Wage Risk, Employment Risk, and the Rise in Wage Inequality

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January 2, 2018

Abstract

We study trends in US male labor market risk over the last three decades accounting for workers' endogenous employment and job mobility decisions. The risk stemming from permanent shocks to idiosyncratic productivity and heterogeneity in pay across offered jobs has increased for most workers. These increases explain 75 percent of the increase in residual wage inequality. On-the-job search decisions of high skilled workers and labor market participation decisions of low skilled workers provide effective insurance mechanisms leading to moderate welfare changes. Unemployment benefits and disability insurance have become more valuable, but scaling back their generosity would still be welfare improving.

Keywords: Wage risk, secular trends, inequality, insurance

JEL: E21, I38, J22, J31, J64

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1 Introduction

The size and structure of idiosyncratic earnings risk is crucial to understand residual earnings inequality (see Storesletten, Telmer and Yaron (2004)), the welfare costs of inequality (see Heathcote, Perri and Violante (2010)), and to appropriately design welfare states (see Low, Meghir and Pistaferri (2010)). No consensus has been reached whether idiosyncratic risk has changed in the US over the last decades. Gottschalk and Moffitt (1994), Blundell, Pistaferri and Preston (2008), and Heathcote, Perri and Violante (2010) all find rising earnings uncertainty since the 1980s. CBO (2007) and Guvenen, Ozkan and Song (2014) find, if any, decreasing uncertainty.

These studies identify idiosyncratic earnings risk from the cross-sectional dispersion of observed residual earnings. We extend on this framework by explicitly modeling workers' employment and job-mobility decisions in response to shocks, similar to Low, Meghir and Pistaferri (2010) and Altonji, Smith and Vidangos (2013). This allows us to differentiate between trends in two types of risk. First, workers face permanent shocks to their idiosyncratic productivity that change their wages irrespective of their current jobs. Second, workers face heterogeneous paying job offers in a frictional labor markets. A worker is not able to locate the highest paying job instantaneously, implying a risk component arising from job search and job loss. The two types of risk affect workers differently because they present different choices. When the demand for their idiosyncratic skills change, workers may choose to become non-employed. When currently holding a relatively poor paying job, a worker may also decide to quit to non-employment, or he may choose to exert search effort to find an alternative job and change jobs when a better opportunity arises.

Using panel data for males from the Survey of Income and Program Participation, we show that the different types of risk have not developed uniformly and that accounting for trends in selection is quantitatively important. The standard deviation of permanent productivity shocks has increased between 16 and 30 percent over the period 1983-2013, depending on workers' education.[1] In addition, heterogeneity in pay between job

[1] We find a declining trend in transitory wage innovations; yet, this may reflect changes in measurement error.

offers has increased over time, but only for workers with at least some college education. For workers with only a high school education, these differences have decreased. Resulting from an increase in the fraction of workers close to their reservation wages over the last decades, the amount of workers quitting to non-employment after a negative productivity shock has increased. If we had ignored this trend in selection, we would have missed several of the increasing trends in risk.

We use counterfactual simulations of the changes in risk between 1983 and 2013 to study their macroeconomic implications.[2] In the model, workers' participation decisions are affected by progressive earnings taxation, unemployment insurance, a means-tested program (Food Stamps), disability insurance, and social security. Furthermore, reduced consumption expenditure needs during non-employment and precautionary savings provide partial insurance against the uncertainty arising from stochastic productivity and job offers. Job mobility is endogenous with both the non-employed and employed choosing the intensity at which they search for job offers. The model provides a good fit of life-cycle participation decisions. Employment rates peak around age 35 and decline by about 35 percentage points after age 50, with most of the decline driven by workers exiting the work-force; i.e., they choose not to search for a job when non-employed. What is more, the model features wage dynamics for workers changing jobs that are similar to the data. The simulation implies that the increase in risk accounts for 75% of the increase in within group wage inequality between 1983 and 2013.[3] The increase in inequality would have been even larger, particularly for low skilled workers, if workers participation decision had not changed. Resulting from the larger risk, the aggregate employment rate drops by 1.5 percentage points, partially resulting from a 2.2 percentage points rise in the rate of workers in disability insurance after age 50.

[2]Other papers that study trends in wage risk are Bowlus and Robin (2004), who permit for trends in wage promotions and demotion rates, Flabbi and Leonardi (2010), who consider trends in labor market transitions and job heterogeneity, and Leonardi (2017), who models changes to the dispersion of match specific productivity shocks.

[3]We concentrate on the rise of within group wage inequality, which explains most of the rise in total residual inequality (see Krueger and Perri (2006)). We see our paper as complement to the literature focusing on between group inequality. This includes a rising college premium (Katz and Autor (1999)) and skill biased technological change (Katz and Murphy (1992)).

These endogenous decisions are important to comprehend the welfare effects of changing labor market risk. An unborn worker is willing to pay 0.61% of life-time consumption to avoid the increase in risk. This is much less than the 4 percent welfare costs of changed income risk found in Heathcote, Storesletten and Violante (2010). We differ in three main aspects. First, we estimate an increase in permanent productivity risk that is about half their estimate. Second, endogenous participation and search decisions provide insurance against productivity shocks. With exogenous search, Low, Meghir and Pistaferri (2010) show that endogenous labor participation provides little insurance against these shocks. We show that this changes once we model endogenous search effort. Those with only a high school education gain from more dispersed productivity shocks. To quit into non-employment will provide relatively good insurance against adverse productivity shocks, if it has little impact on future employment prospects given future productivity developments. Endogenous search effort permits to rejoin the employment pool and to climb the job-ladder relatively fast, thereby, providing this type of insurance. Third, workers with at least some college education compensate an increase in the productivity risk with more dispersed job offers. Workers are willing to pay around 1% of life time consumption for an 0.01 increase in the standard deviation of job offers. In a search model, a rise in the dispersion of job offers creates an option value to the worker: Particular poor jobs terminate early because search allows the worker to find a better job. Again, endogenous search plays a large quantitative role because it allows workers to benefit to a greater degree from the additional opportunities with more dispersed job offers.

To understand the appropriate responses in public insurance to the changes in risk, we study the effects of small increases in the welfare state, using its 1980's level as baseline. Changes in policies are financed by an increase in proportional earnings taxes, treating each education group separately to avoid any redistribution between the groups. We find that the increase in risk has increased the desire for public insurance. However, increasing unemployment benefits or disability payments reduces welfare even with the elevated risk present in the 2000s. Increasing payments from the universal means-tested program leads to smaller welfare losses on average, and even increases in welfare for college graduates. For the same expenditure increase, outcomes under the universal means-tested program perform better compared to unemployment insurance because the aggregate non-employment rate increases by about twice as much with the latter. Put differently, the universal means-tested program allows to provide insurance to low income households with relatively little employment disincentives. Making the tax code less progressive leads to small welfare losses for the low educated, but small welfare gains for the high educated. In general, progressive taxation is an attractive policy tool because it allows to insure against initial heterogeneity and permanent productivity shocks, as in Heathcote, Storesletten and Violante (2017). Yet, these gains need to be weight against the distortionary effects progressive taxation has on endogenous search decisions.

The structure of the paper continues as follows: The next section specifies the theoretical model. The following section discusses the identification of wage risk in the data and presents its estimates. We then proceed with simulating the changes in risk. The last section concludes.

2 A Model of Employment and Mobility

The economy is populated by a finite number of workers $\mathcal{I}$ who have either a high school, some college, or college education. Time is discrete, workers live for H periods, and they discount the future with factor β. The length of a period is one quarter, and workers spend 37 years in the labor market and another ten years in retirement. Within each quarter, workers may be employed, non-employed, or retired. They start their life at age 25 as non-employed.[4]

At the beginning of life, worker i draws his log productivity according to $p_{i1} \sim N(\mu_n, \sigma_n^2)$. Afterwards, his productivity follows a random walk

[4] We choose the sample to start at age 25 to assure that college graduates fully transit to the labor market.

with a drift component that depends on the employment state and age:

$$p_{ih+1} = \begin{cases} p_{ih} + \nu_1 + \epsilon_{ih} & \text{if employed and} \leq 50 \text{ years} \\ p_{ih} + \nu_2 + \epsilon_{ih} & \text{if employed and} > 50 \text{ years} \\ p_{ih} + \delta_1 + \epsilon_{ih} & \text{if non-employed and} \leq 50 \text{ years} \\ p_{ih} + \delta_2 + \epsilon_{ih} & \text{if non-employed and} > 50 \text{ years,} \end{cases}$$

where h denotes the age of the worker and $\epsilon_{ih} \sim N(0, \sigma_\epsilon^2)$ with cumulative distribution function $G(\epsilon)$. These shocks contain promotion decisions, health shocks, and any other changes in the market value of a worker's skills. Wages in the data peak around age 50, and we use ν_1 and ν_2 to match this wage profile. To reduce notation, we refer to the skill parameters in either age period by ν_x and δ_x with $x = 1, 2$. During non-employment, workers have either no skill gains, or their skills depreciate: $\delta_x = min\{0, \nu_x\}$.

Workers endogenously search for jobs in a frictional labor market, both on and off the job. A worker chooses the probability to meet with a new job, s_{ih}, paying convex utility costs: $C(s_{ih}) = \varpi_0 \frac{s_{ih}^{1+\varpi_1}}{1+\varpi_1}$. In the data, a large fraction of workers do not report searching. We rule out workers that exert effort close to zero in the hope to find an extremely well paying job by requiring a minimum search intensity. The intensity is either zero, or $s_{ih} \in [0.15, 1]$. When meeting a job, the worker randomly draws a log job component $\psi_{ij} \sim N(0, \sigma_\psi^2)$ with cumulative distribution function $F(\psi)$. When employed, a worker spends 516 hours a quarter working at an observed hourly gross wage of

$$w_{ih}^g = exp(p_{ih} + \psi_{ij} + e_{ih}), \tag{1}$$

where e_{ih} is measurement error following a $MA(2)$ process.[5] It is instructive to discuss the key assumptions of the wage process. First, following on-the-job search models in the tradition of Burdett and Mortensen (1998) and empirical specifications following Abowd, Kramarz and Margolis (1999), we assume a time invariant job component. Guiso, Pistaferri and Schivardi (2005) show that firms almost perfectly insure workers against idiosyncratic firm risk, supporting this assumption. However, in the presence of some

[5] The results are robust to alternative order specifications for measurement error.

commitment device on the firm side, wages may be back-loaded within a job with stable productivity (see Postel-Vinay and Robin (2002), and Burdett and Coles (2003)). Yet, Low, Meghir and Pistaferri (2010) find that a model of stochastic job component fits the data worse than a model with a stochastic productivity component.[6] Second, in line with a large empirical literature on earnings uncertainty, we assume productivity follows a random walk process.[7] Recently, Guvenen et al. (2017) show that an $AR(1)$ mixture model of highly persistent and transitory shocks matches better the excess kurtosis and negative skewness present in earnings growth data. Extending our model to this process is beyond the scope of this paper. Our focus is on hourly wage growth that shows much less skewness than earnings growth. Given our decomposition of wages, we require that the excess kurtosis is not estimated as a large variance of the permanent shock. We find that trimming the empirical wage growth distribution in our estimation leaves the estimated variance of permanent shocks almost unchanged.[8]

Financial markets are incomplete. Workers have access to a risk free asset, a, that pays returns $R = 1 + r$, and are unable to borrow, $a_{t+1} \geq 0$. The government grants several programs that provide additional insurance against low earnings. First, the earnings tax is progressive. Following Heathcote, Storesletten and Violante (2017), earnings after taxes follow

$$E_{ih} = \tau_c \Big(516 w^g_{ih}\Big)^{\tau_p},$$

where τ_p determines the progressivity of the tax code.

Furthermore, workers receive unemployment benefits that depend on their education level:[9]

$$b_{ih} = \bar{b}.$$

[6]Along this line, Flinn and Mabli (2008), Hagedorn and Manovskii (2010), and Tjaden and Wellschmied (2014) show some counter-factual implications of wage back-loading.

[7]See, for example, Abowd and Card (1989), Topel and Ward (1992), Meghir and Pistaferri (2004) and Low, Meghir and Pistaferri (2010).

[8]Heathcote, Perri and Violante (2010) find the same phenomenon in PSID data.

[9]Legislation usually grants 26 weeks of benefits that replace a fraction of last earnings. We abstract from finite benefit duration to avoid workers taking up and quitting one quarter jobs to receive benefits. Such behavior is deterred by by law by introducing a minimum amount of tenure before a worker is eligible to benefits. Yet, to reduce the state space, we model infinite benefits that depend on education only.

During the last ten working years (age 51 onwards), workers may exit the labor market permanently and receive disability insurance.[10] To apply for benefits, legislation requires a worker to be continuously non-employed for 5 months and to have worked before that period. To approximate this structure in the model, a worker can only apply the quarter after becoming non-employed. Moreover, a worker may not search for a job within the same quarter of application. At its onset, disability insurance required workers to have a health condition that prohibits working. Autor and Duggan (2006) show that in 1984, the government greatly relaxed the eligibility criteria and shifted them towards vocational factors. Michaud, Nelson and Wiczer (2017) show that this resulted in a rise in granted applications due to vocational factors, in contrast to health factors. We proxy the legislation by allowing workers to apply when their last period idiosyncratic productivity change was sufficiently poor: $p_{ih-1} - p_{ih-2} < \bar{\upsilon}$. Moreover, conditional on applying, benefits are only granted with probability υ. Benefits follow

$$S(\bar{E}_{ih}) = \begin{cases} 0.9\bar{E}_{ih} & \text{if } \bar{E}_{ih} \leq d_1 \\ 0.9d_1 + 0.32(\bar{E}_{ih} - d_1) & \text{if } d_1 < \bar{E}_{ih} \leq d_2 \\ 0.9d_1 + 0.32(d_2 - d_1) + 0.15(\bar{E}_{ih} - d_2) & \text{if } \bar{E}_{ih} > d_2, \end{cases}$$

where d_1, d_2 are bend points that govern the concavity of benefits. $\bar{E}_{ih}$ are the average earnings of a worker i over his life-cycle at age h, following

$$\bar{E}_{ih+1} = \begin{cases} (E_{ih} + \bar{E}_{ih}h)/(h+1) & \text{if employed} \\ \bar{E}_{ih}h/(h+1) & \text{if non-employed} \\ \bar{E}_{ih} & \text{if disabled or retired.} \end{cases}$$

Consequently, concave benefits, and their dependence on past earnings, make disability insurance an attractive option for workers with poor earnings outcomes late in life. After working life, workers receive social security benefits that are fixed throughout retirement and follow the same formula as disability insurance.

[10] The legislation permits workers to apply throughout their working life. Yet, most people apply after the age of 50, possibly reflecting the fact that eligibility requirements loosen at that age.

In addition, the government provides an universal means-tested program to all low income workers that mirrors in parts the US *Food Stamps Program*. Denote by y_{ih} total worker's gross income minus a fixed income deductible, transfers are given by

$$F(y_{ih}) = \begin{cases} \overline{F} - 0.3y_{ih} & \text{if } y_{ih} < \underline{y}, \\ 0 & \text{otherwise .} \end{cases}$$

To summarize, the worker's consumption reads

$$c_{ih} = \begin{cases} E_{ih} + F(516w^g_{ih}) + Ra_{ih} - a_{ih+1} & \text{if employed,} \\ b_{ih} + F(b_{ih}) + Ra_{ih} - a_{ih+1} & \text{if non-employed,} \\ S(\bar{E}_{ih}) + F(S(\bar{E}_{ih})) + Ra_{ih} - a_{ih+1} & \text{if disabled or retired.} \end{cases}$$

Aguiar and Hurst (2005) show that households, after exiting employment, use the additional available time to engage in home production and reduce shopping costs. To allow for this type of insurance, we choose an utility function with higher consumption expenditure needs during employment:

$$U_{ih} = \left(\frac{c_{ih}exp(\varphi P_{ih})}{1-\eta}\right)^{1-\eta} - \varpi_0 \frac{s_{ih}^{1+\varpi_1}}{1+\varpi_1}, \tag{2}$$

where P_{ih} is one when the worker is employed and $\varphi \leq 0$. Based on this environment, we proceed with defining the value functions at each employment state. Whenever a worker is retired or disabled, he does not face uncertainty and does not engage in job search. He solves, respectively, the following maximization problem:

$$\mathcal{Q}_h(a, \bar{E}) = \max_{a', s=0} \Big\{ U + \beta \mathcal{Q}_{h+1}(a', \bar{E}') \Big\} \tag{3}$$

$$\mathcal{D}_h(a, \bar{E}) = \max_{a', s=0} \Big\{ U + \beta \mathcal{D}_{h+1}(a', \bar{E}') \Big\}. \tag{4}$$

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

$$\mathcal{U}_h(a, p, \bar{E}) = \max_{a', s} \Big\{ U + \beta EVU_h(a', p, \bar{E}') \Big\}, \tag{5}$$

where EVU_h is the value of search in unemployment:

$$
\begin{aligned}
& EVU_h(a', p, \bar{E}') \equiv (1-s) \int \mathcal{U}_{h+1}(a', p', \bar{E}') dG(\epsilon) \\
& + s \int \int \max \Big\{ \mathcal{W}_{h+1}(a', p', \psi', \bar{E}'), \mathcal{U}_{h+1}(a', p', \bar{E}') \Big\} dF(\psi') dG(\epsilon),
\end{aligned} \tag{6}
$$

with $p' = p + \delta_x + \epsilon$ and $\mathcal{W}_{h+1}$ is the value of employment next period. Define by Θ_h the value of applying for disability insurance. The decision to apply for disability insurance is taken after the asset decision, but before the end of period uncertainty reveals. The worker knows that the application is denied with probability $1 - \upsilon$:

$$
\Theta_h(a', p, \bar{E}') \equiv \upsilon \mathcal{D}_{h+1}(a', \bar{E}') + (1-\upsilon) \int \mathcal{U}_{h+1}(a', p', \bar{E}') dG(\epsilon). \tag{7}
$$

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

$$
\mathcal{U}^D_h(a, p, \bar{E}) = max \Big\{ \underset{a', s=0}{max} \Big\{ U + \beta \Theta_h(a', p, \bar{E}') \Big\}, \mathcal{U}_h(a, p, \bar{E}) \Big\}. \tag{8}
$$

Employed workers may continue to sample job offers. The value of an employed worker of age h solves

$$
\begin{aligned}
\mathcal{W}_h(a, p, \psi, \bar{E}) = \underset{a', s}{max} \Big\{ U + \beta \Big\{ & (1-\omega) \Big[(1-s)\Xi + s\Omega_E \Big] \\
& + \omega \Big[s\Lambda + (1-s)\Pi \Big] \Big\} \Big\},
\end{aligned} \tag{9}
$$

where we have defined the following upper envelops:

$$
\begin{aligned}
\Xi &\equiv \int \max \Big\{ \mathcal{W}_{h+1}(a', p', \psi, \bar{E}'), \mathcal{U}_{h+1}(a', p', \bar{E}') \Big\} dG(\epsilon) \\
\Omega_E &\equiv \int \int \max \Big\{ \mathcal{W}_{h+1}(a', p', \psi, \bar{E}'), \mathcal{U}_{h+1}(a', p', \bar{E}') \\
& \qquad , \mathcal{W}_{h+1}(a', p', \psi', \bar{E}') \Big\} dF(\psi') dG(\epsilon) \\
\Lambda &\equiv \int \int \max \Big\{ \mathcal{W}_{h+1}(a', p', \psi', \bar{E}'), \mathcal{U}_{h+1}(a', p', \bar{E}') \Big\} dF(\psi') dG(\epsilon) \\
\Pi &\equiv \mathbb{I}_{h > H_d} \Big(\int_{-\infty}^{\bar{\upsilon} - \nu_x} \mathcal{U}^D_{h+1}(a', p', \bar{E}') dG(\epsilon) + \int_{\bar{\upsilon} - \nu_x}^{\infty} \mathcal{U}_{h+1}(a', p', \bar{E}') dG(\epsilon) \Big) \\
& \qquad + \mathbb{I}_{h \le H_d} \int \mathcal{U}_{h+1}(a', p', \bar{E}') dG(\epsilon),
\end{aligned}
$$

with $p' = p + \nu_x + \epsilon$. An employed worker keeps his job with exogenous probability $1 - \omega$. In the case he does not receive a new job offer, Ξ, he decides between staying employed or quitting into non-employment. When he receives an offer, Ω_E, he decides between his current job, the outside offer, and non-employment. In case the job is destroyed, he may have generated a job offer and chooses between the new offer and non-employment, Λ. If he does not generate a new offer, he will move to non-employment, Π. Those old enough, $\mathbb{I}_{h>H_d}$, may receive a productivity shock sufficiently negative that makes them eligible to apply for disability insurance, $\epsilon < \bar{\upsilon} - \nu_x$.

3 Estimating Changes in Risk

In this section, we discuss the identification of changes in the dispersion of productivity shocks, σ_ϵ, and the wage offer distribution, σ_ψ, in US data over the last three decades. Importantly, these parameters cannot be directly observed because observed wages result from the true underlying shocks and workers making endogenous decisions. The amount of selection is unlikely to be constant over several decades. The distribution of workers has changed (e.g., the age structure), and the underlying amount of insurance, thus, the reservation wages have changed (e.g., changes in the welfare state). We allow for these changes in our estimation.

3.1 Identification of Risk and Selection

In the data, we allow log gross wages at time t to depend on other worker observables, x_{it}, besides a predictable experience effect:

$$\begin{aligned} ln(w^g_{ijt}) &= \beta x_{it} + \psi_{ij} + p_{it} + e_{it} \\ p_{it} &= p_{it-1} + \epsilon_{it} \\ e_{it} &= MA(2)\iota_{it}, \end{aligned} \tag{10}$$

with $\iota_{it} \sim N(0, \sigma^2_\iota)$. The transitory component may be measurement error, but may also contain truely temporary wage shocks, such as bonuses, that we abstract from in Section 2. The focus of this paper is on the dispersion of ϵ and ψ. For tractability, we assume that workers do not select on purely transitory shocks.

Taking first differences of equation (10) yields individual wage growth:

$$\Delta ln(w^g_{ijt}) = \beta \Delta x_{it} + [\underbrace{\psi_{ij} - \psi_{ij-1}}_{\xi_{it}}] M_{it} + \epsilon_{it} + \Delta e_{it}, \tag{11}$$

where M_{it} is an indicator variable equal to one when the worker changes his job between t and $t-1$. We model the endogenous worker decisions using latent variables for participation in the current and previous period, and job mobility:

$$P^*_{it-1} = \alpha z_{it-1} + \pi_{it-1}, \;\; P_{it-1} = 1\left\{P^*_{it-1} > 0\right\}, \tag{12}$$

$$P^*_{it} = \alpha z_{it} + \pi_{it}, \;\; P_{it} = 1\left\{P^*_{it} > 0\right\}, \tag{13}$$

$$M^*_{it} = \theta \kappa_{it} + \mu_{it}, \;\; M_{it} = 1\left\{M^*_{it} > 0\right\}, \tag{14}$$

where z_{it} and κ_{it} are worker observables, and π_{it} and μ_{it} are unobservables. The unobservable components contain, among other things, the unobserved component of productivity, its innovations, ϵ_{it}, and the job component, ψ_{ij}. To account for the arising correlation between the unobservables, we extend the framework of Low, Meghir and Pistaferri (2010) and assume:

$$\begin{pmatrix} \pi_{it-1} \\ \pi_{it} \\ \mu_{it} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{\pi\pi_{-1}} & \rho_{\pi\mu} \\ \rho_{\pi\pi-1} & 1 & \rho_{\pi_{-1}\mu} \\ \rho_{\pi\mu} & \rho_{\pi_{-1}\mu} & 1 \end{pmatrix}\right].$$

We estimate equations (12)-(14) together with the covariance matrix using a nested trivariate probit, taking into account that mobility is only observed conditional on the individual having worked the current and previous quarter.[11]

Similar to a Heckit model, we use exclusion restrictions, discussed be-

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

low, to obtain unbiased estimates of unexplained wage growth:[12]

$$g_{it} = \Delta ln(w^g_{it}) - \beta \Delta x_{it} = \xi_{it} M_{it} + \epsilon_{it} + \Delta e_{it}. \tag{15}$$

Resulting from the participation and mobility decisions, the distribution of observed residual wage growth is truncated; we do not observe all shocks to productivity and the job component. Given the structure of our problem, residual wage growth follows a truncated multivariate normal distribution, which first two moments are derived by Manjunath and Wilhelm (2012). Online Appendix A derives the moments for our particular case. To provide some intuition for the identification, 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 $\rho_{\xi\pi}$, $\rho_{\xi\pi-1}$ and $\rho_{\xi\mu}$ to be the correlation between changes in the job component and shocks to participation this period, last period, and mobility, respectively. Summarize the results from the probit by the vector $X_{it} = [\alpha z_{it}, \alpha z_{it-1}, \theta\kappa_{it}, \rho_{\pi\pi_{-1}}, \rho_{\mu\pi}, \rho_{\mu\pi_{-1}}]$, the first moments of unexplained wage growth in implicit form are given by

$$E(g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 0) = \rho_{\epsilon\pi}\sigma_\epsilon\phi(-z_{it}\alpha)f_1(X_{it}) - \rho_{\epsilon\mu}\sigma_\epsilon\phi(\theta\kappa_{it})f_2(X_{it})$$
$$E(g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 1) = \sigma_\epsilon\Big[\rho_{\epsilon\pi}\phi(-z_{it}\alpha)f_3(X_{it}) + \rho_{\epsilon\mu}\phi(-\kappa_{it}\theta)f_4(X_{it})\Big]$$
$$+ \sigma_\xi\Big[\rho_{\pi\xi}\phi(-z_{it}\alpha)f_5(X_{it}) + \rho_{\mu\xi}\phi(-\kappa_{it}\theta)f_6(X_{it}) + \rho_{\pi_{it-1}\xi}\phi(-z_{it-1}\alpha)f_7(X_{it})\Big],$$

where ϕ is the PDF of the standard normal distribution and f_x are functions that we show in closed form in online Appendix A. The first moments identify the correlations between wage innovations, mobility and participation decisions, up to the scalars σ_ϵ and σ_ξ. Identification results from comparing the unexplained wage growth of individuals with different participation and mobility probabilities. Abstracting for the moment from transitory shocks, after accounting for selection, the variance of wage growth of job stayers, $E(g^2_{it}|P_{it} = P_{it-1} = 1, M_{it} = 0)$, is sufficient to identify σ_ϵ. Moreover, the variance of wage growth of job switchers, corrected for selection, identifies σ_ξ. Finally, the combination of these four moments, together with the au-

[12] Online Appendix A derives the appropriate selection term.

tocovariance function of wage growth, allows us to identify all parameters of interest.

3.2 Data Sources and Sample Selection

Our analysis requires individual longitudinal information on wages and worker and job characteristics over several decades. The dataset most adequate for these requirements is the Survey of Income and Program Participation (SIPP). It provides a set of panels covering the period of 1983-2013.[13] Every 4 months, the Census conducts an interview with all adult members of participating households asking them about their work and household characteristics during the preceding 4 months. In order to account for the seam-bias effect generated by the recollection period, we aggregate the monthly information to quarterly observations. One concern regarding the data is that the quality of the survey changed over time. We describe the details of our data cleaning procedure in online Appendix B, where we also show that survey redesigns are unlikely to have an impact on our results.

The estimation of the multivariate probits and the moments of unexplained wage growth require sufficient observations on job movers. Io this end, we group the data into three major time periods, such that each covers years of expansion and recession: 1983-1993, 1994-2003, and 2004-2013. We consider three education groups: high school, some college, and college graduates or higher education.[14] Furthermore, we focus on male individuals, aged between 25 and 61, who are not self-employed, enrolled in school, in the armed forces, or recalled by their previous firm after a separation.[15]

We consider a worker employed within a quarter, when he spends most weeks working. We identify a job by the establishment ID assigned by the SIPP.[16] We define a worker's main job as the establishment ID with

[13]We exploit all up to date surveys, except of the surveys from 1985 and 1989: 1984, 1986, 1987, 1988, 1990, 1991, 1992, 1996, 2001, 2004, and 2008. We do not use these two surveys due to the absence of information regarding work experience.

[14]In specific, we group individuals into a. Workers with at most high school education, b. Workers with some college (no three year degree), and c. Workers who received an associate degree, three year college or higher.

[15]Workers being recalled posses a search technology that is not well represented by a random draw from the wage offer distribution.

[16]We interpret within establishment changes in occupation as productivity shocks.

the highest earnings.[17] Whenever the main job changes from one quarter to the other, we count this worker as a job mover. Thus, mobility may result from job changes that occur either with or without an intermediate non-employment spell.[18] We compute wages as total earnings over total hours worked at the main job. To make the results robust to outliers, we do not consider individuals with hourly wage growth below the 1st percentile (above the 99th percentile) of the hourly wage growth distribution by education, period, and job mobility status. Online Appendix C show that, consistent with Guvenen, Ozkan and Song (2014), the resulting cross-sectional variance of wage growth has, if any, a downward trend over time.

3.3 Changes in Labor Market Risk

3.3.1 Probit Results

We estimate the model for each of our three periods and education degrees separately; thereby, we allow for time varying returns to human capital and time varying patterns in participation and mobility. We estimate participation probabilities controlling for quadratic trends in age and work experience, race, marital status, indicators whether a person lives in a metropolitan area or reports being disabled, the unemployment rate at the state level, and time and region fixed effects.[19]

Additionally, we require a set of regressors that identify selection. That is, variables affecting the decision to participate or move jobs, but not independently related to productivity shocks or changes in the job component. For this purpose, we augment the set of explanatory variables including unearned household income, an index for the generosity of the welfare system (state-level unemployment insurance), and an indicator whether the worker owns a house. The former two variables increase reservations wages, thereby, decrease participation. The theoretical effects on mobility are am-

[17]The survey reports the two jobs with the highest earnings per month for each individual.

[18]For our identification, we require that skill depreciation for non-employment spells under one quarter, at most 2 months, is negligible.

[19]The survey provides, in addition, information regarding tenure at the job. We opt not to use this information because the share of observations with reported zero values conditional on working is above 30%. Moreover, tenure information is not available for all jobs before the 1996 panel.

biguous. In principle, being closer to the participation margin should increase mobility because workers are more likely to quit their current job. On the other hand, higher reservation wages limit the possibility of future mobility.[20] Owning a house increases participation through a possible mortgage commitment. Moreover, the resulting moving costs provide us with heterogeneity in mobility costs. Additionally, in the equation for job mobility, we include seven industry and seven occupation fixed effects.[21]

We present the results of the probits in online Appendix D. As expected, high unemployment benefits, high unearned income, and not owning a house reduce the probability of employment. We find that the state level generosity and house ownership reduce the likelihood of a worker to move jobs. We find no consistent and mostly insignificant effects of unearned household income.[22]

The amount of workers close to their participation and mobility thresholds is key for the severeness of workers selecting on shocks. We observe substantial changes along these margins over the last decades. When comparing the third period to the first, employed workers have relatively lower participation probabilities, with more workers in the lower tail of the distribution. Moreover, workers have higher probabilities to change jobs. Inspecting the distribution of workers, we find that observable worker characteristics have shifted in the direction of workers with less stable jobs (singles, minorities, elderly). Moreover, online Appendix D show that changes in the marginal effects of these covariates have also reduced participation, possibly reflecting a welfare state that has become more generous (see Ben-Shalom, Moffitt and Scholz (2011)).

An increasing propensity of workers to leave their job may appear contrary to the literature that finds a decreasing worker reallocation over time. For example, Cairó and Cajner (2013) show in the CPS data that

[20]For the exclusion restrictions to be valid we require that assets or unemployment insurance payments do not affect wage growth through bargaining.

[21]In wage growth, we control for industry dummies and their changes, and changes in occupations as they may be related to changes in the job component. Comparing this identification to Low, Meghir and Pistaferri (2010), they assume that there are no industry shocks driving mobility, while we assume that there are no within industry occupation specific shocks driving it.

[22]We use standard errors that are based on asymptotic distributions that may be unreliable in small samples (see Robinson (1982)).

the monthly employment to non-employment transition rate is falling over time. We show in online Appendix B the same pattern in the non-adjusted SIPP data. However, after our data cleaning, particularly after classifying workers as non-employed with close to zero earnings and dropping workers returning to their previous employers, the trend reverses and the employment to non-employment transition rate becomes increasing over time.

3.3.2 Wage Variance Estimates and Selection

This section presents the estimated correlations and risk components. Estimation is based on minimizing the sum of squared residuals from the first and second moments of equation (15) and the autocovariance terms, where we weight each individual with the underlying survey weight.[23] Following Horowitz (2003), we compute standard errors by block-bootstrapping.

The top panel in Table 1 displays the estimates for permanent productivity risk and the wage offer distribution. All workers face substantial permanent shocks to their productivity, and those shocks become more dispersed with education. Furthermore, we find large dispersion of job effects in wage offers, where those with completed college face the largest dispersion. The standard deviation of the wage offer distribution ranges in the first period from 0.22 to 0.27. Thus, within 2 standard deviations, the wage of the same worker varies by $\pm$ 54 percent depending on his job.[24]

Regarding the secular trends, the standard deviation of permanent productivity shocks has increased for all workers by approximately 0.01. For those with a college degree, the rise materialized in the third period. The increase is close to linear for the other education groups. Low skilled workers have faced the lowest productivity risk in the 1980s; therefore, the relative rise in uncertainty is largest for this group.

For college workers, the standard deviation of the wage offer distribution has increased by 0.03. Again, the rise materializes in the third period.[25] Those with some college have experienced an increase by 0.02.

[23] We use a simplex method to find a local minimum and use 30 different starting points to insure that we find the global minimum.

[24] Averaging over skill groups, the dispersion in the wage offer distribution is similar to the one found in Hall and Mueller (2015), who identify it using information on reported reservation wages.

[25] One concern may be that a decline in spurious job-to-job transitions due to sample

Table 1: Changes in Labor Market Risk

	High School		Some College		College	
	Baseline					
Period	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ
1	0.030	0.260	0.042	0.217	0.050	0.267
	(0.004)	(0.009)	(0.004)	(0.030)	(0.004)	(0.009)
2	0.035	0.262	0.047	0.225	0.048	0.265
	(0.006)	(0.009)	(0.007)	(0.024)	(0.006)	(0.022)
3	0.040	0.225	0.052	0.235	0.058	0.300
	(0.008)	(0.042)	(0.024)	(0.058)	(0.005)	(0.029)
	Within and between job component					
Period	$\sigma_{\psi W}$	$\sigma_{\psi B}$	$\sigma_{\psi W}$	$\sigma_{\psi B}$	$\sigma_{\psi W}$	$\sigma_{\psi B}$
1	0.250	0.275	0.212	0.223	0.268	0.265
2	0.250	0.276	0.220	0.230	0.277	0.249
3	0.230	0.217	0.233	0.239	0.308	0.289
	Not accounting for selection					
Period	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ	σ_ϵ	σ_ψ
1	0.029	0.265	0.040	0.243	0.046	0.270
2	0.017	0.268	0.041	0.252	0.044	0.266
3	0.039	0.268	0.019	0.319	0.051	0.315

Notes: The first panel displays the standard deviation of productivity shocks, σ_ϵ, and the standard deviation of the wage offer distribution σ_ψ from the model described in equations (10)-(15) estimated with SIPP data. Period 1: 1983-1993. Period 2: 1994-2003. Period 3: 2004-2013. Block-bootstrapped standard errors are in parentheses. The second panel differentiates the wage offer distribution of workers switching their industry/occupation, $\sigma_{\psi B}$, and those staying within their industry/occupation, $\sigma_{\psi W}$. The third panel displays the standard deviation of productivity shocks and the standard deviation of the wage offer distribution that result from an estimation which ignores the selection of workers.

Similar to the productivity risk, the rising uncertainty materialized already partially during the 1990s. Contrary to these groups, high school workers have experienced a decline in the dispersion to the wage offer distribution by 0.04 in the third period. Finally, Appendix (A.1) shows that the dispersion to transitory wage shocks declines for all workers. We are unable to differentiate between true transitory shock and measurement error. A falling dispersion, therefore, may be the result of improved interviewing

redesign leads to trends in the estimated wage offer distribution. We describe in online Appendix B the way we attempt to clean the data from such transitions. Moreover, we would expect the major break occurring from the first to the second period, as data quality increased from 1990 onwards.

techniques introduced in the 1996 and 2004 survey (see Moore (2008)).

Appendix (A.1) displays the estimated selection correlations. Workers show substantial persistence in their unobserved participation heterogeneity, consistent with a partially unobserved productivity and match component. In line with this, positive innovations to productivity increase participation. The correlation between the unobserved component of mobility and participation decisions are for most of the cases significant and positive which may suggest heterogeneity in job finding rates. As expected, good outside offers increases the propensity of workers to move jobs. The theoretical effect of productivity shocks on mobility is ambiguous. In the first two periods, we find a negative correlation suggesting that after a negative shock, workers are more likely to quit to non-employment to search for a new job. In the last period, the correlation becomes positive for workers with less than completed college. Put differently, those with completed college are more likely to change their careers after a negative shock, but lower educated workers stay with their jobs. Similarly, Autor et al. (2014) find that following Chinese import penetration, low and medium skilled workers have not been able to offset wage losses, but high skilled workers mostly have offset those by switching jobs.

Our model does not differentiate between job switches within and between occupation/industry groups. To understand the source of the trends in the wage offer distribution, we extend the model allowing the wage offer distribution to be different for those who stay within the same industry and occupation (*Within*), and those who change either occupation or industry (*Between*). Fully estimating this model is beyond the scope of this paper, and we fix the selection correlations to the ones we obtain from our baseline econometric model.[26] The second panel in Table 1 displays the evolution of the job component for the two groups. Regarding workers with at least some college education, the increased dispersion in the wage offer distribution results from more dispersed job offers for both *within* and *between* job switchers. For workers with at most a high school degree, the decrease in the dispersion of the job component is most pronounced for *between* movers. In our data, average wage growth from switching indus-

[26]This implies setting $\rho_{\xi_W \mu} = \rho_{\xi_B \mu} = \rho_{\xi \mu}$, $\rho_{\xi_W \pi} = \rho_{\xi_B \pi} = \rho_{\xi \pi}$ and $\rho_{\xi_W \pi - 1} = \rho_{\xi_B \pi - 1} = \rho_{\xi \pi - 1}$

tries/occupations tends to increase over time for workers with at least some college education, but decreases for high school workers. Taken together with a declining mobility after negative productivity shocks, our results suggest that these workers face worsening opportunities from switching jobs. Whether staying in their current career, or, particularly, when moving to another industry/occupation, they are less likely to encounter a good paying job in the 2000s relative to the 1980s.

Finally we ask, how important is it to account for selection. Using the process for individual wages in Equation (10), we could identify the permanent, transitory, and job component when ignoring selection, using the second moments of (uncorrected) unexplained wage growth for job stayers and movers.[27] The third panel in Table 1 provides the estimated components. Different from our baseline results, productivity risk declines by 50% for workers with some college education. Moreover, if we had ignored selection, 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.

4 Calibration of Remaining Parameters

We calibrate the coefficient of relative risk aversion and the interest rate outside of our data. The former, η, is set to 1.5, consistent with Attanasio and Weber (1995). Following Siegel (2002), we fix the value of r to imply a yearly interest rate of 4%. The remaining parameters are calibrated to match empirical moments of the the first period of our analysis (1983-1993). Most of our calibration targets are education specific. Tables 2 and 3 summarize the calibration, and Appendix A.2 reports the targeted empirical moments.

We set the dispersion of the permanent productivity shock, σ_ϵ, the dispersion of the wage offer distribution, σ_ψ, and the variance of measurement error, σ_ι, to the values estimated in Section 3.3. In order to match the average amount of self-insurance present in the data, we target with β the mean net wealth of the population between ages 25 and 61. To calibrate

[27] In specific, the variance of job stayers would be $\sigma_\epsilon^2 + Var(e_{it})$, and the variance of job movers would be $\sigma_\epsilon^2 + 2\sigma_\psi^2 + Var(e_{it})$.

Table 2: Main Calibration

Parameter	HS	SC	C	Target
σ_ϵ	0.03	0.04	0.049	Dispersion permanent shock
σ_ψ	0.26	0.24	0.27	Dispersion job effects
σ_ι	0.07	0.08	0.11	Measurement error
σ_n	0.32	0.33	0.29	Initial wage dispersion
μ_n	7.04	7.09	7.39	Initial mean wage
r	0.01	0.01	0.01	4% annual interest rate
$(1-\beta)\%$	0.34	0.30	0.28	Mean net wealth < 61
η	1.50	1.50	1.50	Risk aversion
φ	-0.34	-0.25	-0.10	Employment age 42-45
ϖ_0	0.08	0.16	0.36	JTJ flows $\Delta w^g_{ih} \geq 0$
ϖ_1	0.53	1.20	1.15	UE flow rate
ω %	1.96	1.33	1.12	EN flow rate
ν_1 %	0.20	0.35	0.42	Wage growth 25-50
ν_2 %	-1.09	-0.55	-0.13	Wage growth 51-61

Note: The table displays the calibrated parameters using the SIPP data from our first period of analysis: 1983-1993. *HS*: at most a high school diploma. *SC*: some college. *C*: college degree. The left column states the variable, the second, third, and fourth column state the calibrated values. *Initial dispersion*: dispersion of log wages at age 25. *Initial mean log wage*: average log wage at age 25. *Mean net wealth*: net total assets of a household. *JTJ*: rate of job-to-job transitions that result in no wage losses. *UE flow rate*: Job finding rate of the non-employed that report searching for a job. *EN*: flow rate from employment to non-employment. *Wage growth*: mean change in log wages.

the amount of insurance from non-employment, φ, we target the average employment rate between ages 42 to 45. This parameter may also capture other insurance mechanisms that the model abstracts from, such as the labor supply from other members at the household. The calibration implies that low skilled workers derive more benefits from non-working.

We assume that initial wealth is a random draw from the empirical wealth distribution of young workers (between ages 25 and 28). In addition, we set σ_n^2 to match the initial variance of log wage inequality, and μ_n, to match the average wage at the beginning of workers' life. We calibrate the employment specific drift terms of productivity, (ν_1, ν_2) to the average wage changes from age 25 to 50 and from 51 to 61, respectively.

We target average worker flows in the data. In particular, we set the exogenous job destruction rate, ω, to match the movements from employment to non-employment not explained by endogenous separations. We use the scaling and convexity parameter of search costs, (ϖ_0, ϖ_1), to match the

Table 3: Calibration of Welfare State

Parameter	Value	Source
$\bar{b}$	171,254,336	Average benefits by education
$\overline{F}$	680,424	Kerr et al. (1984)
d_1	801	Social Security Administration (2016)
d_2	4836	Social Security Administration (2016)
υ	0.43	Social Security Administration (2015)
$\bar{\upsilon}$	-0.043	7.8% disability after age 50
τ_c	1.84	Equation (16)
τ_p	0.89	Equation (16)

Note: The table displays the calibrated parameters for the welfare state. $\bar{b}$: benefits during non-employment conditional on education. $\overline{F}$: maximum transfers from the universal means-tested program during working life and retirement. d_x: bend points for social security benefits. υ: probability that disability benefits are granted. $\bar{\upsilon}$: the change in log productivity that allows for a disability insurance claim. $\tau_c$and τ_p: see equation (16).

job finding rate of workers in non-employment that search for a job, i.e., the unemployed, and the job-to-job transition rate. Regarding the latter, Tjaden and Wellschmied (2014) show that more than one third of job-to-job transitions result in nominal wage losses. Our model features three reasons for such losses. First, our simulations include measurement error. Second, large negative productivity shocks may off-set wage gains from a better job. Third, workers may loose their job for exogenous reasons, yet created a new job offer that is inferior to the previous job in the same period and accept it. Taken together, our model implies that 10 percent of job-to-job transitions result in wage losses. Therefore, we decide to calibrate the model to the amount of job-to-job transitions that do not result in nominal wage losses, instead of the overall amount. We find that it is more costly for higher skilled workers to generate job offers.

Finally, we calibrate the size of the welfare state to the mid 1980's. Different from legislation, unemployment benefits are indefinite in the model. To compensate, we calibrate benefits to the average we observe in the data by education. We model the universal means-tested program in line with the regulations from the *Food Stamps Program* for a household composed of 4 persons during working age and two persons during retirement. Kerr et al. (1984) describe the *Thrifty food plan* that determines the maximum amount of benefits. We parameterize the bend points d_1 and d_2 in social security transfers according to those reported in Social Security Administration (2016). We choose the probability to be granted disability insurance, υ, to be consistent with the share of accepted claims between 1984 and 1993 that is reported in Social Security Administration (2015). The threshold level that allows workers to apply, $\bar{\upsilon}$, is calibrated such that 7.8 percent of the population receives disability insurance after age 50. Finally, in order to calibrate the parameters of the tax function, we estimate the following equation

$$ln(E_{ih}) = ln(\tau_c) + \tau_p ln(E^g_{ih}) \tag{16}$$

using SIPP data and *TAXSIM* to construct E_{ih} from gross earnings, E^g_{ih}.[28]

4.1 Model Fit

Table 4 compares (untargeted) labor market outcomes that are informative on consumption insurance and sorting through job mobility from the model to the data. To begin with, our model predicts a decline in consumption after a job loss of 0.12 log points. Chetty (2006) summarizes available estimates from the US suggesting a drop of around 0.1 log points. The decline in consumption in our model arise due to insufficient insurance, and from complementarity of work with consumption. The small decline in the data is, therefore, consistent with the latter being small.[29]

Non-employment incidences are not randomly distributed across workers. Jung and Kuhn (2017) show that average tenure at age 50 is a useful summary statistic to measure this heterogeneity in job stability. Consistent with their finding, our model implies large average tenure, almost 13 years, of those employed at age 50.

High average tenure results partially from workers sorting into high paying jobs over the life-cycle. Hornstein, Krusell and Violante (2012) show that the mean residual wage relative to the minimum is a useful statistic to evaluate the amount of sorting across heterogeneous jobs. The

[28]Taxes are filed at the household level. If the household has more than one earner, we compute the individual tax as the share of the household tax according to individual earnings contributions.

[29]Indeed, Browning and Crossley (2003) and Bloemen and Stancanelli (2005) show that consumption does not drop upon unemployment for households with positive financial wealth.

Table 4: Untargeted Moments

	All Workers-Model			All Workers-Data		
$\Delta ln(c)$ EN	-0.12			-0.10°		
Tenure age 50	12.91			$11^{\mp}$		
	HS	SC	C	HS	SC	C
Mean-min ratio	1.89	2.07	2.38	2.17	2.13	2.49
Wage gain JTJ %	27.56	23.78	31.12	28.23	25.62	30.28
Wage loss JTJ %	-8.83	-9.56	-10.98	-25.16	-26.00	-29.07
Wage loss ENE %	-15.74	-14.01	-23.69	-16.97	-13.60	-26.31

Notes: The table compares model implied moments to the data. $^{\circ}$ see Chetty (2006) for a survey on consumption expenditure reductions upon a transition to non-employment. $^{\mp}$ see Jung and Kuhn (2017) for average tenure in CPS data. *HS*: at most a high school diploma. *SC*: some college. *C*: college degree. Data moments refer to the first period of analysis in the data: 1983-1993. *Mean-min ratio*: the ratio between the average residual wage and the 5th percentile residual wage. *Wage gain JTJ*: average change in log wages at a job-to-job transition conditional on a non-negative wage change, *wage loss JTJ* is defined analogously. *Wage loss ENE*: average change in log wages between jobs for workers 35 years or older that transit through a non-employment spell.

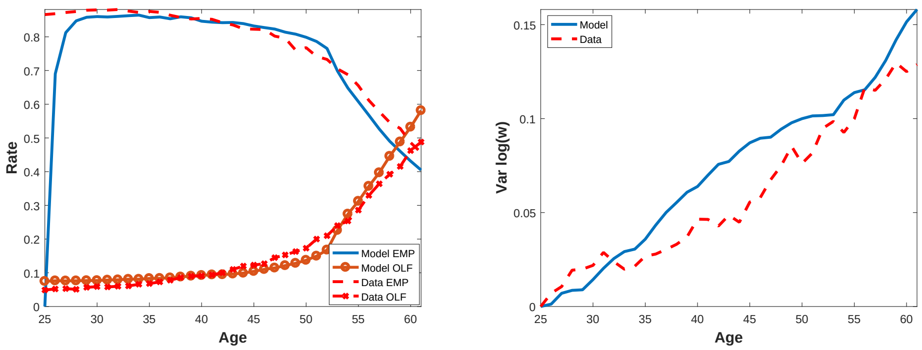
third row in the table shows that our model closely matches the data along this dimension.

An alternative measure to judge the amount of sorting over heterogeneous jobs are the wage dynamics resulting from job-to-job transitions. Rows four and five compare average wage growth, conditional on a positive or negative wage growth. The model matches closely a positive growth around 0.27 log points, but implies too small negative changes. Jacobson, LaLonde and Sullivan (1993) show that high tenured workers suffer substantial earnings reductions when re-entering the employment pool after a job loss. In this spirit, the last row in Table 4 compares log wage changes after job loss of workers 35 or older in the model to the data. The model is able to rationalize the large wage losses we see in the data because workers re-enter the employment pool on average with worse jobs than they have had prior to the job loss.

Earnings uncertainty, together with the labor market friction and the selection, shape employment choices and wage inequality over the life-cycle. Figure IA shows that the model replicates participation patterns from the data well. As in the data, the employment rate drops after the age of 45 by around 30 percentage points. What is more, as in the data, most of those exiting employment late in life find it optimal not to search for a

Figure I: Life Cycle Profiles

(A) Employment (B) Inequality



Notes: The left figure displays the employment rate, *EMP*, in the model and the SIPP data from 1983-1993. It also displays the fraction of non-employed reporting no search, *OLF*. The right figure displays the cross-sectional variance in yearly log hourly wage over the life cycle. The series are normalized to zero at the first age group. In the data, we control for race, region, metropolitan area, marriage, and time fixed effects.

new job. Figure IB shows that the implied cross sectional wage inequality over the life-cycle also matches the data closely.[30] Inequality increases by about 0.15 log points in a close to linear fashion. Note that this increase is smaller than suggested by the variance of permanent shocks. As workers age, lower productive workers leave the market, thereby, reduce inequality.

5 Implications of Changes in Risk

This section simulates counterfactual changes in labor market risk (to the level in 2003-2013), keeping all other parameters at their calibrated levels (in 1983-1993). Thus, in these experiment, we hold the initial dispersion of workers, mean wages, and the institutional framework constant.[31]

[30] We proceed with some data adjustments for the particular analysis regarding the evolution of wage inequality. To begin with, we trim the lowest 1% of observations of hourly income by educational degree. Regarding top income, the surveys censors each source of income above specified top coded levels. To account for this, we follow Heathcote, Perri and Violante (2010) and replace top-coded observations by an appropriate draw from an estimated Pareto distribution.

[31] We parametrize the distributions of risk with $\epsilon_{ih} \sim N(-\frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon^2)$ and $\psi_{ij} \sim N(-\frac{\sigma_\psi^2}{2}, \sigma_\psi^2)$ to assure that changes in the variances do not affect mean wages.

5.1 Rising Inequality and Falling Labor Market Participation

Table 5: Increase in Within-Education Wage Inequality

	High School	Some College	College
SIPP	0.022	0.043	0.040
Model	0.014	0.030	0.044
Model-wage offer	-0.012	0.001	0.006
ΔE %	-2.223	-0.808	-0.445
ΔD %	3.289	1.736	0.193
ΔJTJ %	-0.072	0.035	0.057
Δ wealth Gini	0.010	0.020	0.023

Notes: The upper panel displays the change in the variance of residual log wages from the periods 1983-1993 and 2003-2013. *Model*: The change from model simulation based on the point estimates of changes in productivity risk and changes in the wage offer distribution presented in Section 3.3.2. *Model-Wage offer*: The change in inequality resulting from changes in the wage offer distribution only. The bottom panel displays model implied changes in the employment rate, the disability rate (after age 50), the job-to-job transition rate, and the Gini coefficient of wealth.

Table 5 displays the counterfactual changes in wage inequality in the model and in the data.[32] Our model explains around 65% of the increase in inequality for workers with at most some college and overestimates by 10% the increase in inequality for college workers. The row labeled *Wage offer* displays changes in inequality when the dispersion of the wage offer distribution changes, and the dispersion of productivity shocks remains at the level of the first period. Changes in the wage offer distribution contribute to rising wage inequality for workers with at least some college education, but the vast majority results from increased productivity risk.[33]

Inequality increases the least for workers with only a high school education in the model and in the data. The second panel in Table 5 shows that the reason behind this is that rising wage risk decreases the employment rate of these workers by 2.2 percentage points. With larger uncertainty, more workers see their productivity fall below their reservation wages and

[32] We solve two separate steady states. As far as the data did not yet converge to the new steady state, our model may overestimate the role that changes in risk play.

[33] An increase in the wage offer distribution and a resulting rise of wage inequality is consistent with several recent papers which find that between firm wage dispersion has increased over the last decades. This includes Song et al. (2015) for the US, Mueller, Ouimet and Simintzi (2015) for the UK, and Card, Heining and Kline (2013) for Germany.

decide to move to non-employment. Part of the rise in non-employment results in rising disability insurance claims. For workers with only high school education, the disability rate after age 50 increases by 3.2 percentage points. Employment decreases and disability insurance claims also increase for higher skilled workers, but the changes are much smaller. These workers are on average further away from their participation thresholds; therefore, increases in productivity risk are less likely to trigger non-employment choices. What is more, these workers increase their search effort to take advantage from the more dispersed wage offer distribution, hence, move away from the participation threshold.

The last row shows that the rise in wage uncertainty also leads to a rise in wealth inequality. For one, a higher non-employment rate increases the amount of workers with few wealth. Moreover, the economy with higher risk features more extremely high earning workers that accumulate large wealth for life-cycle reasons.

5.2 Welfare Consequences of Rising Uncertainty

We now assess the welfare consequences of changing wage uncertainty. The change in risk alters the stationary distribution of workers over employment and jobs, thereby, the tax revenue and public expenditures. Consequently, we re-calibrate the tax rate and the generosity of the different governmental programs to assure that the total revenues and program expenditures stay the same. We perform these simulations conditional on workers' education; hence, we abstract from insurance mechanisms that may occur between education groups. Our welfare measure is the willingness to pay in terms of life-time consumption of an unborn.

Table 6 shows the welfare consequences of the changing uncertainty between the first and the third period. The top row shows the willingness to pay before uncertainty about educational status is resolved. On average, an unborn worker is willing to forgo 0.61% of life-time consumption to avoid the additional risk.

These welfare costs are not evenly distributed across education groups. The second row in Table 6 displays the willingness to pay after workers know their educational status. Workers with at most high school education

Table 6: Welfare Effects of Rising Uncertainty

All workers %	0.61		
	High School	Some College	College
Total wage risk %	2.40	-1.49	-1.94
Wage offer %	3.02	-1.86	-3.28
Weaker government %	3.62	-0.46	-0.72

Notes: The table displays the average willingness to pay in consumption equivalence of an unborn worker to avoid the changes in risk that have occurred between the two periods 1983-1993 and 2003-2013. *All workers*: aggregates all education levels. *Total wage risk*: based on changes in permanent productivity risk and changes in the wage offer distribution, by education level. *Wage offer*: only changes in the wage offer distribution, by education level. *Weaker government*: the only insurance programs are social security and one half of the original benefit level of the universal means-tested program.

are willing to pay 2.4 percent of life-time consumption to avoid the change in risk. In contrast, workers with at least some college education experience welfare gains from the increased uncertainty.

The third row displays the welfare effects from changing the wage offer distribution but keeping productivity risk at its old level. All type of workers prefer a more dispersed wage offer distribution. In a search model, an increase in the wage offer dispersion creates an option value to the worker: He can always break away from particular poor matches when he finds a better match. This option value outweighs the costs of increased uncertainty. Quantitatively, increasing the standard deviation by 0.01, increases the willingness to pay by around 1%. Dispersion has increased most for workers with finished college, consequently, they gain the most. Endogenous search is important for this mechanism because it allows workers to take advantage of the new opportunities. When we calculate welfare with exogenous search, we find welfare gains of only half the size.

Comparing total welfare changes to those where only the wage offer distribution changes provides the net effect of changes in productivity risk. These welfare effect are heterogeneous across education types. To avoid an increase of the standard deviation by 0.01, workers with a college degree, some college education and high school eduction are willing to pay 1.39%, 0.37% and -0.62% of life-time consumption, respectively. These costs are increasing in education because higher skilled workers are on average further away from their participation threshold; therefore, they have less insurance against permanent risk. In contrast, endogenous participation provides relatively good insurance against the downside from productivity risk for the least skilled workers. Again, endogenous search plays an important role. For a worker it is relatively attractive to quit into nonemployment after a poor productivity shock when this decision is easily reversible should his productivity develop favorable in the future. Endogenous search effort allows for such a reversion because it is relatively easy to find a new job and climb the job-ladder. Solving the model with exogenous search, we find welfare losses from increased productivity risk also for the least skilled, as in Low, Meghir and Pistaferri (2010).

To evaluate the importance of the government providing insurance against increasing wage risk, the fourth row computes welfare changes from changes in the risk in a hypothetical economy where there is only social security. Hence, there is neither disability insurance nor unemployment insurance, taxes are proportional, and the maximum benefits from the universal means-tested program are reduced by 50%.[34] Comparing the results to the second row, the government plays an important role in shielding workers from rising wage uncertainty. All type of workers would be willing to give up close to 1% of additional life-time consumption to avoid the change in risk in this hypothetical economy.

5.3 Rising Uncertainty and the Welfare State

So far, we have not addressed the question whether the level of governmental insurance in the 1980's was adequate to insure workers and whether the optimal size of the welfare state has changed over the decades. Describing optimal policy is beyond the scope of this paper. Instead, we study the welfare implications of a small increase in the welfare state. Online Appendix E show for each experiment the change in the individual programs. Our first experiment increases unemployment benefits by 10 percent. The resulting changes in governmental revenues and expenditure (across all programs) are financed by an increase in proportional taxes, τ_c, such that the governmental budget is unchanged within each education group. The second row in Table 7 shows that across education groups, the policy reduces

[34] We allow for a low level of means-tested transfers to insure that income is always positive.

Table 7: Welfare Effects of Increasing the Welfare State

	High School		Some College		College	
Period	1	3	1	3	1	3
Unemp. ben. %	2.70	2.23	1.33	1.42	0.29	0.25
Means-tested %	1.64	1.28	0.48	0.53	-0.10	-0.10
Disability ins. %	2.43	1.98	1.28	1.53	0.29	0.29
Progressive tax %	0.24	0.11	-0.02	0.03	-0.02	-0.05

Notes: The table displays the average willingness to pay in consumption equivalence of an unborn worker to avoid the changes in the welfare state. The changes is financed by proportional earnings taxes within each education group. *Period 1*: labor market risk from the 1983-1993 period. *Period 3*: labor market risk from the 2003-2013 period. *Unemp. ben.*: increase in unemployment benefit levels. *Means-tested*: raising the maximum benefits of the universal means-tested program. *Disability ins.*: increase in the disability insurance payments. *Progressive tax*: decrease in the progressive tax.

welfare. Low skilled workers loose the most; in period one (1983-1993), they are willing to pay 2.7 percent of life-time consumption to avoid the policy change. Welfare losses from the same policy are on average smaller in the third period (2003-2013), representing an increased desire for insurance.

Next, we fix for each education group the higher governmental revenue and costs obtained in the previous experiment (with the original unemployment benefits) and change τ_c and the size of the universal means-tested and disability insurance payments, respectively, until the total revenues and expenditures are unchanged. The third row shows that increasing universal means-tested programs payments increases welfare for those with college education, but it leads to losses for those with only high school education. From a welfare perspective, the universal means-tested program performs better than unemployment benefits because it has less disincentive effects on working. Online Appendix E shows that in the economy with higher unemployment benefits, the average employment rate is 2 percentage points lower than in the economy with higher universal means-tested transfers. Increasing disability insurance payments (row 4) has similar welfare consequences as raising unemployment benefits. The decrease in employment is lower than in the latter case, but the withdrawal is permanent which is welfare deteriorating.

Finally, we fix the higher proportional tax rate that arises from higher unemployment benefits, and decrease progressive taxation until the governmental budget is unchanged (row 5). The welfare effects of this experiment are small. Progressive taxation would be a relatively efficient way to redistribute income in our model because there is no intensive labor choice. Yet, it distorts the endogenous search decision because higher paying jobs become relatively less attractive.

6 Conclusion

This paper studies the trends in US labor market risk over the period 1983-2013 in a model of endogenous labor market participation and mobility. We decompose workers' wage risk into permanent shocks to idiosyncratic productivity, and a job specific wage component. Our approach allows us to disentangle from earnings fluctuations the exogenous shocks and the endogenous choices in response to these shocks. Using survey data for males, we find that permanent productivity risk increased by about 0.01 standard deviations for all workers. Heterogeneity in job offers has risen for workers with at least some college education, but it declined for those with only a high school education.

When simulating these increases in risk, we find that these account for 75% of the increase in within education wage inequality in the US during the last three decades. The increase would have been even larger, had there been no adjustment of workers participating in the labor market. As a consequence of more productivity risk, we find that the employment rate of low skilled workers has fallen by 2.2 percentage points.

The welfare costs of increased uncertainty are moderate. Governmental insurance programs, together with an endogenous search decision, shield low skilled workers from most of the increase in productivity risk. In addition, workers with at least some college education compensate the increase in productivity risk with a more dispersed wage offer distribution. More dispersed job offers imply an additional option value to the worker: He can always terminate poor jobs when facing a better offer. Endogenous on-the-job search makes this a particularly effective insurance mechanism.

We find that the welfare state, as present in the mid 1980s, is overall too generous. Particularly unemployment insurance and disability benefits reduce employment and labor force participation without providing a large enough benefit in insurance to offset these disincentive effects. A universal means-tested program performs better because it reduces these disincentive effects. Resulting from larger risk, the welfare state is more valuable in the 2000s; however, scaling back unemployment and disability insurance would still be welfare improving.

We use a partial equilibrium framework; yet, some of the aggregate employment changes we find are sizable and may imply smaller effects in general equilibrium. Also, our analysis focuses only on male workers and does not explicitly model joint household decisions. Yet, spousal labor participation could serve as an additional insurance mechanism against individual labor market risk. Blundell, Pistaferri and Preston (2008) provide an approaches in this direction. They do not make a distinction between exogenous income risk fluctuations and endogenous outcomes. Erosa et al. (2015) propose a framework to estimate shocks to spouses productivity jointly, taking into account the participation margin.

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A Appendix

A.1 Wage Variance Estimates

Table A1: High School

	1983-1993	1994-2003	2004-2013
Standard deviations			
σ_ϵ	0.030	0.035	0.040
	(0.004)	(0.006)	(0.008)
σ_ι	0.071	0.070	0.043
	(0.002)	(0.002)	(0.004)
σ_ψ	0.260	0.262	0.225
	(0.009)	(0.009)	(0.042)
Correlations			
$\rho_{\epsilon\pi}$	0.313	0.670	0.251
	(0.164)	(0.247)	(0.197)
$\rho_{\epsilon\mu}$	-0.358	-1.000	0.013
	(0.184)	(0.125)	(0.349)
$\rho_{\xi\pi}$	0.104	0.046	-0.342
	(0.069)	(0.047)	(0.325)
$\rho_{\xi\pi_{-1}}$	0.180	-0.030	-1.000
	(0.171)	(0.152)	(0.422)
$\rho_{\xi\mu}$	0.039	0.110	0.022
	(0.016)	(0.024)	(0.041)
$\rho_{\pi\pi_{-1}}$	0.933	0.910	0.899
	(0.002)	(0.004)	(0.004)
$\rho_{\pi\mu}$	0.496	0.394	0.141
	(0.090)	(0.130)	(0.151)
$\rho_{\pi_{-1}\mu}$	0.460	0.496	0.401
	(0.102)	(0.110)	(0.135)
MA process			
θ_1	-0.455	-0.403	-0.441
	(0.015)	(0.031)	(0.084)
θ_2	-0.049	-0.016	-0.000
	(0.017)	(0.020)	(0.032)

Notes: σ_ϵ, σ_i, σ_ψ are the standard deviations of the permanent shock, transitory shock, and job offer distribution respectively. Estimation is based on the first and second moments of equation (15). Block bootstrap standard errors in parentheses (100 repetitions). ρ_{xy} is the correlation coefficient between variables x and y. We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1.

Table A2: Some College

	1983-1993	**1994-2003**	**2004-2013**
Standard deviations			
σ_ϵ	0.042	0.047	0.052
	(0.004)	(0.007)	(0.024)
σ_ι	0.079	0.083	0.050
	(0.002)	(0.003)	(0.021)
σ_ψ	0.217	0.225	0.235
	(0.030)	(0.024)	(0.058)
Correlations			
$\rho_{\epsilon\pi}$	0.078	0.805	0.378
	(0.192)	(0.229)	(0.336)
$\rho_{\epsilon\mu}$	-0.714	-0.531	1.000
	(0.167)	(0.208)	(0.481)
$\rho_{\xi\pi}$	-0.250	0.268	-0.441
	(0.234)	(0.192)	(0.539)
$\rho_{\xi\pi_{-1}}$	0.439	0.243	-0.227
	(0.512)	(0.600)	(0.414)
$\rho_{\xi\mu}$	0.111	0.128	-0.138
	(0.040)	(0.038)	(0.101)
$\rho_{\pi\pi_{-1}}$	0.926	0.901	0.907
	(0.004)	(0.007)	(0.005)
$\rho_{\pi\mu}$	0.598	0.283	0.142
	(0.152)	(0.210)	(0.200)
$\rho_{\pi_{-1}\mu}$	0.688	0.521	-0.173
	(0.142)	(0.195)	(0.206)
MA process			
θ_1	-0.433	-0.484	-0.400
	(0.019)	(0.031)	(0.204)
θ_2	-0.040	-0.086	-0.061
	(0.021)	(0.028)	(0.149)

Notes: σ_ϵ, σ_i, σ_ψ are the standard deviations of the permanent shock, transitory shock, and job offer distribution respectively. Estimation is based on the first and second moments of equation (15). Block bootstrap standard errors in parentheses (100 repetitions). ρ_{xy} is the correlation coefficient between variables x and y. We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1.

Table A3: College Degree

	1983-1993	1994-2003	2004-2013
Standard deviations			
σ_ϵ	0.050	0.048	0.058
	(0.004)	(0.006)	(0.005)
σ_ι	0.107	0.114	0.073
	(0.002)	(0.002)	(0.003)
σ_ψ	0.267	0.265	0.300
	(0.009)	(0.022)	(0.029)
Correlations			
$\rho_{\epsilon\pi}$	0.495	0.864	0.679
	(0.220)	(0.187)	(0.143)
$\rho_{\epsilon\mu}$	-0.582	-0.168	-0.847
	(0.163)	(0.171)	(0.134)
$\rho_{\xi\pi}$	0.004	0.057	-0.131
	(0.040)	(0.159)	(0.192)
$\rho_{\xi\pi_{-1}}$	0.147	0.417	-0.953
	(0.219)	(0.234)	(0.793)
$\rho_{\xi\mu}$	0.091	0.081	0.132
	(0.022)	(0.025)	(0.029)
$\rho_{\pi\pi_{-1}}$	0.935	0.889	0.919
	(0.003)	(0.006)	(0.004)
$\rho_{\pi\mu}$	0.404	0.556	0.400
	(0.126)	(0.107)	(0.223)
$\rho_{\pi_{-1}\mu}$	0.419	0.722	0.480
	(0.138)	(0.110)	(0.290)
MA process			
θ_1	-0.435	-0.444	-0.474
	(0.016)	(0.014)	(0.032)
θ_2	-0.047	-0.097	-0.090
	(0.014)	(0.012)	(0.032)

Notes: σ_ϵ, σ_i, σ_ψ are the standard deviations of the permanent shock, transitory shock, and job offer distribution respectively. Estimation is based on the first and second moments of equation (15). Block bootstrap standard errors in parentheses (100 repetitions). ρ_{xy} is the correlation coefficient between variables x and y. We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1.

A.2 Calibration Table

Table A4: Calibration Targets

	HS	SC	C
Initial log wage dispersion	0.38	0.38	0.41
Initial mean log wage	7.17	7.27	7.47
Mean net wealth age < 61 in 1000s	32.43	37.33	57.87
Employment rate age 42-45 %	78.68	88.21	93.59
JTJ flows $\Delta w_{ih}^{g} \geq 0$ %	1.83	1.91	1.53
UE flow rate %	19.77	21.00	23.47
EN flow rate %	2.47	1.63	1.08
Wage growth age 25-50 %	30.07	44.73	55.42
Wage growth age 51-61 %	-3.09	-5.81	-5.69

Note: The table displays the calibration targets using the SIPP data from our first period of analysis: 1983-1993. *HS*: at most a high school diploma. *SC*: some college. *C*: college degree. *Initial dispersion*: dispersion of log wages at age 25. *Initial mean log wage*: average log wage at age 25. *Mean net wealth*: net total assets of a household. *JTJ*: rate of job-to-job transitions that result in no wage losses. *UE flow rate*: Job finding rate of the non-employed that report searching for a job. *EN*: flow rate from employment to non-employment. *Wage growth*: mean change in log wages.