Online appendix to "Wage Risk, Employment Risk, and the Rise in Wage Inequality"

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A Federal Taxation of Governmental Benefits

Table A1: Federal Tax Rates

1986		2006	
Bracket	Rate	Bracket	Rate
\$2480	0.00	\$4075	0.00
\$3670	0.11	\$16541	0.15
\$4750	0.12	\$40043	0.25
\$7010	0.15	\$83540	0.28
\$9170	0.16		
\$11650	0.18		
\$13920	0.20		

Notes: The table displays federal income tax brackets and tax rates for 1986 and 2006. The latter are deflated to 1986 using the CPI.

The model in Section 2 taxes gross *Unemployment Benefits*, ub^g_{ih}, gross *Social Security* transfers, S^g_{ih}, and gross *Supplemental Security Income*, TS^g_{ih} at the federal income tax rates. Table A1 displays the rates for a single person from 1986 and 2006 provided by the Tax Foundation (2023), where we deflate the latter to 1986 using the CPI. In case a worker receives *Supplemental Security Income*, his taxable income is the sum of gross *Social Security* transfers and gross *Supplemental Security Income*.

B Value functions

We begin with the value functions of retired and disabled workers. In those cases, the worker does not face uncertainty and does not engage in job search. He solves, respectively, the following maximization problem:

$$\mathcal{Q}_h(a, \bar{E}) = \max_{a'} \Big\{ U(c, 0) + \beta \mathcal{Q}_{h+1}(a', \bar{E}') \Big\} \tag{B.1}$$

$$\mathcal{D}_h(a, \bar{E}) = \max_{a'} \Big\{ U(c, 0) + \beta \mathcal{D}_{h+1}(a', \bar{E}') \Big\}. \tag{B.2}$$

The value function of a non-employed worker who may not apply for disability solves

$$\mathcal{U}_h(a, p, \bar{E}, D, ub) = \max_{a', s} \Big\{ U(c, 0) - C(s) + \beta SU_h(a', p, \bar{E}', D, s) \Big\}, \tag{B.3}$$

where SU_h is the value of search in unemployment:

$$\begin{aligned} SU_h(a', p, \bar{E}', D, s) &\equiv (1 - s)\mathbb{E}_{D'|D,p'|p}\mathcal{U}_{h+1}(a', p', \bar{E}', D', 0) \\ + s\mathbb{E}_{D'|D,p'|p} &\int \max \Big\{ \mathcal{W}_{h+1}(a', p', \psi', \bar{E}', D'), \mathcal{U}_{h+1}(a', p', \bar{E}', D', 0) \Big\} dF(\psi'), \end{aligned} \tag{B.4}$$

where we have used the fact that unemployment benefits are zero but in the first period of unemployment. With probability $(1-s)$ the worker does not receive a job offer. If he receives a job offer, he decides between staying non-employed and moving to employment, $\mathcal{W}_{h+1}$. Define by Θ_h the value of applying for disability insurance which is only an option for those with bad health: $D = b$. The decision to apply for disability insurance is taken before the end of period uncertainty reveals. The worker knows that the application is denied with probability $1-\upsilon_h$ and he will stay non-employed:

$$\Theta_h(a', p, \bar{E}', b) \equiv \upsilon_h \mathcal{D}_{h+1}(a', \bar{E}') + (1 - \upsilon_h)\mathbb{E}_{D'|b,p'|p}\mathcal{U}_{h+1}(a', p', \bar{E}', D', 0). \tag{B.5}$$

Therefore, the value function of a non-employed worker with the option to apply for disability is given by

$$\mathcal{U}_h^D(a, p, \bar{E}, b, ub) = \max\Big\{ \max_{a'} \Big\{ U(c, 0) + \beta\Theta_h(a', p, \bar{E}', b) \Big\}, \mathcal{U}_h(a, p, \bar{E}, b, 0) \Big\}. \tag{B.6}$$

The value of an employed worker of age h solves

$$\begin{aligned}\mathcal{W}_h(a,p,\psi,\bar{E},D) = \max_{a'}\Big\{U(c,1) + \beta\Big\{(1-\omega(h))\Big[\lambda\Lambda \\ + (1-\lambda)\max_{s}\Big(-C(s) + (1-s)\Xi + s\Omega_E\Big)\Big] + \omega(h)\Pi^B\Big\}\Big\},\end{aligned} \tag{B.7}$$

where we have defined the following objects:

$$\begin{aligned}
\Pi^B &\equiv \mathbb{E}_{D'|D,p'|p}\{\mathbb{I}_{D'=b}\Big(\mathbb{I}_{p'-p\leq 0}\mathcal{U}_h^D(a',p',\bar{E}',b,ub') + (1-\mathbb{I}_{p'-p\leq 0})\mathcal{U}_h(a',p',\bar{E}',b,ub')\Big) \\
&\quad + (1-\mathbb{I}_{D'=b})\mathcal{U}_h(a',p',\bar{E}',g,ub')\} \\
\Pi^{NB} &\equiv \mathbb{I}_{D'=b}\Big(\mathbb{I}_{p'-p\leq 0}\mathcal{U}_h^D(a',p',\bar{E}',b,0) + (1-\mathbb{I}_{p'-p\leq 0})\mathcal{U}_h(a',p',\bar{E}',b,0)\Big) \\
&\quad + (1-\mathbb{I}_{D'=b})\mathcal{U}_h(a',p',\bar{E}',g,0) \\
\Lambda &\equiv \mathbb{E}_{D'|D,p'|p}\int \max\Big\{\mathcal{W}_{h+1}(a',p',\psi',\bar{E}',D'), \Pi^{NB}(a',p',\bar{E}',D')\Big\}dF(\psi') \\
\Xi &\equiv \mathbb{E}_{D'|D,p'|p}\max\Big\{\mathcal{W}_{h+1}(a',p',\psi,\bar{E}',D'), \Pi^{NB}(a',p',\bar{E}',D')\Big\} \\
\Omega_E &\equiv \mathbb{E}_{D'|D,p'|p}\int \max\Big\{\mathcal{W}_{h+1}(a',p',\psi,\bar{E}',D'), \Pi^{NB}(a',p',\bar{E}',D') \\
&\quad , \mathcal{W}_{h+1}(a',p',\psi',\bar{E}',D')\Big\}dF(\psi'),
\end{aligned}$$

If the job is destroyed, $\omega(h)$, the worker moves to non-employment, Π^B and receives unemployment benefits ub'. Those with a disability in the next period, $\mathbb{I}_{D'=b}$, may receive a negative productivity shock, $\mathbb{I}_{p'-p\leq 0}$, making them eligible to apply for disability insurance. When the worker receives a reallocation shock, λ, he is presented with the tradeoff, Λ, between accepting that job offer and non-employment without unemployment benefits, Π^{NB}. If the job is neither destroyed nor a reallocation shock occurs and the worker receives no new job offer, $(1-s)$, he faces the tradeoff, Ξ, between staying with the current job or quitting into non-employment. Finally, when he receives an offer, the tradeoff, Ω_E, is between his current job, the outside offer, and non-employment.

C Data Set, Sample Selection, and Cleaning

The Survey of Income and Program Participation (SIPP) is conducted by the US Census Bureau. It is a longitudinal multi-panel survey, nationally representative of non-institutionalized adults in US households. The survey provides monthly information on the distribution of income, wealth, employment, program eligibility, and labor market participation in society. Individuals are interviewed, depending on the panel, up to 14 times at four-month intervals, and are being asked about their income and work experience during the preceding four months.

Our sample consists of males aged between 25 and 61 years. We do not consider individuals with missing information on education or working status, the self-employed, those enrolled in school, and those in the military. We weigh all observations by the survey weights provided by the Census. We identify jobs by employer ID numbers. Workers may have multiple jobs within the same quarter. We define the main job as the one with the most quarterly earnings.[1] Importantly, for the purpose to identify mobility, the SIPP assigns an identifying number to each firm an individual is working. This allows us to determine whenever the worker changes jobs across time.

We consider a worker employed within a quarter when he reports most weeks of the quarter working. Before aggregating to the quarter, we reclassify weeks as non-working when earnings are non-positive, or the reported monthly hours are less than five. We drop observations where an individual is recalled from his former employer. These workers have a special search technology not well represented by a random draw from the job offer distribution which is an assumption we require for our estimation. Using quarterly employment states implies that employment transition rates represent somewhat persistent changes in employment. Since most unemployment spells in the US are shorter than a month, such employment transitions are not covered by our notion of unemployment risk.[2] It turns out that this focus on somewhat persistent job losses has important implications for trends in labor market transition rates. The left part of Table C1 shows that, consistent with the CPS data analyzed by Cairó and Cajner (2013), the monthly employment to non-employment rate is decreasing over the sample period. However, after time aggregation, the trend reverses and the quarterly employment to non-employment rate becomes increasing over the sample period.[3]

[1] The SIPP collects data of up to two jobs for each individual in each month.

[2] They enter into the estimation of the job offer distribution when they imply a change in employer.

[3] Consistent with this, Hyatt and Spletzer (2017) show that the secular decline in job turnover rates is concentrated at jobs lasting less than one quarter.

With regards to earnings, as the estimation of wage risk relies on wage growth information, we try to avoid interpreting noise arising from statistical imputation of earnings as shocks.[4] We conduct several data cleaning steps to reduce the noise arising from statistical imputation. First, following the recommendation from the US Census Bureau, we do not consider observations for which no interview was obtained. Second, also following the recommendation by the US Census Bureau, we merge the core files and the longitudinal files for the samples from 1984 to 1993 and keep only observations present in both. This assures that we use longitudinal imputation techniques in the earlier surveys consistent with the surveys after 1993. Third, we employ some additional longitudinal information for wage imputation beyond that used by the Census Bureau. In specific, when earnings are imputed for an entire wave, we use longitudinal information from the prior and subsequent waves, instead of relying on the SIPP imputed monthly earnings that are based on cross-sectional imputation:[5] (a) when the worker is paid by the hour in the wave before and after the missing wave and the hourly wage change across the two waves is less than 5%, we impute the mean wage for the missing wave (b) when hours worked are constant within the missing wave and the employer ID does not change across months within the wave, we impose that imputed earnings are constant within the wave (c) we drop observations where imputation leads to an earnings growth of at least 0.3 log points despite no change in hours worked or the employer ID. Besides noise arising from statistical imputation, Daly et al. (2022) show that the first and last observation in individual yearly earnings spells are unusually low and noisy. For example, an individual coming out of unemployment may not have worked the full observation period in the first year with his new job making the observation a non-random earnings draw. We find no evidence for such behavior in your quarterly hourly wage data.

When computing hourly wages, we divide monthly earnings by monthly hours worked. The SIPP does not report monthly hours worked but only hours per week and total weeks employed. As we are interested in wage shocks and not in predictable wage changes arising from some months having 4 and other months having 5 weeks, we construct for each worker two series of hourly wages and choose the one with the lower variation in monthly wage growth rates. To be specific, we

[4] A particular concern would be if the share of earnings observations resulting from statistical imputation would vary significantly across our three time periods. This turns out not to be the case. In our sample, the share of earnings imputed by the Census Bureau is 9.1 percent in the first period, 12.8 percent in the second period, and 7.4 percent in the third period.

[5] The SIPP employs a *hot desk procedure* to impute missing observations. The procedure consists of finding a *close* match of the missing observation of a worker with respondents, based on age, race, gender, marital status, household relationship, education, among others.

Table C1: Non-Employment Inflow Rates

	Monthly			Quarterly		
	HS	SC	C	HS	SC	C
1984-1993	0.69%	0.89%	0.83%	2.58%	1.76%	1.13%
1994-2003	0.55%	0.76%	0.70%	3.08%	2.22%	1.65%
2004-2012	0.42%	0.52%	0.56%	3.74%	2.88%	1.71%

Notes: The table displays monthly and quarterly non-employment inflow rates for three time periods and three education groups. *HS*: at most a high school degree; *SC*: some college education; *C*: college degree.

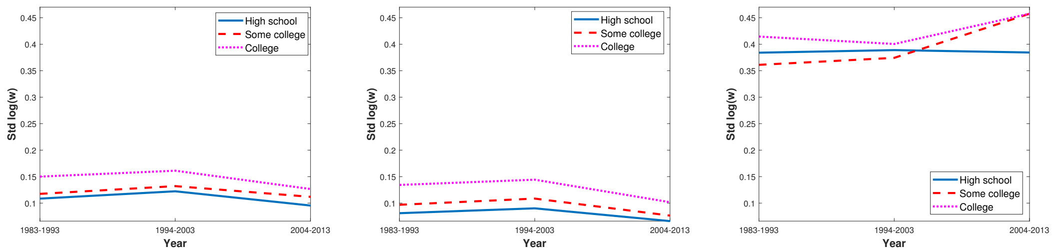
compute hourly wages based on the reported weeks in a month, and we compute hourly wages based on the assumption of 4.3 weeks per month. In a similar fashion, for workers who report being paid by the hour, we construct a series of hourly wages using this information and a series that divides reported monthly earnings by monthly hours worked and keep the series with the lower volatility in hourly wages.

Crucial for the identification of secular trends in wage risk is that the sample redesigns do not alter the precision to which we identify mobility. Starting in the 1996 panel, the SIPP uses dependent interviewing techniques for employer names on which basis the employer ID numbers are assigned. For the panels from 1990–1993, we use the cleaned employer ID numbers from Stinson (2003) that combine the survey data with administrative records to accurately identify these changes. To avoid spurious transitions, particularly before the 1990 panel, we keep the main job constant when the main employer ID changes for one month but is the same in the month before and after and the individual still works at this job. Note that, if the panels prior to 1990 suffered from spurious transitions, we would expect the dispersion of wage growth of job switchers to change from the first to the second period. As we discuss in the main text, this is not the case.

D Moments of Hourly Wage Growth

Figure D1: Hourly Wage Growth Dispersion

(A) All (B) Stayers (C) Movers



Notes: The figures display the standard deviation of cross-sectional quarterly residual wage growth. To obtain the residual wage growth, we estimate a weighted (defined as the survey weights) regression of log hourly wage growth as a function of a quadratic in age and work experience, race, marital status, unemployment rate at the state level, indicators whether a person lives at a metropolitan area or is disabled, industry, occupations, time and region fixed effects. Stayers are workers that stay with their employer in the quarter. Movers are those that switch employers.

Figure D1 displays the standard deviation of cross-sectional residual quarterly wage growth during the last three decades in the SIPP.[6] In line with recent administrative data from Guvenen et al. (2014), none of the education groups show an upward trend. The dispersion of wage growth peaked in the period 1993–2003 and is below its initial level in 2004–2013. We also split our sample into job stayers (workers staying with the current employer) and job movers (employees switching their employer). Job stayers dominate the sample and the evolution of the variance in residual wage growth closely resembles the complete sample. Contrary, the variance of residual wage growth of job movers exhibit a positive trend, particularly after the second period, for workers with at least some college education.

Table D1 reports further moments of residual wage growth of job stayers over time. Comparing the distributions in periods one and three, one observes a decline in large negative wage growth, here expressed as an increase in the 10^{th} percentile of the distribution. As large negative wage growth becomes less likely over time, skewness of the distribution becomes more positive over time.[7]

[6] To obtain the residual wage growth, we estimate a weighted (defined as the survey weights) regression of log hourly wage as a function of a quadratic in age and work experience, race, marital status, unemployment rate at the state level, indicators whether a person lives at a metropolitan area or is disabled, industry, occupations, time and region fixed effects. Coefficients are allowed to vary by education and period.

[7] We display here Kelly's measure of skewness to de-emphasize the tails of the distribution that are possibly resulting from measurement error. Using the standard measure of skewness yields the same qualitative results.

Table D1: Changes in Distribution of Wage Growth

	10^{th} percentile *100			Skewness *100		
Period	HS	SC	C	HS	SC	C
1983–1993	-7.56	-8.96	-13.63	8.92	10.81	6.81
1994–2003	-8.3	-10.35	-14.84	5.03	3.66	5.38
2004–2013	-2.11	-3.54	-8.25	47.51	38.28	15.48

Notes: The table displays the 10^{th} percentile and Kelly's measure of skewness of the distribution of residual wage growth of job stayers. *HS*: at most a high school diploma; *SC*: some college; *C*: college degree.

E Moments for Estimating Wage Risk

The estimation of the dispersion of productivity shocks, σ_ϵ, and the job offer distribution, σ_ψ, proceeds in three steps. In the first step, we estimate Equations (7)-(10) using a nested trivariate probit, taking into account that mobility is only observed conditional on the individual having worked the current and previous quarter.[8] To simplify notation, we summarize the results from this estimation with the vector $X_{ih} = [\alpha z_{ih}, \alpha z_{ih-1}, \theta\kappa_{ih}, \rho_{\pi\pi_{-1}}, \rho_{\mu\pi}, \rho_{\mu\pi_{-1}}]$.

As we are interested in unexpected wage growth, in the second step, we construct residual wage growth, i.e., wage growth after controlling for worker observables, x_{ih}. Here, we have to take into account that we observe wage growth only for workers who endogenously choose to work in two consecutive periods:

$$
\begin{aligned}
E[\Delta w|P = P_{-1} = 1] &= E[\Delta w|P = P_{-1} = 1, M = 0]P(M = 0|P = P_{-1} = 1) \\
&+ E[\Delta w|P = P_{-1} = 1, M = 1]P(M = 1|P = P_{-1} = 1) \\
&= \beta\Delta x \\
&+ P(M = 0|P = P_{-1} = 1)\Bigg\{ \frac{\rho_{\epsilon\pi}\sigma_\epsilon\phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&- \frac{\rho_{\epsilon\mu}\sigma_\epsilon\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Bigg\} \\
&+ P(M = 1|P = P_{-1} = 1)\Bigg\{\sigma_\epsilon\Bigg[\frac{\rho_{\epsilon\pi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\epsilon\mu}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Bigg] \\
&+ \sigma_\xi\Bigg[\frac{\rho_{\pi\xi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\mu\xi}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&+ \frac{\rho_{\pi_{-1}\xi}\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Bigg]\Bigg\}.
\end{aligned}
$$

[8] We compute the multivariate normal probabilities using simulated maximum likelihood methods as in Cappellari and Jenkins (2006).

where

$$\Phi^{11}(y_1, y_2; \rho) = \int_{y_1}^{\infty} \int_{y_2}^{\infty} \phi(x_1, x_2, \rho) dx_1 dx_2,$$
$$\Phi^{111}(y_1, y_2, y_3; \Omega) = \int_{y_1}^{\infty} \int_{y_2}^{\infty} \int_{y_3}^{\infty} \phi(x_1, x_2, x_3, \Omega) dx_1 dx_2 dx_3,$$

and $\rho_{u_1 u_2 \cdot u_3}$ denotes the partial correlation of u_1 and u_2 controlling for u_3. For better readability, we dropped the i and h subscripts on the variables and refer to lagged variables simply by -1. This can be simplified to:

$$\begin{aligned}
&E[\Delta w | P = P_{-1} = 1] = \\
&\quad = \beta \Delta x \\
&\quad + P(M = 0 | P = P_{-1} = 1) \Bigg\{ \frac{\rho_{\epsilon\pi}\sigma_\epsilon \phi(-z\alpha) \Phi^{21}\left(\frac{-\kappa\theta + \rho_{\mu\pi} z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\pi\pi_{-1}} z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi} \right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&\quad - \frac{\rho_{\epsilon\mu}\sigma_\epsilon \phi(-\kappa\theta) \Phi^{11}\left(\frac{-z\alpha + \rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu} \right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \Bigg\} \\
&\quad + P(M = 1 | P = P_{-1} = 1) \Bigg\{ \frac{(\rho_{\epsilon\pi}\sigma_\epsilon + \rho_{\xi\pi}\sigma_\xi) \phi(-z\alpha) \Phi^{11}\left(\frac{-\kappa\theta + \rho_{\mu\pi} z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\pi\pi_{-1}} z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi} \right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&\quad + \frac{(\rho_{\epsilon\mu}\sigma_\epsilon + \rho_{\xi\mu}\sigma_\xi) \phi(-\kappa\theta) \Phi^{11}\left(\frac{-z\alpha + \rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu} \right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \\
&\quad + \frac{\rho_{\pi_{-1}\xi}\sigma_\xi \phi(-z_{-1}\alpha) \Phi^{11}\left(\frac{-z\alpha + \rho_{\pi\pi_{-1}} z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta + \rho_{\mu\pi_{-1}} z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}} \right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)} \Bigg\}.
\end{aligned}$$

where the probabilities $P(M = 0|P = P_{-1} = 1)$ and $P(M = 1|P = P_{-1} = 1)$ can be computed from the data, and $\rho_{\epsilon\pi}\sigma_\epsilon$, $\rho_{\epsilon\mu}\sigma_\epsilon$, $(\rho_{\epsilon\pi}\sigma_\epsilon + \rho_{\xi\pi}\sigma_\xi)$, $(\rho_{\epsilon\mu}\sigma_\epsilon + \rho_{\xi\mu}\sigma_\xi)$, and

$\rho_{\pi_{-1}\xi}\sigma_\xi$ are coefficients of an OLS regression:

$$C1 = \frac{\phi(-z\gamma)\phi(-z\gamma)\Phi^{21}(A_{12}, A_{13}; \rho_{\mu\pi_{-1}\cdot\pi})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1, x_3, \rho_{\pi\pi_{-1}})dx_1dx_3}$$
$$C2 = \frac{\phi(-\kappa\theta)\Phi^{11}(A_{21}, A_{23}; \rho_{\pi_{-1}\pi\cdot\mu})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1, x_3, \rho_{\pi\pi_{-1}})dx_1dx_3}$$
$$C3 = \frac{\phi(-z\gamma)\Phi^{11}(A_{12}, A_{13}; \rho_{\mu\pi_{-1}\cdot\pi})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1, x_3, \rho_{\pi\pi_{-1}})dx_1dx_3}$$
$$C4 = \frac{\phi(-z_{-1}\gamma)\Phi^{11}(A_{31}, A_{32}; \rho_{\mu\pi\cdot\pi_{-1}})}{\int_{-z\gamma}^{\infty}\int_{-z_{-1}\gamma}^{\infty}\phi(x_1, x_3, \rho_{\pi\pi_{-1}})dx_1dx_3},$$

where

$$\Phi^{21}(A_{12}, A_{13}; \rho_{\mu\pi_{-1}\cdot\pi}) = \Phi^{21}\left(\frac{-\kappa\theta + \rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right),$$
$$\Phi^{11}(A_{21}, A_{23}; \rho_{\pi_{-1}\pi\cdot\mu}) = \Phi^{11}\left(\frac{-z\alpha + \rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu}\right),$$
$$\Phi^{11}(A_{12}, A_{13}; \rho_{\mu\pi_{-1}\cdot\pi}) = \Phi^{11}\left(\frac{-\kappa\theta + \rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right),$$
$$\Phi^{11}(A_{31}, A_{32}; \rho_{\mu\pi\cdot\pi_{-1}}) = \Phi^{11}\left(\frac{-z\alpha + \rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta + \rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}}\right),$$
$$\Phi^{21}(y_1, y_2; \rho) = \int_{-\infty}^{y_1}\int_{y_2}^{\infty}\phi(x_1, x_2, \rho)dx_1dx_2.$$

Tables E2 – E4 display the resulting unbiased estimates for β.

Finally, in a third step, we estimate the parameters of interest $(\sigma_\epsilon, \sigma_\psi, \sigma_\iota)$ by minimizing the sum of squared residuals from the first and second moments of residual wage growth of job stayers and job movers, where we weighed each individual with the underlying survey weight. We additionally include autocovariance terms to identify the process of transitory wage changes, e_{ih}.[9] Following Horowitz (2003), we compute standard errors by block-bootstrapping. The key insight is that wage growth follows a truncated multivariate normal distribution, which first two moments are derived by Manjunath and Wilhelm (2012). The strength of selection es summarized by correlation coefficients between shocks and mobility and participation decisions. Denote the correlation between permanent productivity shocks and the unobserved component of participation by $\rho_{\epsilon\pi}$ and the correlation between the former and the unobserved component of mobility by $\rho_{\epsilon\mu}$. Further, define $\rho_{\xi\pi}$,

[9] We use a simplex method to find a local minimum and use 12 different starting points to ensure that we find the global minimum.

$\rho_{\xi\pi-1}$, and $\rho_{\xi\mu}$ to be the correlation between changes in the job component and shocks to participation in this period, last period, and mobility, respectively. Given these definitions, the first moment of residual wage growth of job stayers is given by

$$E(g|P = P_{-1} = 1, M = 0) = \frac{\rho_{\epsilon\pi}\sigma_\epsilon\phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$- \frac{\rho_{\epsilon\mu}\sigma_\epsilon\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}, \tag{E.1}$$

where

$$\Phi^{21}(y_1, y_2; \rho) = \int_{-\infty}^{y_1}\int_{y_2}^{\infty}\phi(x_1, x_2, \rho)dx_1dx_2,$$
$$\Phi^{121}(y_1, y_2, y_3; \Omega) = \int_{y_1}^{\infty}\int_{-\infty}^{y_2}\int_{y_3}^{\infty}\phi(x_1, x_2, x_3, \Omega)dx_1dx_2dx_3.$$

Further, the expected residual wage growth of job switchers is given by:

$$E(g|P = P_{-1} = 1, M = 1) =$$
$$= \sigma_\epsilon\Big[\frac{\rho_{\epsilon\pi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{\rho_{\epsilon\mu}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Big]$$
$$+ \sigma_\xi\Big[\frac{\rho_{\pi\xi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{\rho_{\mu\xi}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$+ \frac{\rho_{\pi_{-1}\xi}\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}\Big]. \tag{E.2}$$

The first moments alone identify the unknown selection terms ($\rho_{\epsilon\pi}$, $\rho_{\epsilon\mu}$, $\rho_{\xi\pi}$, $\rho_{\xi\pi-1}$, $\rho_{\xi\mu}$) up to the scalars σ_ϵ and σ_ξ. To identify the standard deviations separately, we require the variance of wage growth for job stayers and job switchers. The second moment for job stayers is

$$
\begin{aligned}
&E(g^2|P=P_{-1}=1,M=0)=\sigma_\epsilon^2\\
&\quad-\frac{z\alpha\rho_{\epsilon\pi}^2\sigma_\epsilon^2\phi(-z\alpha)\left(\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\pi\mu}z\alpha}{\sqrt{(1-\rho_{\pi\mu}^2)}},\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{(1-\rho_{\pi\pi_{-1}}^2)}},\rho_{\mu\pi_{-1}\cdot\pi}\right)\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\\
&\quad+\frac{\kappa\theta\rho_{\epsilon\mu}^2\sigma_\epsilon^2\phi(-\kappa\theta)\left(\Phi^{11}\left(\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{(1-\rho_{\mu\pi_{-1}}^2)}},\frac{-z\alpha+\rho_{\pi\mu}\kappa\theta}{\sqrt{(1-\rho_{\pi\mu}^2)}},\rho_{\pi\pi_{-1}\cdot\mu}\right)\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\\
&\quad-\frac{\rho_{\pi\epsilon}\rho_{\mu\epsilon}\sigma_\epsilon^2\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\left(1-\Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}\cdot\pi}^2)}}\right)\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\\
&\quad+\frac{\rho_{\pi\epsilon}^2\rho_{\mu\pi}\sigma_\epsilon^2\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\left(1-\Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}\cdot\pi}^2)}}\right)\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\\
&\quad-\frac{\rho_{\pi\epsilon}^2\rho_{\pi\pi-1}\sigma_\epsilon^2\phi(-z\alpha,-z_1\alpha,\rho_{\pi\pi_{-1}})\Phi\left(\frac{-\kappa\theta+\rho_{\pi\mu\cdot\pi_{-1}}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}z_{-1}\alpha}{\sqrt{(1-\rho_{\pi\mu}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}\cdot\pi}^2)}}\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\\
&\quad-\frac{\rho_{\epsilon\mu}\rho_{\pi\epsilon}\sigma_\epsilon^2\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\left(1-\Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}\cdot\mu}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}}^2)}}\right)\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\\
&\quad+\frac{\rho_{\epsilon\mu}^2\rho_{\pi\mu}\sigma_\epsilon^2\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\left(1-\Phi\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}\cdot\mu}^2)}\sqrt{(1-\rho_{\mu\pi_{-1}}^2)}}\right)\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\\
&\quad+\frac{\rho_{\epsilon\mu}^2\rho_{\pi_{-1}\mu}\sigma_\epsilon^2\phi(-z_{-1}\alpha,-\kappa\theta,\rho_{\mu\pi_{-1}})\left(1-\Phi\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z_{-1}\alpha+\rho_{\mu\pi\cdot\pi_{-1}}\kappa\theta}{\sqrt{(1-\rho_{\pi\pi_{-1}\cdot\mu}^2)}\sqrt{(1-\rho_{\mu\pi}^2)}}\right)\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}+Var(\Delta e)
\end{aligned}
$$

where $Var(\Delta e)$ refers to the variance of the transitory component. This equation makes explicit that the true variance σ_ϵ^2 is different from the one observed in the data for job stayers because the latter are a self-selected group. Selection has three aspects. First, part of the true shocks are not observed as workers decide quitting into non-employment given a sufficiently large shock. Second, given that the workers has not switched his job, the realized shock cannot have triggered mobility. Third, the interaction of these two effects and a correction for the autocorrelation in participation decisions enters the selection term.

The variance of wage growth of job switchers is given by:

$$
\begin{aligned}
E(g^2|P=P_{-1}=1,M=1) = \sigma_\epsilon^2\Big[1 &- \frac{\rho^2_{\epsilon\pi} z\alpha\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&- \frac{\rho^2_{\epsilon\mu} \kappa\theta\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \rho_{\pi\epsilon}\Big(\frac{\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}\sqrt{1-\rho^2_{\mu\pi_{-1}\cdot\pi}}}\right)(\rho_{\mu\epsilon}-\rho_{\mu\pi}\rho_{\pi\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-z\alpha,-z_{-1}\alpha,\rho_{\pi\pi_{-1}})\Phi^{1}\left(\frac{-\kappa\theta+\tilde\rho_{\mu\pi}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}z_{-1}\alpha}{\sqrt{1-\rho^2_{\mu\pi}}\sqrt{1-\rho^2_{\mu\pi_{-1}\cdot\pi}}}\right)(-\rho_{\pi\pi_{-1}}\rho_{\pi\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \rho_{\mu\epsilon}\Big(\frac{\phi(-\kappa\theta,-z\alpha,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}\sqrt{1-\rho^2_{\pi\pi_{-1}\cdot\mu}}}\right)(\rho_{\pi\epsilon}-\rho_{\mu\pi}\rho_{\mu\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-\kappa\theta,-z_{-1}\alpha,\rho_{\mu\pi_{-1}})\Phi^{1}\left(\frac{-z\alpha+\tilde\rho_{\mu\pi}\kappa\theta+\rho_{\pi\pi_{-1}\cdot\mu}z_{-1}\alpha}{\sqrt{1-\rho^2_{\mu\pi}}\sqrt{1-\rho^2_{\pi\pi_{-1}\cdot\mu}}}\right)(-\rho\mu\pi_{-1}\rho_{\mu\epsilon})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big)\Big] \\
+ \sigma_\xi^2\Big[1 &- \frac{\rho^2_{\xi\pi} z\alpha\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&- \frac{\rho^2_{\xi\mu} \kappa\theta\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&- \frac{\rho^2_{\xi\pi_{-1}} z_{-1}\alpha\phi(z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \rho_{\pi\xi}\Big(\frac{\phi(-z\alpha,-\kappa\theta,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}\kappa\theta}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}\sqrt{1-\rho^2_{\mu\pi_{-1}\cdot\pi}}}\right)(\rho_{\mu\xi}-\rho_{\mu\pi}\rho_{\pi\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-z\alpha,-z_{-1}\alpha,\rho_{\pi\pi_{-1}})\Phi^{1}\left(\frac{-\kappa\theta+\tilde\rho_{\mu\pi}z\alpha+\rho_{\mu\pi_{-1}\cdot\pi}z_{-1}\alpha}{\sqrt{1-\rho^2_{\mu\pi}}\sqrt{1-\rho^2_{\mu\pi_{-1}\cdot\pi}}}\right)(\rho_{\pi_{-1}\xi}-\rho_{\pi\pi_{-1}}\rho_{\pi\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big) \\
&+ \rho_{\mu\xi}\Big(\frac{\phi(-\kappa\theta,-z\alpha,\rho_{\mu\pi})\Phi^{1}\left(\frac{-z_{-1}\alpha+\tilde\rho_{\mu\pi_{-1}}\kappa\theta+\rho_{\pi\pi_{-1}\cdot\mu}z\alpha}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}\sqrt{1-\rho^2_{\pi\pi_{-1}\cdot\mu}}}\right)(\rho_{\pi\xi}-\rho_{\mu\pi}\rho_{\mu\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-\kappa\theta,-z_{-1}\alpha,\rho_{\mu\pi_{-1}})\Phi^{1}\left(\frac{-z\alpha+\tilde\rho_{\mu\pi}\kappa\theta+\rho_{\pi\pi_{-1}\cdot\mu}z_{-1}\alpha}{\sqrt{1-\rho^2_{\mu\pi}}\sqrt{1-\rho^2_{\pi\pi_{-1}\cdot\mu}}}\right)(\rho_{\pi_{-1}\xi}-\rho\mu\pi_{-1}\rho_{\mu\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big) \\
&+ \rho_{\pi_{-1}\xi}\Big(\frac{\phi(-z_{-1}\alpha,-z\alpha,\rho_{\pi\pi_{-1}})\Phi^{1}\left(\frac{-\kappa\theta+\rho_{\mu\pi_{-1}\cdot\pi}z_{-1}\alpha+\tilde\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}\sqrt{1-\tilde\rho^2_{\mu\pi}}}\right)(\rho_{\pi\xi}-\rho_{\pi\pi_{-1}}\rho_{\pi_{-1}\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+ \frac{\phi(-z_{-1}\alpha,\kappa\theta,\rho_{\mu\pi_{-1}})\Phi^{1}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}\cdot\mu}z_{-1}\alpha+\tilde\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}\sqrt{1-\tilde\rho^2_{\mu\pi}}}\right)(\rho_{\mu\xi}-\rho_{\mu\pi_{-1}}\rho_{\pi_{-1}\xi})}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big)\Big] + Var(\Delta e),
\end{aligned}
$$

where the variance of the job offer distribution follows from $\sigma_\psi^2 = \frac{\sigma_\xi^2}{2}$. Regarding interpretation, a similar logic as for job stayers applies with the important difference that there is now an innovation to the job component. Regarding the latter, additional correction terms arise through its correlation to past participation decisions. The variance of the transitory component is given by

$$Var(\Delta e) = \sigma_i^2\Big[1 + (1+\chi_1)^2 + (\chi_2 - \chi_1)^2 + \chi_2^2\Big].$$

We identify the parameters of this process by the autocovariance function of wage growth up to lag 3. Note that σ_ϵ^2 and σ_ξ^2 do not influence these moments.[10]

$$Cov(g, g_{-1}) = \sigma_i^2\Big[-(1+\chi_1) + (1+\chi_1)(\chi_2 - \chi_1) - \chi_2(\chi_2 - \chi_1)\Big]$$

$$Cov(g, g_{-2}) = \sigma_i^2\Big[-(\chi_2 - \chi_1) - (1+\chi_1)\chi_2\Big]$$

$$Cov(g, g_{-3}) = \sigma_i^2\chi_2.$$

To gain some intuition for identification, note that the first moments together with the estimates from Equations (7)-(10) allow us to control for the strength of selection. To see this, consider again the first moment of unexplained wage growth (in implicit form) for job stayers:

$$E(g_{ih}|P_{ih} = P_{ih-1} = 1, M_{ih} = 0) = \rho_{\epsilon\pi}\sigma_\epsilon\phi(-z_{ih}\alpha)f_1(X_{ih}) - \rho_{\epsilon\mu}\sigma_\epsilon\phi(\theta\kappa_{ih})f_2(X_{ih}).$$

The first moment of job stayers identifies the correlations between permanent productivity shocks and participation and mobility decisions up to the scalar σ_ϵ. Identification results from comparing the unexplained wage growth of individuals with different participation and mobility probabilities, $\phi(-z_{ih}\alpha)$ and $\phi(\theta\kappa_{ih})$. For example, if negative productivity shocks reduce participation, then observed average wage growth will be relatively high for individuals who are relatively close to their participation threshold, $\phi(-z_{ih}\alpha)$ small, because such individuals would not continue working after receiving a negative productivity shock and, hence, would no longer be observed. Put differently, the observed productivity shocks would be more left-truncated for those close to the participation threshold leading to higher observed wage growth relative to workers far away from their participation thresholds.

To better understand the importance of controlling for selection, suppose we would observe random realizations of productivity shocks and workers would move randomly between jobs. In that case, the second moments of unexplained wage growth, g_{ih}, of job

[10]We assume $P(M_{it} = 1|M_{it-1} = 1, M_{it-2} = 1, M_{it-3} = 1, M_{it-4} = 1) = 0$. Estimating the transitory shock process only on job stayers gives practically the same results.

Table E1: Changes in Labor Market Risk

	High School		Some College		College	
	Not accounting for selection					
Period	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ
1983–1993	0.029	0.265	0.040	0.243	0.046	0.270
1994–2003	0.017	0.268	0.041	0.252	0.044	0.266
2004–2013	0.039	0.268	0.019	0.319	0.051	0.315
	Baseline					
Period	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ
1983–1993	0.030	0.260	0.042	0.217	0.050	0.267
1994–2003	0.035	0.262	0.047	0.225	0.048	0.265
2004–2013	0.040	0.225	0.047	0.235	0.058	0.300

Notes: The first panel displays the standard deviation of productivity shocks and the standard deviation of the job offer distribution that result from an estimation that ignores the selection of workers. The second panel displays those to the baseline model estimates from Section 3.2.2.

stayers and job switchers would be, respectively, given by

$$E(g_{ih}^2) = \begin{cases} \sigma_\epsilon^2 + Var(\Delta e_{it}) & \text{if } M_{ih} = 0, \\ \sigma_\epsilon^2 + 2\sigma_\psi^2 + Var(\Delta e_{it}) & \text{if } M_{ih} = 1. \end{cases}$$

Table E1 compares the result of estimating this model to our baseline estimates. When ignoring selection, not only would we incorrectly estimate the level of risk, we would also make mistakes in estimating the changes in risk over time. Most strikingly, different from our baseline results, we would estimate that productivity risk declines by 50% for workers with some college education. Moreover, we would have over-estimated the increase in the job component for workers with at least some college and conclude that it remains flat for high school workers.

The difference relative to the baseline estimates result from more workers being close to their participation thresholds in the later periods relative to the 80's (see the next appendix), and, hence, these workers being more likely to no longer work after poor shocks which make these shocks partially non-observed. The results in Table D1 are consistent with this intuition. That is, a decline in negative skewness of the residual wage growth distribution over time suggests that workers become less likely to stay employed after large negative productivity shocks. We note, however, that this is only suggestive evidence. These moments of the residual wage growth distribution do not distinguish between wage growth resulting from productivity shocks and those resulting from measurement error. Hence, we cannot distinguish between changes driven by changes in selection and changes in the process of measurement error over time. The econometric model described above, however, does exactly that.

Table E2: Wage Growth Regression: High School

	Wage growth (1983-1993)	**Wage growth** (1994-2003)	**Wage growth** (2004-2013)
Age	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)
Age_sq	0.001 (0.000)	0.000 (0.000)	0.000 (0.001)
Married	-0.000 (0.001)	-0.000 (0.002)	0.001 (0.002)
Δ Married	0.007 (0.004)	0.016 (0.007)	0.009 (0.013)
White	0.000 (0.002)	-0.003 (0.002)	0.000 (0.002)
Unemp (%)	-0.066 (0.026)	0.094 (0.070)	-0.076 (0.060)
Δ Unemp (%)	0.053 (0.160)	0.375 (0.336)	0.078 (0.251)
Exper	-0.001 (0.002)	0.011 (0.008)	-0.009 (0.007)
Exper_sq	0.000 (0.001)	-0.002 (0.002)	0.002 (0.002)
Δ Metro	0.007 (0.005)	0.016 (0.015)	0.009 (0.019)
Metro	0.001 (0.001)	-0.001 (0.002)	0.001 (0.002)
Disability	-0.000 (0.002)	-0.005 (0.004)	-0.002 (0.004)
Δ Disability	-0.027 (0.033)	0.001 (0.006)	-0.011 (0.009)
Year dummies	2.57 (10 df)	0.92 (9 df)	2.79 (9 df)
Regional dummies	0.43 (3 df)	0.55 (3 df)	0.14 (3 df)
Δ Regional dummies	1.94 (3 df)	0.92 (3 df)	0.58 (3 df)
Quarter dummies	8.52 (3 df)	3.81 (3 df)	13.31 (3 df)
Industry dummies	2.93 (6 df)	0.79 (6 df)	0.38 (6 df)
Δ Occupation dummies	5.80 (9 df)	4.12 (9 df)	1.09 (9 df)
Δ Industry dummies	4.77 (6 df)	1.50 (6 df)	2.45 (6 df)
C1	0.009 (0.012)	0.014 (0.024)	0.006 (0.016)
C2	0.017 (0.028)	0.064 (0.040)	0.023 (0.060)
C3	0.624 (0.637)	0.388 (0.392)	-0.074 (0.345)
C4	-0.257 (0.352)	-0.917 (0.662)	-0.203 (1.137)
Constant	-0.000 (0.008)	-0.021 (0.015)	0.014 (0.018)
Obs	98956	38362	22483

Notes: The table displays the estimate of equation (6) in the main text. Standard errors are reported in parentheses. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance and the tests' constraint degrees of freedom in parenthesis.

Table E3: Wage Growth Regression: Some College

	Wage growth (1983-1993)	**Wage growth** (1994-2003)	**Wage growth** (2004-2013)
Age	-0.001 (0.001)	-0.002 (0.002)	-0.002 (0.001)
Age_sq	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Married	-0.001 (0.002)	0.004 (0.002)	0.003 (0.002)
Δ Married	-0.002 (0.006)	0.010 (0.009)	0.013 (0.014)
White	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
Unemp (%)	-0.082 (0.047)	-0.064 (0.104)	-0.085 (0.057)
Δ Unemp (%)	-0.098 (0.226)	-0.861 (0.634)	0.243 (0.224)
Exper	0.005 (0.005)	0.008 (0.011)	-0.006 (0.009)
Exper_sq	-0.001 (0.001)	-0.001 (0.002)	0.001 (0.002)
Δ Metro	0.009 (0.008)	0.044 (0.023)	-0.008 (0.019)
Metro	-0.001 (0.002)	0.003 (0.003)	-0.001 (0.002)
Disability	0.001 (0.003)	-0.003 (0.005)	0.000 (0.004)
Δ Disability	0.090 (0.050)	-0.020 (0.009)	-0.001 (0.010)
Year dummies	1.74 (10 df)	1.46 (9 df)	3.40 (9 df)
Regional dummies	0.67 (3 df)	0.08 (3 df)	0.75 (3 df)
Δ Regional dummies	1.50 (3 df)	0.96 (3 df)	0.76 (3 df)
Quarter dummies	1.78 (3 df)	8.13 (3 df)	5.06 (3 df)
Industry dummies	0.48 (6 df)	0.60 (6 df)	0.03 (6 df)
Δ Occupation dummies	3.29 (9 df)	2.52 (9 df)	2.69 (9 df)
Δ Industry dummies	5.13 (6 df)	2.47 (6 df)	1.25 (6 df)
C1	0.012 (0.025)	0.033 (0.037)	-0.005 (0.024)
C2	0.034 (0.037)	0.047 (0.050)	-0.026 (0.071)
C3	-3.813 (1.306)	0.273 (0.434)	0.071 (0.587)
C4	8.725 (3.543)	-0.650 (2.068)	0.111 (0.228)
Constant	0.003 (0.009)	-0.023 (0.020)	0.053 (0.018)
Obs	35903	20346	21815

Notes: The table displays the estimate of equation (6) in the main text. Standard errors are reported in parentheses. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance and the tests' constraint degrees of freedom in parenthesis.

Table E4: Wage Growth Regression: College

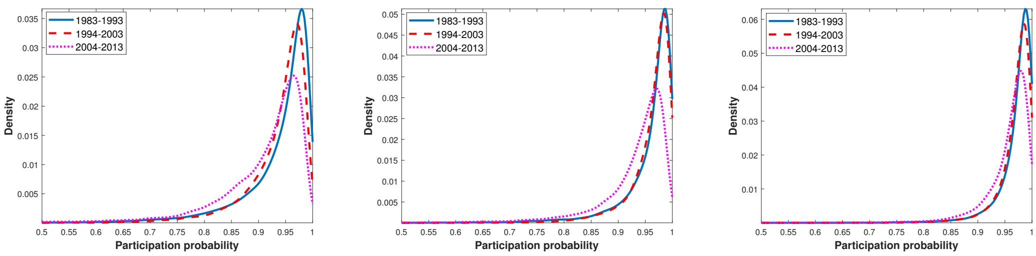
	Wage growth (1983-1993)	**Wage growth** (1994-2003)	**Wage growth** (2004-2013)
Age	-0.001 (0.001)	-0.002 (0.001)	-0.002 (0.001)
Age_sq	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)
Married	0.003 (0.002)	0.001 (0.002)	0.002 (0.002)
Δ Married	0.032 (0.010)	0.024 (0.011)	0.004 (0.008)
White	0.004 (0.003)	0.005 (0.003)	0.004 (0.002)
Unemp (%)	-0.051 (0.041)	-0.024 (0.087)	-0.126 (0.049)
Δ Unemp (%)	-0.113 (0.244)	-0.016 (0.412)	0.354 (0.223)
Exper	0.005 (0.004)	0.007 (0.009)	-0.005 (0.007)
Exper_sq	-0.001 (0.001)	-0.002 (0.002)	0.002 (0.002)
Δ Metro	0.009 (0.008)	-0.030 (0.024)	0.017 (0.026)
Metro	0.000 (0.002)	-0.001 (0.002)	0.003 (0.002)
Disability	-0.006 (0.004)	-0.005 (0.006)	-0.004 (0.005)
Δ Disability	0.006 (0.036)	0.011 (0.010)	0.010 (0.010)
Year dummies	2.63 (10 df)	1.00 (9 df)	9.10 (9 df)
Regional dummies	0.40 (3 df)	0.29 (3 df)	1.15 (3 df)
Δ Regional dummies	0.63 (3 df)	0.18 (3 df)	0.76 (3 df)
Quarter dummies	5.25 (3 df)	5.99 (3 df)	12.58 (3 df)
Industry dummies	2.20 (6 df)	0.80 (6 df)	0.98 (6 df)
Δ Occupation dummies	6.22 (9 df)	3.64 (9 df)	3.83 (9 df)
Δ Industry dummies	4.77 (6 df)	5.33 (6 df)	1.16 (6 df)
C1	-0.003 (0.030)	0.053 (0.037)	0.031 (0.024)
C2	0.062 (0.038)	0.031 (0.042)	0.077 (0.048)
C3	0.978 (1.743)	-4.304 (3.662)	0.814 (2.126)
C4	-1.437 (2.017)	52.256 (31.799)	-4.767 (5.111)
Constant	-0.005 (0.009)	0.001 (0.016)	0.050 (0.014)
Obs	64498	39613	41890

Notes: The table displays the estimate of equation (6) in the main text. Standard errors are reported in parentheses. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance and the tests' constraint degrees of freedom in parenthesis.

F Participation and Mobility over Time

Figure F1: Participation Probabilities over Time

(A) High School (B) Some College (C) College



Notes: The figure displays the density of participation probabilities estimated in Section 3.2. We compute the density by a Gaussian kernel density estimator with bandwidth 0.01.

This appendix shows the results from the probit regression from Section 3.2. Figure F1 shows changes in the density of participation probabilities over time. In specific, we calculate for each observation of an employed worker the participation probability implied by the Probit regression, $\Phi(\hat{\alpha} z_{ih})$, and obtain the density by a Gaussian kernel density estimator. The figure highlights that the distribution of participation probabilities has shifted to the left over time. In particular, there are more workers with relatively low participation probabilities. The shift is particularly pronounced for low-educated workers and in the period 2003–2014. Tables F1 – F3 display the underlying coefficient estimates. We observe fewer changes in the distribution of mobility over time. Mainly, the distribution of mobility likelihoods has increased in 1993–2003 relative to the first period, but it has shifted mostly back by 2004–2013. These results are available upon request from the authors.

Table F1: Nested Trivariate Probit: High School

	Participation (1983-1993)	**Participation** (1994-2003)	**Participation** (2004-2013)
Age	0.069 (0.006)	0.045 (0.009)	-0.008 (0.011)
Age_sq	-0.024 (0.003)	-0.015 (0.005)	-0.016 (0.006)
UI	0.001 (0.001)	-0.001 (0.001)	-0.002 (0.001)
Log(Other Income)	-0.096 (0.002)	-0.086 (0.002)	-0.119 (0.003)
Housing	0.359 (0.011)	0.261 (0.018)	0.340 (0.026)
Disability	-0.644 (0.014)	-0.479 (0.022)	-0.557 (0.020)
Exper	0.246 (0.020)	0.470 (0.036)	0.025 (0.050)
Exper_sq	-0.067 (0.006)	-0.102 (0.009)	0.053 (0.012)
Metro	0.073 (0.012)	0.062 (0.021)	0.114 (0.021)
Married	0.361 (0.011)	0.278 (0.018)	0.119 (0.019)
State Unemp (%)	-9.444 (0.289)	-9.891 (0.720)	-5.215 (0.526)
White	0.527 (0.013)	0.363 (0.022)	0.190 (0.022)
Year dummies	136.04 (10 df)	26.62 (9 df)	33.19 (9 df)
Regional dummies	26.19 (3 df)	51.38 (3 df)	12.20 (3 df)
Quarter dummies	22.47 (3 df)	11.21 (3 df)	33.04 (3 df)
Constant	1.495 (0.046)	1.541 (0.088)	1.612 (0.095)
	Mobility (1983-1993)	**Mobility** (1994-2003)	**Mobility** (2004-2013)
Age	-0.077 (0.008)	-0.055 (0.013)	-0.032 (0.018)
Age_sq	0.017 (0.005)	-0.003 (0.008)	-0.000 (0.011)
UI	-0.002 (0.001)	-0.000 (0.001)	-0.002 (0.002)
Log(Other Income)	-0.007 (0.003)	0.004 (0.004)	0.008 (0.008)
Housing	-0.152 (0.017)	-0.202 (0.025)	-0.064 (0.035)
Exper	-0.330 (0.035)	-0.710 (0.060)	-0.300 (0.084)
Exper_sq	0.086 (0.009)	0.162 (0.015)	0.039 (0.022)
Disability	0.227 (0.025)	0.302 (0.036)	-0.035 (0.075)
Metro	0.054 (0.018)	0.050 (0.027)	-0.050 (0.037)
Married	-0.042 (0.017)	0.005 (0.024)	0.086 (0.033)
State Unemp (%)	-1.304 (0.450)	-1.348 (0.997)	-4.610 (1.006)
White	0.038 (0.023)	-0.020 (0.032)	-0.026 (0.040)
Year dummies	150.24 (10 df)	17.38 (9 df)	17.00 (9 df)
Regional dummies	58.89 (3 df)	25.53 (3 df)	28.20 (3 df)
Quarter dummies	17.08 (3 df)	7.13 (3 df)	6.62 (3 df)
Industry dummies	243.02 (6 df)	39.75 (6 df)	18.09 (6 df)
Occupation dummies	72.76 (9 df)	34.03(9 df)	28.20 (9 df)
Constant	-1.095 (0.098)	-0.724 (0.165)	-0.921 (0.243)
Obs	108831	42121	26339

Notes: The table displays the estimate of equations (13)-(15) in the main text. Standard errors are reported in parentheses and are based on asymptotic distributions. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance and the tests' constraint degrees of freedom in parenthesis.

Table F2: Nested Trivariate Probit: Some College

	Participation (1983-1993)	**Participation** (1994-2003)	**Participation** (2004-2013)
Age	0.032 (0.012)	0.043 (0.016)	-0.052 (0.012)
Age_sq	-0.008 (0.007)	-0.029 (0.009)	0.001 (0.007)
UI	-0.004 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Log(Other Income)	-0.100 (0.003)	-0.105 (0.005)	-0.109 (0.003)
Housing	0.287 (0.022)	0.335 (0.031)	0.217 (0.023)
Disability	-0.650 (0.026)	-0.536 (0.036)	-0.473 (0.030)
Exper	0.219 (0.046)	0.432 (0.071)	0.191 (0.065)
Exper_sq	-0.069 (0.012)	-0.092 (0.018)	0.043 (0.017)
Metro	0.024 (0.026)	0.057 (0.037)	0.066 (0.026)
Married	0.408 (0.022)	0.202 (0.030)	0.181 (0.022)
State Unemp (%)	-8.791 (0.614)	-10.879 (1.229)	-3.642 (0.574)
White	0.458 (0.027)	0.282 (0.037)	0.109 (0.025)
Year dummies	113.04 (10 df)	53.57 (9 df)	59.55 (9 df)
Regional dummies	74.18 (3 df)	21.46 (3 df)	16.82 (3 df)
Quarter dummies	5.22 (3 df)	22.47 (3 df)	41.02 (3 df)
Constant	2.144 (0.098)	2.191 (0.149)	1.422 (0.115)
	Mobility (1983-1993)	**Mobility** (1994-2003)	**Mobility** (2004-2013)
Age	-0.086 (0.015)	-0.125 (0.018)	-0.061 (0.021)
Age_sq	0.024 (0.009)	0.043 (0.011)	0.017 (0.011)
UI	-0.001 (0.001)	0.002 (0.002)	0.004 (0.002)
Log(Other Income)	-0.000 (0.005)	0.008 (0.007)	0.005 (0.008)
Housing	-0.201 (0.028)	-0.198 (0.038)	-0.090 (0.037)
Exper	-0.116 (0.070)	-0.510 (0.098)	-0.013 (0.134)
Exper_sq	0.044 (0.018)	0.107 (0.024)	-0.022 (0.033)
Disability	0.066 (0.042)	0.235 (0.056)	0.128 (0.076)
Metro	0.126 (0.032)	-0.112 (0.041)	-0.035 (0.042)
Married	-0.094 (0.028)	-0.047 (0.035)	-0.038 (0.035)
State Unemp (%)	0.802 (0.779)	-0.180 (1.516)	-3.042 (1.030)
White	0.137 (0.041)	0.038 (0.049)	-0.041 (0.040)
Year dummies	65.42 (10 df)	14.74 (9 df)	12.97 (9 df)
Regional dummies	14.97 (3 df)	1.80 (3 df)	10.48 (3 df)
Quarter dummies	8.58 (3 df)	6.22 (3 df)	3.69 (3 df)
Industry dummies	118.70 (6 df)	58.54 (6 df)	92.33 (6 df)
Occupation dummies	67.53 (9 df)	42.48 (9 df)	26.80 (9 df)
Constant	-1.325 (0.197)	-0.479 (0.292)	-0.266 (0.313)
Obs	38086	21558	24455

Notes: The table displays the estimate of equations (13)-(15) in the main text. Standard errors are reported in parentheses and are based on asymptotic distributions. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance and the tests' constraint degrees of freedom in parenthesis.

Table F3: Nested Trivariate Probit: College

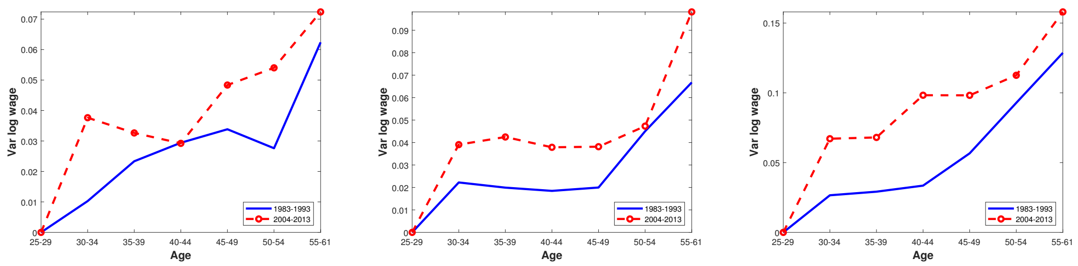
	Participation (1983-1993)	**Participation** (1994-2003)	**Participation** (2004-2013)
Age	0.055 (0.010)	0.066 (0.013)	-0.011 (0.011)
Age_sq	-0.031 (0.006)	-0.040 (0.007)	-0.033 (0.006)
UI	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)
Log(Other Income)	-0.112 (0.003)	-0.113 (0.004)	-0.102 (0.003)
Housing	0.333 (0.020)	0.257 (0.025)	0.235 (0.021)
Disability	-0.662 (0.027)	-0.657 (0.038)	-0.473 (0.034)
Exper	0.289 (0.037)	0.329 (0.058)	0.193 (0.054)
Exper_sq	-0.088 (0.010)	-0.082 (0.014)	0.032 (0.014)
Metro	0.086 (0.024)	0.098 (0.032)	0.096 (0.026)
Married	0.372 (0.019)	0.228 (0.024)	0.171 (0.019)
State Unemp (%)	-6.558 (0.524)	-5.306 (0.975)	-3.831 (0.503)
White	0.406 (0.025)	0.351 (0.030)	0.101 (0.023)
Year dummies	146.28 (10 df)	71.64 (9 df)	59.39 (9 df)
Regional dummies	40.51 (3 df)	10.26 (3 df)	12.81 (3 df)
Quarter dummies	6.70 (3 df)	6.90 (3 df)	22.66 (3 df)
Constant	2.063 (0.086)	1.874 (0.120)	1.777 (0.095)
	Mobility (1983-1993)	**Mobility** (1994-2003)	**Mobility** (2004-2013)
Age	-0.075 (0.012)	-0.041 (0.015)	-0.026 (0.016)
Age_sq	0.016 (0.008)	-0.011 (0.009)	0.002 (0.009)
UI	-0.003 (0.001)	-0.001 (0.001)	-0.000 (0.001)
Log(Other Income)	-0.012 (0.004)	-0.010 (0.005)	-0.015 (0.006)
Housing	-0.187 (0.023)	-0.181 (0.029)	-0.202 (0.029)
Exper	-0.139 (0.053)	-0.558 (0.073)	0.079 (0.088)
Exper_sq	0.046 (0.014)	0.132 (0.018)	-0.036 (0.022)
Disability	0.241 (0.039)	0.232 (0.059)	0.072 (0.074)
Metro	0.012 (0.028)	0.018 (0.037)	-0.052 (0.036)
Married	-0.102 (0.023)	-0.027 (0.027)	0.077 (0.026)
State Unemp (%)	0.652 (0.624)	-0.628 (1.161)	1.384 (0.776)
White	-0.036 (0.032)	0.009 (0.037)	-0.026 (0.031)
Year dummies	73.81 (10 df)	32.87 (9 df)	40.88 (9 df)
Regional dummies	11.14 (3 df)	13.78 (3 df)	10.70 (3 df)
Quarter dummies	11.65 (3 df)	15.41 (3 df)	14.13 (3 df)
Industry dummies	78.12 (6 df)	91.35 (6 df)	58.17 (6 df)
Occupation dummies	94.32 (9 df)	76.86 (9 df)	72.33 (9 df)
Constant	-0.871 (0.194)	-0.701 (0.261)	-1.371 (0.254)
Obs	67018	41350	44764

Notes: The table displays the estimate of equations (13)-(15) in the main text. Standard errors are reported in parentheses and are based on asymptotic distributions. For region, year, quarter, industry and occupation dummies we report the value of the χ^2 statistics of joint significance and the tests' constraint degrees of freedom in parenthesis.

G Further Life Cycle Moments

Figure G1: Inequality over the Life Cycle

(A) High School (B) Some College (C) College



Notes: The figure displays for three different education groups the variance of log residual wages over the life cycle for two different time periods. We obtain residual wages by regressing cross sectional log wages on a square-terms in workers' age and experience, marriage status, race, a dummy for work disability, and time and regional dummies. We then construct 5-year age bins as well as worker cohorts based on their labor market entry. For each cohort/age group, we compute the variance of cross sectional residual wages. Finally, we regress this variance on a full set of age and cohort fixed effects where the figures display the resulting age fixed-effects.

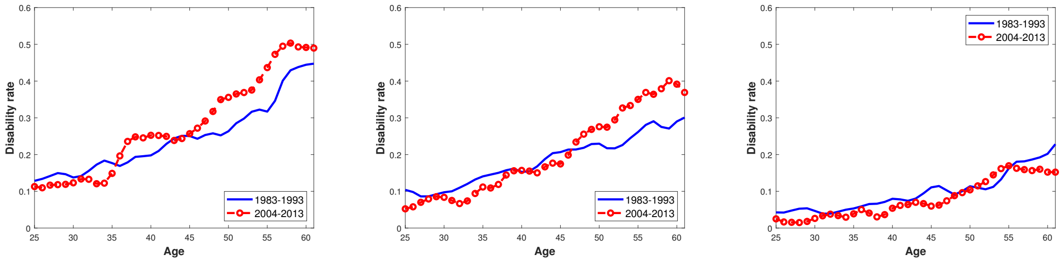
Our identification of individual risk uses the first and second moments of (corrected for selection) residual wage growth. Previous literature, e.g., Heathcote et al. (2010), identifies the variance of permanent risk from the life cycle behavior of the cross sectional variance of residual wages. Section 4.1 shows that using moments of cross sectional inequality over the life cycle to identify the dispersion of the underlying shocks suffers from similar selection problems as using moments of wage growth. Moreover, as we show in the paper, identifying secular changes in risk from moments of cross sectional inequality is problematic when changes in risk lead to changes in the employment rate. Indeed, the decrease in employment rates over time in the U.S. suggests that cross sectional inequality increases by less in response to changes in risk than under the hypothetical case where employment rates are held constant. Nevertheless, Figure G1 shows that cross sectional wage inequality indeed grows by more over the life cycle in the period 2004–2014 than in the period 1983–1994.

Interpreting these figures comes with one caveat beyond the changes in selection. To make the comparison across time periods valid, one needs to assume that we observe a stationary distribution in each of the periods. However, those aged 50+ in 2004–2014 have all already worked in the period 1983–1994. That is, some of the shocks these workers have experienced that result in the inequality we observe among them in 2004–2014 actually reflect labor market conditions from 1983–1994 when, as we find, productivity shocks have been less dispersed. Obviously, when studying moments of wage growth in each period, we avoid this issue.

Figure G2 displays the rate of workers reporting that they have "indicated having a physical, mental, or other health condition which limits the kind or amount of work he can do". The rate is declining in education possibly reflecting that low-skilled occupations

Figure G2: Disability over the Life Cycle

(A) High School (B) Some College (C) College

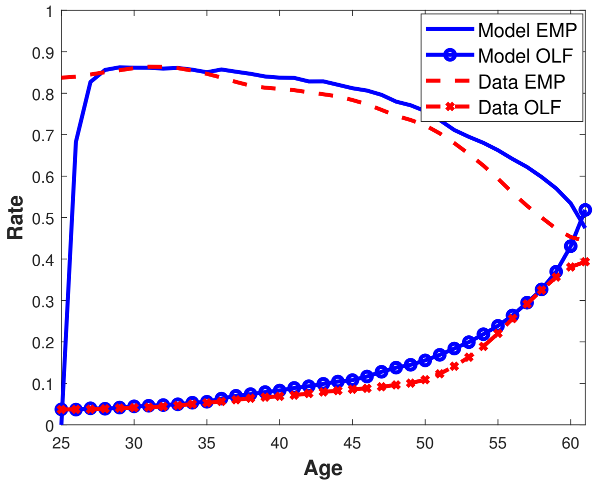


Notes: The figure displays for three different education groups the rate of workers reporting a disability that limits the type of work they can perform over the life cycle for two different time periods.

are physically more demanding. Moreover, the rates are higher in the 2004–2014 period compared to the 1983–1994 period for workers with less than a college degree. The rate of workers with a college degree shows little changes over time.

H Moments for 2004–2013

Figure H1: Employment over the life-cycle profiles



Notes: The figure displays the employment rate, *EMP*, and the out of the labor force rate, *OLF*, in the model and the *SIPP* data from 2004–2013.

Section 3.4 in the main body compares untargeted moments of the calibrated model to the data for the period 1983–1993. Figure H1 shows that the recalibrated model is also matching well employment choices and labor force participation choices over the life cycle in the 2004–2013 period. Moreover, the first panel of Table H1 shows that the model is also consistent with moments of residual cross sectional inequality and rising residual cross sectional inequality over the life cycle in the latter period. Similarly, the second panel displays the model fit with regard to moments of wage growth. Finally, the last panel shows that the model is consistent with the fact that many individuals hold very little net wealth.

Table H1: Untargeted Moments 2004-2013

	Model			Data		
	HS	SC	C	HS	SC	C
$Var(w_{it})$	0.17	0.21	0.31	0.18	0.20	0.25
90/10 ratio	3.00	3.30	4.18	2.96	3.18	3.66
$Gini(w_{it})$	0.24	0.26	0.31	0.24	0.25	0.28
$\Delta Var(w_{it})$*100	2.76	7.39	21.28	7.24	9.82	15.80
Δ90/10 ratio	0.28	0.76	2.27	0.95	1.28	1.61
$\Delta Gini(w_{it})$*100	1.74	4.87	10.79	7.29	8.41	11.14
$\sigma_{stayers}$	0.10	0.11	0.11	0.07	0.08	0.10
σ_{movers}	0.33	0.34	0.44	0.38	0.45	0.45
Wage loss ENE	-0.07	-0.07	-0.10	-0.04	-0.07	-0.03
Wage gain JTJ	0.27	0.28	0.36	0.25	0.31	0.32
Wage loss JTJ	-0.27	-0.27	-0.35	-0.25	-0.28	-0.29
Wealth 25^{th} perc. (1000)	1.01	1.18	28.55	0.52	0.68	10.98
Wealth *EU* replacement	1.78	3.75	10.99	0.71	3.08	6.70

Notes: The table compares model implied moments to the *SIPP* in 2004–2013. *HS*: at most a high school diploma; *SC*: some college; *C*: college degree; $Var(w_{it})$: the variance of log residual wages; 90/10 *ratio*: the 90/10 ratio of residual wages; $Gini(w_{it})$: the Gini-coefficient of residual wages. We construct residuals by regressing cross sectional log wages on a square-terms in workers' age and experience, marriage status, race, a dummy for work disability, and time and regional dummies. Finally, we add back the unconditional mean log wage. $\Delta Var(w_{it})$: the change in the variance of log residual wages over the life-cycle. To compute this, we construct 5-year age bins as well as worker cohorts based on their labor market entry (data only). For each cohort/age group, we compute the variance of log residual wages. Finally, we regress this ratio on a full-set of age and cohort fixed effects; $\sigma_{stayers(movers)}$: the standard deviation of residual log wages of job stayers (movers); *Wage loss ENE*: median log wage change of workers moving from employment to non-employment to employment; *Wage gain (loss) JTJ*: mean log wage change of workers moving job-to-job and experiencing a wage gain (loss); Wealth 25^{th} perc.: the 25^{th} percentile of the cross-sectional wealth distribution of people younger than 61; Wealth *EU* replacement: The median ratio of wealth relative to the earnings in the last period before unemployment.

I Welfare

Table I1: Changes in Risk

	High School	Some College	College
	Productivity shocks		
c tax %	1.40	0.77	0.81
ΔE %	-2.05	-1.26	-1.44
$\Delta\bar{\phi}$ %	0.10	0.05	0.31
ΔJTJ %	-0.01	0.00	0.01
	+ Job offer		
c tax %	2.88	0.10	-0.63
ΔE %	-2.34	-1.09	-1.50
$\Delta\bar{\phi}$ %	-1.66	0.90	2.37
ΔJTJ %	-0.18	0.06	0.11
	+ Other job risk		
c tax %	2.00	1.20	2.12
ΔE %	-1.93	-2.26	-3.89
$\Delta\bar{\phi}$ %	-0.78	0.94	0.90
ΔJTJ %	-0.59	-0.18	0.29
	+ Disability risk		
c tax %	6.53	5.56	2.12
ΔE %	-4.99	-5.11	-3.72
$\Delta\bar{\phi}$ %	-2.47	1.53	0.88
ΔJTJ %	-0.56	-0.12	0.29

Notes: The table displays additional information corresponding to Table 7 in the main text. *Productivity shocks*: based on changes in permanent productivity risk; + *Job offer*: additionally changes in the job offer distribution; + *Other job risk*: additionally changes in exogenous reallocation rates and job destruction rates; + *Disability risk*: additionally changes in disability risk. c tax %: proportional consumption tax needed to keep the government's budget unchanged; ΔE %: change in the employment rate in percentage points; $\Delta\bar{\phi}$: change in the mean job component; ΔJTJ %: change in the job-to-job transition rate in percentage points.

This appendix displays additional information corresponding to Section 4.2 in the main text. Table I1 displays the proportional consumption tax that is needed to keep the government's budget unchanged when changing the level of risk from the 1983–1993 to the 2004–2013 level. Changes in the consumption tax are education-specific such that budgetary changes are absorbed within education groups instead of altering the between education group transfers. Additionally, the table displays the resulting change in the employment rate and the job-to-job transition rate. It displays these outcomes for two counterfactual simulations. The top panel changes both the dispersion of idiosyncratic productivity shocks and the dispersion of the job offer distribution. The bottom panel changes only the latter.

Table I2: Changes in Governmental Policies

	High School		Some College		College	
Period	83–93	04–13	83–93	04–13	83–93	04–13
			Unemployment benefits			
c tax %	0.06	0.06	0.06	0.03	0.06	0.06
ΔE %	0.08	0.09	0.07	-0.14	0.03	0.00
			Food stamps			
c tax %	0.78	1.42	0.37	0.86	0.10	0.10
ΔE %	-0.73	-0.87	-0.63	-1.11	-0.13	-0.08
			SSI			
c tax %	0.61	0.91	0.20	0.38	0.07	0.07
ΔE %	-0.48	-0.44	-0.14	-0.50	-0.03	-0.09
			Disability insurance			
c tax %	0.35	0.64	0.19	0.51	0.13	0.15
ΔE %	-0.25	-0.34	-0.14	-0.58	-0.12	-0.21
			Progressive taxation			
c tax %	-1.97	-1.35	-2.58	-2.08	-2.96	-2.64
ΔE %	-1.61	-1.94	-1.40	-1.86	-0.56	-0.48

Notes: The table displays additional information to the policy experiments corresponding to Table 8 in the main text. *Period 83-93*: model from the 1983–1993 period; *Period 04-13*: model from the 2004–2013 period; c tax %: proportional consumption tax needed to keep the government's budget unchanged; ΔE %: change in the employment rate in percentage points; *Unemp. ben.*: increase in unemployment benefit replacement rate and maximum benefits; *Food stamps*: raising the maximum benefits from Food Stamps; *SSI.*: increase in the maximum Supplemental Security transfers; *Disability ins.*: increase in the disability insurance payments; *Progressive tax*: Change τ_p in Equation (3) from 0.892 to 0.888.

Table I2 displays the proportional consumption tax (again education-specific) that is needed to keep the government's budget unchanged when changing the size of the welfare state. Additionally, it displays the resulting change in the employment rate. Each change in the welfare state is simulated for the level of risk present in 1983–1993 and 2004–2013. Within each period, we offset changes to the budget by the consumption tax. That is, when changing policies given the risk of the period 1983–1993 (2004–2013), we compare the resulting budget to the budget present with the old policies and the level of risk from 1983–1993 (2004–2013).

J Computational algorithm

The computational routine composes of (i) solving the value functions backwards to obtain policy functions and (ii) a Monte Carlo simulation. To solve the value functions, we use 608 non-linearly spaced asset grid points, 30 worker productivity grid points, 15 job productivity grid points, and 6 average life-time earnings grid points. We use 8 choices for the search effort and allow for 2432 asset choices, linearly interpolating the value function from each choice. As unemployment benefits are only paid the first quarter after an employment spell, we can treat them as a lump-sum payment at the end of the employment spell instead of carrying them as a state for the value function of the unemployed. When doing so, we have to adjust the benefits downwards as they reduce Food Stamp transfers. When solving the value functions, we proceed in the following steps:

1. Solve the value function during retirement.
2. Solve the value functions in the last working period where all workers know they move to retirement in the next period.
3. Solve the value functions for all preceding periods
    - Solve the value function of those in Disability Insurance.
    - Solve for the optimal employment choice of the non-employed and the employed with an option for applying to Disability Insurance for next period's states.
    - Compute the expected value function for the non-employed from receiving a random job offer.
    - Compute the expected value function for the employed from receiving a regular job offer and a reallocation offer.
    - Compute the expected value function for the non-employed and employed from productivity shock realizations.
    - Interpolate the expected value functions of the non-employed and employed over their transition in average lifetime earnings and for each possible asset choices. For the expected value resulting from exogenous job destruction, add the resulting unemployment benefits in the asset choice interpolation.
    - Solve for the value functions, optimal asset choices, and optimal search decisions.

The overall program wrapper is written in Matlab. We solve the value functions using an NVIDIA GPU, where the source files are written in C++ and compiled using CUDA 12. These files are embedded in the Matlab code by calling the corresponding *.cu* and

.ptx files. For the code to run, the GPU needs to be able to schedule at least 608 threads per streaming multiprocessor unit. Moreover, it requires around 22 GB of GPU RAM.

The Monte Carlo simulations allow for continuous asset choices and continuous productivity shocks and average life-time earnings. We obtain the resulting policies from 3-D linear interpolation. The corresponding codes run on the CPU and are written in FORTRAN. They are embedded in the Matlab code by calling *.mex* files that are compiled using an Intel FORTRAN compiler.

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