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

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Abstract

U.S. male residual wage inequality rose, and the employment rate fell between 1983–2013. Using a structural labor market model, we show that rising idiosyncratic wage risk and lower taxes at the bottom of the earnings distribution are the main forces behind rising wage inequality. The former contributes to the falling employment rate. Falling real wages and rising disability risk further depressed employment of workers without a college degree and rising exogenous job destruction depressed employment of workers with a college degree. Higher idiosyncratic risk entails large welfare losses with the largest losses among workers without a college degree.

Keywords: Wage risk, secular trends, inequality, participation

JEL: E21, I38, J22, J31, J64

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1 Introduction

Wage inequality among male workers with similar characteristics (residual inequality) increased in the US between 1983 and 2013. Measuring cross-sectional inequality by the 90 to 10 ratio of residual wages (ages 25-61) in the Survey of Income and Program Participation, the increase is around 0.4 for college-educated workers and 0.14 for workers with at most a high school degree (see Table 1). At the same time, employment rates have fallen across education groups, with the decline being more pronounced for non-college-educated workers (13 percentage points) compared to those with a college degree (6 percentage points). These employment adjustments mostly reflect workers exiting the labor force, and the adjustments are concentrated among workers older than age 54.

This paper shows that these trends are intertwined. Increases in idiosyncratic labor market risk deepened cross-sectional wage inequality and also led workers with poor wage outcomes to leave the labor force which, thus, slowed down the increase in wage inequality. Moreover, other economic forces that depressed employment rates of low-educated workers further dampened their increase in wage inequality. Working against it, decreasing tax rates at the bottom of the wage distribution increased employment of low-wage workers and, thus, increased wage inequality.

These results are based on a structural partial equilibrium model that, to address the main channels of employment adjustments, features a life cycle and an explicit distinction between being unemployed and out of the labor force. Workers make employment decisions given a set of governmental and private insurance options against labor market risk. We explicitly model progressive earnings taxation, *Unemployment Insurance*, *Food Stamps*, *Supplemental Security Income*, *Disability Insurance*, and *Social Security*. Furthermore, reduced consumption expenditure needs during non-employment and workers' precautionary savings provide additional private insurance against idiosyncratic labor market risk. The labor market risk can be broadly characterized into two types: First, workers face permanent shocks to their idiosyncratic productivities that change their

Table 1: Changes in Inequality and Employment

	$\Delta 90/10$	ΔE % ages		ΔOLF % ages	
		25-61	55-61	25-61	55-61
High school	0.14	-13.44	-17.77	11.49	14.21
Some college	0.43	-14.53	-16.37	11.61	12.85
College	0.4	-6.24	-4.81	4.43	1.77

Notes: The table displays changes in the 90/10 ratio of residual wages, employment rates, E, and out of the labor force rates, OLF for workers (aged 25–61 and 55–61) between the periods of 1983–1993 and 2004–2013 in the Survey of Income and Program Participation.

wages irrespective of their current jobs. Moreover, disability risk affects idiosyncratic productivities. Second, the labor market is frictional, and workers face stochastic job loss and receive random job offers from a job offer distribution. A worker cannot locate the highest paying job instantaneously, implying income risk arising from job loss and job search. The non-employed and employed optimally choose their job search intensity and make participation and mobility decisions.

In the data, to distinguish labor market risk from workers' endogenous responses to said risk, we extend the framework from Low et al. (2010). In particular, we quantify the dispersion of permanent productivity shocks, disability risk, the dispersion of the job offer distribution, and the risk of exogenous job loss for three time periods: 1983–1993, 1994–2003, and 2004–2013. We find that the standard deviation of quarterly permanent productivity shocks increased between the first and the third period for all education groups.[2] In addition, the productivity risk stemming from disability increased for workers with less than a college degree. The dispersion of the job offer distribution increased over time for workers with at least some college education, and it decreased for workers with only a high school education. Finally, the risk of exogenous job loss increased for workers with at least some college education. Taken together, high-school-educated workers experienced particularly an increase in their productivity risk while workers with at least some college education also experienced an increase in risk associated with their particular jobs.

[2] We find a declining trend in transitory shocks.

The increase in productivity risk implies that wages become more dispersed between the first and third periods. This mechanism alone accounts for the entire observed increase in residual wage inequality among workers with a college degree, 79% of the increase among workers with a high-school education, and 21% among workers with some college education.[3] Moreover, because more workers fall below their reservation productivities, the change in risk leads to a 2.4 (1.1 and 1.5) percentage point drop in the employment rate of high school (some college and college) educated workers. As in the data, most of this decline in employment rates results from elderly workers and those workers leaving the labor force. As employment declines most among those with the lowest labor productivity within that skill group, with fixed employment rates, wage inequality among the employed would have grown by an additional 16 to 100 percent, depending on the skill group. The other principal force behind rising wage inequality is declining tax rates at the bottom of the wage distribution that incentivize employment of low-productivity workers.

We identify rising exogenous job risk as the primary force behind declining employment of workers with a college degree and declining average wages and rising disability risks as the primary forces behind the much larger employment declines among workers without a college degree. Different from rising exogenous job risk, declining average wages and rising disability risks trigger the least productive workers to leave employment and, hence, slow down the rise in residual wage inequality.

Workers without a college degree suffer most in welfare terms from the changes in idiosyncratic risk. This occurs despite those workers suffering the least from a given increase in productivity risk as they are on average closer to their participation margin and, thereby, have more insurance against negative productivity shocks. Their higher welfare costs result from two channels. First, endogenous mobility implies that a more dispersed job offer distribution improves welfare because of an option effect (see Low et al., 2010). In our endogenous search framework, this effect is amplified by workers increasing

[3]We concentrate on the rise of residual wage inequality, which explains most of the rise in total inequality (see Krueger and Perri, 2006). We see our paper as a complement to the literature focusing on between-group inequality such as a rising college premium, e.g., Katz and Autor (1999).

their search effort when the option value of search is particularly large. Thus, a more (less) dispersed job offer distribution mitigates (amplifies) the welfare losses from the increase in productivity risk of college-educated (high-school-educated) workers. Second, rising disability risk poses welfare costs for workers with less than a college degree. In sum, workers with less than a college degree are willing to pay around 11 percent of lifetime consumption to avoid the change in risk between 1983–1993 and 2004–2013. The corresponding number for workers with a college degree is only 7.2 percent.

Finally, we assess whether expanding the welfare state would improve welfare by providing better insurance. To that end, we simulate small increases in the welfare state that are financed by a proportional consumption tax. We treat each education group separately, thus, keeping the total (potential) resources for each group fixed.[4] We find that expanding programs targeted at disability risk has particularly adverse effects on welfare. The reason is the relatively high labor supply elasticity of elderly workers. Similarly, labor supply elasticities are highest for low-educated workers, and they are particularly high in the 2004–2013 period, leading to welfare losses from expanding *Food Stamp* transfers for those workers.

Literature Declining male employment rates (see Abraham and Kearney, 2020, for a survey) and falling labor force participation rates (see Juhn and Potter, 2006; Dotsey et al., 2017), particularly after prime-age, are well-documented. The literature identifies rising generosity of non-employment benefits (see Eberstadt, 2016), an increasing value of leisure (see Aguiar et al., 2021), and stagnating mean real wages (see Moffitt et al., 2012; Wolcott, 2021) as explanations. We show that more dispersed productivity shocks, rising exogenous job destruction rates, and rising disability risk can explain most of the decline in employment and labor force participation rates. Moreover, we show that these forces developed differently across education groups. Finally, we show that lower taxes at the bottom of the income distribution partially offset the declines in employment rates.

[4] To meaningfully study redistribution between groups with different permanent incomes, we would require a framework with a skill investment decision as in Heathcote et al. (2017).

We also link to the literature documenting an increase in wage and earnings inequality since the 1980s (see for example Autor et al., 2008; Heathcote et al., 2010). Kopczuk et al. (2010) and DeBacker et al. (2013) show that most of the increase in earnings inequality stems from larger persistent differences in individual earnings.[5] We make two contributions. First, we show that the rise in residual inequality is mostly driven by rising persistent idiosyncratic productivity risk and lower taxes at the bottom of the income distribution. Second, we show that endogenous employment choices necessarily intertwine the rise in residual wage inequality with the fall in employment rates.

Rising idiosyncratic uncertainty is consistent with Gottschalk and Moffitt (1994) who find that the cross-sectional dispersion of residual earnings growth has become larger over time in the PSID. However, using data from the CPS (Ziliak et al., 2011) and administrative data (Sabelhaus and Song, 2010; Bloom et al., 2017), other studies find, if any, a downward trend in the dispersion of residual earnings growth. Recently, Braxton et al. (2021) show that a decrease in the dispersion of transitory shocks dominates this downward trend and that persistent shocks have become more dispersed.[6] We find the same declining time trend of transitory shocks in hourly wage data. Moreover, we add to this literature by showing that stronger selection into non-employment after negative productivity shocks in the 2004–2013 period compared to the 1983–1993 period partially masks the realized increase in persistent shocks. Moreover, we show that differentiating between productivity risk and job risk reveals differences in secular risks between education groups.

Our distinction between productivity risk and job risk closely follows Low et al. (2010). We add to their framework an explicit distinction between adjustments through unemployment and leaving the labor force. We show that the latter is the dominant adjustment

[5]Another related literature finds that between-firm wage dispersion has increased over the last decades. This includes Song et al. (2019) for the US, Mueller et al. (2017) for the UK, and Card et al. (2013) for Germany. This is broadly consistent with the more dispersed job offer distribution for college-educated workers that we find. Importantly, we study only within education changes while this literature also studies increased sorting between education groups.

[6]They also show that these findings heavily depend on the treatment of earnings observations close to zero which confirms earlier evidence by Carr and Wiemers (2019) using the SIPP.

margin both within a single cohort's life cycle and across cohorts over time. Moreover, we quantify wage risk, employment risk, and disability risk over time and highlight that extensive margin labor supply elasticities of low-educated workers increased over time leading to welfare programs having larger adverse employment effects.

Other papers that rely on structural models to study trends in wage risk are Bowlus and Robin (2004), who permit for trends in wage promotions and demotion rates, Kambourov and Manovskii (2009) who find increasing occupational mobility, 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. Relative to this literature, we allow for productivity risk, employment risk, and disability risk to change over time and study the implications of these changes for employment, labor force participation, and wage inequality. Moreover, we introduce risk-averse workers who self-insure against labor market risk and a detailed model of governmental insurance programs.

The structure of the paper continues as follows: The next section specifies the theoretical model. The following section discusses the identification of risk in the data. 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. They start their life corresponding to age 25 in the data.[7]

Structure of earnings risk: During working life, a worker, i of age h is either non-employed or employed. When employed at job j, his resulting observed hourly gross wage is given by

[7] We choose the sample to start at age 25 to avoid educational choices.

$$w^g_{ijh} = \exp(p_{ih} + \psi_{ij} + e_{ih}), \tag{1}$$

where p_{ih} is a worker's idiosyncratic log productivity, ψ_{ij} is a log job component, and e_{ih} is measurement error following a $MA(2)$ process.[8] As in the data, an employed worker spends 549 hours a quarter working, i.e., quarterly gross earnings are $E^g_{ijh} = 549 w^g_{ijh}$.

Workers face six types of earnings risks over their life cycles. The first three relate to their idiosyncratic productivities. First, at the beginning of life, a worker draws his idiosyncratic initial log productivity according to $p_{i1} \sim N(\mu_n, \sigma^2_n)$. Second, this log productivity follows a random walk with a drift component that depends on the employment state and age.[9] Define the productivity after shocks have realized by $\tilde{p}_{ih+1}$:

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

where $\epsilon_{ih} \sim N(0, \sigma^2_\epsilon)$ with cumulative distribution function $G(\epsilon)$. These shocks contain promotion decisions 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.[10] To reduce notation, we refer to the skill parameters in either age period by ν_x and δ_x

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

[9] A random walk with normally distributed innovations is in line with a large empirical literature on earnings uncertainty (see, e.g., Abowd and Card, 1989; Topel and Ward, 1992; Low et al., 2010). Recently, Sanchez and Wellschmied (2020) and Guvenen et al. (2021) show that an $AR(1)$ mixture model of persistent and transitory shocks matches better the excess kurtosis and negative skewness present in earnings growth data. Different from earnings growth, hourly wage growth displays no systematic negative skewness. 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, i.e., eliminating some excess kurtosis, leaves the estimated variance of permanent productivity shocks almost unchanged. Heathcote et al. (2010) find the same phenomenon in PSID data.

[10] Some papers in the literature estimate deterministic age-productivity profiles instead of employment-specific drift terms. As Tjaden and Wellschmied (2014) show, an employment-specific skill profile can rationalize why workers accept relatively low-paying jobs. Moreover, it creates persistence in employment (non-employment), as current job prospects depend on past employment choices.

with $x = 1, 2$. During non-employment, workers have either no skill gains or their skills depreciate: $\delta_x = min\{0, \nu_x\}$. Third, similar to Low and Pistaferri (2015) and Wellschmied (2021), households experience persistent disability shocks that affect their productivity. When a worker is in good health, $D = g$, he becomes disabled with probability π_h^{gb}, and his log productivity decreases by ς. Reversely, a worker who is disabled, $D = b$, becomes non-disabled with probability π_h^{bg}, and his log productivity increases by ς. Hence, a worker's next period productivity is given by

$$p_{ih+1} = \begin{cases} \tilde{p}_{ih} & \text{if } D = g \text{ and } \pi_h^{gb} = 0, \\ \tilde{p}_{ih} & \text{if } D = b \text{ and } \pi_h^{bg} = 0, \\ \tilde{p}_{ih} - \varsigma & \text{if } D = g \text{ and } \pi_h^{gb} = 1 \\ \tilde{p}_{ih} + \varsigma & \text{if } D = b \text{ and } \pi_h^{bg} = 1. \end{cases}$$

The remaining three types of risk all relate to job risk. First, resulting from labor market frictions, workers face stochastic job offer arrival rates, s_{ih} (specified below). Second, job offers are random draws from a job offer distribution. Those workers generating a new offer, either while employed or unemployed, randomly draw its log job component according to $\psi_{ij} \sim N(0, \sigma_\psi^2)$ with cumulative distribution function $F(\psi)$.[11] After observing the job offer, they decide whether to accept it.[12] Third, employed workers face the risk of losing their current job type. This job risk takes two forms. With age-varying probability, $\omega(h)$, a job is exogenously destroyed, and the worker becomes non-employed. Moreover, as in Tjaden and Wellschmied (2014), workers face reallocation shocks with probability λ. When a reallocation shock occurs, a worker does not have the option to stay with his current job but chooses between an alternative random job offer and

[11] A time-invariant job component follows the on-the-job search models in the tradition of Burdett and Mortensen (1998) and empirical specifications following Abowd et al. (1999). Guiso et al. (2005) show that firms almost perfectly insure non-laid-off workers against idiosyncratic firm risk, supporting this assumption. Moreover, our model features exogenous job loss (discussed below) and, thus, incorporates some job risk.

[12] For our analysis, it is not salient whether heterogeneous job components arise from differences in job quality that are perceived by all workers alike or an idiosyncratic ranking of jobs by individual workers, i.e., match effects.

non-employment. One way to think about these reallocation shocks is that some workers hold temporary jobs or have advanced notice about the dismissal, and, thus, staying with their current job is not possible leading to possible losses in match quality.

Insurance against earnings risks: Workers choose each period their search intensity, $s_{ih} \in \{0.1, 1\}$, that determines the probability of receiving a new job offer.[13] That is, both when non-employed and employed, workers control their chance of job mobility and weigh the gains of additional job offers against convex utility search costs:

$$C(s_{ih}) = \varpi_0 \frac{s_{ih}^{1+\varpi_1}}{1+\varpi_1}. \tag{2}$$

Endogenous search provides workers with partial insurance against employment risk and a currently poor job component, ψ_{ij}. Furthermore, workers make participation decisions that partially insure against low idiosyncratic productivity, p_{ih}. That is, a worker may find it optimal to choose non-employment over employment when productivity is particularly low.

Important for the decisions of whether to work and how hard to search for better job opportunities is the amount of governmental-provided insurance. Thus, we model several of the major insurance programs. First, the earnings tax is progressive. Following Heathcote et al. (2017), earnings after taxes are

$$E_{ijh} = \tau_c \Big(E_{ijh}^g \Big)^{\tau_p}, \tag{3}$$

where τ_p determines the progressivity of the tax code. Second, during the first quarter of non-employment, workers receive gross unemployment benefits: $ub_{ih}^g = \min\{\kappa E_{ijh}^g, \overline{ub}\}$, where κ is the replacement rate and $\overline{ub}$ is a statutory maximum benefit level. Legislation usually grants 26 weeks of benefits. To reduce the state space, we assume benefits are

[13] We impose a minimum search requirement, 0.1, to avoid all employed workers always searching epsilon in the hope of finding a better job. We impose a maximum of one job offer as our estimation of the job offer distribution requires that assumption.

only paid for one quarter and chose a relatively high replacement rate, $\kappa = 0.7$, as in Low et al. (2010). Following legislation, workers only receive unemployment benefits when their job is destroyed and not when they choose to quit into non-employment.

Third, non-employed workers may receive *Disability Insurance* (*DI*) and leave the labor market permanently. To apply for benefits, the legislation requires an "inability to engage in any substantial gainful activity by reason of any medically determinable physical or mental impairment" (Social Security Administration, 2014). Moreover, the legislation requires a worker to be continuously non-employed for 5 months and to have worked before that period. Finally, the application process is characterized by frequent denials of benefit claims. In the model, to capture the health test, a worker must be disabled to apply for benefits.[14] To capture the employment factors, a household may only apply for *DI* the period after becoming non-employed and his work possibilities must have deteriorated in the period of becoming non-employed, $p_{ih} - p_{ih-1} \leq 0$. Moreover, a worker may not search for a job within the same quarter of the application. Finally, applications are only granted with probability υ_h which, reflecting guidance from the Social Security Administration, may vary with age. Gross benefits follow

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

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

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

[14] In the data, only 0.2 percent of non-disabled workers receive *DI*.

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

Those workers receiving low disability or retirement benefits may receive *Supplemental Security Income* (*SSI*). The gross benefits of the program are

$$TS^g(\bar{E}_{ih}) = \begin{cases} \max\{0, \overline{TS} - (S(\bar{E}_{ih}) - ID_S)\} & \text{if } a_{ih+1} \leq \bar{a}, \\ 0 & \text{otherwise .} \end{cases}$$

where $\overline{TS}$ is the maximum transfer, and ID_S is an income deductible. To be eligible, individuals must satisfy an asset test: $a_{ih+1} \leq \bar{a}$. Low-income workers that satisfy the asset test may also receive benefits from an universal means-tested program that mirrors the US *Food Stamps Program* (*FS*). Denote by y_{ih} worker's gross total countable income.[15] Transfers are given by

$$TF(y_{ih}, h) = \begin{cases} \overline{TF}_h - 0.3(y_{ih} - ID_F) & \text{if } y_{ih} < \overline{y}_h \text{ and } a_{ih+1} \leq \bar{a}, \\ 0 & \text{otherwise .} \end{cases}$$

Finally, all gross transfer income other than *FS* are progressively taxed at the federal tax brackets as described in Online Appendix A. We denote by ub_{ih}, $TS(\bar{E}_{ih})$, and $S(\bar{E}_{ih})$ the corresponding transfers after taxes.

In addition to governmental insurance, we also allow for self-insurance. First, workers may purchase a risk-free asset, a, that pays returns $R = 1 + r$, however, they are unable to borrow, $a_{h+1} \geq 0$. Second, reduced consumption needs during non-employment provide partial insurance against the lower income. Aguiar and Hurst (2005) show that households, after exiting employment, use the additional available time to engage in home production and reduce shopping costs. We model this type of insurance by reducing the

[15] In case of labor income, countable income allows for a 20% deduction from gross income.

level of utility derived from a given consumption expenditure when employed:

$$U(c_{ih}, P_{ih}) = \left(\frac{c_{ih}\exp(\varphi P_{ih})}{1-\eta}\right)^{1-\eta}, \tag{4}$$

where P_{ih} is one when the worker is employed and $\varphi \leq 0$. Moreover, working entails a fixed cost f, such as transportation and child-care costs, that reduces consumption c_{ih}:

$$c_{ih} = \begin{cases} E_{ijh} + TF(y_{ih}, h) + Ra_{ih} - a_{ih+1} - f & \text{if employed,} \\ ub_{ih} + TF(y_{ih}, h) + Ra_{ih} - a_{ih+1} & \text{if just unemployed,} \\ TF(y_{ih}, h) + Ra_{ih} - a_{ih+1} & \text{if long term unemployed,} \\ S(\bar{E}_{ih}) + TS(\bar{E}_{ih}) + TF(y_{ih}, h) + Ra_{ih} - a_{ih+1} & \text{if disabled or retired.} \end{cases}$$

We relegate the resulting value functions of workers to Online Appendix B.

3 Model Parametrization

3.1 Data Sources and Sample Selection

The analysis requires individual longitudinal information on worker and job characteristics over several decades. The dataset most adequate for these requirements is the Survey of Income and Program Participation (*SIPP*). We employ the set of panels covering the 1983–2013 period.[16] Every 4 months, the Census interviews all adult members of participating households asking them about their work and household characteristics during the preceding 4 months. To account for the seam-bias effect generated by the recollection period, we aggregate the monthly information into quarterly observations. One concern regarding the data is that the quality of the survey changes over time. We describe the details of our data cleaning procedure in Online Appendix C, where we also show that

[16]We exclude the surveys from 1985 and 1989 due to the absence of information regarding work experience.

survey redesigns are unlikely to have an impact on our results.

We consider male individuals, aged between 25 and 61, who are not self-employed, enrolled in school, in the armed forces, or recalled by their previous job after a separation.[17] The estimation of the job offer distribution requires sufficient job mover observations. To this end, we group the data into three periods, such that each covers years of expansion and recession: 1983–1993, 1994–2003, and 2004–2013. We consider three education groups as these groups display distinct evolutions in wage inequality and employment rates over those periods:[18] High school educated workers and those with some college experienced much larger employment declines than college graduates. At the same time, those with some college and college graduates experienced much larger increases in cross-sectional wage inequality.[19]

We consider a worker employed within a quarter when he spends most weeks working. Hence, workers with brief non-employment spells within a quarter (less than 6 weeks), are classified as employed. Put differently, we only model somewhat persistent unemployment risk. We identify job mobility by changes in the establishment ID assigned by the *SIPP*.[20] We define a worker's main job as the establishment ID with the highest earnings in a quarter.[21] 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 (brief) non-employment spell.[22] Finally, we compute hourly wages as total gross 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

[17] For our estimation, we require that mobility reflects workers who have received one random draw from the job offer distribution. Workers being recalled would violate this assumption.

[18] 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.

[19] We note that the education shares are not constant over time. For example, the share of the high-school group declined by 19 percentage points over time.

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

[21] The survey reports the two jobs with the highest earnings per month for each individual. We include workers with multiple job holdings to increase the number of observations. For identification, we require that they face the same job offer distribution as those with only one job.

[22] For our identification, we require that skill depreciation for non-employment spells under one quarter, at most 6 weeks, is negligible.

the 1st percentile (above the 99th percentile) of the hourly wage growth distribution by education, period, and job mobility status. Online Appendix D shows that, consistent with Sabelhaus and Song (2010) finding for earnings growth, the resulting cross-sectional variance of wage growth displays, if any, a downward trend over time.

3.2 Estimating Changes in Risk Dispersions

The first step of our analysis is to estimate changes in the dispersion of productivity shocks, σ_ϵ, and the job offer distribution, σ_ψ. Our framework implies that the observed distribution of wage growth alone cannot identify these parameters because we do not observe random realizations of shocks, i.e., workers make endogenous decisions on mobility and participation in response to shocks. Following Low et al. (2010), we allow for such endogenous responses by estimating an econometric model that encompasses the structural decision model from Section 2.

3.2.1 Identification of Risk and Selection

In Section 2, individual gross wages are a function of idiosyncratic productivity, p_{ih}, a job effect, ψ_{ij}, and measurement error, e_{ih}. Here, to incorporate a richer demographic structure, we allow gross wages to depend additionally on other worker observables (besides a predictable age and experience effect), x_{ih}. These include, among others, regional variations in wages and wages varying by household composition. The model abstracts from such types of heterogeneity and may be thought to represent the average worker along these dimensions.[23] However, in the data, these variables affect workers' mobility and participation decisions, i.e., they affect the degree of selection upon shocks. What is more, changes in the distribution of these variables over time make the amount of

[23] The model also abstracts from transitory wage changes that are not measurement error, e.g., bonuses. For tractability, we assume that workers do not make participation and mobility decisions based on such transitory wage changes.

selection time-varying. In the data, gross wages are

$$
\begin{aligned}
ln(w^g_{ijh}) &= \Psi x_{ih} + \psi_{ij} + p_{ih} + e_{ih} \\
p_{ih} &= p_{ih-1} + \epsilon_{ih} \\
e_{ih} &= \iota_{ih} - \chi_1 \iota_{ih-1} - \chi_2 \iota_{ih-2}, \text{ with } \iota_{ih} \sim N(0, \sigma^2_\iota).
\end{aligned} \tag{5}
$$

To identify the dispersion of productivity shocks, σ_ϵ, and the job offer distribution, σ_ψ, consider the first difference of Equation (5):

$$
\Delta ln(w^g_{ijh}) = \Psi \Delta x_{ih} + [\underbrace{\psi_{ij} - \psi_{ij-1}}_{\xi_{ih}}] M_{ih} + \epsilon_{ih} + \Delta e_{ih}, \tag{6}
$$

where M_{ih} is an indicator variable equal to one when the worker changes his job between h and $h-1$. This equation describes the wage dynamics of workers who are employed in two consecutive periods. As we discuss in more detail in Online Appendix E, in the absence of selection, σ_ϵ and σ_ψ would be identified by the second moments of unexplained wage growth, g_{ih}, of job stayers and job switchers. However, in the presence of endogenous participation and mobility decisions, residual wage growth of job stayers and job movers follow (below and above) truncated multivariate normal distribution which moments Manjunath and Wilhelm (2021) derive. To determine the strength of the truncation, we require individual participation and mobility probabilities. To obtain those, we follow Low et al. (2010) and model workers' endogenous decisions using latent variables:

$$
P^*_{ih-1} = \alpha z_{ih-1} + \pi_{ih-1}, \;\; P_{ih-1} = 1\left\{P^*_{ih-1} > 0\right\}, \tag{7}
$$

$$
P^*_{ih} = \alpha z_{ih} + \pi_{ih}, \;\; P_{ih} = 1\left\{P^*_{ih} > 0\right\}, \tag{8}
$$

$$
M^*_{ih} = \theta \kappa_{ih} + \mu_{ih}, \;\; M_{ih} = 1\left\{M^*_{ih} > 0\right\}, \tag{9}
$$

where z_{ih} and κ_{ih} are worker observables, and π_{ih} and μ_{ih} are unobservables. Through the lens of the model in Section 2, idiosyncratic productivity, shocks to said productivity, and the job component all affect workers' participation and mobility decisions. As we do not fully observe these variables in the data, they are partly contained in π_{ih} and μ_{ih}. To account for the resulting correlation in the error terms, we extend the framework of Low et al. (2010) and allow for a non-zero correlation between the unobservables:

$$\begin{pmatrix} \pi_{ih} \\ \pi_{ih-1} \\ \mu_{ih} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{\pi\pi_{-1}} & \rho_{\pi\mu} \\ \rho_{\pi\pi-1} & 1 & \rho_{\pi_{-1}\mu} \\ \rho_{\pi\mu} & \rho_{\pi_{-1}\mu} & 1 \end{pmatrix}\right]. \tag{10}$$

As we discuss in more detail in Online Appendix E, combining these individual participation and mobility probabilities with the first and second moments of unexplained wage growth allows us to estimate the strength of selection and the variances of shocks. The intuition is that the strength of selection is summarized by correlation coefficients between shocks and mobility and participation decisions. Looking at it again through the lens of the model in Section 2, productivity shocks alter employment decisions which is summarized by $\rho_{\epsilon\pi}$ and $\rho_{\epsilon\pi-1}$.[24] Similarly, changes in the job component affect participation decisions ($\rho_{\xi\pi}$ and $\rho_{\xi\pi-1}$) and mobility decisions ($\rho_{\xi\mu}$).

3.2.2 Estimates for Selection and Labor Market Risk over Time

Probit estimation We estimate the model for each of our three periods and education groups separately, thereby, we allow for time-varying returns to worker observables. Moreover, we allow for time-varying patterns in how worker observables affect participation and mobility decisions and time variation in unobserved factors. We estimate participation probabilities by controlling for quadratic trends in age and work experience, race, marital status, indicators of 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.[25]

[24] Time aggregation in the data will also create a correlation between productivity shocks and mobility decisions, $\rho_{\epsilon\mu}$, that we discuss below.

[25] 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

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. Following Low et al. (2010) and Liu (2019), we augment the set of regressors by unearned household income, an index for the generosity of the welfare system (state-level unemployment insurance), and an indicator of whether the worker owns a house. The former two variables increase reservation wages, thereby, decrease participation. The theoretical effects on mobility are ambiguous. On the one hand, being closer to the participation margin increases mobility because workers are more likely to quit their current jobs. On the other hand, higher reservation wages limit future movements along the wage ladder.[26] 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.[27]

Online Appendix F shows the results of the probit estimation. As expected, high unemployment benefits, high unearned income, and not owning a house reduce the probability of employment. We find that state-level generosity and house ownership reduce the likelihood of a worker moving jobs. We find no consistent and mostly insignificant effects of unearned household income.[28]

Risk estimates The top panel in Table 2 displays the estimates for permanent productivity risk and the job offer distribution. Inspecting the period 1983–1993, permanent shocks have a standard deviation between 0.03 and 0.05, where the dispersion of these shocks increases with education. Furthermore, we find large dispersions of job effects in

30%. Moreover, tenure information is not available for all jobs before the 1996 panel.

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

[27]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 et al. (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.

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

Table 2: Changes in Labor Market Risk

	High School		Some College		College	
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
	(0.004)	(0.009)	(0.004)	(0.030)	(0.004)	(0.009)
1994–2003	0.035	0.262	0.047	0.225	0.048	0.265
	(0.006)	(0.009)	(0.007)	(0.024)	(0.006)	(0.022)
2004–2013	0.040	0.225	0.047	0.235	0.058	0.300
	(0.007)	(0.048)	(0.027)	(0.055)	(0.004)	(0.029)
p-value	0.11	0.24	0.43	0.39	0.09	0.14

Notes: The table displays the standard deviation of productivity shocks, σ_ϵ, and the standard deviation of the job offer distribution, σ_ψ, from the model described in equations (5)–(10) estimated on *SIPP* data. Block-bootstrapped standard errors are in parentheses. The p-values refer to Welch tests between periods 1983–1993 and 2004–2013.

wage offers, where those with completed college face the highest dispersion. The standard deviation of the job offer distribution ranges from 0.22 to 0.27. Thus, within 2 standard deviations, the wage of the same worker varies by ± 54 percent depending on his job.[29]

Turning to the secular trends in risk, the main focus of the paper, the standard deviation of permanent productivity shocks has increased for all workers. Regarding the point estimates, for those with a college degree, the rise materializes in the third period. The increase occurred already earlier for the other education groups.[30]

For college workers, the standard deviation of the job offer distribution increased by 0.03. Again, the rise materializes in the third period.[31] Those with some college have experienced an increase of 0.02. Contrary to these groups, high school workers experienced a decline in the dispersion of the job offer distribution by 0.03 in the third

[29] Using exclusively the 1993 *SIPP* panel, Low et al. (2010) estimate $\sigma_\psi = 0.23$. For college-educated workers, similar to us, they find a yearly variance of permanent shocks of 0.01 ($4(0.05^2)$ in our case). They find a similar variance for low-educated workers that is larger than our estimate. Besides us also using data from the 80s, they estimate a restricted version of our model ($\rho_{\pi\pi_{-1}} = \rho_{\mu\pi_{-1}} = \rho_{\pi\mu} = 0$) and make somewhat different assumptions on the selection variables.

[30] 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. Online Appendix G shows that consistent with this idea, inequality is growing more rapidly over the life cycle in the 2004–2013 period compared to 1983–1993.

[31] One concern may be that a decline in spurious job-to-job transitions due to sample redesign leads to trends in the estimated job offer distribution. We describe in Online Appendix C the way we attempt to clean the data from such transitions. Moreover, we would expect the major break to occur from the first to the second period, as data quality increased from 1990 onwards.

period.[32] 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 techniques introduced in the 1996 and 2004 surveys (see Moore, 2008).

Selection estimates Appendix A.1 also displays the estimated selection correlations. In all periods, workers show substantial persistence in their unobserved participation heterogeneity, $\rho_{\pi\pi_{-1}}$, which is consistent with partially unobserved idiosyncratic productivity and job components. In line with this, positive innovations to productivity increase participation, $\rho_{\epsilon\pi} > 0$. The correlation between the unobserved component of mobility and participation decisions, $\rho_{\pi\mu}$, is in most cases significant and positive which may suggest heterogeneity in reservation wages that decrease participation and mobility. As expected, good outside offers increase the propensity of workers to move jobs, $\rho_{\xi\mu} > 0$. The theoretical effect of productivity shocks on mobility, $\rho_{\epsilon\mu}$, is ambiguous. Consistent with Low et al. (2010), we find mostly negative correlations, i.e., after a negative shock, workers are more likely to change jobs (possibly through a short non-employment spell). The correlations between outside offers and contemporaneous and lagged participation are mostly insignificant.[33]

If we had abstracted from selection, we would have missed several of the secular increases in risk, as Online Appendix E shows. This results from the fact, as Online Appendix F shows, that employed workers have relatively lower participation probabilities and more workers are in the lower tail of the participation distribution in the period 2004–2013 relative to the period 1983–1993. We find that observable worker characteristics have shifted in the direction of workers with less stable jobs (singles, minorities, elderly). Moreover, changes in the marginal effects of these covariates have also reduced

[32]We find that the decline is most pronounced for workers switching their industry or occupation but it is also present for those staying within their industry and occupation.

[33]Fixing these correlations to zero, we still find an increase in productivity risk for all skill groups. Moreover, we find an increase in the wage offer dispersion for those with at least some college education. However, those estimates imply no change in the wage offer dispersion for high school educated workers. These results are available from the authors upon request.

participation. Put differently, selection effects have become stronger over time leading to a stronger left-truncation of the observed shock distributions. The online appendix provides two additional moments of evidence supporting an increase in this type of selection. First, consistent with a more truncated distribution, Table D1 shows that the distribution of wage growth becomes more right-skewed over time. Second, Table C1 shows that the employment to non-employment transition rate is increasing over time.[34]

3.3 Remaining Parameter Calibration

We calibrate the remaining model parameters for the periods 1983–1993 and 2004-2013. We calibrate the coefficient of relative risk aversion, the interest rate, and the size of the welfare state (discussed below) 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 in our sample. We note that each parameter affects all moments in the model. Nevertheless, to better understand the link between the parameters and data moments, Table 3 links each parameter to the moment most closely associated with it. Appendix A.2 displays the education-specific values of the calibrated moments.

Regarding the distribution of states at age 25, we assume all workers start unemployed. Their initial wealth and disability states are random draws from the empirical distributions of young workers. Regarding idiosyncratic productivity at the beginning of life, 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' lives. We calibrate the employment-specific drift terms of idiosyncratic productivity, ν_1 and ν_2, to the average wage changes from ages 25 to 50 and from 51 to 61, respectively. Comparing the two time periods, low-skilled

[34]Cairó and Cajner (2013) show, using the CPS, that the monthly employment-to-non-employment transition rate is falling over time. We show in Online Appendix C the same pattern holds in the monthly *SIPP* data. However, after aggregating the data to the quarter, the trend reverses and the employment to non-employment transition rate increases over time. Put differently, the decreasing secular trend in employment-to-non-employment transitions in monthly data may result from unemployment spells that are shorter than one month dominating.

Table 3: Calibration of Parameters

	HS		SC		C		
Parameter	83-93	04-13	83-93	04-13	83-93	04-13	Target
σ_ϵ	0.03	0.04	0.04	0.05	0.05	0.06	Section 3.2
σ_ψ	0.26	0.22	0.22	0.23	0.27	0.30	Section 3.2
σ_ι	0.07	0.04	0.08	0.05	0.11	0.07	Section 3.2
σ_n	0.32	0.38	0.34	0.36	0.32	0.28	Wage dispersion age 25
μ_n	8.26	8.18	8.33	8.33	8.55	8.64	Mean earnings age 25
ν_1 *100	0.33	0.27	0.53	0.34	0.60	0.47	Wage growth ages $25-50$
ν_2 *100	-0.08	-0.11	-0.23	-0.28	-0.16	-0.07	Wage growth ages $51-61$
ς	0.26	0.46	0.20	0.50	0.30	0.40	Disability penalty
π^{gb} *100	2.45	2.87	1.73	1.95	1.39	1.00	Disability rate by age
π^{bg} *100	6.94	6.94	7.79	7.79	12.13	12.13	Disability to non-disability
ϖ_0	0.65	0.51	0.45	0.44	0.50	0.51	JTJ flow rate
ϖ_1	1.00	1.05	0.94	0.98	0.92	0.90	UE flow rate
λ *100	2.62	2.17	2.37	2.10	1.80	1.94	Share JTJ $\Delta w_{ij} < 0$
ω_{1-39} *100	2.42	2.89	1.49	2.45	1.06	1.48	EN flow rate ages $25-34$
ω_{40-99} *100	1.35	1.02	1.08	1.35	0.69	1.27	EN flow rate ages $35-49$
$\omega_{100-148}$ *100	1.91	1.98	1.52	1.43	1.16	1.43	EN flow rate ages $50-61$
f	1040	1140	1280	1160	1210	920	Employment rate age 61
η	1.5	1.5	1.5	1.5	1.5	1.5	Attanasio and Weber (1995)
r	0.01	0.01	0.01	0.01	0.01	0.01	Siegel (2002)
$(1-\beta)$ *100	0.52	0.49	0.44	0.59	0.41	0.37	Median wealth $25-61$
φ	-0.48	-0.48	-0.48	-0.48	-0.48	-0.48	6% consumption drop EU

Note: The table displays the calibrated parameters using the *SIPP* data from the 1983–1993 and 2004-2013 periods. Appendix A.2 displays the education-specific values of the calibrated moments. *HS*: at most a high school diploma; *SC*: some college; *C*: college degree. σ_ϵ: std. permanent productivity shocks; σ_ψ: std. job offer distribution; σ_ι: std. measurement error; σ_n: std. initial worker productivity; μ_n: initial mean worker productivity; ν_x: age-dependent learning by doing parameter; π^{gb}: probability to go from good to bad health; π^{bg}: probability to go from bad to good health; ϖ_x: search cost parameters; λ: probability of a reallocation shock; ω: age-dependent job destruction rate; f: fixed-costs of work; η: risk aversion; r: interest rate; β: discount factor; φ: disutility of working.

workers suffer from lower initial skills and lower skill accumulation on the job.[35] High-skilled workers enter the labor market with higher skills but their returns to experience have decreased.

Turning to the disability risk, we use the probability of becoming disabled, π^{gb}, to match the disability rates by age in the data which we display in Online Appendix G. The 1996-2008 SIPP panels allow us to measure the probability of moving from disability to

[35] See also Moffitt et al. (2012) for a discussion on mean real wage changes for different worker groups. Autor et al. (2008) and Acemoglu and Autor (2011) suggest that decreasing demand for low-skilled workers is behind these differential trends. Possible reasons are an increase in import competition (Autor et al., 2014) and an increase in the use of robotics (Acemoglu and Restrepo, 2020).

non-disability by workers' age, π^{bg}, which we assume to be constant across the periods. To calibrate the skill loss associated with disability, ς, we regress in the data and the model, workers' log wages on a dummy for disability and other controls and adjust ς to match the regression coefficient. The calibration implies that the risk of becoming disabled has risen over time but for workers with a college degree, and that the skill loss associated with disability has increased markedly.[36]

Regarding the labor market transition rates, we use the scaling and convexity parameter of search costs, ϖ_0 and ϖ_1, to match the job-finding rate of workers in non-employment who search for a job, i.e., the unemployed, and the job-to-job transition rate. We find relatively low job-finding rates compared to monthly rates usually used in the literature. The reason is our focus on transitions between somewhat persistent employment and unemployment states. Reallocation shocks and exogenous job destruction rates contribute to idiosyncratic job risk. Regarding the former, we calibrate the probabilities to match the fraction of job-to-job transitions that result in nominal wage losses.[37] Regarding the latter, we allow for three different exogenous job destruction rates, $\omega(h)$, to match the movements from employment to non-employment not explained by endogenous separations at ages 25–34, 35–49, and 50–61. We find that the probability of losing a job exogenously increased over time for workers with at least some college education.

Regarding the amount of private insurance, we target with the discount factor, β, the 50^{th} percentile of the wealth distribution of the population between ages 25 and 61. To calibrate the reduced consumption expenditure need during non-employment, φ, we target that log consumption changes by only 0.06 log points when moving from unemployment to employment, as reported by Gruber (1997), where, for parsimony, we assume that the parameter is constant over time. Finally, we calibrate the fixed costs of working to match the employment rate at age 61.

[36] Rising disability risk may be surprising at first. Rising wage penalties suggest that the increase does not merely reflect a changing attitude of respondents when answering the question. Instead, Bhattacharya et al. (2008) show that increasing obesity rates and chronic illnesses contribute to the rise.

[37] Our model features two reasons besides the reallocation shocks that contribute to such losses. First, our simulations include measurement errors. Second, large negative productivity shocks may offset wage gains from better jobs.

Table 4: Calibration of Welfare State

	1983-1993	2004-2013		1983-1993	2004-2013
$\overline{ub}$	2404	3107	$\overline{TS}$	1020	1063
$\overline{y}_{<50}$	2978	3251	ID_S	60	32
$\overline{y}_{\geq 50}$	2378	2587	$\bar{a}$	2000	1093
$\overline{TF}_{<50}$	674	759	d_1	801	1004
$\overline{TF}_{\geq 50}$	468	601	d_2	4836	6050
ID_F	366	366	$\upsilon_{<50}$	0.14/0.11/0.14	0.16/0.17/0.25
τ_c	1.85	2.39	$\upsilon_{\geq 50}$	0.17/0.16/0.21	0.16/0.16/0.25
τ_p	0.89	0.87			

Note: The table displays the calibrated parameters for the welfare state. $\overline{ub}$: maximum unemployment benefits (see Price, 1985; Executive Office of the President, 2011); $\overline{y}_{<50}$: maximum countable income for eligibility to *FS* below age 50. $\overline{TF}_{<50}$: maximum transfers from *FS* below age 50; ID_F: income deductible for *FS* (see Congressional Budget Office, 1988; Congressional Research Service, 2011); $\overline{TS}$: maximum transfers from *SSI*; ID_S income deductible for *SSI* (see Kahn, 1987; Congressional Research Service, 2011); $\bar{a}$: asset test; d_x: bend points for social security benefits; $\upsilon_{<50}$: probability that disability benefits are granted before age 50; τ_c and τ_p: the parameters guiding the level and progressivity of earnings taxes.

Turning to governmental insurance, we calibrate the maximum unemployment benefits to the mean across U.S. states. We parametrize *FS* in line with the regulations for a household composed of three persons until age 50 and two persons afterward. The maximum transfers available from *SSI* are those of a single person. The income deductible available for that program has not been adjusted for inflation leading to a large decrease in their real value. The same has occurred with the maximum assets a household may have to be eligible for *FS* and *SSI*. We parametrize the bend points d_1 and d_2 in social security transfers according to those reported by the Social Security Administration (2016). We calibrate the probability that a worker's application to *DI* is granted to match the shares of workers in the program before and after the age of 50 for each education group. Finally, to calibrate the parameters of the tax function, we estimate the following equation relating gross to net earnings:

$$ln(E_{ih}) = ln(\tau_c) + \tau_p ln(E^g_{ih}), \tag{11}$$

where we use *TAXSIM* to construct E_{ih} from gross earnings, E^g_{ih}, in the *SIPP*.[38] Overall, we find that the welfare state has become slightly more generous over the decades, par-

[38] 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.

ticularly unemployment benefits and *FS*.[39] Moreover, tax rates are lower and the rates have decreased most at the bottom of the earnings distribution.

3.4 Model Fit

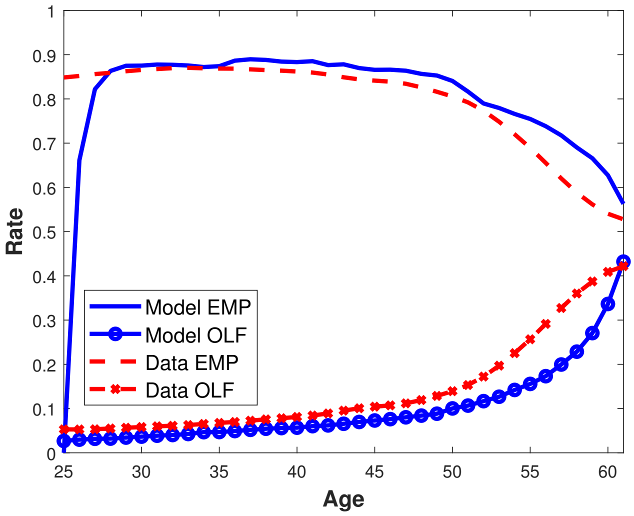
Before analyzing the changes in wage inequality and employment patterns between the periods of 1983–1993 and 2004–2014, we compare (untargeted) moments from the calibrated model to the data. This serves two purposes. First, we show that the model is indeed able to match moments of inequality and employment. Second, as described in Section 3.2.2, we identify changes in idiosyncratic uncertainty from wage dynamics of job stayers and job movers, and we show that the model is indeed consistent with these wage dynamics. This section discusses the model fit in the 1983–1993 and Online Appendix H shows that the model fit is similar for the 2004–2014 period.

Starting with workers' participation decisions, Figure I shows that the model matches closely the life-cycle behavior of employment choices, i.e., the employment rate declines starkly between ages 45 and 61. The model rationalizes this decline by two factors. First, average idiosyncratic productivities start to decline after age 50. Second, the non-employed find it less attractive, relative to younger workers, to search for a new job because search is costly and any future job will have only a relatively short duration until retirement. The model also rationalizes that, as in the data, most non-employment results from workers being out of the labor force and that the decline of employment after age 45 almost exclusively results from workers leaving the labor force. The latter is rationalized by costly job search and workers entering into *DI*.

Turning to the models' ability to match cross-sectional inequality, the top panel of Table 5 compares three measures of inequality to the data: the variance of log residual wage inequality, the 90^{th} to the 10^{th} percentile of residual wages, and the Gini coefficient of residual wages. Overall, the model matches both the level of inequality as well as the

[39] See also Eberstadt (2016) for a discussion on the expansion of means-tested governmental transfers over time.

Figure I: 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 1983–1993.

fact that inequality is highest among workers with a college degree. However, the model overstates the cross-sectional inequality of workers with some college education.

The large cross-sectional inequality is a combination of inequality at the beginning of the working life (which we have calibrated) and inequality growing over workers' life cycles as their careers take different paths. Table 5 shows that the model is broadly consistent with inequality growing over the life-cycle being an important driver of overall cross-sectional inequality. However, it somewhat underpredicts the increase for high school-educated workers.[40]

The rise in cross-sectional wage inequality over the life cycle results from labor market shocks that we estimate in Section 3.2 using the first and second moments of individual wage growth for job stayers and job switchers. Reassuring, the model matches closely the standard deviations of residual wage growth as the second panel of Table 5 shows. To better assess the forces behind the large cross-sectional dispersion of wage growth of job switchers, we consider wage changes at particular observable events. The table shows that the model closely matches (a) the median wage loss of workers changing jobs

[40]Note, the comparison assumes that the distribution in the data is a steady state, i.e., older workers have received shocks from the same distributions when they were young as those workers that are young in 1983–1993.

Table 5: Untargeted Moments 1983–1993

	Model			Data		
	HS	SC	C	HS	SC	C
$Var(w_{it})$	0.16	0.20	0.26	0.16	0.15	0.22
90/10 ratio	2.84	3.21	3.76	2.82	2.75	3.26
$Gini(w_{it})$	0.23	0.25	0.29	0.22	0.21	0.26
$\Delta Var(w_{it})$*100	2.93	7.16	15.68	6.24	6.68	12.86
Δ90/10 ratio	0.30	0.75	1.66	0.84	0.93	1.31
$\Delta Gini(w_{it})$*100	2.10	4.61	8.55	6.01	5.82	9.42
$\sigma_{stayers}$	0.10	0.11	0.15	0.09	0.10	0.14
σ_{movers}	0.38	0.32	0.40	0.38	0.36	0.40
Wage loss ENE	-0.06	-0.06	-0.09	-0.09	-0.09	-0.09
Wage gain JTJ	0.31	0.26	0.33	0.28	0.26	0.30
Wage loss JTJ	-0.30	-0.26	-0.32	-0.25	-0.26	-0.29
		All Workers			All Workers	
Wage change JTJ $0-2.5$		0.18			0.17	
Wage change JTJ $2.5-5$		0.09			0.12	
Wage change JTJ $5-7.5$		0.06			0.08	
Wage change JTJ $7.5-10$		0.05			0.06	
Wealth 25^{th} perc. (1000)	3.06	8.53	20.95	3.68	8.18	16.57
Wealth EU replacement	4.44	6.00	9.04	4.03	4.05	6.65

Notes: The table compares model implied moments to the *SIPP* in 1983–1993. *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 wage growth 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); *Wage change JTJ*: mean log wage change conditional on labor market experience intervals see (see Topel and Ward, 1992); Wealth 25^{th} perc.: the 25^{th} percentile of the cross-sectional wealth distribution of people younger than age 61; Wealth *EU* replacement: The median ratio of wealth relative to the earnings in the last period before unemployment.

through an intervening period of non-employment, (b) the average wage gain of those making a job-to-job transition and experiencing a wage gain, and (c) the average wage loss of those making a job-to-job transition and experiencing a wage loss. Moreover, the model not only matches average moments of wage growth at job-to-job transition but also conditional on work experience. In the model, closely matching the data reported by Topel and Ward (1992), during the first two and a half years of labor market experience, the average wage growth associated with a job-to-job transition is 0.18 log points. Average wage growth declines to 0.05 log points during the years seven and a half and ten.

The last panel of Table 5 shows that the model matches the low amount of workers' self-insurance in terms of assets observed in the data. At the 25^{th} percentile of the wealth distribution, high-school-educated workers hold just above three thousand dollars of net wealth. Even those with some college and with a college degree hold just around 8.5 and 21 thousand dollars of net wealth at the 25^{th} percentiles. Low-income workers have an incentive to hold little precautionary savings because of the asset test in *FS* and *SSI*, as first pointed out by Hubbard et al. (1995). As a result, many workers are poorly prepared when entering unemployment. The median high-school-educated worker has enough wealth to replace about four-quarters of his past earnings. These ratios are 6 and 9 quarters for workers with some college and college education, respectively.

4 Results

With the calibrated model at hand, we now perform a series of counterfactual simulations. First, we decompose the rise in inequality and falling labor market participation into structural changes in the economy.[41] Afterward, we turn to welfare results.

4.1 Understanding Changes in Inequality and Employment

The rows labeled "Productivity risk" in Table 6 display the counterfactual effects of changing the dispersion of idiosyncratic productivity shocks from their 1983–1993 values to the values in 2004–2013 keeping all other parameters at their 1983–1993 values.[42] Those changes by themselves explain the increase in residual wage inequality among workers with a college degree. They explain about 79% of the increase among workers with a high-school education and 21% among workers with some college education. Higher productivity risk implies that more workers fall below their reservation productivities and

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

[42]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.

leave the labor force and, in part, enter *DI*. We find that employment rates decline by 2.1, 1.3, and 1.5 percentage points for those with high school education, some college, and finished college, respectively. Employment declines most among high-school-educated workers as they are on average closer to their participation margins and, hence, have higher extensive margin labor supply elasticities. The model implies an uncompensated elasticity of 0.17 for high-school-educated workers, 0.13 for those with some college, and 0.06 for those with a college degree.[43] We also find that, as in the data, employment declines the most among workers older than age 50 who have the highest labor supply elasticities.

The rows entitled "+ job dispersion" additionally simulate the changes in the job offer distributions. A growing (shrinking) dispersion for those with at least some college (high school) translates into growing (shrinking) inequality. The effects on employment vary by education group. For low-educated workers, a lower dispersion implies that there are also fewer good jobs available and, hence, their employment declines. As the least productive workers leave employment, this selection amplifies the declining wage inequality caused by the decline in the job offer dispersion. For highly educated workers, an increasing dispersion implies that the option value of waiting in unemployment increases and, hence, their employment also slightly declines. This mechanism operates throughout the entire productivity distribution of highly skilled workers and, hence, does not dampen the increase in cross-sectional inequality.

This discussion highlights that employment choices affect the way rising uncertainty shapes wage inequality. The row entitled "Fixed policies" quantifies this mechanism by simulating the changes in productivity risk and job offer dispersion but fixes workers' employment and mobility decisions to those from the baseline simulation. The same change in risk would have led to a two times larger increase in inequality for high-school-educated workers. The increase would be about 36% larger for workers with some college

[43] We compute the elasticity as the change in the employment rate from a one-time permanent drop in log productivity by 0.1. We find a population average of 0.13. Chetty et al. (2013) surveys estimates and reports a range from 0.13 to 0.43. Most of these estimates are those of women for whom one would expect a higher elasticity.

Table 6: Decomposing Labor Market Changes

	HS	SC	C	HS	SC	C	HS	SC	C
	$\Delta Var^{*}100$			$\Delta 90/10$			$\Delta Gini(w_{it})^{*}100$		
SIPP	2.24	4.57	3.58	0.14	0.43	0.40	2.58	3.71	2.16
Productivity risk	1.78	0.98	3.35	0.18	0.10	0.37	1.22	0.60	1.74
+ job dispersion	1.05	1.27	4.11	0.12	0.13	0.44	0.74	0.77	2.10
Fixed policies	2.16	1.73	4.75	0.23	0.17	0.49	1.31	0.94	2.34
+ other job risk	1.06	1.27	4.06	0.12	0.13	0.44	0.75	0.78	2.09
+ ini. disp	2.60	1.50	2.66	0.28	0.15	0.28	1.77	0.89	1.36
+ disability	1.74	0.70	2.76	0.19	0.07	0.29	1.27	0.48	1.43
+ wage	1.11	-0.23	2.68	0.13	-0.03	0.29	1.09	0.18	1.41
+ welfare	1.89	0.56	3.07	0.21	0.05	0.32	1.51	0.49	1.47
	ΔE %			ΔOLF %			ΔDI %		
SIPP	-13.44	-14.53	-6.24	11.49	11.61	4.43	8.86	7.47	2.00
Productivity risk	-2.06	-1.28	-1.46	1.71	1.11	1.23	0.54	0.21	0.11
+ job dispersion	-2.43	-1.11	-1.50	2.19	0.88	1.21	0.86	0.21	0.15
+ other job risk	-1.96	-2.29	-3.93	1.84	1.18	2.26	0.58	0.42	0.34
+ ini. disp	-2.86	-2.41	-3.77	2.57	1.08	2.19	0.45	0.13	0.41
+ disability	-5.90	-5.01	-3.64	4.89	2.86	2.03	2.08	1.10	0.18
+ wage	-10.31	-10.49	-4.36	8.48	7.36	2.55	3.27	1.93	0.29
+ welfare	-11.62	-12.84	-5.61	9.68	9.64	3.80	5.60	6.37	2.37

Notes: The table displays changes in labor market outcomes resulting from counterfactual model simulations that change the idiosyncratic risk from the period 1983–1993 to the risk present in the period 2004–2013. *HS*: at most a high school diploma; *SC*: some college; *C*: college degree. The upper panel displays the change in the variance of log residual wages, the 90/10 ratio, and 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. ΔE: change in the employment rate; ΔOLF: change in the out of the labor force rate; ΔDI: change in the rate of disability insurance recipients. *Fixed policies*: simulates the change in risk but fixes workers' employment and mobility decisions to those from the baseline simulation.

education and 16% larger for workers with a college degree.

The row entitled "+ other job risk" additionally simulates the changes in the reallocation probabilities and the exogenous job destruction rate, i.e., we simulate the entire change in the measured productivity and job risk. The additional effects on residual wage inequality are negligible reflecting that this type of job risk is exogenous. At the same time, the increases in job risks are major contributors to the employment declines of workers with at least some college education. Turning to changes in the productivity distribution at the beginning of working life, the rising (falling) dispersion of initial productivity heterogeneity of those without (with) a college degree leads to rising (falling) overall wage inequality, as the row entitled "+ ini. disp" shows. Similar to rising productivity risk, an increase in productivity dispersion at birth contributes to falling employment and labor force participation rates as the least productive find it optimal not to work. Taken together, the combined changes in productivity and job risk explain between 16 and 63 percent of the falling employment and labor force participation rates, respectively, and the majority of the rise in wage inequality among the employed.

The rows "+ disability" and "+ wage" show that higher disability risk and decreasing wages dampened the increase in cross-sectional wage inequality for workers without a college degree.[44] Both effects increase the share of workers whose productivity is below their reservation productivities and, thereby, further left-truncate the wage distribution. In fact, together, these two channels explain about 55% of the decrease in the employment and labor force participation rates of workers with less than a college education. Moreover, they explain around 30% of the rise in their *DI* rates. Regarding the latter, the rise in disability risk is the main contributor but lower average wages also increase *DI* rates through making work less attractive. These two forces developed very differently for those with a college degree, which explains to a large extent why their employment rate has fallen by less. Though, the decreasing experience profile also leads to a small rise in non-employment among those workers who are older than age 54.

The row entitled "Welfare" displays the additional effects stemming from changes in the welfare state. Starting with the employment effects, we find that the changes in the welfare state decreased employment rates slightly. To understand the moderate changes, note that two forces are working against each other. On the one hand, the more generous programs decrease employment rates, and we find this effect to be particularly strong for those with the option to apply for *DI*, i.e., the changes in the welfare state are the single largest contributor to the observed increases in *DI* rates. On the other hand, lower tax rates, particularly at the lower end of the earnings distribution, provide incentives for work. As a result, employment at the bottom of the wage distribution increases. More

[44]We note that the impact of falling wages of low-educated workers on residual inequality is, thus, very different from the impact on between-group inequality.

employment at the bottom, in turn, leads to significantly higher wage inequality.[45]

4.2 Welfare

Changing risk changes workers' welfare. Our welfare measure is the willingness to pay of an unborn in terms of lifetime consumption, i.e., the percent of per-period consumption over the life cycle. The changes in risk decrease employment rates and alter workers' productivities, thereby, changing public expenditures and tax revenues. There are several possibilities to deal with the resulting change in the government's budget, each making assumptions on which group of workers will carry the resulting burden. We make two choices. First, all budgetary changes are absorbed within education groups instead of altering the between-education-group transfers. This choice assures that the average (potential) resources available to each education group are unchanged and, thus, facilitates the understanding of the welfare changes. Second, we finance the change in the government's budget by introducing a proportional consumption tax, i.e., changing taxes affects both employed and non-employed households which leaves the trade-offs at the participation margin relatively unaltered:[46]

$$\begin{aligned}\sum_i \sum_h (E^g_{ijh} - E_{ijh}) - TF(y_{ih}, h) - ub_{ih} - TS(\bar{E}_{ih}) - S(\bar{E}_{ih}) = \\ \sum_i \sum_h (\hat{E}^g_{ijh} - \hat{E}_{ijh}) + \hat{\tau}_{con}\hat{c}_{ih} - TF(\hat{y}_{ih}, h) - \hat{ub}_{ih} - TS(\hat{\bar{E}}_{ih}) - S(\hat{\bar{E}}_{ih}), \quad (12)\end{aligned}$$

where variables without a head represent outcomes in the baseline and those with a hat are the outcomes in the counterfactual.

[45] As *DI* pays relatively high replacement rates, those workers leaving employment tend not to be the least productive workers creating only small effects on wage inequality.

[46] The alternatives would be to change program generosity and, thus, changing the value of non-employment, or altering labor taxation and, thus, the value of employment.

4.2.1 Changes in Uncertainty

Table 7 shows the welfare costs of changes in uncertainty between the periods 1983–1993 and 2004–2013. Table I1 in Online Appendix I displays the tax changes required to balance the government's budget and the employment responses. The first row displays the welfare effects stemming from changes in productivity shock dispersion. Workers with a high school education are willing to pay 2.6 percent of lifetime consumption to avoid the increase in risk. The corresponding numbers are 1.9 percent for those with some college and 3.8 percent for those with a college degree. For a given change in the standard deviation of productivity risk, high-school-educated workers have somewhat lower welfare losses. These workers are on average closer to their participation margin and, thereby, have more insurance against downward risk. The decline in employment comes at the cost of higher taxes but we find that the insurance effect dominates in terms of welfare.

Endogenous mobility decisions imply that all types of workers are willing to pay for a more dispersed wage offer distribution, as the second row shows. That is, the welfare of high-school-educated workers, for whom the dispersion declines, decreases markedly, and the welfare of workers with college education increases. Workers benefit from a more dispersed distribution because it creates an option value for the worker as he can always break away from particular poor matches when he finds a better match. This option value outweighs the costs of increased uncertainty. What is more, some workers allocating to highly productive jobs increase the government's revenue, as shown in Table I1, and, thus, allows for lower consumption taxes which increases welfare. Table I1 also shows that endogenous search amplifies these mechanisms through workers intensifying their search effort to take advantage of the new opportunities.

This discussion highlights that endogenous choices provide insurance against changes in the dispersion of shocks. To quantify the role of endogenous choices for welfare, we compute the willingness to pay to avoid the change in the dispersions of shocks in an alternative, recalibrated model where workers make no endogenous decisions. That is, workers always choose employment, all job-to-job transitions result from reallocation shocks, and

Table 7: Welfare Costs of Rising Uncertainty

	High School	Some College	College
Productivity shocks %	2.61	1.86	3.79
+ Job offer %	5.47	0.48	0.65
No selection %	2.63	2.53	5.81
+ Other job risk %	3.99	3.50	7.36
+ Disability risk %	11.41	10.53	7.20

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 2004–2013. *Productivity shocks*: based on changes in permanent productivity risk; + *Job offer*: additionally changes in the job offer distribution; *No selection*: the same as + *Job offer* but in a recalibrated model where workers do not make employment or mobility decisions and search in non-employment is exogenous; + *Other job risk*: additionally changes in exogenous reallocation rates and job destruction rates; + *Disability risk*: additionally changes in disability risk.

search during non-employment is exogenous. The row entitled "No selection" in Table 7 shows that in this alternative model, the relative welfare costs are very different. In particular, the welfare costs for high school-educated workers are now substantially smaller than those for workers with a college degree. As workers no longer make endogenous mobility decisions, a decrease in the dispersion of the job offer distribution, as experienced by high-school-educated workers, is now welfare-enhancing as its only effect is a reduction in risk.

The row entitled "+ Other job risk" additionally simulates the change in the exogenous job transition rates. As risk declines for high-school-educated workers, their employment rates increase, their average job match improves, and taxes decline. The result is an increase in welfare by almost 1.5 percentage points. The opposite occurs to workers with a college education, particularly to those with a college degree, who suffer large welfare losses. Finally, the last row additionally simulates the changes in disability risks. Rising disability risk predominately affects workers with less than a college degree leading to large welfare losses. In fact, these welfare losses are larger than the losses resulting from any other change in risk.

4.2.2 Governmental Policies

Next, we turn to to the welfare consequences of governmental insurance programs. Describing optimal policy is beyond the scope of this paper. Instead, we study the welfare

Table 8: Willingness to Pay to Avoid an Increase in the Welfare State

	High School		Some College		College	
Period	83–93	04–13	83–93	04–13	83–93	04–13
Unemp. ben. %	-0.06	-0.06	-0.03	-0.08	0.01	-0.02
Food stamps %	0.21	0.32	-0.09	0.06	-0.08	-0.09
SSI %	0.43	0.59	0.08	0.19	0.03	0.03
Disability ins. %	0.27	0.49	0.15	0.40	0.11	0.11
Progressive tax %	1.25	1.59	0.96	1.11	0.60	0.63
Labor supply elasticity	0.17	0.23	0.13	0.17	0.06	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 consumption taxes within each education group. *Period 83-93*: model from the 1983–1993 period; *Period 04-13*: model from the 2004–2013 period; *Unemp. ben.*: increase in unemployment benefit replacement rate and maximum benefits; *Food stamps*: raising the maximum benefits of 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; *Labor supply elasticity*: the uncompensated extensive-margin labor supply elasticity.

implications of a small increase in the welfare state both in 1983–1993 and 2004–2013. Table I2 in Online Appendix I show for each experiment the resulting change in the consumption tax.[47]

The first experiment increases the unemployment benefits replacement rate from $\kappa = 0.7$ to 0.8 and the maximum benefits $\overline{ub}$ by 10 percent. The row entitled "Unemp. ben." in Table 8 shows that across education groups, the welfare effects from the reform are small and positive for workers with less than a college degree in the period 1983–1993. Recall from Table 5 that low-educated workers enter unemployment with little wealth, hence, unemployment benefits are an importance insurance for these workers. At the same time, the asset test for welfare programs limits their value because it implies poor consumption-smoothing behavior. The adverse employment effects of the policy are also minor, as Online Appendix I shows, which results from workers having only access to the benefits when exogenously losing their job and benefits lasting only one period. As exogenous job destruction rates increased for college-educated workers in the period 2004–2013, higher unemployment benefits become somewhat more valuable for these workers.

[47] Note, we off-set changes to the budget within each period. That is, when changing policies given the risk of the period 2004–2013, we compare the resulting budget to the budget present with the old policies but the level of risk from 2004–2013 instead of 1983–1993.

The row entitled "Food stamps" simulates a five percent increase in the maximum amount of *FS* transfers. The increase leads to welfare losses for high-school-educated workers and welfare gains for those with a college education in the 1983–1993 period. The reason for the welfare losses of low-educated workers are high uncompensated labor supply elasticities that we show in the row entitled "Labor supply elasticity". When elasticities are high, increasing *FS* transfers has a stronger negative effect on employment which leads to higher taxes for these workers. This latter effect dominates the additional insurance effect in terms of welfare. The table also shows that labor supply elasticities become substantially higher for workers with less than a college degree over time. This has two reasons: First, as highlighted in Section 4.1, declining average wages and increases in disability risk push these workers closer to their reservation wages. Moreover, the increase in idiosyncratic productivity dispersion implies that more workers are close to their reservation wages. As labor supply elasticities of these workers increase, the welfare trade-off from increasing transfers becomes less favorable in the 2004–2013 period.

The row entitled "SSI" simulates a ten percent increase in the maximum *SSI* transfers. The reform has two effects on workers' labor supply. First, it makes *DI* more attractive to workers with a poor earnings history. Second, it lowers the rewards that employment brings for retirement benefits. Online Appendix I shows that the result is a decline in employment across education groups. We find that the resulting rise in taxes outweighs the gains from better insurance in welfare terms for all types of workers. This tradeoff worsens for workers without a college degree in the 2004–2013 period.

As for *SSI* transfers, increasing *DI* transfers by five percent reduces welfare for all workers, as the row entitled "Disability ins." shows. The same reform has particularly large adverse employment effects in the 2004–2013 period leading to larger welfare losses. As disability risk is more pronounced for workers with less than a college degree in the later period, employment responses to benefit changes become larger. Moreover, the program has become more generous, particularly for workers with a college degree which also increases their employment responses.

The last row displays the results from making the income tax more progressive, i.e., decrease τ_p. Across education groups, the policy reduces welfare, and the effect is again particularly large in the later period. Labor taxation makes employment relatively less attractive, and Table I2 shows that the result is a decline in employment. Put differently, from a welfare perspective, labor taxation is too high in both periods, and there would be benefits to switch to consumption-based taxation that is paid by the employed and non-employed.

5 Conclusion

U.S. male residual wage inequality rose, and their employment rates fell between 1983–2013. Using a structural model of the labor market, we show that these trends are intertwined. Increases in idiosyncratic productivity risk deepened cross-sectional wage inequality and also led workers with poor wage outcomes to leave the work force which, thus, slowed down the increase in wage inequality. Moreover, falling average wages and rising disability risk depressed employment rates of workers with less than a college degree which further slowed down the increase in wage inequality within that group. Working against it, decreasing tax rates at the bottom of the wage distribution increased employment of low-productivity workers and, thus, increased wage inequality.

Higher uncertainty implies large declines in workers' welfare: High-school-educated workers suffer the most and are willing to pay 11.4 percent of life time consumption to avoid the increase in risk. This number is 10.5 and 7.2 percent for workers with some college education and a college degree, respectively. The changes in risks driving these results differ across education groups. Endogenous employment choices provide workers with a high school education with relatively good insurance against productivity risk. Differently, endogenous mobility choices create benefits for workers with at least some college education from more dispersed job offers. At the same time, those workers suffer from increased exogenous job destruction rates. Finally, workers with less than a college degree suffer from higher disability risk.

Endogenous employment choices provide a challenge to governments when providing insurance against idiosyncratic risks. We find that making social assistance programs that provide transfers to low-educated workers or insurance against disability risk more generous leads to welfare losses. The reason is that the low-educated and elderly have particularly high extensive margin labor supply elasticities.[48] Moreover, these elasticities increased over time and, thus, expansions of the welfare state deteriorate welfare even more in 2004–2013 compared to 1983–1993.

[48]Importantly, our welfare statements are based on calculations that study insurance within permanent education groups. We are silent on whether the increase in risk may justify more insurance between education groups.

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)	(0.007)
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)	(0.048)
Correlations			
$\rho_{\epsilon\pi}$	0.313	0.670	0.220
	(0.164)	(0.247)	(0.162)
$\rho_{\epsilon\mu}$	-0.358	-1.000	-0.193
	(0.184)	(0.125)	(0.254)
$\rho_{\xi\pi}$	0.104	0.046	-0.337
	(0.069)	(0.047)	(0.345)
$\rho_{\xi\pi_{-1}}$	0.180	-0.030	-1.000
	(0.171)	(0.152)	(0.765)
$\rho_{\xi\mu}$	0.039	0.110	0.039
	(0.016)	(0.024)	(0.040)
$\rho_{\pi\pi_{-1}}$	0.933	0.910	0.899
	(0.002)	(0.004)	(0.004)
$\rho_{\pi\mu}$	0.496	0.394	0.219
	(0.090)	(0.130)	(0.151)
$\rho_{\pi_{-1}\mu}$	0.460	0.496	0.549
	(0.102)	(0.110)	(0.135)
MA process			
$e_{ih} = \iota_{ih} - \chi_1 \iota_{ih-1} - \chi_2 \iota_{ih-2}$			
χ_1	-0.455	-0.403	-0.441
	(0.015)	(0.031)	(0.070)
χ_2	-0.049	-0.016	-0.000
	(0.017)	(0.020)	(0.035)

Notes: σ_ϵ, σ_i, σ_ψ are the standard deviations of the permanent shock, transitory shock, and job offer distribution respectively. 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 χ to be negative and above -1.

Table A2: Some College

	1983-1993	**1994-2003**	**2004-2013**
Standard deviations			
σ_ϵ	0.042	0.047	0.047
	(0.004)	(0.007)	(0.027)
σ_ι	0.079	0.083	0.053
	(0.002)	(0.003)	(0.023)
σ_ψ	0.217	0.225	0.231
	(0.030)	(0.024)	(0.055)
Correlations			
$\rho_{\epsilon\pi}$	0.078	0.805	0.395
	(0.192)	(0.229)	(0.413)
$\rho_{\epsilon\mu}$	-0.714	-0.531	1.000
	(0.167)	(0.208)	(0.596)
$\rho_{\xi\pi}$	-0.250	0.268	-0.470
	(0.234)	(0.192)	(0.503)
$\rho_{\xi\pi_{-1}}$	0.439	0.243	-0.213
	(0.512)	(0.600)	(0.491)
$\rho_{\xi\mu}$	0.111	0.128	-0.121
	(0.040)	(0.038)	(0.123)
$\rho_{\pi\pi_{-1}}$	0.926	0.901	0.908
	(0.004)	(0.007)	(0.005)
$\rho_{\pi\mu}$	0.598	0.283	0.030
	(0.152)	(0.210)	(0.200)
$\rho_{\pi_{-1}\mu}$	0.688	0.521	-0.213
	(0.142)	(0.195)	(0.206)
MA process			
$e_{ih} = \iota_{ih} - \chi_1\iota_{ih-1} - \chi_2\iota_{ih-2}$			
χ_1	-0.433	-0.484	-0.4256
	(0.019)	(0.031)	(0.203)
χ_2	-0.040	-0.086	-0.086
	(0.021)	(0.028)	(0.175)

Notes: σ_ϵ, σ_i, σ_ψ are the standard deviations of the permanent shock, transitory shock, and job offer distribution respectively. 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 χ 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)	(0.004)
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)	(0.140)
$\rho_{\epsilon\mu}$	-0.582	-0.168	-0.847
	(0.163)	(0.171)	(0.132)
$\rho_{\xi\pi}$	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)	(0.801)
$\rho_{\xi\mu}$	0.091	0.081	0.132
	(0.022)	(0.025)	(0.028)
$\rho_{\pi\pi_{-1}}$	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			
$e_{ih} = \iota_{ih} - \chi_1\iota_{ih-1} - \chi_2\iota_{ih-2}$			
χ_1	-0.435	-0.444	-0.474
	(0.016)	(0.014)	(0.030)
χ_2	-0.047	-0.097	-0.090
	(0.014)	(0.012)	(0.031)

Notes: σ_ϵ, σ_i, σ_ψ are the standard deviations of the permanent shock, transitory shock, and job offer distribution respectively. 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 χ to be negative and above -1.

A.2 Calibration Table

		1984–1993			2004–2013		
		HS	SC	C	HS	SC	C
Wage dispersion age 25	Data	0.38	0.38	0.41	0.40	0.41	0.40
	Model	0.38	0.39	0.42	0.39	0.40	0.41
Mean log earnings age 25	Data	8.33	8.44	8.63	8.27	8.42	8.69
	Model	8.31	8.40	8.60	8.29	8.41	8.67
Wage growth ages 25-50 %	Data	30.0	44.64	55.53	24.57	29.15	40.75
	Model	29.4	45.74	54.71	24.28	29.92	41.11
Wage growth ages 51-61 %	Data	-3.07	-4.24	-3.46	-1.46	-4.18	1.01
	Model	-3.07	-4.19	-3.53	-1.51	-4.14	1.04
Disability wage penalty	Data	-0.16	-0.13	-0.22	-0.24	-0.28	-0.25
	Model	-0.16	-0.13	-0.22	-0.25	-0.29	-0.25
UE flow rate %	Data	19.4	23.1	24.5	20.8	22.1	24.4
	Model	20.5	24.1	24.6	20.2	22.0	24.6
JTJ flow rate %	Data	3.53	3.46	2.81	3.28	3.26	2.84
	Model	3.52	3.48	2.79	3.31	3.25	2.83
Share JTJ $\Delta w_{ij} < 0$	Data	0.43	0.43	0.42	0.40	0.39	0.42
	Model	0.43	0.43	0.42	0.40	0.39	0.42
EN flow rate ages $25 - 34$ %	Data	3.05	1.85	1.17	4.17	3.08	1.54
	Model	3.06	1.80	1.14	4.20	3.13	1.52
EN flow rate ages $35 - 49$ %	Data	1.96	1.46	0.84	2.97	2.49	1.47
	Model	1.97	1.45	0.82	3.01	2.53	1.48
EN flow rate ages $50 - 61$ %	Data	2.96	2.40	1.92	4.55	3.34	2.27
	Model	2.94	2.39	1.88	4.42	3.33	2.25
50^{th} wealth perc. (1000s)	Data	24.61	35.63	60.20	11.53	22.69	71.24
	Model	24.48	35.75	59.46	11.48	23.16	71.45
Employment rate age 61 %	Data	49.9	57.4	59.4	31.8	41.9	55.9
	Model	50.9	56.5	59.7	33.0	42.0	54.9
Disability rate	Data	0.25	0.19	0.10	0.28	0.20	0.08
	Model	0.25	0.19	0.10	0.28	0.21	0.08
DI rate $25 - 49$ %	Data	3.94	1.53	0.58	8.90	5.21	1.30
	Model	3.97	1.54	0.57	8.62	5.23	1.34
DI rate $50 - 61$ %	Data	11.46	5.78	3.32	25.19	17.09	6.60
	Model	11.50	5.61	3.26	24.79	17.25	6.81

Note: The table displays the calibration targets using the *SIPP* data from the periods 1983–1993 and 2004–2013 as well as the model fit. *HS*: at most a high school diploma; *SC*: some college; *C*: college degree.

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