Wage Risk, Employment Risk and the Rise in Wage Inequality

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Abstract

We decompose individual wage growth in US for the period 1984-2013 into a permanent, transitory, and job specific component, explicitly accounting for selection into employment and job mobility. We find that the evolution of income risk differ substantially by education level. Workers with less than college degree experienced a large increase of the permanent income risk, while individuals with at least some college faced considerably higher dispersion of the wage offer distribution. Using a structural life-cycle on-the-job search model, we show that these facts can explain most of the rise in within group wage inequality in US. The welfare costs of larger wage risk are XXX .

Keywords: Wage risk, insurance, wage inequality
JEL:

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1 Introduction

Understanding trends in earnings uncertainty is crucial to comprehend the welfare costs of incomplete insurance markets and changes in earnings inequality. A common approach decomposes residual individual earnings growth innovations into transitory and permanent shocks. While an earlier literature suggest that these have become more dispersed in the US over the last decades[1], recent research by CBO (2007) and Guvenen et al. (2014b) find the dispersion of earnings growth to be almost flat since the 1980s.

This paper contributes the literature in two respects. First, we derive from wage changes three underlying shocks, within education, with different time trends: Permanent and transitory wage shocks, and a job specific component. Second, in doing so, we extend the econometric framework of Low et al. (2010), which explicitly account for workers' endogenous responses to these shocks. Workers may switch jobs resulting from good outside offers, select into non-employment or different jobs after poor wage shocks. Our framework allows the selection mechanism to have secular trends of their own which allows us to uncover the underlying shocks.

Using panel data from the Survey of Income and Program Participation (SIPP) for males over the period 1983-2013, we find that differentiating between different types of shocks and accounting for selection is crucial. Despite the dispersion of wage growth showing a decining trend, we find that risk has substantially increased for all workers. Workers with less than college degree experienced a large increase of the permanent income risk (27%), while individuals with at least some college faced considerably higher dispersion of the wage offer distribution (28%). Finally, for all groups, the dispersion of transitory shocks declines over time.

As Low et al. (2010) and Altonji et al. (2013), we estimate the wage growth process in reduced form, including a set of equations which take into account labor market transitions as a result of endogenous choices. An alternative approach would be to estimate the process in a fully specified structural model. To the best of our knowledge, no structural search model exists which allows jointly for changes in the dispersion of wage risk and

[1] See Gottschalk and Moffitt (1994), Blundell et al. (2008), and Heathcote et al. (2010a).

variations in the dispersion of the wage offer distribution over time. The papers closest to this idea are Bowlus and Robin (2004), who permit for trends in wage promotions and demotion rates, Flabbi and Leonardi (2010), who consider time trends in labor market transitions and the wage offer distribution, and Leonardi (2015), who models an increase to the dispersion of match specific productivity shocks.

Our reduced form approach allows us to avoid controversial structural assumptions which Hornstein et al. (2012) show have large consequences for wage outcomes in search models. However, our econometric model is silent with respect to the quantitative role that changes in risk play in explaining rising wage inequality, and the social welfare consequences of these changes. To these ends, we build a partial equilibrium model of wage and employment risk over the life-cycle. The model features workers facing heterogeneous job offers which they sample randomly on and off the job. Workers' wage potential evolves stochastically. They can insure against uncertain match offers and wage potential by means of precautionary savings.

[**UPDATE ONCE GET NEW RESULTS**] When simulating the increase in wage risk, the model is able to explain most of the growth in within education wage inequality observed in the data.[2] At the same time, the social welfare costs of rising wage uncertainty are much smaller than those in Heathcote et al. (2010b). This arises despite the fact that increasing permanent wage risk has large welfare costs: To avoid a 10% rise in permanent wage risk, low skilled workers are willing to pay 0.85% and high skilled workers 0.87% of life-time consumption. However, our estimate of increased permanent wage risk is significantly smaller than theirs. Moreover, while high skilled workers suffer from the increase in permanent wage risk, they gain from the more dispersed wage offer distribution. The intuition is simple. In a search model a rise in the dispersion of the wage offer distribution creates a option value to the worker: He can always break up

[2] 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)), import competition (Autor et al. (2014) and Krishna and Senses (2014)), skill biased technological change (Katz and Murphy (1992)), and the gender pay gap (Goldin (2006)).

from particular poor matches and search to find a better match.

An increase in the wage offer distribution and a resulting increase in 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. Our findings suggest that for high skilled workers, the increase in between firm pay results from an increase in the wage offer distribution, not from changes in search technology.

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

2 Empirical Findings

2.1 Data Source and Sample Selection

Our analysis requires detailed longitudinal information on wages, worker and job characteristics over several decades. The data set most adequate for these requirements is the Survey of Income and Program Participation (SIPP) which panels range from 1983-2013.[3] It is a representative sample of the noninstitutionalized civilian US population maintained by the US Census Bureau. Every 4 month (defined as a wave) the Census conducts an interview with all adult member of participating households, asking them about their experience during the preceding 4 months. We aggregate the monthly information to quarterly observations. We consider a worker employed within the quarter, when he spends most months of the quarter working. To each worker, we assign his main job based on the job where

[3] 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.

he earns most of his income.[4] One concern regarding the data is that the survey quality changed over time. We describe the details of our data cleaning procedure in online Appendix 1, where we also argue that our results are not driven by survey redesigns.

As one of our main goals is to analyze how income risk evolved over time, we group the data into three major time periods, each covering 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, some college, and college graduates or higher education. We focus on working-age male individuals, aged between 25 and 61, who are not self-employed, nor enrolled in school, in the armed forces, or recalled by their previous firm after a separation.[5] Finally, to make the results robust to outliers, we do not consider individuals at which the hourly wage growth is below the 1st percentile (above the 99th percentile) of the hourly wage growth distribution by education, period, state of job mobility.

2.2 Stylized facts

Figure I display the dispersion of the residual quarterly wage growth in the last three decades.[6] In line with recent administrative data from Guvenen et al. (2014b), none of the education groups show an upward trend. The dispersion of wage growth peaked in the period 1993-2003, and well below its initial level in 2004-2013.

To identify trends in the dispersion of job effects, workers who switch

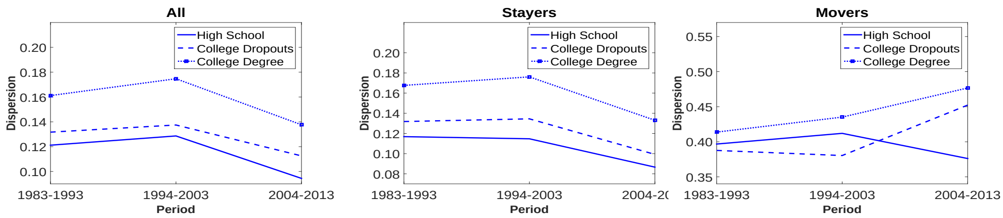
[4]The survey reports at most two jobs per month for each individual. In case an individual holds more than two jobs, the two jobs with most hours worked are reported.

[5]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.

[6]To obtain the residual wage growth, we estimate a weighted (defined as the survey weights) regression of log hourly wage as a function of a quadratic in age and work experience, race, marital status, unemployment rate at the state level, time and region fixed effects, indicators whether person lives at a metropolitan area, is disable and is the only is the only adult (above 22 years old) in the household. Coefficients are allowed to vary by education and period. The survey provides, in addition, information regarding tenure at the job. Yet, the share of observations with reported zero values at these two characteristics conditional on working is above 30%. Consequently, we opt not to use this variable for our analysis.

their job are of particular interest. Therefore, we split our sample into observations of job stayers (workers staying with the current employer) and job movers (employees switching their employer). On the one hand, job stayers dominate the sample and the evolution of the variance in wage growth closely resembles the complete sample. On the other hand, the variance in wage growth at job movers exhibit a positive trend, specially at college graduates. Yet, how did the components of income risk evolved over time? Are there differences across education groups? To answer these questions, the next section develops an econometric framework which allows us to infer the dispersion of wage shocks and the dispersion of the wage offer distribution, using the realized wage growth of job stayers and movers.

Figure I: Hourly Wage Growth Dispersion



Notes: The solid line is the dispersion of residual hourly wage growth for low skilled workers (high-school degree or less), while the dashed line corresponds to high skilled workers (more than high-school degree). To obtain residual hourly wage growth, we estimate a linear regression of hourly wage growth, by skill level and period, as a function of a quadratic in age, race, marital status, unemployment rate at the state level, time and region fixed effects, indicators whether person lives at a metropolitan area, is disable, is the only individual above 18 in the household, and whether the wave in the panel have changed across quarters (to account mean effects from changes across seams.

2.3 Econometric Model

We assume that the quarterly real log wage of individual i working at firm j in time t is given by

$$\begin{aligned} w_{ijt} &= \beta x_{it} + \phi_{ij} + u_{it} + e_{it} \qquad (1) \\ u_{it} &= u_{it-1} + \zeta_{it} \\ e_{it} &= \Theta(q)\iota_{it}, \end{aligned}$$

where x_{it} is a vector of worker observables, ϕ_{ij} denotes the firm-worker match specific component, u_{it} is the permanent component associated with wages, and e_{it} is the transitory component, which follows an $MA(q)$ process. We assume $\phi \sim N(0, \sigma_\phi^2)$, $\zeta \sim N(0, \sigma_\zeta^2)$, and $\iota \sim N(0, \sigma_\iota^2)$ i.e., shocks to the permanent component, to the wage offer distribution, and to the transitory component are log normally distributed and independent of each other.[7]

While the specification of log additive wages following a unit root process with additional transitory shocks is common in the literature it is not uncontroversial.[8] First, there is a substantial literature about the process of u_{it}. Guvenen et al. (2015) argue for a substantially more complicated process than the one employed here, yet, its estimation is beyond this paper. Moreover, the match component could vary over time. Guiso et al. (2005) show that firms almost perfectly insure workers against firm risk; however, the literature on contracts with some form of commitment on the firm side shows that the match component may be time varying even in the absence of shocks to firm productivity (see Postel-Vinay and Robin (2002)).[9]

Given our specification in Equation (1), individual wage growth is determined by

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

where M_{it} is an indicator variable equal to one when the worker changed jobs between t and $t-1$.

Central to our approach, wage growth realizations may be influenced by endogenous job mobility and labor market participation decisions. To make this explicit, note that observed wage growth is conditional on the

[7]Guvenen et al. (2014a) show that earnings growth shows excess kurtosis over a normal distribution. We decompose wage growth into three components. A log-normal wage offer distribution is consistent with the observed wage distribution. Regarding the normality assumption of permanent wage shocks, we try different truncation points for within job wage growth and find that our results are robust to these changes.

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

[9]Hagedorn and Manovskii (2010) and Tjaden and Wellschmied (2014) show some counterfactual implications of this wage back loading. Along this line, Low et al. (2010) find that a model of stochastic match component fits the data worse than a model with fixed match component.

worker participating in two consecutive periods. What is more, the worker may stay with the current firm, or change to another employer:

$$E[\Delta w_{it}|P_{it}=1,P_{it-1}=1]=E[\Delta w_{it}|P_{it}=1,P_{it-1}=1,M_{it}=0]$$
$$+E[\Delta w_{it}|P_{it}=1,P_{it-1}=1,M_{it}=1]=\beta\Delta x_{it}+G_{it}, \tag{3}$$

where G_{it} is a selection term which we derive in Appendix 5.1. In order to obtain unbiased estimates of the parameters, we employ a Heckit model where we explicitly account for mobility and participation:

$$P^*_{it-1}=\alpha z_{it-1}+\pi_{it-1},\ \ P_{it-1}=1\left\{P^*_{it-1}>0\right\}, \tag{4}$$
$$P^*_{it}=\alpha z_{it}+\pi_{it},\ \ P_{it}=1\left\{P^*_{it}>0\right\}, \tag{5}$$
$$M^*_{it}=\gamma\kappa_{it}+\mu_{it},\ \ M_{it}=1\left\{M^*_{it}>0\right\}. \tag{6}$$

Wage growth does not depend by assumption on the current ability of a worker. However, ability, among other things, may lead to persistent unobserved heterogeneity in participation decisions. To account for this, we extend the framework of Low et al. (2010) allowing for serial correlation at the unexplained component of participation. That is, we assume

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

As π_{it} and π_{it-1} are correlated, we consider a bivariate probit for the participation decision at time t and $t-1$, constraining estimated coefficients to be constant at Equation (4) and (5). This approach allows us to identify $\rho_{\pi\pi-1}$. While for mobility, given our assumption of serial independence, we estimate an univariate probit model.[10] The selection equations are estimated for each period and education degree separately; thereby, we allow for time varying returns to human capital, and time varying patterns in

[10]Given our econometric model, we do not need to account for the serial correlation at the unexplained component of mobility for two reasons. First, we assume $Cov(\zeta_{it},\mu_{it-1})=Cov(\xi_{it},\mu_{it-1})=0$. Second, the estimated coefficients at the univariate probit will still be consistent under the assumption that errors are homoskedastic and that the distribution of explanatory variables is stationary and ergodic, see for more details Wooldridge (1986).

participation and mobility.

Draws from the wage offer distribution and permanent wage shocks affect participation and mobility decisions. Denote the correlation between permanent wage shocks and participation by $\rho_{\zeta\pi}$, while the correlation between the former and mobility is defined as $\rho_{\zeta\mu}$. Moreover define $\rho_{\xi\pi}$, $\rho_{\xi\pi-1}$ and $\rho_{\xi\mu}$ to be the correlation between shocks to the match component and shocks to participation this period, last period, and mobility, respectively. We identify these correlations together with the dispersions to permanent wage risk and the wage offer distribution (σ_ξ, σ_ϕ) from the first and second moments of the unexplained component of wage growth:

$$g_{it} = \Delta w_{it} - \beta \Delta x_{it} = \xi_{it} M_{it} + \zeta_{it} + \Delta\Theta(q)\iota_{it}. \tag{7}$$

As in a standard Heckit model, the selection rules (4)-(6) imply that we observe only a truncated portion of the true underlying shocks. Based on the moment generating function of the multivariate truncated normal distribution derived in Manjunath and Wilhelm (2012), Appendix 5.1 shows these moments for our particular case. We assume a $MA(4)$ process for transitory shocks (e_{it}) and assume there is no selection on these shocks. Therefore, we identify these from the autocovariance function of wage growth up to lag 5.

2.4 Empirical Results

2.4.1 Probit Results

In order to estimate the participation probability at Equation (4) and (5), we control for a quadratic in age and work experience, race, unemployment rate at the state, marital status, time and region fixed effects, and indicators referring to whether the person lives at a metropolitan area, is declared disable or is the only adult (above 22 years old) in the household. While for the mobility Equation (6), we include, in addition, industry and occupation fixed effects.[11]

[11] In specific, we create major industry and occupation groups based on the job of the worker. For the former, group industries into agriculture, construction, manufacturing, transportation, finance, non-financial services, public administration, and non-profit organization. While for the latter we follow Autor and Dorn (2013), and we group occu-

Importantly, we require a set of regressors which identify selection. That is, variables which affect the decision of the worker to participate or move jobs, but do not impact directly wage growth. Hence, we augment the set of explanatory variables at the probit equations including unearned household income, an index of generosity of the welfare system (state-level unemployment insurance), earnings from another member at the household, and an indicator variable whether the worker owns a house.[12] As expected, high unemployment benefits, high unearned income, and not owning a house, reduce labor market participation. 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 unearned household income and state level generosity reduce the likelihood of a worker to move jobs, while not owning a house income in the household and former two variables to reduce the probability of a worker to move jobs, while if a worker does not own a house or other member of the household receives income from labor, is more likely to move jobs.

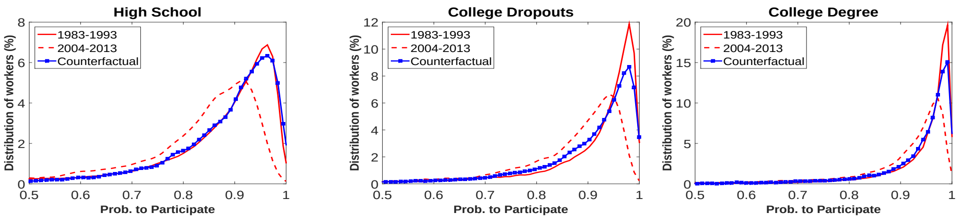
Figure II and III present the estimated probability to participate at the current and previous quarter and the estimated probability to move jobs, conditional on individuals effectively participating at consecutive quarters, for the periods 1983-1993 and 2004-2013 (solid and dashed red line, respectively). Comparing the period of the 2000's with respect to the 1980's, employed workers have relatively lower participation probabilities. Additionally, workers who did not finish college have a somewhat higher likelihood to change jobs.[13]

pations into management, administrative support, low skill services, craft and precision production, machine operators, and transportation/construction/minining/agricultural occupations. We include these dummies into the wage growth equation, implying that workers can predict wage growth based on their current industry/occupation, but we interpret changes to these variables as shocks.

[12] Compared to Low et al. (2010), we further add to the exclusion restriction the latter two variables. The literature have consider these variables as potential predictors of job mobility and participation while not affecting directly wage growth (see for example Blanchflower and Oswald (2013), Bowen and Finegan (2015), [**COMPLETE**] among others).

[13] Our finding does not contradict the study from (Davis and Haltiwanger, 2014), who report a declining trend at worker reallocation in United States, as our measure of movers allows for job changes that occur via unemployment within the given quarter.

Figure II: Estimated Probability to Participate at Consecutive Quarters



Notes: The solid red line (dashed red line) is the distribution of workers with respect to the probability to participate at consecutive quarters (conditional on effectively doing it) for the period 1983-1993 (2004-2013). The blue solid-squared line corresponds to the estimated probability to participate at consecutive quarters for the period 2004-2013, keeping fixed the estimated coefficients from the period 1983-1993. To estimate the bivariate probit at participation, we control for a quadratic in age and work experience, race, marital status, unemployment rate at the state, time and region fixed effects, unearned household income, earned income from another member at the household, an index of generosity of the welfare system (state-level unemployment insurance, and indicators referring to whether the person lives at a metropolitan area, is declared disable, is the only adult (above 22 years old) in the household, or owns a house.

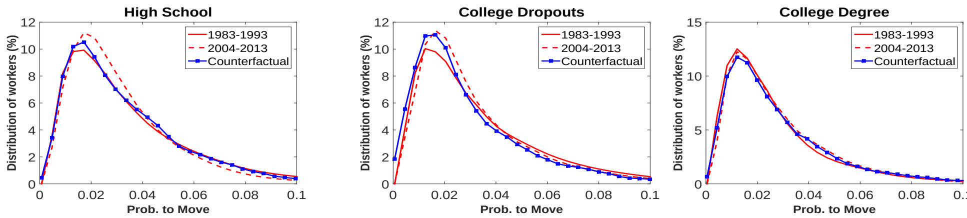
Why do we observe variations in the propensity to work and job-changes over different periods in time? In principle, these variations can be attributed to changes in the characteristics of the working population or changes in the marginal effects of these characteristics. Figures II and III display the counterfactual distributions at the period 2004-2013, keeping the marginal effects of worker characteristics constant at their 1984-1993 level. Variations in worker characteristics are important in explaining changes in the participation probabilities for workers with some college education and for explaining shifts in mobility probabilities. Nevertheless, trends in marginal effects are still important for all groups.

2.4.2 Wage Variance Estimates and Selection

This section presents the estimated correlations and wage variance components that we obtain from the first and second moments of Equation (7). We estimate the model by generalized method of moments, weighting each moment at the individual level by the underlying weight given from the survey data, and obtain standard errors by block-bootstrap procedure proposed by Horowitz (2003).

Figure VI displays for our three education groups the trends in wage

Figure III: Estimated Probability to Change Jobs



Notes: The solid red line (dashed red line) is the distribution of workers with respect to the probability to change firms (conditional on participating at consecutive quarters) for the period 1983-1993 (2004-2013). The blue solid-squared line corresponds to the estimated probability to change firms at the period 2004-2013, keeping fixed the estimated coefficients from the period 1983-1993. To estimate the mobility probit, we control for a quadratic in age and work experience, race, marital status, unemployment rate at the state, time and region fixed effects, unearned household income, earned income from another member at the household, an index of generosity of the welfare system (state-level unemployment insurance, industry and occupation fixed effects, and indicators referring to whether the person lives at a metropolitan area, is declared disable, is the only adult (above 22 years old) in the household, or owns a house.

risk.[14] Workers with less than college degree experienced a large increase of the permanent component of wage risk (27%), while the increment is minor at college graduates (5%).

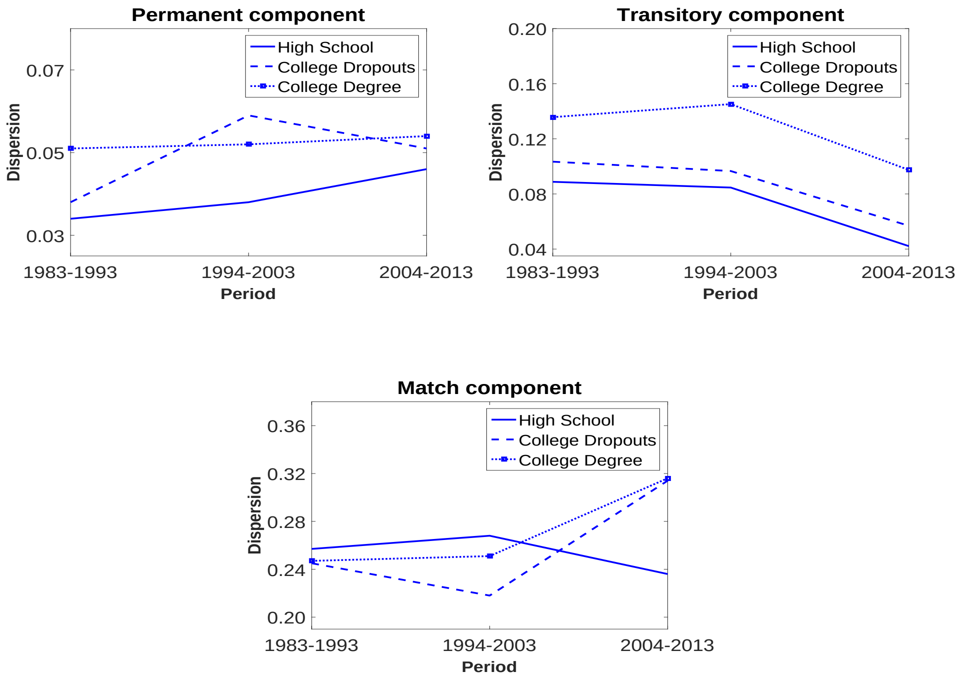
In contrast, workers with at least some college education faced considerably higher dispersion in the wage offer distribution (28%), while it decreased for workers with high school education (-8%).[15] Finally, transitory wage risk is falling for all groups. Unfortunately, we are unable to isolate from the estimated dispersion of the transitory component, the transitory shock and the measurement error process. Consequently, the presented results represent a mixed between the two. A falling dispersion; therefore, could also result from improved interviewing techniques introduced in the 1996 and 2004 survey (see Moore (2008)).

Regarding the selection correlations, we find that the serial correlation of the unobserved heterogeneity at participation is highly significant, with

[14]For the sake of clarity, we present the point estimates from each dispersion. The detailed results containing the estimated standard errors and the estimated correlations are relegated to Appendix (5.2).

[15]The described changes of the dispersion of the wage offer distribution happen mostly after the second period. 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 Online Appendix XXX, 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 IV: 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 5. Correlations and bootstrap standard errors are available in Appendix (5.2).

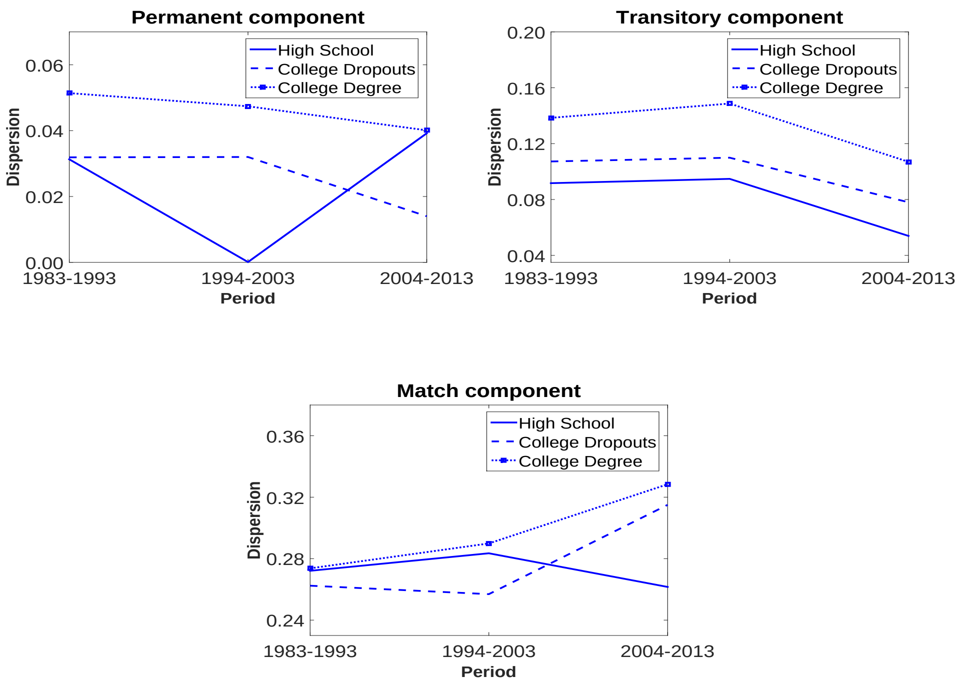
correlation above 0.90 for all cases. In addition, a positive innovations to ζ is always positively correlated with the unexplained component of participation and negatively with the unexplained component of mobility. Our specification of job mobility, that is, an employee who works at different employers in consecutive quarters, allows for job changes that occur via unemployment and without an unemployment spell. Note that for identification, we do not have to spell out the reason for changing employers.[16] The model captures possible secular trends in voluntary and involuntary quits by changes in $\rho_{\xi\mu}$ and $\rho_{\zeta\mu}$. Finally, we obtain that a good outside offer increases the propensity of a worker to move jobs. The model does not well identify the relationship between shocks to outside offers and participation.

Given our findings, we aim to answer some questions. First, how important is it to account for selection? Using the process for individual wages

[16]Our implicit assumption is 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.

at Equation (1), we could identify the permanent, transitory and match component, from the second moment of unexplained wage growth, and the autocovariance function of wage growth ignoring selection.[17] The estimated components are provided at Figure V. Different from our baseline results, permanent wage risk decreased for workers with at least some college (-39%), while the match component raised at this group (20%). Further, workers with at most high school degree do not exhibit major differences at the permanent and match component when comparing the first and last period of analysis.

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



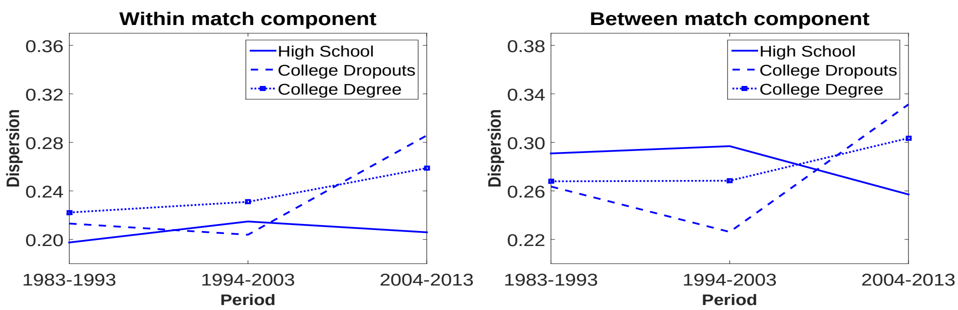
Notes: Estimation is conducted by period and education degree group. To identify the components, we make use of the second moment of the residual wage growth conditional on the job-mobility state: $E(g_{it}^2|M_{it}=0)=\sigma_\zeta^2+Var(e_{it})$, $E(g_{it}^2|M_{it}=1)=\sigma_\zeta^2+2\sigma_\phi^2+Var(e_{it})$. To identify $Var(e_{it})$, we use the autocovariance function of wage growth up to lag 5, see for more details Appendix (5.1).

Second, can we relate the trends in the dispersion of the wage offer distribution to the literature of occupational mobility (see for example

[17]In specific, we make use of the second moment of the residual wage growth conditional on the job-mobility state: $E(g_{it}^2|M_{it}=0)=\sigma_\zeta^2+Var(e_{it})$, $E(g_{it}^2|M_{it}=1)=\sigma_\zeta^2+2\sigma_\phi^2+Var(e_{it})$.

Kambourov and Manovski (2009))? To this end, we extend our econometric model and allow the wage offer distribution to be different for those who stay within the same industry and occupation (*Within*), and those who change it (*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 implying $\rho_{\xi_W \mu} = \rho_{\xi_B \mu} = \rho_{\xi \mu}$. Figure VI displays the evolution of the match component for these two groups. Regarding workers with at least some college education, the increased dispersion in the wage offer distribution occurring after the 90's results from more dispersed job offers when staying and switching industries. For workers with at most a high school degree, the slight decrease in the dispersion comes mostly from workers switching their occupation or industry. Interestingly, average wage growth from switching industries tends to increase over time for workers with some college education, but decreases for workers without. Put differently, workers with only a high school education who switch industry or occupation in the 2000s are less likely to find a better paying job, relatively to the 80s and 90s, and there is less difference between the offered jobs.

Figure VI: Evolution of the Match Component: Within vs. Between



Notes: Within (Between) match 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 5. Selection correlations are fixed to the estimated ones in the baseline model.

3 The Effects of Risk Changes on Wage Inequality and Welfare

Our empirical results identify the changes in underlying risk that households faced over the last decades. Yet, they are silent about the quantitative consequences for wage inequality and its welfare implications. In order to identify these effects, we develop a partial equilibrium, life-cycle incomplete-markets model with search frictions. The model features a wage process and selection mechanism which are consistent with our empirical analysis.

The resulting quantitative effect of the wage offer distribution on wage inequality depends on the way workers sort across job types, in other words, on the underlying job-search technology. Further, the welfare consequences of rising uncertainty is determined on the capacity of workers to insurance against downward risk, that is, the job-search technology, value of leisure, and insurance provided by the government. 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 Structural Model

The economy is populated by a a unit mass of workers who are either low or high skilled workers, and may become employed, unemployed, or retired. Time is discrete and agents discount the future with factor β. The length of a period is one quarter.

Workers spend 40 years in the labor market and another ten years in retirement. During working life, they face idiosyncratic risk to their wages. Importantly, we assume that financial markets are incomplete and the only way of insurance beyond governmental transfers is self-insurance through assets a which pay a safe returns $R = 1 + r$. The worker faces a borrowing constraint of the form $a_{t+1} \geq 0$.

At the beginning of life, worker i draw a log wage potential from $p_{i1} \sim N(\mu_N, \sigma_N^2)$. Afterwards, their wage potential follow a random walk with a drift component, which depends on the employment state:

$$p_{ih+1} = \begin{cases} p_{ih} + \nu + \epsilon_{ih} & \text{if } \textit{employed} \\ p_{ih} - \delta + \epsilon_{ih} & \text{if } \textit{unemployed}, \end{cases}$$

where $\epsilon_{ih} \sim N(0, \sigma_{\epsilon}^2)$, and h denotes the age of worker. The terms ν and δ represents experience gains and skill depreciation, respectively. Note that wage potential does not depend on transitory shocks, which we abstract from. Nevertheless, we simulate wages including transitory shocks consistent with our estimates; thus, giving it the interpretation of pure measurement error.

When meeting an employer, workers draw random job offers with log wage contribution Γ following a cumulative distribution function $F(\Gamma)$ with support $[\Gamma_m, \Gamma_M]$. We assume workers face a 20% tax rate, approximately the tax rate paid by low earning households in 1986. Consequently, wages net of taxes τ are given by:

$$w_{ih} = (1 - \tau) exp(p_{ih} + \Gamma).$$

The government provides four types of insurance schemes to workers. First, it provides a universal means-tested program to all low income workers. Denote by y total worker gross income minus a fixed income deductible. Transfers are given by:

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

Second, the government provides unemployment insurance which replaces a constant fraction of worker's last quarter wage subject to a cap. In the data, unemployment befits last usually two quarters. To account for that, we opt for a relatively generous replacement rate relative to the data:

$$b_{ih} = min\{0.7 w_{ih-1}, b_{max}\}.$$

Third, at the end of working life, workers receive social security benefits which are fixed throughout retirement. Social security is calculated according to:

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

where d_1, d_2 are bend points, and $\bar{w}_{ih}$ is the average earnings of a worker i over his life-cycle at age h, which takes the following law of motion

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

Finally, during the last ten working years, households may receive disability insurance whose benefits are computed according to the same formula as social security. Moving to disability insurance is a permanent exit from the labor market. The worker can only apply in the period after loosing his job. His application is accepted with probability ψ which we take from Social Security Administration (2015) to be 0.43 between 1984 and 1993. When choosing to apply, the worker may not search for a job within the same period.

Summing up, transfers are

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

Given the taxes, transfers, and subsidies, the resulting consumption of the worker is

$$c_{ih} = \begin{cases} Ra_{ih} + w_{ih} + T_{ih} - a_{ih+1} & \text{if employed} \\ Ra_{ih} + T_{ih} - a_{ih+1} & \text{if unemployed} \\ Ra_{ih} + S + T_{ih} - a_{ih+1} & \text{if disabled} \\ Ra_{ih} + S + T_{ih} - a_{ih+1} & \text{if retired,} \end{cases}$$

which workers' value is given by CRRA preferences with preferences for leisure:

$$U_{ih} = \Big(\frac{c_{ih} exp(\phi P_{ih})}{1-\theta}\Big)^{1-\theta}.$$

Given these definitions, we can now proceed with defining the value functions at each employment state. To begin with, the value function of a retired worker of age h solves:

$$\mathcal{Q}_h(a, \bar{w}) = \underset{a'}{max}\Big\{U_h + \beta \mathcal{Q}_{h+1}(a', \bar{w}')\Big\}.$$

During the ten years before retirement, a worker may receive disability insurance. The value function for the disable worker solves

$$\mathcal{D}_h(a, \bar{w}) = \underset{a'}{max}\Big\{U_h + \beta \mathcal{D}_{h+1}(a', \bar{w}')\Big\}.$$

The decision to apply for disability insurance is done after the asset decision, but before end of period uncertainty reveals. The worker knows that his claim for disability is denied with probability ψ. When applying, he forgoes the possibility to search for a job the same period. Define the upper envelope

$$\begin{aligned} \Theta_{h+1}(a', p, \bar{w}) = max\Big\{&\psi \mathcal{D}_{h+1}(a', \bar{w}') \\ &+ (1-\psi)\int \mathcal{U}_{h+1}(a', p'|p, \bar{w}')dp', \int EVU(a', p'|p, \bar{w}')dp'\Big\}, \end{aligned}$$

where $\mathcal{U}_{h+1}(a', p', \bar{w}')$ is the value of being unemployed the next period with assets a', productivity p' and accumulated earnings $\bar{w}'$, and $EVU(a', p', \bar{w}')$ is the value of searching in unemployment. Let λ_u be the job finding rate when unemployed. The value of of searching in unemployment solves:

$$EVU(a',p',\bar{w}') = (1-\lambda_u)\int \mathcal{U}_{h+1}(a',p'|p,\bar{w}')dp' \\ + \lambda_u \int\int_{\Gamma_m}^{\Gamma_M} \max\{\mathcal{W}_{h+1}(a',p'|p,\Gamma',\bar{w}'), \mathcal{U}_{h+1}(a',p'|p,\bar{w}')\}dF(\Gamma)dp',$$

where $\mathcal{W}_{h+1}$ is the value of being employed next period. Note, individual productivity shocks and wage offers realize before the worker has to decide about job acceptance.

Thus, the value function of a worker who just became unemployed at age h solves:

$$\mathcal{U}_h(a,p,\bar{w}) = \underset{a'}{max}\Big\{U_h + \beta\mathbb{E}_h\Theta_{h+1}(a',p,\bar{w}')\Big\}.$$

Moreover, the value function of a worker who has no option to apply for disability insurance, either because he is longer unemployed, or is too young, solves:

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

Employed workers continue to sample job offers from the same distribution as the unemployed. Following Tjaden and Wellschmied (2014), we allow for job to job transitions as the result of a 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. Incidences where the worker may not have the option to stay with the old job are temporary jobs, advanced layoff notice, or immediate firm bankruptcy. The value of an employed worker of age h solves:

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

where we have defined the following upper envelops:

$$\Xi = \max\{\mathcal{W}_{h+1}(a', p', \Gamma, \bar{w}'), \mathcal{U}_{h+1}(a', p', \bar{w}')\}$$
$$\Omega_E = \int_{\Gamma_m}^{\Gamma_M} \max\{\mathcal{W}_{h+1}(a', p', \Gamma, \bar{w}'), \mathcal{U}_{h+1}(a', p', \bar{w}'), \mathcal{W}_{h+1}(a', p', \Gamma', \bar{w}')\} dF(\Gamma')$$
$$\Lambda = \int_{\Gamma_m}^{\Gamma_M} \max\{\mathcal{W}_{h+1}(a', p', \Gamma', \bar{w}'), \mathcal{U}_{h+1}(a', p', \bar{w}')\} dF(\Gamma').$$

An employed worker does not loose his job exogenously with probability $1-\omega$ in which case he may receive an on-the-job offer. If he receives no offer, he decides whether staying employed, or moving to unemployment conditional on the idiosyncratic productivity shock (Ξ). If he receives an offer, it may be a regular job 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, his only option are the new offer or unemployment (Λ).

3.2 Calibration

We calibrate our model to aggregate statistics from the 1980's, mostly from SIPP. As we allow workers to spend 40 years in the labor market, we extend our calibration targets from the SIPP for male workers between 22 and 61. Table 1 summarizes the calibration. Several of our calibration targets are education specific. Table 8 in Appendix 5.3 reports the particular data values.

To begin with, we set the dispersion of the permanent shock at Equation 3.1 to be equal to the identified dispersion in the SIPP data. Further, we assume the lower bound of the match component to be equal to $-2\sigma_\phi$. Analogously, we set the upper bound of the match component as $2\sigma_\phi$.

Consistent with findings from Siegel (2002), we set r to imply a yearly interest rate of 4%. To match the average amount of self-insurance present in the data, we target with β the median wealth to earnings ratios in the data. We consider households risk aversion parameter to be 2. To calibrate the amount of insurance from leisure, we calibrate ϕ to imply that households reduce consumption expenditure upon non-employment by 15%, consistent with Hall (2007). The reduction in consumption expenditure may reflect the response on changes in income, reduced work related

Table 1: Calibration

	HS	SC	C	Target
σ_ϵ	0.044	0.048	0.061	Dispersion permanent shock
σ_Γ	0.257	0.245	0.247	Dispersion match shock
σ_N	0.22	0.22	0.24	Initial wage dispersion
μ_N	7.08	7.15	7.41	Initial mean wage
r	0.01	0.01	0.01	4% annual interest rate
$(1-\beta)\%$	0.66	0.43	0.25	Wealth to earnings ratio
θ	2	2	2	Risk aversion
ϕ	-0.18	-0.15	-0.01	Expenditure drop NE
ω %	1.43	0.97	0.62	EU flow rate
λ_u %	15.19	16.93	18.31	UE flow rate
λ %	3.43	3.32	3	JTJ flow rate
λ_d %	49.41	51.14	46.88	% of wage cuts upon
ν %	0.53	0.82	1.02	Wage growth life-cycle
δ %	1.2	1.23	1.43	Wage losses from U

Notes: The left column states the calibrated variable, while the second and third column states the relevant moment. NE stands for non-employment, EU for employment to unemployment, UE for unemployment to employment, JTJ for job to job movements, and U for unemployment.

consumption, and the increase in time for home production.

We assume that workers start with no assets at the beginning of life. We set σ_N^2 to match the initial variance of log wage inequality not explained by job effects and μ_N to match the average wage at the beginning of workers' life. The values are education specific. For the productivity process, we target average wage gains over a worker's life and average wage losses from unemployment.

Further, we target education specific worker flow rates in our SIPP sample. In particular, the exogenous job destruction rate ω is set to match the movements from employment to unemployment not explained by endogenous separation. We set λ_u such that it matches the job finding rate in the data.

Information on job to job movements and accompanying wage changes identify λ and λ_d. The education specific λ is set to target the job to job transition rate we observe in the data. To this end, we define a job to job transition when the worker reported to have been mostly employed in both quarters, and never spend time searching between the two jobs in non-employment. Our identifying assumption for separating voluntary and involuntary movements is that voluntary movements 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.

3.3 Model Fit and Mechanisms

One way to evaluate the results from the calibrated model, is to compare its implications for selection and wage dispersion over the complete life-cycle. For the former, table 2 reports the estimated correlation components at the wage growth equation once we simulate the economy under different levels of food stamp transfers. This exercise aims to resemble the different degree of goverment insurance programs at the state level that we make use at our empirical estimation. In addition, this table reports the share of disable male workers above 50 years old and the ratio between the average wage and the lowest wage paid in the economy (defined as the wage paid at the 5th percentile). For both moments, the model is able to explain, on average, 80% of the data counterpart.

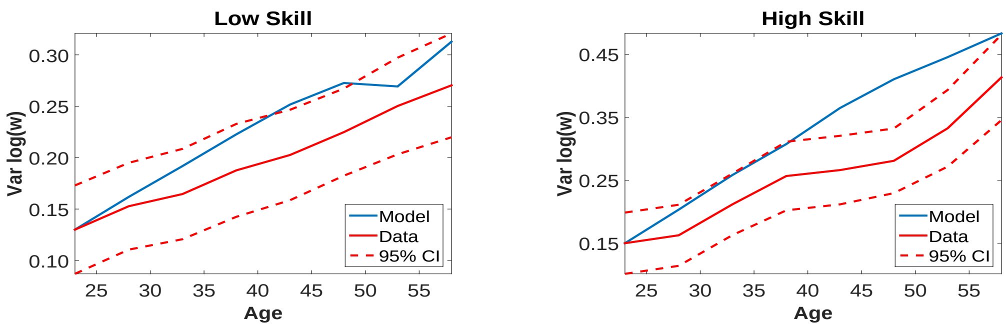
Table 2: Untargeted Moments

	Model			Data		
Moment	HS	SC	C	HS	SC	C
Disability above 50 (%)		10.39			6.9	
Mean-min ratio	2.32	2.44	2.95			
$\rho_{\epsilon\pi}$						
$\rho_{\epsilon\mu}$						
$\rho_{\Omega\pi}$						
$\rho_{\Omega\pi-1}$						
$\rho_{\Omega\mu}$						

Notes: LS refers to low skilled workers, while HS to high skilled workers. Data moments refer to the first period of analysis in the data: 1983-1993. *Disability above 50 (%):* share of workers above 50 years old who receive disability insurance benefits. *Mean-min ratio:* is the ratio between the average wage and the 5th percentile wage, by education level. $\rho_{\epsilon\pi}$ ($\rho_{\epsilon\mu}$): correlation between the permanent shock and participation (mobility) premium. $\rho_{\Omega\pi}$ ($\rho_{\Omega\pi-1}$): correlation between shocks to the match component and participation premium this (previous) period. $\rho_{\Omega\mu}$: correlation between shocks to the match component and mobility premium.

In order to analyze the implications of the model over the life cycle relative to the data, we rely on an additional survey in US that is designed to follow the same indviduals over the whole period of working life: Panel Study of Income Dynamics (PSID). Figure VII compares the cross sectional variance of log hourly wage over the life-cycle from the model and the data.[18] The model is able to match the profile of wage inequality over the life cycle at low skilled workers, while we overestimate the increase at high skilled workers by 20% approximately. Yet, the model is able to replicate the fact that wage dispersion growth substantially slower for low skilled workers over the life-cycle.

Figure VII: Hourly Wage Dispersion over the Life-cycle



Notes: The figure displays the variance in yearly log hourly wage over the life cycle in the model and PSID data. *95% CI:* 95% bootstrap confidence interval. To ameliorate the effect of small amount of observations at old workers in the data, we compute the variance in log hourly wage by age bins of 5 years. 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, number of kids, 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 from the risk parameters estimated for the 2000's.[19] 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.

[18]The data features a series of worker characteristics not present in the model. To make the two comparable, we control in the data for race, region, metropolitan area, marriage, number of kids, and time fixed effects.

[19]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.

Table 3: Increase of Wage Inequality

	High School	Some College	College
Data %			
Model %	10.85	18.21	6.06
Wage offer %	-2.57	4.37	3.14

Notes: The table displays the percentage change in the standard deviation of residual wage inequality between the 1980s and 2000s conditional on education. *Data*: Results from SIPP samples. *Model*: The change from model simulation based on the point estimates of risk presented in Section 2.4.2. *Wage offer*: The percentage change in residual wage dispersion resulting from changes in the wage offer distribution.

Table 3 displays the percentage change in the standard deviation of log wages between the periods.

The model is able to explain a significant part of the rise in wage dispersion. Higher dispersion at the wage offer distribution accounts for a 1.9% increase in wage inequality at high skill workers, while at low skilled workers, wage inequality slightly decreased through this channel (-0.12%).

3.5 Welfare Consequences of Rising Uncertainty

To assess the welfare consequences of changing wage uncertainty we again simulate the change in risk measured in the data between the 1980's and 2000's. The change in risk alters the distribution of workers over employment and jobs; thereby, the tax revenue and public expenditure. We recalibrate the tax rate to assure that in both periods, conditional on education group, the government budget is the same:[20]

$$\mathcal{B} = \int \sum_{0}^{H} \left(b_{ih} E_{ih}^{UI} (1 - E_{ih}^{DI}) + S(\bar{\omega_{ih}}) E_{ih}^{DI} \right) (1 - P_{ih}) + F_h(y_{ih}) E_{ih}^{T} d\Psi - \int \sum_{0}^{H} \tau \omega_{ih} P_{ih} d\Psi,$$

where Ψ is the distribution of workers over states, while E_{ih}^{UI}, E_{ih}^{D}, E_{ih}^{T}, and P_{ih} are indicators that reflect whether person receives unemployment bene-

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

Table 4: Welfare Effects of Rising Uncertainty

All workers %		0.11	
	High School	Some College	College
Total wage risk %	-0.037	0.49	0.0925
Wage offer %			

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 1980s and 2000s. *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 1980s and 2000s. *Wage offer*: The willingness to pay resulting from only changes in the wage offer distribution, by skill level, between the 1980s and 2000s.

fits, disability insurance, transfers, or whether he is employed, respectively.

Our welfare measure is the willingness to pay in terms of life-time consumption of an unborn worker to avoid the extra risk. Let c_{ih} be the consumption of a worker of age h in the 1980's, and $\hat{c}_{ih}$ be the consumption in the 2000's. The fraction of consumption which makes the worker indifferent between being born in the two different periods solves:

$$\int E \sum_{h=1}^{H} \beta^h U(c_{ih}, P_{ih}) d\Psi_1 = \int E \sum_{h=1}^{H} \beta^h U(\hat{c}_{ih} \hat{P}_{ih}[1+\omega]) d\hat{\Psi}_1, \qquad (8)$$

where Ψ_1 and $\hat{\Psi}_1$ are the distribution of workers over states at age one. We always set $\hat{\Psi}_1 = \Psi_1$, i.e., we assume that initial conditions do not change. One can show that

$$\omega = \left(\frac{\int V_1 d\Psi_1}{\int \hat{V}_1 d\hat{\Psi}_1} \right)^{\frac{1}{1-\theta}} - 1.$$

Table 4 shows the results of the policy experiments. We first document the willingness to pay for the entire economy. Second, we disaggregate by education group. Finally, we consider the willingness to pay under the hypothetical case that the wage offer distribution changes, but the dispersion of permanent wage shocks remains at its level from the 1980's.

On average, the welfare costs of increased wage uncertainty are 0.86% of life-time consumption. Workers suffer from an increase in permanent wage risk, which clearly reduces welfare. Surprisingly, the aggregate welfare costs do not differ across education groups, even though the evolution of the wage risk components are clearly distinct. This result is influenced by the insurance schemes provided by the government, used proportionally more by low skilled workers.

At the same time, high skilled workers are willing to receive to avoid the more dispersed wage offer distribution. An unborn high skilled worker is willing to receive 0.20% of life-time consumption for a 10% increase in its dispersion. In a search model an increase in the wage offer dispersion creates a 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.

4 Conclusion

This paper estimates the dispersion to permanent wage shocks and the wage offer distribution in the US from 1983-2013. Our approach explicitly takes into account workers reacting to shocks, and we allow this endogenous selection to vary over time.

We find that accounting for changes in the size of the shocks by education level is important to understand the increase of income inequality over the latter decades, and the welfare implications that this leads to. The dispersion of the permanent wage shock increased substantially at low skilled workers, while the dispersion at the match component has rather remained constant over time. In contrast, high skilled workers experienced a minor increase in the permanent component, while they face considerably more dispersion of the wage offer distribution.

In order to understand, quantitatively, the implications of our empirical findings for wage inequality and welfare, we build a structural search model which is consistent with the endogenous selection mechanisms present in the data and simulate the increase in wage uncertainty. We find that the model is able to explain most of the increase in within group wage inequality found empirically, the welfare costs of increased uncertainty are small, and do not differ by education group.

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5 Appendix

5.1 Moments for the Wage Variance

We begin by deriving the selection term present in wage growth:

$$
\begin{aligned}
&E[\Delta w_{it}|P_{it}=1,P_{it-1}=1] = E[\Delta w_{it}|P_{it}=1,P_{it-1}=1,M_{it}=1]Pr(M_{it}) \\
&+ E[\Delta w_{it}|P_{it}=1,P_{it-1}=1,M_{it}=0](1-Pr(M_{it})) \\
&= \beta\Delta x_{it} + \Phi(-\kappa_{it}'\theta)\left[\frac{\rho_{\zeta\pi}\sigma_\zeta\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})} - \frac{\rho_{\zeta\mu}\sigma_\zeta\phi(-\kappa_{it}'\theta)}{\Phi(-\kappa_{it}'\theta)}\right] \\
&+ (1-\Phi(-\kappa_{it}'\theta))\left\{\sigma_\zeta\left[\frac{\rho_{\zeta\mu}\phi(-\kappa_{it}'\theta)}{1-\Phi(-\kappa_{it}'\theta)} + \frac{\rho_{\zeta\pi}\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}\right]\right. \\
&+ \sigma_\xi\left[\frac{\rho_{\xi\mu}\phi(-\kappa_{it}'\theta)}{1-\Phi(-\kappa_{it}'\theta)} + \frac{\rho_{\xi\pi}\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}\right. \\
&\left.\left.+ \frac{\rho_{\xi\pi_{-1}}\phi(-z_{it-1}'\gamma)\left(1-\Phi\left(\frac{-z_{it}'\gamma+\rho_{\pi\pi_{-1}}z_{it-1}'\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}\right]\right\} \\
&= \beta\Delta x_{it} + \frac{\rho_{\zeta\pi}\sigma_\zeta\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})} + \sigma_\xi\rho_{\xi\mu}\phi(-\kappa_{it}'\theta) \\
&+ \frac{\sigma_\xi\left(1-\Phi(-\kappa_{it}'\theta)\right)\rho_{\xi\pi}\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})} \\
&+ \frac{\sigma_\xi\Phi^1(-\kappa_{it}'\theta)\rho_{\xi\pi_{-1}}\phi(-z_{it-1}'\gamma)\Phi^1\left(\frac{-z_{it}'\gamma+\rho_{\pi\pi_{-1}}z_{it-1}'\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}
\end{aligned}
$$

where

$$\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}}) = \int_{-z_{it}'\gamma}^{\infty}\int_{-z_{it-1}'\gamma}^{\infty}\phi(x_1,x_2,\rho_{\pi\pi_{-1}})dx_1dx_2,$$

which we obtain from (5).

Given our wage model specification, we can derive the expected wage growth for job stayers and movers. The expected value for the former is:

$$E(g_{it}|P_{it}=P_{it-1}=1,M_{it}=0)=\frac{\rho_{\zeta\pi}\sigma_{\zeta}\phi(-z'_{it}\gamma)\left(1-\Phi\left(\frac{-z'_{it-1}\gamma+\rho_{\pi\pi_{-1}}z'_{it}\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z'_{it}\gamma,-z'_{it-1}\gamma,\rho_{\pi\pi_{-1}})}-\rho_{\zeta\mu}\sigma_{\zeta}\tilde{\lambda}^M_{it}, \tag{9}$$

where $\tilde{\lambda}^M_{it}\equiv\frac{\phi(-\kappa'_{it}\theta)}{\Phi(-\kappa'_{it}\theta)}$ which we obtain from (6).

Economic theory would suggest that negative shocks to wage potential decrease participation. Hence, because the worker participates, his shock to ζ could not be too negative. The first term of (9), simply speaking, relates the probability to participate, correcting for autocorrelation, to wage growth of job stayers, which identifies $\rho_{\zeta\pi}$.

Similarly, the relationship between wage growth of job stayers and $\tilde{\lambda}^M_{it}$ identifies $\rho_{\zeta\mu}$. M_{it} may be one when the worker leaves her 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:

$$\begin{aligned}&E(g_{it}|P_{it}=P_{it-1}=1,M_{it}=1)=\\&=\sigma_{\zeta}\left[\rho_{\zeta\mu}\lambda^M_{it}+\frac{\rho_{\zeta\pi}\phi(-z'_{it}\gamma)\left(1-\Phi\left(\frac{-z'_{it-1}\gamma+\rho_{\pi\pi_{-1}}z'_{it}\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z'_{it}\gamma,-z'_{it-1}\gamma,\rho_{\pi\pi_{-1}})}\right]\\&+\sigma_{\xi}\left[\rho_{\xi\mu}\lambda^M_{it}+\frac{\rho_{\xi\pi}\phi(-z'_{it}\gamma)\left(1-\Phi\left(\frac{-z'_{it-1}\gamma+\rho_{\pi\pi_{-1}}z'_{it}\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z'_{it}\gamma,-z'_{it-1}\gamma,\rho_{\pi\pi_{-1}})}+\frac{\rho_{\xi\pi_{-1}}\phi(-z'_{it-1}\gamma)\left(1-\Phi\left(\frac{-z'_{it}\gamma+\rho_{\pi\pi_{-1}}z'_{it-1}\gamma}{\sqrt{1-\rho^2_{\pi\pi_{-1}}}}\right)\right)}{\Phi^{11}(-z'_{it}\gamma,-z'_{it-1}\gamma,\rho_{\pi\pi_{-1}})}\right]\end{aligned} \tag{10}$$

where $\lambda^M_{it}\equiv\frac{\phi(-\kappa'_{it}\theta)}{1-\Phi(-\kappa'_{it}\theta)}$. 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 ζ 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_ζ 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

$$E(g_{it}^2|P_{it}=P_{it-1}=1,M_{it}=0)=\sigma_\zeta^2\Bigg[1-\frac{z_{it}'\gamma\rho_{\zeta\pi}^2\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}+\kappa_{it}'\theta\rho_{\zeta\mu}^2\tilde{\lambda}_{it}^M$$

$$-2\rho_{\pi\zeta}\rho_{\mu\zeta}\frac{\phi(-z_{it}'\gamma)\tilde{\lambda}_{it}^M\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}-\rho_{\pi\zeta}^2\rho_{\pi\pi-1}\frac{\phi(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi-1})}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}\Bigg]+Var(e_{it})$$

where $Var(e_{it})$ refers to the variance in the transitory component. This equation makes explicit that the true variance σ_ζ^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 autocorrelation in participation decisions.

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

$$E(g_{it}^2|P_{it}=P_{it-1}=1,M_{it}=1)=\sigma_\zeta^2\Bigg[1-\rho_{\zeta\mu}^2\kappa_{it}'\theta\lambda_{it}^M-\frac{\rho_{\zeta\pi}^2 z\gamma_{it}'\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{(1-\rho_{\pi\pi_{-1}}^2)}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}+$$

$$+\frac{2\rho_{\zeta\pi}\rho_{\zeta\mu}\phi(-z_{it}'\gamma)\lambda_{it}^M\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}-\frac{\rho_{\zeta\pi}^2\rho_{\pi\pi_{-1}}\phi(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}\Bigg]+$$

$$+\sigma_\xi^2\Bigg[1-\rho_{\xi\mu}^2\kappa_{it}'\theta\lambda_{it}^M-\frac{\rho_{\xi\pi_{-1}}^2 z_{it-1}'\gamma\phi(-z_{it-1}'\gamma)\left(1-\Phi\left(\frac{-z_{it}'\gamma+\rho_{\pi\pi_{-1}}z_{it-1}'\gamma}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}$$

$$-\frac{\rho_{\xi\pi}^2 z_{it}'\gamma\phi(-z_{it}'\gamma)\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}+\frac{2\rho_{\xi\pi}\rho_{\xi\mu}\phi(-z_{it}'\gamma)\lambda_{it}^M\left(1-\Phi\left(\frac{-z_{it-1}'\gamma+\rho_{\pi\pi_{-1}}z_{it}'\gamma}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}+$$

$$-\frac{\rho_{\pi\xi}^2\rho_{\pi\pi-1}\phi(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi-1})}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi-1})}+\frac{2\rho_{\xi\mu}\rho_{\xi\pi_{-1}}\phi(-z_{it-1}'\gamma)\lambda_{it}^M\left(1-\Phi\left(\frac{-z_{it}'\gamma+\rho_{\pi\pi_{-1}}z_{it-1}'\gamma}{\sqrt{1-\rho_{\pi\pi_{-1}}^2}}\right)\right)}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi-1})}$$

$$+\frac{2\rho_{\xi\pi_{-1}}\rho_{\xi\pi}\phi(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi_{-1}})}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi-1})}-\frac{\rho_{\pi-1\xi}^2\rho_{\pi\pi-1}\phi(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi-1})}{\Phi^{11}(-z_{it}'\gamma,-z_{it-1}'\gamma,\rho_{\pi\pi-1})}\Bigg]+Var(e_{it})$$

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 match component. Regarding the latter, additional correction terms arise through its correlation to past participation decisions. The variance of the transitory component is given by:

$$Var(e_{it}) = \sigma_i^2\Big[1 + (1+\theta_1)^2 + (\theta_2-\theta_1)^2 + (\theta_3-\theta_2)^2 + (\theta_4-\theta_3)^2 + \theta_4^2\Big].$$

We identify these process by the autocovariance function of wage growth up to lag 5. Note that σ_ζ^2 and σ_ξ^2 are not part of these moments.[21]

$$Cov(g_{it}, g_{it-1}) = \sigma_i^2\Big[-(1+\theta_1) + (1+\theta_1)(\theta_2-\theta_1) + (\theta_3-\theta_2)(\theta_2-\theta_1) + (\theta_4-\theta_3)(\theta_3-\theta_2) - (\theta_4-\theta_3)\theta_4\Big]$$

$$Cov(g_{it}, g_{it-2}) = \sigma_i^2\Big[-(\theta_2-\theta_1) + (1+\theta_1)(\theta_3-\theta_2) + (\theta_4-\theta_3)(\theta_2-\theta_1) - (\theta_3-\theta_2)\theta_4\Big]$$

$$Cov(g_{it}, g_{it-3}) = \sigma_i^2\Big[-(\theta_3-\theta_2) + (1+\theta_1)(\theta_4-\theta_3) - (\theta_2-\theta_1)\theta_4\Big]$$

$$Cov(g_{it}, g_{it-4}) = \sigma_i^2\Big[-(\theta_4-\theta_3) - (1+\theta_1)\theta_4\Big]$$

$$Cov(g_{it}, g_{it-5}) = \sigma_i^2\theta_4$$

5.2 Wage Variance Estimates

[21] 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 5: High School

	1983-1993	1994-2003	2004-2013
Standard deviations			
σ_ζ	0.044	0.048	0.056
	(0.)	(0.)	(0.013)
σ_i	0.073	0.068	0.034
	(0.)	(0.)	(0.015)
σ_ϕ	0.257	0.268	0.236
	(0.)	(0.)	(0.026)
Correlations			
$\rho_{\zeta\pi}$	0.383	0.265	-0.001
	(0.)	(0.)	(0.073)
$\rho_{\zeta\mu}$	-1.000	-0.999	-0.999
	(0.)	(0.)	(0.183)
$\rho_{\xi\pi}$	0.078	0.030	-0.008
	(0.)	(0.)	(0.153)
$\rho_{\xi\pi-1}$	0.039	0.070	-0.120
	(0.)	(0.)	(0.150)
$\rho_{\xi\mu}$	0.132	0.138	0.195
	(0.)	(0.)	(0.073)
$\rho_{\pi\pi-1}$	0.969	0.942	0.931
	(0.001)	(0.002)	(0.002)
MA process			
θ_1	-0.426	-0.348	-0.408
	(0.)	(0.)	(0.225)
θ_2	-0.041	-0.014	-0.003
	(0.)	(0.)	(0.122)
θ_3	-0.000	-0.020	-0.111
	(0.)	(0.)	(0.353)
θ_4	-0.015	-0.089	-0.104
	(0.)	(0.)	(0.277)

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

Table 6: College Dropouts

	1983-1993	1994-2003	2004-2013
Standard deviations			
σ_ζ	0.048	0.069	0.061
	(0.)	(0.011)	(0.018)
σ_i	0.085	0.079	0.046
	(0.)	(0.007)	(0.021)
σ_ϕ	0.245	0.218	0.314
	(0.)	(0.016)	(0.027)
Correlations			
$\rho_{\zeta\pi}$	0.022	0.207	0.070
	(0.)	(0.119)	(0.171)
$\rho_{\zeta\mu}$	-1.000	-1.000	-1.000
	(0.)	(0.023)	(0.244)
$\rho_{\xi\pi}$	-0.129	0.352	-0.393
	(0.)	(0.275)	(0.130)
$\rho_{\xi\pi-1}$	-0.084	0.106	0.372
	(0.)	(0.188)	(0.245)
$\rho_{\xi\mu}$	0.165	0.253	0.164
	(0.)	(0.054)	(0.064)
$\rho_{\pi\pi-1}$	0.966	0.942	0.946
	(0.001)	(0.002)	(0.002)
MA process			
θ_1	-0.412	-0.381	-0.331
	(0.)	(0.053)	(0.206)
θ_2	-0.053	-0.069	-0.056
	(0.)	(0.040)	(0.272)
θ_3	-0.000	-0.000	-0.002
	(0.)	(0.006)	(0.142)
θ_4	-0.037	-0.074	-0.045
	(0.)	(0.032)	(0.273)

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

Table 7: College Degree

	1983-1993	**1994-2003**	**2004-2013**
Standard deviations			
σ_ζ	0.061	0.062	0.064
	(0.006)	(0.010)	(0.014)
σ_i	0.111	0.119	0.079
	(0.003)	(0.005)	(0.01)
σ_ϕ	0.247	0.251	0.316
	(0.015)	(0.018)	(0.032)
Correlations			
$\rho_{\zeta\pi}$	0.080	0.099	0.401
	(0.112)	(0.149)	(0.159)
$\rho_{\zeta\mu}$	-0.918	-1.000	-1.000
	(0.104)	(0.097)	(0.106)
$\rho_{\xi\pi}$	-0.091	0.437	0.207
	(0.178)	(0.259)	(0.282)
$\rho_{\xi\pi-1}$	0.292	0.421	-0.589
	(0.242)	(0.222)	(0.181)
$\rho_{\xi\mu}$	0.190	0.237	0.203
	(0.038)	(0.050)	(0.062)
$\rho_{\pi\pi-1}$	0.972	0.941	0.958
	(0.001)	(0.003)	(0.002)
MA process			
θ_1	-0.392	-0.382	-0.371
	(0.023)	(0.033)	(0.089)
θ_2	-0.053	-0.101	-0.041
	(0.026)	(0.030)	(0.065)
θ_3	-0.007	-0.003	-0.000
	(0.018)	(0.015)	(0.060)
θ_4	-0.068	-0.097	-0.088
	(0.016)	(0.015)	(0.072)

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

5.3 Calibration Tables

Table 8: Calibration Targets

	Low skilled	High skilled
Wealth to earnings	7.13	7.82
Consumption drop EU	0.15	0.15
Job finding %	15.05	20.08
Unemployment inflow %	1.88	1.07
Job to job %	2.11	1.91
Share wage decrease	0.43	0.42
Wage growth life-cycle %	54.16	100.06
Wage loss U %	11.3	13.3
Initial dispersion	0.37	0.40
Initial log wage	7.02	7.19

Note: The table displays the calibration targets using the SIPP data from our first period of analysis: 1983-1993. *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. *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).