Online Appendix

The Changing Value of Employment

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Abstract

This Online Appendix provides information and analysis supporting the main text.

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E Production sector: derivations

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

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

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho} - \sum_i \tilde{w}_{ij} L_{ijv} \tag{30}$$

the associated first order condition is

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho} \rho \left(\sum_{i'} \beta_{i'j} L_{i'jv} \right)^{\rho-1} \beta_{ij} \tag{31}$$

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

$$z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv} \right)^{\rho-1} = z_{jv'}^{\rho} \left(\sum_i \beta_{ij} L_{ijv'} \right)^{\rho-1} \tag{32}$$

$$\sum_i \beta_{ij} L_{ijv'} = \frac{z_{jv}^{\frac{\rho}{\rho-1}}}{z_{jv'}^{\frac{\rho}{\rho-1}}} \sum_i \beta_{ij} L_{ijv} \tag{33}$$

Integrating over $v' \in V_j$ we get

$$\sum_i \beta_{ij} L_{ij} = z_{jv}^{\frac{\rho}{\rho-1}} \int_{v' \in V_j} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \sum_i \beta_{ij} L_{ijv} \tag{34}$$

$$\sum_i \beta_{ij} L_{ijv} = z_{jv}^{\frac{-\rho}{\rho-1}} \left(\int_{v' \in V_j} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv' \right)^{-1} \sum_i \beta_{ij} L_{ij} \tag{35}$$

The aggregate production function is given by

$$Y = \left(\int_v \upsilon_{jv}^{\rho} dv\right)^{\frac{1}{\rho}} \tag{36}$$

$$= \left(\sum_j \int_{v\in V_j} \upsilon_{jv}^{\rho} dv\right)^{\frac{1}{\rho}} \tag{37}$$

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

Using (35) this gives

$$Y = \left[\sum_j \int_{v\in V_j} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv}\right)^{\rho} dv\right]^{\frac{1}{\rho}} \tag{39}$$

$$= \left[\sum_j \int_{v\in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv \left(\int_{v'} \frac{1}{z_{jv'}^{\frac{\rho}{\rho-1}}} dv'\right)^{-\rho} \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{40}$$

$$= \left[\sum_j \underbrace{\left(\int_{v\in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv\right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{41}$$

$$= \left[\sum_j \tilde{\alpha}_j \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{42}$$

$$= A\left[\sum_j \alpha_j \left(\sum_i \beta_{ij} L_{ij}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{43}$$

where $\alpha_j = \frac{\tilde{\alpha}_j}{\sum_{j'} \tilde{\alpha}_{j'}}$ and $A = \left(\sum_{j'} \tilde{\alpha}_{j'}\right)^{\frac{1}{\rho}}$. Moreover, substituting (35) into (31) we have

$$\tilde{w}_{ij} = PY^{(1-\rho)}\rho \underbrace{\left(\int_{v\in V_j} z_{jv}^{\frac{\rho}{1-\rho}} dv\right)^{1-\rho}}_{\tilde{\alpha}_j} \left(\sum_{i'} \beta_{i'j} L_{i'j}\right)^{\rho-1} \beta_{ij} \tag{44}$$

$$\frac{\tilde{w}_{ij}}{P} = Y^{(1-\rho)}\rho\tilde{\alpha}_j \frac{\sum_{j'} \tilde{\alpha}_{j'}}{\sum_{j'} \tilde{\alpha}_{j'}} \left(\sum_{i'} \beta_{i'j} L_{i'j}\right)^{\rho-1} \beta_{ij} \tag{45}$$

$$w_{ij} = \rho A^{\rho} \alpha_j \beta_{ij} \left(\frac{Y}{\sum_{i'} \beta_{i'j} L_{i'j}}\right)^{(1-\rho)} \tag{46}$$

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

F Model with capital inputs

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

$$\max_{p_{jv},\lambda_{jv},L_{ijv}} \quad p_{jv}\lambda_{jv} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{47}$$

$$\text{s.t.} \quad \lambda_{jv} = z_{jv} \left(\sum_i \beta_{ij} L_{ijv}\right)^{\gamma} (\eta_j K_{jv})^{1-\gamma} \tag{48}$$

$$p_{jv} = \left[\frac{\lambda_{jv}}{Y}\right]^{-(1-\rho)} P \tag{49}$$

Equivalently

$$\max_{L_{ijv}} \quad PY^{(1-\rho)} z_{jv}^{\rho} \left(\sum_i \beta_{ij} L_{ijv}\right)^{\rho\gamma} (\eta_j K_{jv})^{\rho(1-\gamma)} - \sum_i \tilde{w}_{ij} L_{ijv} - rK_{jv} \tag{50}$$

The associated first order conditions are

$$\tilde{w}_{ij} = PY^{(1-\rho)} z_{jv}^{\rho} \rho\gamma \left(\sum_{i'} \beta_{i'j} L_{i'jv}\right)^{\rho\gamma-1} (\eta_j K_{jv})^{\rho(1-\gamma)} \beta_{ij} \tag{51}$$

and

$$r = PY^{(1-\rho)} z_{jv}^{\rho} \rho (1-\gamma) \left(\sum_{i'} \beta_{i'j} L_{i'jv}\right)^{\rho\gamma} (\eta_j K_{jv})^{\rho(1-\gamma)-1} \eta_j \tag{52}$$

Dividing the two first order conditions by each other we get

$$\frac{\tilde{w}_{ij}}{r} = \beta_{ij}\frac{\gamma}{1-\gamma}\frac{K_{jv}}{\sum_{i'}\beta_{i'j}L_{i'jv}} \Rightarrow K_{jv} = \frac{w_{ij}\left(1-\gamma\right)}{r\gamma\beta_{ij}}\sum_{i'}\beta_{i'j}L_{i'jv} \tag{53}$$

Notice that this implies

$$\frac{K_{jv}}{\sum_{i'}\beta_{i'j}L_{i'jv}} = \frac{\tilde{w}_{ij}\left(1-\gamma\right)}{r\gamma\beta_{ij}} = \frac{K_j}{\sum_{i'}\beta_{i'j}L_{i'j}} \tag{54}$$

where $K_j = \int_{v'\in V_j} K_{jv}dv$ and $L_{ij} = \int_{v'\in V_j} L_{ijv}dv$.
Using (53) into (51) we get

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

$$w_{ij} = \Xi\eta_j^{\frac{\rho(1-\gamma)}{1-\rho(1-\gamma)}}z_{jv}^{\frac{\rho}{1-\rho(1-\gamma)}}\beta_{ij}\left(\sum_{i'}\beta_{i'j}L_{i'jv}\right)^{\frac{\rho-1}{1-\rho(1-\gamma)}} \tag{56}$$

where $\Xi = \left[Y^{(1-\rho)}\rho\gamma\left(\frac{1-\gamma}{r\gamma}\right)^{\rho(1-\gamma)}\right]^{\frac{1}{1-\rho(1-\gamma)}}$ and $w_{ij} = \frac{\tilde{w}_{ij}}{P}$ as before.
Notice that (56) implies the same relationship described in (33) and, thus, equation (35). Using (35) in (56) we get

$$w_{ij} = \Xi\Lambda_j\beta_{ij}\left(\sum_{i'}\beta_{i'j}L_{i'j}\right)^{\frac{\rho-1}{1-\rho(1-\gamma)}} \tag{57}$$

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

$$\log\left(\frac{w_{ij}}{w_{i2}}\right) = \log\left(\frac{\Lambda_j}{\Lambda_1}\right) + \log\left(\frac{\beta_{ij}}{\beta_{i1}}\right) + \frac{\rho-1}{1-\rho(1-\gamma)}\log\left(\frac{\sum_{i'}\beta_{i'j}L_{i'j}}{\sum_{i'}\beta_{i'1}L_{i'1}}\right) \tag{58}$$

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

$$W_{ijmt} = \gamma_{jt} + \psi\hat{B}_{ijt} + \phi\hat{\Lambda}_{jmt} + \epsilon_{ijmt} \tag{59}$$

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

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

$$1 - \rho^{\text{base}} = \frac{1-\rho}{1-\rho(1-\gamma)} \tag{60}$$

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

$$\rho^{\text{base}} < \rho \tag{61}$$

This implies that if the baseline estimate ρ^{base} is a lower bound of the curvature parameter ρ.

Assuming $\gamma = 2/3$, a common choice in the literature, the baseline estimate of $\hat{\phi} = -0.61$ delivers $\rho = 0.49$ which implies an elasticity of substitution of about 1.96.

G Shift-share instrument

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

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

$$\text{IV}_{jmt} = \Delta\hat{\Lambda}^h_{jmt} = \hat{\Lambda}^h_{jmt} - \log\left(\frac{L^h_{jmt-10}}{L^h_{1mt-10}}\right) \tag{62}$$

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

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

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

Table 9: Estimation results for equation (13) in first differences using the Bartik instrument.

Table 9 shows that the estimation results using the Bartik instrument are comparable to the results presented in the main text.

G.1 Technology shares by worker group: match level estimates

Figure 6 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.

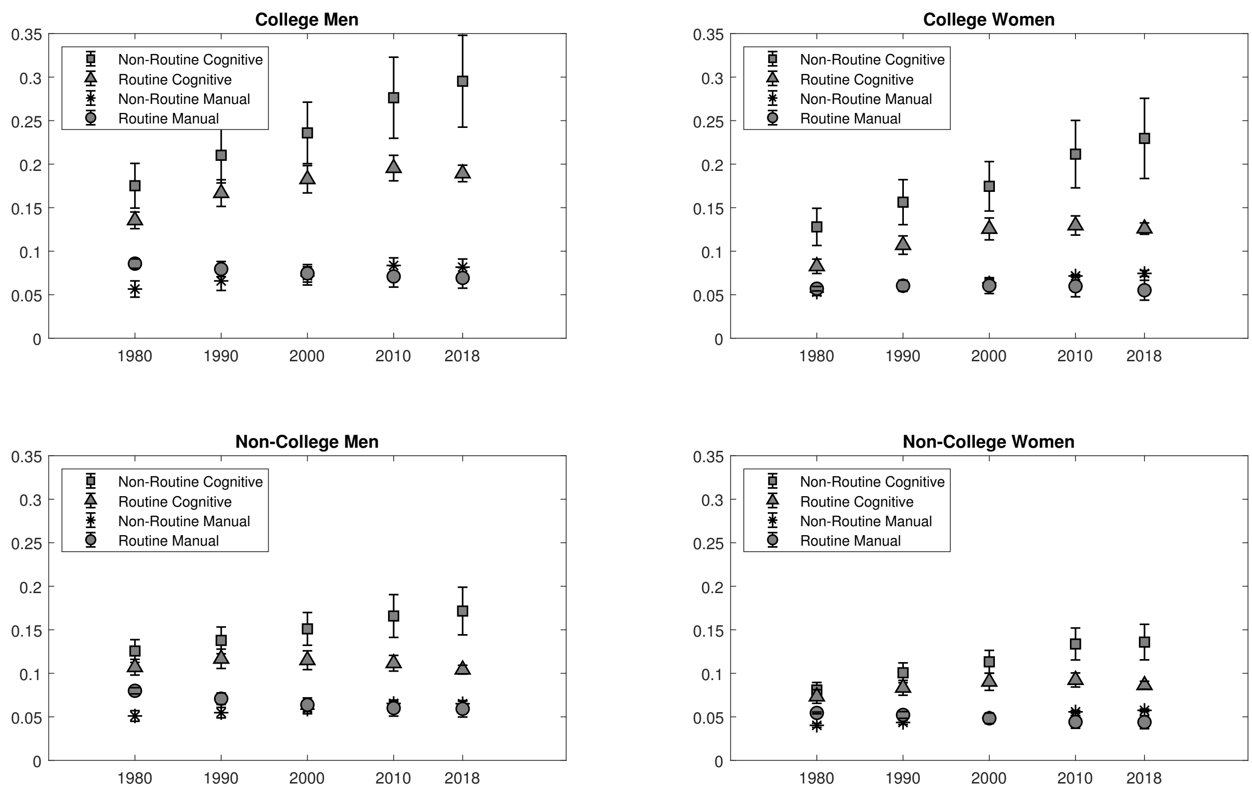

Figure 6: Average production shares of four broad occupation categories by worker demographic group (based on estimates of $\alpha_{jt}\beta_{ijt}$). Brackets are 95-percent confidence intervals around point estimates.

H Robustness: model with flexible disutility of work

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

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

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

With this specification, within each demographic group workers are allowed to value time spent at work differently. Figure 7 shows the goodness of fit for this model. Just like the baseline model, the enriched model can explain 99% and 95% of the variation in employment and wages. Yet it performs better in terms of hours worked explaining 87% of total variation.

Despite the improvement in terms of goodness of fit, Table 11, which is the counterpart of Table 5, show that the flexible model produces comparable compensating differentials. As for rents, Table 10, the counterpart of Table 3, shows that the model produces slightly lower rents but growth patterns are comparable to those in the main text.

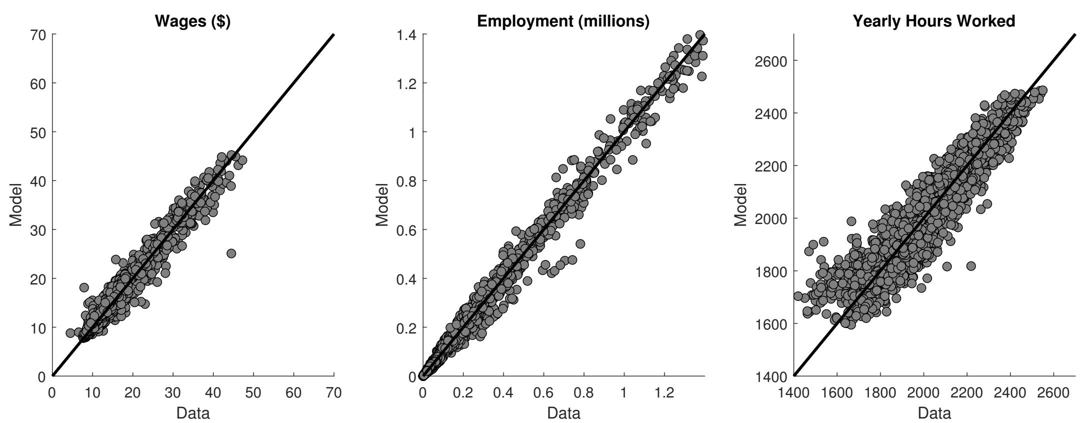

Figure 7: Goodness of fit. Left: model implied wages vs. data. Center: model implied employment vs. data. Right: model implied hours worked vs. data.

Average Rents (year 2000 $)

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

Table 10: Estimated average rents by year and demographic group.

Average Compensating Differentials (year 2000 $)

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

Table 11: Average absolute compensating differentials by year and demographic group.

I Analytical derivations: rents and compensating differentials

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

$$R_{ijmt} = E[R^{\iota}_{ijmt}] \tag{63}$$

$$= \int_0^{w_{ijmt}} (w_{ijmt}h_{ijmt} - wh_i(w, y_{imt})) \frac{1}{\mu_{ijmt}(w_{ijmt})} \frac{\partial \mu_{ijmt}(w)}{\partial w} dw \tag{64}$$

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

$$f_{ijmt}(w) = \frac{1}{\mu_{ijmt}(w_{ijmt})} \frac{\partial \mu_{ijmt}(w)}{\partial w} \tag{65}$$

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

Before solving the integral numerically, we note that

$$\frac{\partial \mu_{ijmt}(w)}{\partial w} = B_{ijmt}(w) C_{ijmt}(w) \frac{A_{imt}(w) - C_{ijmt}(w)}{A^2_{ijmt}(w)} \mu_{imt} \tag{66}$$

where

$$A_{ijmt}(w) = \exp\left(\frac{u_c(y_{imt})}{\sigma_\theta}\right) + \exp\left(\frac{u_c(wh_i(w, y_{imt}) + y_{imt}) - u_h^i(h_i(w, y_{imt})) + b_{ijt}}{\sigma_\theta}\right) + \tag{67}$$

$$+ \sum_{j' \neq j} \exp\left(\frac{u_c(w_{ij'mt} h_i(w_{ij'mt}) + y_{imt}) - u_h^i(h_i(w_{ij'mt})) + b_{ij'mt}}{\sigma_\theta}\right) \tag{68}$$

$$B_{ijmt}(w) = \frac{1}{\sigma_\theta}\left[(wh_i(w, y_{imt}) + y_{imt})^{-\sigma} - h_i(w, y_{imt})^{-\gamma} \frac{\partial h_i(w, y_{imt})}{\partial w}\right] \tag{69}$$

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

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

$$(wh + y)^{-\sigma} w = \psi h^{-\gamma} \tag{71}$$

$$\left[(wh + y)^{-\sigma} - \sigma(wh + y)^{-\sigma-1} wh\right] dw + \left[-\sigma(wh + y)^{-\sigma-1} w^2\right] dh = -\gamma\psi h^{-\gamma-1} dh$$

$$\frac{\partial h}{\partial w} = \frac{(wh + y)^{-\sigma} - \sigma(wh + y)^{-\sigma-1} wh}{\sigma(wh + y)^{-\sigma-1} w^2 - \gamma\psi h^{-\gamma-1}}$$

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

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

$$
\begin{gathered}
\tilde{U}_i(w_{ijmt} - \tilde{R}^{\iota}_{ijj'mt}, y_{imt}) + b_{ijt} + \theta^{\iota}_j = \tilde{U}_i(w_{ij'mt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'} \\
\Rightarrow b_{ijt} + \theta^{\iota}_j - b_{ij't} - \theta^{\iota}_{j'} = \tilde{U}_i(w_{ij'mt}, y_{imt}) - \tilde{U}_i(w_{ijmt}, y_{imt})
\end{gathered}
\tag{72}
$$

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

$$
\begin{aligned}
CD^{\iota}_{ijj'mt} &= \tilde{U}_i(w_{ijmt}, y_{imt}) + b_{ij't} + \theta^{\iota}_{j'} - \tilde{U}_i(w_{ijmt}, y_{imt}) - b_{ijt} - \theta^{\iota}_j \\
&= b_{ij't} + \theta^{\iota}_{j'} - b_{ijt} - \theta^{\iota}_j
\end{aligned}
\tag{73}
$$

Substituting eq. (72) into (73), we have that

$$
CD^{\iota}_{ijj'mt} = \tilde{U}_i(w_{ijmt}, y_{imt}) - \tilde{U}_i(w_{ij'mt}, y_{imt}) = CD_{ijj'mt} \tag{74}
$$

Combining equations (73) and (74) we obtain Proposition 1. Finally, we define the dollar value of the compensating differential as

$$
u_c(w_{ijmt}h_{ijmt} + y_{imt} - CD^{\$}_{ijj'mt}) - u_h(h_{ijmt}) = u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}) \tag{75}
$$

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

$$
CD^{\$}_{ijj'mt} = w_{ijmt}h_{ijmt} + y_{imt} - (u_c)^{-1}\left(u_c(w_{ij'mt}h_{ij'mt} + y_{imt}) - u_h(h_{ij'mt}) + u_h(h_{ijmt})\right). \tag{76}
$$

J Alternative measures of compensating differentials

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

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

We compute this covariance separately for each year and demographic group and we show the results in Panel A of Table 12. We find a positive and increasing covariance for college graduates, with the growth being particularly pronounced among men. For non-college workers we find negative covariations and a trend towards lower covariances among men. The positive and increasing covariances for college men are in line with the findings of Lehmann (2022), which restricts attention to male workers who experience job-to-job transitions. Transitions that bypass unemployment tend to over-sample educated men, which is consistent with our findings.

To extend our analysis, in Panel B of Table 12 we report similar measures of covariation after including the average idiosyncratic workers' valuations within each cell. The average idiosyncratic job values $\bar{\theta}_{ijmt}$ are obtained by simulating the model. Specifically, we compute the following covariances

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

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

K Occupation-specific wage dispersion and rents

Some occupations may carry higher wage risk than others. For example, if there are differences in the performance-based component of wages across jobs, one might observe differences in the dispersion of ex-post pay. In this section, we examine whether workers in riskier occupations are compensated for higher wage uncertainty. To answer this question we compute the standard deviation of wage rates within each $ijmt$-cell and use it as a reference measure of wage risk for each $ijmt$ worker-occupation-market triplet. Then, within a $ijmt$ cell, we compute four distinct outcomes (that is, four measures of occupation returns) and separately project each return measure on the corresponding standard deviation of wages.

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

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

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

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

Table 12: Covariances between observable and latent components of employment surplus, by year and demographic group. All covariances are normalized by the variance of idiosyncratic values, σ_θ^2.

The four measures of returns are: (i) rents; (ii) total surplus; (iii) observable current wage in a job; and (iv) occupation latent value. One should note that the latter two measures are the fundamental components that add up to total surplus. To facilitate comparisons, we normalize total surplus and its components by the standard deviation of total surplus so that the estimated coefficients convey information about the way total surplus components change with occupation-level wage risk.

Table 13 reports the main findings of this exercise. For every dependent variable we first run a regression with no controls; then we run a regression including demographic controls (education, age, and gender fixed effects), occupation fixed effects, and year fixed effects. The results indicate that higher wage risk is associated with higher returns. Estimates in Columns 1 and 2 are semi-elasticities. Column 2, in particular, shows that a 10-dollar increase in the standard deviation of wages is associated with a 4.5% increase in rents. Moreover, Column 4 shows that the same increase in risk is associated with an increase of about 0.3 standard deviations in total match surplus. Comparing this estimate to those in Columns 6 and 8 suggests that both the pecuniary and latent components of surplus contribute to the positive risk-return relationship. In addition, they highlight that latent values are proportionally larger, as a share of total surplus, in occupations characterized by higher wage risk.

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

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

Table 13: Projection of rents, surplus, and components of surplus on measures of wage risk (standard deviations of wages). For each dependent variables we report the simple projection and a projection with controls for demographics, occupation, and time. Columns (1) and (2) report the results for log-rents. The coefficients can be interpreted as semi-elasticities. Columns (3) and (4) show the results for total surplus. The dependent variable is standardized. Columns (5) and (6) show the results for the pecuniary component of surplus. To ensure comparability with the coefficients of the previous two columns, the dependent variable has been normalized by the standard deviation of total surplus. The same normalization is applied to the latent value of surplus in columns (7) and (8).

L Robustness: market variation in latent returns

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

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

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

Table 14 shows estimates of the market-occupation component b_{jm}. Identification requires that all values must be estimated relative to a reference region-occupation. The table shows that many coefficients are statistically significant. However, their values are not economically significant as the magnitudes of the b_{jm} terms are much smaller than the b_{ijt} components. Through a variance decomposition, we show that the b_{jm} contribution is less than one percent of the total variation across the overall latent returns b_{ijmt}. We have verified that such magnitudes are not sufficient to affect the subsequent estimation and results.

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

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

Table 14: Estimates of the market and occupation specific component of non-pecuniary returns.

M Additional tables and results

M.1 Geography and urban amenities

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

Arguably, urban areas tend to offer more and better amenities making occupations that are concentrated in urban areas more attractive. To explore this relationship we regress our estimates of latent returns on several measures of the geographic location of occupations.[6] For each occupation we compute: (i) the fraction of workers living in urban areas, (ii) the fraction of workers in a central city, defined as the central city of a metropolitan area, and the fraction of workers in urban areas excluding central cities (this measure is not available for 1990), (iii) average local population (available after the year 2000). We project our estimates of latent returns on these three measures separately for men and women.

Table 15 show the estimation results. Columns 1, 3, and 5 report the results from regressing b_{ijt} on the geographic variables without any other control. For men the coefficients are often not significant and the R2 is always very low (low explanatory power). For women we have always significant coefficients and relatively high R2, which suggests that geography is more important in determining the occupational choices of women than those of men. In all cases, the coefficients are positive: jobs in urban, dense areas are preferred. Adding controls for age and education (columns 2, 5, and 6) makes the estimated coefficient bigger and more significant for both men and women.

M.2 Rents and compensating differentials by occupation category

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

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

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

Standard errors in parentheses

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

Table 15: Results for job location.

Average Rents (year 2000 $)

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

Table 16: Estimated average rents by year and occupation type.

Average Compensating Differentials (year 2000 $)

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

Table 17: Average absolute compensating differentials by year and occupation type.

Rents: 2018 vs 1980, by occupation category.

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

Table 18: Actual and counterfactual changes in rents between 1980-2018. Values are ratios of average rents in 2018 to average rents in 1980.

M.3 Various counterfactual exercises

CD 2018 ÷ CD 1980	All	College		Non-College	
		Men	Women	Men	Women
(1) Baseline					
Estimated growth	1.38	1.45	1.48	1.29	1.42
(2) Hold latent values at 1980 levels					
Counterfactual growth	1.49	1.67	1.55	1.4	1.42
(3) Hold technology at 1980 levels					
Counterfactual growth	1.39	1.13	0.69	1.73	1.37

Table 19: Counterfactual vs baseline growth of compensating differentials (2018-2000) by worker group.

Rents 2000 ÷ Rents 1980	College		Non-College	
	Men	Women	Men	Women
(1) Baseline				
Estimated growth	1.21	1.28	0.94	1.17
(2) Hold latent values at 1980 levels				
Counterfactual growth	1.24	1.27	0.95	1.17
(3) Hold technology at 1980 levels				
Counterfactual growth	1.01	0.95	1.03	0.99

Table 20: Counterfactual vs baseline growth of average rents (2000-1980) by worker group.

Rents 2018 ÷ Rents 2000	College		Non-College	
	Men	Women	Men	Women
(1) Baseline				
Estimated growth	1	1.04	0.87	0.9
(2) Hold latent values at 1980 levels				
Counterfactual growth	1.01	1.03	0.88	0.93
(3) Hold technology at 1980 levels				
Counterfactual growth	0.97	0.98	1.02	0.99

Table 21: Counterfactual vs baseline growth of average rents (2018-2000) by worker group.

References

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