The Changing Value of Employment and Its Implications*

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Abstract

We estimate the components of worker-occupation match values within a model that distinguishes between wages and latent returns. The equilibrium exhibits heterogeneous rents and we derive a welfare measure that has three properties: (i) it illustrates the impact of marginal workers on the welfare of everyone else; (ii) it delivers inequality measures that account for non-wage values and compensating differentials; (iii) it relates welfare shifts to changes in different match value components. We use this measure to show that similar patterns of wage inequality can be associated with vastly different welfare outcomes.

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

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1 Introduction

Shifts in the structure of U.S. employment and earnings over the past five decades suggest a rapidly changing environment where the fortunes of some workers rise while others stagnate. This has prompted questions about what constitutes a favorable labor market outcome for any group of workers. The early literature on inequality (Katz and Murphy, 1992; Heckman et al., 1998; Katz and Autor, 1999; Krusell et al., 2000; Goldin and Katz, 2008; Autor et al., 2006; Acemoglu and Autor, 2011) set the tone by focusing on the evolution of earnings for workers classified by education, occupation or gender. This focus is reasonable since earnings are a natural metric to approximate returns. There is, however, growing recognition that other factors account for a significant part of the value that workers derive from jobs. For example, job injuries suggest that earnings dispersion is an imperfect measure of US labor market inequality in the 1990s (Hamermesh, 1999). Maestas et al. (2018) and Dube et al. (2022) argue that employment conditions contribute to job choice, employee retention, and overall compensation. Moreover, tastes for non-wage rewards vary systematically with gender, age, and education. In a frictional model of human capital accumulation and occupation decisions, Taber and Vejlin (2020) find that about $\frac{1}{3}$ of observed choices would be different if workers cared only about pecuniary aspects. Lehmann (2022) shows that a positive correlation between wages and other amenities exacerbates inequality in the Austrian labor market between 1996 and 2011. Lamadon et al. (2022) estimate that workers would pay a nontrivial share of their wages to remain with their current employer.

In this study we adopt a revealed preference approach to estimate the components that add up to the value of a worker-occupation match, and we document how these components have shaped labor market outcomes since the 1980s.

We carry out the analysis in an equilibrium setting with discrete occupation choices and technological change. The model allows for imperfect substitution in production between worker-occupation matches, and distinguishes between observable and latent components of match values. The latent part consists of an idiosyncratic (worker-specific) element and a common (group-specific) component. The common component is defined within narrow demographic groups.

The observable match components reflect the value of earnings and hours worked;[1] the latent ones reflect non-pecuniary attributes of a match as well as heterogeneity in compensation. It is worth noting that, due to imperfect information, employers cannot make wage offers contingent on idiosyncratic job valuations. Therefore, the match value components are bundled within a job and cannot be freely traded against each other. One consequence of this non-separability is that workers can earn rents from ongoing employment.

[1] Occupations vary in their time demands (Erosa et al., 2022a). Heterogeneous preferences contribute to occupation choice, e.g., if wages are a convex function of time (Aaronson and French, 2004; Erosa et al., 2022b).

In equilibrium, rent values depend on the attributes of marginal workers (individuals who are indifferent between their match and an alternative). Marginal workers determine the compensating differential in each worker-occupation pair and pinpoint the wage of all workers in the same match, including the inframarginal ones. To elaborate on this point, we show that compensating differentials and rents can be mapped into measures of welfare dispersion within and between groups. Then, we use these measures to characterize the welfare outcomes of different demographic groups.

The empirical analysis imposes few restrictions, apart from the low-level requirements of a Roy model, and flexibly accommodates diverse sources of heterogeneity (e.g., Wiswall and Zafar, 2018 show that women value work schedules and job stability more than men). Estimation relies on data from all worker-occupation pairs, including those observed infrequently; as a consequence, we draw inference from the relative scarcity of matches as well as from pecuniary returns and hours worked. This is helpful to quantify the returns from rarely observed worker-occupation matches where wages are uninformative in isolation. An advantage of this approach is that we can estimate the model using repeated cross-sections (Census, ACS) of earnings, hours worked and employment headcounts, focusing on combinations of gender, education, age, and occupation.

Our findings can be summarized in two steps. First, we document that match values are not well approximated by wages and hours alone: similar jobs have vastly different returns for different workers (Autor et al., 2014; Cortes et al., 2017); moreover, latent components are more dispersed than observable ones. Second, money-metric welfare measures suggest that a significant share of average earnings (up to 1/3) reflects rents at the match level. The distribution of yearly rent values has changed significantly between 1980 and 2018: the rents of college graduates have increased by almost 25% and gains were especially large for college educated women. On the other hand, lower education workers have experienced declining rents (men) or stagnating rents (women).

Analytical forms for rents and compensating differentials highlight that not all wage dispersion translates into welfare dispersion, and that welfare changes depend critically on the responsiveness of labor supply to the wage and non-wage components of match values. In particular, the labor supply elasticities determine the characteristics of the marginal workers. In this respect, our estimates indicate significant discrepancies between the elasticities of labor supply to different match value components. Specifically, we find that latent returns exert a strong influence on participation and aggregate employment, and that labor supply responds more elastically to latent match values than to wages (see Appendix D).

This asymmetric responsiveness plays a key role in the dynamics of rents and welfare. The mechanism is simple and we illustrate it by contrasting the reaction of rents to an exogenous change in either wages or the latent components of match values. A positive wage (productivity) change at the occupation-worker level induces higher labor demand, which boosts compensating differentials. However, following this initial impulse, the relatively mild labor supply response results in little or no change in the composition of workers who populate the match. Put differently, the marginal worker has similar characteristics before and after the shock. In turn, this means that all workers end up benefitting from higher wages so that rents increase for most of them. By contrast, when we consider an increase in the latent match value at the occupation-worker level, the higher average surplus is offset by changes in the marginal worker characteristics: specifically, the increase in the common latent component attracts marginal types with lower idiosyncratic match values. This inflow offsets the initial increase in the common match component so that compensating differentials do not change and the marginal rate of substitution between wage and non-wage returns is close to what it was before the shock. On the whole, following a change in the common latent value, the more vigorous response of marginal workers implies that incumbent workers enjoy higher rents (due to the increase in the common latent value) while newcomers have lower idiosyncratic match values and, therefore, lower rents. The combination of higher rents for incumbents and lower rents for new entrants results in little change for average rents but larger welfare dispersion among workers within the same match.

Taken together, these findings deliver three messages: (1) the phenomenon of job polarization is not exclusively about technological change, as latent values play a non-trivial role in accounting for employment and welfare changes; (2) rent-based measures of inequality deliver useful insights into the mechanism that maps compensating differentials into welfare inequality; (3) the characteristics of marginal workers determine welfare changes for all other workers in the same match.

We have organized the paper as follows. After presenting the model (Section 2), in Section 3 we outline the analysis of rents and compensating differentials, and we describe the theoretical link with welfare. In particular, we show that rent differences between and within matches depend on the characteristics of the marginal workers within each match. This analysis emphasizes that similar patterns of wage inequality are associated with varying degrees of welfare dispersion. We estimate the model in Section 4, and then we use our estimates to break down the contributions of technology and latent values to the evolution of wages and employment in the US labor market between 1980 and 2018 (Section 5), and to characterize changes in rents and compensating differentials over the same period (Section 6).

2 Model

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

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

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

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

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

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

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

where $u_c(\cdot)$ is consumption utility and $u_h^i(\cdot)$ is the disutility from work that can vary across types; b_{ijt} denotes latent benefits accruing to a type i worker in occupation j and period t. The systematic component of utility can differ across markets since wages and non-labor income depend on the specific (m,t) pair. The latent component of utility varies with occupation, demographic group, and time.[2]

We normalize the latent value of not working to zero so that the systematic utility of non-employment ($j = 0$) is $U_{i0t}(0, y_{imt}) = u_c(y_{imt}) - u_h(0)$. The normalization $b_{i0t} = 0$ for all t and all i implies no loss of generality and is necessary because b_{i0t} is not separately

[2]Latent components do not vary across markets since we assume that local amenities are enjoyed by workers in all occupations and, therefore, they cancel out in the definition of surplus. We empirically assess the robustness of this restriction by re-estimating the model under the alternative assumption that latent returns can change across labor markets (Appendix N).

identified from all other b_{ijt}. Given the normalization of b_{i0t} and additive separability of the match value, all the b_{ijt} terms include the value of home production. Since differences between employment and non-employment reflect the value of home production, estimated variation in b_{ijt} conveys also information about changes in productivity at home.

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

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

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

By the properties of the Extreme Value distribution, the fraction of workers of type i supplying labor to occupation j in market m is

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

Firms. Within each market and period, a representative final good producer uses a continuum of size one of intermediate goods to produce its output. Each intermediate is produced by a different firm, indexed by v. Intermediate good producers employ one occupation j and intermediate goods can be thought of as the output of an individual occupation. Since each intermediate firm produces a differentiated good, they have market power in the intermediate good's market, and non-zero profits are made. Labor markets are competitive. For convenience we partition intermediate firms into subsets $\{V_{jt}\}_{j=1,\ldots,J}$ such that, for any pair of firms $v, v' \in V_{jt}$, their production technologies differ up to an idiosyncratic productivity shock (TFP). The V_{jt} partition splits the continuum of intermediate producers into a finite number of subsets containing producers that employ the same input j. In Appendix C we generalize the model to a setting where intermediate producers employ capital and labor.[3]

Final good production. The final good producer solves:

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

[3]In the appendix we show that the key empirical relationships are unchanged. Estimates of substitutability between worker-occupation labor inputs based on the baseline model without capital are a lower bound.

where λ_{jmtv} denotes quantity of each intermediate good's demand. The final good price P_{mt} in market (m,t) is a function of intermediate prices p_{jmtv},

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

Optimality for the production problem implies

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

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

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

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

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

The aggregate production function (see Appendix B for the full derivation) is then:

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

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

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

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

1. given wages and preferences, each worker solves the problems described in equations (1)

Average Rents (year 2000 $)

Year	All	College Men	College Women	Non-College Men	Non-College Women
1980	14,515	22,663	14,170	15,832	9,014
1990	14,762	24,336	16,024	14,855	9,677
2000	16,052	27,377	18,199	14,878	10,501
2010	14,980	26,454	17,974	12,703	9,392
2018	15,985	27,451	18,861	12,903	9,460

Table 1: Estimated average rents by year and gender-education group.

and (2);

2. the final good producer and the intermediate firms behave optimally and solve (4) and (5), respectively;

3. all markets clear. Labor market clearing implies that for all matches (i,j) and markets (m,t), it is the case that $L_{ijmt} = \mu_{ijmt} h_{ijmt}$ where $L_{ijmt} = \sum_{v \in V_{jt}} L_{ijmtv}$.

3 Rents, Compensating Differentials, and Welfare

Job matches comprise bundles of observable and latent components, which cannot be separately rented out. As a result, the value of the current match of many workers is strictly higher than their outside option (higher than the second best match they have access to). We refer to these workers as inframarginal and define their employment rent as the pecuniary value that makes them indifferent between the current job and the outside option.

3.1 Measuring rents

Consider a worker ι in demographic group i. Let j be their current occupation and j' the second best option. We define $\tilde{R}^{\iota}_{ijj'mt}$ as the change in worker ι's wage that makes them indifferent between current match and outside option. The wage gap $\tilde{R}^{\iota}_{ijj'mt}$ is such that:

$$\tilde{U}_i(w_{ijmt} - \tilde{R}^{\iota}_{ijj'mt}, y_{imt}) + b_{ijt} + \theta^{\iota}_j = \tilde{U}_i(w_{ij'mt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'} \tag{8}$$

where $\tilde{U}_i(w,y) = u_c(wh_i(w,y) + y) - u^i_h(h_i(w,y))$. The total employment rent of worker ι, accounting for labour supply, is

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

which is the difference between the earnings in the current match and the earnings when the wage is changed to the point of indifference between j and j'. The rent that the worker extracts from match (i, j) are increasing in the wage differential between current job and second best job, as well as in the difference between latent returns (both systematic and idiosyncratic).

The definition illustrates how rents can be broken down in different elements. As an example, suppose that the wage differential between different matches grows. Wage inequality alone would suggest an increase in welfare inequality. Yet welfare inequality does not change if the larger wage gap is accompanied by a reduction in the differential between latent values (i.e. wage differentials are compensating for changes in latent values). In this case, wage changes in isolation would be a misleading measure of inequality while rents would correctly approximate welfare changes. This example shows that the dynamics of welfare inequality depend on the measurement of the interaction between wages and latent values (systematic and idiosyncratic) in equilibrium. In this section we show that this interaction can be characterized by changes in the characteristics of marginal workers over time. We use the notion of compensating differential to establish a theoretical link between equilibrium rents and the characteristics of marginal workers.

3.2 Compensating differentials

In what follows we denote the marginal worker within a match as $\bar{\iota}$. The compensating differential between the current occupation j and an outside option j' is the difference between the utility that worker $\bar{\iota}$ gets in the j' (if paid at the same rate as in the current match) and the utility that the worker gets from the current match. We define the compensating differential between j and j' as

$$CD^{\bar{\iota}}_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) + b_{ij't} + \theta^{\bar{\iota}}_{j'} - \tilde{U}_i(w_{ijmt}, y_{imt}) - b_{ijt} - \theta^{\bar{\iota}}_{j} \tag{9}$$

Conveniently, the compensating differential for worker $\bar{\iota}$, denoted as $CD^{\bar{\iota}}_{ijj'mt}$, can be estimated from a function of average earnings and hours worked in the (i, j) and the (i, j') matches (see derivation in Appendix J), and we can write

$$CD^{\bar{\iota}}_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) - \tilde{U}_i(w_{ij'mt}, y_{imt}) = CD_{ijj'mt}. \tag{10}$$

Since the quantity $CD_{ijj'mt}$ can be recovered from average match values, it is straightforward to define the compensating dollar value for any pair of occupations j and j' as the change in average labor income in the current match that makes $CD_{ijj'mt} = 0$, that is

$$u_c(w_{ijmt}h_{ijmt} + y_{imt} - CD^{\$}_{ijj'mt}) - u_h(h_{ijmt}) = u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}). \tag{11}$$

3.3 The role of marginal workers

The characteristics of marginal workers are key to understand the evolution of rents, as these workers set the wage for the inframarginal ones in the same match. To illustrate this point, we use the definitions of compensating differentials in (9) and (10) to obtain,

$$CD_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) - \tilde{U}_i(w_{ij'mt}, y_{imt}) = b_{ij't} - b_{ijt} + \theta^{\bar{\iota}}_{j'} - \theta^{\bar{\iota}}_{j}. \tag{12}$$

It is apparent that the (money metric) compensating differential reflects the difference between the latent value of (i, j) and the outside option (i, j'). This difference consists of two elements: (i) a systematic common component that affects all agents within a match equally $(b_{ij't} - b_{ijt})$; (ii), an idiosyncratic component that is specific to the marginal worker in the match (i, j).

The common component (i) does not depend on the composition of workers in match (i, j) but the idiosyncratic component (ii) does. To be precise, the idiosyncratic component of the marginal workers matters for the compensating differential. In turn, this means that, if the marginal worker characteristics change significantly, so does the compensating differential. Below we describe two thought experiments that help clarify this mechanism. The first considers the adjustments that follow an exogenous change in the common latent value b_{ijt}. The second examines what happens after an increase in the productivity of workers in match (i, j).

An exogenous change in b_{ijt}. Suppose that the latent value b_{ijt} increases. Ceteris paribus, this boosts rents for all workers in match (i, j). However, the total equilibrium effect on rents depends on how the characteristics of the marginal worker change in response to the shock, which in turn depends on the elasticity of labor supply. If the elasticity of labor supply to changes in b_{ijt} is high, the increase in b_{ijt} causes an inflow of workers with lower idiosyncratic latent values (lower θ). In the new equilibrium the marginal worker's $\theta^{\bar{\iota}}_{j}$ is lower and, using equation (12), the increase in b_{ijt} is offset by a fall in $\theta^{\bar{\iota}}_{j}$ so that the compensating differentials, and wages, in match (i, j) remains approximately stable. It follows that average rents in the (i, j)-cell are little changed. Interestingly the variance of rents within the (i, j) cell must grow as incumbents and new entrants become more different in their idiosyncratic values (θ).

On the other hand, if the elasticity of labor supply to changes in b_{ijt} is low, the characteristics of the marginal worker do not change much; in this case, equation (12) shows that compensating differentials, and wages w_{ijmt}, must fall. This implies that average rents and the whole distribution of rents in the (i, j)-cell are little changed: this follows from the observation that, while every worker enjoys a higher b_{ijt}, they all get lower wages. This example highlights that using only wage changes to measure welfare responses can be misleading.

To sum up, the effects of exogenous changes in b_{ijt} on rents depend on the magnitude of the elasticity of labor supply. A high elasticity results in little or no change in within group averages but leads to large effects on within group dispersion. A low elasticity implies little changes in the within group distribution of rents but in significant changes in average compensating differentials and earnings.

An increase in match-specific productivity. Next, we consider the case of an increase in the productivity of workers in match (i, j). Upon impulse, demand for workers increases; if the elasticity of labor supply to wages is low, wages have to grow substantially to attract extra workers. Equation (12) requires that wages grow up to the level where they accommodate the lower idiosyncratic $\theta_j^{\bar{\iota}}$ of the new marginal worker. Higher wages and constant latent component $b_{i,j}$ imply that the marginal rate of substitution between money and latent returns must also grow. Put differently, the incumbent workers (those already in match (i, j) before the productivity change) benefit from higher wages without suffering any loss in their latent match values. Moreover, due to the low elasticity of labor supply, the inflow of new workers with low θ is modest implying that the average θ in the (i, j) match is only slightly lower. The productivity impulse results in higher rents for most workers with little change in the dispersion of rents within the group. In other words, technological change has strong effects on between-group (between-match) rent inequality but small effects on within-group (within-match) inequality.

By the same token, if the elasticity of labor supply is high, more workers will switch to occupation j. Wages will still increase but to a lesser extent since the new marginal worker is characterized by a lower $\theta_j^{\bar{\iota}}$. On average, the wage increase will be offset by lower average θ so that average rents are not much changed. At the same time, within group rent inequality increases since the incumbent workers enjoy higher wages without any loss of latent values.

To sum up, exogenous changes in productivity have a different impact on rents depending on the magnitude of the elasticity of labor supply to wages. A low elasticity induces strong responses in between group (between match) rent inequality, but small effects on within-group dispersion. In contrast, a high elasticity implies smaller effects on between-group inequality but stronger changes in within-group rent inequality.

4 Identification and Estimation

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

4.1 Data

We use decennial Census data from 1980, 1990, and 2000; in addition, we pool together three years of the American Community Survey (King et al., 2010) to get samples of comparable size for 2010 (2009-2011) and 2018 (2017-2019). We consider individuals aged between 25 and 54 and exclude those in education as well as workers in farming, forestry, and fishing. We define worker-side heterogeneity as a combination of gender, age (three groups: 25-34, 35-44, 45-54), and education (college graduates and above; less than college). This results in 12 distinct worker groups, indexed by $i \in I$. On the demand side, we consider a set of 13 occupations, in addition to the non-employment state. The occupation states are indexed by $j \in J$ and reported in Table 2 along with their aggregation into four broad task clusters (see Acemoglu and Autor, 2011; Cortes and Gallipoli, 2018). We consider four geographical markets, indexed by $m \in M$, corresponding to U.S. Census regions (Northwest, Midwest, South, and West).

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

4.2 Identification

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

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

$$\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right) = \frac{U_{ijt}(w_{ijmt}, y_{imt}) - U_{i0t}(0, y_{imt})}{\sigma_\theta}. \tag{13}$$

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

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

Table 2: Occupation categories used for estimation.

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

Under these parametric restrictions, equation (13) shows that we can use cross-sectional variation in employment, hours worked and wages to estimate: (i) the latent return b_{ijt} for occupation-worker pair (i, j) in period t, and (ii) the scaling parameter σ_θ, which dictates the dispersion of idiosyncratic preferences. Optimality of labor supply in the worker's problem (1) implies

$$\left(w_{ijmt}h_{ijmt} + y_{imt}\right)^{-\sigma} w_{ijmt} = \psi_i h_{ijmt}^{-\gamma} \tag{14}$$

If $\gamma \leq 0$, the disutility from work is a convex function and (14) has a unique solution. We do not restrict γ but find that its estimated value satisfies the condition for uniqueness.

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

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

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

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho - 1)\log\left(\frac{\sum_{i'} \beta_{i'jt} L_{i'jmt}}{\sum_{i'} \beta_{i'1t} L_{i'1mt}}\right) \tag{15}$$

The second regressor on the right-hand side of equation (15) is $\hat{B}_{ijt} = \log\left(\frac{\hat{\beta}_{ijt}}{\hat{\beta}_{i1t}}\right)$; this term should have a coefficient equal to one, a restriction that we can test.

The third regressor on the right-hand side of (15) is $\hat{\Lambda}_{jmt} = \log\left(\frac{\sum_{i'} \hat{\beta}_{i'jt}\mu_{i'jmt}h_{i'jmt}}{\sum_{i'} \hat{\beta}_{i'1t}\mu_{i'1mt}h_{i'1mt}}\right)$, which measures the supply of labor efficiency units to occupation j. Therefore, the empirical counterpart of the relationship in (15) is,

$$W_{ijmt} = \gamma_{jt} + \psi\hat{B}_{ijt} + \phi\hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{16}$$

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

4.3 Estimation of preference parameters

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

Curvature parameters and disutility of labor. We use the optimality condition in (14) to express hours worked as a function of wages and non-labor income:

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

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

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

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

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

Extensive margin of labor supply. The definition of surplus in (13) implies that the occupation choice is a function $g\left(\boldsymbol{X}_{ijmt}; \boldsymbol{\Omega}_i\right)$ such as

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

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

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

In practice, we use the following moment conditions:

$$E\left[\Upsilon_{ijmt} - g\left(\boldsymbol{X}_{ijmt}, \boldsymbol{\Omega}_{ijt}\right) | i, j, t\right] = 0 \tag{19}$$

$$E\left[\left(\Upsilon_{ijmt} - g\left(\boldsymbol{X}_{ijmt}, \boldsymbol{\Omega}_{ijt}\right)\right) \boldsymbol{Z}^2_{ijmt}\right] = 0 \tag{20}$$

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

Simulated method of moments. We denote as $\boldsymbol{X}$ the data vector of wages and hours worked. To calculate the cell averages we consider people reporting at least 15 hours of work per week and positive earnings. Given the parameter matrix $\boldsymbol{\Omega} = \{\boldsymbol{\Omega_{ijt}}\}$, where

$\boldsymbol{\Omega}_{ijt} = [\sigma;\ \gamma;\ \psi_i] \bigcup [\sigma_\theta;\ b_{ijt}]$, we solve the estimation problem:

$$\hat{\boldsymbol{\Omega}} = \underset{\boldsymbol{\Omega}}{\arg\min}\, \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}\right)^T \boldsymbol{W} \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}\right) \tag{21}$$

where $\boldsymbol{W}$ is a positive definite weighting matrix[4], $\boldsymbol{Z}$ is the vector of instruments, $\boldsymbol{M}$ is the set of target moments described in (17), (18), (19) and (20).

The problem in (21) is computationally demanding as it requires solving the labor supply first order conditions in (14) for all the (i, j) and (m, t) pairs. Therefore, we reformulate the problem by specifying the first order conditions as constraints (Su and Judd, 2012). We let $\boldsymbol{\Omega}^+$ be the union of the parameter matrix $\boldsymbol{\Omega}$ and $\{\hat{h}_{ijmt}\}_{\forall i,j,m,t}$, where the latter is the set of model-generated labor supplies. The estimation problem becomes:

$$\hat{\boldsymbol{\Omega}} = \underset{\boldsymbol{\Omega}^+}{\arg\min}\, \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}^+\right)^T \boldsymbol{W} \boldsymbol{M}\left(\boldsymbol{X}, \boldsymbol{Z}; \boldsymbol{\Omega}^+\right) \tag{22}$$

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

where the constraints represent the FONC with respect to the intensive margin of labor supply. The constraints ensure that labor supply satisfies the first order conditions (i.e. that the numerical approximation of the "hours worked" function $f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)$ holds). This approach does not require solving for the optimal hours in each iteration of the optimization algorithm and substantially reduces computation time.

We report estimates of the parameter matrix $\boldsymbol{\Omega}$ in Appendix O. We use 10 and 20-year lagged wages as instruments for current wages. Table 7 shows estimates of the curvature of the consumption utility and of the scaling factor of the extreme value preference shocks (respectively, σ and σ_θ). Table 8 shows estimates of both weight and curvature of dis-utility from labor (ψ, γ). Tables 9-13 report all estimates of latent match-specific values (b_{ijt}) for different years.

4.4 Estimation of technology parameters

We estimate the worker-occupation shares β_{ijt} using within-occupation wage ratios. With those in hand, we recover the α_{jt} and ρ using a first-difference specification of the wage conditions in (16). This specification flexibly allows for the use of instrumental variables to account for endogeneity of input demands.

To illustrate the estimation steps, we begin by noting that $\hat{\rho} = \hat{\phi} + 1$, and $\hat{\phi}$ can be recovered estimating (16) in first differences. Next, we recover the $\gamma_{jt} = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right)$ in (16) by projecting the residuals $\tilde{W}_{ijmt} = W_{ijmt} - \hat{B}_{ijt} - \hat{\phi}\hat{\Lambda}_{jmt}$ on occupation-year fixed effects. Finally, we obtain the value of each occupation weight α_{jt} in the production technology (6)

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

from the restriction $\sum_j \alpha_{jt} = 1$ for all t. The full set of estimated α_{jt} and β_{ijt} shares, alongside plots of the combined $\alpha_{jt} \times \beta_{ijt}$ weights, are in Appendix F.

Endogenous production inputs. We use two different approaches to account for potential endogeneity of labor inputs. Each strategy instruments the changes in labor input log-ratios $\Delta\hat{\Lambda}_{jmt}$ in (16) with predicted log-ratios of headcounts.

The model suggests that, within each demographic group, differences in the labor participation (headcount) in each occupation over time are the by-product of differences in the relative valuation of occupations by different workers. Changes in relative valuations and, as a consequence, in labor supply can be caused by changes in the pecuniary component of returns (i.e. wages) or changes to latent returns.

The first identification strategy leverages changes in the relative attractiveness of one occupation due to changes in the pecuniary returns in other occupations. Given estimates of labor supply parameters, we compute cross elasticities of labor supply shares (see Appendix D) and can define the elasticity $\varepsilon^{cross}_{ijj'mt} = \frac{ds_{ijmt}}{dw_{ij'mt}} \frac{w_{ij'mt}}{s_{ijmt}} = \frac{d\mu_{ijmt}}{dw_{ij'mt}} \frac{w_{ij'mt}}{\mu_{ijmt}}$, which measures the change in employment shares in occupation j in response to changes in the wage rate of another occupation j'. Using the cross-elasticities, we can obtain predicted changes in labor supply to occupation j due to changes in the wages paid to other occupations. Specifically, we denote the employment shares observed in the preceding decade $(t-10)$ as $s_{ijmt-10}$ and compute the predicted shares of workers of demographic group i choosing occupation j as

$$\hat{s}_{ijmt} = s_{ijmt-10} \sum_{j' \neq j} e^{\varepsilon^{cross}_{ijj'mt-10}\left[\log(w_{ij'mt}) - \log(w_{ij'mt-10})\right]} \tag{23}$$

The predicted labor supply to occupation j is $\hat{L}^h_{jmt} = \sum_i \hat{s}_{ijmt}\mu_{imt}$, where h denotes the headcount. We use the latter measure to construct the predicted *relative* labor supply $\hat{\Lambda}^h_{jmt} = \log\left(\frac{\hat{L}^h_{jmt}}{\hat{L}^h_{1mt}}\right)$ in period t. The instrument can then be written as,

$$\text{IV1}_{jmt} = \Delta\hat{\Lambda}^h_{jmt} = \hat{\Lambda}^h_{jmt} - \log\left(\frac{L^h_{jmt-10}}{L^h_{1mt-10}}\right), \tag{24}$$

where L^h_{jmt-10} is the actual number of workers in occupation j in market m at time $t-10$.

The second identification strategy relies more directly on theoretical restrictions as, by definition, shifts in latent returns affect occupation-specific employment given observed wages. One can therefore develop a set of instruments from changes in occupation shares due to variation in latent returns b_{ijt}. Equation (13) implies:

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

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

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

We estimate a set of counterfactual shares as $\hat{s}_{ijmt} = \frac{\exp(\hat{\varrho}_{ijmt})}{1+\sum_{j'=1,\ldots,J}\exp\left(\hat{\varrho}_{ij'mt}\right)}$, which can be used to predict labor inputs as $\hat{L}^h_{jmt} = \sum_i \hat{s}_{ijmt}\mu_{imt}$. We employ these fitted values to construct a set of instruments (IV2_{jmt}), as described in equation (24). In appendix E, we examine robustness by adopting an alternative identification strategy that leverages aggregate demographic changes as exogenous shifters of labor supply. This results in a Bartik (1991) instrument that does not depend on first step estimation and delivers qualitatively and quantitatively similar results (see Table 6).

Substitution among worker-occupation inputs. Table 3 shows values of the coefficients on $\Delta\hat{\Lambda}_{jmt}$ and $\Delta\hat{B}_{ijt}$ from the first-differenced estimation of (16). Endogeneity introduces a positive bias in the estimates of ϕ. Columns 2 and 3 show estimates after instrumenting $\Delta\hat{\Lambda}_{ijmt}$ with either of the two instrument sets. Estimates of ρ suggest that the elasticity of substitution between worker-occupation inputs (that is, $\frac{1}{1-\rho}$) is larger than one and between 1.7 and 1.9.

We consider the values in column 4 as our baseline estimate, implying an elasticity of substitution of 1.87. When using multiple instruments together, one can compute a p-value for the over-identification test (Sargan, 1958) and we find that the validity of the instruments cannot be rejected. Under all identification strategies, the estimated coefficient on $\Delta\hat{B}_{ijt}$ is not significantly different from one, which is consistent with the theoretical restrictions of the model.

Prices and quantities: comparing model and data. Figure 1 compares data on average wages and employment in each worker-occupation cell (i, j) with their model counterparts obtained by solving for the equilibrium in each market and year. Simulated prices and quantities match data observations closely. The model accounts for, respectively, 99%, 95%, and 72% of total variation in employment, wages, and hours worked.[5]

[5]In appendix G, we consider a version of the model that allows for the disutility of work to change with demographic characteristics and occupations to allow for more flexible preferences. The more flexible specification can account for a bigger share of variation in hours worked without affecting other estimation results.

	OLS	IV		
	(1)	(2)	(3)	(4)
$\hat{\phi}$	-0.0834	-0.5681***	-0.5414***	-0.5344***
	(0.0610)	(0.1212)	(0.1348)	(0.1256)
$\hat{\psi}$	0.9771***	0.9771***	0.9771***	0.9771***
	(0.0413)	(0.0414)	(0.0414)	(0.0414)
Observations	2,496	2,496	2,496	2,496
Instrument set		IV1	IV2	IV1-IV2
Test $\hat{\psi} = 1$ (p-val)	0.5796	0.5812	0.5810	0.5812
OverId p-val				0.6204
Implied ρ	0.9166***	0.4319***	0.4586***	0.4656***
	(0.0610)	(0.1212)	(0.1348)	(0.1256)
Implied elast. of sub.	11.9974	1.7604***	1.8472***	1.8711***
	(58.5230)	(0.3740)	(0.4802)	(0.4036)

Bootstrapped standard errors in parentheses

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

Table 3: Estimation results for equation (16), estimated in first differences.

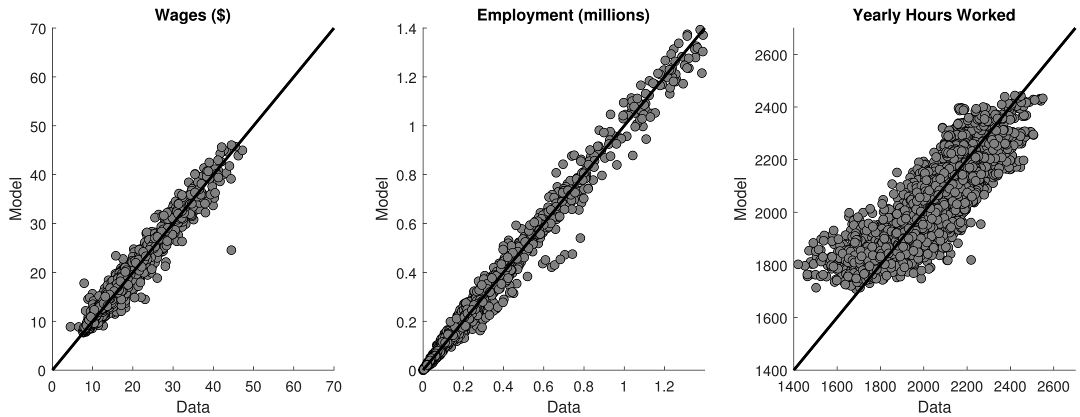

Figure 1: Goodness of fit. Left: model implied wages vs. data. Center: model implied employment vs. data. Right: model implied hours worked vs. data.

4.5 Match input shares in production

Wages vary with the productivity of each worker-job pair. In turn, the productivity responds to shifts in labor supply and technology. We find evidence of divergence in the productivity of worker-occupation inputs between 1980 and 2018. The marginal product of a type-i worker in occupation j at time t is proportional to the production share $\alpha_{jt}\beta_{ijt}$. Figure 2 plots the (employment-weighted) $\alpha_{jt}\beta_{ijt}$ of four broad occupation categories (levels in left panel, growth rates post-1980 in right panel). Productivity in routine manual jobs has steadily declined after 1980, as the $\alpha_{jt}\beta_{ijt}$ are about 25% lower in 2018 than in 1980. The shares of other occupation categories started diverging in the 1990s. Non-routine cognitive jobs experienced a cumulative rise in production share close to 70% by 2018. In contrast, non-routine manual and routine cognitive occupations had less vigorous growth, with cumulative changes of $\alpha_{jt}\beta_{ijt}$ between 40% and 20% over the sample period. The fanning out of production shares underlies changes in wages and employment. In Appendix F we present match-level estimates by intersecting occupation category with worker type and we find similar patterns.

4.6 Latent heterogeneity

Next, we combine information on quantities (employment) and prices (wages) to distinguish between observable and latent components of returns. Figure 3 shows the distribution of match values and of their components, expressed in utility metric. We plot the distribution of: (i) utility from observable wages; (ii) the dis-utility from hours worked; and (iii) the latent match utility net of hours worked. As one migt expect, latent utility varies significantly across worker-occupation matches. However, the dis-utility from time spent working is very

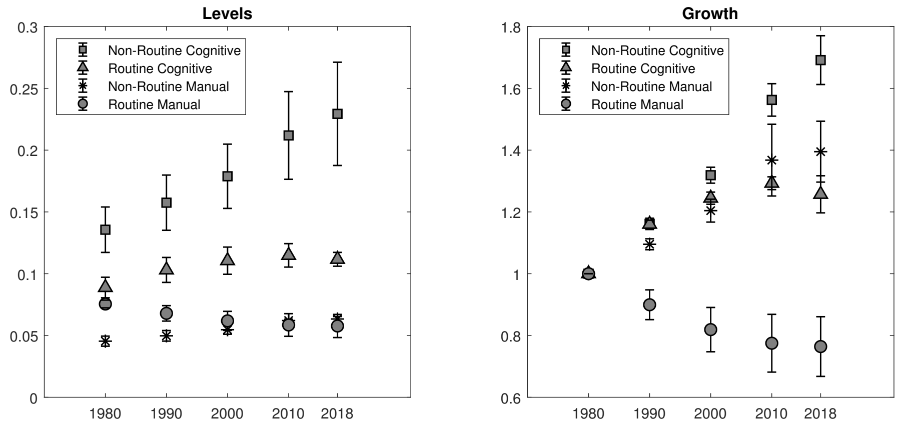

Figure 2: Production shares of four major occupation categories (based on estimates of $\alpha_{jt}\beta_{ijt}$). Left panel: levels. Right panel: growth relative to 1980 base year.

concentrated.[6] In Section 6 we develop money-metric measures of rents and compensating differentials, and we show that latent match values account for a non-trivial share of the total labor market return.

5 Technological Progress with a Changing Workforce

To explore the interaction between wages and latent returns, we leverage the equilibrium model developed in Section 2 and perform several counterfactual exercises. First, we ask how employment and wages would have changed if the distribution of latent returns had stayed at its 1980 levels. Second, we compute counterfactuals holding technology parameters at their 1980 levels.

Finally, to distinguish between partial and general equilibrium effects, we consider two additional experiments. In one, we compute employment changes holding wages at their 1980 levels and illustrate how employment responds to latent match values when general equilibrium price responses are muted. Next, we explore wage changes holding quantities at their 1980 levels (constant employment shares) and illustrate the partial equilibrium effects of technological progress when employment responses are muted.

The experiments highlight the ongoing race between technology and a changing workforce. We show that the concurrent growth in the supply of educated workers and in their productivity has generated an expanding surplus for a large set of worker-job matches. In this respect, we make three observations:

1. Aggregate employment in each demographic group responds strongly to changes in latent

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

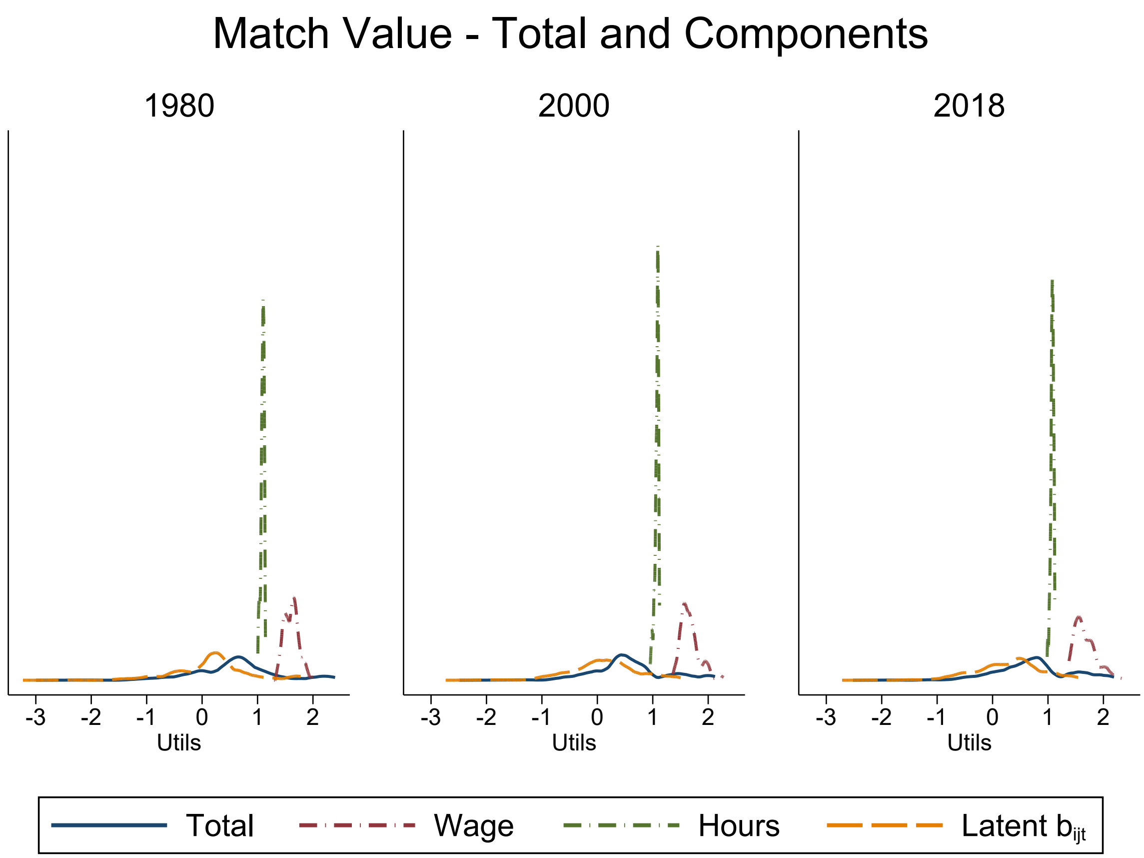

Figure 3: The figure shows, for different years, the cross-sectional distributions (densities) of: (1) total match values (total of all systematic, non random components); (2) observable wage components of match values; (3) dis-utility from hours worked; (4) latent components b_{ijt}. The unit of observation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

match values. Technology has a smaller impact on overall employment.

2. However, the distribution of employment across occupations does depend on technological change. The flight from routine occupations towards non-routine ones is largely driven by technological change. This is in line with the literature on job-polarization and with the finding in point (3) below.

3. Wage gaps between demographic groups are tightly linked to technological change. Latent match values have smaller influence on match-specific wages.

Taken together, these observations suggest that technology is key to account for the distribution of occupational choices through changes in wage returns. The differential sensitivities of aggregate labor force participation and occupation choice to technology turn out to be important when we examine rents and welfare. In Appendix D we report estimates of the elasticities of labor supply to changes in wages (driven by technology) and to changes in latent values. We find that the extensive margin labor supply elasticity to changes in wages is on average between 0.5 and 0.6 while the elasticity to changes in latent values is on average between 1.3 and 1.6. In what follows we briefly overview the counterfactual analysis.

5.1 Counterfactual exercises: employment changes

Figure 4 plots the cumulative employment changes (1980-2018) of four demographic types defined by gender and education.[7] The black bars show observed changes in employment.

Male work force. The decline in men's participation is small for the college-educated (one percentage point) and substantial for the less educated (-4 percentage points). The participation of both groups responds strongly to latent components of returns. Holding latent values at their 1980 level has the largest impact on employment outcomes. When we hold technology parameters at their 1980 level, we see that technological change impacts men differently by education. For college workers, technological change offsets the negative impact of latent returns on labor force participation. For non-college men, however, technology and latent values reinforce each other, contributing to lower employment. The lesson from these exercises is that latent match values are the most influential force in the labor market participation of men.

Female work force. The patterns are different among women: changes are positive and more pronounced, with both high-education (+15) and low-education (+14) individuals experiencing employment growth. Both the latent returns and technology[8] have lifted female labor force participation. However, latent returns explain most of the growth in employment.

[7] For the evolution of employment and wages, see Appendix O.

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

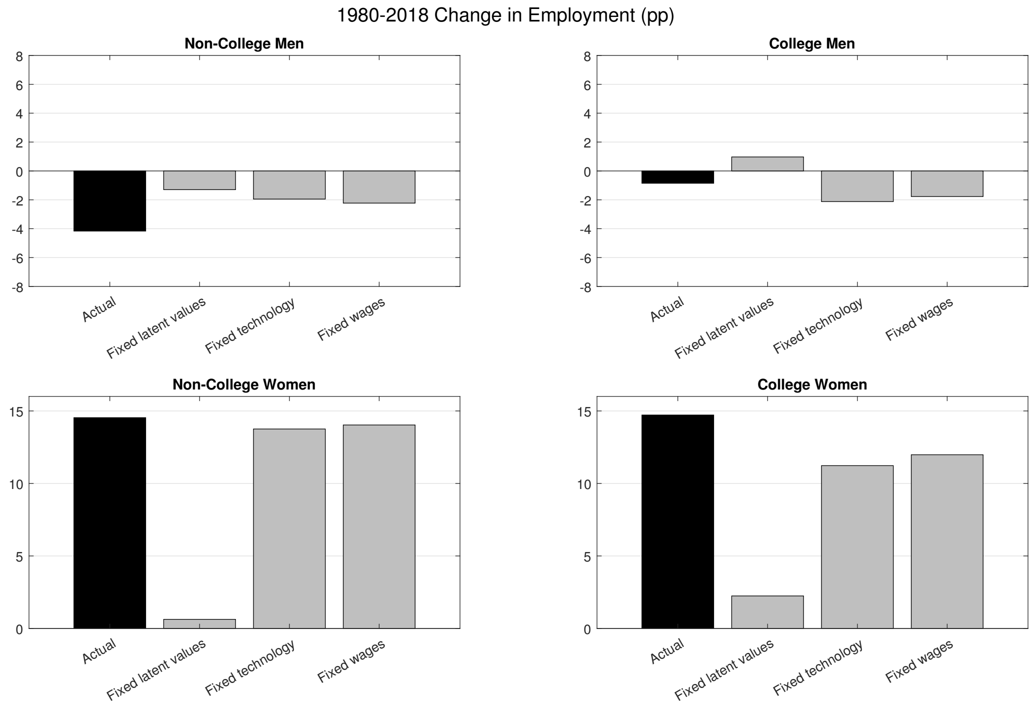

Figure 4: Changes in employment rates by demographic group. Comparisons of baseline and counterfactual scenarios between 1980 and 2018. Changes are in percentage points.

Partial equilibrium effects. The rightmost bar in each panel shows the partial equilibrium impacts of latent values on employment. In this exercise, we hold wages at their 1980 level so that the counterfactuals allow for changes in latent values but shut down wage responses. In all four panels, the outcomes closely align with the bars corresponding to the fixed technology scenario and suggest that price adjustments have little impact on employment. As we discuss below, however, equilibrium responses are stronger when we consider the distribution of employment shares across occupation categories: this indicates that price responses do influence the composition of jobs and occupation shares, conditional on aggregate employment.

Employment changes by occupation category. We replicate the counterfactual analysis by occupation group. The objective is to gauge the importance of technology, as opposed to latent match values, for different job matches. Details about these exercises are in the Appendix Section I. We consider four broad occupation categories (by routine and cognitive intensity). The results suggest that technological change has been the main force behind changes in employment across job matches. The exception is non-routine manual occupations where the largest contribution comes from latent returns: since this occupation category experienced a large drop after 1980, only people with high match values have stayed in those job matches.

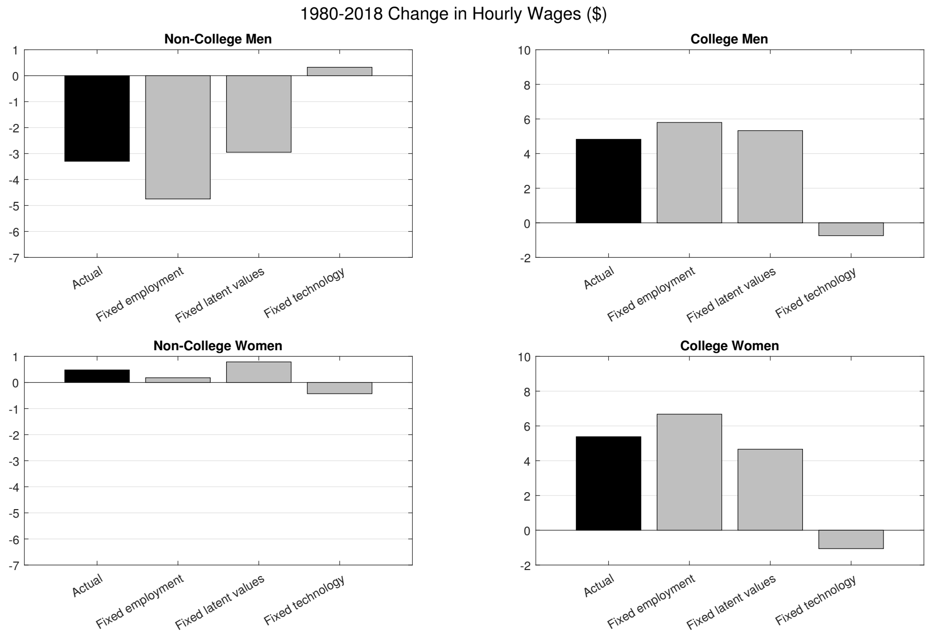

Figure 5: Changes in average hourly wage by demographic group. Actual versus counterfactual scenarios between 1980 and 2018.

5.2 Counterfactual exercises: wages

We run similar exercise to examine the forces underpinning wage changes. Figure 5 shows the actual and counterfactual wage changes for different worker types. After 1980, hourly wages increased for college graduates (right panels). This was mostly driven by technological change while the equilibrium effects originating from latent components were small (their magnitude can be appreciated by looking at the small gaps between "fixed employment" and "fixed latent" experiments). In contrast, wages for non-college men declined over the sample period. Also in this case technological change was the main contributor but equilibrium effects mitigated the wage drops. The bottom left panel shows that low-education women experienced a small increase in wages, which has led to a reduction of the gender wage gap. Technology was a key driver of these patterns.

Wage changes by occupation group. In Appendix Figure 11 we plot the actual and counterfactual changes in hourly wages by occupation category. Significant changes occurred in non-routine cognitive (NRC) and routine manual (RM) occupations. These changes mirror those observed among college graduates and non-college men in Figure 5. The counterfactual analysis (Appendix I) confirms that technological change is the leading force behind wage divergence and occupation selection, whereas latent employment values have a strong influence on the aggregate labor supply of different demographic groups.

6 Rents and welfare

6.1 The distribution of employment rents

We compute the average rent within each (i, j, m, t) cell and denote the cell-specific averages as R_{ijmt} (derivations in Appendix J). Table 1 reports estimates of monetary rents by year, gender and education (in year 2000 dollars). The average rent (first column) has grown over the past four decades, rising by roughly 10% from about \$14,500 in 1980 to almost \$16,000 in 2018. However, not all rents have risen and the gap between education groups has widened. While college rents have gone up, non-college rents have stagnated or fallen, like in the case of non-college men. The latter observation indicates that male workers in non-college jobs have experienced a shrinking labor market surplus (see also Aguiar et al., 2017). We probe the mounting disparities in rents by plotting (Figure 6) the employment-weighted kernel density of rents in different years (all in year 2000 dollar equivalents). The top panel shows the cross-sectional distribution of rents. The bottom panels show rent densities conditional on gender and education. It is apparent that the distribution of rents among educated workers has shifted to the right, while that of non-college men shifted sharply to the left (Cortes et al., 2018). Moreover, rents have become more dispersed within each demographic group. The growing dispersion is partly explained by widening gaps among occupations (Table 29 of Appendix O): the main occupational divide is between growing rents in cognitive jobs and shrinking rents in manual jobs.

6.2 What drives changes in rents?

Rents respond more strongly to shifts in technology than to changes in latent values. This finding becomes intuitive when we examine the attributes of marginal workers and the type of trade-offs they encounter.

Counterfactual rents. It helps to revisit the counterfactual exercises of Section 5, notably the fixed technology and the fixed latent values experiments. Table 4 shows the growth rate of rents between 1980 and 2018 in the baseline model and in the two counterfactual scenarios with fixed technology and fixed latent values. The top panel confirms that rents have grown for college graduates of all gender; at the same time they stagnated for non-college women and fell for non-college men. The middle and bottom panels report two counterfactual outcomes: first, we use the model to compute rents holding latent values at their 1980 levels; second, we compute rents holding technology parameters at their 1980 values. For both experiments we report the ratio of average rents in 2018 to average rents in 1980 (the counterfactual growth ratio that we obtain after assuming no change in technology or latent values). We make two observations:

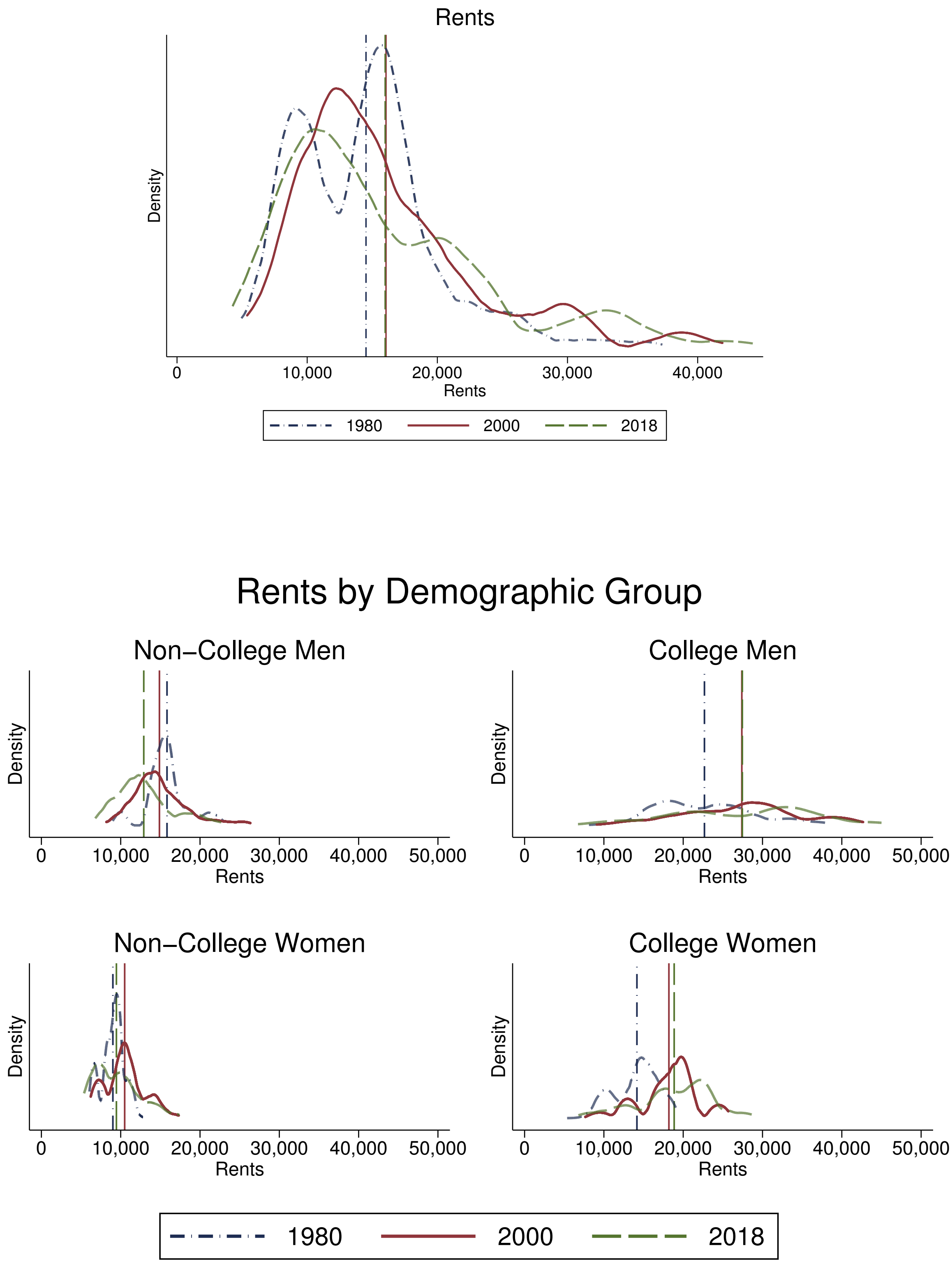

Figure 6: Distribution of job rents (employment-weighted): pooled (top panel) and disaggregated (bottom four panels). All values are in year 2000 dollar-equivalents. Vertical lines show averages in different years.

Rents: 2018 vs 1980, aggregate and by worker group.

		College		Non-College	
	All	Men	Women	Men	Women
Baseline					
1980	14,515	22,663	14,170	15,832	9,014
2018	15,985	27,451	18,861	12,903	9,460
Ratio: 2018/1980	1.10	1.21	1.33	0.82	1.05
Latent values at 1980 level					
Counterfactual ratio	1.14	1.25	1.29	0.84	1.08
Technology at 1980 level					
Counterfactual ratio	1.02	0.97	0.92	1.04	0.96

Table 4: Actual and counterfactual changes in rents between 1980 and 2018. Ratios: average rents in 2018 divided by average rents in 1980. Dollar values ($) are in year 2000 dollars.

1. holding latent values fixed (while letting technology free to change) results in rents' growth similar to what we have observed between 1980 and 2018;
2. holding technology fixed (while letting latent values free to change) delivers almost no change in rents (the counterfactual growth ratio between current and past rents is close to one).

These observations remain valid even when we split the sample by occupation (see Table 31 in Appendix O).

6.3 Marginal vs inframarginal workers

Why are rents so sensitive to technological shifts? To answer this question we focus on marginal workers who are close to indifference between their current occupation j and the second best alternative j'. By focusing on this group, we identify the marginal rate of substitution between observable and latent components in each worker-occupation pair; that is, we measure the compensating differential for that set of workers.[9]

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

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

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

Average Compensating Differentials (year 2000 $)

Year	All	College Men	College Women	Non-College Men	Non-College Women
1980	5,727	10,269	6,683	5,311	3,930
1990	6,750	11,050	7,236	6,368	5,131
2000	8,398	16,522	8,874	7,414	5,797
2010	7,963	13,509	9,356	6,908	6,447
2018	7,906	14,881	9,884	6,853	5,580

Table 5: Average absolute compensating differentials by year and demographic group.

where $\omega_{ijj'mt}$ is the fraction of workers in occupation j whose second best occupation is j' (defined as $\omega_{ijj'mt} = \frac{\mu_{ij'mt}}{\sum_{j''=1,..,J;j''\neq j'} \mu_{ij''mt}}$).

The first column of Table 5 shows the employment-weighted average of $\overline{CD}^{\$}_{ijmt}$ by year. The remaining columns show the evolution of compensating differentials by demographic group. The estimates suggest that the mean absolute compensating differentials have increased in all groups and growth is larger among the college educated. The marginal rate of substitution between latent returns and wages was much higher in 2018 than 1980. The higher marginal rate of substitution between latent returns and wages indicates that latent components of job values are exchanged at higher prices than before. There can be different reasons for this phenomenon and, in Section 7, we show evidence that higher CDs are strongly associated to more frequent mobility across occupations, which is key to select preferable job bundles. In Appendix O we show that average compensating differentials (mean absolute values) for workers who are indifferent between two jobs in the same broad occupation category have grown in all occupation categories and are highest in non-routine ones (Table 30).

Relating rent and compensating differentials The rationale for the fact that the evolution of rents is almost entirely explained by technological change is rooted in the analysis developed in section 3. There we argued that technological changes are reflected in rents when the elasticity of labor supply to wages, which we estimate to be on average between 0.5 and 0.6, is relatively low. Suppose productivity increases.As a consequence demand increases. Since workers are hard to attract because of the low elasticity, wages have to increase a lot. All existing workers enjoy higher wages while keeping the same latent values. Moreover since only a handful of workers switch to the new occupation the within group composition is almost unchanged. Average rents increase. The increase in the rents accruing to college graduate is then explained by the increase in the productivity in occupations typically held by college graduates that we documented in section4.

In section 5 we have seen that changes in latent values have driven the increase in labor force participation of women. This increase in latent values is not accompanied by a corresponding increase in rents exactly because of the strong response of labor supply to changes in latent values. In section 3 we have argued that when the elasticity of labor supply to changes in latent values is high (between 1.3 and 1.6 in our estimates) an increase in latent values is offset by a fall in the average idiosyncratic evaluation and a fall in the idiosyncratic evaluation of the marginal workers which mutes wage responses. As a result rents do not change much. This is particularly evident for non-college women whose participation in the labor force has increase substantially over time while their rents have stagnated.

7 Extensions and Robustness

In what follows we consider extensions and assess robustness to alternative assumptions. The first two extensions relate to modeling assumptions. First, we estimate a model where latent returns can vary across labor markets. Second, we consider a model with endogenous capital in intermediate production and use it to check the robustness of the empirical relationships estimated in the baseline model. The remaining extensions relate to our estimates of latent values, rents, and compensating differentials. First, we investigate whether latent values reflect preferences for the local amenities in the area where jobs are located. We find that jobs within cities and city centers are associated with higher latent values, especially for women. Next, we examine whether wage risk matters for rents and show that larger rents may partly compensate for higher wage risk. In the third extension, we provide evidence that job mobility is correlated with compensating differentials. Finally, we compute alternative measures of compensating differentials and verify how they relate to our own measure.

7.1 Variation in latent values across locations

The latent components of match value may vary systematically across locations. In Appendix N we study a model that allows for heterogeneity in latent returns across markets. Identification requires that we cast the component b_{ijmt} as the sum of a time-varying demographic-and-occupation component (like in the baseline model) and a term that can change across market-occupation pairs. The latter term reflects possible differences in the latent value of an occupation due to location-specific features. In practice, this amounts to redefining $b_{ijmt} = b_{ijt} + b_{jm}$ so that identification requires that all values be estimated relative to a reference region-occupation b_{jm}. Table 28 in Appendix N shows estimates of the b_{jm} for different census regions and occupations. Estimates of local effects are small relative to the b_{ijt} components. A variance decomposition illustrates that the contribution of the local b_{jm} terms is less than one percent of the total variance of systematic latent returns b_{ijmt}.

7.2 Capital inputs in intermediate production

In Appendix C we examine the robustness of results to the introduction of capital inputs in production. Specifically, we generalize the intermediate production technology to account for endogenous capital choices. The analysis shows that, just like in the baseline model, the distribution of labor inputs in the cross-section of intermediate good producers can be expressed as a function of match productivities (producer-level TFPs). Moreover, the relationship that we use to estimate technology parameters (equation (16)) remains valid. Match-specific shares and elasticities can be recovered using the baseline identification strategy. The one difference is that a correction must be applied to account for capital shares in the estimation of the elasticity of substitution between worker-occupation aggregates. This is necessary because, in the baseline model, the ϕ parameter in equation (16) gives a point estimate of $(\rho^{\text{base}} - 1)$, where ρ^{base} denotes the baseline estimate of the substitution parameter ρ. In a model with endogenous capital inputs, however, the parameter ϕ delivers an estimate of $\frac{\rho-1}{1-\rho(1-\gamma)}$ and $1 - \rho^{\text{base}} = \frac{1-\rho}{1-\rho(1-\gamma)}$, where γ is the capital share in intermediates' production. Assuming a positive value of γ means that the baseline estimate ρ^{base} is a lower bound of the curvature parameter ρ. This results in an upward rescaling of the elasticity of substitution and suggests that estimates of price responses in the counterfactuals are an upper bound of the equilibrium effects. For example, given the baseline estimate of $\hat{\phi} = -0.61$ in (16), if we set $\gamma = 2/3$ we obtain $\rho = 0.49$ and an elasticity of substitution of 1.96 (as opposed to 1.65 in the baseline model of Table 3).

7.3 Latent heterogeneity and preferences for location

Jobs are unevenly distributed across locations and some occupations occur more frequently in urban areas. To the extent that urban settings offer different amenities, the latent value of a match may be related to its geographic prevalence. That is, the latent value of a worker-occupation pair may depend on the location where it occurs more frequently. Occupations concentrated in urban areas might therefore exhibit higher b_{ijt} if the latter components capture the value of urban amenities. We explore this conjecture by projecting estimates of latent returns b_{ijt} on measures that capture how frequent occupations are in specific settings (urban vs rural; by population density). We find (see Appendix H) that urban and central city effects are not precisely estimated for men, although there is a positive and significant correlation between latent components and population density. Estimates for women, in contrast, are highly significant and larger (see Table 22 of Appendix H). This suggests that location attributes are relatively more important in the occupation choices of women. In all cases, the coefficients are positive as jobs in urban areas have higher latent returns.

7.4 Wage dispersion and rents

Does wage risk matter for rents? In Appendix M we explore this question by examining the relationship between the dispersion of wages within each $ijmt$-cell and average rents. We find that more wage dispersion is associated with higher rents. A 10-dollar increase in the standard deviation of wages is associated with a 4.3% increase in monetary rents. Moreover, the same increase in risk is associated with a positive change of about 0.3 standard deviations in total match value. Both the observable and latent components of surplus contribute to the positive risk-return relationship; however, the latent value accounts for a larger share of total surplus in riskier occupations. This implies that latent employment values are proportionally larger, as a share of total surplus, in occupations that exhibit more wage dispersion.

7.5 Compensating differentials and occupational mobility

Compensating differentials describe the trade-off between wages and latent returns for workers who are indifferent between occupations. To illustrate the trade off, consider two occupations denoted as A and B, which offer the same wage; however, A offers more amenities than B. For simplicity, suppose that workers are homogeneous and value the latent aspects of each occupation in the same way. If workers can freely move across occupations, those in B would rationally switch to A. In equilibrium, this flow of workers would cause a change in relative wages up to the point where the total return in occupation A equals that in occupation B. When occupational mobility is not impeded, equilibrium forces result in systematic compensating differentials that equalize overall returns. By the same token, higher switching costs and less mobility imply that latent components are less accurately reflected in wage differences. For this reason, compensating trade-offs may appear lower when job mobility is limited and wages do not consistently respond to changes in the value of latent components. In Appendix L we examine the relationship between compensating differentials and occupational mobility (Kambourov and Manovskii, 2008; vom Lehn et al., 2022) by using workers' gross flows across occupation pairs as a proxy for the cost of occupational mobility (see Cortes and Gallipoli, 2018). Appendix Table 26 shows that compensating differentials respond to changes in mobility across occupation pairs. A 1% increase in the flow of workers within an occupation pair is associated with an almost 10% increase in the monetary value of compensating differentials.

7.6 Alternative measures of compensating differentials

Our definition of compensating differentials emphasizes the trade-off between wages and latent match values for workers who are marginal in their occupation choice. By definition, this measure includes the idiosyncratic valuations of the two marginal occupations. On the other hand, the empirical literature often resorts to indirect measures of compensating differentials based on covariation between current wages and proxies of non-wage compensation. In Appendix

K we report two different measures of covariation between the wages and latent components of overall returns. The first measure is based on the value of $cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt})$, which we estimate for each year and demographic group. Panel A of Appendix Table 25 reports the results of this exercise and documents a positive and growing covariance for college graduates, especially among men. For non-college workers we find negative covariations, with a trend towards lower covariances among men. The positive and increasing covariances for college men are in line with findings in Lehmann (2022), which estimates wage and non-wage compensation for a sample of male workers who experience job-to-job transitions. The covariances reported in Panel A of Table 25 do not account for the idiosyncratic job valuations across workers in the same demographic group. We extend our analysis and, as shown in Panel B of Appendix Table 25, we report measures of covariation that include the average of the idiosyncratic match values within each cell. The cell-specific averages of idiosyncratic match values $\bar{\theta}_{ijmt}$ are obtained through model simulations and we use them to estimate the following covariances:

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

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

8 Conclusions

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

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

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

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

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

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

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

References

Aaronson, D. and French, E. (2004). The effect of part-time work on wages: Evidence from the social security rules. *Journal of Labor Economics*, 22(2):329–352.

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, 4:1043–1171.

Aguiar, M., Bils, M., Charles, K. K., and Hurst, E. (2017). Leisure luxuries and the labor supply of young men. Working Paper 23552, National Bureau of Economic Research.

Altonji, J. G. and Segal, L. M. (1996). Small-sample bias in gmm estimation of covariance structures. *Journal of Business & Economic Statistics*, 14(3):353–366.

Autor, D. H., Dorn, D., Hanson, G. H., and Song, J. (2014). Trade adjustment: Worker-level evidence. *The Quarterly Journal of Economics*, 129(4):1799–1860.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). The polarization of the US labor market. *The American Economic Review*, 96(2):189–194.

Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute.

Cortes, G. M. and Gallipoli, G. (2018). The costs of occupational mobility: An aggregate analysis. *Journal of the European Economic Association*, 16(2):275–315.

Cortes, G. M., Jaimovich, N., and Siu, H. E. (2017). Disappearing routine jobs: Who, how and why? *Journal of Monetary Economics*, 91:69–87.

Cortes, G. M., Jaimovich, N., and Siu, H. E. (2018). The "end of men" and rise of women in the high-skilled labor market. *NBER Working Paper No. 24274*.

Dube, A., Naidu, S., and Reich, A. D. (2022). Power and dignity in the low-wage labor market: Theory and evidence from wal-mart workers. Technical report, National Bureau of Economic Research.

Erosa, A., Fuster, L., Kambourov, G., and Rogerson, R. (2022a). Hours, occupations, and gender differences in labor market outcomes. *American Economic Journal: Macroeconomics*, 14(3):543–90.

Erosa, A., Fuster, L., Kambourov, G., and Rogerson, R. (2022b). Labor supply and occupational choice. Technical report, National Bureau of Economic Research.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4):1091–1119.

Goldin, C. and Katz, L. (2008). *The race between education and technology.* Belknap Press.

Hamermesh, D. S. (1999). Changing inequality in markets for workplace amenities. *The Quarterly Journal of Economics*, 114:1085–1123.

Heckman, J. J., Lochner, L., and Taber, C. (1998). Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents. *Review of Economic Dynamics*, 1(1):1–58.

Hsieh, C.-T., Hurst, E., Jones, C. I., and Klenow, P. J. (2019). The allocation of talent and U.S. economic growth. *Econometrica*, 87(5):1439–1474.

Kambourov, G. and Manovskii, I. (2008). Rising occupational and industry mobility in the United States: 1968-97. *International Economic Review*, 49(1):41–79.

Katz, L. and Autor, D. (1999). Changes in the wage structure and earnings inequality. *Handbooks of Labor Economics*, 3:1463–1558.

Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: Supply and demand factors. *The Quarterly Journal of Economics*, 107(1):35.

King, M., Ruggles, S., Alexander, T., Flood, S., Genadek, K., Schroeder, M. B., Trampe, B., and Vick, R. (2010). Integrated Public Use Microdata Series, Current Population Survey: Version 3.0. [Machine-readable database]. Technical report, University of Minnesota, Minneapolis, MN.

Krusell, P., Ohanian, L. E., RÃos-Rull, J.-V., and Violante, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, 68(5):1029–1053.

Lamadon, T., Mogstad, M., and Setzler, B. (2022). Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market. *American Economic Review*, 112(1):169–212.

Lehmann, T. (2022). Non-wage job values and implications for inequality. *Working Paper.*

Maestas, N., Mullen, K. J., Powell, D., von Watcher, T., and Wenger, J. B. (2018). The value of working conditions in the united states and implications for the structure of wages. *NBER Working Paper No. 25204.*

Moretti, E. (2013). Real wage inequality. *American Economic Journal: Applied Economics*, 5(1):65–103.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica*, 26(3):393–415.

Su, C.-L. and Judd, K. L. (2012). Constrained optimization approaches to estimation of structural models. *Econometrica*, 80(5):2213–2230.

Taber, C. and Vejlin, R. (2020). Estimation of a roy/search/compensating differential model of the labor market. *Econometrica*, 88:1031–1069.

vom Lehn, C., Ellsworth, C., and Kroff, Z. (2022). Reconciling occupational mobility in the current population survey. *Journal of Labor Economics*, 40(4):1005–1051.

Wiswall, M. and Zafar, B. (2018). Preference for the workplace, investment in human capital, and gender. *The Quarterly Journal of Economics*, 133:457–507.

A Identification and estimation

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

Identification: utility and technology parameters

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

$$\begin{aligned} U_{ijmt} = \max_{h_{ijmt}} \quad & \frac{c_{ijmt}^{1-\sigma} - 1}{1-\sigma} - \psi_i \frac{h_{ijmt}^{1-\gamma}}{1-\gamma} + b_{ijt} \\ \text{s.t.} \quad & c_{ijmt} = w_{ijmt} h_{ijmt} \end{aligned} \tag{25}$$

the associated first order condition in logarithmic form is

$$\log\left(h_{ijmt}\right) = -\frac{1}{\sigma-\gamma}\log\left(\psi_i\right) + \frac{1-\sigma}{\sigma-\gamma}\log\left(w_{ijmt}\right) \tag{26}$$

The empirical counterpart of this is

$$\log\left(h_{ijmt}\right) = \alpha_i + \beta\log\left(w_{ijmt}\right) + \epsilon_{ijmt}^1 \equiv f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) + \epsilon_{ijmt}^1 \tag{27}$$

with

$$\alpha_i = -\frac{1}{\sigma-\gamma}\log\left(\psi_i\right) \qquad \beta = \frac{1-\sigma}{\sigma-\gamma} \tag{28}$$

With the linear specification of $f(\cdot,\cdot)$, moments (17) and (18) describe an OLS estimator of (27). From the estimation of the latter equation we can obtain γ and ψ_i as a function of σ:

$$\gamma = \sigma - \frac{1-\sigma}{\beta} \qquad \psi_i = \exp\left(-\frac{1-\sigma}{\beta}\alpha_i\right) \tag{29}$$

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 (19) and (20), given that $\boldsymbol{Z}_{ijmt}^2$ has at least two elements

$Z^2_{1,ijmt}$ and $Z^2_{2,ijmt}$. From eq. (19) we have

$$\tilde{b}_{ijt} = E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u_h^i\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta}\middle| i,j,t\right] \tag{30}$$

where $\tilde{b}_{ijt} = \frac{b_{ijt}}{\sigma_\theta}$. Plugging this into (20) gives

$$E\left[\left(\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u_h^i\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta}\right.\right.$$
$$\left.\left. - E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u_h^i\left(\hat{h}_{ijmt}\right) - u_c(0)}{\sigma_\theta}\middle| i,j,t\right]\right)\boldsymbol{Z}^2_{ijmt}\right] = 0 \tag{31}$$

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. (30) identifies b_{ijt}.

Production function identification.

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

$$\frac{w_{ijmt}}{w_{i'jmt}} = \frac{\beta_{ijt}}{\beta_{i'jt}} \tag{32}$$

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

$$\frac{w_{ijmt}}{w_{ij'mt}} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\widetilde{L}_{j'mt}}{\widetilde{L}_{jmt}}\right)^{1-\rho} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}}\left(\frac{\sum_{i'}\beta_{i'j't}L_{i'j'mt}}{\sum_{i'}\beta_{i'jt}L_{i'jmt}}\right)^{1-\rho} \tag{33}$$

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

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho-1)\log\left(\frac{\sum_{i'}\beta_{i'jt}L_{i'jmt}}{\sum_{i'}\beta_{i'1t}L_{i'1mt}}\right) \tag{34}$$

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:

$$W_{ijmt} = \gamma_{jt} + \psi B_{ijt} + \phi\Lambda_{jmt} + \epsilon_{ijmt} \tag{35}$$

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

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

B Production sector: derivations

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

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

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} - \sum_i \tilde{w}_{ij} L_{ijv} \tag{36}$$

the associated first order condition is

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho} \rho \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho-1} \beta_{ij} \tag{37}$$

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

$$z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho-1} = z_{jv'}^{\rho} \left(\sum_i \beta_{ij} L_{ijv'} \right)^{\rho-1} \tag{38}$$

$$\sum_i \beta_{ij} L_{ijv'} = \frac{z_{jv}^{\frac{\rho}{\rho-1}}}{z_{jv'}^{\frac{\rho}{\rho-1}}} \sum_i \beta_{ij} L_{ijv} \tag{39}$$

Integrating over $v' \in V_j$ we get

$$\sum_i \beta_{ij} L_{ij} = z_{jv}^{\frac{\rho}{\rho-1}} \int_{v' \in V_j} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \sum_i \beta_{ij} L_{ijv} \tag{40}$$

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

The aggregate production function is given by

$$Y = \left(\int_v \upsilon_{jv}^{\rho} dv \right)^{\frac{1}{\rho}} \tag{42}$$

$$= \left(\sum_j \int_{v \in V_j} \upsilon_{jv}^{\rho} dv \right)^{\frac{1}{\rho}} \tag{43}$$

$$= \left(\sum_j \int_{v \in V_j} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} dv \right)^{\frac{1}{\rho}} \tag{44}$$

Using (41) this gives

$$Y = \left[\sum_j \int_{v \in V_j} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} dv \right]^{\frac{1}{\rho}} \tag{45}$$

$$= \left[\sum_j \int_{v \in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \left(\int_{v'} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \right)^{-\rho} \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{46}$$

$$= \left[\sum_j \underbrace{\left(\int_{v \in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{47}$$

$$= \left[\sum_j \tilde{\alpha}_j \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{48}$$

$$= A \left[\sum_j \alpha_j \left(\sum_i \beta_{ij} L_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \tag{49}$$

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 (41) into (37) we have

$$\tilde{w}_{ij} = P Y^{(1-\rho)} \rho \underbrace{\left(\int_{v \in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_{i'} \beta_{i'j} L_{i'j} \right)^{\rho-1} \beta_{ij} \tag{50}$$

$$\frac{\tilde{w}_{ij}}{P} = Y^{(1-\rho)} \rho \tilde{\alpha}_j \frac{\sum_{j'} \tilde{\alpha}_{j'}}{\sum_{j'} \tilde{\alpha}_{j'}} \left(\sum_{i'} \beta_{i'j} L_{i'j} \right)^{\rho-1} \beta_{ij} \tag{51}$$

$$w_{ij} = \rho A^{\rho} \alpha_j \beta_{ij} \left(\frac{Y}{\sum_{i'} \beta_{i'j} L_{i'j}} \right)^{(1-\rho)} \tag{52}$$

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

C Model with capital inputs

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

$$\max_{p_{jv},\lambda_{jv},L_{ijv}} \quad p_{jv}\lambda_{jv} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{53}$$

$$\text{s.t.} \quad \lambda_{jv} = z_{jv} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\gamma} (\eta_j K_{jv})^{1-\gamma} \tag{54}$$

$$p_{jv} = \left[\frac{\lambda_{jv}}{Y} \right]^{-(1-\rho)} P \tag{55}$$

Equivalently

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho\gamma} (\eta_j K_{jv})^{\rho(1-\gamma)} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{56}$$

The associated first order conditions are

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho} \rho\gamma \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho\gamma-1} (\eta_j K_{jv})^{\rho(1-\gamma)} \beta_{ij} \tag{57}$$

and

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

Dividing the two first order conditions by each other we get

$$\frac{\tilde{w}_{ij}}{r} = \beta_{ij} \frac{\gamma}{1-\gamma} \frac{K_{jv}}{\sum_{i'} \beta_{i'j} L_{i'jv}} \Rightarrow K_{jv} = \frac{w_{ij}(1-\gamma)}{r\gamma\beta_{ij}} \sum_{i'} \beta_{i'j} L_{i'jv} \tag{59}$$

Notice that this implies

$$\frac{K_{jv}}{\sum_{i'} \beta_{i'j} L_{i'jv}} = \frac{\tilde{w}_{ij}(1-\gamma)}{r\gamma\beta_{ij}} = \frac{K_j}{\sum_{i'} \beta_{i'j} L_{i'j}} \tag{60}$$

where $K_j = \int_{v' \in V_j} K_{jv} dv$ and $L_{ij} = \int_{v' \in V_j} L_{ijv} dv$.
Using (59) into (57) we get

$$\tilde{w}_{ij} = \left(\frac{\tilde{w}_{ij}}{r} \right)^{\rho(1-\gamma)} PY^{(1-\rho)} z_{jv}^{\rho} \rho \gamma^{1-\rho(1-\gamma)} (1-\gamma)^{\rho(1-\gamma)} \eta_j^{\rho(1-\gamma)} \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho-1} \beta_{ij}^{1-\rho(1-\gamma)} \tag{61}$$

$$w_{ij} = \Xi \eta_j^{\frac{\rho(1-\gamma)}{1-\rho(1-\gamma)}} z_{jv}^{\frac{\rho}{1-\rho(1-\gamma)}} \beta_{ij} \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\frac{\rho-1}{1-\rho(1-\gamma)}} \tag{62}$$

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 (62) implies the same relationship described in (39) and, thus, equation (41). Using (41) in (62) we get

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

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

$$\log\left(\frac{w_{ij}}{w_{i2}}\right) = \log\left(\frac{\Lambda_j}{\Lambda_1}\right) + \log\left(\frac{\beta_{ij}}{\beta_{i1}}\right) + \frac{\rho - 1}{1 - \rho(1-\gamma)} \log\left(\frac{\sum_{i'} \beta_{i'j} L_{i'j}}{\sum_{i'} \beta_{i'1} L_{i'1}}\right) \tag{64}$$

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

$$W_{ijmt} = \gamma_{jt} + \psi \hat{B}_{ijt} + \phi \hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{65}$$

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

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

$$1 - \rho^{\text{base}} = \frac{1-\rho}{1-\rho(1-\gamma)} \tag{66}$$

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

$$\rho^{\text{base}} < \rho \tag{67}$$

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

D Elasticity of labor supply

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

D.1 Uncompensated elasticity: intensive margin

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

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

The total differential of the MRS is:

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

After rearranging:

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

The uncompensated elasticity at the intensive margin is,

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

Figure 7a shows the distribution of the intensive margin elasticity of labor supply in the population based on model estimates. The average elasticity is 0.15.

D.2 Uncompensated elasticity: extensive margin

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

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

From equation (3) we get:

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

Figure 7b shows the distribution of extensive margin elasticities in the population, obtained from the model estimates. The average elasticity is between 0.55 and 0.60 across all years.

D.3 Uncompensated elasticity: total response

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

$$\varepsilon_{ijmt}^{tot} = \frac{L_{ijmt}}{dw_{ijmt}} \frac{w_{ijmt}}{L_{ijmt}} = \left(\frac{d\mu_{ijmt}}{dw_{ijmt}} h_{ijmt} + \frac{dh_{ijmt}}{dw_{ijmt}} \mu_{ijmt} \right) \frac{w_{ijmt}}{L_{ijmt}} \tag{68}$$

Figure 7c shows the distribution of total elasticity estimates in the population. The average is 0.72. Equation (68) allows one to compute the relative contribution of the extensive margin (first term in the summation) and the intensive margin (second term) to total elasticity. On average the extensive margin accounts for about 78% of the total elasticity.

D.4 Aggregate elasticity

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

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

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

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

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

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

The aggregate elasticity is between 0.75 and 0.78, depending on the year.

D.5 Uncompensated cross-elasticities: extensive margin

The elasticity of labor supply of occupation j in response to a change in the wage paid to occupation j' for demographic group i is defined as

$$
\varepsilon_{ijj'mt}^{cross} = \frac{d\mu_{ijmt}}{dw_{ij'mt}}\frac{w_{ij'mt}}{\mu_{ijmt}}.
$$

From equation (3), we have

$$
\begin{aligned}
\frac{d\mu_{ijmt}}{dw_{ij'mt}} &= -\frac{1}{\sigma_\theta}e^{U_{ijmt}/\sigma_\theta}\left(\sum_{j'=0}^{J}e^{U_{ij'mt}/\sigma_\theta}\right)^{-2}e^{U_{ij'mt}/\sigma_\theta}\frac{dU_{ij'mt}}{dw_{ij'mt}}\mu_{imt} \\
&= -\frac{1}{\sigma_\theta}\frac{\mu_{ijmt}\mu_{ij'mt}}{\mu_{imt}}\frac{dU_{ij'mt}}{dw_{ij'mt}}
\end{aligned}
$$

where from the first to the second line we used equation (3) twice for occupations j and j', and

$$
\begin{aligned}
\frac{dU_{ij'mt}}{dw_{ij'mt}} &= \frac{d\left(u_c(w_{ij'mt}h_{ij'mt}+y_{imt})-u_h^i\left(h_{ij'mt}\right)\right)}{dw_{ij'mt}} \\
&= \left(w_{ij'mt}h_{ij'mt}+y_{imt}\right)^{-\sigma}\left(h_{ij'mt}+w_{ij'mt}\frac{dh_{ij'mt}}{dw_{ij'mt}}\right)-\psi_i h_{ij'mt}^{-\gamma}\frac{dh_{ij'mt}}{dw_{ij'mt}}.
\end{aligned}
$$

Finally, the derivative of hours supplied with respect to wages can be obtained from the equation that defines the MRS between hours and wages for the intensive labor supply choice:

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

The total differential is given by:

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

which, after rearranging, gives

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

D.6 Uncompensated elasticities to latent values

The extensive margin elasticity of labor supply to changes in latent values is defined as the ratio of the percentage change in the number of workers choosing a particular occupation and the percentage change in the latent value of that occupation. That is,

$$\varepsilon_{ijmt}^b = \frac{d\mu_{ijmt}}{db_{ijt}}\frac{|b_{ijt}|}{\mu_{ijmt}}.$$

where the absolute value operator is needed as 98% of the estimated values for b_{ijt} are negative. From equation (3) we get:

$$\frac{d\mu_{ijmt}}{db_{ijt}} = \mu_{imt}\frac{\frac{1}{\sigma_\theta}e^{U_{ijmt}/\sigma_\theta}}{\left[\sum_{j'=0}^{J}\exp\left(U_{ij'mt}/\sigma_\theta\right)\right]^2}\sum_{j'=0,j'\neq j}^{J}\exp\left(U_{ij'mt}/\sigma_\theta\right)$$

Figure 7d shows the distribution of these elasticities in the population, obtained from the model estimates. The average elasticity is between 1.33 and 1.57 across all years.

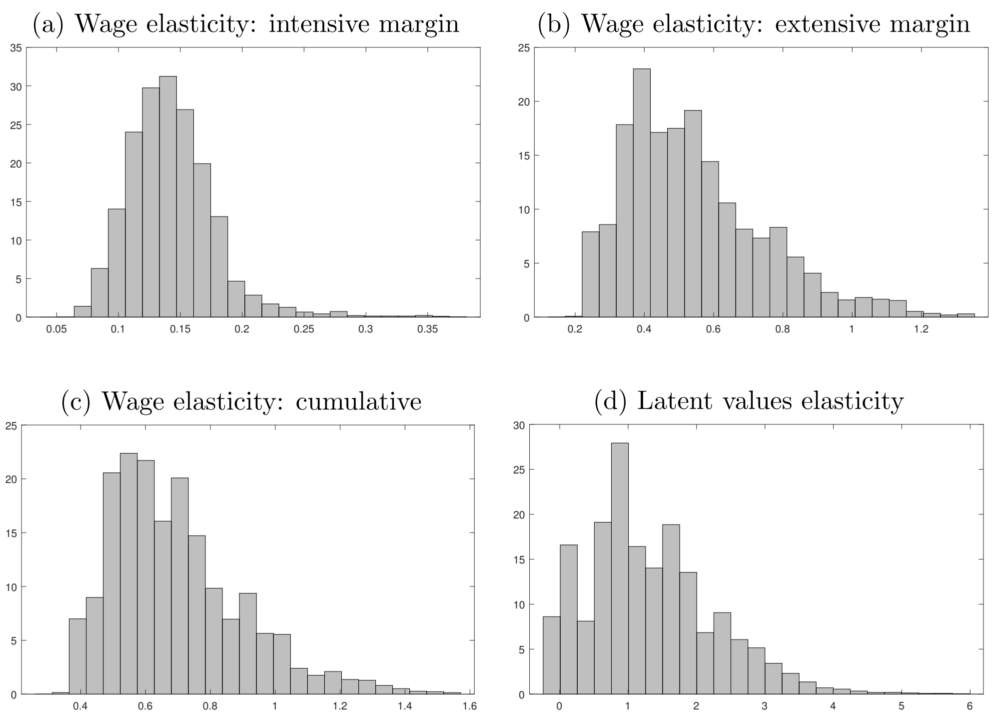

Figure 7: Distribution of the elasticities of labor supply (extensive and intensive margin) to changes in wages and latent values.

E Bartik instrument

In this appendix, we provide an additional instrumental variable to estimate the parameters governing labor demand. The model suggests that differences in the labor participation (head-count) in each occupation over time are the by-product of worker match values, conditional on their demographic group, or due to shifts in the overall demographic composition of the labor force.

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

$$\text{IV}_{jmt} = \Delta\hat{\Lambda}^h_{jmt} = \hat{\Lambda}^h_{jmt} - \log\left(\frac{L^h_{jmt-10}}{L^h_{1mt-10}}\right) \tag{69}$$

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

Table 6 shows that the estimation results using the Bartik instrument are comparable to the results presented in the main text.

	OLS	IV
	(1)	(2)
$\hat{\phi}$	-0.0834	-0.6041***
	(0.0610)	(0.1665)
$\hat{\psi}$	0.9771***	0.9771***
	(0.0413)	(0.0413)
Observations	2,496	2,496
Test $\hat{\psi} = 1$ (p-val)	0.5796	0.5798
Implied ρ	0.9166***	0.3959**
	(0.0610)	(0.1665)
Implied elast. of sub.	11.9974	1.6554
	(58.5230)	(100.5079)

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

Table 6: Estimation results for equation (16) in first differences using the Bartik instrument.

F Method-of-moments estimates

F.1 Preference parameters and production technology share

Table 7 shows estimates of the curvature of consumption utility (σ) and of the scale parameters of the extreme value preference shock (σ_θ). Column 1 reports estimates obtained without using instruments. That is, $\boldsymbol{Z}^1_{ijmt}$ includes the logarithm of contemporaneous wages and non-labor income, $\boldsymbol{Z}^2_{ijmt}$ are the logarithm of contemporaneous wages. In columns (2), (3), and (4) we instrument for wages and non-labor income using their 10-year and 20-year lagged values. We refer to column (2) as our baseline specification. Results are not sensitive to using the estimates in columns (3) or (4). Table 8 shows estimates of the remaining utility parameters: the weight and curvature of disutility from labor (ψ, γ). Estimates of the latent match-specific surplus for different (i, j) matches for different years (b_{ijt} are in tables 9 to 13) As for the production function estimates, tables 14 to 19 show point estimates and standard errors (in parenthesis) for technology input shares in different years (1980, 1990, 2000, 2010, 2018). Share estimates are presented for all occupation-worker combinations.

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

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

Table 7: Results from the GMM estimator in equation (21). Prameters and standard errors for $\hat{\sigma}_\theta$ are scaled down by 1000.

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

Bootstrapped standard errors in parentheses

Table 8: Estimates of the utility parameters realtive to the disutility of hours worked from the GMM estimator in equation (21). Parameter estimates and standard errors for ψ_i are scaled up by 10^{14}.

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

Bootstrapped standard errors in parentheses

Table 9: Estimates of the non-pecuniary component of surplus for 1980 normalized by $\hat{\sigma}_\theta$.

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

Bootstrapped standard errors in parentheses

Table 10: Estimates of the non-pecuniary component of surplus for 1990 normalized by $\hat{\sigma}_\theta$.

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

Bootstrapped standard errors in parentheses

Table 11: Estimates of the non-pecuniary component of surplus for 2000 normalized by $\hat{\sigma}_{\theta}$.

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

Bootstrapped standard errors in parentheses

Table 12: Estimates of the non-pecuniary component of surplus for 2010 normalized by $\hat{\sigma}_\theta$.

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

Bootstrapped standard errors in parentheses

Table 13: Estimates of the non-pecuniary component of surplus for 2018 normalized by $\hat{\sigma}_{\theta}$.

Occupation	Year 1980	1990	2000	2010	2018
Exec., Admin., Manag.	0.1165	0.1234	0.1329	0.1347	0.1408
	(0.0087)	(0.0096)	(0.0104)	(0.0118)	(0.0129)
Manag. rel.	0.0578	0.0667	0.0740	0.0851	0.0900
	(0.0055)	(0.0040)	(0.0038)	(0.0036)	(0.0021)
Professional	0.1242	0.1411	0.1512	0.1625	0.1672
	(0.0119)	(0.0144)	(0.0161)	(0.0193)	(0.0215)
Technicians	0.0574	0.0647	0.0694	0.0751	0.0813
	(0.0056)	(0.0052)	(0.0051)	(0.0057)	(0.0050)
Sales	0.0854	0.0985	0.0971	0.0927	0.0872
	(0.0021)	(0.0044)	(0.0035)	(0.0033)	(0.0019)
Admin. Support	0.1056	0.1009	0.0968	0.0902	0.0818
	(0.0064)	(0.0056)	(0.0059)	(0.0043)	(0.0024)
Protective Services	0.0386	0.0419	0.0441	0.0499	0.0466
	(0.0062)	(0.0067)	(0.0069)	(0.0070)	(0.0067)
Other Services	0.0525	0.0540	0.0566	0.0603	0.0624
	(0.0014)	(0.0012)	(0.0008)	(0.0012)	(0.0009)
Mechanics	0.0630	0.0578	0.0563	0.0516	0.0471
	(0.0040)	(0.0043)	(0.0045)	(0.0055)	(0.0061)
Construction Traders	0.0622	0.0555	0.0519	0.0492	0.0505
	(0.0037)	(0.0042)	(0.0042)	(0.0051)	(0.0056)
Precision Prod.	0.0710	0.0569	0.0509	0.0424	0.0397
	(0.0034)	(0.0053)	(0.0053)	(0.0060)	(0.0062)
Machine Operators	0.0823	0.0676	0.0549	0.0445	0.0430
	(0.0007)	(0.0024)	(0.0039)	(0.0050)	(0.0055)
Transportation	0.0834	0.0710	0.0639	0.0616	0.0625
	(0.0009)	(0.0010)	(0.0017)	(0.0020)	(0.0020)

Bootstrapped standard errors in parentheses

Table 14: Estimates of α_{jt}.

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

Bootstrapped standard errors in parentheses

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

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

Bootstrapped standard errors in parentheses

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

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

Bootstrapped standard errors in parentheses

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

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

Bootstrapped standard errors in parentheses

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

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

Bootstrapped standard errors in parentheses

Table 19: Estimates of β_{ijt} for 2018.

F.2 Technology shares by worker group: match level estimates

Figure 8 breaks down changes in production shares by worker type and shows that the share of routine manual occupations dropped or stagnated for all gender and education groups.

Workers in college-level jobs experienced large gains in all but routine manual occupations. College-level gains in cognitive occupations are the largest, suggesting a growing match-specific return. However, a college degree did not significantly improve productivity in manual occupations.

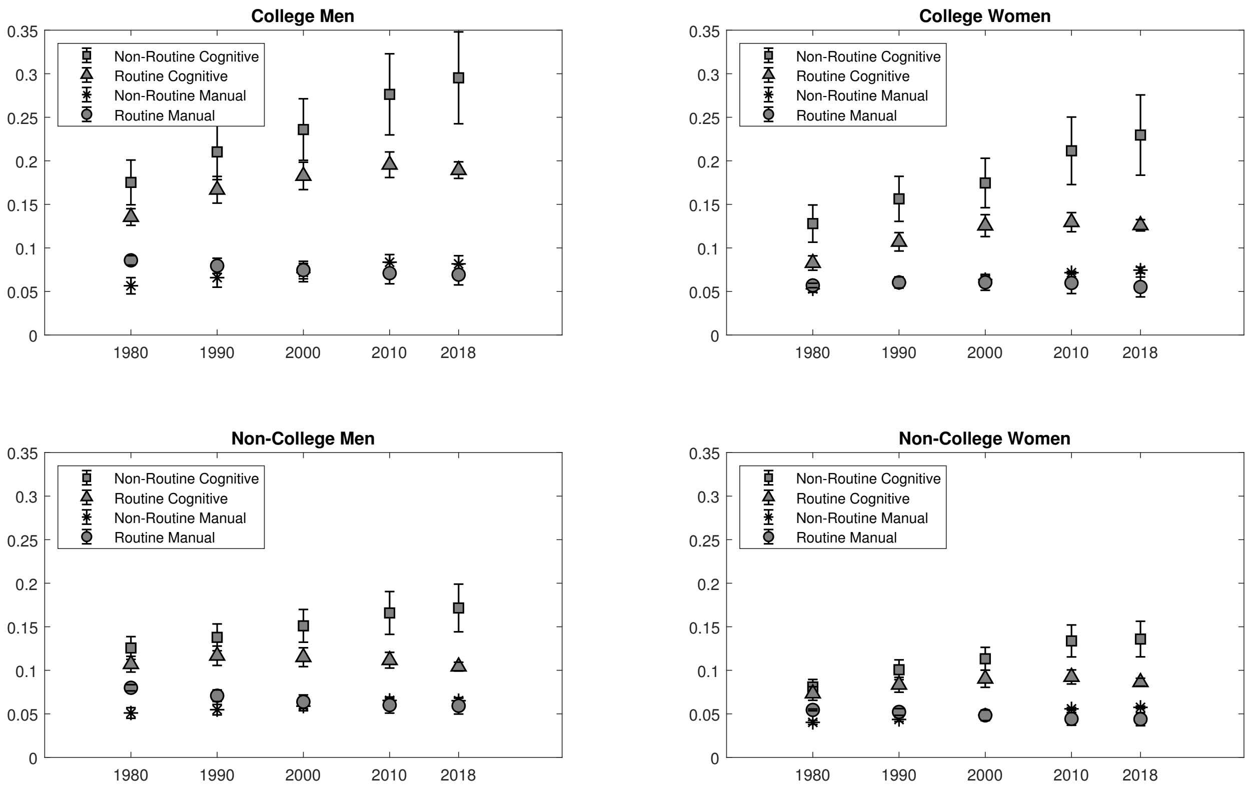

Figure 8: Average production shares of four broad occupation categories by worker demographic group (based on estimates of $\alpha_{jt}\beta_{ijt}$). Brackets are 95-percent confidence intervals around point estimates.

G Robustness: model with flexible disutility of work

In this appendix, we consider a model in which we allow te disutility of work to be a flexible function of both demographic (as it is in he main text) and occupation. The exercise aims at exploring the possibility that there is some important hidden heterogeneity of workers' preferences for different occupations that might be relevant for our analysis of rents and compensating differentials. It is no surprise that the more flexible model can better explain the variability of hours worked in the data but, as we show here, our results concerning rents and compensating differentials are not substantially affected.

In practice we re-estimate the model using a more flexible specification for the utility cost of hours worked, namely

$$u_h^i(h) = \psi_{ij} \frac{h^{1-\gamma}}{1-\gamma}.$$

With this specification, within each demographic group workers are allowed to value time spent at work differently. Figure 9 shows the goodness of fit for this model. Just like the baseline model, the enriched model can explain 99% and 95% of the variation in employment and wages. Yet it performs better in terms of hours worked explaining 87% of total variation.

Despite the improvement in terms of goodness of fit, tables 20 and 21, which are the counterparts of tables 1 and 5, show that the flexible model produces comparable compensating differentials. As for rents, the model produces slightly lower rents but growth patterns are comparable to those in the main text.

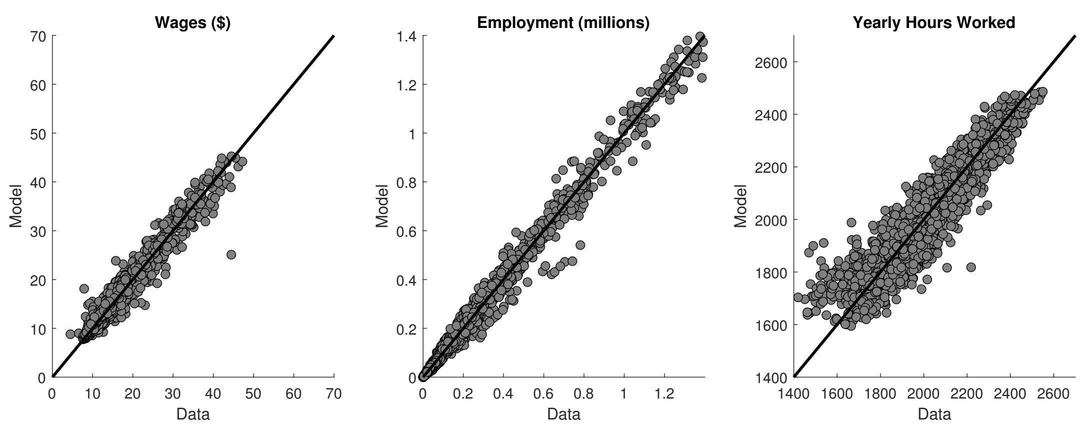

Figure 9: Goodness of fit. Left: model implied wages vs. data. Center: model implied employment vs. data. Right: model implied hours worked vs. data.

Average Rents (year 2000 $)

Year	All	College Men	College Women	Non-College Men	Non-College Women
1980	12,700	20,559	11,697	13,891	7,737
1990	12,915	22,093	13,374	13,054	8,301
2000	14,035	24,813	15,242	13,110	8,979
2010	13,100	23,983	15,134	11,210	7,994
2018	13,966	24,798	15,938	11,366	8,044

Table 20: Estimated average rents by year and demographic group.

Average Compensating Differentials (year 2000 $)

Year	All	College Men	College Women	Non-College Men	Non-College Women
1980	5,537	9,499	6,765	5,185	3,861
1990	6,513	10,374	7,077	6,162	5,042
2000	8,116	15,641	8,437	7,213	5,724
2010	7,715	12,759	9,022	6,734	6,355
2018	7,655	14,078	9,560	6,688	5,489

Table 21: Average absolute compensating differentials by year and demographic group.

H Projecting latent returns on observables

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

H.1 Geography and urban amenities

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

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

Table 22 show the estimation results. Columns 1, 3, and 5 report the results from regressing b_{ijt} on the geographic variables without any other control. For men the coefficients are often not significant and the R2 is always very low (low explanatory power). For women we have always significant coefficients and relatively high R2, which suggests that geography is more important in determining the occupational choices of women than those of men. In all cases, the coefficients are positive: jobs in urban, dense areas are preferred. Adding controls for age and education (columns 2, 5, and 6) makes the estimated coefficient bigger and more significant for both men and women.

H.2 Gender-specific frictions

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

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

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

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

Standard errors in parentheses

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

Table 22: Results for job location.

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

Table 23 shows the results of these projections. In Column 1, we see that the gap in unemployment rates can explain alone 13.6% of the variation in the gender gap of latent returns. The estimated coefficient is sizable in magnitude and of the expected sign (all variables are standardized). An increase of one standard deviation in the unemployment gap corresponds to a fall of 0.37 standard deviations in b_{ijt}. In Column 2 we include year fixed effects, age and education fixed effects to control for differences in preferences of men and women that arise with age (e.g. women of childbearing age might be less keen on working in certain occupations), as well as education fixed effects. Results are not affected by these additional controls.

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

A possible concern is that, in occupations where the unemployment gap is largest, women search for longer and are pickier about work conditions (e.g. flexibility in hours). Several things can be said in this respect: (i) if the concern is about total hours worked, this shouldn't matter as hours are not part of the b_{ijt} as we account for them through a type-specific "disutility of hours" term; (ii) if the concern is about work schedule flexibility, this might introduce a bias. If women prefer jobs that allow for more flexibility and, conditional on choosing an occupation, they search for longer to find the most flexible employer, the coefficient on the unemployment gap would become more negative (that is, the coefficient would not only reflect frictions but also longer search times due to preferences). For this reason, the coefficient we estimate is a lower bound and, to get an upper bound, we add controls for occupation type (Column 4) or occupation fixed effects (Column 5). These controls should also capture some of the frictions' impacts (averaged over time) and reduce the predictive power of the difference in unemployment. That is indeed what we observe in Columns 4 and 5.

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

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

Standard errors in parentheses

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

Table 23: Results for gender frictions.

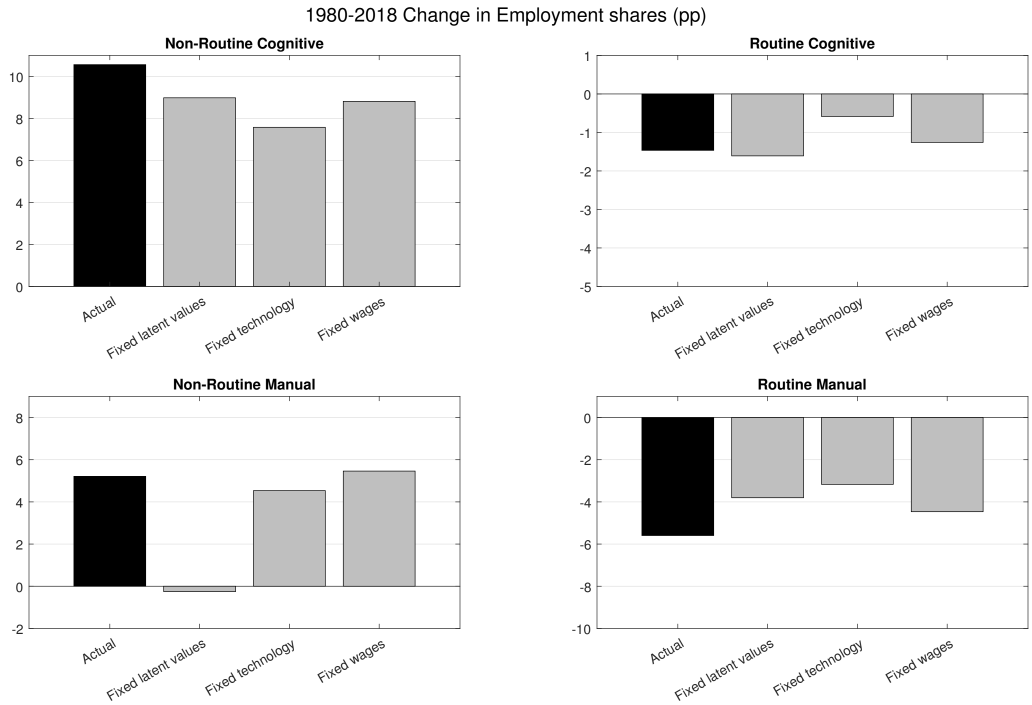

Figure 10: Changes in employment shares by occupation category. Comparison of baseline and counterfactual scenarios between 1980 and 2018. Changes in percentage points.

I Counterfactual exercises: employment changes by occupation category

Figure 10 summarizes how changes in technology and latent returns have influenced employment in four broad occupation categories (defined in Table 2).

Non-routine occupations. The black bar in the top-left panel shows the well-documented increase in non-routine cognitive (NRC) employment. From 1980 to 2018 the NRC employment share climbed by 10 percentage points. How much did technological change contribute to this run-up? The impact of holding technology parameters fixed at their 1980 values is twice as large as holding latent returns at their 1980 values. This shows that technology made a considerably larger contribution to NRC employment growth.

The rightmost bar in each panel shows partial equilibrium outcomes where wages are held at their 1980 levels. In the fixed wage experiments, like in the fixed technology ones, the effects of technological change are muted. The key difference between fixed-technology and fixed-wages is that the fixed-technology experiment allows for price responses to exogenous labor supply changes like workforce composition. What we learn is that technological and workforce composition changes have been comparatively more important drivers of NRC employment than latent employment values.

The second fastest growing occupation category was non-routine manual jobs (NRM), which experienced employment growth of about 5 percentage points. Unlike NRC occupations, this increase was almost exclusively driven by latent return components. In fact, in the fixed-latent values experiment, the NRM employment growth collapses. Technological change and equilibrium price adjustments contributed little to NRM employment patterns.

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

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

To sum up, technological change has been a key driver of run-ups in the share of cognitive and routine manual jobs. In NRM occupations the largest contribution has come from latent return components. A comparison between Figure 4 and 10 (in particular, the counterfactual exercises in which we keep technology at its 1980 level) shows that, while technology has had a limited impact on the overall labor force participation of each demographic group, it did have a significant impact on the type of occupation workers chose. Figure 10 illustrates that technological change has contributed to the shift from routine occupations to non-routine ones, especially in cognitive jobs.

Finally, in keeping with the findings for occupation shares, Figure 11 indicates that age changes across occupation categories are driven by technological change, as opposed to latent match values.

I.1 Accounting for changes in workforce and technology

Between 1980 and 2018, technological change played a pivotal role in shaping occupation choice and relative wages. At the same time, the workforce changed significantly in terms of its composition and latent valuations of employment. Table 24 shows wage deviations (in percentage terms) relative to wages observed in 2018.

Each row in the table refers to a different counterfactual. The first row shows the wage deviations when the distribution of total employment is the same as in 1980. This partial equilibrium experiment corresponds to the one described in Figure 11 and reflects the direct and short-term impact of technological change on wages. The positive gaps for college workers, as opposed to the negative ones for non-college workers, confirm the asymmetric impact of technology across education groups. In the second row, we allow for employment responses

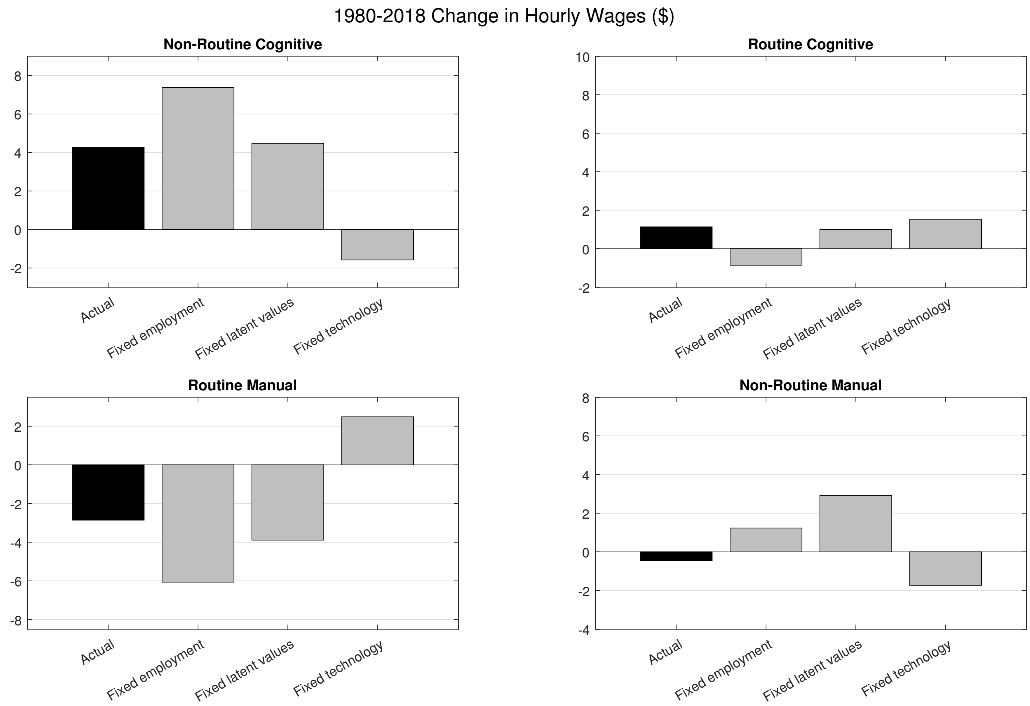

Figure 11: Changes in average hourly wage in four occupation categories. Actual versus counterfactual scenarios between 1980 and 2018.

Counterfactual percentage change, relative to actual 2018 wages.

	Demographic group			
Holding fixed:	College Men	College Women	Non-College Men	Non-College Women
1980 Employment share	3.25%	5.79%	-9.93%	-2.54%
1980 Pop. composition and b_{ijt}	1.51%	-1.32%	-4.40%	-4.50%
1980 Pop. composition only	-0.23%	0.77%	-6.33%	-5.38%
Wage/hour in 2018	29.9	22.3	14.6	11.8

Table 24: Impact of demographic change on end-of-period (2018) wages.

but hold the latent values b_{ijt} and the population composition fixed at their 1980 levels. A comparison between the first row (1980 Employment share) and the second (1980 Pop. Composition and b_{ijt}) show that the equilibrium responses to technological change depressed the wages of college graduates, especially women. Growing returns to cognitive and non-routine manual occupations attracted more workers and limited the wage growth among college educated workers, who are employed in these occupations. At the same time, declines in the wages of non-college men were mitigated by the outflow from routine manual occupations.

In the third row, we allow for the historical changes in latent valuations of employment while holding the population composition fixed. Therefore, the deviations shown in the third row are due exclusively to changes in workforce demographic composition between 1980 and 2018. This row shows that a shrinking share of non-college workers lifted wages in this group. Holding the workforce composition fixed at its 1980 levels, the wages of non-college workers are lower than observed.

These findings highlight the presence of significant equilibrium responses due to changes in workforce composition and latent employment valuations. They add to the evidence in Figure 5 by confirming the prominent quantitative impact of technological change on relative wages.

J Analytical derivations of rents and of compensating differentials

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

$$R_{ijmt} = E[R^{\iota}_{ijmt}] \tag{70}$$

$$= \int_0^{w_{ijmt}} (w_{ijmt}h_{ijmt} - wh_i(w, y_{imt})) \frac{1}{\mu_{ijmt}(w_{ijmt})} \frac{\partial \mu_{ijmt}(w)}{\partial w} dw \tag{71}$$

where $\mu_{ijmt}(w_{ijmt})$ is the conditional labor supply function. The term

$$f_{ijmt}(w) = \frac{1}{\mu_{ijmt}(w_{ijmt})} \frac{\partial \mu_{ijmt}(w)}{\partial w} \tag{72}$$

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

Before solving the integral numerically, we note that

$$\frac{\partial \mu_{ijmt}(w)}{\partial w} = B_{ijmt}(w) C_{ijmt}(w) \frac{A_{imt}(w) - C_{ijmt}(w)}{A^2_{ijmt}(w)} \mu_{imt} \tag{73}$$

where

$$A_{ijmt}(w) = \exp\left(\frac{u_c(y_{imt})}{\sigma_\theta}\right) + \exp\left(\frac{u_c(wh_i(w, y_{imt}) + y_{imt}) - u^i_h(h_i(w, y_{imt})) + b_{ijt}}{\sigma_\theta}\right) + \tag{74}$$

$$+ \sum_{j' \neq j} \exp\left(\frac{u_c(w_{ij'mt}h_i(w_{ij'mt}) + y_{imt}) - u^i_h(h_i(w_{ij'mt})) + b_{ij'mt}}{\sigma_\theta}\right) \tag{75}$$

$$B_{ijmt}(w) = \frac{1}{\sigma_\theta}\left[(wh_i(w, y_{imt}) + y_{imt})^{-\sigma} - h_i(w, y_{imt})^{-\gamma} \frac{\partial h_i(w, y_{imt})}{\partial w}\right] \tag{76}$$

$$C_{ijmt}(w) = \exp\left(\frac{u_c(wh_i(w, y_{imt}) + y_{imt}) - u^i_h(h_i(w, y_{imt})) + b_{ijt}}{\sigma_\theta}\right) \tag{77}$$

The function $h_i(w, y)$ can be solved numerically and the derivative $\frac{\partial h_i(w,y)}{\partial w}$ can be computed using the envelope theorem on the first order necessary conditions for hours. Dropping the subscripts for clarity, we obtain

$$
\begin{aligned}
&(wh+y)^{-\sigma} w = \psi h^{-\gamma} \qquad (78)\\
&\left[(wh+y)^{-\sigma} - \sigma(wh+y)^{-\sigma-1}wh\right] dw + \left[-\sigma(wh+y)^{-\sigma-1}w^2\right] dh = -\gamma\psi h^{-\gamma-1}dh\\
&\frac{\partial h}{\partial w} = \frac{(wh+y)^{-\sigma} - \sigma(wh+y)^{-\sigma-1}wh}{\sigma(wh+y)^{-\sigma-1}w^2 - \gamma\psi h^{-\gamma-1}}
\end{aligned}
$$

In the numerical implementation, we approximate the integral over the $[0, w_{ijmt}]$ support partitioned into 999 equal intervals. To approximate the function $h_i(w, y_{imt})$ we solve the first order condition of hours worked over 500 equally spaced grid points of wages; then, we use linear interpolation to compute the function for off-grid wage values.

Compensating Differentials. Consider a worker ι who is marginal in the current occupation match j and whose next best match is with occupation j'. If a worker is marginal, i.e. indifferent between the first choice and the second choice, then $\tilde{R}^{\iota}_{ijj'mt} = 0$ so that equation (8) becomes

$$
\begin{aligned}
\tilde{U}_i(w_{ijmt} - \tilde{R}^{\iota}_{ijj'mt}, y_{imt}) + b_{ijt} + \theta^{\iota}_j &= \tilde{U}_i(w_{ij'mt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'}\\
\Rightarrow b_{ijt} + \theta^{\iota}_j - b_{ij't} - \theta^{\iota}_{j'} &= \tilde{U}_i(w_{ij'mt}, y_{imt}) - \tilde{U}_i(w_{ijmt}, y_{imt})
\end{aligned}
\qquad (79)
$$

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

$$
\begin{aligned}
CD^{\iota}_{ijj'mt} &= \tilde{U}_i(w_{ijmt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'} - \tilde{U}_i(w_{ijmt}, y_{imt}) - b_{ijt} - \theta^{\iota}_j\\
&= b_{ij't} + \theta^{\iota}_{j'} - b_{ijt} - \theta^{\iota}_j
\end{aligned}
\qquad (80)
$$

Substituting eq. (79) into (80), we have that

$$
CD^{\iota}_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) - \tilde{U}_i(w_{ij'mt}, y_{imt}) = CD_{ijj'mt} \qquad (81)
$$

Finally, we define the dollar value of the compensating differential as

$$
u_c(w_{ijmt}h_{ijmt} + y_{imt} - CD^{\$}_{ijj'mt}) - u_h(h_{ijmt}) = u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}) \qquad (82)
$$

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

$$
CD^{\$}_{ijj'mt} = w_{ijmt}h_{ijmt} + y_{imt} - u_c^{-1}\left(u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}) + u_h(h_{ijmt})\right). \qquad (83)
$$

K Alternative measures of compensating differentials

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

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

We compute this covariance separately for each year and demographic group and we show the results in Panel A of Table 25. We find a positive and increasing covariance for college graduates, with the growth being particularly pronounced among men. For non-college workers we find negative covariations and a trend towards lower covariances among men. The positive and increasing covariances for college men are in line with the findings of Lehmann (2022), which restricts attention to male workers who experience job-to-job transitions. Transitions that bypass unemployment tend to over-sample educated men, which is consistent with our findings.

To extend our analysis, in Panel B of Table 25 we report similar measures of covariation after including the average idiosyncratic workers' valuations within each cell. The average idiosyncratic job values $\bar{\theta}_{ijmt}$ are obtained by simulating the model. Specifically, we compute the following covariances

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

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

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

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

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

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

Table 25: Covariances between observable and latent components of employment surplus, by year and demographic group. All covariances are normalized by the variance of idiosyncratic values, σ_θ^2.

L Occupational mobility and compensating differentials

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

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

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

$$\Xi_{ijj'mt} = \frac{\xi_{imt,j\to j'} + \xi_{imt,j'\to j}}{\mu_{ijmt} + \mu_{ij'mt}} \tag{84}$$

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

$$\Delta \log(CD_{ijj'mt}) = \beta_0 + \beta_1 \Delta \log(\Xi_{ijj'mt}) + \epsilon_{ijj'mt} \tag{85}$$

If more intense job flows facilitate the emergence of systematic compensating differentials, the estimated value of β_1 should be positive. Table 26 illustrates our findings. Panel A (top panel) reports estimates including all the years in the sample. Panel B (bottom panel) reports results for the three decades after 2000.

Column (1) shows result for the full sample where all job pairs are considered, including rarely observed job flows. Column (2) includes only (j, j') occupation pairs in which both occupations belong to the same occupation category. These are the occupation pairs where most of the worker flows occur. The β_1 coefficient are precisely estimated in the sub-sample featuring common transitions, which suggests that considering all transitions adds more noise than signal. Estimated elasticities are larger for the later years 2000-2018 (as opposed to the full sample 1980-2018); on average, an increment of 1% in the gross flow of workers within an occupation pair is associated with an increase of 8.7% (19.7% after the year 2000) in the compensating differential between those occupations. Columns (3) to (6) lend similar evidence but they consider each broad occupation category separately. The stronger significance for non-routine cognitive (NRC) and routine-manual (RM) jobs is likely due to the much larger sample sizes in those occupation categories. Columns (7) and (8) split the sample of Column (2) by gender and show that the effects are larger and more precisely identified for men. This latter observation is consistent with the finding that compensating differentials tend to be lower among women (see table 5).

M Occupation-specific wage dispersion and rents

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

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

t statistics in parentheses

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

Table 26: Projection of compensating differentials on job flows: Estimates of Equation (85). The unit of observation is the occupation pair. Column (1) refers to a sample where all job pairs are considered, including rarely observed job flows. Column (2) includes only (j, j') occupation pairs in which both occupations belong to the same broad occupation category. These are the occupation pairs where most of the worker flows occur. Columns (3) to (6) consider each broad occupation category separately. Columns (7) and (8) split the sample in column (2) by gender.

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

Table 27 reports the main findings of this exercise. For every dependent variable we first run a regression with no controls; then we run a regression including demographic controls (education, age, and gender fixed effects), occupation fixed effects, and year fixed effects. The results indicate that higher wage risk is associated with higher returns. Estimates in Columns 1 and 2 are semi-elasticities. Column 2, in particular, shows that a 10-dollar increase in the standard deviation of wages is associated with a 4.5% increase in rents. Moreover, Column 4 shows that the same increase in risk is associated with an increase of about 0.3 standard deviations in total match surplus. Comparing this estimate to those in Columns 6 and 8 suggests that both the pecuniary and latent components of surplus contribute to the positive risk-return relationship. In addition, they highlight that latent values are proportionally larger, as a share of total surplus, in occupations characterized by higher wage risk.

N Robustness: market variation in latent returns

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

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

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

Table 28 shows estimates of the market-occupation component b_{jm}. Identification requires that all values must be estimated relative to a reference region-occupation. The table shows that many coefficients are statistically significant. However, their values are not economically significant as the magnitudes of the b_{jm} terms are much smaller than the b_{ijt} components. Through a variance decomposition, we show that the b_{jm} contribution is less than one percent of the total variation across the overall latent returns b_{ijmt}. We have verified that such magnitudes are not sufficient to affect the subsequent estimation and results.

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

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

Table 27: Projection of rents, surplus, and components of surplus on measures of wage risk (standard deviations of wages). For each dependent variables we report the simple projection and a projection with controls for demographics, occupation, and time. Columns (1) and (2) report the results for log-rents. The coefficients can be interpreted as semi-elasticities. Columns (3) and (4) show the results for total surplus. The dependent variable is standardized. Columns (5) and (6) show the results for the pecuniary component of surplus. To ensure comparability with the coefficients of the previous two columns, the dependent variable has been normalized by the standard deviation of total surplus. The same normalization is applied to the latent value of surplus in columns (7) and (8).

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

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

Table 28: Estimates of the market and occupation specific component of non-pecuniary returns.

O Additional tables

Average Rents (year 2000 $)

Year	Non-Routine Cognitive	Routine Cognitive	Non-Routine Manual	Routine Manual
1980	18,718	12,131	9,149	14,315
1990	19,414	12,803	9,199	13,248
2000	22,002	13,836	9,820	13,162
2010	21,615	12,655	8,401	11,448
2018	22,620	13,167	8,839	11,742

Table 29: Estimated average rents by year and occupation type.

Average Compensating Differentials (year 2000 $)

Year	Non-Routine Cognitive	Routine Cognitive	Non-Routine Manual	Routine Manual
1980	8,047	4,130	7,969	4,121
1990	8,945	5,111	8,885	5,330
2000	12,444	6,107	9,391	6,158
2010	10,922	6,228	9,495	6,106
2018	11,220	5,962	9,002	6,035

Table 30: Average absolute compensating differentials by year and occupation type.

Rents: 2018 vs 1980, by occupation category.

	Cognitive		Manual	
	Non-Routine	Routine	Non-Routine	Routine
Baseline				
1980	18,718	12,131	9,149	14,315
2018	22,620	13,167	8,839	11,742
Ratio	1.21	1.09	0.97	0.82
Latent values at 1980 level				
Counterfactual ratio	1.24	1.08	1.31	0.75
Technology at 1980 level				
Counterfactual ratio	0.92	1.12	0.84	1.18

Table 31: Actual and counterfactual changes in rents between 1980-2018. Values are ratios of average rents in 2018 to average rents in 1980.