The Changing Value of Employment*

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Abstract

Are earnings informative about the returns from work? We estimate the value of worker-occupation matches in an equilibrium model that distinguishes between wages and latent returns and derive a measure of rents that has three properties: (i) it reflects wages and unobserved match values; (ii) it delivers a monetary metric for compensating differentials; (iii) it illustrates how the marginal workers within a match affect the rents of others. We show that earnings closely track rents between 1980 and 2018. The results highlight a dichotomy: while the existence of rents is due to latent values, their evolution is driven by technology.

JEL Codes: D5, E2, J2, J3, J6.

Keywords: employment, equilibrium, heterogeneity, inequality, occupations, rents, compensating differentials, wages, technological change.

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1 Introduction

What constitutes a favorable labor market outcome for a group of workers? The early empirical literature (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 earnings of workers grouped by education, occupation, and gender. This is reasonable as earnings are a readily available metric. There is, however, a growing interest in other factors that affect the value that workers derive from employment. Empirical studies indicate that tastes for non-wage rewards vary systematically with gender, age, and education, and that employment conditions contribute to job choice, employee retention, and overall compensation (Maestas et al., 2018; Dube et al., 2022; Morchio and Moser, 2024). For example, surveys suggest that employees value the option to work from home two to three days per week at 5 percent of pay, on average, with higher valuations for women, people with children, and those with longer commutes (Aksoy et al., 2022). Direct measures of job injuries have been used to show how earnings inequality can understate the inequality in the returns from employment in the U.S. labor market (Hamermesh, 1999). More generally, the availability of welfare-relevant job features, such as flexible schedules or paid sick-leave, have significant effects on the value of employment and reinforce labor market inequality (Adams-Prassl et al., 2023a,b; Lehmann, 2022).

The importance of job amenities is reflected in employment patterns. Taber and Vejlin (2020) find that about $\frac{1}{3}$ of observed employment choices would be different if workers cared only about pecuniary aspects. Lamadon et al. (2022) estimate that workers would pay 1/10 of their wages to remain with their current employer, while Lamadon et al. (2024) estimate that about 1/5 of job-to-job moves can be attributed to preference heterogeneity. Moreover, there is evidence that changes in worker preferences and in the availability of perks across jobs shape the dynamics of labor market aggregates and earnings (Bagga et al., 2023).

A recurring question is whether the evolution of wages across jobs provides a reliable measure of changes in the returns from employment. The challenge is that observed wages may reflect changes in total return or compensation for shifts in latent job values (i.e. compensating differentials).

What do we overlook by focusing solely on wage inequality or the evolution of wages? Do new insights emerge when we pose questions about the evolution of rents? We examine these questions by comparing wage dynamics and worker rents in an equilibrium model of the labor market. The model delivers a monetary measure of employment rents, defined as the willingness of inframarginal workers to pay in order to stay in their current occupation. From the definition of rents we also derive a monetary measure of compensating differentials, which are defined as the difference between the returns that the marginal workers get in their current match and what they would get in their second best occupation if paid at the same rate (Lamadon et al., 2022).

To characterize the relationship between wage dynamics and rents, we proceed in two steps. First, we show that earnings deliver an accurate portrayal of changes in rents when certain conditions on the labor supply elasticities are met. Second, we estimate the model and assess whether these conditions hold empirically in U.S. data between 1980 and 2018. Our findings suggest that the evolution of earnings provides a reliable description of long-term changes in the rents of different workers.

We carry out the analysis in a setting with occupation choices and technological change, and adopt a revealed-preferences approach to identify the components that contribute to the value of an employment match. We focus on latent occupational amenities rather than amenities that vary at the firm level. Therefore, our emphasis is on non-wage occupation differences that are valued by workers; these might reflect aspects like health hazards, flexible schedules, the presence of night shifts, status and other characteristics that vary across occupations.

The model allows for imperfect substitution in production between inputs corresponding to worker-occupation matches, and distinguishes between wage and latent match value. The latent component consists of an idiosyncratic worker-specific element that is not observed by employers, and a common group-specific component that employers (but not econometricians) can observe. We define the common component within narrow demographic groups. Estimates of worker-occupation match values reflect measurable earnings and hours worked alongside latent values.[1] Latent values summarize the preferences of workers for occupation characteristics and delayed pecuniary returns (wage growth or career opportunities).[2] Over time the latent value of a worker-occupation match may vary because of changes in either the occupation characteristics or their value to workers (see Bagga et al., 2023). We do not take a stand about whether the evolution of latent values is driven by occupation characteristics or their value to workers. However, we do show that our estimates correlate with occupation characteristics.

Because employers cannot make wage offers contingent on the unobservable idiosyncratic latent values, employees can be inframarginal in their current employment match. This information asymmetry implies that the workers' overall return can exceed their outside option so that some workers earn discrete rents from ongoing employment. In equilibrium,

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

[2] In this respect, latent values account for future income and, therefore, influence job choices (see Lentz et al., 2023).

rent values depend on the attributes of marginal workers, who are indifferent between their match and the outside option. Marginal workers determine the compensating differential in their group (that is, in their worker-occupation match) and pinpoint the wage of all workers in the same match, including the inframarginal ones.

In the empirical section we map compensating differentials and rents into monetary measures that characterize the welfare outcomes of different groups of workers. The monetary value of rents is a gauge of the workers' willingness to pay in order to keep their occupation. This measure accounts for latent values that cannot be otherwise compared across demographic groups and occupations.

The theoretical analysis in Section 3 delivers several results about the measurement of rents and compensating differentials. Two of them are especially intuitive and useful for the measurement of employment values: (i) wage changes track total returns if their dynamics are driven by technology; however, wage changes can be misleading if driven by latent values. The problem with using earnings to gauge welfare arises from the fact that, after observing a wage change, one cannot immediately distinguish whether it is compensating workers for a change in latent returns with no effect on total returns. (ii) The severity of the disconnect between changes in wages and rents depends on the magnitude of labor supply responses to technological shocks and match values. Specifically, if the elasticity of labor supply to technology is smaller than the elasticity to latent values, wage dynamics are generally more informative about rents and welfare.

The empirical analysis accommodates diverse sources of heterogeneity (for example, Wiswall and Zafar, 2018 show that women value work schedules and job stability more than men; Le Barbanchon et al., 2021 show that men and women value commuting costs differently). Estimation relies on data on worker-occupation pairs, including those observed infrequently: that is, we draw inference from the relative frequency of matches as much as from pecuniary returns and hours worked. An advantage of this approach is that we can estimate the model from repeated cross-sections of earnings, hours worked and employment headcounts, which are fairly accessible to most researchers.

Our empirical findings can be summarized as follows. First, workers derive different returns from similar jobs; moreover, latent components are more dispersed than observable ones. Between 1980 and 2018, the average rent increased for college graduates and declined for lower education workers.

Second, labor supply responds differently to each distinct match value component. The labor supply is more elastic with respect to latent match values than to wage changes (see Appendix B). These elasticities influence the evolution of rents and wages by determining the characteristics of the marginal workers.

Third and last, despite the heterogeneity in latent match values, wage changes provide an accurate description of changes in occupational rents between 1980 and 2018. Equilibrium adjustments and differences in the elasticities of labor supply to different components of the match value are important for this finding. A positive productivity shock at the occupation-worker level induces higher labor demand, which boosts compensating differentials. However, following the initial impulse, a weak labor supply response induces little change in the composition of the 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 benefit from higher wages so that the average rent grows.

By contrast, changes in the common latent return of a worker-occupation match elicit strong employment responses. Therefore, the initial increase in the latent match value is offset by changes in the marginal worker characteristics due to a large inflow of new entrants who have lower idiosyncratic values and induce lower wages. Therefore, after the equilibrium adjustments, there is little or no growth in the average rent within the worker-occupation match.

These findings point to a dichotomy. One contribution of our work is to highlight that, while the existence of rents originates from latent values, the evolution of rents depends on the evolution of technology, productivity and wages. The theoretical analysis in Section 3 accounts for this apparent contradiction and illustrates how it is explained by the labor supply elasticities to different match value components. The intuition is that, after equilibrium adjustments, the accrual of positive productivity shocks generates higher returns for most workers within a match (incumbents and newcomers). Instead, higher latent values are offset by larger workers' inflows and do not result in higher rents on average. The methodological contribution is to show how repeated cross-sections of employment and wage data convey information about the total returns that different workers enjoy in the labor market.

A caveat is in order: our analysis is not an attempt to estimate total welfare inequality; rather, we highlight that, over much of our sample period, wage gaps across-occupations have not simply compensated workers for changes in amenities but have provided a reliable measure of the changing values of different worker-occupation matches.

In the next two sections we overview the model and present analytical derivations of rents and compensating differentials. The analysis emphasizes how rents vary with the characteristics of marginal workers. After estimating the model (Section 4), we use it to explore the forces that shape the evolution of earnings, employment and rents between 1980 and 2018 (Section 5).

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. In section 4, we estimate the model for different decades from repeated cross-sectional data. The index t is used below to indicate which variables and parameters are allowed to change over time.

Markets. There is a finite number $M > 1$ of geographically segmented labor markets, indexed by m. Each (m, t) pair identifies 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 static (period t) problem of a worker of type i in two steps. First, conditional on matching with occupation j, the systematic utility of the worker, net of the idiosyncratic value, 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 $u_c\left(\cdot\right)$ is consumption utility and $u_h^i\left(\cdot\right)$ is the disutility from work that can vary with demographic types i. The 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 b_{ijt} varies with occupation, demographic group, and time.[3]

With no loss of generality, 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 is necessary because b_{i0t} is not separately identified from all other b_{ijt}. Given the normalization of b_{i0t} and additive separability, 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. This accommodates changes that occur along the participation margin (Cortes et al., 2017).

Workers in occupation j receive an additional return from the idiosyncratic unobserved component θ_j^ι, which captures the individual-specific value of an occupation match. 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 worker's problem is the occupation choice. Given a set of idiosyncratic preference shocks $\{\theta_j^\iota\}_{j=1}^J$, the worker ι solves

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

As our focus is on the estimation of average group-specific rents, we do not examine residual wage variation within smaller sets of workers with similar age, gender and education. Occupation sorting within a group depends on idiosyncratic latent values so that two workers of comparable productivity (within a narrowly defined demographic group) have similar wages in similar jobs. This would, for example, occur if the distribution of (residual) individual productivity within a group is i.i.d. but firms cannot observe this productivity, so that workers within a (i, j, m, t) cell are paid the same.

As in Lamadon et al. (2022), selection depends on latent factors that reflect amenities or delayed pecuniary compensation, which is consistent with the view that employers do not fully observe the idiosyncratic values of individuals and cannot price discriminate with respect to workers' reservation values. As a result, the equilibrium allocation of workers to firms is associated with rents for inframarginal workers.

[3]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 (Online Appendix L).

It is worth emphasizing that modelling rich patterns of heterogeneous productivity within group would add significant complexity but little further insights because proportional shifts in the wages of the first and second best options offset each other and have negligible influence on group-level rents and compensating differentials, as we discuss in Section 3 below.

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. Each intermediate is produced by a different firm, indexed by v. Intermediate good producers employ one occupation j and intermediate goods are the output of an individual occupation. Each intermediate firm produces a differentiated good and has market power in the intermediate good's market. Labor markets are competitive.

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 occupation input j. In Online Appendix F we generalize the model to a setting where intermediate producers employ capital and labor.[4]

Final good production. The final good producer solves:

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

where λ_{jmtv} denotes the demand for each intermediate good. The final good price P_{mt} in market (m, t) is a function of intermediate prices p_{jmtv},

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

[4]The empirical implications are unchanged in the model with capital.

Optimality 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 productivity drawn from an occupation-specific distribution ($z_{jtv} \sim F_{jt}(v)$). Optimality implies that profits are,

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

The aggregate production function (derived in Online Appendix E) is:

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

where $\alpha_{jt} = \frac{\tilde{\alpha}_{jt}}{\sum_{j'} \tilde{\alpha}_{j't}}$ and $A_t = \left(\sum_{j'} \tilde{\alpha}_{j't}\right)^{\frac{1}{\rho}}$ with $\tilde{\alpha}_{jt} = \left(\int_{v \in V_{jt}} z_{jmtv}^{\frac{\rho}{1-\rho}} dv\right)^{1-\rho}$. In the appendix we show that the wage function for match (i, j) and 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, workers solve the problems in equations (1) and (2);
2. the final good producer and 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 $L_{ijmt} = \int_{v \in V_{jt}} L_{ijmtv} dv$.

3 Rents and Compensating Differentials

Each (i, j) match is a bundle of observable and latent returns, which cannot be separately traded in the labor market. Workers are inframarginal in their employment choice if the current match value is larger than the outside option.

3.1 Measuring rents

Consider a worker ι in demographic group i (that is, $\iota \in i$). Let j be the current occupation and j' the second best option. The indirect utility from consumption and hours worked is $\tilde{U}_i(w, y) = u_c(wh_i(w, y) + y) - u_h^i(h_i(w, y))$, where $h_i(w, y)$ is the intensive margin labor supply function. We define the rent $\tilde{R}^{\iota}_{ijj'mt}$ as the wage change that makes the worker indifferent between current match and outside option. The $\tilde{R}^{\iota}_{ijj'mt}$ is such that:

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

We use the value of $\tilde{R}^{\iota}_{ijj'mt}$ to define a rent measure based on earnings.

Definition 1 *Let the labor supply in match (i, j) and market (m, t) be $h_i(w_{ijmt}, y_{imt})$. Then, the rent $\tilde{R}^{\iota}_{ijj'mt}$ of a worker ι who belongs to demographic group i is the difference between realized earnings in job j and counterfactual earnings if the wage is reduced by $\tilde{R}^{\iota}_{ijj'mt}$. That is, the monetary rent $R^{\iota}_{ijj'mt}$ is such that:*

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

The measure $R^{\iota}_{ijj'mt}$ reflects both wages and latent values. If we restrict wages to be non-negative, the upper bound of rent $R^{\iota}_{ijj'mt}$ is $w_{ijmt} \times h_i(w_{ijmt}, y_{imt})$ so that rents cannot exceed the monetary return of the current job. The employment rent is the share of earnings above and beyond what makes the worker indifferent between current job and outside option.

3.2 Marginal workers and compensating differentials

Holding constant market m and time t, the marginal worker in match (i, j) has zero rent but sets the wage and the compensating differential in match (i, j) and, therefore, determines the rents of inframarginal workers.

Denoting the marginal worker in match (i, j) as $\bar{\iota}$, the compensating differential between current match (i, j) and outside option (i, j') is the difference between the utility that the marginal worker enjoys in j' if paid the same wage as the current match, and the utility that the worker gets from the current match j (Lamadon et al., 2022).[5] In utility units, the compensating differential between (i, j) and (i, j') in market (m, t) is:

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

The value of $CD^{\bar{\iota}}_{ijj'mt}$ can be estimated using the average earnings and hours worked in cells (i, j, m, t) and (i, j', m, t), as we show in Online Appendix I. This implies that we can ignore the superscript $\bar{\iota}$ and write $CD^{\bar{\iota}}_{ijj'mt} = CD_{ijj'mt}$. The intuition behind this result is that the marginal worker $\bar{\iota}$ is the price setter and their idiosyncratic preferences are already reflected in the equilibrium wages.

In Online Appendix I we prove that the compensating differential between matches (i, j) and (i, j') is a function of the latent values in matches (i, j) and (i, j'). This result is summarized in the following proposition.

Proposition 1 *The compensating differential $CD_{ijj'mt}$ between matches (i, j) and (i, j') is:*

$$CD_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) - \tilde{U}_i(w_{ij'mt}, y_{imt}) = -\underbrace{(b_{ijt} - b_{ij't})}_{\text{(a) systematic gap}} - \underbrace{(\theta^{\bar{\iota}}_{j} - \theta^{\bar{\iota}}_{j'})}_{\text{(b) idiosyncratic gap}}$$

The $CD_{ijj'mt}$ reflects: (a) the systematic common values that affect all agents equally $(b_{ijt} - b_{ij't})$ and (b) the idiosyncratic values of the marginal worker $\bar{\iota}$.

This result illustrates that changes in the idiosyncratic gap $(\theta^{\bar{\iota}}_{j} - \theta^{\bar{\iota}}_{j'})$ influence the CD's response to an initial shock. However, the CD's response depends on the type of shock (whether it is a shock to match productivity or to latent values). In particular, the magnitude of changes in the idiosyncratic gap depends on the labor supply elasticity to, respectively, latent factors and productivity. In the empirical analysis we estimate these elasticities and we show that the labor supply response to latent values is twice as large as the response to productivity shocks. This finding implies that changes in compensating differentials are mostly the by-product of technological progress.

3.3 The link between rents and compensating differentials

The magnitude of rents and compensating differentials is tightly linked to the way latent values vary across matches. Using the indifference condition in Proposition 1 and equation (8), it is possible to show that one of three possible equilibria will prevail:

[5] Empirical definitions of compensating differentials often rely on covariances of wage and non-wage returns (see Lehmann, 2022). In Online Appendix J we examine how these covariances relate to our estimates.

(a) If there is no cross-sectional variation in latent values b_{ij} and θ^{ι}_j, compensating differentials and rents are zero (equilibrium with no latent returns, no compensating differentials, no rents).

(b) If the variation in latent values occurs only through the observable b_{ij} (but the unobserved idiosyncratic values θ^{ι}_j have a degenerate distribution), the compensating differentials are not zero. However, there are no rents in equilibrium and all workers are marginal in their occupation choice (equilibrium with observable latent returns, non-zero compensating differentials but no rents).

(c) If there is cross-sectional variation in both b_{ij} and θ^{ι}_j, the compensating differentials are not zero, there are positive rents in equilibrium and only a subset of workers is marginal in the occupation choice (equilibrium with asymmetric information, positive rents and inframarginal workers).

We consider the less restrictive case (c), where the equilibrium allows for a relationship between rents and compensating differentials. To see this relationship, we substitute the marginality condition of Proposition 1 into the (inframarginal) rent equation (8) and show that the rent $\tilde{R}^{\iota}_{ijj'}$ of an inframarginal worker, denoted as ι, depends on changes in the compensating differential that are dictated by the idiosyncratic latent values of the marginal worker $\bar{\iota}$ in match (i, j),:

$$\tilde{U}(w_{ijmt} - \tilde{R}^{\iota}_{ijj'}, y_{imt}) - \tilde{U}(w_{ijmt}, y_{imt}) = \underbrace{(\theta^{\bar{\iota}}_j - \theta^{\bar{\iota}}_{j'})}_{\text{marginal worker}} - \underbrace{(\theta^{\iota}_j - \theta^{\iota}_{j'})}_{\text{inframarginal worker}} \leq 0. \tag{10}$$

Compensating differentials and labor supply. When the difference on the right hand side of (10) falls in absolute value, the rent $\tilde{R}^{\iota}_{ijj'}$ must decrease. If the marginal worker's idiosyncratic preference for job j becomes larger, the wage will drop for all workers and so will the rents of inframarginal workers. Equation (10) also highlights that, in equilibrium, the rent of the inframarginal worker depends on the curvature of the utility function $\tilde{U}(\cdot, \cdot)$ with respect to wages. These influences are summarized in the following proposition.

Proposition 2 *If we approximate the left-hand side of* (10) *around $R = 0$, the rent of the inframarginal worker ι is*

$$\tilde{R}^{\iota}_{ijj'} \approx -\frac{1}{\tilde{U}'_i(w_{ijmt}, y_{imt})} \left[\underbrace{(\theta^{\bar{\iota}}_j - \theta^{\bar{\iota}}_{j'})}_{\textit{marginal worker}} - \underbrace{(\theta^{\iota}_j - \theta^{\iota}_{j'})}_{\textit{inframarginal worker}} \right]$$

This results states that rents respond to changes in $(\theta_j^{\bar{\iota}} - \theta_{j'}^{\bar{\iota}})$ of the marginal worker, and the size of this response is a function of the curvature of the utility $\tilde{U}(\cdot, \cdot)$. This implies that the response of rents is stronger if the elasticity of labor supply to wages is smaller: to see this, note that $\tilde{U}_i'(w_{ijmt}, y_{imt})$ is proportional to the elasticity of labor supply (see Appendix B.2).

Proposition 1 and equation (10) jointly illustrate how rents and compensating differentials co-move following a shock that affects the characteristics of the marginal worker. To make sense of their comovement, suppose that the non-idiosyncratic match value b_{ij} increases but this has no effect on the characteristics of the marginal worker in equilibrium. The results above suggest that this change will reduce the compensating differential but will not affect rents. The explanation is intuitive: following the initial shock, the marginal worker stays the same only if wages drop sufficiently to fully offset the gain in latent values, so that the rents of incumbent workers are unaffected.

This hypothetical example highlights that the relationship between rents and compensating differentials crucially depends on how equilibrium wages respond to shocks. In turn, wage responses are a function of the prevailing elasticities of labor supply (with respect to changes in latent values or wages) and of the nature of the initial shock (whether a shock to technology or preferences). We rely on these insights in the empirical analysis.

3.4 The information content of wage changes: two results

What is the information content of wage changes? Are wage dynamics a reliable measure of changes in the overall return to employment? The previous analysis implies two empirically useful results, one positive and one negative.

The positive one is that, following a technology shock that affects the output-productivity of workers in match (i, j), wages deliver reliable information about rents.

Proposition 3 *Consider a change in the output-productivity of workers in match (i, j), which induces an initial and concordant response in wages (i.e., higher wages if productivity grows). Given a sufficiently low elasticity of labor supply to wages, average rents change in the same direction as wages. In contrast, if the elasticity of labor supply to wages is sufficiently high, neither average rents nor wages are materially affected in equilibrium. Proof in Appendix D.*

Proposition 3 posits that, after a productivity shock, wages convey valuable information about rents. The effect of the initial productivity shock on the average welfare within the match depends on the response of wages, which is concordant with rents (higher wages and higher rents).

Proposition 1 and equation (10) imply that the compensating differential in match (i, j) must also vary in the same direction as wages and rents; moreover, the response of compensating differentials is larger when the elasticity of labor supply to match productivity is lower. As we document below, this is exactly what we observe when productivity shocks accrue over our sample period: technological change affects rents, and its effects are visible in the evolution of compensating differentials.

The negative result is that, following a change in systematic latent values b_{ijt}, wages are uninformative in isolation.

Proposition 4 *Consider a change in the match value b_{ijt}. If the elasticity of labor supply to b_{ijt} is sufficiently low, most of the adjustment occurs through concordant changes in rents (i.e., higher rents if higher b_{ijt}) while wage responses are muted. In fact, for very low elasticities, rents reflect the full change in b_{ijt} while wages are unchanged. In contrast, if the elasticity of labor supply to b_{ijt} is sufficiently large, wages exhibit a discordant response to b_{ijt} (they change in the opposite direction) while the response of rents is muted. Proof in Appendix D.*

Proposition 4 emphasizes that, after a change in the latent value b_{ijt}, the evolution of wages in match (i, j) is not informative about rents and one should exercise caution. In addition, Proposition 4, reveals that, following a shock to latent values b_{ij}, compensating differentials will only change when rents do not (and viceversa).

Taken together the positive and the negative result, we conclude that: (i) changes in wage earnings are informative about rents if they are triggered by a technology shock; and (ii) if labor supply responds more elastically to latent values than to wages, then changes in compensating differentials are a useful complement to establish whether earnings are responding to initial shocks in latent value b_{ij} or, rather, in match (i, j) productivity.

In our empirical analysis, we verify that compensating differentials do in fact change significantly during periods of technological progress. Specifically, we estimate the magnitudes of labor supply elasticities and examine the evidence on the joint evolution of rents, earnings and compensating differentials between 1980 and 2018. Our findings suggest that, even with all the theoretical caveats, wage dynamics deliver a fairly accurate portrayal of rent changes over the past four decades. Estimates of compensating differentials indicate that the bulk of rents' and earnings' changes were the by-product of technological progress.

These findings highlight a dichotomy: while rents arise in equilibrium because of the presence of latent values, the evolution of rents is driven by changes in productivity and technology.

4 Identification and Estimation

We estimate model parameters from cross-sectional data on employment matches, labor supply and earnings. The estimation follows two steps: first, we recover the parameters dictating utility and labor supply through GMM; next, conditional on estimates from the first step, we estimate technology parameters (input shares, elasticity of substitution between inputs). Below, we describe the data, overview the identification of utility and production parameters, and discuss the estimation (details in Appendix A).

4.1 Data

We use decennial Census data from 1980, 1990, and 2000, and 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 25 to 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 worker types, indexed by $i \in I$. On the demand side, we consider a set of 13 occupations, in addition to the non-employment state. The occupations are indexed by $j \in J$ and are listed in Table 1 under four broad task clusters (see Acemoglu and Autor, 2011; Cortes and Gallipoli, 2018). We distinguish four geographical markets indexed by $m \in M$ corresponding to U.S. Census regions (Northwest, Midwest, South, and West) and create data cells corresponding to matches (i, j) in markets (m, t). Then, for each cell, we compute total employment, average hours worked, average wages, and average non-labor income. To account for differences in cost of living across regions we adjust the income measures by a local CPI index based on the cost of housing (Moretti, 2013). We measure total employment using population weights that count a worker as employed if they report working at least 15 hours per week. Non-labor income is the sum of incomes from businesses and farms.

4.2 Identification

Parameters are identified by variation in employment shares across occupations and by differences in labor supply and wages across workers. Details and proofs are in Appendix A.

Preferences. The employment shares $\frac{\mu_{ijmt}}{\mu_{imt}}$ are instrumental to linking rents to wages and latent returns. Using equation (3), we express match values relative to non-employment

Table 1: Occupation categories used for estimation.

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

($j = 0$) as,

$$\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right) = \frac{U_{ijt}(w_{ijmt}, y_{imt}) - U_{i0t}(0, y_{imt})}{\sigma_\theta}. \tag{11}$$

Next, we posit isoelastic utility for consumption and leisure:

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

Under these restrictions, the cross-sectional variation of employment, hours worked and wages identifies: (i) the latent match return b_{ijt}; and (ii) the scaling parameter σ_θ, which dictates the dispersion of idiosyncratic preferences.

Technology. The closed-form solution for wages in equation (7) implies

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

where $\widetilde{L}_{jmt} = \sum_{i'} \beta_{i'jt} L_{i'jmt}$ is the efficiency-weighted labor supply in occupation j and market (m, t). The β parameters (match-specific production shares) are identified up to a normalization by within-occupation wage ratios of the form $\frac{w_{ijmt}}{w_{1jmt}}$. Given estimates of $\hat{B}_{ijt} = \log\left(\frac{\hat{\beta}_{ijt}}{\hat{\beta}_{i1t}}\right)$, the between-occupation wage ratios identify the remaining technology parameters. More precisely, one can show that the following holds:

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho - 1)\log\left(\frac{\sum_{i'} \beta_{i'jt} L_{i'jmt}}{\sum_{i'} \beta_{i'1t} L_{i'1mt}}\right) \tag{12}$$

The equation above decomposes the relative wage (left hand side) into occupation specific fixed effect ($\frac{\alpha_{jt}}{\alpha_{1t}}$), match-specific effect ($\frac{\beta_{ijt}}{\beta_{i1t}}$), and a linear function of efficiency-weighted labor supply in the occupation. This relationship suggests a projection approach to estimate the α shares and the curvature parameter ρ. The empirical counterpart of (12) is,

$$W_{ijmt} = \tilde{\alpha}_{jt} + \varsigma \hat{B}_{ijt} + \phi \hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{13}$$

where $W_{ijmt} = \log\left(\frac{w_{ijmt}}{w_{i1mt}}\right)$ is computed from data, $\tilde{\alpha}_{jt} = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right)$ is an occupation fixed effect, $\phi = \rho - 1$, and $\hat{\Lambda}_{jmt} = \log\left(\frac{\sum_{i'} \hat{\beta}_{i'jt} L_{i'jmt}}{\sum_{i'} \hat{\beta}_{i'1t} L_{i'1mt}}\right)$ is computed using employment data and the estimated β_{ijt}. The projection coefficient for $\hat{B}_{ijt}$ should be $\varsigma = 1$, a restriction that we explicitly test and cannot reject.

Estimation of equation (13) requires that we account for the simultaneity bias due to the labor input. Below, we discuss the instrumental variables approach that we use.

4.3 Estimation: preference parameters

To recover the preference parameters, we develop a GMM estimator from the workers' optimality conditions with respect to the intensive and extensive margin of labor supply. From these estimates we recover the elasticities of labor supply across matches with respect to wages and to latent values. Establishing the magnitude of these elasticities is essential to characterize the empirical relationship between earnings and rents. We find that match-specific labour supply responds much more strongly to latent values than to wages; our estimates suggest that the latent values' elasticity is twice as strong as the wage elasticity. This is a positive finding since the results of Section 3 would imply that earnings must move in the same direction as rents. However, the intensity of the covariation remains an empirical question and must be examined through model simulations.

Hours worked, conditional on the match. From the worker's problem, optimal labor supply implies

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

We note that, if $\gamma \leq 0$, the disutility of work is a convex function and (14) has a unique solution. We do not restrict γ but we test and do not reject that its estimated value satisfies the condition for uniqueness.

Using (14), we express hours worked in match (i, j, m, t) as an implicit function of wages and non-labor income:

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

where $\boldsymbol{X}_{ijmt} = [w_{ijmt};\ y_{imt}]$ is data, $\tilde{\boldsymbol{\Omega}}_i = \{\sigma;\ \gamma;\ \psi_i\}$ is a set of parameters that must be estimated, and ϵ^1_{ijmt} is a mean-zero i.i.d. error. We employ two sets of moments in the GMM estimation of labor supply parameters:

$$\begin{aligned} E\left[\log(h_{ijmt}) - f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) |i\right] &= 0 \\ E\left[\left(\log(h_{ijmt}) - f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)\right) \boldsymbol{Z}^1_{ijmt}\right] &= 0 \end{aligned} \tag{15}$$

The second set of moments imposes orthogonality with respect to a set of instruments $\boldsymbol{Z}^1_{ijmt}$. This accounts for possible endogeneity biases. The logarithm of hours worked predicted by the model is $\log(\hat{h}_{ijmt}) = f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)$.

Extensive margin of labor supply across matches. Using (11), we write the (i,j,m,t) match value $g\left(\boldsymbol{X}_{ijmt};\boldsymbol{\Omega}_{ijt}\right)$ as

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

where $\boldsymbol{\Omega}_{ijt}=\tilde{\boldsymbol{\Omega}}_i\bigcup\{\sigma_\theta;\ b_{ijt}\}$. The empirical counterpart of (11) is then

$$\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right)=g\left(\boldsymbol{X}_{ijmt};\boldsymbol{\Omega}_{ijt}\right)+\epsilon^2_{ijmt},$$

where $\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right)$ is the relative employment share in match (i,j) and market (m,t), and ϵ^2_{ijmt} is mean-zero i.i.d. noise. To estimate the matrix $\boldsymbol{\Omega}_{ijt}$ of match-specific parameters, we use the following moment conditions:

$$\begin{aligned} E\left[\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right)-g\left(\boldsymbol{X}_{ijmt},\boldsymbol{\Omega}_{ijt}\right)|i,j,t\right]&=0 \\ E\left[\left(\log\left(\frac{\mu_{ijmt}}{\mu_{i0mt}}\right)-g\left(\boldsymbol{X}_{ijmt},\boldsymbol{\Omega}_{ijt}\right)\right)\boldsymbol{Z}^2_{ijmt}\right]&=0 \end{aligned} \tag{16}$$

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

4.4 The moments' matching problem

We denote the data matrix of wages and hours worked as $\boldsymbol{X}=\{\boldsymbol{X_{ijmt}}\}$ and calculate the average data values in each (i,j,m,t) cell from workers reporting at least 15 hours per week and positive earnings. The parameters' matrix $\boldsymbol{\Omega}=\{\boldsymbol{\Omega_{ijt}}\}_{\forall i,j,t}$ includes utility parameters and latent match value. The minimization problem is:

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

where $\boldsymbol{W}$ is a positive definite weighting matrix, and $\boldsymbol{Z}$ is a matrix of instruments.[6] The operator $\boldsymbol{M}$ generates the target moments in (15) and (16).

The minimization is computationally demanding as it requires solving for labor supply optimality conditions for all the (i,j) and (m,t) pairs. We use methods developed by Su and Judd (2012) to reformulate the problem so that first order conditions for the intensive

[6] To reduce small sample biases (see Altonji and Segal, 1996) we set W to the identity matrix.

margin of labor supply are treated as constraints. The parameter matrix in the Su-Judd problem, denoted as $\boldsymbol{\Omega}^+$, consists of the original matrix $\boldsymbol{\Omega}$ plus the set of model labor supplies $\{\hat{h}_{ijmt}\}_{\forall i,j,m,t}$. The problem becomes:

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

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

Including the optimality conditions for the intensive margin of labor supply as constraints, ensures that labor supply satisfies the first order conditions and the numerical approximation of the hours worked function, $\hat{h}_{ijmt} = f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right)$, holds. The approach does not require solving for hours worked in each iteration of the optimization and significantly reduces computation time. The matrix $\boldsymbol{Z}$ features instrumental variables to account for potential heterogeneity, and includes 10 and 20-year lagged wages. In Appendix C we report results from the GMM estimation.

4.5 Estimates of labor supply elasticities

The results in Section 3 highlight how the labor supply elasticities regulate the relationship between earnings and rents in equilibrium. In appendix B, we derive analytical expressions for these elasticities and use the estimated utility parameters, along with data, to derive some estimates. Below we summarize our estimates, which suggest that the elasticity to latent match values is twice as large as the elasticity to wages.

Elasticity of hours, conditional on a match. The uncompensated wage elasticity of labor supply conditional on match (i, j, m, t) is

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

We plot the distribution of $\hat{\varepsilon}^{int}_{ijmt}$ in the appendix Figure 4a. The average wage elasticity of hours in the cross-section of (i, j, m, t) cells is 0.15, which is within the range of existing estimates (see, for example, Blundell and MaCurdy, 1999; Chetty et al., 2011; Chetty, 2012; Keane and Rogerson, 2015; Attanasio et al., 2018)

The extensive margin of labor supply across matches: wage elasticity. The extensive margin elasticity across matches is 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,

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

We plot the distribution of $\hat{\varepsilon}^{ext}_{ijmt}$ in the appendix Figure 4b. We find that the average elasticity of labor supply across matches varies between 0.55 and 0.60, depending on the period considered. This elasticity captures the response of individuals moving to an occupation after a wage change, and includes both unemployed people and people working in other occupations.

The extensive margin of labor supply across matches: the elasticity to latent values. The extensive margin elasticity to changes in latent values b_{ijt} is the ratio of the percentage change in the number of workers in a particular occupation and the percentage change in the latent value of that occupation. That is,

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

The absolute value operator is needed because the b_{ijt} can be negative. In Appendix B we estimate these elasticities for different matches, periods and locations (Figure 4d). The average ε^{b}_{ijmt} is large; its value is between 1.33 and 1.57, depending on the year.

4.6 Estimation: technology parameters

We estimate the worker-occupation shares β_{ijt} using within-occupation wage ratios (see Appendix A). With these in hand, we recover estimates of the occupation weights α_{jt} and of the production curvature ρ as follows:

1. We note that $\hat{\rho} = \hat{\phi} + 1$ and recover $\hat{\phi}$ by estimating (13) in first differences.
2. We recover the $\tilde{\alpha}_{jt} = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right)$ in (13) by projecting the residuals $\tilde{W}_{ijmt} = W_{ijmt} - \hat{B}_{ijt} - \hat{\phi}\hat{\Lambda}_{jmt}$ on occupation-year fixed effects.
3. We impose the restriction $\sum_j \alpha_{jt} = 1$ for all t and obtain the value of each occupation weight α_{jt} in the production technology (6).

For estimates, see discussion in Appendix C.

Endogeneity of production inputs. To control for the endogeneity of the labor input log-ratios, $\Delta\hat{\Lambda}_{jmt}$, in the first-differenced specification of (13), we propose two different instrumental variables.

The first strategy leverages relative changes in the attractiveness of each occupation due to changes in the pecuniary returns of *other* occupations. Specifically, we compute the cross elasticities of labor supply (see Appendix B) and we 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 how the (i,j) employment share responds to wage changes in the (i,j') match. Using the cross-elasticities, we generate predicted changes in labor supply to occupation j from wage changes in other occupations. Denoting the employment shares observed in the preceding decade $(t-10)$ as $s_{ijmt-10}$, we compute the predicted shares of workers of demographic group i in occupation j as

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

The predicted labor supply to occupation j is $\hat{L}^h_{jmt} = \sum_i \hat{s}_{ijmt} \mu_{imt}$, where the superscript h denotes that the variable is a headcount. The predicted *relative* labor supply is $\hat{\Lambda}^h_{jmt} = \log\left(\frac{\hat{L}^h_{jmt}}{\hat{L}^h_{1mt}}\right)$ in period t. The instrument is,

$$\text{IV1}_{jmt} = \Delta \hat{\Lambda}^h_{jmt} = \hat{\Lambda}^h_{jmt} - \log\left(\frac{L^h_{jmt-10}}{L^h_{1mt-10}}\right), \tag{17}$$

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

The second strategy relies on shifts in latent returns that affect occupation-specific employment. That is, we develop instruments using changes in occupation shares due to variation in latent values b_{ijt}. The resulting instrument is valid under the theoretical restriction that latent values shift labor supply without affecting labor demand. Equation (11) 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 observable component of utility. Setting $\Delta \Pi_{ijmt} = 0$, the equation above delivers a counterfactual $\hat{\varrho}_{ijmt}$ that only varies with the latent values:

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

We estimate a set of counterfactual shares $\hat{s}_{ijmt} = \frac{\exp(\hat{\varrho}_{ijmt})}{1+\sum_{j'=1,\ldots,J} \exp\left(\hat{\varrho}_{ij'mt}\right)}$ and use them to

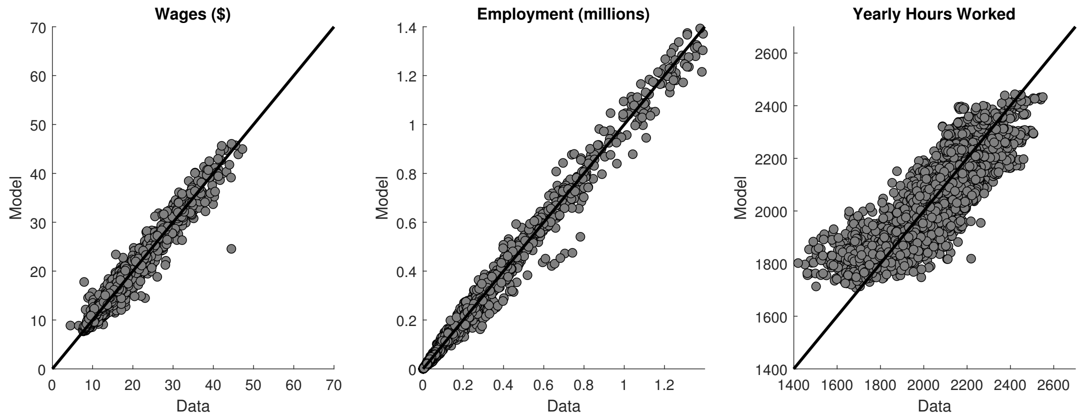

Figure 1: Goodness of fit. Left: model implied wages vs. data. Center: model implied employment vs. data. Right: model implied hours worked vs. data.

define predicted labor inputs $\hat{L}^h_{jmt} = \sum_i \hat{s}_{ijmt}\mu_{imt}$. Then, trough the same approach as for the instruments in equation (17), we employ these fitted values to construct a set of instruments (IV2_{jmt}). In Online Appendix G, we run robustness checks and implement a third alternative strategy that leverages aggregate demographic changes as exogenous shifters of labor supply. This delivers a Bartik (1991) instrument that does not depend on first step estimates. Results are qualitatively and quantitatively similar (see Table 9).

Substitution among production inputs. Table 2 shows estimates of the coefficients on $\Delta\hat{\Lambda}_{jmt}$ and $\Delta\hat{B}_{ijt}$ from the first-differenced specification of (13). Column (1) shows the OLS estimates of $\hat{\phi}$. Columns 2 and 3 report estimates after instrumenting $\Delta\hat{\Lambda}_{ijmt}$ with either of the two instrument sets. Estimates of ρ imply that the elasticity of substitution between worker-occupation inputs (that is, $\frac{1}{1-\rho}$) is between 1.7 and 1.9. Burstein et al. (2019) and Xiang and Yeaple (2025) estimate a similar parameter for the substitution of occupation inputs and their estimates are between 1.7 and 1.8.

In column 4, we combine all instruments and estimate an elasticity of substitution of 1.87. When using multiple instruments, we are able to 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 strategies, the estimated coefficient on $\Delta\hat{B}_{ijt}$ is not significantly different from one, which further validates the theoretical restrictions of the model.

4.7 Prices and quantities: comparing model and data

Figure 1 juxtaposes empirical observations of wages and employment in each worker-occupation cell (i, j) over their model counterparts, obtained by solving for the equilibrium in each market and year. Simulated prices and quantities match data reasonably well. The model can

	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 2: Estimation results for equation (13) in first-differences. OLS and IV estimates.

account for, respectively, 99%, 95%, and 72% of total variation in employment, wages, and hours worked. We also estimate a model version where the disutility of work depends on demographic characteristics and occupations (Online Appendix H). This specification accounts for a slightly larger share of variation in hours worked with no difference in other estimation results.

4.8 The fanning out of match-specific productivities: 1980-2018

The productivity of a type-i worker in occupation j is proportional to the production share $\alpha_{jt} \times \beta_{ijt}$. Figure 2 shows the evolution of these quantities (aggregated over i and m). In routine manual jobs, productivity declined steadily after 1980 and was about 25% lower in 2018 than in 1980. Other occupation categories diverged in the 1990s: non-routine cognitive jobs experienced a cumulative rise in their production share of about 70%; in contrast, non-routine manual and routine cognitive occupations had less vigorous growth, with cumulative changes between 40% and 20% over the sample period. The fanning out of productivity underpins changes in wages, rents and employment. In the Appendix Figure 5 we plot production shares by broad occupation category and show that the share of routine manual occupations dropped or stagnated for all gender and education groups.

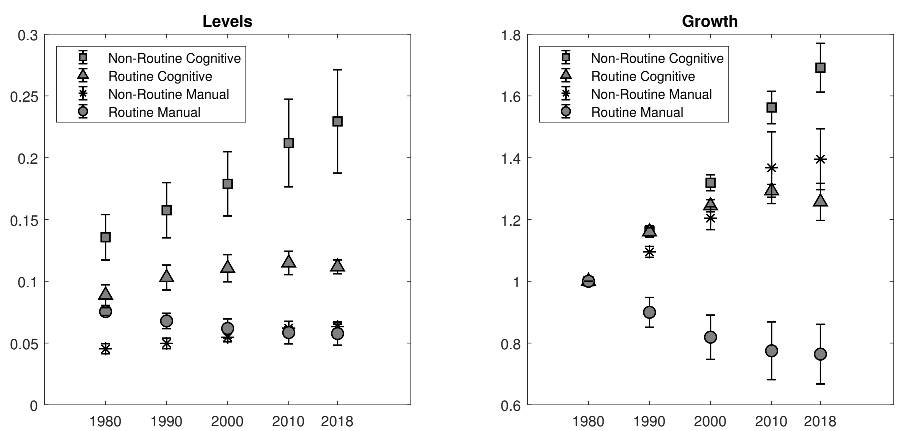

Figure 2: Production shares of four major occupation categories (based on estimates of $\alpha_{jt}\beta_{ijt}$). Left panel: levels. Right panel: growth relative to 1980 base year.

5 Estimates of rents and compensating differentials

Latent values and technology determine the distribution of workers across jobs. How are these forces reflected in workers' rents? How informative are earnings about the unobserved rents? To explore these questions, we bring together the analytical discussion of Section

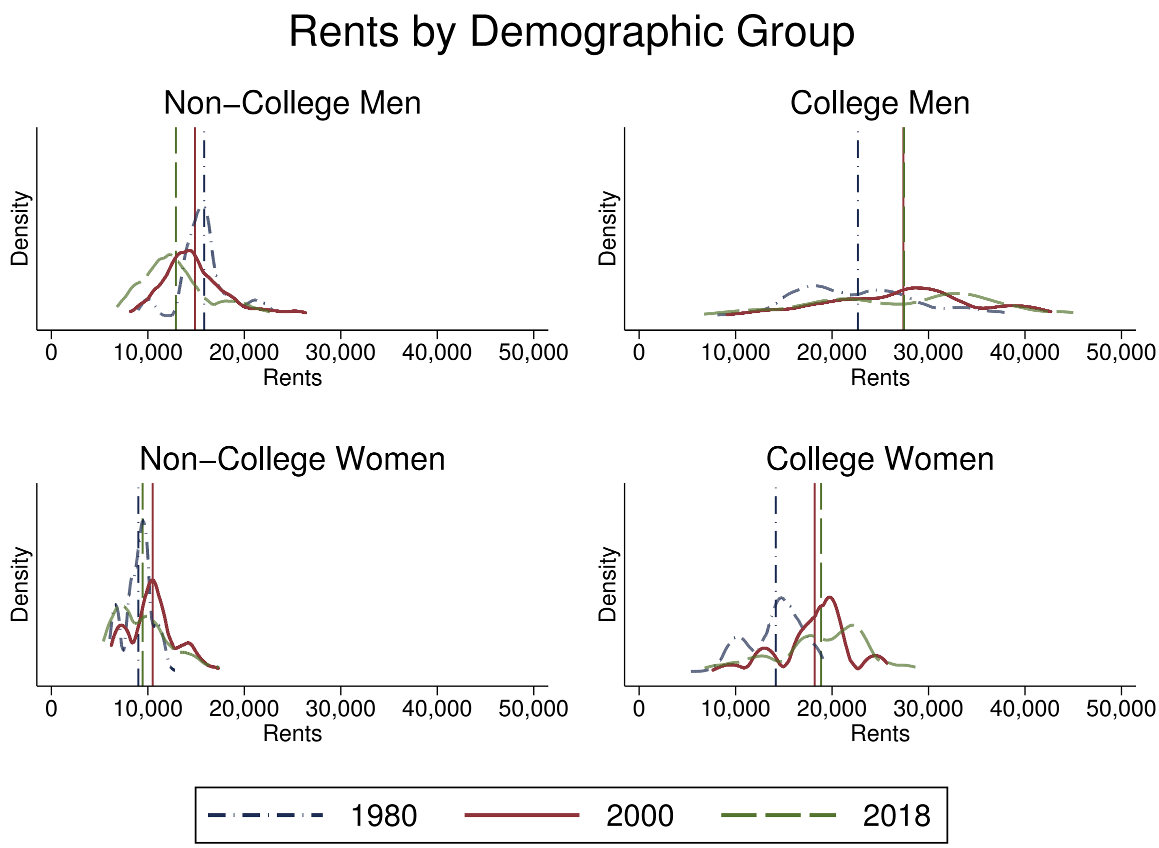

Figure 3: Distribution of job rents (employment-weighted) by year, gender and education. All values are in constant year 2000 dollars. Vertical lines show averages in different years.

3 and the model estimates of Section 4. First, we summarize the evolution of rents and earnings. Then, we draw attention to the role of labor supply and of marginal workers in the adjustment process following changes in technology or in latent values.

Estimates of rents: 1980-2018. Table 3 shows estimates of rents by year, gender and education (in constant year 2000 dollars). During this period the education gap expanded; Figure 3 illustrates the mounting disparities: as the rents of educated men shifted to the right, those of non-college men moved sharply to the left (Cortes et al., 2018). Rents have also become more dispersed within each demographic group (see Figure 3). This suggests a widening of the occupational divide between cognitive and manual jobs, as we document in Table 16 of Online Appendix M.

Rents vs earnings. A key finding of Section 3 is that earnings convey information about rents if the labor supply responses to latent values are more elastic than the labor

Average Rents (year 2000 $)

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

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

supply responses to productivity shocks. Our estimates indicate that the elasticity of labor supply with respect to match-specific productivity is between 0.5 and 0.6, which is about half as large as the elasticity to latent values (between 1.3 and 1.6). These estimates imply that rents and earnings' changes should track each other closely. In Table 4 we compare rents and earnings between 1980 and 2018. Their strong association confirms that earnings convey information about rents over the sample period.

To establish the relative importance of occupation and worker characteristics for rent variation, we run a variance decomposition and find that occupations account for the largest share in rents' variation (21%), followed by education (17%) and gender (14%). A similar decomposition for earnings attributes 21% of their variation to occupation, followed by education (19%) and gender (9%). This suggests that rents and earnings have been shaped by similar forces over the sample period.

Earnings growth vs rents growth: 1980-2018

	College		Non-College	
	Men	Women	Men	Women
Rents 2018 ÷ Rents 1980	1.21	1.33	0.82	1.05
Earnings 2018 ÷ Earnings 1980	1.23	1.37	0.80	1.06

Table 4: Growth of average rents vs average earnings, by worker group.

Estimates of compensating differentials: 1980-2018. In Section 3 we emphasize that compensating differentials can provide a useful complement to wage earnings: if the variation in compensating differentials are due to technology, then wage changes convey information about the direction and size of rents' changes.

Our estimates suggest that compensating differentials vary significantly across workers (see also Lamadon et al., 2024). In utility metric, we compute the compensating differential between each pair of occupations and for each demographic group using the result in Proposition 1 (see also derivations in Online Appendix I):

$$CD_{ijj'mt} = u_c(w_{ijmt}h_{ijmt} + y_{imt}) - u_h(h_{ijmt}) - (u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}))$$

Translated into a money metric, the compensating differential $CD^{\$}_{ijj'mt}$ is the income drop in the chosen occupation that would make the utility differential computed in the previous equation equal to zero, namely:

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

Table 5 reports the average absolute compensating differential by year and worker demographic group. These values are the population weighted averages of the monetary measure of CDs defined above. We find that CDs have grown in all groups but notably more among the college educated who experienced a 50% growth over the sample period, as opposed to the significantly lower growth among non-college. The bulk of the growth was concentrated between 1980 and 2000.

Average Compensating Differentials (year 2000 $)

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

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

Based on the results of Section 3, the only way to account for the concurrent growth of rents and compensating differentials is to attribute the evolution of labor market returns to technological change. In the next section we verify this conjecture and show that technology, rather than latent values, is the largest contributor to the evolution of rents after 1980.

5.1 Rents: technology or latent match values?

Higher compensating differentials mean that latent match values are traded at higher prices than before. Given our estimates of labor supply elasticities, we conjecture this phenomenon is mostly due to technological change. We can explicitly verify this conjecture through the counterfactual experiments summarized in Table 6. First, we compute 2018 rents holding

Rents 2018 ÷ Rents 1980	College		Non-College	
	Men	Women	Men	Women
(1) Baseline				
Estimated growth	1.21	1.33	0.82	1.05
(2) Hold latent values at 1980 levels				
Counterfactual growth	1.25	1.29	0.84	1.08
(3) Hold technology at 1980 levels				
Counterfactual growth	0.97	0.92	1.04	0.96

Table 6: Counterfactual vs baseline growth of average rents (2018-1980) by worker group.

latent values at their 1980 levels. Second, we compute 2018 rents holding technology parameters at their 1980 values. The table reports the counterfactual ratio of 2018 rents to 1980 rents, under each of the two scenarios. For comparison we also report the actual historical ratio.[7] We make two observations:

1. holding latent values fixed has modest effects on rent growth;

2. holding technology fixed reduces rent growth, making it negative for most groups.

The observations are consistent with our estimates of labor supply elasticities and confirm the tight connection between technology and rents. Interestingly, as shown in Tables 20 and 21 in Online Appendix M, the gains of college workers are concentrated in the first half of the period between 1980 and 2000. After 2000, we estimate almost no additional rent gains for college workers (Beaudry et al., 2016; Valletta, 2017). Moreover, between the years 2000 and 2018, we find evidence of rent losses among non-college workers, induced by drops in latent match values. We make similar observations after splitting the sample by occupation (Table 18, Online Appendix M).

Theory suggests that, following a technology shock, rents and compensating differential should both change. We verify this through a counterfactaul exercise: Table 19 in Online Appendix M shows that, holding latent values fixed at 1980 values, technological change does cause an increase in compensating differentials through its impact on the idiosyncratic preferences of the marginal worker. This change in marginal worker characteristics affects the rents of all inframarginal workers.

[7]The technology counterfactual delivers a lower bound of the impact of technology if technological change influences future income in unexpected ways, not captured in latent values.

6 Extensions and Robustness

In what follows we consider extensions and assess robustness to alternative assumptions. The first two extensions relate to model assumptions. First, we estimate a version of the 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 analysis examines some features of 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 workers for higher wage risk. Finally, we compute alternative measures of compensating differentials and verify how they relate to our estimates.

6.1 Latent values and location

Latent match values might vary systematically across locations. In Online Appendix L 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 term (like in the baseline model) and a term that can change across market-occupation pairs. The latter 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 14 in Online Appendix L 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}.

6.2 Capital inputs in intermediate production

In Online Appendix F we examine the robustness of results to the introduction of capital inputs in production. 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 (13), 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 (13) 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 $\frac{\rho-1}{1-\rho(1-\gamma)}$, where γ is the labor 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 (13), 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 2).

6.3 Latent heterogeneity and preferences for location

Jobs are unevenly distributed across locations and some occupations occur more frequently in urban areas. If urban settings offer different amenities, the latent value of a match may be related to its prevalence across different locations. 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 the frequency of occupations in different locations (urban vs rural). We find (see Online Appendix M.1) 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. On the other hand, estimates for women are significant and larger (see Table 15 of Online Appendix M.1). This suggests that location attributes may play a more pivotal role in the occupation choices of women. In all cases, the coefficients are positive as jobs in urban areas have higher latent returns.

6.4 Wage dispersion and rents

Does wage risk matter for rents? In Online Appendix K we explore how the dispersion of wages within each *ijmt*-cell is related to 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 the average rent. 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 match values contribute to the positive risk-return relationship; however, the latent value accounts for a larger share of the total return in riskier occupations.

6.5 Other measures of compensating differentials

Our definition of compensating differentials emphasizes the trade-off between wages and latent match values for the subset of workers who are marginal in their occupation choice. These workers have no rent from employment but do influence the rents of inframarginal workers. On the other hand, the empirical literature often resorts to indirect measures of compensating differentials based on the covariation between current wages and some proxy of non-wage returns. In Online Appendix J we report two measures of covariation between wages and latent components of returns. The key difference is that only one of the two measures includes information about workers' idiosyncratic values.

The first measure is the covariance $cov(u_c(c_{ijmt}) - u_h^i(h_{ijmt}), b_{ijt})$, which we estimate for each year and demographic group. Panel A of Table 12 in Online Appendix J reports the results of this exercise and documents a positive and growing covariance between observable and latent match values for college graduates. For non-college workers we find negative covariation, with a trend towards lower covariances among men. The positive and increasing covariances for college workers are in line with findings in Lehmann (2022), who estimates wage and non-wage compensation for a sample workers who experience job-to-job transitions. The covariances reported in Panel A of Table 12 do not account for the workers' idiosyncratic match values. Therefore, we also consider measures of covariation that include the average of the idiosyncratic match values within each cell, shown in Panel B of Table 12. The cell-specific averages of idiosyncratic match values $\bar{\theta}_{ijmt}$ are estimated through model simulations and we use them to recover the following covariances:

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

The resulting covariances are quite different from the estimates in Panel A. Panel B shows negative and diminishing covariation for all demographic groups. This indicates growing compensating differentials and is consistent with estimates based on our baseline definition of compensating differentials. In turn, this suggests that taking into account the idiosyncratic values (including those of workers are the tails like marginal workers) may change what we learn from the covariance of observable earnings and unobservable latent values.

7 Conclusions

There is a recognition that the gains from employment entail non-pecuniary and latent components. Therefore, using wage earnings in isolation as a measure of labor market returns has been questioned (Sorkin, 2018). The challenge is that, after observing a wage increase in one occupation, one cannot immediately infer whether the increase reflects a boost in overall returns or, rather, a compensation for changes in the latent returns of marginal workers, who must be indifferent by definition. This raises the question of whether, and under which conditions, wage dynamics are a reliable measure of the returns from employment. We address this question by studying an equilibrium model of the labor market that leverages information on employment shares, earnings and hours worked. The model delivers a monetary measure of match-specific (worker-occupation) rents that reflects the workers' willingness to pay in order to stay in their current job.

To guide the analysis, we derive analytical results that establish conditions for wages to deliver an informative signal about rents. Specifically, we show that wage earnings convey information about rent dynamics when the elasticity of labor supply to latent match values is higher than the elasticity of labor supply with respect to productivity (that is, with respect to technological change). These results suggest that it may be impossible to draw inference about rents from wage changes if the elasticity conditions are not met. That is, wage dynamics are only partially instructive and researchers need alternative ways to establish to what extent observed changes are due to shifts in latent values rather than shifts in the productivity of different matches.

Our empirical findings indicate that the labor elasticity conditions do hold, so that wages are informative about the evolution of employment returns over the sample period. We explicitly verify these findings through counterfactual model experiments. The latter confirm that earnings across worker-occupation groups provide a reliable portrayal of the concurrent rent changes between 1980 and 2018. The results highlight a dichotomy: while the existence of rents is due to the presence of latent values, the evolution of rents is driven by productivity and technology.

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A Identification and estimation

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

Identification: utility and technology parameters

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

$$\begin{aligned} U_{ijmt} = \max_{h_{ijmt}} \quad & \frac{c_{ijmt}^{1-\sigma} - 1}{1-\sigma} - \psi_i \frac{h_{ijmt}^{1-\gamma}}{1-\gamma} + b_{ijt} \\ \text{s.t.} \quad & c_{ijmt} = w_{ijmt} h_{ijmt} \end{aligned} \tag{18}$$

the associated first order condition in logarithmic form is

$$\log\left(h_{ijmt}\right) = -\frac{1}{\sigma-\gamma}\log\left(\psi_i\right) + \frac{1-\sigma}{\sigma-\gamma}\log\left(w_{ijmt}\right) \tag{19}$$

The empirical counterpart of this is

$$\log\left(h_{ijmt}\right) = \alpha_i + \beta\log\left(w_{ijmt}\right) + \epsilon^1_{ijmt} \equiv f\left(\boldsymbol{X}_{ijmt}, \tilde{\boldsymbol{\Omega}}_i\right) + \epsilon^1_{ijmt} \tag{20}$$

with

$$\alpha_i = -\frac{1}{\sigma - \gamma} \log\left(\psi_i\right) \qquad \beta = \frac{1-\sigma}{\sigma-\gamma} \tag{21}$$

With the linear specification of $f(\cdot,\cdot)$, the moments in (15) describe an OLS estimator of (20). The latter equation shows that we can identify α_i and β from the covariance of hours and wages within each demographic group. From α_i and β, we can obtain γ and ψ_i as a function of σ:

$$\gamma = \sigma - \frac{1-\sigma}{\beta} \qquad \psi_i = \exp\left(-\frac{1-\sigma}{\beta}\alpha_i\right) \tag{22}$$

We are now left with three sets of parameters to estimate, namely σ, σ_θ, and b_{ijt}, and three sets of moments from the equations in (16) in the main text, given that $\boldsymbol{Z}^2_{ijmt}$ has at least two elements $Z^2_{1,ijmt}$ and $Z^2_{2,ijmt}$. From the first moment condition in (16) we have

$$\tilde{b}_{ijt} = E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u^i_h\left(\hat{h}_{ijmt}\right) - u_c\left(0\right)}{\sigma_\theta}\middle| i,j,t\right] \tag{23}$$

where $\tilde{b}_{ijt} = \frac{b_{ijt}}{\sigma_\theta}$. Plugging this into the second moment condition gives

$$E\left[\left(\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u^i_h\left(\hat{h}_{ijmt}\right) - u_c\left(0\right)}{\sigma_\theta}\right.\right.$$
$$\left.\left.-E\left[\Upsilon_{ijmt} - \frac{u_c\left(w_{ijmt}\hat{h}_{ijmt}\right) - u^i_h\left(\hat{h}_{ijmt}\right) - u_c\left(0\right)}{\sigma_\theta}\middle| i,j,t\right]\right)\boldsymbol{Z}^2_{ijmt}\right] = 0 \tag{24}$$

which is a system of at least two equations in two unknowns, σ and σ_θ. Once σ and σ_θ are identified from this system, eq. (23) 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

$$\frac{w_{ijmt}}{w_{i'jmt}} = \frac{\beta_{ijt}}{\beta_{i'jt}} \tag{25}$$

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

$$\frac{w_{ijmt}}{w_{ij'mt}} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}} \left(\frac{\widetilde{L}_{j'mt}}{\widetilde{L}_{jmt}}\right)^{1-\rho} = \frac{\alpha_{jt}\beta_{ijt}}{\alpha_{j't}\beta_{ij't}} \left(\frac{\sum_{i'} \beta_{i'j't} L_{i'j'mt}}{\sum_{i'} \beta_{i'jt} L_{i'jmt}}\right)^{1-\rho} \tag{26}$$

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

$$\log\left(\frac{w_{ijmt}}{w_{i1mt}}\right) = \log\left(\frac{\alpha_{jt}}{\alpha_{1t}}\right) + \log\left(\frac{\beta_{ijt}}{\beta_{i1t}}\right) + (\rho - 1)\log\left(\frac{\sum_{i'} \beta_{i'jt} L_{i'jmt}}{\sum_{i'} \beta_{i'1t} L_{i'1mt}}\right) \tag{27}$$

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:

$$W_{ijmt} = \gamma_{jt} + \psi B_{ijt} + \phi \Lambda_{jmt} + \epsilon_{ijmt} \tag{28}$$

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 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.

B.1 Uncompensated elasticity: intensive margin

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

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

The total differential of the MRS is:

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

After rearranging:

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

The uncompensated elasticity at the intensive margin is,

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

Figure 4a shows the distribution of the intensive margin elasticity of labor supply in the population based on model estimates. The average elasticity is 0.15.

B.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:

$$\frac{d\mu_{ijmt}}{dw_{ijmt}}=\mu_{imt}\frac{e^{U_{ijmt}/\sigma_\theta}\frac{1}{\sigma_\theta}U'_{i,j,m,t}}{\left[\sum_{j'=0}^{J}\exp\left(U_{ij'mt}/\sigma_\theta\right)\right]^2}\sum_{j'=0,j'\neq j}^{J}\exp\left(U_{ij'mt}/\sigma_\theta\right)$$

where $U'_{ijmt}=u'_c(c_{ijmt})\left(h_{ijmt}+\frac{dh_{ijmt}}{dw_{ijmt}}w_{ijmt}\right)-u^{i'}(h_{ijmt})\frac{h_{ijmt}}{dw_{ijmt}}$. Figure 4b shows the distribution of extensive margin elasticities in the population, obtained from the model estimates. Notice that the term between square brackets in the numerator is the derivative of the indirect utility from consumption and leisure from occupation j. The average elasticity is between 0.55 and 0.60 across all years.

B.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

$$\varepsilon^{tot}_{ijmt} = \frac{dL_{ijmt}}{dw_{ijmt}}\frac{w_{ijmt}}{L_{ijmt}} = \left(\frac{d\mu_{ijmt}}{dw_{ijmt}}h_{ijmt} + \frac{dh_{ijmt}}{dw_{ijmt}}\mu_{ijmt}\right)\frac{w_{ijmt}}{L_{ijmt}} \tag{29}$$

Figure 4c shows the distribution of total elasticity estimates in the population. The average is 0.72. Equation (29) 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.

B.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

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

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

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

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,

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

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

B.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

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

From equation (3), and using the exponential notation $e^x = \exp(x)$, 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:

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

The total differential is given by:

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

which, after rearranging, gives

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

B.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,

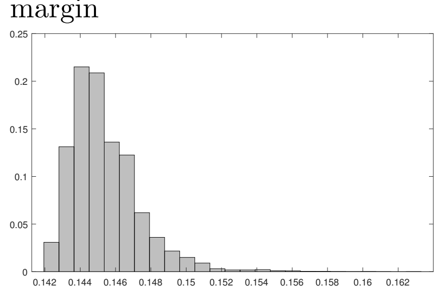
$$\varepsilon^{b}_{ijmt} = \frac{d\mu_{ijmt}}{db_{ijt}} \frac{|b_{ijt}|}{\mu_{ijmt}}.$$

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

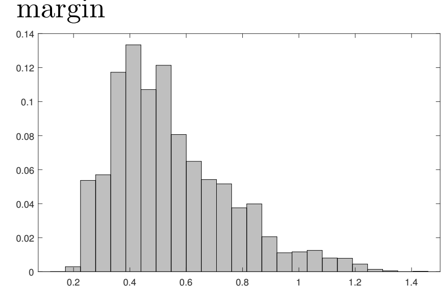
$$\frac{d\mu_{ijmt}}{db_{ijt}} = \mu_{imt} \frac{\frac{1}{\sigma_\theta} e^{U_{ijmt}/\sigma_\theta}}{\left[\sum_{j'=0}^{J} \exp\left({}^{U_{ij'mt}}/_{\sigma_\theta}\right)\right]^2} \sum_{j'=0, j' \neq j}^{J} \exp\left({}^{U_{ij'mt}}/_{\sigma_\theta}\right)$$

Figure 4d 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.

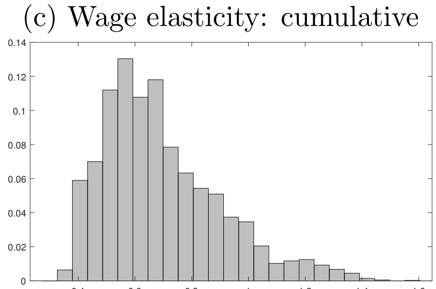
(a) Wage elasticity: intensive margin



(b) Wage elasticity: extensive margin



(c) Wage elasticity: cumulative



(d) Latent values elasticity

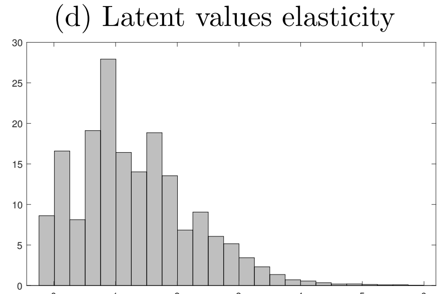


Figure 4: Distribution of the elasticities of labor supply (extensive and intensive margin) to changes in wages and latent values.

C Method-of-moments estimates

C.1 Preference parameters and production technology shares

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 available from the authors for different years between 1980 and 2018. Similarly, point estimates and standard errors for technology input shares in different years (1980, 1990, 2000, 2010, 2018) are available for all occupation-worker combinations (for brevity, we do not report them in the appendix; for any given year there are 168 estimates; each estimate corresponds to a gender-education-age-occupation match).

	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 (17). Parameters and standard errors for $\hat{\sigma}_\theta$ are scaled down by 1,000.

				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: Disutility of hours worked: parameter estimates based on the GMM estimator in equation (17). Both the estimates and standard errors for ψ_i are scaled up by 10^{14}.

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

Figure 5 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.

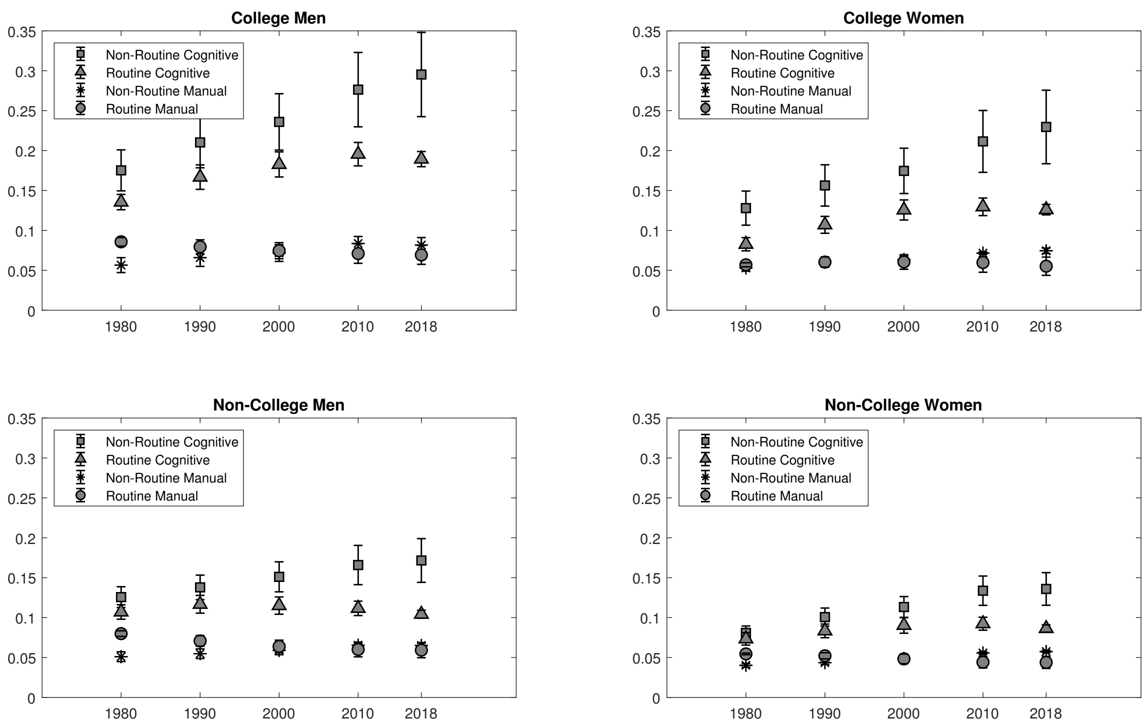


Figure 5: Average production shares of four broad occupation categories by worker demographic group (based on estimates of $\alpha_{jt}\beta_{ijt}$). Brackets are 95-percent confidence intervals around point estimates.

D Proofs

Proof of proposition 3

The proof is trivial. Without loss of generality, consider a positive shock to the productivity of workers of type i in occupation j; that is, match (i, j) produces more output than before. If the elasticity of labor supply to wages is low and there are no changes in employment, the original shock must translate into higher wages and all workers match (i, j) enjoy higher wages, which mechanically increases the rents of incumbent workers (equation 8).

If the elasticity of labor supply is larger, an inflow of workers of type i to occupation j does exert downward pressure on wages, which offsets and reduces their initial growth. In this case, incumbent workers will enjoy only marginally higher wages and rents than before the shock. Since newcomers are characterized by lower idiosyncratic preferences θ for occupation j, their rents will be lower than incumbent workers. The total effect on average rents is therefore ambiguous and depends on whether the gains of incumbent workers are enough to offset the lower rents of newcomers.

Proof of proposition 4

Without loss of generality, consider an increase in the systematic (common) latent value for worker-occupation match (i, j); that is, an increase of b_{ijt}. If the elasticity of labor supply with respect to the latent values is low (for example, if it becomes sufficiently close to zero), labor supply to occupation j is unaffected by the change in b_{ijt} and wages do not change. Workers in occupation j enjoy higher b_{ijt} without any changes in their wages. Rents increase.

Conversely, if the elasticity of labor supply to the latent values is sufficiently high, an inflow of workers does exert downward pressure on wages. This has a negative impact on rents, as the original gain from higher b_{ijt} is offset by lower wages. However, the fall in wages can never completely undo the initial gain in rents. To see this, suppose that the inflow of workers is such that for some incumbent workers the fall in wages is sufficient to completely revert the rent gain from the initial increase in b_{ijt}. If the rents of incumbent workers are unchanged, then new entrants would find it unprofitable to enter occupation j since they have, by definition, lower idiosyncratic match values θ. This leads to a contradiction since employment in occupation j must increase for wages to drop. Therefore, we conclude that incumbent workers of type i always experience growth in their rents following an increase in latent values b_{ijt}, even if wages fall. Note that, since newcomers of type i are characterized by lower idiosyncratic preferences θ for occupation j, their rents are lower than the incumbents. The net effect of the change in b_{ijt} on the average rents in match (i, j) becomes smaller.

Overall, with a high elasticity, a positive shock to b_{ijt} induces a fall in wages but a marginal increase in rents.