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DISCUSSION PAPER SERIES

IZA DP No. 10451

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ABSTRACT

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

We estimate the changes in US male labor market risk over the last three decades in a model of endogenous labor supply and job mobility. Across education groups permanent shocks to productivity have become more dispersed. Moreover, heterogeneity in pay across offered jobs has increased for workers with at least some college education. Simulating these changes in a life-cycle model with search frictions, we show that the estimated changes in risk can account for 85 percent of the increase in within group wage inequality. The welfare costs of rising risk are small.

JEL Classification: D91, J11, J22, J31, J64

Keywords: wage risk, secular trends, insurance

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1 Introduction

Individuals face substantial idiosyncratic earnings uncertainty in the labor market.[1] Whether this risk has changed over the last decades is a key question to comprehend changes in earnings inequality, the welfare costs of incomplete markets, and to appropriately redesign the welfare state. Yet, no consensus has been reached.[2]

In this study, we quantify trends in labor market risks over the last three decades in the US. We estimate risk resulting from idiosyncratic shocks to a worker's productivity that change his market wage irrespective of his current job. Moreover, we identify the risk arising from different jobs paying heterogeneous wages for the same worker. In the presence of search frictions, a worker is not able to locate the highest paying job instantaneously, implying a risk component arising from job search. The distinction between productivity and a job component is pertinent from the worker perspective. A worker may choose exiting the labor market when his idiosyncratic skills are suddenly less demanded. On the contrary, when facing a specific job offer, a worker has the option to accept it or to stay with his current job.

Different from the existing empirical literature on trends in labor market risk, we disentangle these endogenous choices from the shocks that triggered them. As Low et al. (2010) and Altonji et al. (2013), we uncover the true variances of shocks from observed wage changes by explicitly modeling participation and job-mobility decisions as reaction to these shocks. The amount of endogenous selection of workers upon shocks depends on the distribution of worker types and the institutional setting. Both of these changed considerably since the 1980's in the US; the share of workers with weak labor market attachment has grown, and the welfare state became more generous in many instances (see Ben-Shalom et al. (2011)). To account for these changes, we allow the amount of selection in the data to have secular trends of its own.

Using panel data from the Survey of Income and Program Participation (SIPP) for males over the period 1983-2013, we find that differentiating be-

[1]For early contributions see Lillard and Willis (1978), Lillard and Weiss (1979) and MaCurdy (1982).

[2]Early studies like Gottschalk and Moffitt (1994), Blundell et al. (2008), and Heathcote et al. (2010a) find income uncertainty to have increased. Recent evidence by CBO (2007) and Guvenen et al. (2014) do not find such secular trends.

tween different types of risk and accounting for selection is important. While observed quarterly wage volatility is close to constant over time, the standard deviation of permanent risk has increased between 16 and 30 percent, depending on workers' education.[3] Moreover, heterogeneity in job offers increased over time for workers with at least some college education. On the contrary, this dispersion decreased for workers with at most high school education, particularly, when changing careers.

To quantify the role that these changes in risk play in explaining rising wage inequality and their consequences for social welfare, we simulate the estimated risk in a structural partial equilibrium model of life-time utility maximization. Workers' productivity evolves stochastically, and workers search for heterogeneous paying jobs on and off the job. Utility for leisure and precautionary savings provide partial insurance against uncertainty arising from job offers and productivity. Additionally, our model puts emphasis on the insurance provided by the government and the resulting employment decisions. Workers have access to unemployment insurance, a means-tested program, disability insurance, and social security. Furthermore, the government runs a progressive tax schedule. We find the model provides a good fit of key data moments given the estimated wage process. Moreover, it features selection into employment and across jobs consistent with our data estimates. When simulating the increase in estimated risk, the model can account for 85% of the increase in within group wage inequality in United States during the last three decades.[4]

Other papers which use structural models of the labor market to understand trends in wage inequality are Bowlus and Robin (2004), who permit for trends in wage promotions and demotion rates, Flabbi and Leonardi (2010), who consider trends in labor market transitions and job heterogeneity, and Leonardi (2015), who models changes to the dispersion of match specific productivity shocks. Our model differs from this literature by explicitly modeling a rich set of governmental programs, workers selecting into these, and by allowing jointly for productivity and wage offer risk.

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

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

We find that those dimensions are important to comprehend the welfare effects of changing labor market risk. The overall welfare costs of rising wage uncertainty are small. An unborn worker is willing to pay 0.23% of life-time consumption to avoid the increase in risk. This is in contrast to the large welfare costs of changed income risk found in Heathcote et al. (2010b). We differ in three main aspects. First, our estimated increase of permanent productivity risk is significantly smaller than theirs. Second, workers with higher educational degree compensate an increase of permanent risk with more dispersed job offers. These workers are willing to pay between 0.25% and 0.32% of life time consumption for an 0.01 increase in the standard deviation of job offers. The intuition is simple. In a search model, a rise in the dispersion of job offers creates a option value to the worker: Particular poor jobs terminate early because search allows the worker to find a better job. Third, we find the government plays a crucial role in insuring workers. Welfare losses from changing wage risk would be about five times larger when the government provides only social security.

Using small increases in the welfare state as counterfactual experiments, we ask whether the welfare state present in the 1980s was efficient in insuring workers against labor market risk. Consistent with Chetty (2006), we find that the complementarity of employment and consumption is quantitatively low, therefore, our model favors programs with low employment disencentive effects. Consequently, an increase in unemployment benefits reduces welfare, but an increase in universal means-tested transfers leads to a moderate welfare gain. The latter program provides insurance against persistent wage losses, but has only moderate employment disincentives. Autor and Duggan (2006) show that eligibility requirements for disability insurance were weakened over the last decades, and this threatens its financial soundness. We find that such a weakening implies substantial welfare losses. The losses occur because disability insurance provides incentives for elderly workers with poor past outcomes to quit the workforce.

The structure of the paper continues as follows: The next section specifies our econometric model, discusses identification, and presents the results of changing wage uncertainty over time. The following section presents our life-cycle model, discuses the implications of changing wage uncertainty for wage inequality and discuses its welfare implications. The last section concludes.

2 Estimating Changes in Risk

2.1 Identification of Risk and Selection

Workers differ in their amount of log human capital u_{it}, which follows a random walk with exogenous innovations $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$. These shocks contain promotion decisions, health shocks, and any other changes in the market value of a worker's skills. In addition to human capital, wages depend on a log job component ψ_{ij}, which stays constant for the duration of the job. Our framework allows us to be silent about the source of this job component. It may arise from different firms paying different wages, or from an individual match component between the worker and the firm. Within a quarter, workers may receive up to one outside job offer from a wage offer distribution. Outside offer draws are random across time with $\psi_{ij} \sim N(0, \sigma_\psi^2)$. Consequently, the real log wage of individual i working at job j at time t is given by

$$\begin{aligned} w_{ijt} &= \beta x_{it} + \psi_{ij} + u_{it} + e_{it} \qquad (1) \\ u_{it} &= u_{it-1} + \epsilon_{it} \\ e_{it} &= \mathcal{X}(q)\iota_{it}, \end{aligned}$$

where x_{it} is a vector of worker observables, and e_{it} is a transitory component, which follows an $MA(q)$ process with $\iota_{it} \sim N(0, \sigma_\iota^2)$. The latter may be true temporary wage shocks, such as bonuses, or measurement error in the data. Given his newly realized human capital, current job component, and possible outside offer, an individual decides each quarter whether to work and, conditional on working, whether to move to another job. The focus of this paper is on the dispersion of ϵ and ψ. For tractability, we assume that workers do not select on purely transitory shocks which may lead to a wrong inference of their size.[5]

The above representation embraces a large class of search models, yet, it is instructive to discuss the key assumptions. First, we assume a time invariant job component which is in line with on-the-job search models following Bur-

[5] We assume a $MA(2)$ process for transitory shocks e_{it}. Consequently, we identify this component from the autocovariance function of wage growth up to lag three. The estimated results are robust to alternative order specifications for the MA process.

dett and Mortensen (1998) and empirical specifications following Abowd et al. (1999). Relatedly, Guiso et al. (2005) show that firms almost perfectly insure workers against idiosyncratic firm risk, supporting our assumption. However, in the presence of some commitment device on the firm side, wages may be back loaded within a job with stable productivity (see Postel-Vinay and Robin (2002), and Burdett and Coles (2003)). Yet, Low et al. (2010) find that a model of stochastic job component fits the data worse than a model with a stochastic human capital component.[6] Second, we assume human capital to follow a random walk process, in line with a large empirical literature on earnings uncertainty.[7] Recently, Guvenen et al. (2015) show that estimating an $AR(1)$ mixture model of highly persistent and more transitory shocks helps to match the kurtosis and skewness present in earnings growth data. Extending our model including this process is beyond the scope of this paper. Given our decomposition of wages, we require that the excess kurtosis is not estimated as large variance of the permanent shock. We trim the distribution of wage growth and find that only the variance from transitory shocks is significantly affected.[8]

Taking first differences of (1) yields individual wage growth:

$$\Delta w_{ijt} = \beta \Delta x_{it} + [\underbrace{\psi_{ij} - \psi_{ij-1}}_{\xi_{it}}] M_{it} + \epsilon_{it} + \Delta e_{it}, \tag{2}$$

where M_{it} is an indicator variable equal to one when the worker changes his job between t and $t-1$. Central to our approach, observed wage growth realizations result from endogenous labor market participation and job mobility decisions. Naturally, these decisions depend on the worker's current wage prospects, as well as the shock to his human capital and outside offers. We model these decisions using latent variables for participation in the current and previous

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

[7]See, for example, Abowd and Card (1989), Topel (1991), Topel and Ward (1992), Meghir and Pistaferri (2004) and Low et al. (2010).

[8]Heathcote et al. (2010a) find the same phenomenon in PSID data.

period, and job mobility:

$$P^*_{it-1} = \alpha z_{it-1} + \pi_{it-1}, \ \ P_{it-1} = 1\left\{P^*_{it-1} > 0\right\}, \tag{3}$$

$$P^*_{it} = \alpha z_{it} + \pi_{it}, \ \ P_{it} = 1\left\{P^*_{it} > 0\right\}, \tag{4}$$

$$M^*_{it} = \theta \kappa_{it} + \mu_{it}, \ \ M_{it} = 1\left\{M^*_{it} > 0\right\}, \tag{5}$$

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

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

We estimate (3)-(5) together with the covariance matrix using a nested trivariate probit, taking into account that mobility is only observed conditional on the individual having worked the current and previous quarter.[9]

Similar to a standard Heckit model, we use exclusion restrictions, discussed below, to obtain unbiased estimates of unexplained wage growth:[10]

$$g_{it} = \Delta w_{it} - \beta \Delta x_{it} = \xi_{it} M_{it} + \epsilon_{it} + \Delta \mathcal{X}(q)\iota_{it}. \tag{6}$$

Resulting from the participation and mobility decisions, the distribution of observed residual wage growth is truncated; we do not observe all shocks to productivity and the job component. Given the structure of our problem, residual wage growth follows a truncated multivariate normal distribution, which first two moments are derived by Manjunath and Wilhelm (2012).[11] To provide some intuition for identification, denote the correlation between permanent wage shocks and the unobserved component of participation by $\rho_{\epsilon\pi}$, and the correlation between the former and the unobserved component of mobility by

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

[10] Appendix 5.1 derives the appropriate selection term.

[11] Appendix 5.1 derives the moments for our particular case.

$\rho_{\epsilon\mu}$. Further, define $\rho_{\xi\pi}$, $\rho_{\xi\pi-1}$ and $\rho_{\xi\mu}$ to be the correlation between changes in the job component and shocks to participation this period, last period, and mobility, respectively. Summarize the results from the probit by the vector $X_{it} = [\alpha z_{it}, \alpha z_{it-1}, \theta\kappa_{it}, \rho_{\pi\pi_{-1}}, \rho_{\mu\pi}, \rho_{\mu\pi_{-1}}]$, then the first moments of unexplained wage growth in implicit form are given by

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

where ϕ is the PDF of the standard normal distribution and f_x are functions that we show in closed form in Appendix 5.1. The first moments identify the correlations between wage innovations with mobility and participation decisions, up to the scalars σ_ϵ and σ_ξ. Identification results from comparing unexplained wage growth of individuals with different participation and mobility probabilities. Abstracting for the moment from measurement error, the second moments of unexplained wage growth achieve joint identification of σ_ϵ, σ_ξ, and selection correlations. Accounting for selection, the variance of wage growth of job stayers, $E(g_{it}^2|P_{it} = P_{it-1} = 1, M_{it} = 0)$, is sufficient to identify σ_ϵ. Moreover, the variance of wage growth of job switchers, corrected for selection, identifies σ_ξ. Finally, the combination of these four moments, together with the autocovariance function of wage growth, allows us to identify all parameters of interest.

2.2 Data Sources and Sample Selection

Our analysis of labor market risk requires individual longitudinal information on wages and worker and job characteristics over several decades. The dataset most adequate for these requirements is the Survey of Income and Program Participation (SIPP). It provides a set of panels covering the period of 1983-2013.[12] Every 4 month (defined as a wave) the Census conducts an interview

[12] We exploit all up to date surveys, except of the survey from 1985 and 1989: 1984, 1986, 1987, 1988, 1990, 1991, 1992, 1996, 2001, 2004, and 2008. We do not these two surveys due to the absence of information regarding work experience, which is used at our estimation strategy.

with all adult members of participating households, asking them about their work and household characteristics during the preceding 4 months. In order to account for the seam-bias effect generated by the recollection period, we aggregate the monthly information to quarterly observations. One concern regarding the data is that the quality from the survey changed over time. We describe the details of our data cleaning procedure in online Appendix 1, where we also show that survey redesigns are unlikely to have an impact on our main results.

We group the data into three major time periods, such that each covers years of expansion and recession: 1983-1993, 1994-2003, and 2004-2013. For the analysis, we consider three education groups based on the maximum attainable degree level: high school, college dropouts, and college graduates or higher education.[13] Furthermore, we focus on working-age male individuals, aged between 25 and 61, who are not self-employed, enrolled in school, in the armed forces, or recalled by their previous firm after a separation.[14]

Given the aggregation of the information at quarterly frequency, we need to establish some definitions with respect to employment and job-mobility at this frequency level. We consider a worker employed within a quarter, when he spends most weeks of the quarter working. We identify different jobs by the establishment ID assigned by SIPP.[15] We define a worker's main job based on the establishment ID with the highest earnings.[16] 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 via a non-employment or without a non-employment spell.[17] For each quarter, we compute hourly wages as total earnings over total hours worked at the main job. To make the results robust to outliers, we do not consider individuals with hourly wage

[13]In specific, we group individuals into a. Workers with at most high school education (high school), b. Workers with some college (not degree) and excluding individuals who received an associate degree, and c. Workers who received an associate degree, college or higher.

[14]We choose the sample to start at age 25 to assure that college graduates fully transit to the labor market. Workers being recalled posses a search technology not well represented by our model.

[15]Our choice implies that we interpret within establishment changes in occupation as productivity shock and not as a change in the job component.

[16]The survey reports at most two jobs per month for each individual. In case an individual holds more than two jobs, the two jobs with most hours worked are reported.

[17]For identification, we require that skill depreciation for unemployment less than one quarter is negligible. Based on our employment definition, a worker with a mobility can have spend at most 2 months in unemployment.

growth below the 1st percentile (above the 99th percentile) of the hourly wage growth distribution by education, period, and job mobility status.

2.3 Empirical Results

2.3.1 Probit Results

We estimate the model for each of our three periods and education degrees separately; thereby, we allow for time varying returns to human capital and time varying patterns in participation and mobility. In order to estimate the participation probability, we control for a quadratic in age and work experience, race, marital status, indicators whether a person lives in a metropolitan area or reports being disable, the unemployment rate at the state level, and time and region fixed effects.[18] Importantly, we require a set of regressors that identify selection. That is, variables affecting the decision to particpate or move jobs, but not independently related to ϵ_{it} and ξ_{it}. For this purpose, we augment the set of explanatory variables including unearned household income, an index of generosity of the welfare system (state-level unemployment insurance), and an indicator whether the worker owns a house.[19]

Additionally, we include seven industry and seven occupation fixed effects to estimate the probability to move jobs.[20] We present the results of the probits in Online Appendix 2. As expected, high unemployment benefits, high unearned income, and not owning a house reduce the probability of employment. The theoretical effects on mobility are ambiguous. In principle, being closer to the participation margin should increase mobility because workers are more likely to quit their current job. On the other hand, higher reservation wages limit the possibility of future mobility. We find that state level generosity and house

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

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

[20]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. Low et al. (2010) assume that there are no industry shocks driving mobility, while we assume that there are no within industry occupation specific shocks driving it. Also, we use the housing exclusion restriction that the literature considers a predictors of job mobility while not affecting directly wage growth (see for example Blanchflower and Oswald (2013), Bowen and Finegan (2015)).

ownership reduce the likelihood of a worker to move jobs. We find no consistent, and mostly insignificant effects, of unearned household income.

The amount of workers close to the participation and mobility margin is key for the severeness of workers selecting on shocks. We observe substantial changes along this margins over the decades under analysis. In particular, when comparing the third period with respect to the first, employed workers have relatively lower participation probabilities, with more workers in the lower tail of the distribution. Moreover, workers have higher probabilities to change jobs. When decomposing effects, we find that observable worker characteristics have shifted in the direction of workers with less stable jobs (singles, minorities, elderly), and the marginal effects of these covariates have also changed.

2.3.2 Wage Variance Estimates and Selection

This section presents the estimated correlations and risk components. Estimation is based on minimizing the sum of squared residuals from the first and second moments of Equation (6) and the autocovariance terms, where we weight each individual contribution with the underlying survey weight.[21] We compute standard errors by the block-bootstrap procedure proposed by Horowitz (2003).

Figure II displays the point estimates for wage risk. Appendix (5.2) contains the corresponding estimated standard errors and the estimated correlations. All workers face substantial permanent shocks to their human capital, and those shocks become more dispersed with education. Furthermore, we find large dispersion of job effects in wage offers; those with completed college facing the largest dispersion. The standard deviation of the wage offer distribution ranges in the first period from 0.22 to 0.27. This implies that within 2 standard deviations, the wage of the same worker varies by $\pm$ 54 percent depending on his job.[22]

Regarding secular trends, the standard deviation of permanent wage risk increased for all workers by approximately 0.01. For those with a college degree, the rise materialized in the third period, while the increase is close to linear for the other education groups. Low skilled workers faced a substantial lower

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

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

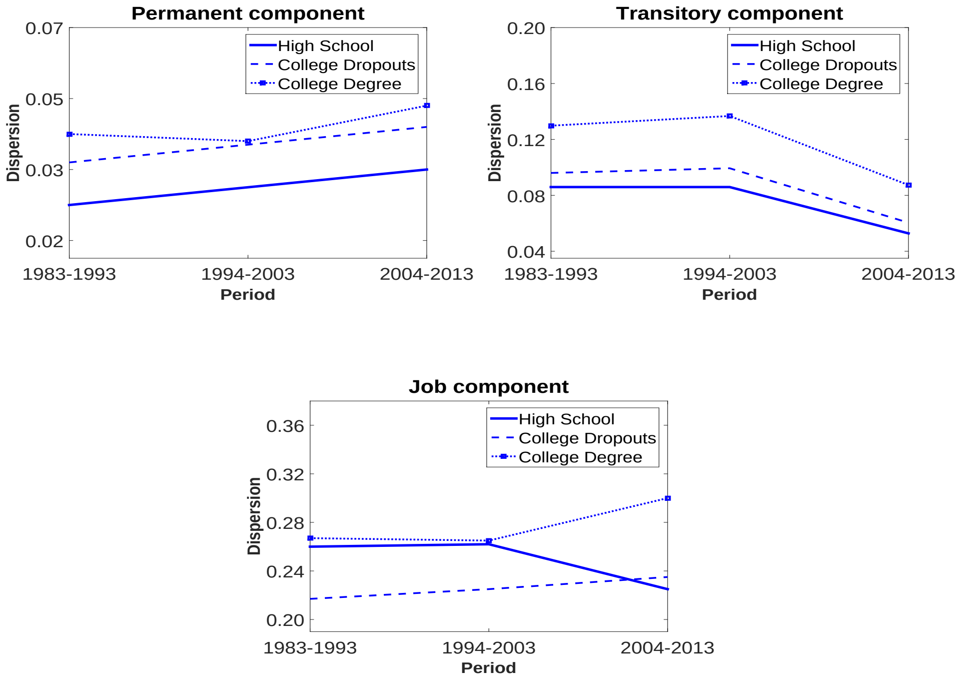
permanent risk in the 1980s. Therefore, in relative terms, lower skilled worker experience the most rise in uncertainty.

The dispersion of the wage offer distribution changed substantially for all workers. For college workers, the standard deviation increased by 0.03. Again, the rise materializes in the third period.[23] Similarly, college dropouts experienced an increase of 0.02. Similar to permanent risk, the rising uncertainty materialized already partially during the 1990s. Contrary to these groups, high school workers experienced a decline in the dispersion to the wage offer distribution by 0.04 in the third period. Finally, the dispersion to transitory wage shocks declines for all workers. Unfortunately, we are unable to differentiate between true transitory shock and measurement error. Consequently, the result represent a mix between the two. A falling dispersion; therefore, may be the result of improved interviewing techniques introduced in the 1996 and 2004 survey (see Moore (2008)).

Appendix (5.2) displays the estimated selection correlations. Workers show substantial persistence in unobserved participation heterogeneity, consistent with the productivity and match component being partially unobserved. In line with this, a positive innovations to productivity increase participation. The correlation between the unobserved component of mobility and participation decisions are for most of the cases significant and positive which may suggest heterogeneity in job finding rates. The theoretical effects of shocks to human capital and mobility are ambiguous. In the first two periods, we find a negative correlation suggesting that, after a positive shock, workers are less likely to quit to non-employment to search for a new job. In the last period, the correlation becomes positive for workers with less than completed college. Put differently, after a negative shock those with completed college are more likely to change their career, but lower educated workers stay with their job. Similarly, Autor et al. (2014) find that following Chinese import penetration, low and medium skilled workers have not been able to offset wage losses, but high skilled workers mostly have offset those by switching jobs. Finally, we find that a good outside offer increases the propensity of a worker to move jobs. The model does not

[23] One concern may be that a decline in spurious job to job transitions due to sample redesign leads to trends in the estimated wage offer distribution. As described in the Online Appendix, we attempt to clean the data from such transitions. Moreover, we would expect the major break occurring from the first to the second period, as data quality increased from 1990 onwards.

Figure I: Evolution of the Wage Variance Components: Accounting for Selection



Notes: Estimation is conducted by period and education degree group. To identify the components, we use the first and second moments of wage growth, and the autocovariance function of wage growth up to lag 3. Appendix (5.2) provides the correlations and bootstrapped standard errors.

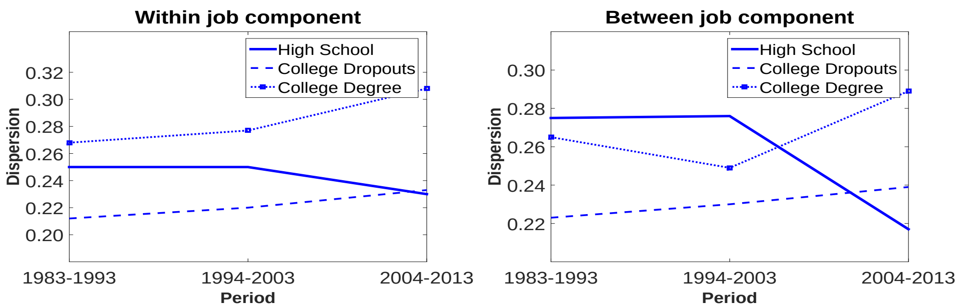
identify well the relationship between shocks to outside offers and participation.

Our model does not differentiate between job switches within and between occupation/industry groups. To understand the source of trends in the wage offer distribution, we extend the model allowing the wage offer distribution to be different for those who stay within the same industry and occupation (*Within*), and those who change either occupation or industry (*Between*). Fully estimating this model is beyond the scope of this paper, and we fix the selection correlations to the ones we obtain at our baseline econometric model.[24]. Figure II displays the evolution of the job component for these two groups. Regarding workers with at least some college education, the increased dispersion in the wage offer distribution results from more dispersed job offers for both within and between job switchers. For workers with at most a high school degree, the decrease in the dispersion of the job component is most pronounced for between movers.

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

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

Figure II: Evolution of the job Component: Within vs. Between

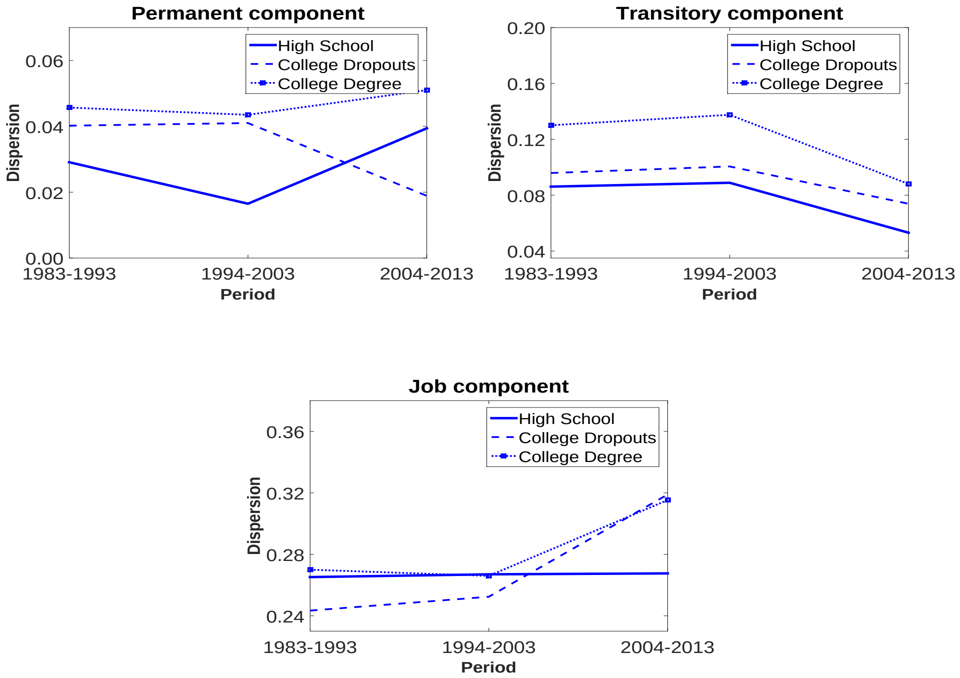


Notes: Within (Between) job component is identified through workers who stay (change) at the current industry and occupation conditional on changing the employer. Estimation is conducted by period and education degree group. To identify the components, we use the first and second moments of wage growth, and the autocovariance function of wage growth up to lag 3. Selection correlations are fixed to the estimated ones in the baseline model.

Finally we ask, how important is it to account for selection? Using the process for individual wages at Equation (1), we could identify the permanent, transitory and job component when ignoring selection, using the second moments of (uncorrected) unexplained wage growth for job stayers and movers.[25] Figure III provides the estimated components. Different from our baseline results, permanent wage risk declines by 50% for workers with some college education. Moreover, if we had ignored selection, we would have over-estimated the increase in the job component at workers with at least some college and conclude it remains flat for high school workers.

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

Figure III: Evolution of the Wage Variance Components: Ignoring Selection



Notes: Estimation is conducted by period and education degree group. To identify the components, we make use of the second moment of (uncorrected) residual wage growth of job stayers, $(\sigma_\epsilon^2 + Var(e_{it}))$, and job movers, $(\sigma_\epsilon^2 + 2\sigma_\psi^2 + Var(e_{it}))$, and the autocovariance function up to lag 3.

3 The Effects of Changes in Risk on Wage Inequality and Welfare

Our empirical results identify the changes in underlying risk that workers faced over the last decades. Yet, they are silent about the quantitative consequences for wage inequality and welfare. In order to identify these effects, we develop a partial equilibrium, life-cycle incomplete-markets model, consistent with the wage process and the selection mechanisms from Section 2.

Importantly, we explicitly model workers' insurance against risk through leisure, government insurance, and an on-the-job search technology. Our model extends the life-cycle model developed by Low et al. (2010) with job-to-job transitions resulting from reallocation shocks, which Tjaden and Wellschmied (2014) show to be important to infer the underlying distribution of workers over heterogeneous jobs.

3.1 Model

The economy is populated by a finite number of workers $\mathcal{I}$ who have either high school, some college, or college degree education. Time is discrete, workers live for H periods and discount the future with factor β. As in our empirical analysis, the length of a period is one quarter.

Workers spend 37 years in the labor market and another ten years in retirement. Within each quarter, workers may be employed, unemployed, disabled, or retired.[26] Importantly, we assume that financial markets are incomplete, such that workers have only access to a risk free asset a that pays returns $R = 1 + r$, and are unable to borrow, $a_{t+1} \geq 0$.

At the beginning of life, worker i draws a log human capital according to $p_{i1} \sim N(\mu_N, \sigma_N^2)$. Afterwards, human capital follows a random walk with a drift component that depends on the employment state and age:

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

where $\epsilon_{ih} \sim N(0, \sigma_\epsilon^2)$, and h denotes the age of the worker. Wages in the data peak around age 50, and we use ν_1 and ν_2 to match this wage profile. We make use of δ to reflect skill depreciation during unemployment.

Workers search for jobs in a frictional labor market, both on and off the job. When meeting a job, they randomly draw a log job component ψ_{ij} from a normal distribution with cumulative distribution function $F(\psi)$. Consequently, gross earnings for the employed are[27]

$$w_{ih}^g = exp(p_{ih} + \psi_{ij}).$$

The government grants several programs insuring workers against low earnings. First, the earnings tax is progressive. Following Heathcote et al. (2015),

[26] We allow agents in the model to work for, at most, 37 years such that it coincides with the same age span we consider in our empirical analysis.

[27] We abstract from intensive hours decisions and transform hourly wages from the data into earnings assuming a 40 hour workweek. Furthermore, our simulations include transitory shocks to earning but we assume to be measurement error.

earnings after taxes are given by

$$w_{ih} = \tau_c {w_{ih}^g}^{\tau^p},$$

where $\tau^p < 1$ determines the progressivity of the tax code.

Furthermore, we allow workers to receive unemployment benefits for the quarter following job destruction. The benefits replace a constant fraction of worker's last quarter earnings subject to a cap:[28]

$$b_{ih} = min\{\bar{b}w_{ih-1}, b_{max}\}.$$

During the last ten working years, workers may receive disability insurance.[29] Moving to disability insurance is a permanent exit from the labor market. At its onset, disability insurance required workers to have a health condition that prohibits working, something we abstract from in our model. Autor and Duggan (2006) show that in 1984, the government greatly relaxed the eligibility criteria, which used to require workers being unable to function in a work setting, and shifted the criteria to alternative factors such as mental illness. As a result, applications have risen substantially, particularly during recessions, and applicants have the opportunity to challenge denial of benefits with three appeal steps. We model this application procedure in such a way that benefits are only granted with probability υ. To apply for benefits, legislation requires a worker to be continuously non-employed for 5 months, and having worked before that period. To approximate this structure, the worker can only apply one quarter after becoming non-employed. Moreover, the worker may not search

[28]Legislation usually grants 26 weeks of benefits. Reducing benefits to one quarter allows us to treat it similar to a lump-sum payment to those becoming unemployed. Consequently, the benefits affect employment decisions only through a wealth effect. This assumption allows us to simplify the problem of the unemployed worker as past earnings are not part of the state space of the unemployed.

[29]By legislation, workers may apply to disability insurance throughout their working life. Yet, most people enter after the age of 50, possibly reflecting the fact that the acceptance probability rises with that age.

for a job within the same quarter of application. Benefits follow

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

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

$$\bar{w}_{ih+1} = \begin{cases} \frac{w_{ih} + \bar{w}_{ih} h}{h+1} & \text{if employed} \\ \frac{\bar{w}_{ih} h}{h+1} & \text{if unemployed} \\ \bar{w}_{ih} & \text{if disabled or retired.} \end{cases}$$

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

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

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

To summarize, total government transfers are

$$T_{ih} = \begin{cases} F_h(w^g_{ih}) & \text{if employed,} \\ F_h(b_{ih}) + b_{ih} & \text{if just became unemployed} \\ F_h(0) & \text{if unemployed,} \\ F_h(\bar{w}_{ih}) + S(\bar{w}_{ih}) & \text{if disabled,} \\ F_h(\bar{w}_{ih}) + S(\bar{w}_{ih}) & \text{if retired.} \end{cases}$$

Finally, workers derive utility from consumption and leisure. Aguiar and Hurst (2005) show that households, after exiting employment, use the additional available time to engage in home production and reduce shopping costs.

To allow for this type of insurance, we choose an utility function with complementarity between consumption and work:

$$U_{ih} = \Big(\frac{c_{ih} exp(\varphi P_{ih})}{1-\eta}\Big)^{1-\eta},$$

where the resulting consumption of the worker is given by

$$c_{ih} = \begin{cases} Ra_{ih} + w_{ih} + T_{ih} - a_{ih+1} & \text{if employed,} \\ Ra_{ih} + T_{ih} - a_{ih+1} & \text{if non-employed.} \end{cases}$$

Based on this environment, we proceed with defining the value functions at each employment state. Whenever a worker is retired or disabled, he does not face uncertainty and solves, respectively, the following maximization problem:

$$\begin{aligned} \mathcal{Q}_h(a, \bar{w}) &= \underset{a'}{max}\Big\{U + \beta \mathcal{Q}_{h+1}(a', \bar{w}')\Big\} \\ \mathcal{D}_h(a, \bar{w}) &= \underset{a'}{max}\Big\{U + \beta \mathcal{D}_{h+1}(a', \bar{w}')\Big\}. \end{aligned}$$

The value function of an unemployed worker with the option to apply for disability is given by:

$$\mathcal{U}_h(a, p, \bar{w}) = \underset{a'}{max}\Big\{U + \beta \Theta_h(a', p, \bar{w}')\Big\},$$

where Θ_h is the upper envelope over applying for disability insurance and searching for a job. The decision to apply for disability insurance is taken after the asset decision, but before the end of period uncertainty reveals. The worker knows that the application is denied with probability $1 - \upsilon$:

$$\begin{aligned} \Theta_h(a', p, \bar{w}') \equiv max\Big\{&\upsilon \mathcal{D}_{h+1}(a', \bar{w}') + (1-\upsilon) \int \mathcal{U}_{h+1}(a', p'|p, \bar{w}')dp' \\ &, \int EVU_h(a', p'|p, \bar{w}')dp'\Big\}, \\ EVU_h(a', p, \bar{w}') \equiv (1 - \lambda_u) &\int \mathcal{U}_{h+1}(a', p'|p, \bar{w}')dp' \\ + \lambda_u \int \int \max &\Big\{\mathcal{W}_{h+1}(a', p'|p, \psi', \bar{w}'), \mathcal{U}_{h+1}(a', p'|p, \bar{w}')\Big\} dF(\psi)dp', \end{aligned}$$

where λ_u is the job finding rate when unemployed. EVU_h is the value of search in unemployment that a worker forgoes when applying to disability insurance.

The value function of an unemployed worker who is unable to apply for disability, solves the following problem

$$\mathcal{U}_h(a,p,\bar{w}) = \underset{a'}{max}\Big\{U + \beta EVU_h(a',p,\bar{w}')\Big\}.$$

Employed workers continue to sample job offers from the same distribution as the unemployed. Searching jobs while being on the job is an important insurance mechanism against poor draws from the wage offer distribution. Following Tjaden and Wellschmied (2014), we allow job to job transitions to be a result of reallocation shocks. An employed worker receives a job offer with probability λ and can in general decide to stay with his old match, or form a new one. However, with probability λ_d, his choice is between the outside offer and unemployment. Examples of the latter are temporary jobs, advanced layoff notice, or firm bankruptcy. Consequently, the value of an employed worker of age h solves

$$\begin{aligned}\mathcal{W}_h(a,p,\psi,\bar{w}) = \underset{a'}{max}\Big\{U_h + \beta\mathbb{E}_h\Big\{(1-\omega)\\ \Big[(1-\lambda)\Xi + \lambda[(1-\lambda_d)\Omega_E + \lambda_d\Lambda]\Big] + \omega\mathcal{U}_{h+1}(a',p',\bar{w}')\Big\}\Big\},\end{aligned}$$

where we have defined the following upper envelops:

$$\begin{aligned}\Xi &\equiv \int \max\Big\{\mathcal{W}_{h+1}(a',p'|p,\psi,\bar{w}'),\mathcal{U}_{h+1}(a',p'|p,\bar{w}')\Big\}dp'\\ \Omega_E &\equiv \int\int \max\Big\{\mathcal{W}_{h+1}(a',p'|p,\psi,\bar{w}'),\mathcal{U}_{h+1}(a',p'|p,\bar{w}'),\mathcal{W}_{h+1}(a',p'|p,\psi',\bar{w}')\Big\}dF(\psi')dp'\\ \Lambda &\equiv \int\int \max\Big\{\mathcal{W}_{h+1}(a',p'|p,\psi',\bar{w}'),\mathcal{U}_{h+1}(a',p'|p,\bar{w}')\Big\}dF(\psi')dp'.\end{aligned}$$

An employed worker keeps his job with exogenous probability $1-\omega$, in which case he may receive an on-the-job offer. In the case of no offer, he may decide between staying employed or quit and move into unemployment. When he receives an offer, it may be a regular offer or a reallocation shock. In the former case he decides between his current job, the outside offer, and unemployment, Ω_E. In the latter case, the set of alternatives are the new offer or unemployment, Λ.

3.2 Calibration

We calibrate the coefficient of relative risk aversion and the interest rate outside of our data. The former, η, is set to 1.5, consistent with Attanasio and Weber (1995). Following Siegel (2002), we fix the value of r to imply a yearly interest rate of 4%. The remaining parameters in the model are calibrated to match empirical moments of the 1980's in the United States; the first period of our empirical analysis. Most of our calibration targets are education specific. Tables 1 and 2 summarize the calibration, and Appendix 5.3 reports the targeted empirical moments.

We set the dispersion of the permanent shock from Equation 3.1 to the value obtained in our empirical section. Similarly, we set the dispersion of the wage offer distribution, σ_ψ to its estimated value. In order to match the average amount of self-insurance present in the data, we calibrate β to target the mean wealth of the population between age 25 and 61. To calibrate the amount of insurance from leisure (φ), we target the drop in employment rates between age 45 and 61. In our framework, the utility of leisure may also capture other insurance mechanisms that we abstract from the model, such as home production, reduced shopping costs of non-employed workers, and the labor supply from other members at the household. The calibration implies that high skilled workers derive substantially more utility from non-working, but the complementarity is not large for any group.

We allow individuals to start with positive wealth at the beginning of their life. To do so, we assume that initial wealth is a random draw from the estimated empirical wealth distribution of young workers (between age 25 and 28). In addition, we set σ_N^2 to match the initial variance of log wage inequality, and μ_N, to match the average wage at the beginning of workers' life. Human capital, after the first period, follows a random walk that depends on the employment state. The terms ν_1, ν_2, and δ are calibrated to target the average wage changes from age 25 to 50 and from 51 to 61, and median wage losses from unemployment.

Given the estimated parameters of the wage process, it remains to calibrate the parameters that allows us to target the worker transition rates and the government programs. In particular, the exogenous job destruction rate, ω, is set to match the movements from employment to unemployment not explained

Table 1: Main Calibration

Parameter	HS	SC	C	Target
σ_ϵ	0.03	0.04	0.049	Dispersion permanent shock
σ_ψ	0.26	0.24	0.27	Dispersion job effects
σ_N	0.29	0.31	0.29	Initial wage dispersion
μ_N	7.22	7.3	7.48	Initial mean wage
r	0.01	0.01	0.01	4% annual interest rate
$(1-\beta)\%$	0.59	0.54	0.44	Wealth to earnings ratio
η	1.50	1.50	1.50	Risk aversion
φ	-0.06	-0.1	-0.12	Employment drop 45-60
ν_1 %	0.46	0.61	0.71	Wage growth 25-50
ν_2 %	-0.40	-0.58	-0.76	Wage growth 51-61
δ %	1.30	0.81	1.25	Wage losses from U
ω %	1.40	0.63	0	EU flow rate
λ_u %	17.62	18.51	20.04	UE flow rate
λ %	4.06	4.01	3.77	JTJ flow rate
λ_d %	49.90	48.15	42.40	% of wage cuts upon

Notes: HS refers to workers with at most a high school diploma, while SC to college dropouts, and C to college degree. The left column states the variable, and the second, third, and fourth column state the calibrated value. EU stands for employment to unemployment, UE for unemployment to employment, JTJ for job to job movements, and U for unemployment.

Table 2: Calibration of Welfare State

Parameter	Value	Source
$\bar{b}$	0.70	Anderson and Meyer (1997)
b_{max}	1992	Price (1985)
$\overline{F}$	680	Kerr et al. (1984)
d_1	801	Social Security Administration (2016)
d_2	4836	Social Security Administration (2016)
υ	0.43	Social Security Administration (2015)
τ^c	1.84	Tax schedule intercept
τ^p	0.89	Tax progessivity

by endogenous separation, and λ_u to match the job finding rate in the data.[30] Additionally, the information on job to job movements and accompanying wage changes identify λ and λ_d. To this end, we define job to job transitions whenever the worker reported to have been mostly employed in both quarters, and never spend time searching between the two jobs when not employed. Our identifying assumption for separating voluntary and involuntary movements consists in that the former always result in expected wage increases. Together with the losses due to stochastic idiosyncratic shocks to wage potential and transitory shocks, setting λ_d allows us to replicate the share of job to job movements resulting in nominal wage losses.

Further, we calibrate the size of the welfare state to the mid 1980's. Unemployment benefits usually last two quarters in the United States. However, in the model, they only last one quarter. To compensate, we calibrate the replacement rate to be twice the level estimated by Anderson and Meyer (1997). Moreover, we compute the maximum benefit as the average maximum benefits paid by US states.[31] We model the universal means-tested program in line with the regulations from the *Food Stamps Program* for a household composed of 4 persons. The maximum amount of benefits is calculated as the need for basic nutrition according to the *Thrifty food plan* detailed in Kerr et al. (1984). The bend points d_1 and d_2 determine the concavity of social security transfers. Social Security Administration (2016) reports the appropriate values. The probability of acceptance into disability benefits, υ, is calibrated to match the share of accepted claims between 1984 and 1993 that is reported in Social Security Administration (2015). Finally, in order to calibrate the parameters of the tax function, we estimate the following equation

$$ln(w_{ih}) = ln(\tau^c) + \tau^p ln(w_{ih}^g),$$

using SIPP data and *TAXSIM* to construct w_{ih}.[32]

[30] To compute the latter, we only consider individuals who report searching for employment at least one week within the quarter.

[31] See Price (1985).

[32] 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.

3.3 Model Fit

Given the specified calibration, our model is able to provide implications in regards to (untargeted) labor market outcomes. To begin with, our model predicts a decline in consumption after a job loss of 0.06 log points, while the available estimates from US predict a drop of less of 0.1 log points (see Chetty (2006)). The decline in consumption in our model arise due to insufficient insurance, and from complimentarity of work with consumption. The small decline in the data is; therefore, is consistent with the latter being small.[33]

Following Hornstein et al. (2012), the mean-minimum residual wage is a useful statistic to evaluate the performance of search models with heterogeneous jobs. Particularly, it allows us to assess the amount of sorting of workers over these heterogeneous jobs. The second row in the table shows that our model closely matches the data. An alternative measure to judge the amount of sorting over heterogeneous jobs are the wage dynamics conditional job to job transitions. Rows three and four compare average wage growth, conditional on positive or negative wage growth. Based on the data so as our model predictions, workers experience on average wage changes around 0.26 log points. Approximately, 50% of transitions result in wage loses, consequently, average wage gains from job to job transitions are close to zero.

Further, the excess variance of job stayers over job switchers is informative on the dispersion of the wage offer distribution. The model predicts relatively lower excess variance, particularly for college dropouts. Put differently, the statistic suggests that workers are somewhat better sorted over jobs in the model than in the data. However, the difference is small. Moreover, the model implies the correct ordering across education groups.

Instead of studying only the excess variance of job switchers, we ask whether our model is able to replicate our empirical results from Section 2.3. Our baseline model does not feature heterogeneity that would allow us to use exclusion restriction to identify selection. We discuss in Appendix 5.4 an extended model which features additional heterogeneity which allows us to obtain identification. The model replicates the sign of the correlation coefficients found in Section 2.3. Similar to our finding above, the model implies a somewhat smaller estimate

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

Table 3: Untargeted Moments

	All Workers-Model			All Workers-Data		
$\Delta ln(c)$ EU	-0.06			-0.10^{*}		
	HS	SC	C	HS	SC	C
Mean-min ratio	2.18	2.29	2.53	2.17	2.13	2.49
Wage gain JTJ %	29.29	24.98	29.72	28.23	25.62	30.28
Wage loss JTJ %	-30.00	-25.50	-29.77	-25.16	-26.00	-29.07
$V(\Delta w_i^b)$-$V(\Delta w_i^w)$	0.13	0.09	0.12	0.14	0.12	0.15

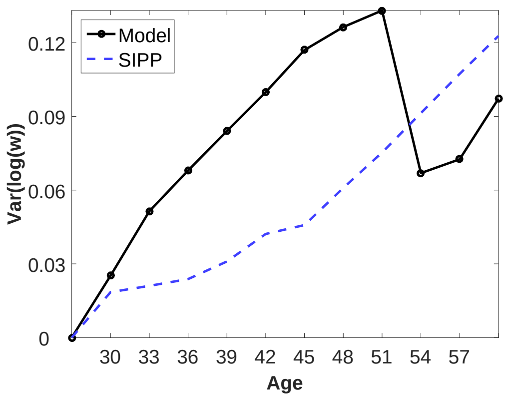
Notes: $-0.1*$ denotes less than -0.1 log points (in absolute value). HS refers to workers with at most a high school degree, while SC to college dropouts, and C to college degree. Data moments refer to the first period of analysis in the data: 1983-1993. *Mean-min ratio:* is the ratio between the average wage and the 5th percentile wage. $V(\Delta w_i^b)$-$V(\Delta w_i^w)$*:* is the excess variance of residual wage growth of job movers relative to job stayers.

for σ_ϕ.

Finally, we analyze the implications of inequality over the life cycle. The estimated earnings uncertainty, together with the labor market friction and the selection, shape wage inequality over the life-cycle. Figure IV compares this cross sectional wage inequality over the life-cycle in the model relative to the data.[34] Both in model and the data, inequality increases to similar amounts over the life-cycle. However, the model implies a too steep increase early in life, and too little increase for elderly workers. The discrepancy may arise from two sources. First, the model is simulated for a cohort which is followed for the entire life-cycle, something impossible to do in the SIPP data. Consequently, our empirical estimates are based on workers with, possibly, different wage risk at different stages of their lives. Second, we get a pronounced decrease in inequality in the model at age 50 coming from the selection into disability, while we do not observe this pattern empirically. In this respect, we assume that workers may only apply to disability from age 50, while in the data workers may apply to disability earlier in life, which may also explain the relatively lower increase of inequality over the life-cycle in the data.

[34]We proceed with some data adjustments for the particular analysis regarding the evolution of wage inequality. To begin with, we trim the lowest 1% of observations of hourly income by educational degree. Regarding top income, the surveys censors each source of income above specified top coded levels. To account for this problem, we follow Heathcote et al. (2010a) and estimate the upper tail of the income distribution assuming it follows a Pareto distribution. Further, we replace each right-censored observation with a random draw from the fitted distribution, conditional on being larger than the top-coded threshold.

Figure IV: Life Cycle Wage Profile



Notes: The figure displays the variance in yearly log hourly wage over the life cycle in the model and the SIPP. To ameliorate the effect of small amount of observations in the data, we compute the variance in log hourly wage by age bins of 5 years. All series are normalized to zero at the first age group. The data features a series of worker characteristics not present in the model. To make it comparable, we control in the data for race, region, metropolitan area, marriage, and time fixed effects.

3.4 Sources of Rising Wage Inequality

To quantify how changes in underlying risk translate into changes in observed wage dispersion, we simulate our structural model with the risk parameters estimated for the 1980's and compare it to a simulation based on the risk parameters estimated for the 2000's.[35] In this experiment, changes in risk are the only difference between the two periods; the initial dispersion of workers, mean wages, and the institutional framework are unchanged.

Table 4: Increase of Within-Education Wage Inequality

	High School	College Dropouts	College
SIPP	0.022	0.043	0.040
Model	0.017	0.039	0.046
Model-Wage offer	-0.020	0.003	0.007

Notes: The table displays the change in the variance of residual log wages between the first and last period. *Model*: The change from model simulation based on the point estimates of risk and wage offer distribution presented in Section 2.3.2. *Model-Wage offer*: The change in inequality resulting from changes in the wage offer distribution only.

Table 4 compares the changes in inequality in the model to the data. Our

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

model can explain 84% of the increase in inequality for workers with at most some college, while we overestimate by 15% the increase in inequality at college workers. Furthermore, empirically, inequality has increased least in the group of workers with high school education, and the model is consistent with this pattern. The row labeled *Wage offer* displays changes in inequality when the dispersion of the wage offer distribution changes, and the dispersion of wage shocks remains at the level of the first period. Changes in the wage offer distribution contributed significantly to rising wage inequality for college dropouts, but little for the other skill groups.[36]

3.5 Welfare Consequences of Rising Uncertainty

To assess the welfare consequences of changing wage uncertainty we simulate the change in risk measured in the data between the first and the third period. The change in risk alters the distribution of workers over employment and jobs; thereby, the tax revenue and public expenditure. Consequently, we re-calibrate the tax rate to assure that in both periods, conditional on education, the size of the government budget remains unchanged:[37]

$$\mathcal{B} \;=\; \sum_{i=1}^{\mathcal{I}}\sum_{1}^{H} b_{ih}E_{ih}^{UI} \;+\; S(\bar{w}_{ih})E_{ih}^{S} \;+\; F_h(y_{ih})E_{ih}^{F} \;-\; \sum_{i=1}^{\mathcal{I}}\sum_{1}^{H} P_{ih}(w_{ih}^{g} \;-\; \tau_c {w_{ih}^{g}}^{\tau^p}),$$

where E_{ih}^{UI}, E_{ih}^{D}, and E_{ih}^{T} are indicators that reflect whether a person receives unemployment benefits, disability/social security insurance, and means tested transfers, respectively.

Our welfare measure is the willingness to pay in terms of life-time consumption. Let c_{ih} be the consumption of a worker of age h in the original economy, and $\hat{c}_{ih}$ be the consumption in the alternative economy. The fraction of consumption which makes the worker indifferent between being born in the two different economies solves:

$$\mathbb{E}_0 \sum_{h=1}^{H} \beta^h U(c_{ih}, P_{ih}) = \mathbb{E}_0 \sum_{h=1}^{H} \beta^h U((1+\omega)\hat{c}_{ih}, \hat{P}_{ih}), \tag{7}$$

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

[37]Hence, we abstract from insurance mechanisms that may occur between education groups.

We assume the initial distribution over states to be the same; thus, the willingness to pay is given by

$$\omega = \left(\frac{\mathbb{E}_0 V_1}{\mathbb{E}_0 \hat{V}_1}\right)^{\frac{1}{1-\nu}} - 1.$$

Table 5: Welfare Effects of Rising Uncertainty

	High School	College Dropouts	College
Total wage risk %	0.51	0.56	-0.5
Wage offer %	0.41	-0.45	-1.07
Weaker government %	1.05	1.2	1.09

Notes: *All workers*: The table displays the average willingness to pay of an unborn worker, aggregating low skilled and high skilled workers, to avoid the increase in wage risk and wage offer distribution between the 1980's and 2000's. *Total wage risk*: The willingness to pay based on changes in permanent wage risk and changes in the wage offer distribution, by skill level, between the 1980's and 2000's. *Wage offer*: The willingness to pay resulting from only changes in the wage offer distribution, by skill level, between the 1980's and 2000's. *Weaker government*: The only insurance program is one half of the original benefit level of the universal means-tested program.

Table 5 shows the welfare consequences of changing uncertainty between the first and the third period. The top rows shows the willingness to pay, before uncertainty about educational status is resolved. On average, an unborn worker is willing to forgo 0.23% of life-time consumption to avoid the additional risk.

These welfare costs are not evenly distributed across education groups. The first row in Table 5 displays the willingness to pay after workers know their educational status. Workers with at most high school education and college dropouts are willing to pay 0.5 percent of life-time consumption to avoid the change in risk. In contrast, workers with completed college experience welfare gains from the increased uncertainty.

To shed some light on these results, we disentangle the effects of changes in permanent wage risk, and changes in the wage offer distribution. To this end, the second row displays the welfare effects from changing the wage offer distribution but keeping permanent wage risk at its old level. All type of workers prefer a more dispersed wage offer distribution. In a search model, an increase in the wage offer dispersion creates an option value to the worker: He can always break away from particular poor matches and search to find a better match. This option value outweighs the costs of increased uncertainty. Quantitatively, the increase in dispersion is largest for workers with finished college; consequently, they gain the most. Moreover, for a given increase in dispersion, the welfare implications are largest for these workers. Increasing the standard deviation by 0.01, increases the willingness to pay by 0.32 for this group, but only by 0.12 and 0.25 for the other two groups.

Comparing total welfare changes to those where only the wage offer distribution changes, provides the net effect of changes in permanent wage risk. All workers are willing to pay to reduce this type of risk, but again, there is substantial heterogeneity. To avoid an increase of the standard deviation by 0.01, workers are willing to pay between 0.1 and 1 percent of life-time consumption. The heterogeneity arises from the different degree of insurance resulting from self-insurance, leisure, and the government.

To evaluate the importance of the government providing insurance against increasing wage risk, the third row computes welfare changes for a hypothetical economy where there is only social security. Hence, we do not consider disability insurance nor unemployment insurance, taxes are proportional, and the maximum benefits from the universal means-tested program are reduced by 50%.[38] Comparing the results to the second row, the government plays an important role in shielding workers from rising wage uncertainty. All type of workers would be willing to give up substantial more life-time consumption to avoid the change in risk in this hypothetical economy.

Table 6: Welfare Effects of Increasing the Welfare State

	High School	College Dropouts	College
More UI %	0.31	0.39	0.54
More UM %	0.04	-0.14	-0.14
More DI %	0.55	0.53	0.58

Notes: *All workers*: The table displays the average willingness to pay of an unborn worker to avoid an increase in the welfare state financed by a 1.66 percentage point rise in average taxes. *More UI*: *Unemployment insurance*. *More UM*: Universal means-tested program. *More DI*: Increase acceptance probability of *disability insurance*.

So far, we did not address the question whether the level of governmental insurance in the 1980's was adequate to insure workers. Table 6 provide welfare outcomes when we increase the level of different governmental programs in this period, each financed by an incremental change of average taxes by 1.66 percentage points. Raising average and maximum benefits of unemployment insurance leads to welfare losses for all three type of workers, particularly the higher skilled. There are small welfare gains present when increasing benefits of the universal means-tested program, except for workers with at most high

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

school education. This program has relatively weak employment disincentive effects, and it provides insurance against persistent earnings losses. Disability insurance is one of the fasted growing income support programs. Autor and Duggan (2006) show that its growth is closely linked to widening eligibility criteria, an increase in υ in our framework. The last row shows that across education groups, workers are willing to spend around 0.5% of life-time consumption to avoid the more generous eligibility requirement. Disability insurance has relatively large employment affects after age 50 in our economy. The resulting increase in the tax burden creates the large welfare losses. The finding is in contrast to Low and Pistaferri (2015) who find welfare gains of loosening eligibility requirements. One difference is that they explicitly model health status that affects acceptance probabilities. Another difference is that we infer a much smaller value for the complementarity of consumption and leisure for low skilled.[39] As a result, our model favors transfer programs that keep workers employed; such as the universal means-tested program.

4 Conclusion

This study estimates trends in labor market risk in US for the last three decades, decomposing workers' earning risk into permanent shocks to idiosyncratic productivity, and a job specific wage component. Importantly, our approach allows us distangle exogenous fluctuations at earnings from endogenous choices in response to these shocks. Using data for males over the period 1983-2013, we find that wage risk has evolved differently across education groups over the last decades. While permanent wage risk increased by about 0.01 for all workers, heterogeneity in job offers has only risen for workers with at least some college education.

In order to quantitatively understand the implications of our empirical findings for wage inequality and welfare, we build a structural partial equilibrium model of life-time utility maximization, which is consistent with the endogenous selection mechanisms present in the data. When simulating the increase in wage risk obtained empirically, we find that the model can account for 85% of the increase in within education wage inequality in US during the last three

[39]A further difference is that in contrast to them, average earnings is a state variable in our model which makes past earnings shocks part of the decision for disability insurance.

decades.

At the same time, the welfare costs of increased uncertainty are small. Our model explicitly models government transfer programs and workers endogenously selecting into these. These very programs shield workers from most of the increase in earnings risk. In addition, workers with at least some college education, compensate the increase in productivity risk with a more dispersed wage offer distribution. Larger dispersion in the latter creates an option value to the worker: He can always terminate poor matches and search for a better match.

Our analysis focuses only on male workers and does not explicitly model joint household decisions. Yet, spousal labor participation could serve as an additional insurance mechanism against individual labor market risk. Some interesting initial approaches in this direction are Shore (2010) and Blundell et al. (2008). These studies do not make a distinction between exogenous income risk fluctuations and endogenous outcomes. Erosa et al. (2012) propose a framework to estimate shocks to spouses productivity jointly, taking into account the participation margin.

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5 Appendix

5.1 Moments for the Wage Variance

To reduce notation, we drop the i and t subscripts on variables. We begin by deriving the selection term present in wage growth:

$$E[\Delta W_{is}|P_{is}=P_{is-1}=1]=E[\Delta W_{is}|P_{is}=P_{is-1}=1,M_{is}=0]P(M_{is}=0|P_{is}=P_{is-1}=1)$$

$$+E[\Delta W_{is}|P_{is}=P_{is-1}=1,M_{is}=1]P(M_{is}=1|P_{is}=P_{is-1}=1)$$

$$=\beta\Delta x_{is}+P(M_{is}=0|P_{is}=P_{is-1}=1)\Big[\frac{\rho_{\epsilon\pi}\sigma_\epsilon\phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}};\rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}$$

$$-\frac{\rho_{\epsilon\mu}\sigma_\epsilon\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}};\rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big]$$

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

$$+\frac{\rho_{\epsilon\mu}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}};\rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big]$$

$$+\sigma_\xi\Big[\frac{\rho_{\pi\xi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}};\rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}$$

$$+\frac{\rho_{\mu\xi}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}};\rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}$$

$$+\frac{\rho_{\pi_{-1}\xi}\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}},\frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}};\rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big]\Big]$$

$$=\beta\Delta x_{is}+P(M_{is}=0|P_{is}=P_{is-1}=1)\Big[\frac{\rho_{\epsilon\pi}\sigma_\epsilon\phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}};\rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}$$

$$-\frac{\rho_{\epsilon\mu}\sigma_\epsilon\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}};\rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big]$$

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

$$+\frac{(\rho_{\epsilon\mu}\sigma_\epsilon+\rho_{\xi\mu}\sigma_\xi)\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}},\frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}};\rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}$$

$$+\frac{\rho_{\pi_{-1}\xi}\sigma_\xi\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}},\frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}};\rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big]$$

where

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

and $\rho_{u_1 u_2 \cdot u_3}$ denotes the partial correlation of u_1 and u_2 controlling for u_3.

Given our wage model specification, we can derive the expected wage growth for job stayers and movers not explained by observable person characteristic. The expected value for the former is:

$$E(g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 0) = \frac{\rho_{\epsilon\pi}\sigma_\epsilon \phi(-z\alpha)\Phi^{21}\left(\frac{-\kappa\theta + \rho_{\mu\pi} z\alpha}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\pi\pi_{-1}} z\alpha}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}$$
$$- \frac{\rho_{\epsilon\mu}\sigma_\epsilon \phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha + \rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho_{\mu\pi}^2}}, \frac{-z_{-1}\alpha + \rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho_{\mu\pi_{-1}}^2}}; \rho_{\pi\pi_{-1}\cdot\mu}\right)}{\Phi^{121}(-z\alpha, -\kappa\theta, -z_{-1}\alpha; \Omega)}, \tag{8}$$

where

$$\Phi^{21}(y_1, y_2; \rho) = \int_{-\infty}^{y_1} \int_{y_2}^{\infty} \phi(x_1, x_2, \rho) dx_1 dx_2,$$
$$\Phi^{121}(y_1, y_2, y_3; \Omega) = \int_{y_1}^{\infty} \int_{-\infty}^{y_2} \int_{y_3}^{\infty} \phi(x_1, x_2, x_3, \Omega) dx_1 dx_2 dx_3.$$

Economic theory would suggest that negative shocks to wage potential decrease participation. Hence, because the worker participates, his shock to ϵ could not be too negative. The first term of (8), simply speaking, relates the probability to participate, correcting for autocorrelation, to wage growth of job stayers, which identifies $\rho_{\epsilon\pi}$.

Similarly, the relationship between wage growth of job stayers and the probability to change jobs identifies $\rho_{\epsilon\mu}$. M_{it} may be one when the worker leaves his former job due to a poor wage potential draw. Consequently, we expect a positive relationship, i.e., a person who is likely to make a mobility, but did not do so, cannot have had a too large negative wage shock.

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

$$
\begin{aligned}
&E(g_{it}|P_{it}=P_{it-1}=1, M_{it}=1)= \\
&=\sigma_\epsilon\Big[\frac{\rho_{\epsilon\pi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+\frac{\rho_{\epsilon\mu}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big] \\
&+\sigma_\xi\Big[\frac{\rho_{\pi\xi}\phi(-z\alpha)\Phi^{11}\left(\frac{-\kappa\theta+\rho_{\mu\pi}z\alpha}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\pi\pi_{-1}}z\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}; \rho_{\mu\pi_{-1}\cdot\pi}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+\frac{\rho_{\mu\xi}\phi(-\kappa\theta)\Phi^{11}\left(\frac{-z\alpha+\rho_{\mu\pi}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi}}}, \frac{-z_{-1}\alpha+\rho_{\mu\pi_{-1}}\kappa\theta}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\pi_{-1}\pi\cdot\mu}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)} \\
&+\frac{\rho_{\pi_{-1}\xi}\phi(-z_{-1}\alpha)\Phi^{11}\left(\frac{-z\alpha+\rho_{\pi\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}, \frac{-\kappa\theta+\rho_{\mu\pi_{-1}}z_{-1}\alpha}{\sqrt{1-\rho^2_{\mu\pi_{-1}}}}; \rho_{\mu\pi\cdot\pi_{-1}}\right)}{\Phi^{111}(-z\alpha,-\kappa\theta,-z_{-1}\alpha;\Omega)}\Big]. \qquad (9)
\end{aligned}
$$

The parameter $\rho_{\xi\mu}$ is expected to be positive, i.e., a large positive innovation in the job component should encourage mobility. We would also think that the estimated $\rho_{\xi\pi}$ should be positive, i.e., a good outside offer increases participation. However, this variable is likely not well identified. The population of workers which identifies it are those who had a large enough negative ϵ shock to trigger quitting into non-employment, but at the same time a sufficient large positive innovation in ξ to prevent this move. These are likely to be very few.

The first moments alone identify the selection terms up to the scalars σ_ϵ and σ_ξ. To identify the standard deviations separately, we require the variance of the wage growth for job stayers and job switchers. The wage growth for job stayers is defined as

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

where $Var(e_{it})$ refers to the variance in the transitory component. This equation makes explicit that the true variance σ_ϵ^2 is different from the one observed in the data for job stayers because the latter are a self-selected group. First, part of the true shocks are not observed as workers decide quitting into non-employment given a sufficiently large negative shocks. Second, given that the workers made no mobility, the realized shock cannot have been too negative. Third, the interaction of these two effects enters and a correction for the auto-correlation in participation decisions.

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

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

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

$$Var(e_{it}) = \sigma_i^2 \Big[1 + (1+\chi_1)^2 + (\chi_2 - \chi_1)^2 + \chi_2^2\Big].$$

We identify these process by the autocovariance function of wage growth up to lag 3. Note that σ_ϵ^2 and σ_ξ^2 are not part of these moments.[40]

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

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

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

5.2 Wage Variance Estimates

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

Table 7: High School

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

Notes: σ_ϵ, σ_i, σ_ϕ are the standard deviations of the permanent shock, transitory, and job respectively. Block bootstrap standard errors in parentheses (100 repetitions). We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1.

Table 8: College Dropouts

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

Notes: σ_ϵ, σ_i, σ_ϕ are the standard deviations of the permanent shock, transitory, and job respectively. Block bootstrap standard errors in parentheses (100 repetitions). We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1. For the period 2004-2013, we set $(\rho_{\epsilon\pi}, \rho_{\epsilon\mu}, \rho_{\xi\pi}, \rho_{\xi\pi_{-1}}, \rho_{\pi\mu})$ to the estimated correlations from period 1994-2003 due to problems to capture selection for this particular case.

Table 9: College Degree

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

Notes: σ_ϵ, σ_i, σ_ϕ are the standard deviations of the permanent shock, transitory, and job respectively. Block bootstrap standard errors in parentheses (100 repetitions). We constrain all the correlation coefficients to lie between -1 and 1, and estimated θ to be negative and above -1.

5.3 Calibration Table

Table 10: Calibration Targets

	High School	College dropouts	College degree
Wealth to earnings ratio	12.98	16.03	14.38
Employment drop 45-61 %	-25.49	-26.83	-30.79
Job finding %	16.48	17.52	18.25
Unemployment inflow %	2.15	1.45	0.09
Job to job %	2.82	2.78	2.30
Share wage decrease	43	43	42
Wage growth 25-50 %	35.10	54.94	74.52
Wage growth 51-61 %	-3.07	-4.78	-5.87
Wage loss U %	-11.84	-11.74	-15.58
Initial dispersion	0.38	0.38	0.41
Initial log wage	7.17	7.27	7.47

Note: The table displays the calibration targets using the SIPP data from our first period of analysis: 1983-1993. *Wealth to earnings ratio*: median of the wealth to labor income ratio. *Employment drop 45-61*: change in the participation rate at age 58-61 relative to age 45-47. *Job finding*: share of workers who are employed at the current quarter but where not employed at the previous quarter. *Unemployment inflow*: share of workers who are not employed at the current quarter but where employed at the previous quarter. *Job to job*: share of workers who changed the firm which are working across consecutive quarters. *Share wage decrease*: share of job to job transitions that implied a decrease in the hourly wage. *Wage growth 25-50*: change in the average hourly wage at age 50 relative to age 25. *Wage growth 51-61*: change in the average hourly wage at age 51 relative to age 61. *Wage loss U*: average change in hourly wage when returning back to employment. *Initial dispersion*: dispersion of log wage not explained by job effects at the beginning of workers' life (below 25 years old). *Initial log wage*: average wage at the beginning of workers' life (below 25 years old).

5.4 Can our Simulated Model Recover Back the Risk Components?

We would like to analyze whether our model is capable of reproducing the wage variance components found empirically. To do so, we simulate our structural model with the risk parameters estimated for the 1980's for 1,000 workers, and re-estimate the wage variance components accounting for selection into mobility and participation.

Our identification of the selection into employment and across jobs hinged on the availability of exclusion restrictions which predict employment and mobility, but do result from innovations to wages. Similar to the data, we solve the model under a high unemployment benefit regime ($b_{ih} = 1.4w_{ih-1}$) and our baseline ($b_{ih} =$

$min\{0.7w_{ih-1}, b_{max}\})$. Our model does not feature sufficient heterogeneity to replicate the exclusion restrictions used to identify mobility in the data. Our empirical results suggest that identification for mobility results predominantly from time aggregation of workers moving away from a poor job prospect. Therefore, to identify selection into mobility, we include different degrees of job destruction rates ($90\%\omega$, ω, $110\%\omega$) together with time aggregation. Similar to the data, we simulate the model on a monthly basis and aggregate to a quarter.

Table 11 provides the resulting estimates of the wage variance components resulting for the simulation of this model. For simplicity, we simulate the model without measurement error. As in section 2.3, We estimate a nested trivariate probit as a function of a quadratic in age, experience, state of unemployment benefits and job destruction rates. The latter two variables are excluded from the wage growth equation.

Overall, we are able to recover the original estimated permanent and match component for high school and college degree workers, while we somehow over-estimate the size of the permanent shock at college dropouts. Also the selection terms implied by our model are similar to the data. As in our empirical estimation, positive innovations to productivity increase participation. Moreover, we obtain a negative correlation between shocks to productivity and unobserved heterogeneity in mobility, which suggests that workers quit to non-employment to search for a new job. Finally, we find that a good outside offer increases the propensity of a worker to move jobs.

Table 11: Wage Variance Components Based on Model Simulation

	High School	College dropout	College degree
Standard deviations			
σ_ϵ	0.051	0.065	0.045
σ_ϕ	0.237	0.177	0.217
Correlations			
$\rho_{\epsilon\pi}$	0.642	0.891	0.333
$\rho_{\epsilon\mu}$	-1.000	-1.000	-1.000
$\rho_{\xi\pi}$	0.023	-0.048	-0.184
$\rho_{\xi\pi_{-1}}$	-0.395	-0.280	0.331
$\rho_{\xi\mu}$	0.207	0.307	0.186
$\rho_{\pi\pi_{-1}}$	0.962	0.963	0.962
$\rho_{\pi\mu}$	0.449	0.307	0.136
$\rho_{\pi_{-1}\mu}$	0.306	0.261	0.057

Notes: σ_ϵ, σ_ϕ are the standard deviations of the permanent shock and job component shock respectively. We estimate the process based on a model simulation from the first period of analysis. We constrain all the correlation coefficients to lie between -1 and 1.