the β parameters are identified up to a normalization by the within-occupation ratios of wages across different demographic groups groups. This follows from the assumption that within an occupation, workers from different demographic groups are perfect substitutes. Thus, after having normalized $\beta_{1jt} = 1$ for all $j = 1, ..., J$ and all t, we can estimate all the remaining β's as the average within-occupation wage ratio across markets:

$$\hat{\beta}_{ijt} = \frac{1}{M} \sum_{m=1}^{M} \frac{w_{ijmt}}{w_{1jmt}} \tag{25}$$

The resulting estimates are reported in Appendix D.

Estimated values of the remaining parameters are obtained through the estimation of the empirical counterpart of the wage equation (45) in Appendix A, reported here for convenience

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho - 1)\log\left(\frac{\sum_{i'} \beta_{i'jt} L_{i'jmt}}{\sum_{i'} \beta_{i'1t} L_{i'1mt}}\right) \tag{26}$$

The empirical counterpart of the second term is simply

$$\hat{B}_{ijt} = \log\left(\frac{\hat{\beta}_{ijt}}{\hat{\beta}_{i1t}}\right) \tag{27}$$

and we expect the estimated coefficient on this term to equal one. Finally, the empirical counterpart of the third term is

$$\hat{\Lambda}_{jmt} = \log\left(\frac{\sum_{i'} \hat{\beta}_{i'jt}\mu_{i'jmt}h_{i'jmt}}{\sum_{i'} \hat{\beta}_{i'1t}\mu_{i'1mt}h_{i'1mt}}\right) \tag{28}$$

This quantity measures the relative supply of labor efficiency units to occupation j. The estimated value of ρ is then recovered as $\hat{\rho} = \hat{\phi} + 1$. Equation (26) then becomes

$$W_{ijmt} = \gamma_{jt} + \psi\hat{B}_{ijt} + \phi\hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{29}$$

where $W_{ijmt} = \log\left(\frac{w_{ijmt}}{w_{i1mt}}\right)$.

First, we estimate a value for ρ by estimating the above equation in first differences. This choice is mainly driven by the instrumental variable strategy we implement to control for the usual endogeneity problem in estimating a demand function. These instruments are, in fact, better suited to be used in a growth regression rather than one in levels. The estimated value of ρ is then recovered as $\hat{\rho} = \hat{\phi} + 1$.

After having estimated a value for ρ, we recover all the γ_{jt}'s by projecting $\tilde{W}_{ijmt} = W_{ijmt} - \hat{B}_{ijt} - \hat{\phi}\hat{\Lambda}_{jmt}$ on a set of occupation-year fixed effects. The values for each α_{jt} are then recovered using the restriction that $\sum_j \alpha_{jt} = 1$ for all t. The resulting estimates of α_{jt}'s are reported in Appendix D.

Instrumental variable approaches. To account for the endogeneity of employment in the growth (differences) version of equation (29) we resort to two alternative sets of instrumental variables. In both cases, we instrument the change in labor input log-ratios, $\Delta\hat{\Lambda}_{jmt}$, with predicted log-ratios of headcounts. In the model, changes in labor supply (headcounts) to each occupation can result from changes in the choices of workers in each demographic group (e.g. a smaller share of young, non-college men choosing to work in construction) or changes in the demographic composition of the labor force (e.g. fewer young, non-college men).

The first instrument takes advantage of aggregate demographic shifts that exogenously impact local labor markets, holding constant the occupation shares of workers within a market and demographic group. Let s_{ijmt} be the share of type i workers choosing to work in occupation j in market m. The predicted labor supply to occupation j is $\hat{L}^h_{jmt} = \sum_i s_{ijmt-1}\mu_{imt}$, where h stands for headcount. We use the latter measure to construct predicted relative supply at time t

$$\hat{\Lambda}^h_{jmt} = \log\left(\frac{\hat{L}^h_{jmt}}{\hat{L}^h_{1mt}}\right) \tag{30}$$

The instrument is then

$$\text{IV1}_{jmt} = \Delta\hat{\Lambda}^h_{jmt} = \hat{\Lambda}^h_{jmt} - \log\left(\frac{L^h_{jmt-1}}{L^h_{1mt-1}}\right) \tag{31}$$

where L^h_{jmt-1} is the actual number of workers in occupation j in market m at time $t-1$. Given the exogeneity of aggregate shifts in the demographic composition of the labor force, this is a valid instrument as it is correlated with the regressor since it predicts it, but it is uncorrelated with the error term.

A second set of instruments relies more directly on the theoretical restrictions of the model. As stated above, changes in labor supply to each occupation can be due to changes in the choices of workers. The latter can occur because of shifts in either the pecuniary or non-pecuniary returns associated with each occupation. By construction, shifts in non-pecuniary returns affect employment but do not depend on wages. Therefore, a set of instruments can be built using changes in occupation shares due to variation in non-pecuniary returns b_{ijt}. From equation (12) we have

$$\varrho_{ijmt} = \log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right) = \frac{b_{ijt} + \Pi_{ijmt}}{\sigma_\theta} \quad \Longrightarrow \quad \Delta\varrho_{ijmt} = \frac{\Delta b_{ijt} + \Delta\Pi_{ijmt}}{\sigma_\theta} \tag{32}$$

where $\Pi_{ijmt} = U_{ijmt} - U_{i0mt}$ is the pecuniary component of the returns. By setting $\Delta\Pi_{ijmt} = 0$ in the equation above, we obtain counterfactual $\hat{\varrho}_{ijmt}$ as follows

$$\hat{\varrho}_{ijmt} = \Delta\hat{\varrho}_{ijmt} + \varrho_{ijmt-1} = \frac{b_{ijt} - b_{ijt-1}}{\sigma_\theta} + \varrho_{ijmt-1} \tag{33}$$

and we can compute our counterfactual shares as

$$\hat{s}_{ijmt} = \frac{\exp\left(\hat{\varrho}_{ijmt}\right)}{1 + \sum_{j'=1,\ldots,J} \exp\left(\hat{\varrho}_{ij'mt}\right)} \tag{34}$$

We use the the latter to predict labor supply as

$$\hat{L}^h_{jmt} = \sum_i \hat{s}_{ijmt}\mu_{imt} \tag{35}$$

and, thus, to construct our second instrument, IV2_{jmt}, as in equation (31).

	OLS	IV		
	(1)	(2)	(3)	(4)
$\hat{\phi}$	-0.0834	-0.6041***	-0.5482***	-0.6045***
	(0.0614)	(0.1238)	(0.1247)	(0.1255)
$\hat{\psi}$	0.9771***	0.9771***	0.9771***	0.9771***
	(0.0419)	(0.0420)	(0.0420)	(0.0420)
Observations	2,496	2,496	2,496	2,496
Instrument set		IV1	IV2	IV1-IV2
Test $\hat{\psi} = 1$ (p-val)	0.5851	0.5866	0.5863	0.5866
OverId p-val				0.1972
Implied ρ	0.9166***	0.3959***	0.4518***	0.3955***
	(0.0614)	(0.1238)	(0.1247)	(0.1255)
Implied elast. of sub.	11.9974	1.6554***	1.8243***	1.6541***
	(39.5290)	(0.3824)	(0.4917)	(0.3881)

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

Table 3: Estimation results for equation (29) in first differences.

Estimation results. Table 3 reports the estimated coefficients on $\Delta\hat{\Lambda}_{jmt}$ and $\Delta\hat{B}_{ijt}$ for different specifications with bootstrapped standard errors. Column 1 reports the OLS estimates, for comparison with IV estimates in the other columns; the effects of endogeneity are apparent in the positive bias on estimates of ϕ. Columns 2 and 3 report results obtained instrumenting $\Delta\hat{\Lambda}_{ijmt}$ with each of the two instrument sets, separately. The range of estimated values for ρ suggests an elasticity of substitution between occupations within the interval $1.65-1.82$. Our preferred specification is reported in column 4 where we use both instruments to control for endogeneity. The implied value for ρ is 0.40, which corresponds to an elasticity of substitution of 1.65. In this case, we are also able to compute a p-value for the overidentification test (Sargan, 1958), finding that we cannot reject the validity of the instruments at conventional significance levels. Finally, consistent with the theoretical model, we find that the estimated coefficient on $\Delta\hat{B}_{ijt}$ is not significantly different from one.

4 The Distribution of Employment Surplus

In its most basic form, our approach allows us to characterize the distribution of total worker surplus at different points in time. This distribution summarizes the total value of a job (relative to non-employment) for each subset of workers. The job surplus reflects both pecuniary and non-pecuniary returns.

The top panel of Figure 1 plots the distribution of the total (pecuniary and non-pecuniary) systematic worker surplus, across demographics and occupations, in three different years (1980, 2000, and 2018).[6] It is apparent that the distribution of the systematic component of worker surplus has become more concentrated over time, with the probability mass of its right tail shifting noticeably to the left. This implies that the mean of the distribution has slightly shifted to the left.

The latter observation can be better qualified by looking at more disaggregated distributions of the worker-job surplus. The bottom panel of Figure 1 separately reports the distributions of total surplus for gender-education groups. This more disaggregated view shows that the leftward shift of the right tail is mostly driven by falling surpluses among men, especially among the less educated. This is in line with the recent evidence of falling labor supply from men (Aguiar et al., 2017). In contrast, the distribution of job surpluses for women seems to have shifted rightwards, especially among the well-educated. This suggests that many of the matches involving more educated women are increasingly characterized by higher wages and/or better non-pecuniary returns (Cortes et al., 2018).

The mechanics of the changing distribution of worker surplus over time can be further examined by separately looking at the distribution of its pecuniary and non-pecuniary components. Figure 2 plots the density of total surplus and its three components for different years. This makes it clear that (i) pecuniary surplus is much more concentrated than non-pecuniary surplus; (ii) the component of the surplus attributable to the disutility from hours worked is way more concentrated than the other components. The latter suggests that differences in hours worked across occupations are not major determinants of the differences in the workers' evaluation of the various occupations.

These facts convey information about match-specific shifts in the relative value of money, time, and other job-specific attributes. We re-examine these questions in some detail after estimating production technology parameters.

4.1 Components of Worker Surplus

One key question is what accounts for the total surplus of specific worker-job matches. Specifically, one might ask how large are monetary rewards net of the disutility from working ("net-pecuniary"), relative to systematic non-pecuniary benefits, as well as whether different types of returns are positively or negatively related.

Figure 3 reports the weighted average of the absolute values of net-pecuniary and non-pecuniary rewards (in utils) within bins defined by gender, broad occupation, and year. The

[6] The distribution is obtained through an employment-weighted kernel estimation. The equivalent unweighted estimates can be found in Appendix D.

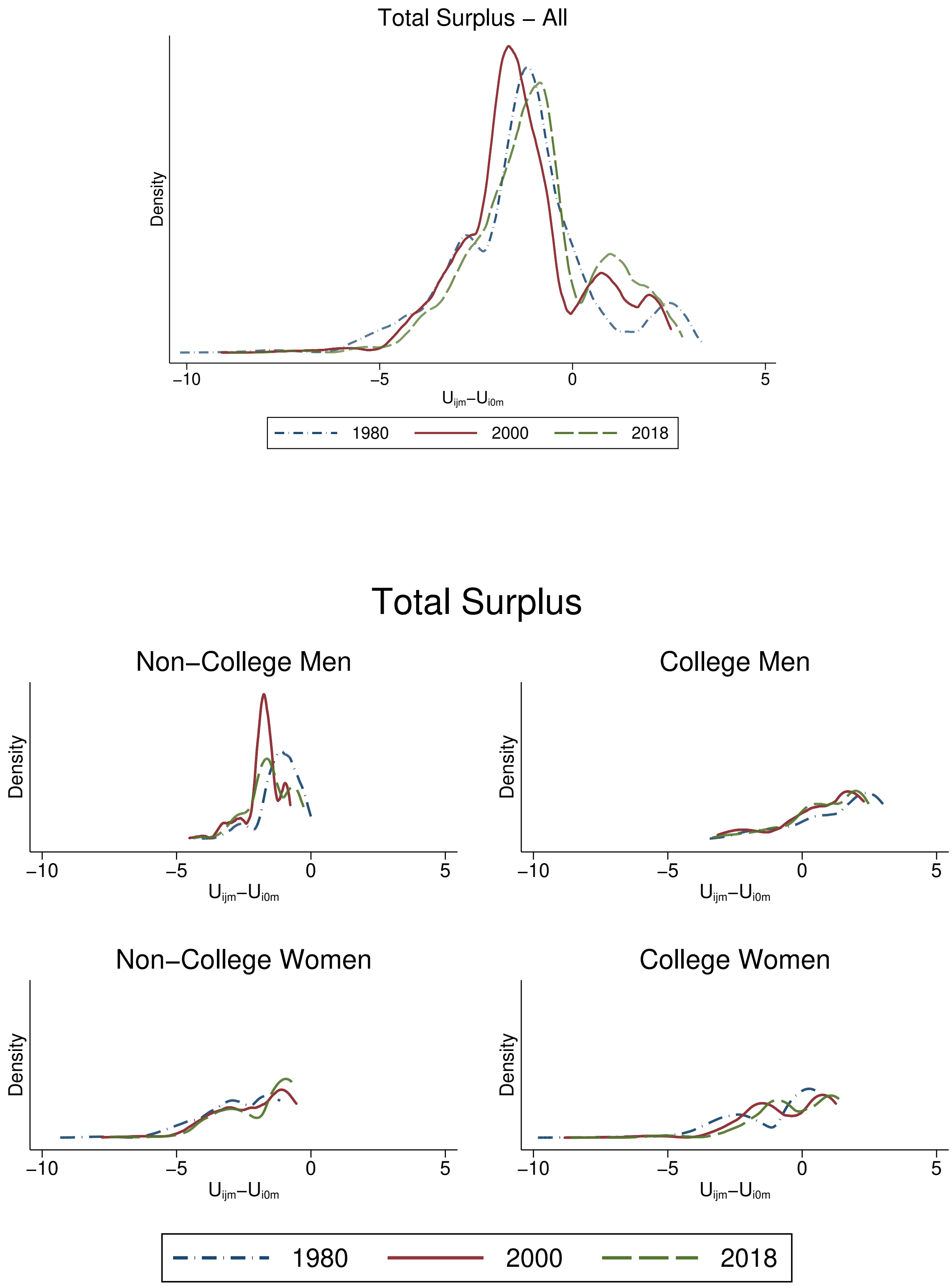

Figure 1: Distribution of surplus (employment-weighted): aggregate (top panel) and disaggregated (bottom four panels).

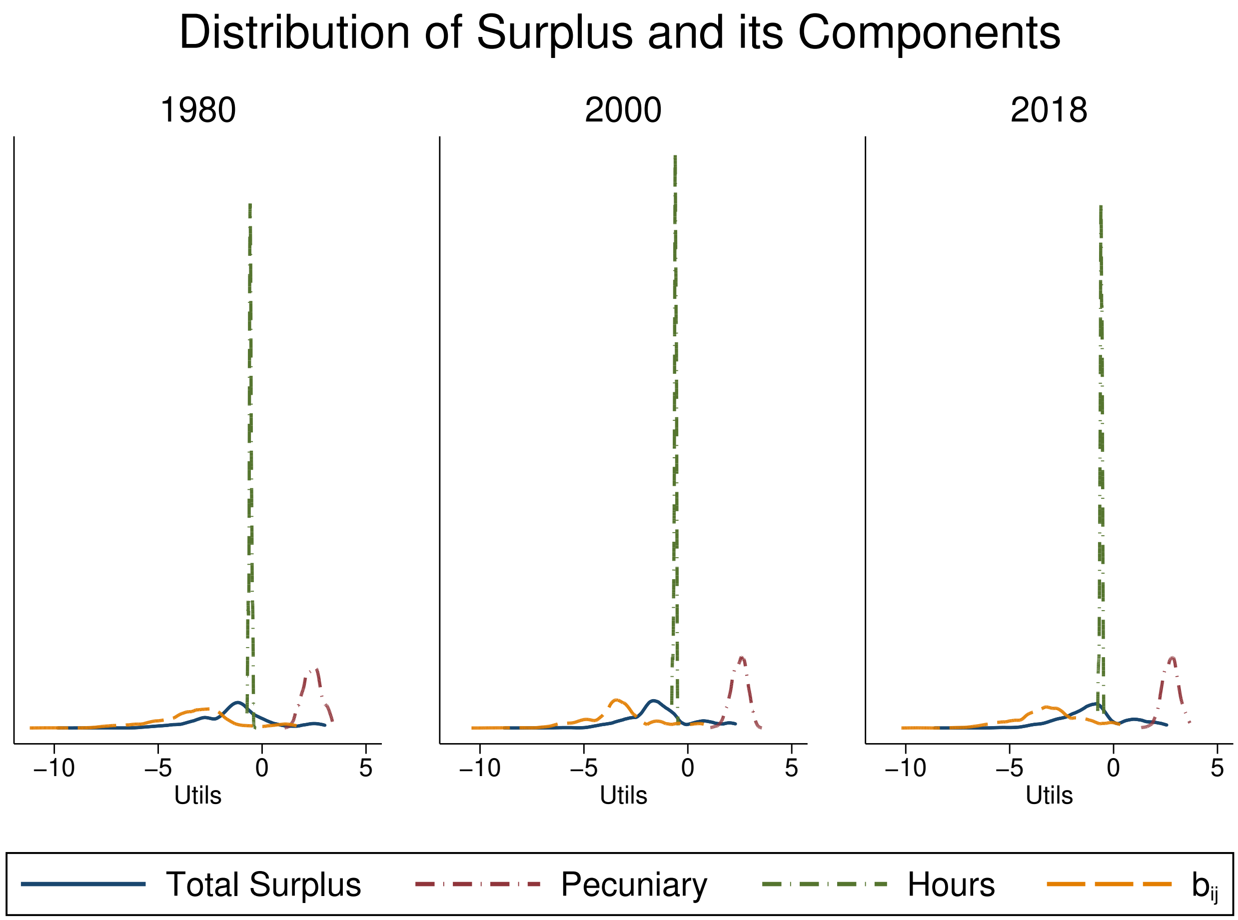

Figure 2: Distribution of surplus (employment-weighted): this figure reports, for different years, the density functions of (i) total systematic surplus across worker-job matches; (ii) its pecuniary surplus component; (iii) its component concerning the disutility from hours worked; (iv) its non-pecuniary surplus component.

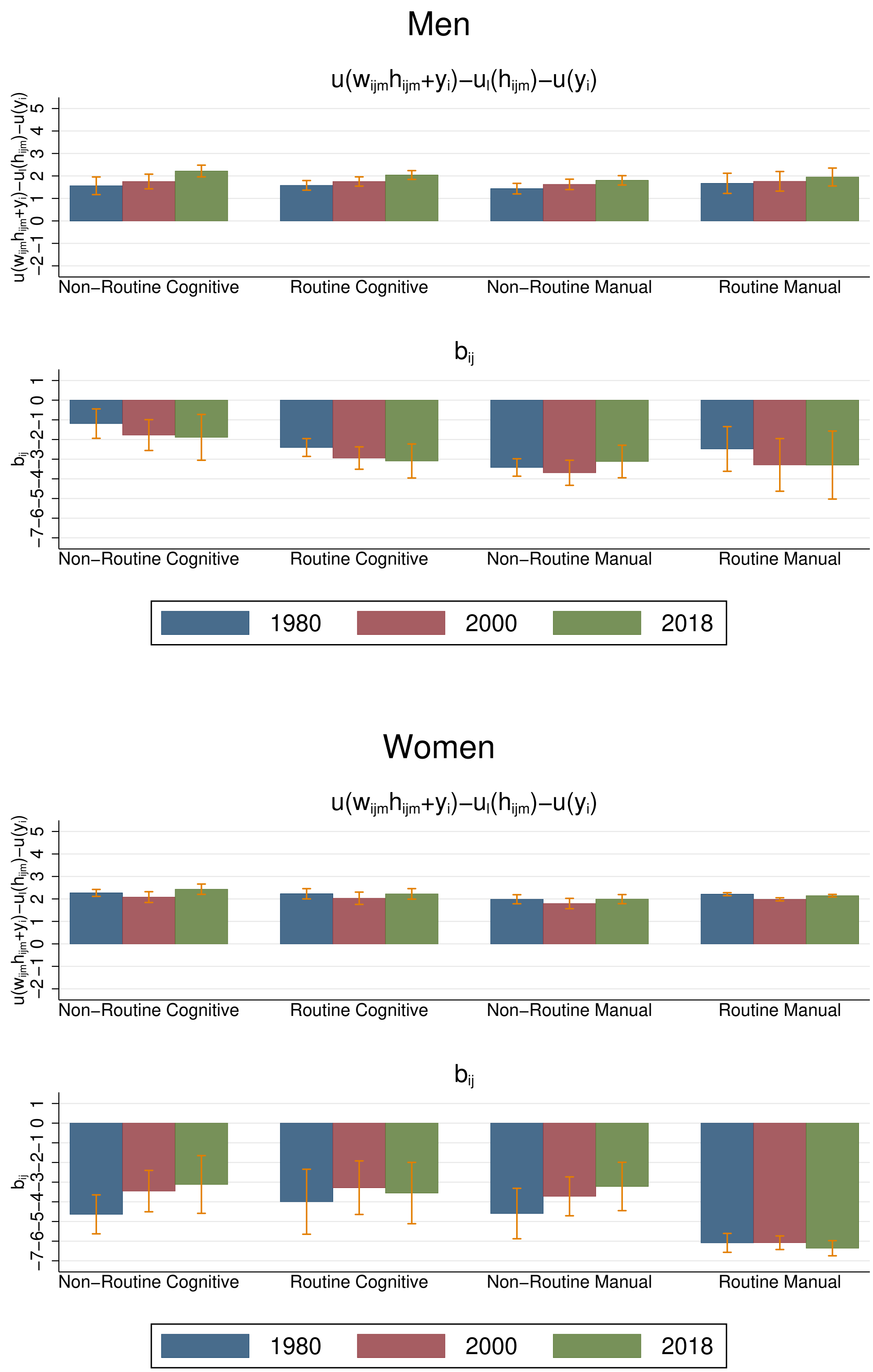

Figure 3: Net-pecuniary (pecuniary net of disutility from working) and non-pecuniary surplus by gender, occupation and year with bootstrapped counfidence intervals. All values are expressed in utility equivalents (higher value corresponds to higher utility).

patterns over time are quite different for male and female workers: while men experience an increase in the absolute returns for the net-pecuniary component of surplus and a fall in the non-pecuniary component (except for non-routine manual occupations), with these changes being stronger in cognitive occupations, women have a more nuanced set of changes. Specifically, the net-pecuniary surplus does not change as strongly, partly because of the underlying change in the value of non-employment. However, the non-pecuniary returns improve significantly in all occupations but the routine manual occupations.

4.2 Compensating differentials

A different way to gauge the composition of labor market rewards is presented in Figures 4 and 5, which reports scatter plots of net-pecuniary (average across markets) vs non-pecuniary surplus for each i, j pair (demographic i and occupation j combination) for cognitive and non-cognitive occupations respectively.

With 12 demographic groups (defined by education, gender, and age) and 13 occupation categories, we have 156 observations per year. This allows us to draw some inference about the covariation of different components of total surplus: fitted lines in the scatter plots capture the linear relationship between pecuniary and non-pecuniary returns in different years. Negative comovement between money and non-money rewards would be consistent with the standard view of compensating differentials.

Figure 4 shows that the latter relation is clearly detectable and stable over time among cognitive occupations for non-college graduates while it is graphically dubious for college graduates. To shed light on this relation between the two components of the surplus and on the differences in the extent of compensating differentials across education groups, we regress the net-pecuniary component on the non-pecuniary controlling for year fixed effects, age, and gender and allowing for different slopes across education groups. The regression results suggest that compensating differentials are present for college graduates as well, with an estimated slope of -0.02 (-0.03, -0.01), but it is significantly stronger among less-educated workers with an estimated slope of -0.06 (-0.08, -0.05). The stronger presence of compensating differentials among college graduates is consistent with lower occupation mobility among college graduates: high specialization and the accumulation of occupation-specific human capital, in fact, makes it harder for college graduates to arbitrage out differences in the two components of surplus.

Similarly, Figure 5 shows that there is a negative correlation between the two components of the surplus for all the demographic subgroups across non-cognitive occupations. This time, the graph suggests that this relation is overall steeper for men than it is for women. As before, to corroborate the graphic intuition we project the net-pecuniary on the non-pecuniary component of surplus allowing for different slopes for men and women and controlling for age and education. The estimated slope of the relation between the two components of the surplus is -0.11 (-0.13, -0.9) for men and -0.05 (-0.06, -0.05). These results also suggest that overall compensating differentials are stronger among non-cognitive occupations than among cognitive ones, consistent with more churn among the former.

4.3 Taking Stock

The evidence presented so far indicates that a significant amount of heterogeneity exists in the match value of jobs to workers. This heterogeneity reflects both pay and non-pecuniary surplus. The split between these components is rather uneven across different demographic-occupation matches. Moreover, the relative magnitude of specific returns also changed over time, occasionally in unexpected ways. The following observations summarize our basic findings so far:

1. The distribution of surplus has changed for all workers since the 1980s. This aggregate shift, with average surplus becoming higher over time, masks vast heterogeneity.

2. Looking at gender differences, the pecuniary surplus went up for men significantly more than it did for women: while this might seem unexpected when contrasted to wage dynamics, it is important to consider that the monetary surplus is defined as an increment relative to the baseline value of non-employment. Hence, movements in wages and the value of non-employment both play a role. This evidence partly reflects the uneven variation in the value of non-employment across genders.

3. At the same time, the non-pecuniary surplus worsened for men, while it went in the opposite direction for most women. As a consequence, gains associated with employment for men have become more dependent on monetary rewards, since the latter provide compensation for a worsening non-pecuniary surplus. For women, instead, increased participation aligns more closely with improvements in non-pecuniary surplus.

4. Compensating differentials (negative covariation of pecuniary and non-pecuniary surplus) are detected for all workers and occupation groups. The magnitudes of these differentials display a lot of heterogeneity across demographic groups. They are the strongest among men in non-cognitive occupations, consistent with lower occupation switching costs that make it easier for workers to arbitrage out differences in pecuniary and non-pecuniary returns. The extent of compensating differentials is overall smaller among cognitive occupations. Within this group, college graduates display the smallest degree of compensating differentials, consistent with lower occupational churn.

5. Non-pecuniary returns are more dispersed in the population than pecuniary ones; the disutility from hours worked is very concentrated, suggesting that differences in hours worked play a little role in occupational choices.

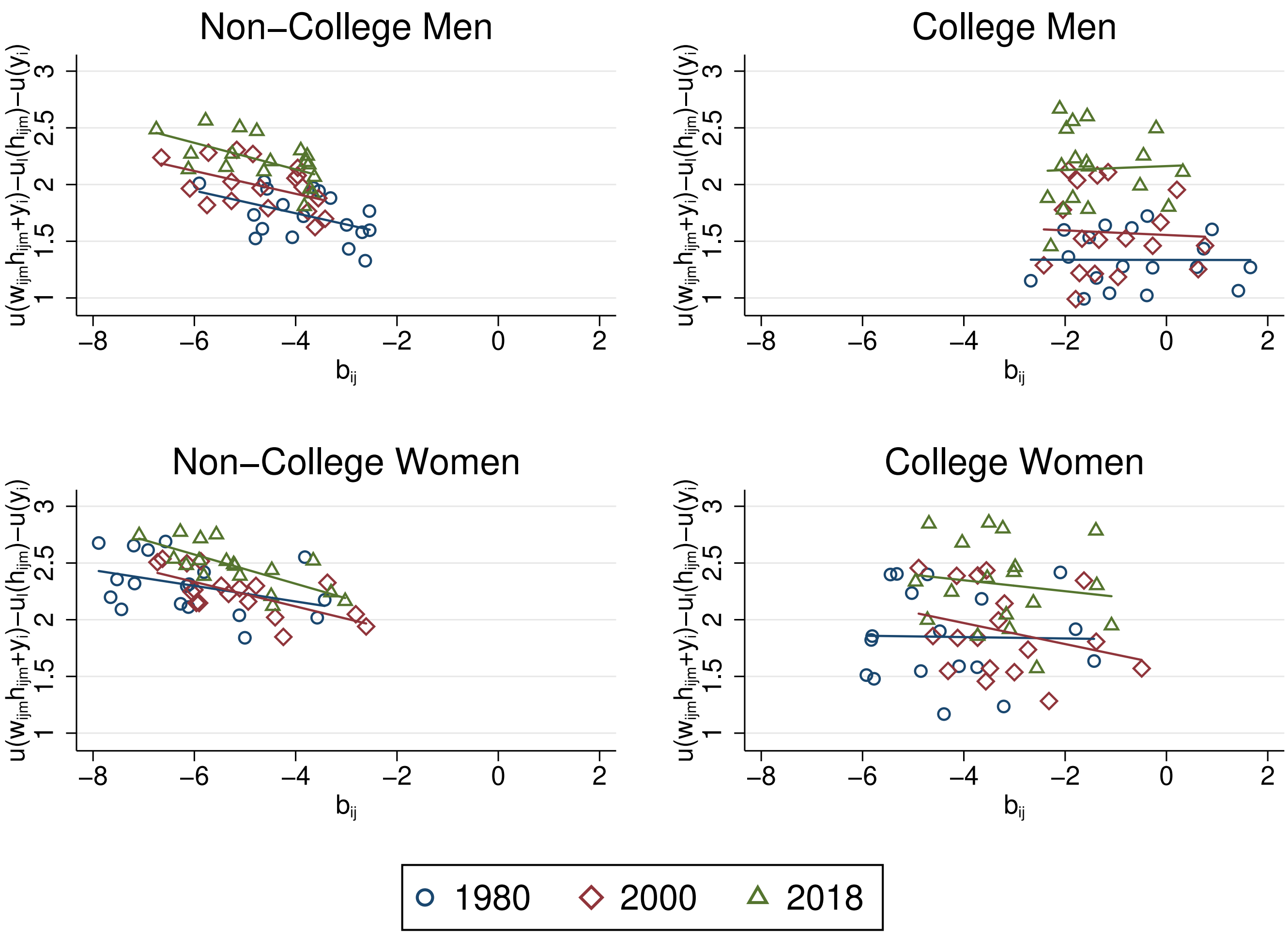

Figure 4: Each panel plots the distribution of net-pecuniary and non-pecuniary returns over the set of cognitive occupations within an education-gender group. Data points are color-coded to distinguish between different years.

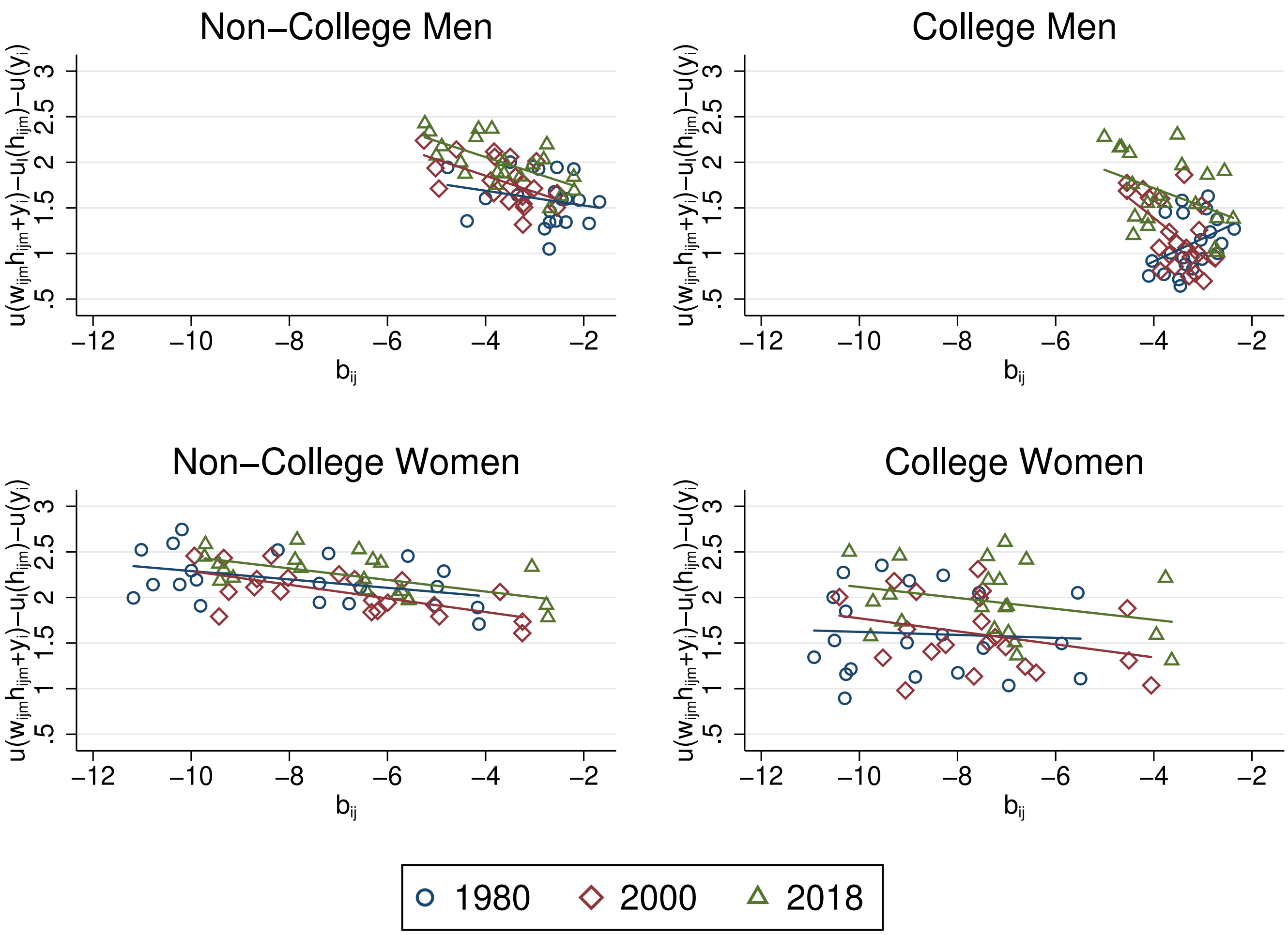

Figure 5: Each panel plots the distribution of net-pecuniary and non-pecuniary returns over the set of non-cognitive occupations within an education-gender group. Data points are color-coded to distinguish between different years.

Some of these observations are the outcome of the equilibrium interaction of demand for, and supply of, different worker-occupation inputs. We examine the mechanics of these interactions using a production technology that aggregates labor inputs from heterogeneous occupation and demographic groups.

5 Production Share Estimates

Changes in the pecuniary component of workers' surplus depend on the relative productivity of their labor input. In turn, the productivity of each worker-job pair is the by-product of both supply of and demand for their labor input.

From wage equation (11), we know that the marginal productivity of a type i worker in occupation j at time t is proportional to $\alpha_{jt}\beta_{ijt}$. Figure 6 shows the evolution of an employment-weighted average of the labor loadings $\alpha_{jt}\beta_{ijt}$ for four major occupation categories (the left panel reports levels, while the right one shows growth relative to the 1980 baseline). All occupation types have experienced growth in their production shares with the exception of Routine Manual occupations, for which we observe a steady decline reaching -26% in 2018 relative to 1980. The occupation types exhibiting growth show a similar pattern during the 1980s (+10-15%); however, their paths started diverging in the 1990s with non-routine cognitive jobs the only group sustaining a steady growth rate until the turn of the century after which we observe an increase in the rate of growth. This resulted in a staggering jump in the production shares of non-routine cognitive occupations between 1980 and 2018, adding up to about 70%. Non-routine manual occupations and routine cognitive occupations, while exhibiting lower increments, also experienced significant long-term growth (+42% and +23% over the sample period). The fanning out of the production shares is a key determinant of pecuniary surplus and employment across different demographic groups and, as we show below, plays an important role for the labor market shifts of the past decades.

Production shares by type of worker. To zoom into the evolution of production shares for heterogeneous labor inputs, Figure 7 shows the counterparts of the left panel in Figure 6 for different demographic groups. The drop in the share of Routine Manual occupations is almost entirely due to the falling productivity of men; the loading of women in these occupations has remained roughly constant while the college-educated rarely work in these occupations.

Besides being lower in levels, relative production shares for college men have increased more than for college women both in non-routine cognitive occupations and in routine cognitive occupations. The opposite is true in non-routine manual occupations. Interestingly, in routine manual occupations, the productivity of non-college men has declined to a larger extent than for non-college women.

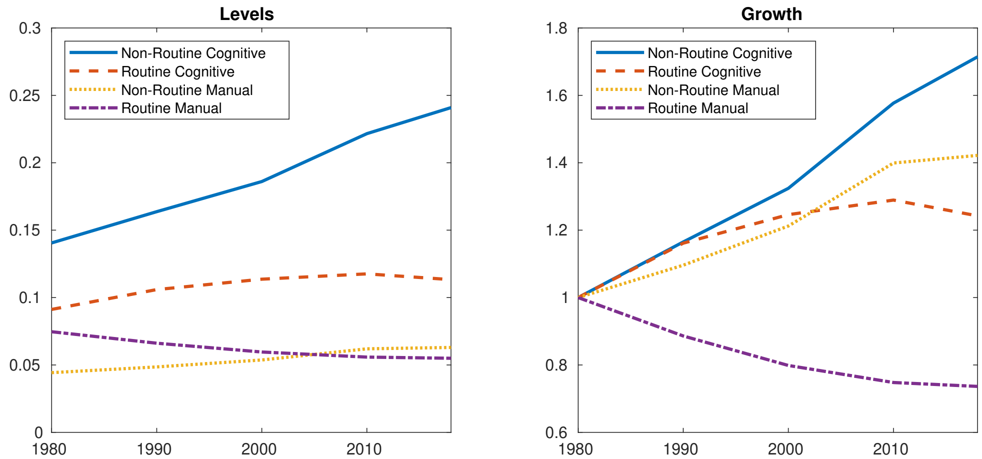

Figure 6: Weighted average production shares ($\alpha_{jt}\beta_{ijt}$) of major occupation groups. Right: levels. Left: growth relative to 1980.

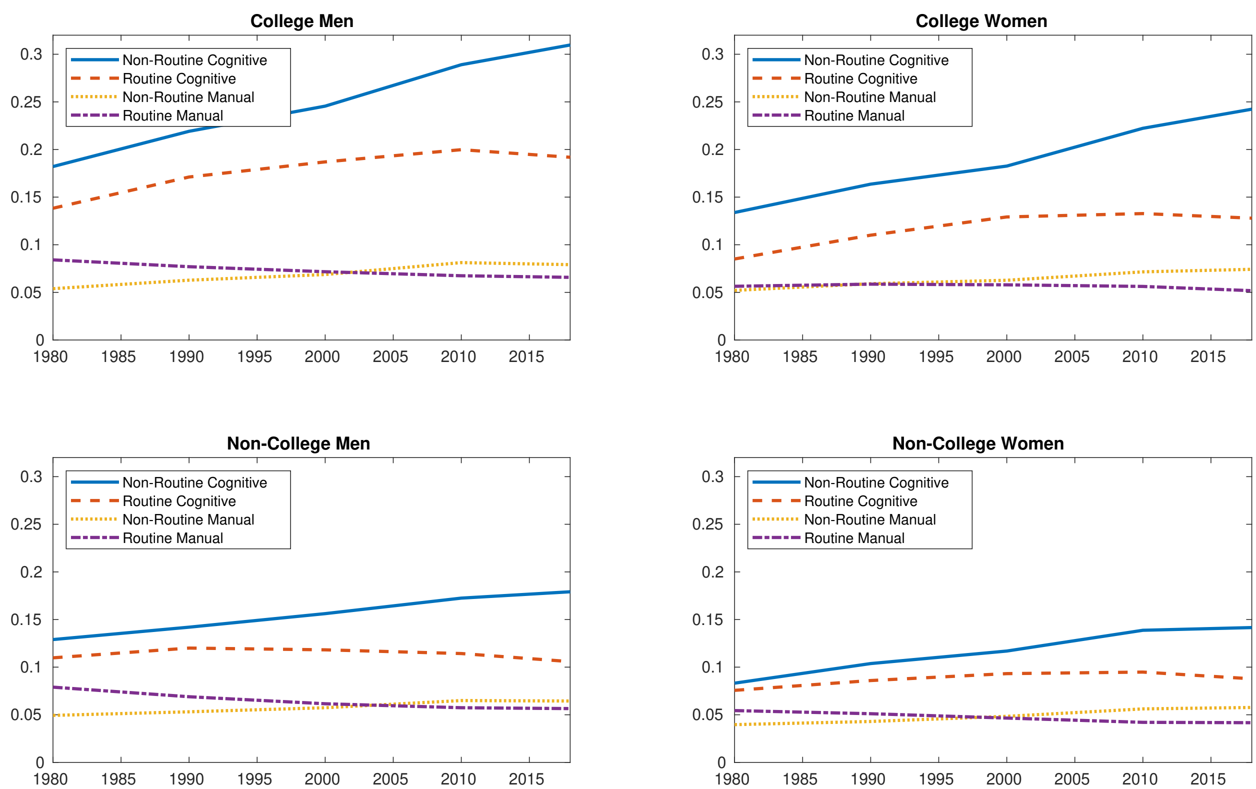

Figure 7: Weighted average production shares ($\alpha_{jt}\beta_{ijt}$) of major occupation groups for different demographics.

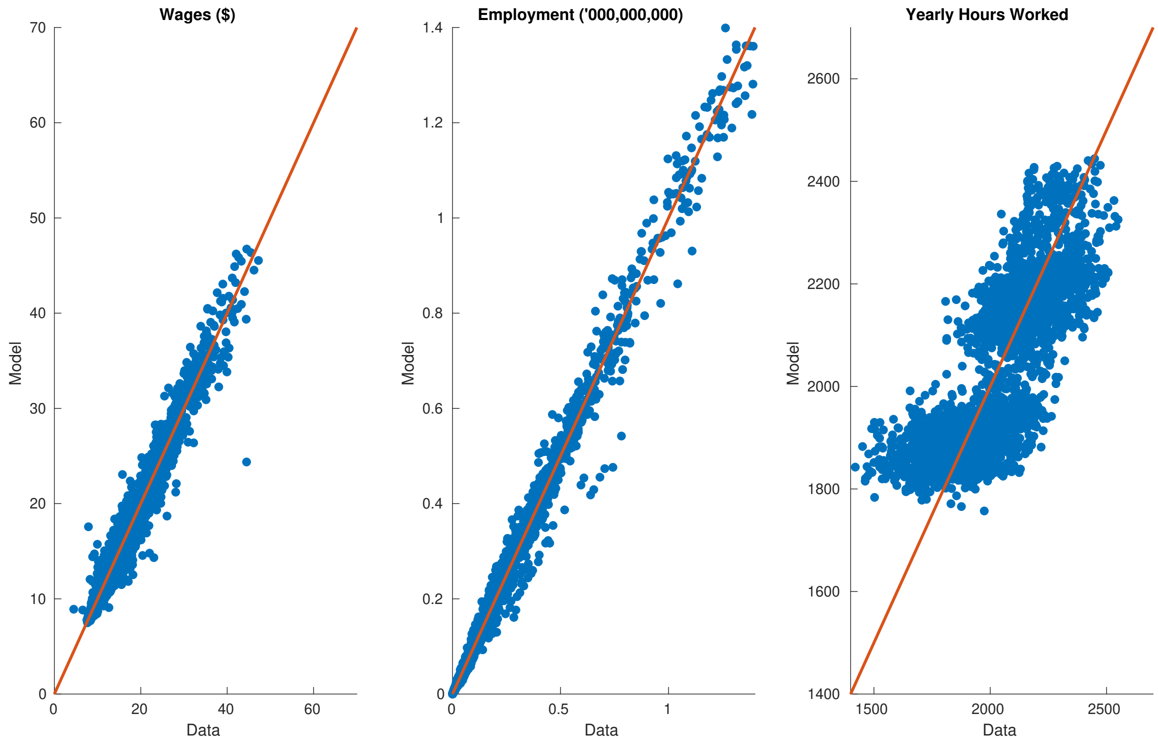

Figure 8: Goodness of fit. Left: model implied wages vs. data. Center: model implied employment vs. data. Right: model implied hours worked vs. data.

Figure 7 also highlights the productivity share premium of cognitive over manual occupations. This gap is much wider for college graduates. Perhaps not surprisingly, a college degree does not improve productivity much when working in manual occupations.

6 Equilibrium and Counterfactuals

To establish the quantitative importance of different forces for the large structural changes observed in the labor market, one needs to account for the way employment and returns are determined in equilibrium. Given parameter estimates, we compute equilibrium prices and quantities for different time periods. These reflect changes in both technology and non-pecuniary returns from jobs. Then, by holding constant the value of selected parameters, we leverage this structure to perform counterfactual exercises and quantitative comparisons.

Prices and quantities: model vs data. One can compute all prices and quantities using the model. In Figure 8 we compare data on the average wages and employment within each (i, j) cell (demographic-occupation pair) to their counterparts obtained by solving the model equilibrium for each market and year. Model-generated prices and quantities closely match data observations, accounting for, respectively, 99%, 95%, and 60% of total variation in

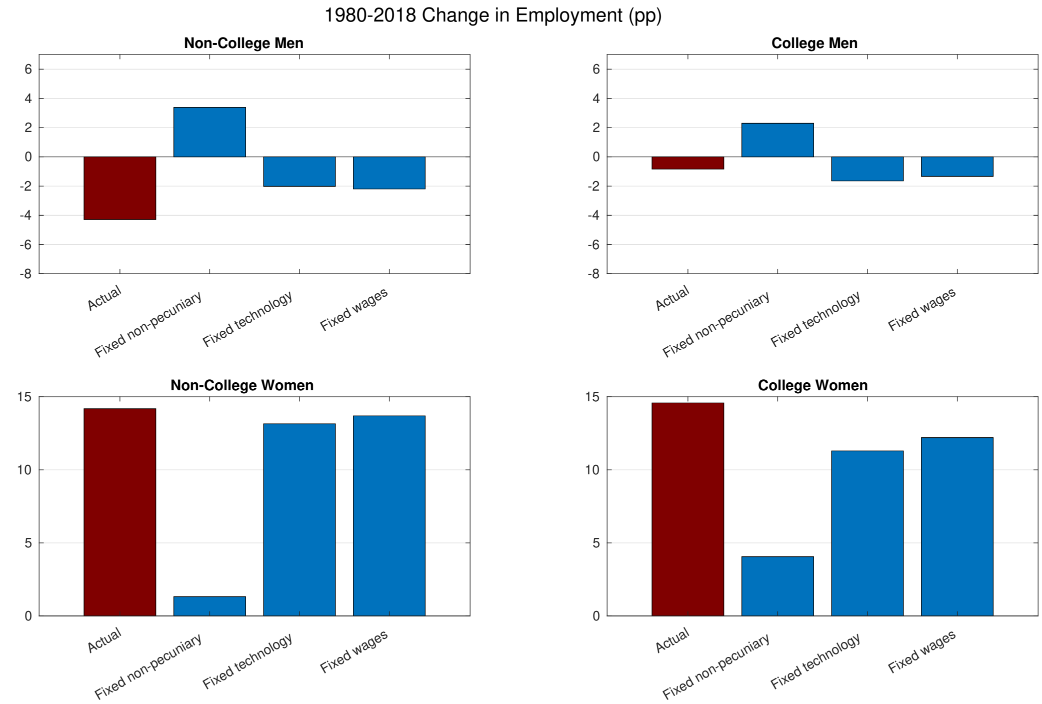

Figure 9: Changes in employment rates of different demographic groups. Comparisons of baseline and counterfactual scenarios from 1980 to 2018.

employment, wage rates, and hours worked. The tight correspondence between model output and data is reassuring since the equilibrium restrictions from Section 2, are not explicitly targeted in the estimation.

6.1 Counterfactual Analysis

We perform two sets of numerical exercises. First, we explore how labor supply and wages would have changed if the value of non-pecuniary returns had stayed at its 1980 levels. Next, we examine the impact of non-technological shifters; specifically, we compute the counterfactual employment and wages holding constant production function parameters at their 1980 levels. For each set of experiments, we also perform partial equilibrium exercises. For employment, we compute counterfactual scenarios keeping wages at 1980 levels. By comparing the latter results to the ones obtained when prices are free to adjust, we quantify the impact of equilibrium adjustments on both the level and composition of employment. Similarly, for wages we consider the partial equilibrium effects of changing technology parameters while holding employment at its 1980 levels.

Employment. Figure 9 reports the 1980-2018 change in total employment (share) of four demographic groups defined by gender and education.[7] The red bars show the historical evolution of employment.[8] Overall participation has declined for men during the 1980-2018 period; the drop was small for college-educated men (-1 percentage points) and more substantial for the less educated (-4 percentage points). Among women, both high (+14) and low (+13) education individuals increased their labor force participation.

Counterfactual experiments reveal interesting aspects of these changes. The first blue bar in each of the four panels shows the counterfactual scenarios in which we keep non-pecuniary returns at their 1980 level, while the second refers to experiments in which we keep technology constant. It is clear that changes in labor force participation of both men and women are mostly explained by changes in non-pecuniary returns. In fact, had these returns stayed the same, the participation of both high and low-educated men would have actually increased by 2 and 3 percentage points. For women we also would have observed a smaller increase in employment: just 1 percentage point for the non-college-educated and 4 points for the college-educated.

Technological change had an asymmetric effect on men with different education. For college-educated men, technological change partially offset the negative impact of changes in non-pecuniary returns on labor force participation. Employment rates would have been, in fact, lower had technology stayed at the 1980 levels. The opposite is true for non-college men. Both the change in non-pecuniary returns and technology supported the growing labor force participation of women. For low-education women non-pecuniary returns take the lion's share, explaining most of the observed change in participation. Changes in technology explain less than a tenth of the changes in total employment of non-college women. For women with a college degree, changes in non-pecuniary returns are also the main driver of the increase in employment. However, technology is also important as it accounts for about a quarter of the changes in the employment rates of educated women.[9]

Finally, the rightmost bar in each panel shows the partial equilibrium effects of changes in non-pecuniary returns, obtained by holding wages at their 1980 level. In all four panels, these changes almost perfectly align with the bars corresponding to the fixed technology scenario, suggesting that price adjustments play a negligible role in explaining changes in employment across demographic groups. As we will see below, equilibrium effects are more relevant in explaining employment changes across occupation types.

[7]Graphical representations of the evolution of employment, along with that of wages, can be found in Appendix D.

[8]For easier comparability, these quantities are obtained by simulating data from the full model. The high predictive power of the model implies that the simulated histories are almost identical to actual data.

[9]Technological changes subsume possible changes in wage discrimination as in Hsieh et al. (2019).

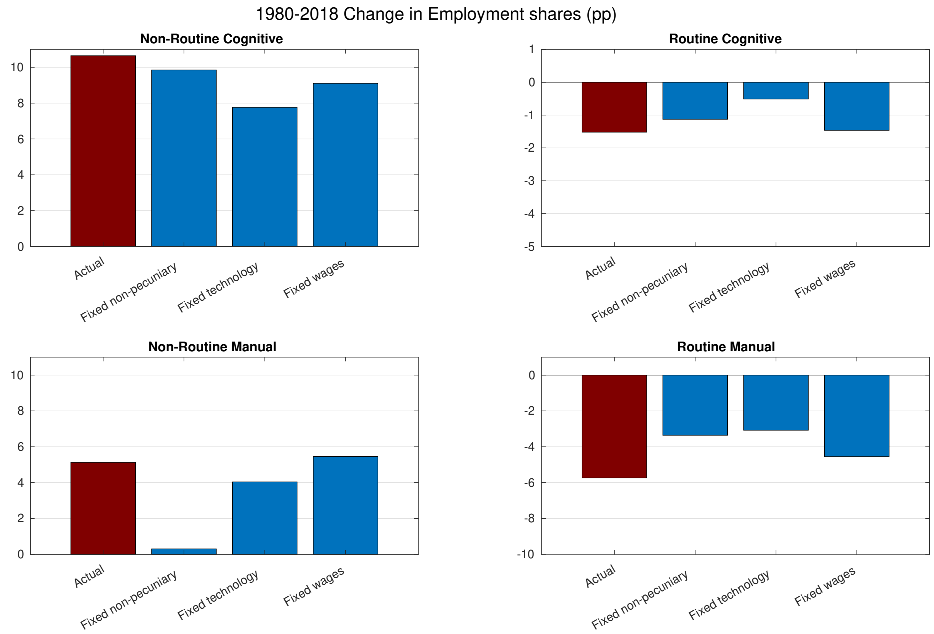

Figure 10: Changes in employment shares in four major occupation groups. Comparison of baseline and counterfactual scenarios from 1980 to 2018.

Broad Occupation Groups. In Figure 10, we perform similar counterfactuals to assess the role of technology and non-pecuniary returns for the evolution of employment across the four major occupation groups defined in Table 1. The red bar in the top-left panel shows the well-documented increase in the fraction of the population employed in non-routine cognitive (NRC) jobs. From 1980 to 2018 this fraction climbed about 10 percentage points. Contrasting this pattern with the counterfactual scenario where production parameters are held at their 1980 values, we gauge the role played by technological progress: without the latter, we would observe only three-quarters of the increase in NRC employment.

The rightmost bar in each panel reports the partial equilibrium counterfactual where we keep wages at their 1980 levels; this should be compared to the fixed technology scenario, as in both cases the effects of technological change are muted. The difference between the two is that the latter allows for price adjustments in response to exogenous labor supply changes. It is apparent that technological progress and price responses account for much of the growth in the share employed in NRC jobs. Also negligible is the contribution of changes in non-pecuniary returns to the employment share of NRC jobs. Keeping these at their 1980 level delivers an outcome that is no different from the actual data.

Next, we consider the second growing group of occupations in the non-routine manual category (NRM). The share of the population employed in these occupations increased by about 5 percentage points. Unlike NRC occupations, this increase is almost entirely explained by changes in non-pecuniary returns. In contrast changes in technology can only explain about a fifth of the change. Interestingly, equilibrium effects are more relevant for this type of job. Without wage adjustments, the change in non-pecuniary returns would cause an even larger increase in the employment share of NRM.

The top-right panel performs the same exercises for routine cognitive (RC) occupations. Overall, we observe a slight decline in the fraction of the population employed in such occupations (-1 percentage point). The counterfactual experiments show that both technological changes and changes to non-pecuniary returns have contributed to the historical trajectory. Nevertheless, technology takes the lion's share.

Finally, the bottom-right panel shows the results for routine manual (RM) occupations. Both technology and non-pecuniary returns have contributed to the observed 6 percentage point fall in the fraction of workers in routine manual occupations. Technology and non-pecuniary returns had a comparable impact over the whole sample period. Interestingly, the difference between the partial equilibrium scenario and fixed technology one suggests that general equilibrium effects mitigate the negative impact of technological change on the share of the population working in routine manual occupations: as workers flow out of these jobs, marginal returns tend to go up and slow down the outflows.

To summarize, we observe that technological change has been the main driver of the employment boom in NRC jobs and of the employment bust in RM jobs. In NRM occupations a big part of the changes can be attributed to non-pecuniary returns. Finally, in RC jobs there is little change overall, but technological change still exerts a strong influence.

Wages. Figure 11 shows both actual and counterfactual changes in the wage rate of different demographic groups, following the same scheme used in Figure 10. Between 1980 and 2018 hourly wage income experienced a large increase for college graduates (right panels); this is almost entirely driven by technological change. The equilibrium effects originating from changes in non-pecuniary returns are smaller and have opposite implications for men and women. Changes in non-pecuniary returns have essentially no impact for college-educated men and are associated with a small increase in the hourly wage rate of college-educated women.

Wages of non-college men declined over the sample period and technological change is the main contributor to this pattern. Notably, the equilibrium effects, as captured by the differences in the fixed employment scenario and the fixed non-pecuniary scenario, helped mitigate the wage drop experienced by this demographic group.

The bottom left panel shows that, while low-educated women experienced a small increase in their labor income, they substantially reduced their gap with men; this pattern is almost entirely explained by technological changes. As for non-college men, general equilibrium effects contributed positively to their wages.

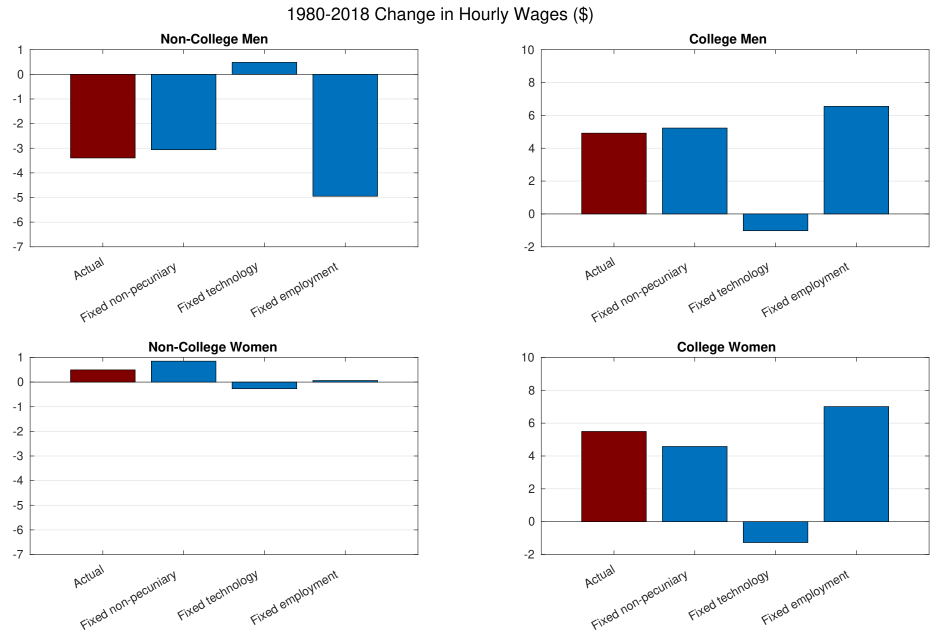

Figure 11: Changes in the average hourly wage received by the different demographic groups in the baseline model (which replicates the data) and in the counterfactual scenarios from 1980 to 2018.

7 Discussion and Conclusions

Significant labor market shifts, often occurring within the span of a decade, have been observed since the 1980s. From the point of view of workers, changes in labor market structure are embodied in the pecuniary and non-pecuniary surplus derived from different job matches. This study examines these patterns as the equilibrium outcome of the interaction between technological progress and non-pecuniary job returns. The latter reflect heterogeneity in the worker-job match values that can be estimated by combining data on job assignments, earnings and hours worked. The analysis emphasizes that similar jobs are valued differently by workers. These differences can be further separated into monetary and non-monetary returns from employment. In principle, pecuniary and non-pecuniary job surplus could be traded off by workers when making job choices. However, the intensity of these trade-offs varies: when we explore the hypothesis of compensating differentials (negative covariation of pecuniary and non-pecuniary surplus), we find that trade-offs are detected among almost all workers but especially strong among non-college workers and, more generally, among women. The intensity of these trade-offs seems to also change over time.

Our analysis suggests that shifts in non-pecuniary surplus are key to account for the total surplus that workers derive from employment. Men have experienced a severe deterioration of their non-pecuniary surplus over time, while women have enjoyed a significant improvement.

The pecuniary surplus increased for both groups over the sample period.

Having estimated worker-job match surplus, we consider a production technology to describe the aggregation of different labor factors and estimate its parameters, separately, over different decades. To bypass the endogeneity of prices and quantities in the estimation of technology parameters, we employ moment restrictions based on exogeneity restrictions.

Having recovered production technology parameters for different decades, we explore the quantitative contribution of both demand and supply forces to the observed shifts in employment and wages. By contrasting the impact of technological change to that of heterogeneous job valuations, these exercises shed light on the mechanics of structural change in the labor market and provide a way to rationalize some of the observations described in the first part of the paper.

Non-pecuniary factors play a central role in the employment patterns of men. Had these stayed at their 1980 levels, the participation of both high and low-educated men would be much higher in 2018. Technological partially offset the negative impact of changes in non-pecuniary returns on the labor force participation of college-educated men, while further reducing the participation of non-college men.

The story is different for women, as changes in both non-pecuniary returns and technology have bolstered their labor force participation. For less-educated women, non-pecuniary returns and technological change play a similar role in explaining the increase in participation. For non-college-educated women, changes in non-pecuniary returns are the most important driver of increased participation. For college-educated women, a substantial role is played by technology as well.

Finally, we show that, while employment patterns are the by-product of both technology and preferences, the evolution of wages can almost entirely be explained by technological progress. This is true across all gender and education groups. Price responses due to changes in worker supply, while clearly present, are relatively less important than the price effects induced by technological change.

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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.

A.1 Identification of 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

$$\begin{aligned} U_{ijmt} = \max_{h_{ijmt}} \quad & \frac{c_{ijmt}^{1-\sigma} - 1}{1-\sigma} - \psi_i \frac{h_{ijmt}^{1-\gamma}}{1-\gamma} + b_{ijt} \\ \text{s.t.} \quad & c_{ijmt} = w_{ijmt} h_{ijmt} \end{aligned} \tag{36}$$

the associated first order condition in logarithmic form is

$$\log\left(h_{ijmt}\right) = -\frac{1}{\sigma-\gamma}\log\left(\psi_i\right) + \frac{1-\sigma}{\sigma-\gamma}\log\left(w_{ijmt}\right) \tag{37}$$

The empirical counterpart of this is

$$\log\left(h_{ijmt}\right) = \alpha_i + \beta\log\left(w_{ijmt}\right) + \epsilon_{ijmt}^1 \equiv f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) + \epsilon_{ijmt}^1 \tag{38}$$

with

$$\alpha_i = -\frac{1}{\sigma-\gamma}\log\left(\psi_i\right) \qquad \beta = \frac{1-\sigma}{\sigma-\gamma} \tag{39}$$

With the linear specification of $f(\cdot,\cdot)$, moments (17) and (18) describe an OLS estimator of (38). From the estimation of the latter equation we can obtain γ and ψ_i as a function of σ:

$$\gamma = \sigma - \frac{1-\sigma}{\beta} \qquad \psi_i = \exp\left(-\frac{1-\sigma}{\beta}\alpha_i\right) \tag{40}$$

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 (21) and (22), given that $\boldsymbol{Z}_{ijmt}^2$ has at least two elements

$Z^2_{1,ijmt}$ and $Z^2_{2,ijmt}$. From eq. (21) we have

$$\tilde{b}_{ijt} = E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u^i_h\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta}\middle| i,j,t\right] \tag{41}$$

where $\tilde{b}_{ijt} = \frac{b_{ijt}}{\sigma_\theta}$. Plugging this into (22) gives

$$E\Bigg[\Bigg(\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u^i_h\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta} \\ -E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u^i_h\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta}\middle| i,j,t\right]\Bigg)\boldsymbol{Z}^2_{ijmt}\Bigg] = 0 \tag{42}$$

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. (41) identifies b_{ijt}.

Identification of production function parameters. On the firm side, taking the ratio between the wages for two demographic groups within an occupation (eq. (11)),we have that

$$\frac{w_{ijmt}}{w_{i'jmt}} = \frac{\beta_{ijt}}{\beta_{i'jt}} \tag{43}$$

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

$$\frac{w_{ijmt}}{w_{ij'mt}} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\widetilde{L}_{j'mt}}{\widetilde{L}_{jmt}}\right)^{1-\rho} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\sum_{i'}\beta_{i'j't}L_{i'j'mt}}{\sum_{i'}\beta_{i'jt}L_{i'jmt}}\right)^{1-\rho} \tag{44}$$

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. (44) for $j' = 1$ gives

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho-1)\log\left(\frac{\sum_{i'}\beta_{i'jt}L_{i'jmt}}{\sum_{i'}\beta_{i'1t}L_{i'1mt}}\right) \tag{45}$$

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:

$$W_{ijmt} = \gamma_{jt} + \psi B_{ijt} + \phi\Lambda_{jmt} + \epsilon_{ijmt} \tag{46}$$

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. (7) that, plugging the constraints into the objective function, becomes

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} - \sum_i \tilde{w}_{ij} L_{ijv} \tag{47}$$

the associated first order condition is

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho} \rho \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho-1} \beta_{ij} \tag{48}$$

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

$$z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho-1} = z_{jv'}^{\rho} \left(\sum_i \beta_{ij} L_{ijv'} \right)^{\rho-1} \tag{49}$$

$$\sum_i \beta_{ij} L_{ijv'} = \frac{z_{jv}^{\frac{\rho}{\rho-1}}}{z_{jv'}^{\frac{\rho}{\rho-1}}} \sum_i \beta_{ij} L_{ijv} \tag{50}$$

Integrating over $v' \in V_j$ we get

$$\sum_i \beta_{ij} L_{ij} = z_{jv}^{\frac{\rho}{\rho-1}} \int_{v' \in V_j} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \sum_i \beta_{ij} L_{ijv} \tag{51}$$

$$\sum_i \beta_{ij} L_{ijv} = z_{jv}^{\frac{-\rho}{\rho-1}} \left(\int_{v' \in V_j} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \right)^{-1} \sum_i \beta_{ij} L_{ij} \tag{52}$$

The aggregate production function is given by

$$Y = \left(\int_v v_{jv}^{\rho} dv \right)^{\frac{1}{\rho}} \tag{53}$$

$$= \left(\sum_j \int_{v \in V_j} v_{jv}^{\rho} dv \right)^{\frac{1}{\rho}} \tag{54}$$

$$= \left(\sum_j \int_{v \in V_j} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} dv \right)^{\frac{1}{\rho}} \tag{55}$$

Using (52) this gives

$$Y = \left[\sum_j \int_{v \in V_j} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} dv \right]^{\frac{1}{\rho}} \tag{56}$$

$$= \left[\sum_j \int_{v \in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \left(\int_{v'} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \right)^{-\rho} \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{57}$$

$$= \left[\sum_j \underbrace{\left(\int_{v \in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{58}$$

$$= \left[\sum_j \tilde{\alpha}_j \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{59}$$

$$= A \left[\sum_j \alpha_j \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{60}$$

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 (52) into (48) we have

$$\tilde{w}_{ij} = P Y^{(1-\rho)} \rho \underbrace{\left(\int_{v \in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_{i'} \beta_{i'j} L_{i'j} \right)^{\rho-1} \beta_{ij} \tag{61}$$

$$\frac{\tilde{w}_{ij}}{P} = Y^{(1-\rho)} \rho \tilde{\alpha}_j \frac{\sum_{j'} \tilde{\alpha}_{j'}}{\sum_{j'} \tilde{\alpha}_{j'}} \left(\sum_{i'} \beta_{i'j} L_{i'j} \right)^{\rho-1} \beta_{ij} \tag{62}$$

$$w_{ij} = \rho A^{\rho} \alpha_j \beta_{ij} \left(\frac{Y}{\sum_{i'} \beta_{i'j} L_{i'j}} \right)^{(1-\rho)} \tag{63}$$

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

C Model with capital

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

$$\max_{p_{jv},\lambda_{jv},L_{ijv}} \quad p_{jv}\lambda_{jv} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{64}$$

$$\text{s.t.} \quad \lambda_{jv} = z_{jv} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\gamma} (\eta_j K_{jv})^{1-\gamma} \tag{65}$$

$$p_{jv} = \left[\frac{\lambda_{jv}}{Y} \right]^{-(1-\rho)} P \tag{66}$$

Equivalently

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho\gamma} (\eta_j K_{jv})^{\rho(1-\gamma)} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{67}$$

The associated first order conditions are

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho} \rho\gamma \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho\gamma - 1} (\eta_j K_{jv})^{\rho(1-\gamma)} \beta_{ij} \tag{68}$$

and

$$r = PY^{(1-\rho)} z_{jv}^{\rho} \rho (1-\gamma) \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho\gamma} (\eta_j K_{jv})^{\rho(1-\gamma)-1} \eta_j \tag{69}$$

Dividing the two first order conditions by each other we get

$$\frac{\tilde{w}_{ij}}{r} = \beta_{ij} \frac{\gamma}{1-\gamma} \frac{K_{jv}}{\sum_{i'} \beta_{i'j} L_{i'jv}} \Rightarrow K_{jv} = \frac{w_{ij}(1-\gamma)}{r\gamma\beta_{ij}} \sum_{i'} \beta_{i'j} L_{i'jv} \tag{70}$$

Notice that this implies

$$\frac{K_{jv}}{\sum_{i'} \beta_{i'j} L_{i'jv}} = \frac{\tilde{w}_{ij}(1-\gamma)}{r\gamma\beta_{ij}} = \frac{K_j}{\sum_{i'} \beta_{i'j} L_{i'j}} \tag{71}$$

where $K_j = \int_{v' \in V_j} K_{jv} dv$ and $L_{ij} = \int_{v' \in V_j} L_{ijv} dv$.
Using (70) into (68) we get

$$\tilde{w}_{ij} = \left(\frac{\tilde{w}_{ij}}{r} \right)^{\rho(1-\gamma)} PY^{(1-\rho)} z_{jv}^{\rho} \rho \gamma^{1-\rho(1-\gamma)} (1-\gamma)^{\rho(1-\gamma)} \eta_j^{\rho(1-\gamma)} \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho-1} \beta_{ij}^{1-\rho(1-\gamma)} \tag{72}$$

$$w_{ij} = \Xi \eta_j^{\frac{\rho(1-\gamma)}{1-\rho(1-\gamma)}} z_{jv}^{\frac{\rho}{1-\rho(1-\gamma)}} \beta_{ij} \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\frac{\rho-1}{1-\rho(1-\gamma)}} \tag{73}$$

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 (73) implies the same relation in (50) and, thus, equation (52). Using (52) in (73) we get

$$w_{ij} = \Xi \Lambda_j \beta_{ij} \left(\sum_{i'} \beta_{i'j} L_{i'j} \right)^{\frac{\rho-1}{1-\rho(1-\gamma)}} \tag{74}$$

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

$$\log\left(\frac{w_{ij}}{w_{i2}}\right) = \log\left(\frac{\Lambda_j}{\Lambda_1}\right) + \log\left(\frac{\beta_{ij}}{\beta_{i1}}\right) + \frac{\rho-1}{1-\rho(1-\gamma)} \log\left(\frac{\sum_{i'} \beta_{i'j} L_{i'j}}{\sum_{i'} \beta_{i'1} L_{i'1}}\right) \tag{75}$$

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

$$W_{ijmt} = \gamma_{jt} + \psi \hat{B}_{ijt} + \phi \hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{76}$$

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

Note: In the baseline model we have $\phi = \rho^{\text{base}} - 1$ while here $\phi = \frac{\rho-1}{1-\rho(1-\gamma)}$. Thus

$$1 - \rho^{\text{base}} = \frac{1-\rho}{1-\rho(1-\gamma)} \tag{77}$$

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

$$\rho^{\text{base}} < \rho \tag{78}$$

This implies that if our baseline model is misspecified and the model described here is the correct one, ρ^{base} is a lower bound for the actual ρ.
Assuming $\gamma = 0.66$, a common choice in the literature, our baseline estimate of $\hat{\phi} = -0.60$ delivers $\rho = 0.50$ which implies an elasticity of substitution of about 2.00.

D Additional Tables and Graphs

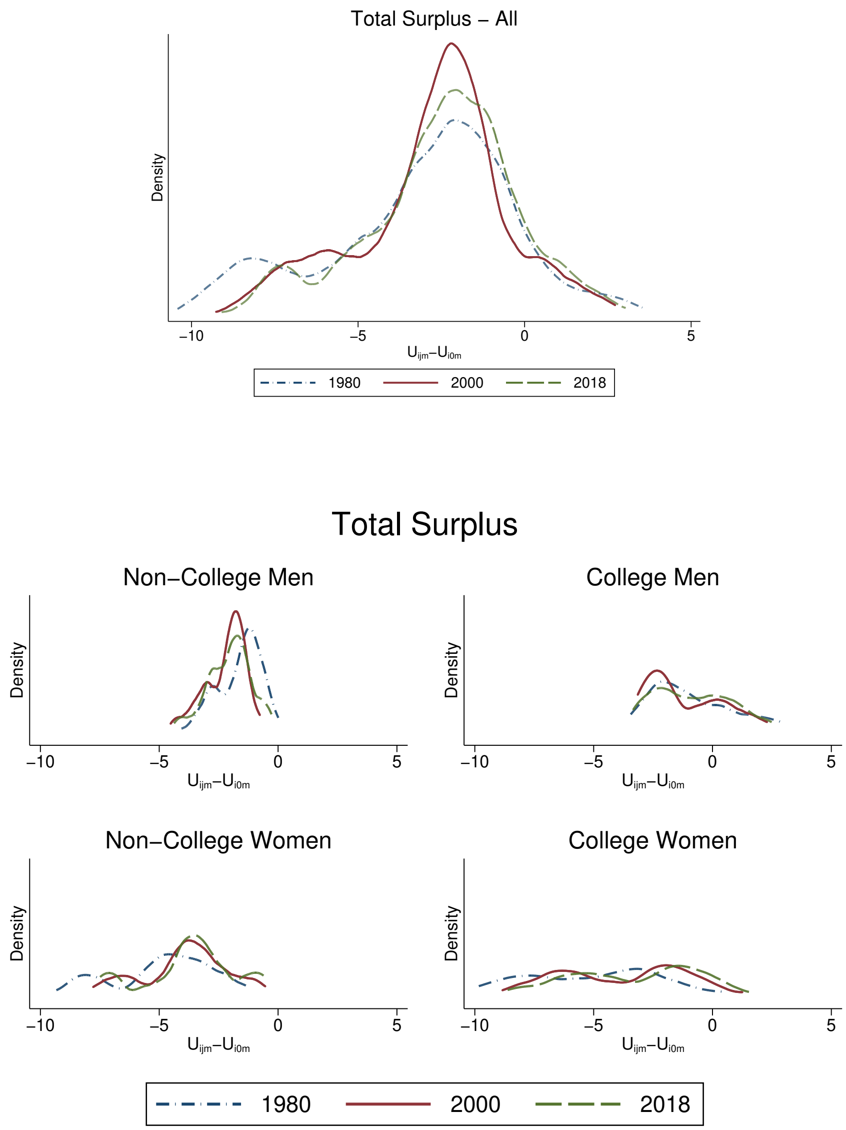

Figure 12: Distribution of surplus (unweighted): aggregate (top panel) and disaggregated (bottom four panels).

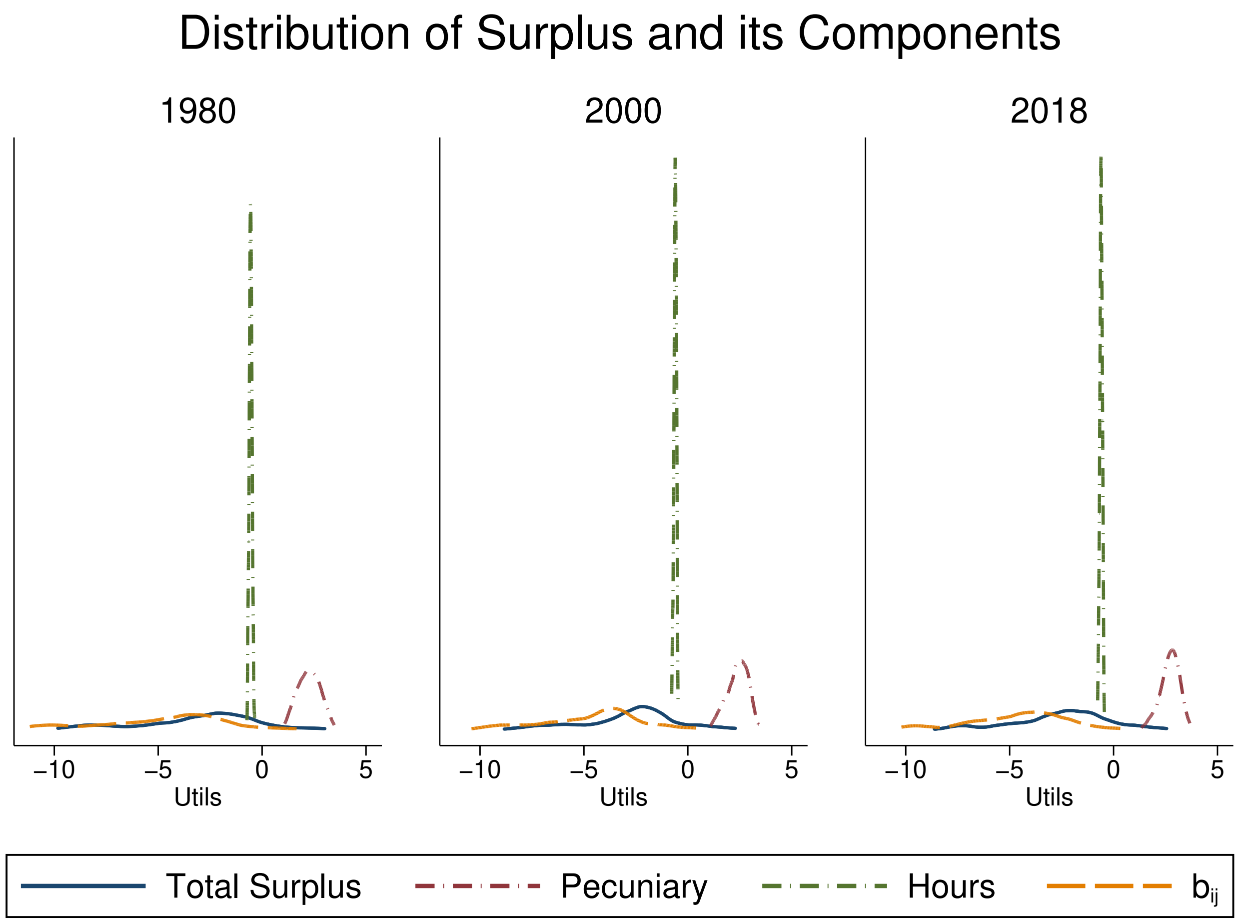

Figure 13: Distribution of surplus (unweighted): this figure reports, for different years, the density functions of (i) total systematic surplus across worker-job matches; (ii) its pecuniary surplus component; (iii) its component concerning the disutility from hours worked; (iv) its non-pecuniary surplus component.

			NON-IV	IV		
			(1)	(2)	(3)	(4)
		$\hat{\gamma}$	-0.5173	-0.5130	-0.5253	-0.5253
			(0.1391)	(0.0995)	(0.0739)	(0.0812)
ψ_i						
Age 25-34	Non-college	Men	8.240e-06	8.435e-06	7.774e-06	7.774e-06
			(5.236e-04)	(6.019e-05)	(1.281e-05)	(1.303e-03)
		Women	1.052e-05	1.077e-05	9.940e-06	9.940e-06
			(6.009e-04)	(7.260e-05)	(1.563e-05)	(1.429e-03)
	College	Men	7.789e-06	7.972e-06	7.348e-06	7.348e-06
			(4.925e-04)	(5.744e-05)	(1.206e-05)	(1.383e-03)
		Women	9.576e-06	9.802e-06	9.044e-06	9.044e-06
			(5.600e-04)	(6.793e-05)	(1.435e-05)	(1.430e-03)
Age 35-44	Non-college	Men	7.721e-06	7.902e-06	7.283e-06	7.283e-06
			(4.925e-04)	(5.673e-05)	(1.201e-05)	(1.347e-03)
		Women	1.005e-05	1.029e-05	9.494e-06	9.494e-06
			(5.777e-04)	(6.857e-05)	(1.497e-05)	(1.398e-03)
	College	Men	6.931e-06	7.089e-06	6.536e-06	6.536e-06
			(4.376e-04)	(5.060e-05)	(1.071e-05)	(1.371e-03)
		Women	9.473e-06	9.694e-06	8.950e-06	8.950e-06
			(5.358e-04)	(6.289e-05)	(1.397e-05)	(1.692e-03)
Age 44-54	Non-college	Men	7.617e-06	7.794e-06	7.185e-06	7.185e-06
			(4.804e-04)	(5.540e-05)	(1.178e-05)	(1.368e-03)
		Women	9.698e-06	9.927e-06	9.160e-06	9.160e-06
			(5.647e-04)	(6.709e-05)	(1.451e-05)	(1.352e-03)
	College	Men	6.628e-06	6.775e-06	6.248e-06	6.248e-06
			(4.122e-04)	(4.702e-05)	(1.015e-05)	(1.373e-03)
		Women	8.782e-06	8.984e-06	8.292e-06	8.292e-06
			(5.009e-04)	(5.312e-05)	(1.297e-05)	(1.250e-03)
		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 4: Estimates of the utility parameters realtive to the disutility of hours worked from the GMM estimator in equation (23).

	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.	-1.8199	-3.8890	0.3752	-2.4078	-1.1245	-3.4595	1.0496	-2.4284	-1.2880	-3.4943	0.8630	-2.3188
	(0.3795)	(0.5155)	(0.3275)	(0.4643)	(0.3354)	(0.4477)	(0.2658)	(0.3597)	(0.2987)	(0.4110)	(0.2344)	(0.3008)
Manag. rel.	-3.4102	-4.5510	-0.2396	-2.8402	-2.7392	-4.3940	-0.1198	-3.3985	-2.7630	-4.5407	-0.3980	-3.4751
	(0.3839)	(0.5269)	(0.3107)	(0.4656)	(0.3285)	(0.4613)	(0.2388)	(0.3468)	(0.2889)	(0.4265)	(0.1959)	(0.2819)
Professional	-2.4706	-3.6159	1.2137	-0.5729	-2.0577	-3.4102	1.6423	-0.5496	-2.2570	-3.5934	1.3614	-0.3922
	(0.3768)	(0.5323)	(0.3033)	(0.4704)	(0.3261)	(0.4568)	(0.2346)	(0.3683)	(0.2875)	(0.4163)	(0.1969)	(0.3140)
Technicians	-2.5022	-4.0646	-0.8217	-2.9063	-2.2984	-4.1451	-0.8597	-3.3951	-2.6718	-4.4369	-1.4158	-3.6230
	(0.3891)	(0.5245)	(0.3035)	(0.4658)	(0.3444)	(0.4555)	(0.2550)	(0.3553)	(0.3021)	(0.4071)	(0.2179)	(0.2909)
Sales	-1.6220	-3.1673	0.1048	-2.6996	-1.1879	-2.8219	0.2668	-2.8072	-1.3377	-2.8236	0.0909	-2.6508
	(0.3608)	(0.4803)	(0.3068)	(0.4340)	(0.3023)	(0.4009)	(0.2352)	(0.2970)	(0.2508)	(0.3589)	(0.1886)	(0.2239)
Admin. Support	-1.7647	-1.7435	-0.4928	-1.7340	-1.4848	-1.6063	-0.5010	-2.0246	-1.5101	-1.7524	-0.7729	-1.7909
	(0.3719)	(0.5035)	(0.2902)	(0.4234)	(0.3121)	(0.4262)	(0.2172)	(0.3014)	(0.2684)	(0.3925)	(0.1828)	(0.2367)
Protective Services	-2.6083	-6.2707	-1.8180	-5.7873	-2.2085	-6.0930	-1.6848	-6.4206	-2.5459	-6.1028	-2.4676	-7.1953
	(0.3732)	(0.5139)	(0.2981)	(0.4512)	(0.3023)	(0.4336)	(0.2152)	(0.3900)	(0.2553)	(0.3759)	(0.1716)	(0.3234)
Other Services	-1.7387	-2.5528	-1.5058	-3.1139	-1.4797	-2.2110	-1.9046	-3.5532	-1.4938	-2.2590	-2.1844	-3.4605
	(0.3129)	(0.4566)	(0.2348)	(0.4029)	(0.2376)	(0.3728)	(0.1543)	(0.2874)	(0.1964)	(0.3335)	(0.1233)	(0.2102)
Mechanics	-1.4078	-6.0900	-2.0812	-6.4609	-1.1225	-6.1515	-2.1820	-6.6323	-1.3745	-6.3216	-2.6122	-6.7661
	(0.3752)	(0.5421)	(0.2780)	(0.4564)	(0.3009)	(0.4446)	(0.1919)	(0.3191)	(0.2525)	(0.4211)	(0.1469)	(0.2784)
Construction Traders	-1.3360	-6.7008	-1.3669	-6.5295	-1.0604	-6.7142	-1.4766	-6.9041	-1.2871	-7.0312	-2.0298	-6.8959
	(0.3702)	(0.4999)	(0.2587)	(0.3967)	(0.3015)	(0.4291)	(0.1843)	(0.2477)	(0.2550)	(0.4025)	(0.1715)	(0.2795)
Precision Prod.	-1.7033	-4.8407	-1.3883	-4.9031	-1.2098	-4.3647	-1.1614	-5.2214	-1.3389	-4.4394	-1.4652	-5.4427
	(0.3837)	(0.4954)	(0.3108)	(0.4342)	(0.3164)	(0.4231)	(0.2383)	(0.3108)	(0.2740)	(0.3776)	(0.2055)	(0.2497)
Machine Operators	-1.0687	-3.0092	-1.8549	-4.5102	-0.8832	-2.7072	-1.9754	-4.6316	-1.1473	-2.8216	-2.2999	-4.3871
	(0.3737)	(0.4836)	(0.2710)	(0.4039)	(0.2993)	(0.4138)	(0.1794)	(0.2764)	(0.2523)	(0.3715)	(0.1422)	(0.2043)
Transportation	-0.8371	-4.1155	-1.4917	-5.5275	-0.6054	-3.7982	-1.7273	-5.7619	-0.8234	-4.0195	-2.1508	-5.8554
	(0.3689)	(0.4932)	(0.2815)	(0.4314)	(0.2953)	(0.4177)	(0.1769)	(0.3013)	(0.2498)	(0.3771)	(0.1293)	(0.2529)

Bootstrapped standard errors in parentheses

Table 5: Estimates of the non-pecuniary component of surplus for 1980.

	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.	-1.9975	-3.1742	0.4422	-1.4802	-1.4814	-2.6993	0.9149	-1.5091	-1.4473	-2.8078	0.7499	-1.3698
	(0.4193)	(0.5346)	(0.3520)	(0.4461)	(0.3769)	(0.4700)	(0.2735)	(0.3618)	(0.3560)	(0.4357)	(0.2635)	(0.3179)
Manag. rel.	-3.4420	-3.7221	-0.0116	-1.6238	-2.9465	-3.3148	-0.0102	-2.1236	-2.9018	-3.5759	-0.3289	-2.2302
	(0.4099)	(0.5400)	(0.3324)	(0.4406)	(0.3705)	(0.4662)	(0.2468)	(0.3370)	(0.3268)	(0.4352)	(0.2259)	(0.2824)
Professional	-2.6253	-3.1994	1.2653	-0.2265	-2.1752	-2.6438	1.4696	-0.0300	-2.3167	-2.9044	1.2603	0.2034
	(0.4250)	(0.5553)	(0.3349)	(0.4453)	(0.3609)	(0.4693)	(0.2497)	(0.3489)	(0.3336)	(0.4289)	(0.2348)	(0.3094)
Technicians	-2.4737	-3.6027	-0.3104	-2.2142	-2.3412	-3.3145	-0.5765	-2.5406	-2.6484	-3.7472	-1.1733	-2.5771
	(0.4244)	(0.5428)	(0.3337)	(0.4440)	(0.3645)	(0.4636)	(0.2410)	(0.3353)	(0.3451)	(0.4205)	(0.2401)	(0.2897)
Sales	-1.5555	-2.5869	0.4384	-1.7247	-1.2897	-2.2882	0.5095	-2.0553	-1.2832	-2.3387	0.1491	-1.8201
	(0.4036)	(0.4925)	(0.3386)	(0.4317)	(0.3454)	(0.4130)	(0.2425)	(0.3202)	(0.3074)	(0.3680)	(0.2278)	(0.2482)
Admin. Support	-1.8422	-1.4997	-0.4043	-1.3154	-1.6425	-1.1750	-0.4423	-1.4588	-1.7238	-1.3181	-0.9141	-1.3252
	(0.4002)	(0.5132)	(0.2970)	(0.3960)	(0.3407)	(0.4311)	(0.2125)	(0.2870)	(0.3104)	(0.3954)	(0.1901)	(0.2382)
Protective Services	-2.6494	-5.4325	-1.6412	-4.6744	-2.3857	-5.0936	-1.3758	-5.0778	-2.5038	-5.4560	-1.9564	-5.3654
	(0.4191)	(0.5562)	(0.3142)	(0.4517)	(0.3520)	(0.4486)	(0.2202)	(0.3402)	(0.3045)	(0.4045)	(0.2025)	(0.2952)
Other Services	-1.4853	-2.0487	-1.2705	-2.5199	-1.4855	-1.8024	-1.4381	-2.7980	-1.5360	-1.8449	-1.9977	-2.7666
	(0.3461)	(0.4467)	(0.2529)	(0.3557)	(0.2749)	(0.3656)	(0.1598)	(0.2603)	(0.2334)	(0.3364)	(0.1455)	(0.2162)
Mechanics	-1.5143	-5.6662	-1.9859	-5.3885	-1.3484	-5.3638	-1.7934	-5.5461	-1.4752	-5.7389	-2.3950	-6.1611
	(0.3999)	(0.5319)	(0.2968)	(0.4163)	(0.3387)	(0.4803)	(0.1980)	(0.3230)	(0.2955)	(0.4226)	(0.1698)	(0.2994)
Construction Traders	-1.3313	-6.0813	-1.6295	-5.9723	-1.2199	-5.8631	-1.3283	-5.9083	-1.4526	-6.2163	-2.0586	-6.4455
	(0.3972)	(0.5024)	(0.2660)	(0.4169)	(0.3251)	(0.4081)	(0.1698)	(0.2674)	(0.2915)	(0.3955)	(0.1658)	(0.2685)
Precision Prod.	-1.9987	-4.4729	-1.9314	-4.5682	-1.7046	-4.1102	-1.5643	-4.5497	-1.6941	-4.1496	-1.9526	-4.6142
	(0.4146)	(0.4946)	(0.3239)	(0.4211)	(0.3527)	(0.4176)	(0.2246)	(0.2915)	(0.3172)	(0.3779)	(0.2092)	(0.2385)
Machine Operators	-1.3582	-2.9077	-1.8917	-4.0987	-1.2316	-2.5751	-1.7331	-4.1084	-1.3756	-2.6458	-2.2627	-4.1433
	(0.3974)	(0.4818)	(0.2755)	(0.3637)	(0.3321)	(0.4085)	(0.1893)	(0.2566)	(0.2913)	(0.3745)	(0.1551)	(0.2070)
Transportation	-0.9535	-3.7539	-1.4577	-4.8532	-0.8281	-3.4679	-1.3567	-4.9427	-0.9151	-3.5981	-1.9526	-4.7290
	(0.3881)	(0.4946)	(0.2761)	(0.3763)	(0.3214)	(0.4158)	(0.1786)	(0.2824)	(0.2804)	(0.3769)	(0.1449)	(0.2317)

Bootstrapped standard errors in parentheses

Table 6: Estimates of the non-pecuniary component of surplus for 1990.

	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.	-2.5388	-3.3902	-0.0335	-1.5803	-1.9979	-2.9880	0.5258	-1.5828	-1.9674	-2.9022	0.3473	-1.2623
	(0.4430)	(0.4923)	(0.4022)	(0.4724)	(0.3978)	(0.4489)	(0.3108)	(0.3792)	(0.3761)	(0.4313)	(0.2709)	(0.3316)
Manag. rel.	-3.8216	-3.7970	-0.4777	-1.7319	-3.5152	-3.4086	-0.3736	-1.9463	-3.3458	-3.3317	-0.5527	-1.8440
	(0.4314)	(0.4927)	(0.3886)	(0.4621)	(0.3740)	(0.4340)	(0.2820)	(0.3484)	(0.3435)	(0.4141)	(0.2245)	(0.2990)
Professional	-2.7465	-3.2057	0.8486	-0.2874	-2.5742	-2.7336	1.0765	-0.3211	-2.5077	-2.6599	0.8980	0.2301
	(0.4475)	(0.4920)	(0.3724)	(0.4527)	(0.3754)	(0.4400)	(0.2716)	(0.3420)	(0.3395)	(0.4159)	(0.2309)	(0.2985)
Technicians	-3.1594	-3.7054	-0.5780	-2.5226	-2.9308	-3.3561	-0.5972	-2.5434	-3.0053	-3.3679	-1.2157	-2.4481
	(0.4410)	(0.4954)	(0.4037)	(0.4734)	(0.3876)	(0.4364)	(0.2843)	(0.3523)	(0.3515)	(0.4135)	(0.2365)	(0.2934)
Sales	-1.9774	-2.5137	-0.1966	-2.0320	-1.7874	-2.3359	0.0073	-2.2168	-1.7501	-2.2963	-0.2402	-1.9395
	(0.4157)	(0.4500)	(0.3956)	(0.4612)	(0.3583)	(0.3898)	(0.2835)	(0.3474)	(0.3230)	(0.3563)	(0.2178)	(0.2795)
Admin. Support	-2.0428	-1.5211	-0.7757	-1.4436	-1.9804	-1.2238	-0.7288	-1.5331	-1.9195	-1.1222	-0.8891	-1.1625
	(0.3966)	(0.4561)	(0.3378)	(0.4144)	(0.3350)	(0.3961)	(0.2267)	(0.2902)	(0.3091)	(0.3749)	(0.1799)	(0.2441)
Protective Services	-2.8465	-4.9619	-1.6830	-4.4375	-2.7827	-4.8019	-1.6667	-4.6004	-2.8133	-4.9781	-1.9473	-4.6044
	(0.4337)	(0.4807)	(0.3553)	(0.4445)	(0.3695)	(0.4321)	(0.2337)	(0.3362)	(0.3251)	(0.4006)	(0.1943)	(0.2830)
Other Services	-1.6913	-1.8522	-1.5535	-2.4995	-1.6938	-1.6361	-1.5683	-2.6568	-1.7744	-1.6942	-1.8290	-2.4431
	(0.3576)	(0.4041)	(0.2911)	(0.3656)	(0.2864)	(0.3344)	(0.1801)	(0.2447)	(0.2482)	(0.3104)	(0.1273)	(0.2001)
Mechanics	-1.8979	-5.6304	-2.3190	-5.7167	-1.6097	-5.2717	-2.0328	-5.7796	-1.6596	-5.3257	-2.1421	-5.5557
	(0.4097)	(0.4737)	(0.3237)	(0.4304)	(0.3376)	(0.4268)	(0.2055)	(0.3092)	(0.3074)	(0.4081)	(0.1559)	(0.2861)
Construction Traders	-1.6782	-6.0060	-2.3172	-6.5549	-1.4823	-5.7067	-1.9012	-6.2014	-1.6845	-5.9255	-2.0080	-5.9472
	(0.3972)	(0.4836)	(0.3072)	(0.3971)	(0.3261)	(0.3971)	(0.1807)	(0.2587)	(0.2917)	(0.3403)	(0.1356)	(0.2097)
Precision Prod.	-2.4446	-4.0850	-2.5378	-4.4727	-2.0588	-3.6821	-2.0976	-4.5255	-2.0534	-3.7187	-2.2077	-4.1414
	(0.4152)	(0.4430)	(0.3420)	(0.3952)	(0.3440)	(0.3815)	(0.2291)	(0.3004)	(0.3143)	(0.3543)	(0.1812)	(0.2359)
Machine Operators	-1.9130	-3.2031	-2.5223	-4.4777	-1.8095	-2.8266	-2.2894	-4.4019	-1.8794	-2.7977	-2.4123	-4.0478
	(0.3980)	(0.4294)	(0.3215)	(0.3806)	(0.3298)	(0.3690)	(0.1956)	(0.2792)	(0.2991)	(0.3463)	(0.1431)	(0.2292)
Transportation	-1.3317	-3.8706	-2.0807	-5.4265	-1.1675	-3.4665	-1.7733	-5.1775	-1.2167	-3.6499	-1.8925	-4.8583
	(0.3890)	(0.4306)	(0.3061)	(0.4082)	(0.3161)	(0.3765)	(0.1878)	(0.2776)	(0.2849)	(0.3580)	(0.1451)	(0.2160)

Bootstrapped standard errors in parentheses

Table 7: Estimates of the non-pecuniary component of surplus for 2000.

Occupation	Age 25-34				Age 35-44							
	Non-college		College		Non-college		College		Non-college		College	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	-2.6965	-3.3708	-0.2911	-1.5416	-2.1101	-2.9378	0.3601	-1.5305	-2.0993	-2.8351	0.1736	-1.3010
	(0.4564)	(0.4903)	(0.4763)	(0.5378)	(0.4148)	(0.4520)	(0.4052)	(0.4441)	(0.4030)	(0.4592)	(0.3455)	(0.3963)
Manag. rel.	-4.1513	-4.0017	-0.6814	-1.6906	-3.7520	-3.5737	-0.5100	-1.8546	-3.7538	-3.4400	-0.7845	-1.6993
	(0.4717)	(0.5011)	(0.4795)	(0.5419)	(0.4082)	(0.4529)	(0.3971)	(0.4260)	(0.3834)	(0.4510)	(0.3208)	(0.3683)
Professional	-2.9362	-3.0777	0.5690	-0.1992	-2.6418	-2.7709	0.8571	-0.3761	-2.8100	-2.7321	0.5601	-0.1374
	(0.4728)	(0.5101)	(0.4605)	(0.5317)	(0.4120)	(0.4522)	(0.3800)	(0.4161)	(0.3847)	(0.4545)	(0.3144)	(0.3562)
Technicians	-3.3803	-3.6197	-0.8092	-2.5415	-3.1093	-3.3099	-0.7067	-2.8378	-3.2825	-3.3176	-1.1763	-2.6155
	(0.4782)	(0.5194)	(0.4814)	(0.5370)	(0.4191)	(0.4524)	(0.3805)	(0.4199)	(0.4007)	(0.4491)	(0.3122)	(0.3673)
Sales	-2.0616	-2.3365	-0.4469	-1.9486	-1.8744	-2.2992	-0.1918	-2.2128	-1.9580	-2.2775	-0.4334	-1.9831
	(0.4292)	(0.4374)	(0.4588)	(0.5110)	(0.3761)	(0.3852)	(0.3840)	(0.4013)	(0.3465)	(0.3739)	(0.2981)	(0.3263)
Admin. Support	-2.1347	-1.6616	-0.9205	-1.3834	-2.0738	-1.3482	-0.9692	-1.6626	-2.2116	-1.2256	-1.1974	-1.3091
	(0.4168)	(0.4577)	(0.4088)	(0.4735)	(0.3556)	(0.4011)	(0.3242)	(0.3481)	(0.3366)	(0.4001)	(0.2539)	(0.2873)
Protective Services	-2.9742	-4.7675	-1.7943	-4.2135	-2.6752	-4.4867	-1.4720	-4.4321	-3.0133	-4.5815	-2.0941	-4.3640
	(0.4637)	(0.4920)	(0.4432)	(0.5185)	(0.4041)	(0.4390)	(0.3414)	(0.4055)	(0.3759)	(0.4242)	(0.2761)	(0.3484)
Other Services	-1.4109	-1.4356	-1.2781	-2.1047	-1.3908	-1.2839	-1.4060	-2.5145	-1.6500	-1.3811	-1.7125	-2.2234
	(0.3658)	(0.4019)	(0.3458)	(0.4200)	(0.2917)	(0.3251)	(0.2496)	(0.2757)	(0.2729)	(0.3184)	(0.1729)	(0.2227)
Mechanics	-2.1806	-5.9012	-2.5705	-5.8837	-1.9036	-5.6853	-2.2086	-5.8967	-1.9470	-5.5849	-2.4590	-5.6173
	(0.4378)	(0.4666)	(0.4096)	(0.5135)	(0.3678)	(0.4257)	(0.2921)	(0.3968)	(0.3418)	(0.4392)	(0.2200)	(0.3163)
Construction Traders	-1.9019	-6.4371	-2.5569	-7.0354	-1.6634	-6.0202	-2.1367	-6.7095	-1.8703	-5.9193	-2.3627	-6.0288
	(0.4295)	(0.4696)	(0.3869)	(0.4835)	(0.3560)	(0.4055)	(0.2791)	(0.3806)	(0.3294)	(0.3925)	(0.2019)	(0.2637)
Precision Prod.	-2.9486	-4.0359	-3.0188	-4.3424	-2.5303	-3.8382	-2.5696	-4.7072	-2.4905	-3.7886	-2.6735	-4.4057
	(0.4313)	(0.4568)	(0.4161)	(0.4667)	(0.3678)	(0.3857)	(0.3200)	(0.3606)	(0.3479)	(0.3842)	(0.2601)	(0.3182)
Machine Operators	-2.3512	-3.6925	-3.0079	-4.6301	-2.0595	-3.1928	-2.4896	-4.6514	-2.2281	-3.1539	-2.7907	-4.4456
	(0.4168)	(0.4157)	(0.3984)	(0.4787)	(0.3460)	(0.3558)	(0.2916)	(0.3547)	(0.3231)	(0.3558)	(0.2313)	(0.2854)
Transportation	-1.4095	-3.9118	-2.1348	-5.4133	-1.1385	-3.3779	-1.8345	-5.2225	-1.2823	-3.3624	-1.9612	-4.8833
	(0.4079)	(0.4210)	(0.3636)	(0.4489)	(0.3346)	(0.3646)	(0.2607)	(0.3197)	(0.3088)	(0.3630)	(0.1812)	(0.2610)

Bootstrapped standard errors in parentheses

Table 8: Estimates of the non-pecuniary component of surplus for 2010.

Occupation	Age 25-34				Age 35-44							
	Non-college		College		Non-college		College		Non-college		College	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Exec., Admin., Manag.	-2.4176	-3.1032	-0.1523	-1.2602	-1.8117	-2.8143	0.4696	-1.2239	-1.8082	-2.7395	0.3522	-1.0541
	(0.4818)	(0.5427)	(0.5045)	(0.5504)	(0.4354)	(0.4912)	(0.4293)	(0.4663)	(0.4181)	(0.4872)	(0.3731)	(0.4101)
Manag. rel.	-3.7934	-3.9596	-0.3535	-1.4391	-3.4168	-3.5171	-0.3425	-1.6018	-3.5077	-3.3945	-0.5964	-1.4516
	(0.4915)	(0.5433)	(0.4975)	(0.5597)	(0.4393)	(0.4911)	(0.4152)	(0.4536)	(0.4134)	(0.4854)	(0.3534)	(0.3905)
Professional	-2.6626	-2.8785	0.7542	0.0196	-2.3187	-2.7311	0.9527	-0.1218	-2.4529	-2.6923	0.6782	-0.0484
	(0.4879)	(0.5429)	(0.4852)	(0.5465)	(0.4236)	(0.4791)	(0.3999)	(0.4433)	(0.4073)	(0.4665)	(0.3396)	(0.3718)
Technicians	-3.1172	-3.3810	-0.4999	-2.2710	-2.8679	-3.1785	-0.4653	-2.6284	-2.9709	-3.1799	-0.9596	-2.5583
	(0.4990)	(0.5489)	(0.5174)	(0.5572)	(0.4380)	(0.4915)	(0.4226)	(0.4504)	(0.4119)	(0.4631)	(0.3527)	(0.3799)
Sales	-1.8812	-2.2324	-0.4746	-1.8682	-1.7682	-2.3040	-0.3373	-2.1542	-1.8770	-2.3405	-0.4347	-1.9401
	(0.4474)	(0.4827)	(0.4832)	(0.5271)	(0.3955)	(0.4263)	(0.4086)	(0.4327)	(0.3758)	(0.4144)	(0.3347)	(0.3556)
Admin. Support	-1.8615	-1.6383	-0.6614	-1.2146	-1.8560	-1.4865	-0.7876	-1.4519	-2.0133	-1.3233	-1.0640	-1.2163
	(0.4284)	(0.4998)	(0.4213)	(0.4830)	(0.3685)	(0.4367)	(0.3370)	(0.3670)	(0.3474)	(0.4212)	(0.2739)	(0.2994)
Protective Services	-2.7606	-4.5069	-1.6293	-3.9420	-2.6184	-4.6181	-1.3890	-4.1772	-2.7606	-4.5879	-1.6353	-4.1727
	(0.4732)	(0.5217)	(0.4507)	(0.5097)	(0.4188)	(0.4703)	(0.3525)	(0.4235)	(0.3977)	(0.4529)	(0.2893)	(0.3725)
Other Services	-1.2228	-1.2987	-1.0878	-1.8386	-1.1193	-1.2223	-1.2076	-2.1846	-1.3288	-1.2557	-1.5022	-2.0573
	(0.3971)	(0.4627)	(0.3725)	(0.4326)	(0.3146)	(0.3724)	(0.2608)	(0.3029)	(0.2867)	(0.3469)	(0.1927)	(0.2497)
Mechanics	-2.0404	-5.7789	-2.4579	-5.6908	-1.7807	-5.7535	-2.1423	-5.8878	-1.8606	-5.5833	-2.4465	-5.7244
	(0.4618)	(0.5092)	(0.4187)	(0.4817)	(0.3899)	(0.4632)	(0.3135)	(0.4081)	(0.3593)	(0.4363)	(0.2465)	(0.3257)
Construction Traders	-1.8437	-5.9881	-2.5081	-6.1735	-1.4115	-5.6231	-2.0905	-6.0051	-1.6376	-5.7607	-2.3309	-6.2259
	(0.4621)	(0.4936)	(0.4213)	(0.4997)	(0.3826)	(0.4564)	(0.2939)	(0.3798)	(0.3526)	(0.4304)	(0.2643)	(0.3053)
Precision Prod.	-2.7351	-3.6833	-2.6791	-3.7402	-2.4015	-3.7283	-2.4816	-4.2342	-2.3938	-3.7382	-2.5349	-4.3005
	(0.4553)	(0.5019)	(0.4454)	(0.4724)	(0.3861)	(0.4299)	(0.3425)	(0.3672)	(0.3598)	(0.4103)	(0.2629)	(0.3142)
Machine Operators	-2.1324	-3.5226	-2.3934	-4.2963	-1.9242	-3.2941	-2.4029	-4.5754	-2.0107	-3.1635	-2.6568	-4.2181
	(0.4442)	(0.4772)	(0.4111)	(0.4762)	(0.3651)	(0.3924)	(0.2983)	(0.3649)	(0.3358)	(0.3853)	(0.2286)	(0.2981)
Transportation	-1.1399	-3.3993	-1.7033	-4.3369	-0.8538	-3.1952	-1.4090	-4.4180	-0.9255	-3.1601	-1.5405	-4.2976
	(0.4285)	(0.4698)	(0.3840)	(0.4358)	(0.3545)	(0.4028)	(0.2648)	(0.3143)	(0.3241)	(0.3856)	(0.1965)	(0.2633)

Bootstrapped standard errors in parentheses

Table 9: Estimates of the non-pecuniary component of surplus for 2016.

	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)	(0.0083)	(0.0090)	(0.0083)	(0.0140)	(0.0151)	(0.0099)	(0.0065)	(0.0136)	(0.0167)
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)	(0.0103)	(0.0142)	(0.0120)	(0.0143)	(0.0119)	(0.0266)	(0.0231)	(0.0167)	(0.0136)	(0.0250)	(0.0306)
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)	(0.0102)	(0.0130)	(0.0106)	(0.0137)	(0.0102)	(0.0182)	(0.0133)	(0.0165)	(0.0112)	(0.0195)	(0.0140)
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)	(0.0105)	(0.0101)	(0.0150)	(0.0483)	(0.0216)	(0.0424)	(0.0187)	(0.0089)	(0.0383)	(0.0204)
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)	(0.0048)	(0.0109)	(0.0177)	(0.0089)	(0.0059)	(0.0294)	(0.0214)	(0.0114)	(0.0067)	(0.0211)	(0.0207)
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)	(0.0040)	(0.0103)	(0.0066)	(0.0087)	(0.0044)	(0.0146)	(0.0092)	(0.0108)	(0.0047)	(0.0167)	(0.0101)
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)	(0.0216)	(0.0299)	(0.0255)	(0.0109)	(0.0418)	(0.0202)	(0.0901)	(0.0131)	(0.0139)	(0.0279)	(0.1408)
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)	(0.0192)	(0.0199)	(0.0097)	(0.0077)	(0.0480)	(0.0839)	(0.0114)	(0.0074)	(0.0764)	(0.0407)
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)	(0.0247)	(0.0163)	(0.0578)	(0.0069)	(0.0177)	(0.0254)	(0.1049)	(0.0084)	(0.0275)	(0.0335)	(0.0819)
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)	(0.0316)	(0.0132)	(0.0456)	(0.0087)	(0.0285)	(0.0271)	(0.0750)	(0.0069)	(0.0366)	(0.0412)	(0.1308)
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)	(0.0138)	(0.0124)	(0.0197)	(0.0081)	(0.0163)	(0.0289)	(0.0422)	(0.0109)	(0.0103)	(0.0296)	(0.0443)
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)	(0.0305)	(0.0169)	(0.0074)	(0.0058)	(0.0251)	(0.0431)	(0.0068)	(0.0048)	(0.0460)	(0.0245)
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)	(0.0074)	(0.0191)	(0.0445)	(0.0065)	(0.0067)	(0.0213)	(0.0373)	(0.0070)	(0.0073)	(0.0326)	(0.0771)

Bootstrapped standard errors in parentheses

Table 10: 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)	(0.0088)	(0.0177)	(0.0120)	(0.0112)	(0.0094)	(0.0178)	(0.0131)	(0.0150)	(0.0103)	(0.0197)	(0.0234)
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)	(0.0115)	(0.0174)	(0.0144)	(0.0569)	(0.0132)	(0.0224)	(0.0174)	(0.0179)	(0.0131)	(0.0342)	(0.0248)
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)	(0.0143)	(0.0182)	(0.0164)	(0.0182)	(0.0148)	(0.0252)	(0.0188)	(0.0232)	(0.0151)	(0.0318)	(0.0188)
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)	(0.0081)	(0.0232)	(0.0137)	(0.0120)	(0.0106)	(0.0278)	(0.0144)	(0.0212)	(0.0107)	(0.0365)	(0.0277)
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)	(0.0065)	(0.0155)	(0.0131)	(0.0110)	(0.0082)	(0.0157)	(0.0193)	(0.0136)	(0.0066)	(0.0254)	(0.0251)
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)	(0.0063)	(0.0190)	(0.0110)	(0.0103)	(0.0063)	(0.0142)	(0.0134)	(0.0156)	(0.0069)	(0.0251)	(0.0149)
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)	(0.0338)	(0.0193)	(0.0851)	(0.0161)	(0.0126)	(0.0226)	(0.0297)	(0.0181)	(0.0333)	(0.0265)	(0.0631)
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)	(0.0088)	(0.0242)	(0.0167)	(0.0140)	(0.0095)	(0.0313)	(0.0499)	(0.0139)	(0.0140)	(0.0695)	(0.0489)
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)	(0.0174)	(0.0196)	(0.0340)	(0.0098)	(0.0359)	(0.0825)	(0.0461)	(0.0119)	(0.0195)	(0.0601)	(0.1138)
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)	(0.0231)	(0.0218)	(0.0736)	(0.0082)	(0.0371)	(0.0262)	(0.0689)	(0.0148)	(0.0528)	(0.0586)	(0.2305)
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)	(0.0108)	(0.0516)	(0.0369)	(0.0125)	(0.0116)	(0.0355)	(0.0333)	(0.0145)	(0.0118)	(0.0323)	(0.0612)
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)	(0.0074)	(0.0138)	(0.0256)	(0.0088)	(0.0085)	(0.0359)	(0.0312)	(0.0095)	(0.0081)	(0.0352)	(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)	(0.0137)	(0.0295)	(0.0254)	(0.0083)	(0.0139)	(0.0219)	(0.0508)	(0.0121)	(0.0193)	(0.0295)	(0.0455)

Bootstrapped standard errors in parentheses

Table 11: 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)	(0.0134)	(0.0192)	(0.0159)	(0.0164)	(0.0145)	(0.0281)	(0.0236)	(0.0195)	(0.0148)	(0.0315)	(0.0189)
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)	(0.0283)	(0.0420)	(0.0318)	(0.0383)	(0.0253)	(0.0546)	(0.0407)	(0.0453)	(0.0269)	(0.0542)	(0.0374)
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)	(0.0129)	(0.0153)	(0.0132)	(0.0161)	(0.0129)	(0.0208)	(0.0177)	(0.0167)	(0.0134)	(0.0229)	(0.0162)
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)	(0.0142)	(0.0231)	(0.0267)	(0.0201)	(0.0146)	(0.0289)	(0.0237)	(0.0230)	(0.0163)	(0.0396)	(0.0225)
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)	(0.0150)	(0.0292)	(0.0288)	(0.0176)	(0.0149)	(0.0336)	(0.0302)	(0.0225)	(0.0119)	(0.0347)	(0.0400)
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)	(0.0107)	(0.0257)	(0.0155)	(0.0149)	(0.0091)	(0.0256)	(0.0266)	(0.0164)	(0.0101)	(0.0240)	(0.0190)
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)	(0.0152)	(0.0348)	(0.0340)	(0.0203)	(0.0181)	(0.0222)	(0.0255)	(0.0161)	(0.0220)	(0.0205)	(0.0301)
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)	(0.0131)	(0.0361)	(0.0234)	(0.0202)	(0.0116)	(0.0520)	(0.0325)	(0.0169)	(0.0116)	(0.0363)	(0.0282)
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)	(0.0392)	(0.0225)	(0.0537)	(0.0116)	(0.0218)	(0.0314)	(0.0656)	(0.0138)	(0.0214)	(0.0286)	(0.0577)
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)	(0.1290)	(0.0461)	(0.0668)	(0.0118)	(0.0549)	(0.0313)	(0.0663)	(0.0104)	(0.0262)	(0.0330)	(0.0820)
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)	(0.0335)	(0.0287)	(0.0216)	(0.0163)	(0.0483)	(0.0523)	(0.0209)	(0.0163)	(0.0399)	(0.0431)
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)	(0.0382)	(0.0250)	(0.0142)	(0.0130)	(0.0332)	(0.0396)	(0.0138)	(0.0119)	(0.0246)	(0.0486)
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)	(0.0144)	(0.0299)	(0.0766)	(0.0095)	(0.0113)	(0.0459)	(0.0743)	(0.0118)	(0.0196)	(0.0355)	(0.0459)

Bootstrapped standard errors in parentheses

Table 12: 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)	(0.0130)	(0.0173)	(0.0148)	(0.0162)	(0.0130)	(0.0261)	(0.0192)	(0.0156)	(0.0144)	(0.0299)	(0.0219)
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)	(0.0177)	(0.0279)	(0.0206)	(0.0287)	(0.0178)	(0.0404)	(0.0272)	(0.0271)	(0.0199)	(0.0429)	(0.0291)
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)	(0.0117)	(0.0130)	(0.0127)	(0.0151)	(0.0127)	(0.0214)	(0.0153)	(0.0153)	(0.0126)	(0.0206)	(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)	(0.0254)	(0.0212)	(0.0227)	(0.0174)	(0.0311)	(0.0278)	(0.0324)	(0.0187)	(0.0356)	(0.0262)
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)	(0.0076)	(0.0240)	(0.0157)	(0.0144)	(0.0114)	(0.0317)	(0.0222)	(0.0142)	(0.0096)	(0.0306)	(0.0273)
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)	(0.0061)	(0.0188)	(0.0105)	(0.0093)	(0.0066)	(0.0283)	(0.0116)	(0.0108)	(0.0066)	(0.0233)	(0.0117)
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)	(0.0187)	(0.0163)	(0.0257)	(0.0117)	(0.0155)	(0.0180)	(0.0287)	(0.0139)	(0.0165)	(0.0200)	(0.0307)
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)	(0.0172)	(0.0161)	(0.0097)	(0.0065)	(0.0310)	(0.0194)	(0.0094)	(0.0070)	(0.0364)	(0.0190)
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)	(0.0229)	(0.0210)	(0.0837)	(0.0092)	(0.0254)	(0.0291)	(0.0637)	(0.0106)	(0.0347)	(0.0250)	(0.0668)
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)	(0.0567)	(0.0288)	(0.0939)	(0.0104)	(0.0489)	(0.0324)	(0.0881)	(0.0110)	(0.0361)	(0.0402)	(0.0905)
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)	(0.0276)	(0.0226)	(0.0116)	(0.0131)	(0.0382)	(0.0448)	(0.0136)	(0.0139)	(0.0535)	(0.0640)
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)	(0.0272)	(0.0442)	(0.0100)	(0.0089)	(0.0392)	(0.0796)	(0.0112)	(0.0081)	(0.0386)	(0.0425)
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)	(0.0122)	(0.0220)	(0.0525)	(0.0080)	(0.0116)	(0.0387)	(0.0600)	(0.0091)	(0.0090)	(0.0289)	(0.0485)

Bootstrapped standard errors in parentheses

Table 13: 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)	(0.0180)	(0.0331)	(0.0221)	(0.0225)	(0.0189)	(0.0382)	(0.0301)	(0.0266)	(0.0201)	(0.0542)	(0.0350)
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)	(0.0164)	(0.0304)	(0.0280)	(0.0309)	(0.0278)	(0.0426)	(0.0320)	(0.0299)	(0.0371)	(0.0526)	(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)	(0.0207)	(0.0185)	(0.0201)	(0.0147)	(0.0289)	(0.0234)	(0.0194)	(0.0168)	(0.0352)	(0.0238)
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)	(0.0161)	(0.0280)	(0.0243)	(0.0211)	(0.0288)	(0.0387)	(0.0311)	(0.0251)	(0.0200)	(0.0431)	(0.0325)
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)	(0.0147)	(0.0422)	(0.0314)	(0.0276)	(0.0210)	(0.0618)	(0.0481)	(0.0329)	(0.0223)	(0.0595)	(0.0382)
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)	(0.0122)	(0.0180)	(0.0167)	(0.0158)	(0.0122)	(0.0334)	(0.0195)	(0.0169)	(0.0138)	(0.0411)	(0.0203)
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)	(0.0181)	(0.0171)	(0.0243)	(0.0173)	(0.0206)	(0.0225)	(0.0428)	(0.0190)	(0.0230)	(0.0255)	(0.0496)
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)	(0.0165)	(0.0273)	(0.0209)	(0.0135)	(0.0123)	(0.0301)	(0.0249)	(0.0152)	(0.0131)	(0.0364)	(0.0956)
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)	(0.0320)	(0.0299)	(0.0430)	(0.0090)	(0.0754)	(0.0340)	(0.0841)	(0.0118)	(0.0324)	(0.0410)	(0.0891)
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)	(0.0316)	(0.0520)	(0.0965)	(0.0160)	(0.0723)	(0.0450)	(0.1228)	(0.0270)	(0.0504)	(0.3664)	(0.1649)
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)	(0.0116)	(0.0337)	(0.0544)	(0.0142)	(0.0120)	(0.0388)	(0.0390)	(0.0136)	(0.0212)	(0.0583)	(0.0537)
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)	(0.0149)	(0.0272)	(0.0384)	(0.0129)	(0.0118)	(0.0456)	(0.0778)	(0.0153)	(0.0173)	(0.0457)	(0.0515)
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)	(0.0148)	(0.0258)	(0.0310)	(0.0130)	(0.0154)	(0.0264)	(0.0678)	(0.0123)	(0.0159)	(0.0354)	(0.0428)

Bootstrapped standard errors in parentheses

Table 14: Estimates of β_{ijt} for 2016.

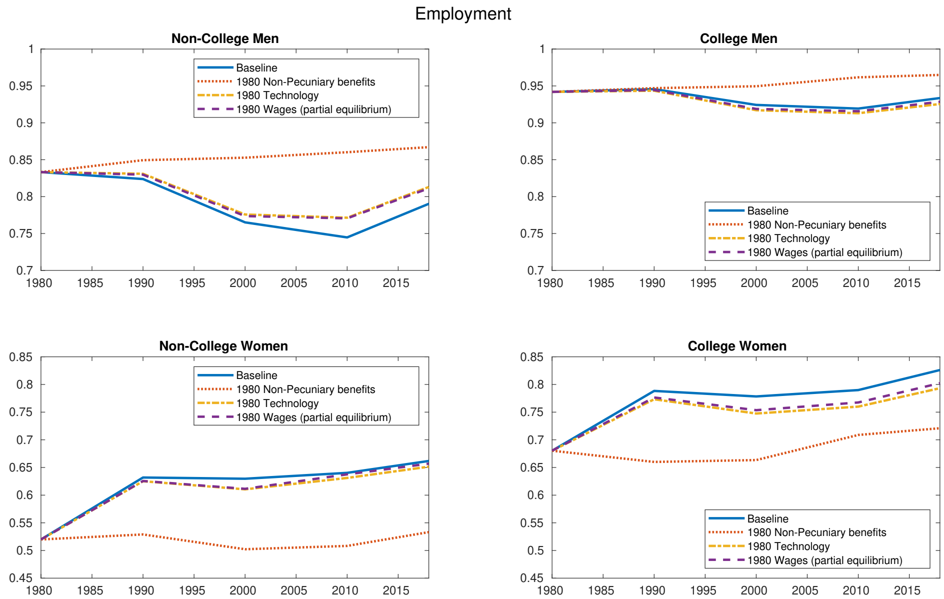

Figure 14: Evolution of the labor force participation of demographic groups in the baseline model (which replicates the data) and in the counterfactual scenarios.

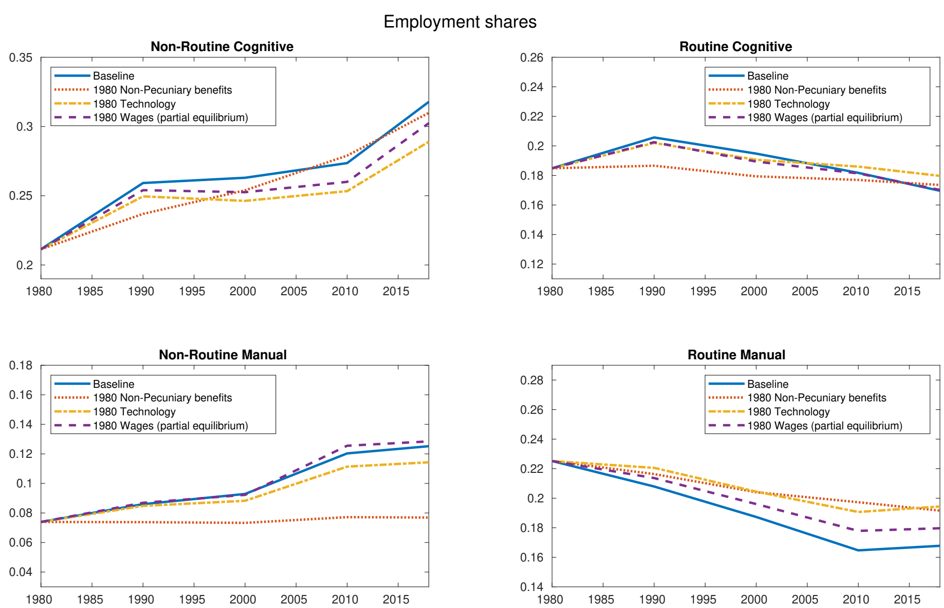

Figure 15: Evolution of the shares of the population employed in four major occupation groups in the baseline model (which replicates the data) and in the counterfactual scenarios.

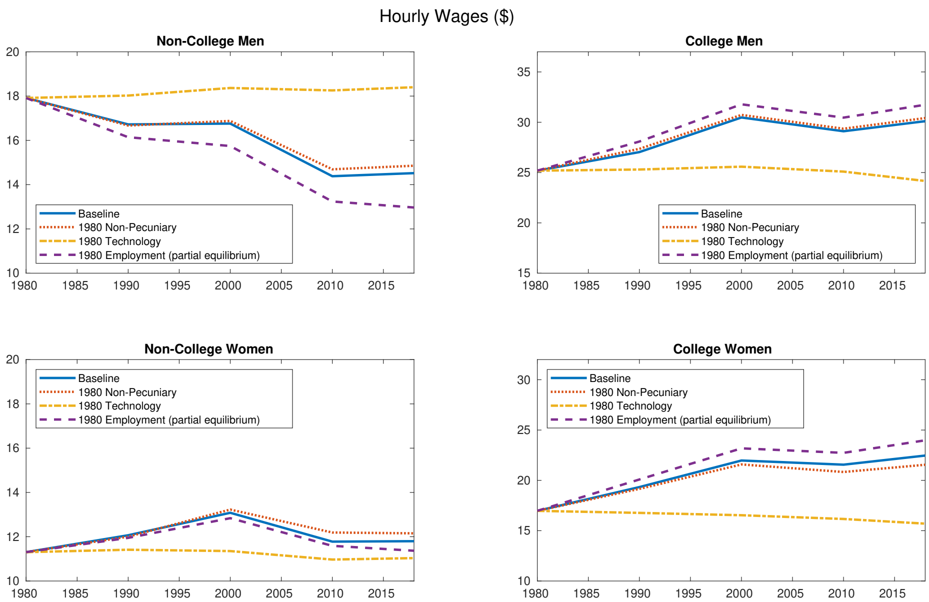

Figure 16: Evolution of the average hourly wage received by the different demographic groups in the baseline model (which replicates the data) and in the counterfactual scenarios.