Wage Risk and Employment Risk over the Life Cycle

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Abstract

We specify a life-cycle model of consumption, labor supply and job mobility in an economy with search frictions. We distinguish different sources of risk, including shocks to productivity, job arrival and job destruction. Allowing for job mobility has a large effect on the estimate of productivity risk. Increases in the latter impose a considerable welfare loss. Increases in employment risk have large effects on output and, primarily through this channel, affect welfare. The welfare value of programs such as Food Stamps, partially insuring productivity risk is greater than the value of unemployment insurance which provides (partial) insurance against employment risk.

JEL Classification: D91, H31, J64

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1 Introduction

There is an extensive literature analyzing individuals’ precautionary response to income risk under incomplete markets. The theoretical literature has clarified the circumstances under which precautionary behavior arises. Empirical analysis has concentrated on assessing the levels of income risk and the persistence of shocks;\textsuperscript{1} on showing that insurance markets are indeed incomplete;\textsuperscript{2} and on measuring the effects of uninsurable idiosyncratic risk on life-cycle consumption profiles and wealth accumulation.\textsuperscript{3} In most studies idiosyncratic risk is identified as the variance of an appropriately defined residual in a panel data model of income but the underlying sources of risk are not distinguished and exogenous shocks are not disentangled from the effects of actions (such as changes in labor supply and job mobility) taken in response to such shocks. While we have learned a lot from this first generation of models, to obtain a better understanding of individual responses to risk and to carry out policy analysis, it is necessary to go deeper and to understand the sources of risk and to recognize that many of the observed fluctuations are the result of endogenous choices. Indeed the key first steps for assessing the effects on allocations and welfare of various social insurance policies that are designed to help deal with risk are to understand and to quantify the underlying sources of the uncertainty that individuals face.

In order to disentangle shocks from the responses to the shocks, we specify a structural life-cycle model of consumption, labor supply and job mobility. We then specify the underlying sources of shocks that are the key drivers of observed fluctuations in earnings. These include shocks to individual productivity that persist across different jobs and across time; firm-level shocks that lead to job destruction; the stochastic process of job offers when employed and unemployed; and variation in the quality of the match offered. Our model captures how these basic underlying shocks transmit into observed behavior, welfare and earnings fluctuations. Without the labor supply and job mobility choices, we would obtain a misleading picture on the extent to which individuals can self-insure and the extent to which observed earnings fluctuations reflect risk.\textsuperscript{4}

\textsuperscript{1} For example, see Thomas E. MaCurdy (1982), John M. Abowd and David Card (1989), Costas Meghir and Luigi Pistaferri (2004) and Fatih Guvenen (2007).
\textsuperscript{4} Per L. Krussell et al. (2008) highlight the importance of modeling labor market frictions alongside labor supply choices in understanding the aggregate implications of incomplete markets.
Within our framework, we can distinguish between employment risk and productivity risk. Productivity risk is individual-specific uncertainty that exists independently of the employer’s characteristics. Employment risk captures the uncertainty about having a job and also about the firm type. This includes the possibility of firm closure or job destruction, the difficulty of finding a new job match while unemployed, and the extent of unobserved heterogeneity across firms. In a fully competitive labor market with no worker-firm match heterogeneity and no search costs, the distinction between employment and productivity risk would be meaningless because unemployment would arise only due to low productivity resulting in the individual’s market wage being below the reservation wage. Unemployment itself would not be a source of risk.\(^5\)

Shocks differ in their available insurance opportunities. For example, layoffs are usually partially insured by the unemployment insurance system, while individual productivity shocks, other than major observable health shocks, are rarely insured in any formal way because of moral hazard and limited enforcement and commitment reasons. It is precisely this lack of formal insurance that prompts prudent individuals to engage in precautionary behavior. Furthermore, the individual’s response to earnings risk will depend partly on the availability of outside insurance - private or public. With few exceptions (R. Glenn Hubbard, Jonathan S. Skinner and Zeldes, 1995), the literature on precautionary savings has assumed that only self-insurance is available. In this paper, we propose a model in which people can self-insure, but may also be eligible for government-provided insurance mirroring three popular programs in the US: Unemployment Insurance (UI), Disability Insurance (DI) and Food Stamps. These systems provide partial insurance only.

The parameters of our model are obtained partly from estimating the characteristics of the wage process with endogenous employment and mobility choices, and partly from calibrating our life-cycle model to fit observed employment profiles and unemployment durations. We use longitudinal wage and job mobility data from the Survey of Income and Program Participation (SIPP) and employment and unemployment duration data from the Panel Study of Income Dynamics (PSID).

The empirical results we report relate to the nature of the income process and the basic im-

\(^5\)Some recent papers have analyzed the joint precautionary saving-labour supply decision. Hamish Low (2005), Josep Pijoan-Mas (2006), and David Domeij and Martin Floden (2006) analyze the joint saving and labour supply decision, but in a context without exogenous job destruction, search frictions or job mobility. Eric French (2005) analyzes labour supply and savings behavior, but focuses on older workers. Jonathan Heathcote, Kjetil Storesletten, and Giovanni L. Violante (2007) consider a joint saving-labor supply decision, again without frictions, and focusing on the degree of partial insurance.
lications of the model. First, we show that our preferred stochastic process for income (the sum of a random walk, an i.i.d. component, and a firm-worker match fixed effect) provides a good fit of the key facts in the data. Second, we find that if mobility is ignored the estimated variance of the permanent innovation to wages doubles, leading to an impression of much greater risk in the earnings process. This is because many of the wage fluctuations are due to individuals moving to jobs with better match-specific effects; ignoring this biases measured uncertainty upwards.

Turning to counterfactual experiments, we assess the effects of different types of risk by varying some key parameters one at a time (including the variance of productivity risk, and the job destruction rate) and reporting the change in labor supply, output, and savings. We also compute the willingness to pay to avoid the various changes in risks. Changes in these sources of risk affect the level of individual output, as well as the variance. This is because changes in risk change labor market participation. Some of these changes are exogenous: greater job destruction directly reduces employment; others are endogenous: greater variability in productivity leads to wage offers being more likely to fall below an individual’s reservation wage. When productivity risk increases, therefore, individuals are worse off because of the increased risk but also because output declines. However, individuals are willing to pay substantially more than the output loss to compensate for the increased risk. When job destruction increases, output also declines and unemployment increases, as we would expect. The environment becomes riskier as highly valued jobs can be lost at a faster rate, but the welfare effects of this risk are mitigated by the utility value of leisure (which in our model is a substitute for consumption). Overall, although welfare falls as job destruction increases, the willingness to pay to return to the original lower rate of job destruction is less than the loss in output.

To compare the two risks we consider, first, changing the variance of productivity shocks and, second, changing the rate of job destruction so as to achieve a decline of 5 percent in the variance of income growth. We compute the willingness to pay for each of these two changes. Individuals value more the decline in productivity risk than the decline in the rate of job destruction, both of which achieve the same decline in the variance of income growth. The underlying reason is that, in contrast to permanent productivity shocks to wages, job destruction leads to a transitory shock in income.
Finally, we measure the value that people assign to an increase in the various government-provided insurance programs in our model, and compare this to the value of a revenue equivalent cut in proportional taxes. The welfare value of programs such as Food Stamps, which partially insure productivity risk, is greater than the value of unemployment insurance which provides (partial) insurance against employment risk and no insurance against persistent shocks. This relatively low value of unemployment insurance is in line with the results of Gary D. Hansen and Ayse Imrohoroglu (1992).6

The layout of the paper is as follows. Section 2 presents the model and discusses the distinction between employment and productivity risk. Section 3 describes the data. Section 4 describes the estimation strategy and results for estimating the wage process. Section 5 presents the calibration process for the remaining parameters. Section 6 discusses possible alternatives to our wage process. Section 7 presents our calculations of the behavioral effects and the welfare costs of uncertainty and the welfare benefit of government insurance programs, followed by conclusions.

2 Model

2.1 Overview

We specify a model where individuals choose consumption and make work decisions so as to maximize an intertemporal utility function, in an environment with search frictions. We view the key sources of shocks underlying earnings fluctuations as being shocks to individual productivity, firm-level shocks leading to job destruction, the process of job offers when unemployed and when employed, and the quality of the match offered. Thus individuals face multiple sources of uncertainty: in each period employed individuals may be laid off or may receive offers of alternative employment; unemployed workers may or may not be offered a job; all individuals face uninsurable shocks to their productivity.

The economy offers partial social insurance in the form of a number of programs. These are Food Stamps, Unemployment Insurance, Disability Insurance and Social Security (pensions). When simulating the model, changes to these programs are funded by proportional taxation; thus individuals

6Rasmus Lenz (2003) also analyzes the value of unemployment insurance, allowing for the interaction between search frictions and saving. James S. Costain (1997) proposes an equilibrium search model with precautionary savings that attempts to measure the welfare effects of unemployment insurance. Silvio Rendon (2006) examines the relationship between wealth accumulation and job search dynamics in a model where the motivation for accumulating wealth is to finance voluntary quits in order to search for a better job. However, all these papers, along with Hansen and Imrohoroglu (1992), ignore the risk to individuals’ own productivity which is independent of any particular match.
are linked through the government budget constraint. The model has numerous sources of dynamics. These include asset accumulation, the fact that job offer probabilities are state dependent, and that current actions affect future eligibility to the various programs. We consider two types of individual separately: the lower-educated individuals, which include all those with a high school diploma or less, and the higher-educated individuals with at least some college.

In this section we start by describing the stochastic process of wages. Then we describe the process of job arrival and job destruction. With the sources of shocks specified we then describe the individual optimization problem and the distinction between employment and productivity risk. The empirical analysis follows in the next sections.

2.2 Structure of Wages and Shocks

We begin the model specification by outlining the process for wages. We assume that wages $w_{it}$ in the data are governed by the process:

$$\ln w_{it} = d_t + x'_{it}\psi + u_{it} + e_{it} + a_{ij(t_0)}$$

(1)

where $w_{it}$ is the real hourly wage, $d_t$ represents the log price of human capital at time $t$, $x_{it}$ a vector of regressors including age, $u_{it}$ the permanent component of wages, and $e_{it}$ the transitory error component. All parameters of the wage process are education specific.

In principle, the term $e_{it}$ might be thought to represent a mix between a transitory shock and measurement error. In the usual decomposition of shocks into transitory and permanent components, researchers work with annual earnings data where transitory shocks may well be important because of unemployment spells. In our framework, this source of transitory shocks is modeled explicitly through the employment and job mobility. We show below that the model generates a stochastic process for earnings similar to that estimated using earnings from, say, the PSID. Thus, we assume that all estimated transitory shocks to wages represent measurement error.\footnote{Further, in the empirical section we find that the variance of $e_{it}$ is low, and indeed lower than the variance of measurement error obtained on annual earnings by validation studies on the SIPP data we use (see Abowd and Martha H. Stinson, 2005).}

The term $a_{ij(t_0)}$ denotes a firm-worker match-specific component where $j$ ($t_0$) indexes the firm that the worker joined in period $t_0 \leq t$.\footnote{We should formally have a $j$ subscript on wages but since it does not add clarity we have dropped it. Note also that in the absence of firm data one cannot distinguish between a pure firm effect and a pure match effect. In the latter case, one can imagine $a_{ij(t_0)}$ as being the part of the matching rent that accrues to the worker. We take the bargaining process that produces this sharing outcome as given.}

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variance $\sigma_\epsilon^2$. We model the match effect as constant over the life of the worker-employer relationship. If the worker switches to a different employer between $t$ and $t+1$, however, there will be some resulting wage growth which we can term a mobility premium denoted as $\xi_{it+1} = a_{ij(t+1)} - a_{ij(t_0)}$. The match effect is assumed normally distributed and successive draws of $a_{ij(t)}$ are assumed independent; however, because of the endogenous mobility decisions successive realizations of the match effect will be correlated. Since offers can be rejected when received, only a censored distribution of $\xi_{it+1}$ is observed. The match effect $a_{ij(\cdot)}$ is complementary to individual productivity.\(^9\) Both the match effect and the idiosyncratic shock have education-specific distributions. The information structure is such that workers and firms are completely informed about $u_{it}$ and $a_{ij(\cdot)}$ when they meet (jobs are “search goods”). The importance of match effects in explaining wages has been stressed by Robert H. Topel and Michael P. Ward (1992) and Abowd, Francis Kramarz, and David N. Margolis (1999). Fabien Postel-Vinay and Jean-Marc Robin (2002) show in an equilibrium setting how firm and individual heterogeneity translate into a match effect.

Finally, we assume that there are constant returns to scale in labor implying that the firm is willing to hire anyone who can produce non-negative rents. However, we assume the firm does not respond to outside offers. If firms did respond, this would imply that the match-specific effect would increase each period with some probability and would manifest itself as a return to job tenure. However, returns to tenure are thought to be small, once one controls for endogeneity of job mobility.\(^10\) This provides some evidence that outside offers are not an important source of wage growth on the job. While dealing with the effect of outside offers may be interesting, we leave this for future research.

We assume that the permanent component of wages follows a random walk process:

$$u_{it} = u_{i(t-1)} + \zeta_{it}$$  \hspace{1cm} (2)$$

The random shock to the permanent process, $\zeta_{it}$, is normally distributed with mean zero and variance $\sigma_\zeta^2$ and is independent over time. We assume this shock reflects uncertainty.\(^11\) We assume

\(^9\) Ideally we would like to allow also for shocks to the match effect. These will act as within-firm aggregate shocks. Restricting match effects to be constant is forced upon us by the lack of matched firm and individual data. In Section 6, we consider the alternative assumption of modeling individual productivity as a fixed effect and the match component as a random walk.

\(^10\) Joseph G. Altonji and Nicolas Williams (2005) assess this literature and conclude that their preferred estimate for the US is a return to tenure of 1.1 percent a year.

\(^11\) An issue is how much of the period-to-period variability of wages reflects uncertainty. A large component of this
that the permanent shock, $\zeta_{it}$, occurs each quarter with probability 0.25. Thus, on average, the permanent component of wages changes once per year.

Given a particular level of unobserved productivity, the worker will be willing to work for some firms but not for others, depending on the value of the match. We assume that the measurement error $e_{it}$ is normally distributed with variance $\sigma^2_e$ and independent over time. As far as the policy implications of the model are concerned, we are interested in estimating $\sigma^2_e$ and $\sigma^2_\zeta$. We describe later how these are estimated.

The specification we present, while consistent with much of the evidence and in line with a number of papers,\textsuperscript{12} is not uncontroversial. Two alternatives might be a model with a stationary AR(1) process with a fixed effect in wage growth\textsuperscript{13} or a model where the match-specific effect evolves stochastically over time. We discuss these alternatives in Section 6 and justify our choice.

### 2.3 Job Destruction and Job Arrival Rates

In each period workers receive an alternative job offer with probability $\lambda^f$. Those who are currently unemployed receive an offer with probability $\lambda^n$. Individuals become unemployed either because they choose to quit following particular wage realizations or because of exogenous job destruction, which happens each period with probability $\delta$. The friction parameters (as well as the variance parameters discussed earlier) are all assumed to be specific to an education group.

The composition of those becoming unemployed is not random in our model, despite the fact that the job destruction rate acts as a random shock independently of individual skill levels. First, people with bad productivity shocks will quit their jobs and the extent to which this happens depends on the variance of the wage innovations. Second, the job destruction rates can differ by education group. Thus there is selection into the unemployment pool both in terms of observable and unobservable skill characteristics, and this selection means those becoming unemployed are less productive on average than the employed.

We assume there is no exogenous depreciation of skills following job loss. Instead, the loss of the variability is measurement error, which we control for. Beyond that, primarily for lack of adequate data, we abstract from the important issues that have to do with consumers having superior information vis-à-vis the econometrician. For discussions and empirical analysis see Blundell and Ian Preston (1998), Charles F. Manski (2004), Pistaferri (2001, 2003), and Flavio Cunha, James J. Heckman, and Salvador Navarro-Lozano (2005).


\textsuperscript{13}This is sometimes referred to as the "random growth model".
particular match on entering unemployment may lead to wages on re-entry being lower because the new firm will on average have a lower match value. This is the case because individuals in work will have improved over the average offer through job mobility, before a job in which they are employed is destroyed.\textsuperscript{14} Thus firm heterogeneity implies that exogenous job destruction will lead to wage losses and appear as “scarring”, which we document in the empirical analysis below.

We assume that job destruction and job offer arrival rates are constant over time and so we ignore business-cycle effects. We focus instead on the implications of idiosyncratic risk for behavior and for welfare. By contrast, Robert E. Lucas (1987) and others focus on the welfare benefit of smoothing out the aggregate business-cycle risk, and Storesletten, Chris I. Telmer, and Amir Yaron (2001) focus on smoothing out the variation in idiosyncratic risk. In our comparative static analysis, however, we show the effects of different values of job destruction and job offer arrival rates across a range consistent with the variation observed over the business cycle.

2.4 Individual Optimization

We consider an individual with a period utility function

$$U_t = U(c_{it}, P_{it})$$

where $P$ is a discrete \{0, 1\} employment variable and $c$ is consumption. The individual is assumed to maximize lifetime expected utility,

$$\max_{c,P} V_{it} = E_t \sum_{s=t}^{L} \beta^{s-t} U(c_{is}, P_{is})$$

where $\beta$ is the discount factor and $E_t$ the expectations operator conditional on information available in period $t$ (a period being a quarter of a year). Individuals live for $L$ periods, may work from age 22 to 62, and face an exogenous mandatory spell of retirement of 10 years at the end of life. The date of death is known with certainty.

The labor supply choice in our model is a discrete choice. However, since one period is one quarter, this discrete choice can generate substantial variation in annual hours of work.\textsuperscript{15} The

\textsuperscript{14}Indeed, as stated by Louis S. Jacobson, Robert J. LaLonde, and Daniel G. Sullivan (1993), “workers possessing skills that were especially suited to their old positions are likely to be less productive, at least initially, in their subsequent jobs. Such a fit between workers’ skills and the requirements of their old jobs could have resulted from on-the-job investment in firm-specific human capital or from costly search resulting in particularly good match with their old firms”.

\textsuperscript{15}In the data, the variation in annual hours is predominantly due to changes in employment status during the year.
worker’s problem is to decide whether to work or not if an offer is available and, if the opportunity arises, whether to switch firms. When unemployed he has to decide whether to accept a job that may have been offered or wait longer. If eligible, the unemployed person will have the option to apply for disability insurance. Whether employed or not, the individual has to decide how much to save and consume. Accumulated savings can be used to finance spells out of work and early retirement.

We use a utility function of the form

\[ U(c, P) = \frac{c \cdot \exp \{\eta P\}^{1-\gamma}}{1 - \gamma} \]

We consider cases where \( \gamma > 1 \) and \( \eta < 0 \), implying that individuals are reasonably risk averse, working reduces utility and that consumption and employment are Frisch complements (i.e. the marginal utility of consumption is higher when working). We use this specification because it is consistent with findings showing that consumption and leisure are not additively separable.\(^{16}\)

The intertemporal budget constraint during the working life has the form

\[ A_{it+1} = R \left[ A_{it} + (w_i h (1 - \tau_w) - F_{it}) P_{it} + (B_{it} E_{it}^{UI} (1 - E_{it}^{DI}) + D_{it} E_{it}^{DI} (1 - P_{it}) + T_{it} E_{it}^T - c_{it}) \right] \]

where \( A \) are beginning-of-period assets, \( R \) is the interest factor, \( w \) the hourly wage rate, \( h \) a fixed number of hours (corresponding to 500 hours per quarter), \( \tau_w \) a proportional tax rate that is used to finance social insurance programs, \( F \) the fixed cost of work, \( B_{it} \) unemployment benefits, \( T_{it} \) the monetary value of food stamps received, \( D_{it} \) the amount of disability insurance payments obtained, and \( E_{it}^{UI} \), \( E_{it}^{DI} \), and \( E_{it}^T \) are recipiency \{0, 1\} indicators for unemployment insurance, disability insurance, and the means-tested transfer program, respectively. Note also that there are costs of applying for disability insurance which we discuss below.

We assume that individuals are unable to borrow either against the social insurance programs or against future earnings:

\[ A_{it} \geq 0 \]

By using a quarter as the decision time we are able to generate substantial variation over the year. Hours elasticities for workers are found to be very small in most empirical microeconomic studies for men; see MaCurdy, David A. Green, and Harry J. Paarsch (1990), John Pencavel (2002), and Meghir and David Phillips (2008) as examples.\(^{16}\)

In practice, this constraint has bite because it precludes borrowing against unemployment insurance, against disability insurance, against social security, and against the means-tested program.

At retirement, people collect social security benefits which are paid according to a formula similar to the one we observe in reality (see below). These benefits, along with assets that people have voluntarily accumulated over their working years, are used to finance consumption during retirement.

**Unemployment Insurance.** We assume that unemployment benefits are paid only for the quarter immediately following job destruction. We define eligibility for unemployment insurance $E_{t}^{UI}$ to mirror current legislation: benefits are paid only to people who have worked in the previous period, and only to those who had their job destroyed (job quitters are therefore ineligible for UI payments, and we assume this can be perfectly monitored).\(^{17}\) We assume $B_{it} = b \times w_{it} - h$, subject to a cap, and we set the replacement ratio $b = 75\text{percent}$. The replacement ratio is set at this high value because the payment that is made is intended to be of a magnitude similar to the maximum available to someone becoming unemployed. The cap is set according to the median state (Bruce Meyer, 2002).

In the US, unemployment benefit provides insurance against job loss and insurance against not finding a new job. However, under current legislation benefits are only provided up to 26 weeks (corresponding to two periods of our model) and so insurance against not finding a new job is limited. Our assumption is that there is no insurance against the possibility of not receiving a job offer after job loss. This simplifying assumption means that unemployment benefit is like a lump-sum payment to those who exogenously lose their job. This implies that UI introduces two types of distortion on labor supply. The first is due to the tax on wages that finances the program. The other is the effect of UI payments on asset accumulation decision, which in turn affects job acceptance.

**Universal Means-Tested Program.** In modeling the universal means-tested program, our intention was to mirror partially the actual Food Stamps program but with three simplifying dif-

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\(^{17}\) We have simplified considerably the actual eligibility rules observed in the US. A majority of states have eligibility rules that are tougher than the rule we impose, both in terms of the number of quarters necessary to be eligible for any UI and in terms of the number of quarters of work necessary to be eligible for the maximum duration (Meyer, 2002). However, making eligibility more stringent in our model is numerically difficult because the history of employment would become a state variable. Our assumption on eligibility shows UI in its most generous light.
ferences. First, the means testing is only on income rather than on income and assets;\textsuperscript{18} second, the program provides a cash benefit rather than a benefit in kind;\textsuperscript{19} and third, we assume there is 100 percent take-up. These assumptions mean that in our model there is no direct disincentive for poor individuals to hold assets (as in Hubbard, Skinner, and Zeldes, 1995); there is still however the disincentive to accumulate caused by the programs, as the public insurance will lead to a lower need for precautionary savings.

For the purposes of the program gross income is defined as

$$y_{it}^{\text{gross}} = w_{it} h P_{it} + (B_{it} E_{it}^{UI} (1 - E_{it}^{DI}) + D_{it} E_{it}^{DI}) (1 - P_{it})$$

(giving net income of $y = (1 - \tau_{w}) y_{it}^{\text{gross}} - d$, where $d$ is the standard deduction that people are entitled to when computing net income for the purpose of determining food stamp allowances. The value of the program is then given by

$$T_{it} = \begin{cases} T - 0.3 \times y_{it} & \text{if } y_{it} \leq y \\ 0 & \text{otherwise} \end{cases}$$

where $T$ is the maximum payment and where $y$ should be interpreted as a poverty line. In the actual Food Stamp program, only people with net earnings below the poverty line are eligible for benefits (which we denote by $E_{it}^{T} = 1$). The maximum value of the payment, $T$, is set assuming a household with two adults and two children, although in our model there is only one earner.

**Disability Benefits and Social Security.** Workers may find themselves in circumstances that would lead them to apply for disability insurance, the final element of the budget constraint. First, we allow only individuals who face a negative productivity shock to apply for disability. The requirement of a negative shock to wages is meant to mimic a health shock, on the basis of which an individual could claim to be eligible. Second, we require people to remain unemployed for at least one quarter before being able to apply for disability insurance and then they must remain unemployed in the quarter in which the application is made. Again, this is meant to reflect the actual rules of the system: there is a waiting period of 5 months between application and receipt of

\textsuperscript{18}The difficulty with allowing for an asset test in our model is that there is only one sort of asset that individuals use for retirement saving as well as for short-term smoothing. In reality, the asset test applies only to liquid wealth and thus excludes pension wealth (as well as real estate wealth and other durables). Finally, note that in 1996 a work test was also introduced for Food Stamps. This is outside our sample period.

\textsuperscript{19}We assume that the means-tested transfer is paid in cash rather than in the form of coupons (as with Food Stamps). While this is in contrast with the reality, it would be of little practical importance if stamps were inframarginal or if there were “trafficking”. Moffitt (1989) finds evidence for both phenomena.
benefits, and during this period the individual must be unemployed. Third, we assume that only workers above the age of 50 are eligible to apply for disability benefits.\footnote{Interestingly, this was an actual requirement of the program at the time of inception (1956). In our model, it reflects the fact that health shocks triggering disability are rare before this age.}

Conditional on applying, individuals have a fixed probability of obtaining the benefit, which we obtain from actual data (50 percent, see John Bound et al., 2004). If successful, the individual remains eligible for the rest of their working life and disability insurance becomes an absorbing state. If not successful, the individual has to remain unemployed another quarter before taking up a job. Individuals can only reapply in a subsequent unemployment spell. The combination of disability and the means-tested program turns out to be very important in fitting the decline in employment with age. Disability payments can provide a high replacement rate which is not affected by the duration of unemployment. However, the requirement that individuals spend two quarters unemployed before the disability application is resolved would discourage a large proportion of applicants were it not for the means-tested (Food Stamps) program which provides a floor to income during this application process.

The value of disability insurance is given by

\[
D_{it} = \begin{cases} 
0.9 \times \bar{w}_i & \text{if } \bar{w}_i \leq a_1 \\
0.9 \times a_1 + 0.32 \times (\bar{w}_i - a_1) & \text{if } a_1 < \bar{w}_i \leq a_2 \\
0.9 \times a_1 + 0.32 \times (a_2 - a_1) + 0.15 \times (\bar{w}_i - a_2) & \text{if } a_2 < \bar{w}_i \leq a_3 \\
0.9 \times a_1 + 0.32 \times (a_2 - a_1) + 0.15 (a_3 - a_2) & \text{if } \bar{w}_i > a_3
\end{cases}
\]

where $\bar{w}_i$ is average earnings computed before the time of the application and $a_1$, $a_2$, and $a_3$ are thresholds we take from the legislation. We assume $\bar{w}_i$ can be approximated by the value of the permanent wage at the time of the application. Whether an individual is eligible (i.e., $E^{DI}_{it} = 1$) depends on the decision to apply ($DI_{it} = 1$) while being out of work, on having received a large negative productivity shock and on the application being successful. We assume that the probability of success is independent of age. Eligibility does not depend on whether an individual quits or the job is destroyed.

By contrast with our assumption of a 50 percent probability of success for DI is our assumption of 100 percent take-up for our universal means-tested program and for unemployment insurance. We assume that this difference arises because of the difficulty of verifying disability compared to the income test and the unemployment test.
In retirement, all individuals receive social security calculated using the same formula used for disability insurance.

2.5 Employment Risk and Wage Risk

We allow for different types of shock that constitute risk an individual is facing and we distinguish earnings and employment fluctuations driven by endogenous decisions versus unexpected shocks. The direct shocks to wages are interpreted as productivity risk. The job destruction process, the rate at which job offers are sampled in and out of work, and the heterogeneity of firms constitute employment risk.

The distinction between employment and wage risk becomes relevant in the presence of search frictions and is further reinforced by the probability of job destruction. Firm heterogeneity adds another dimension to this risk: it means that some jobs may be available with a match value that would lead to a wage worth taking for an unemployed individual, even following a very bad productivity shock. Search frictions, however, make it hard to find such a job and create uncertainty in both the length of unemployment and in prospective earnings. Moreover firm heterogeneity generates an option value to waiting in the unemployment state if the job arrival rate when on the job is lower than the job arrival rate when unemployed. The model allows us to identify the effects of changes in each of these risks from the behavioral reactions to their presence/change.

The productivity shocks that we observe are assumed to be uninsurable uncertainty. These productivity shocks may, for example, reflect health shocks or demographic shocks but we do not specify their source in this model. We assume that there is no commitment from the side of the firm (or the worker), so Milton Harris and Bengt Holmstrom (1982) - type contracts are not implementable. Further, we assume there is no private insurance market against employment risk. This incomplete markets set-up is consistent with results from Attanasio and Davis (1996) and others.\textsuperscript{21}

\begin{footnote}
\textsuperscript{21}It is possible that observed wages may have already been smoothed out relative to productivity by implicit agreements within the firm. This means that productivity risk may be greater than observed wage movements within a firm, which implies that the process for productivity shocks is not properly identified for the unemployed. In other words, productivity shocks are a combination of actual shocks plus insurance, but this insurance is only present if the individual is working. If the unemployed experience greater productivity risk than estimated, this will impact on the reservation wage and on job search. For the time being we ignore this issue as far as permanent shocks are concerned.
\end{footnote}
2.6 Value Function and Model Solution

The solution of the model consists of policy functions for consumption, the decision to work and realizations of earnings, career paths, assets, etc. There is no analytical expressions for these. Instead, the model must be solved numerically, beginning with the terminal condition on assets, and iterating backwards, solving at each age for the value functions conditional on work status. In this section we discuss the key features of the solution. More details on the method are provided in Appendix A.

When employed, the state variables are \( \{A_{it}, u_{it}, a_{ij(t_0)}\} \), corresponding to current assets, individual productivity and the match effect. The match effect is indexed by \( t_0 \), which is the date the job began.\(^{22}\) When unemployed and not on disability, the state variables are \( \{A_{it}, u_{it}, D_{it}^{Elig}\} \), corresponding to current assets, individual productivity and an indicator of whether the individual is eligible to apply for disability in that period. When unemployed and receiving disability, the state variables are \( \{A_{it}, D_{it}\} \) where \( D_{it} \) is the amount of disability benefit received defined by equation (6). Consumption is chosen to maximize each value function conditional on all other decisions. Once consumption is substituted out of each value function the discrete labour supply and mobility decisions can be made.

The value function for an employed individual incorporates the fact that in the next period he will have the choice of quitting into unemployment, moving to a new job if he gets an alternative offer or staying with the firm. However if the job is destroyed the individual will have to move to

\(^{22}\) Ideally we should model the behavior of the firm. If the firm has a fixed number of positions, and if there are firing costs, a firm with characteristic \( a_{ij(\cdot)} \) may not make an offer to any worker. High \( a_{ij(\cdot)} \) firms may wish to wait to locate high \( u_{it} \) workers, in the same way that high \( u_{it} \) workers may wish to wait for high \( a_{ij(\cdot)} \) firms. At present we ignore this issue.
unemployment. Thus the value function for an individual \( i \) who is working in period \( t \) is

\[
V_t^e \left( A_{it}, u_{it}, a_{ij(t_0)} \right) = U(c_{it}, P_{it} = 1) + \\
\beta \delta E_t \left[ V_{t+1}^n \left( A_{it+1}, u_{it+1}, DI_{t+1}^{Elig} = 1 \right) \right] \\
+ \beta (1 - \delta) (1 - \lambda^e) E_t \left[ \max \left\{ \begin{array}{ll}
V_{t+1}^n \left( A_{it+1}, u_{it+1}, DI_{t+1}^{Elig} = 1 \right), \\
V_{t+1}^c \left( A_{it+1}, u_{it+1}, a_{ij(t_0)} \right) \end{array} \right\} \right] \\
+ \beta (1 - \delta) \lambda^e E_t \left[ \max \left\{ \begin{array}{ll}
V_{t+1}^n \left( A_{it+1}, u_{it+1}, DI_{t+1}^{Elig} = 1 \right), \\
V_{t+1}^c \left( A_{it+1}, u_{it+1}, a_{ij(t_0)} \right) \end{array} \right\} \right] \\
\right]
\]

The expectation operator is conditional on information at time \( t \). If there is no offer available in \( t+1 \), the expectation operator is over the productivity shock only; if an offer is an offer in \( t+1 \), the expectation taken in \( t \) is also over the type of firm making the offer.

Among the unemployed, we distinguish between those who have the option of applying for disability and those who are ineligible to apply (either because the individual is under 50 or because he has not had a negative productivity shock or because he has has an application turned down in the current unemployment spell).

For an individual who is eligible to apply for disability, the value function is given by

\[
V_t^n \left( A_{it}, u_{it}, DI_{t}^{Elig} = 1 \right) = \max_{c, \text{Apply}} \left\{ u(c_{it}, P_{it} = 0) + \beta \left\{ \begin{array}{ll}
V_{t+1}^A \text{ if Apply = 1} \\
V_{t+1}^{NA} \text{ if Apply = 0} \end{array} \right\} \right\}
\]

where

\[
V_{t+1}^{NA} = \lambda^n E_t \left[ \max \left\{ \begin{array}{ll}
V_{t+1}^n \left( A_{it+1}, u_{it+1}, DI_{t+1}^{Elig} = 1 \right), \\
V_{t+1}^c \left( A_{it+1}, u_{it+1}, a_{ij(t_0)} \right) \end{array} \right\} \right] \\
+ (1 - \lambda^n) E_t \left[ V_{t+1}^n \left( A_{it+1}, u_{it+1}, DI_{t+1}^{Elig} = 0 \right) \right]
\]

\[
V_{t+1}^A = S \times V_{t+1}^{DI} \left( A_{it+1}, DI_{it+1} \right) + (1 - S) \times E_t \left[ V_{t+1}^n \left( A_{it+1}, u_{it+1}, DI_{t+1}^{Elig} = 0 \right) \right]
\]

and \( S \) is the exogenous probability of a successful application. When deciding whether or not to apply, the individual already knows if he has a job offer in that period. If the disability application is successful, we can calculate the resulting value function, \( V_{t+1}^{DI} \), analytically: the amount of the disability insurance payment, \( D_{it} \), depends on the permanent wage only and not on the particular
firm that the individual has most recently been working for. This amount is earned each year until retirement.

Based on a comparison of the value functions, in each period the individual decides whether or not to work; and if working, whether or not to move to another job if the opportunity arises; and if not working, whether or not to apply for disability benefit. The decision about whether or not to move to another job if an outside offer is received is, in practice, more straightforward than the other decisions because we assume that there is no cost of switching firm. This means that the decision to switch firm involves a simple comparison of the $a_{ij(t)}$ and the individual will move if the new offer is from a higher $a_{ij(t)}$ firm than the current one.23

Because of the discrete nature of labour supply, consumption may not be continuous in assets and value functions may not be necessarily differentiable, which complicates the optimization problem. See Appendix A for a discussion of these issues.

3 Data

We use the 1993 panel of the Survey of Income and Program Participation (SIPP) to estimate our wage dynamics parameters because it records all job-to-job transitions and the resulting new wage each time. However, the SIPP follows individuals for only 3 years and this means that it is less useful for duration analysis. We use the 1988-1996 Panel Study of Income Dynamics (PSID) to construct employment and unemployment duration profiles. In both data sets, we stratify the sample by education, low (those with a high school diploma or less), and high (those with some college or more).

3.1 The SIPP

The main objective of the Survey of Income and Program Participation (SIPP), conducted by the US Census Bureau, is to provide accurate and comprehensive information about the income and welfare program participation of individuals and households in the United States. The SIPP offers detailed information on cash and non-cash income on a sub-annual basis. The survey also collects data on taxes, assets, liabilities, and participation in government transfer programs.

23 If we were to allow for a cost of switching firm in the numerical solution, then the decision about whether or not to switch would depend on a comparison of the value function at the existing firm and the value function at the new firm. This difference will depend on the expected duration of the new job, the worker’s horizon and all elements of the dynamic programming problem.
The SIPP is a nationally representative sample of individuals 15 years of age and older living in households in the civilian non-institutionalized population. Those individuals, along with others who subsequently come to live with them, are interviewed once every 4 months for a certain number of times (from a minimum of 3 to a maximum of 13 times). Each year, a new panel starts, so some overlapping is expected. The first sample, the 1984 Panel, began interviews in October 1983 and surveyed individuals 9 times. The second sample, the 1985 Panel, began in February 1985 and surveyed individuals 8 times. We use the 1993 Panel, which has 9 interviews in total (or 36 months of data for those completing all interviews).24

The Census Bureau randomly assigns people in each panel to four rotation groups. Each rotation group is interviewed in a separate month. Four rotation groups thus constitute one cycle, called a wave, of interviewing for the entire panel. At each interview, respondents are asked to provide information covering the 4 months since the previous interview. The 4-month span is the reference period for the interview.

Our sample selection is as follows. The raw data have 62,721 records, one for each member of the survey households, corresponding to 1,767,748 month/person observations (note that, due to attrition, not all individuals complete 9 interviews). We drop females, those aged below 22 or above 61, those completing less than 9 interviews, the self-employed, those who are recalled by their previous employer after a separation, those with missing information about the state of residence, and those with outlier earnings.25 Our final sample includes 6,494 individuals corresponding to 233,784 month-person observations. We report some sample statistics in Table 7 in Appendix C.

Our measure of (firm-specific) hourly wage is obtained by dividing annual earnings earned at the firm by annual hours worked at the firm.26 Individuals may have multiple hourly wage observations within a year if they work for multiple firms (concurrently or not). We use only the main job (the one that pays the highest proportion of annual earnings). In the SIPP, each firm an individual is working for is assigned an ID.27 We set $M_{it} = 1$ if the employer the individual is working for at time $t$ is different from the one he was working for at time $t - 1$. We allocate individuals to the low and

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24 The raw data can be obtained at http://www.nber.org/data/sipp.html.
25 An outlier is defined as one whose annualized earnings fall by more than 75 percent or grow by more than 250 percent. This is not influenced by periods of unemployment.
26 The average hourly wage data refer to 1993, 1994, and 1995. Due to the rotating nature of the 1993 SIPP panel, there are some individuals who report wage data for 1, 2, or 3 months in 1992. We do not use these data because they may not be informative about wages over the entire year.
27 We use corrected firm IDs (see Stinson, 2003).
high education groups based on response to a question about the highest grade of school attended. An important advantage of the SIPP over the PSID when it comes to estimating the wage process allowing for job mobility is that the SIPP does not average pay over different employers. Thus the full effect of a move from one employer to another is observed.

3.2 The PSID

The PSID data are drawn from the 1988-1996 family and individual-merged files. The PSID started in 1968 collecting information on a sample of roughly 5,000 households. Of these, about 3,000 were representative of the US population as a whole (the core sample), and about 2,000 were low-income families (the Census Bureau’s SEO sample). Thereafter, both the original families and their split-offs (children of the original family forming a family of their own) have been followed. In the empirical analysis we use the heads of the core sample households after 1988 because detailed data on monthly employment status and other variables of interest are available only after that year and only for household heads.

Our sample selection is as follows. As with the SIPP, we focus on working-age males, aged 22-61. We drop those with missing records on education and the monthly employment status question, and the self-employed. Education level is computed using the PSID variable with the same name.

The PSID asked individuals to report their employment status in each month of the previous calendar year and their year of retirement (if any). We use these questions to construct a quarterly employment indicator for each individual and the duration of unemployment spells. We classify as not employed in a given month those who report to be unemployed/temporarily laid off, out of the labor force, or both, in that month. We treat unemployment and out-of-labor force as the same state; this tallies with the definition of unemployment that we use in the simulations (see Christopher J. Flinn and Heckman, 1983, for a discussion of the difference between these two reported states). In principle, the durations are both left- and right-censored. Some spells begin before the time of the first interview, while some spells are still in progress at the time of the last interview. To avoid problems of left censoring we only use spells that begin in the sample and drop those with less than 3 years of data. In calculating durations, we take our sample to be individuals who exit between

\[28\] The raw data are available at http://psidonline.isr.umich.edu/.

\[29\] If the distinction in the data between out-of-labor force and unemployment reflects a difference in search intensity, we could make a meaningful distinction in our model only if we introduced a search decision with a cost attached.
1988 and 1992. However, we use more recent years of PSID data (1993-1996) to calculate durations for those whose spells are right-censored by the 1988-1992 window. This reduces the censoring from 13.09 percent of all spells to 5.29 percent.

4 Estimating the Wage Process

In estimating the wage process, we take the difference of the wage equation (1) between years.30 Taking the process for permanent shocks (2) and recalling that  \( \xi_{it} = (a_{ij(t)} - a_{ij(t_0)}) \), we obtain:

\[
\Delta \ln w_{it} = \Delta d_{it} + \Delta x_{it}'\psi + \zeta_{it} + \Delta e_{it} + \xi_{it}M_{it}
\]

where the indicator  \( M_{it} \) is one for those who changed employer and zero otherwise. Wage growth is only observed for those who work in both periods. If one were to ignore selection issues, under the assumptions discussed in section 2.2 the variance of the permanent shock to wages can be estimated using the residual within-firm wage growth  \( g_{it,w} = \zeta_{it} + \Delta e_{it} \) based on the expression  \( \sigma^2_{\zeta} = E(g_{it,w}^2) + 2E(g_{it,w}g_{it-1,w}) \), where the subscript  \( w \) denotes “within”. The measurement error variance is recovered by  \( \sigma^2_{e} = -E(g_{it}g_{it-1}) \) using data for the whole sample of workers. Finally, the variance of the match effect can then be estimated based on the variance of residual wage growth between firms  \( g_{it,b} = \zeta_{it} + \Delta e_{it} + a_{ij(t)} - a_{ij(t_0)} \) using the expression  \( \sigma^2_{a} = \frac{1}{2} \left( E(g_{it,b}^2) - \sigma^2_{\zeta} - 2\sigma^2_{e} \right) \), where the subscript  \( b \) denotes “between”.

However, selection issues are central in our model: wages are observed conditional on individuals working; within-firm wage growth, which identifies the variance of permanent productivity shocks, is only observed if the individual does not change job; between firm-wage growth, which helps identify heterogeneity across firms, is observed only for job movers. Further, employment and mobility decisions are all endogenous and if this is ignored we risk biasing the estimates of the variances to wages and of firm heterogeneity.

To address this problem our approach is as follows: first we model the selection process into and out of work and between firms. We then construct sample selection terms and estimate wage growth equations conditioning on these terms. We finally obtain the estimates of the variances of interest.

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30 To smooth the effect of the well-known seam bias in the SIPP, in our estimation procedure we focus on annual wage growth rather than quarterly growth. In Appendix B we discuss how the timing involved in our estimation procedure is reconciled with the model.
by modeling the first and second moments of unexplained wage growth for various subgroups.

Define the latent utility from working as $P_{it}^* = z_{it}' \varphi + \pi_{it}$. The associated labor market employment index is $P_{it} = 1 \{P_{it}^* > 0\}$, which is unity for workers. Workers separate from their current employer voluntarily (quits) or involuntarily (layoffs). As argued by George J. Borjas and Sherwin Rosen (1980), job turnover, regardless of who initiates it, represents the same underlying phenomenon, that of workers’ marginal product being higher elsewhere. Let $M_{it}^* = k_{it}' \theta + \mu_{it}$ denote the latent utility from moving in period $t$ to an employer that is different from the one in $t-1$. We have that $M_{it} = 1 \{M_{it}^* > 0\}$. We assume: $(\pi_{it}, \pi_{it-1}, \mu_{it})' \sim N(0, I)$ and serially independent.

Selection into and out of work and into new jobs is accounted for by the correlations between $\pi_{it}$ and $\zeta_{it}$ ($\rho_{\zeta \pi}$), $\pi_{it}$ and $\xi_{it}$ ($\rho_{\xi \pi}$), $\pi_{it}$ and $\xi_{it-1}$ ($\rho_{\xi \pi_{-1}}$), $\mu_{it}$ and $\zeta_{it}$ ($\rho_{\zeta \mu}$), and $\mu_{it}$ and $\xi_{it}$ ($\rho_{\xi \mu}$).

Suppose now that we select only those who work at $t$ and $t-1$ ($P_{it} = 1$ and $P_{it-1} = 1$). It is easy to show that:

$$E(\Delta \ln w_{it} | P_{it} = 1, P_{it-1} = 1) = E(\Delta \ln w_{it} | P_{it} = 1, P_{it-1} = 1, M_{it} = 1) \Pr(M_{it} = 1)$$

$$+ E(\Delta \ln w_{it} | P_{it} = 1, P_{it-1} = 1, M_{it} = 0) (1 - \Pr(M_{it} = 1))$$

$$= \Delta d_t + \Delta x_{it}' \psi + G_{it}$$

where $G_{it}$ is a selection term induced by employment and inter-firm mobility (see Appendix B for details).\(^{31}\) We estimate the components of this selection term in a first stage by running separate probit regressions,\(^{32}\) and use these to then estimate the parameters of (9) consistently in a second stage using only workers in both periods.

We now need to estimate the variance of the permanent shocks, the variance of the firm-level heterogeneity and the variance of the measurement error. Estimation is based on the moments of unexplained wage growth (observed only for workers in both periods):

$$g_{it} = \Delta (\ln w_{it} - d_t - x_{it}' \psi) = \zeta_{it} + \Delta e_{it} + \xi_{it} M_{it}$$

We use the first and second moments of (10) for movers ($M_{it} = 1$) and for stayers ($M_{it} = 0$), as well as the first-order autocovariance, always correcting for selection due to employment and

\(^{31}\)In estimation we do not use the restrictions on the parameters of interest imposed by (9). This only results in a loss of efficiency, but it does not affect consistency. We estimate the standard errors by the block bootstrap.

\(^{32}\)The assumed orthogonality assumption between $\pi_{it}$ and $\mu_{it}$ allows us to do this.
mobility. In addition to the two variances of interest we also estimate the relevant correlations that drive selection. The estimation process takes into account that the wage growth we model is annual, while the work decision is quarterly, in accordance with the model. The details of the entire estimation process are given in Appendix B.

Standard errors are computed using the block-bootstrap procedure suggested by Joel L. Horowitz (2002). In this way we account for serial correlation of arbitrary form, heteroskedasticity, as well as for the fact that we use a multi-step estimation procedure, pre-estimated residuals and selection terms. We should point out that this procedure is likely to be conservative, since it allows for more serial correlation than that implied by the moment conditions we use.

4.1 Results
4.1.1 Employment and Mobility

We start by estimating quarterly probits for employment using the SIPP data. Our regressors include a quadratic in age, a dummy for whites, region dummies, a dummy for married, year dummies as well as unearned household income and an index of generosity of the welfare system, which here we proxy with the generosity of the state-level UI system.\textsuperscript{33} The latter two are excluded from the wage equation and are the instruments that identify selection into work - the unearned income as a pure income effect and the generosity of the UI system as a fixed cost of work.\textsuperscript{34} The probit estimates for each quarter are reported in Appendix C, Table 8. The main point is that unearned income has a strong and significantly negative effect on the probability of working. The generosity of the UI system is also a significant factor discouraging work, but only for the lower education group and not for the college graduates.

We also estimate a mobility probit, which will allow us to control for the censoring of between-firm wage growth. The dependent variable is whether an individual who was working in period $t$ is

\textsuperscript{33}Unearned household income is defined as total household income net of household earnings and means-tested cash benefits. To obtain a measure of the generosity of the UI program in the state where the worker lives, we rank states according to the maximum weekly UI benefit (which we take from current legislation). Our measure of generosity is the rank variable, which varies over time and across states. We obtain similar results if we rank states pooling data for all years. Ideally, one would like to use an index of generosity of the Food Stamps program, but this is a federal program and its time-series variability is negligible.

\textsuperscript{34}We exploit variation over states and time that exists in the generosity of the UI system. For this exclusion restriction to be valid the US labor market should be sufficiently integrated and sufficient trade should be taking place, so that variability in benefits in one state does not affect wage in that state. For the unearned income exclusion restriction to be valid requires that UI payments do not affect wages through bargaining, as in Christopher A. Pissarides (2000), or through compensating differentials, as in Topel (1984). Our model imposes the weaker condition that these instruments can be excluded from wage growth.
in a different job in period \( t+1 \). Thus for the purposes of this estimation, mobility may include those moving jobs via unemployment. The mobility probit includes the same variables as the employment equation, as well as industry dummies and an indicator as to whether the person was working for a non-profit organization, in both cases for period \( t \). Unearned income influences mobility positively for both education groups; UI generosity influences mobility positively for the lower education group but not the college graduates. The effect of UI on mobility is theoretically ambiguous. On the one hand, it increases the reservation wage leading to individuals quitting employment following negative wage shocks and increasing mobility through this mechanism. On the other hand, when UI is low, durations of unemployment will be shorter and wage increases will occur through job-to-job mobility; the former effect dominates. Our results also show that mobility declines with age for both groups. This decline arises because of a selection effect: older individuals have had the opportunity to move to jobs with higher match components, and thus it becomes increasingly unlikely that an outside offer is sufficiently good to trigger mobility. Job destruction is an important force disrupting this age effect. Table 9 in Appendix C presents the results.

4.1.2 Variance Estimates

Armed with these results, we move on to estimate the parameters of the wage process by the method of moments, imposing constraints across equations. The results are reported in Table 1. The \( \sigma \) parameters refer to the standard deviations of the various stochastic components of wages. The \( \rho \) parameters are the correlations between the various stochastic shocks and the shocks driving selection. They are defined in Appendix B, which also reports the moments we fit and the corrections for selection. We estimate the model for the whole sample to have a comparison with previous work (column 1) and separately by the two education groups (columns 2 and 3).

When we control for selection into employment and for job mobility, we find that in the whole sample the standard deviation of the permanent shock, \( \sigma_\zeta \), is about 0.10, the standard deviation of the measurement error, \( \sigma_e \), 0.09, and the standard deviation of the match-specific effect, \( \sigma_a \), 0.23. These parameters are all very precisely estimated. They imply that match heterogeneity is a very important component of wage dispersion: wages for the same individual drawing different match components could vary by as much as \( \pm 46\% \) (i.e. \( \pm \) two standard deviations) with a probability of 95 percent.
### Table 1: Wage Variance Estimates

<table>
<thead>
<tr>
<th></th>
<th>Whole sample (1)</th>
<th>Low education (2)</th>
<th>High education (3)</th>
<th>Neglect mobility (All) (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Standard Deviations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_\zeta$</td>
<td>0.103</td>
<td>0.095</td>
<td>0.106</td>
<td>0.152</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.022)</td>
<td>(0.017)</td>
<td>(0.009)</td>
</tr>
<tr>
<td></td>
<td>[0%]</td>
<td>[3%]</td>
<td>[0%]</td>
<td>[0%]</td>
</tr>
<tr>
<td>$\sigma_c$</td>
<td>0.087</td>
<td>0.084</td>
<td>0.088</td>
<td>0.086</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.035)</td>
<td>(0.016)</td>
<td>(0.005)</td>
</tr>
<tr>
<td></td>
<td>[0%]</td>
<td>[0%]</td>
<td>[0%]</td>
<td>[0%]</td>
</tr>
<tr>
<td>$\sigma_a$</td>
<td>0.228</td>
<td>0.226</td>
<td>0.229</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.019)</td>
<td>(0.015)</td>
<td></td>
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<td></td>
<td>[0%]</td>
<td>[0%]</td>
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</tr>
</tbody>
</table>

**Correlations**

|                |                    |                   |                    |                           |
| $\rho_\zeta\pi$ | 0.153             | 0.214             | −0.104             | 0.509                     |
|                | (0.244)           | (0.254)           | (0.293)            | (0.171)                   |
|                | [40%]             | [22%]             | [74%]              | [1%]                      |
| $\rho_\zeta\mu$ | −0.847           | −0.990            | −0.871             |                           |
|                | (0.410)           | (0.469)           | (0.498)            |                           |
|                | [0%]             | [0%]             | [0%]               |                           |
| $\rho_\xi\pi$  | −0.036            | 0.164             | 0.149              |                           |
|                | (0.351)           | (0.417)           | (0.402)            |                           |
|                | [43%]             | [91%]             | [8%]               |                           |
| $\rho_\xi\pi_{−1}$ | 0.190          | −0.071            | 0.190              |                           |
|                | (0.229)           | (0.254)           | (n.a.)             |                           |
|                | [4%]             | [99%]             | [n.a.]             |                           |
| $\rho_\xi\mu$  | 0.324            | 0.353             | 0.333              |                           |
|                | (0.165)           | (0.202)           | (0.216)            |                           |
|                | [0%]             | [2%]             | [1%]               |                           |

Notes: $\sigma_\zeta$, $\sigma_c$, and $\sigma_a$ are the standard deviations of the permanent shock, measurement error, and the match component. $\rho_\zeta\pi$ ($\rho_\xi\pi$) is the correlation between the permanent shock (mobility premium $\xi = a_j - a_{j-1}$) and unobserved heterogeneity in the employment equation. $\rho_\pi\mu$ ($\rho_\xi\mu$) is the correlation between the mobility premium and unobserved heterogeneity in the employment equation and in the mobility equation. Standard errors (in parenthesis) are computed using the block bootstrap (400 replications). Bootstrap p-values in square brackets. We constrain all the correlation coefficients to lie between minus 1 and 1. In column (3) we set $\rho_\pi\mu$ to the whole sample estimate due to convergence problems.
Columns (2) and (3) report the results of estimating the model separately for our two education groups. There are some differences in the stochastic process of wages of the two education groups. For example, the high educated face a higher variance of the permanent shock than the low educated.

What happens if we ignore the fact that mobility is endogenous and attribute all wage fluctuations to the permanent and transitory shocks ($\sigma_\zeta$ and $\sigma_\epsilon$)? This, implicitly, has been the assumption made in papers estimating the covariance structure of earnings (MaCurdy, 1982; Abowd and Card, 1989; Meghir and Pistaferri, 2004) and in the precautionary savings papers estimating risk via the standard transitory/permanent shock decomposition (Carroll and Samwick, 1997; Gourinchas and Parker, 2002). In column (4) we report the results of this experiment for the whole sample. The estimated standard deviation of the permanent shock $\sigma_\zeta$ increases by about 50 percent: a large proportion of wage fluctuations usually attributed to unexpected shocks is in fact a result of endogenous mobility choices. This is likely to be important for the welfare costs of risk because individuals change jobs quite frequently and because they do not have to accept worse-paying jobs than the one they have. However match dispersion does itself introduce risk: first because individuals with good matches who are displaced can expect to be hired at a lower rate (on average); and second, because individuals face uncertainty about the quality of offers they are likely to receive. On the other hand, match dispersion also offers the possibility of job improvements, which as we shall see is a dominant factor in the effect of such dispersion on welfare when the arrival rate is sufficiently high.

The estimated correlations that drive selection are reported in the lower panel of Table 1 and conform to the expected signs. The most significant is the negative correlation between the permanent shock and mobility ($\rho_{\zeta\mu}$). For the purposes of correcting for selection in estimation, mobility is defined as any job change, including those taking place through unemployment. Since a good productivity shock will encourage people to work, it will also result in fewer job changes than otherwise - hence the negative and significant correlation. The next most important one, with an overall $p$-value below 1 percent is the correlation between a good alternative offer and mobility, which is positive and quite large, as expected.
Table 2: Parameters Obtained through Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>High education</th>
<th>Low education</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job destruction rate $\delta$</td>
<td>0.028</td>
<td>0.049</td>
</tr>
<tr>
<td>Job arrival rate - unemployed $\lambda^n$</td>
<td>0.82</td>
<td>0.76</td>
</tr>
<tr>
<td>Job arrival rate - employed $\lambda^e$</td>
<td>0.72</td>
<td>0.67</td>
</tr>
<tr>
<td>Fixed cost of work $F$</td>
<td>$1213$</td>
<td>$1088$</td>
</tr>
<tr>
<td>Disutility of working $\eta$</td>
<td>$-0.62$</td>
<td>$-0.55$</td>
</tr>
</tbody>
</table>

Notes: The values of $\delta$, $\lambda^n$, and $\lambda^e$ are given as quarterly rates. The value of the fixed cost $F$ for each education group is per quarter.

5 Calibrated Parameters

We now need to set the remaining parameters required to complete the model. We set the coefficient of relative risk aversion $\gamma$ equal to 1.5, taken from Attanasio and Weber (1995), whose model of consumption also allows for nonseparable labor supply. The real interest rate is set equal to the real return on 3-month treasury bills, at an annual rate $r = 0.015$, and this is set equal to the discount rate $(\frac{1}{\beta} - 1)$. The remaining parameters we obtain through calibration using the structural model outlined in Section 2.

Given the estimated parameters of the wage process and those set above, we now set the remaining parameters to fit the life-cycle employment profile and unemployment duration profile for men, by education group. Our approach is to choose the parameters for each education group to minimize the absolute distance between statistics calculated in the data and corresponding simulated statistics.

The statistics we use are the average employment rate in four 10-year age bands (22-31, 32-41, 42-51 and 52-61) and the mean duration of unemployment in eight 5-year age bands. In Table 10 in Appendix C we show the fit of the moments we have targeted. In Table 2, we present the calibrated parameter values, with job destruction and arrival rates given at quarterly rates. In Figures 1 and 2 we show the calibrated profiles.

The job destruction rate is about 75 percent higher for the lower-educated individuals than for the higher-educated ones. The contact rates are higher for the more educated and they are higher for those out of work than when in work, possibly reflecting increased costs of search when working.
or different incentives to search in the two states. The value of $\eta$ for high-education individuals implies that work is equivalent to a 46 percent loss of consumption. For those of low education the equivalent consumption loss is 42 percent. These values also imply that consumption and leisure are substitutes, and thus it is consistent with the observed fall of consumption upon retirement (or unemployment). Finally, the fixed costs of work for both education groups are expressed in dollar values per quarter. For the low educated, this corresponds to about $91 per week in 1992 prices, which is equivalent to 7 hours a week evaluated at the average wage of those working. For the high educated, the cost is $101, equivalent to about 5 hours a week. French (2005) estimates the fixed cost in terms of hours, rather than dollars, and his preferred estimate corresponds to a fixed cost of about 5 hours a week for all workers.

Figure 1 shows employment profiles for the high educated and low educated. Each figure compares the profile in the data with the calibrated profile (labelled “employed”). For both education groups, employment rates are constant or display a slow decline until the age of 45, followed by a sharp decline to age 62. Part of this fall reflects early retirement, rather than temporary periods out of the labor force. Since early retirement is an endogenous labor supply response, we treat this in the same way as we treat unemployment. There is a level difference between the two groups: the high educated work more than the low educated up to age 45 (employment rates around 96 percent, compared to 90 percent for the low educated), and the subsequent decline is less marked. Our match of employment is fairly good for both skill groups.

We also plot the employment rate that would be obtained if all offers received (including those offers from an existing employer) were accepted. Since the offer rate is constant over the life cycle, the downturn in employment with age is due to more offers being rejected.

Figure 2 compares mean unemployment durations over the life cycle in the simulations and in the data for both education groups. Durations have a maximum length determined by the number of quarters until age 62. In the data, durations are measured in months and are expressed as fractions of a quarter. We are able to match very well the durations for the high-education individuals. For the low educated, we simulate a very similar profile to the one in the data but shifted somewhat to earlier ages.

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35 The consumption equivalent is calculated as $1 - \exp(\eta)$.

36 The profiles from the data are calculated controlling for cohort effects and assuming that time effects average out to zero and are orthogonal to the time trend. The estimated employment rate is equal to the actual rate at age 40.
Figure 1: Employment over the Life Cycle

Figure 2: Mean Unemployment Duration over the Life Cycle
In the model $\lambda^n, \lambda^e, \delta, F$, and $\eta$ are independent of age and so the age effects that we find in all the simulated profiles can be explained only by endogenous saving and labor supply behavior in response to the budget constraint and the welfare benefit structure: the match in the slope of profiles over the life cycle is not an artefact of age-varying parameters and is a demonstration of the strength of the model. Average unemployment durations increase over the life cycle because of the increase in assets held by the individual, and this counteracts the fact that older individuals have higher wages and thus a greater incentive to work. In addition, as individuals get older the amount of future uncertainty declines, thus reducing the precautionary motive for working (Low, 2005).

5.1 Implications of the Model

We have calibrated the model using only employment rates and unemployment duration data, given the pre-estimated wage process and given an intertemporal substitution parameter from the literature. However, the model has implications for a range of different variables. In particular, we use the model to predict the wage loss associated with a spell of unemployment, the extent of consumption loss on unemployment, the arrival rate of accepted offers, and the ratio of mean wealth over stages of the life cycle to mean life-cycle income. Table 3 reports the model predictions and corresponding statistics, obtained from various different sources of data, for a number of statistics that are not used in the calibration.

The Cost of Displacement. There is empirical evidence that displaced workers experience earnings losses following job loss. Some authors impute this to exogenous skill depreciation during periods of unemployment (Richard Rogerson and Martin Schindler, 2002; Lars Ljungqvist and Thomas J. Sargent, 2002). An alternative that is consistent with our model is that wages on re-entry may be lower than before job loss because of the loss of a particular good match on entering unemployment. We report in Table 3 the extent of the wage fall on re-entry.

For the high educated, wages on re-entry are, on average, 20 percent lower than before displacement. For the low educated, the loss is 14 percent. These figures are similar to those found in the literature. In particular, we compare these figures with those reported by Jacobson, LaLonde, and Sullivan (1993) for their non-mass layoff sample (after controlling for time trends). They report that one quarter after displacement, earnings of displaced workers are 19 percent less than before
Table 3: Model Implications

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High education</td>
<td>Low education</td>
</tr>
<tr>
<td>Mean wage loss&lt;sup&gt;(a)&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln w_{\tau} - \ln w_{t}$</td>
<td>$-0.19$</td>
<td>$-0.20$</td>
</tr>
<tr>
<td>$\ln w_{\tau+4} - \ln w_{t}$</td>
<td>$-0.076$</td>
<td>$-0.091$</td>
</tr>
<tr>
<td>Mean consumption loss (Age 25-60)&lt;sup&gt;(b)&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\frac{c_{t+1} - c_t}{y_{t+1} - y_t}$</td>
<td>$0.56$</td>
<td>$0.45$</td>
</tr>
<tr>
<td>Arrival rate of accepted job offers (Age &lt;40):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>On-the-job</td>
<td>$0.034$</td>
<td>$0.038$</td>
</tr>
<tr>
<td>From unemployment</td>
<td>$0.51$</td>
<td>$0.45$</td>
</tr>
<tr>
<td>Fraction of job offers accepted (Age &lt;40):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>On-the-job</td>
<td>$0.047$</td>
<td>$0.057$</td>
</tr>
<tr>
<td>From unemployment</td>
<td>$0.62$</td>
<td>$0.59$</td>
</tr>
<tr>
<td>Mean wealth / Mean annual income&lt;sup&gt;(c)&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 30-35</td>
<td>$1.58$</td>
<td>$1.71$</td>
</tr>
<tr>
<td>Age 50-55</td>
<td>$7.27$</td>
<td>$5.13$</td>
</tr>
<tr>
<td>Decomposition of earnings&lt;sup&gt;(d)&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of permanent component</td>
<td>$0.17$</td>
<td>$0.20$</td>
</tr>
<tr>
<td>Standard Deviation of transitory component</td>
<td>$0.12$</td>
<td>$0.15$</td>
</tr>
</tbody>
</table>

<sup>(a)</sup>The data numbers for wage loss are taken from Jacobson, LaLonde, and Sullivan (1993). $w_t$ is the wage at displacement, $w_{\tau}$ is the wage at re-entry, $w_{\tau+4}$ is the wage 1 year later.

<sup>(b)</sup>The data numbers for consumption loss are taken from Browning and Thomas F. Crossley (2001).

<sup>(c)</sup>The wealth data come from the 1994 PSID wealth supplement and include housing wealth and private pension holdings. Mean annual income is defined as average annual household income for heads of household aged 22-62.

<sup>(d)</sup>Income growth is defined as growth in annual earnings. This is then decomposed into permanent and transitory components by estimating the variance of the growth of earnings, and the autocovariance of growth. For the data, we report results taken from the lower panel of table III in Meghir and Pistaferri (2004). For our lower education group we take a weighted average of the results in the two lower groups in that paper. For the data generated by the simulations, we impose an MA(1) in the levels of the transitory shock, implying an MA(2) for the overall residual earnings growth. This is consistent with the simulated autocovariance of earnings as well as the earnings data in the PSID.
displacement. Finally, one implication of our model is that the displacement costs are likely to be relatively short-lived. Indeed, we calculate that 1 year after returning to work, wages of the low educated are only 6.1 percent below their pre-displacement wages; for high educated individuals the figure is 9.1 percent. These figures are very close to the ones we extrapolate from Jacobson, LaLonde, and Sullivan (1993) over a similar time horizon.

**Consumption Fall at Unemployment.** Jonathan Gruber (1997) and Browning and Crossley (2001) have explored empirically the consumption loss associated with unemployment. Consumption will be lower in unemployment if the job loss followed a permanent loss in productivity, which implies a life-cycle wealth effect and a lower incentive to work. In addition if there are non-separabilities between consumption and leisure, as in our model, and leisure is a substitute for consumption, individuals will cut back on consumption as leisure increases. Finally, if individuals are unable to smooth consumption through borrowing against future income they will also have to cut back more than they otherwise would. Our model contains these three effects, with the source of the income loss being the loss of the match as well as possibly the wealth effect implied by a negative permanent shock; the non-separability being built into the structure of the utility function; the liquidity constraint being the restriction that assets have to be non-negative.

In Table 3 we report average consumption loss by education group and compare it to Browning and Crossley (2001).\(^\text{37}\) They use data from a Canadian sample that includes many two-earner households; moreover the Canadian welfare system implies different replacement rates. To control for these differences we compare the percentage consumption lost relative to the percentage income lost following unemployment. Our figures are remarkably close to the Browning and Crossley number, whose comparable figure is 56 percent.\(^\text{38}\) We calculate a 61 percent relative loss for the low educated and a 45 percent loss for the high educated. The Browning-Crossley sample contains 70 percent low-educated individuals. So on this score the model fits the facts very well indeed.

**Arrival Rate of Offers.** Table 3 reports the arrival rate of accepted job offers among workers and among the unemployed. For workers, the arrival rate of accepted offers is low because workers

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\(^{37}\)Our numbers are not comparable to the Gruber calculation because he only uses food. One would need to inflate his number by dividing it by the marginal budget share for food to get back to a total consumption figure.

\(^{38}\)Their figures are a 14 percent consumption loss and a 25 percent loss in income, which imply the number we report (56 percent).
only choose to move if they receive a better offer than the wage at their existing firm. Among the unemployed a much higher proportion of offers are accepted: the table shows that, among the low educated, 62 percent of offers are accepted by the unemployed, whereas only 4.7 percent of offers are accepted by the employed. The fast movement out of unemployment is not surprising because the offer arrival rate when employed is not much lower than it is for the unemployed, making the option value of unemployment low.

**Wealth Accumulation.** Table 3 reports, for individuals aged 30-35 and 50-55, the ratio of average wealth holdings to average annual income. Our model captures fairly accurately the level of wealth holdings of the low educated at both stages of life. For the high educated, the model underpredicts slightly the wealth holdings, but the rate of wealth accumulation is similar.

**Variability of Income.** As noted earlier, despite there being no explicit transitory shocks in the wage process, the interaction of job destruction, the participation and mobility decisions, and other components of employment risk generate a permanent/transitory structure in the time series of earnings from the model. These have very similar time-series properties to the ones for the PSID reported by Meghir and Pistaferri (2004). As in that paper, the growth of earnings is consistent with a transitory/permanent shock decomposition, with the latter being MA(1) in levels (MA(2) in growth). The estimates of the variances of each component are remarkably similar. Moreover, the MA coefficient for the transitory shock for the high-education group is $-0.65$, which compares to $-0.51$ reported in the paper. The low-education MA parameters are however a bit further apart with the one from the model being $-0.53$ and the one estimated from the PSID $-0.26$.

**Wages and Wage Variability.** Figure 3 shows how wages and the cross-section variance of wages evolve over the lifecycle for the two education groups. The top line reports the wage profile for those who are working. Average wages increase with age in the model partly due to search leading to changes in the match component, partly due to deterministic growth in productivity (as reflected in the estimated age effects), and partly due to the composition change caused by selection into work. Early in life, much of wage growth is due to search leading to improved matches. This can be seen by the increase in the difference between the path of actual wages and the path of wages net

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of the match effect. The difference between this latter line and the offered wage profile shows the contribution of selection, which only becomes a substantial factor after the age of 50.

Figure 3: Life-Cycle Wage Profiles

Figure 4 shows how the variance of wages increases over the lifecycle (pooled over both education groups). The line labelled “data” reports the actual cross-sectional variance in the SIPP at each age, while the line labelled “predicted age effect” reports the predicted cross-sectional variance using the unit root specification for wages assumed in our model. The line labelled “simulations” shows how the cross-section variance of wages for workers in the simulations evolve over the lifecycle. The flattening out in the cross-section variance that occurs at older ages in the data and is also observed in the simulations arises because of the sharp decline in participation among men over 50.

6 Evidence on the Wage Process and Alternatives

Our choice of specification for the stochastic process of wages is based on a long and well-established literature. However this does not make it uncontroversial. In this section, we address three issues regarding the specification: first, we consider whether controlling for mobility affects estimates of the persistence of shocks; second, we consider modeling the match component as evolving stochastically over time; finally, we consider introducing heterogeneity in income growth rates, in the way that Guvenen (2006) does.

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40 The “estimated age effect” is obtained controlling for cohort effects and assuming that time effects average out to zero and are orthogonal to a time trend.
Mobility and Persistence of Shocks. One difficulty with relying on the existing literature to support our specification of a unit root in wages is that the papers that provide supporting evidence do not control for worker mobility. In particular, job mobility decisions might create the impression of greater persistence in income: for example, if mobility is ignored, wage increases due to moving firms will be seen as permanent shocks, whereas when we control for mobility, shocks are identified from within-firm wage movements which may be less persistent. Our specification imposes a unit root on within-firm wage movements, but the concern is that wages are not as persistent as they seemed to be when mobility was ignored. To address this, we estimate the autocovariance properties of wage growth residuals for workers who do not change jobs, controlling for selection. These autocovariances still conform to the random walk process, rather than to one with less than unit-root persistence. In particular the autocovariances are statistically and economically insignificant after the first two lags and there is no evidence of a gradually declining pattern which would have been observed if a simple AR(1) process had generated the data.\footnote{We construct an estimate of the wage growth residual in the PSID using the estimates from the SIPP discussed in Section 4. Growth is measured annually. We use the 1987-1992 PSID because it allows us to look at longer autocovariances. In the PSID whether one is a mover or stayer is identified correctly (up to measurement error). For stayers, the autocovariances at lags 0, 1, 2, 3, and 4 are, respectively, 0.0854 (s.e. 0.0038), −0.0213 (0.0015), −0.0005 (0.0013), 0.0021 (0.0018), and −0.0029 (0.0030).} Thus allowing for mobility cannot account for the earlier finding of a random walk.

Stochastic Match Component. The analysis in this paper has been based on the assumption that the match-specific effect is constant for the duration of the match and that the shocks to
individual productivity persist beyond the current job. In fact, since these shocks are permanent, they persist forever. If we had matched employer-employee data, we could have allowed for a richer specification for the match component. Given our data restrictions, however, the alternative assumption that we explore is that individual heterogeneity is captured by a fixed effect, while the match effect is subject to permanent stochastic shocks.\footnote{The results reported in this section are available in the web appendix.}

This specification has a number of interesting implications. First, the shock to the match-specific effect is in effect transitory from an economic point of view: the individual can change jobs following a bad realization of the match effect, thus wiping the slate clean from past shocks even if these are permanent at the match level. This has important implications for the cross-sectional variance of wages by age. In the data, this increases almost linearly with age. We find that our preferred model matches the growth of the variance by age far better than the alternative model, which instead predicts almost a flat profile due to the absence of very persistent economic shocks (see Figure 4).

The second piece of evidence in support of our preferred model comes from the estimates of the variance of initial wages required in the two specifications. Evidence from MaCurdy and Thomas Mroz (1995) and others shows that more recent cohorts face a higher variance on entering the labor market. In our preferred specification the variance of initial wages is indeed higher for more recent cohorts, while in the alternative specification it decreases with year of birth. The reason for the latter is that the only way the alternative model can fit the increasing variance of wages by age that exists in the data is to attribute the increase to cohort effects, i.e. older cohorts have a higher variance on entering the labor market.

Third, we find that the alternative specification is incapable of capturing the downturn in employment from about age 45 onwards and the increased duration of unemployment spells for older people that is present in the data. This contrasts with the success of our preferred specification. The reason is that with the alternative wage specification anyone quitting due to a negative shock to the match-specific effect can start again with a new job and “wash away” the past. By contrast, when these negative shocks are individual specific and so persist across matches, an individual is more likely to remain unemployed, particularly with the availability of government insurance.

Thus overall, the alternative stochastic specification with the random walk in the match com-
ponent is not consistent with the data and does not allow the model to match key moments of the
data anywhere near as well as we do with our preferred model. This is not to say that a richer
model that combined aspects of both stochastic specifications for wages could not do even better.
However, given the data limitations, we offer a parsimonious model, that is capable of replicating
basic features of the data.

**Heterogeneous Income Growth Model.** Guvenen (2008) argues that the increase in the cross-
sectional variance with age can also be achieved by allowing for heterogeneity in income growth
rates (as in Michael Baker, 1997), alongside a lower degree of persistence of income shocks (an
AR(1) parameter of 0.82). This specification will produce an increase in the cross-section variance
of income with age, as in the data and in our preferred specification. If there were less persistence
in income shocks but without the income growth heterogeneity, then the variance would be concave
in age and so both components are needed to match the data.

Distinguishing this specification from one with a permanent shock is not straightforward: in the
data, the autocovariance of earnings growth is zero for observations more than two or three periods
apart, which is consistent with the permanent shock model and not quite in line with the model
allowing for an individual-specific fixed effect in growth (the “random growth model”), which would
imply nonzero autocovariances at all lags. Guvenen points out that with a high-enough positive
autoregressive coefficient the effects of the random growth on the autocovariance structure can be
obscured and its presence can only be identified by considering the covariance of income growth many
years apart when the persistent shock has little effect (12 lags or so, see Guvenen, 2009). However,
long panel data sets have too much attrition over such long time periods to provide a reliable test
of this view. A further difficulty with this specification, as pointed out by Guvenen (2007), is that
it would not match the growth in the variance of consumption because of the limited innovations to
income over the life cycle. In order to match the growth in the variance of consumption when the
income process does not have a unit root, it is necessary to assume that individuals do not know
their own growth term and have to learn about it over time. This gives rise to innovations over
the life cycle leading to an increasing variance of consumption; however, it is difficult to distinguish
statistically between learning about a random growth model and a model with a permanent shock.43

43Henry Farber and Robert Gibbons (1996) assume that individual productivity is unknown to the firm, but it is
Further, Steven Haider and Gary Solon (2006) suggest that such heterogeneity in trends may be most important early in the life cycle, but that there is little evidence for its importance beyond age 30. Guvenen and Anthony Smith (2008) use consumption and income data to try to separate out the two models. Further, we do not preclude that introducing labor supply choices into a Guvenen framework might generate interesting alternative implications. We have chosen what is a parsimonious specification that fits the data well both in terms of income and in terms of consumption behavior.

7 The Implications of Risk

Our model and characterization of shocks has important implications for the impact of risk on behavior and welfare. Understanding these is relevant particularly when designing and evaluating policies such as unemployment insurance, food stamps or other transfers (e.g. tax credits), which effectively insure part of the risk individuals face. In this model, we have exogenous, uninsurable idiosyncratic shocks and so welfare would increase if insurance were provided in a non-distortionary way. We also have behavioral responses to insurance built in both through changes in employment and through changes in savings. This means we can quantify the risk-sharing benefits of different sorts of insurance as well as identifying the behavioral effects induced by the insurance programs.

In this section, we show first the effects of varying productivity risk, looking at the impact on employment, output, and asset accumulation, as well as welfare. We then show the effects of varying the various aspects of employment risk, including job destruction and firm heterogeneity.

In the model the actions of individuals are linked to each other because we require the government budget to balance over the life cycle of a cohort, which is assumed to have $N$ members. Thus we impose

$$\sum_{i=1}^{N} \sum_{t=1}^{T} \frac{1}{R_t} \left[ (B_{it} E_{it}^{UI} (1 - E_{it}^{DI}) + D_{it} E_{it}^{DI} (1 - P_{it}) + E_{it}^{T} T_{it} \right] = \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{1}{R_t} \tau_{w} w_{it} h P_{it} + \text{Deficit}$$

(11)

where $B_{it}$ is unemployment insurance, $D_{it}$ is disability insurance and $T_{it}$ are food stamps; $E_{it}^{UI}$, $E_{it}^{DI}$ and $E_{it}^{T}$ are 1/0 indicators of recipiency for each of the programs, respectively, and $P_{it} = 1$ denotes learned over time through observation of output, and so wages are updated in a Bayesian sense. They prove that this will result in the wage residual being a martingale. Thus our unit-root characterization can also be consistent with a less-than-complete information case, but we have not considered the implications of the learning case as yet.
employment. On the right-hand side \( \tau_w w_t h P_t \) represents tax revenue from a working individual. The deficit term represents unaccounted expenditures or revenues and will be kept constant across all simulation experiments. Following a simulated policy change we select the tax rate \( \tau_w \) to satisfy this government budget constraint; individuals take \( \tau_w \) as given.\(^{44}\) Budget balance is imposed within a particular education group. We therefore abstract from the insurance between groups that Attanasio and Davis (1996) found to be important. Allowing the budget to balance over all education groups would confound the issue we are considering with distributional questions.

To define the welfare cost of risk write the lifetime expected utility of an individual as

\[
E_0 U_k = E_0 \sum_t \beta_t \left( \frac{c_{kt} \exp\{\eta P_{kt}\}}{1 - \gamma} \right) \]

where the subscript \( k \) refers to the implied consumption and labor supply stream in the baseline economy \((k = 1)\) or an alternative economy with different risk characteristics \((k = 2)\) and \( E_0 \) is the expectation at the beginning of working life. Now define \( \pi \) as the proportion of consumption an individual is willing to pay to be indifferent between environment \( k = 2 \) and \( k = 1 \). This is implicitly defined by

\[
E_0 U_{2|\pi} = E_0 \sum_t \beta_t \left( \frac{(1 - \pi) c_{2t} \exp\{\eta P_{2t}\}}{1 - \gamma} \right) = E_0 U_1
\]

which implies that \( \pi = 1 - \left[ \frac{E_0 U_1}{E_0 U_{2|\pi = 0}} \right]^{\frac{1}{\gamma}} \).

Since there are no aggregate shocks in the economy and no business-cycle fluctuations, we do not consider the value of, for example, smoothing the effect of the business cycle (as in Lucas, 1987) or the value of removing variation in the extent of idiosyncratic risk over the life cycle (as in Storesletten, Telmer, and Yaron, 2001). Such insurance removes heteroskedasticity but the average level of risk remains. Thus we focus entirely on the cost to the individual of idiosyncratic risk, which would be insured in a first best setting.

### 7.1 Wage Risk

We start by considering the impact of the permanent shock to wages. We have already shown that allowing for job mobility substantially reduces the amount of risk that we attribute to unexpected changes in productivity. Indeed this reduction is likely to be very important.

\(^{44}\)We assume that unemployment insurance and disability insurance are financed by the tax on wages, even though in reality the financing is partly imposed upon the firms. However, if the incidence of the tax falls on the workers, as most empirical studies find, our assumption is inconsequential.
In Figure 5 we report $\pi$, the willingness to pay to avoid changes in risk relative to the estimated baseline.\footnote{In all our counterfactual experiments we hold constant the job arrival rates, the job destruction rates and the implicit pay policy of the firm that determines in equilibrium how the match surplus is shared between workers and the firm. These could all change and could be endogenised in an extension of our model.} This willingness to pay arises because individuals are averse to the greater risk associated with increases in $\sigma \zeta$. Note that when we change the risk faced by the individual many aspects of behavior will change, including labor supply as well as unemployment and employment durations. These will result in output changes, which we also show on the graph, labelled as $\Delta \ln y$. The willingness-to-pay parameter has factored in all these aspects. While changes in wage risk end up implying relatively low changes in output (particularly for the higher educated), they imply large welfare losses. Thus a 50 percent increase of $\sigma \zeta$ to 0.159 for the high-educated individuals implies a 3.7 percent loss in output but a willingness to pay to avoid this increase of 19.2 percent of consumption (the numbers are in Table 4). It is not straightforward to compare across education groups because the baseline is different. However, we note that if we increase the variance for the low educated to the same level (0.159), welfare goes down by less (16.4 percent). This is partly due to the effect of the welfare programs, which are more important for this lower wage group. Output declines by more for the low educated, as is visible from the graph, driven by the decrease in employment shown in Figure 6. However, the overwhelming impression here is that wage risk is a major determinant of welfare, well beyond its impact on output, making insurance for such risk potentially very valuable.

Figure 5: Welfare Costs and Output Effects of Varying $\sigma \zeta$

More detail on the effects of varying wage risk is provided in Table 4: productivity shocks have substantial effects on unemployment durations, on consumption growth, and on rates of asset
accumulation, particularly among the young. In particular, for the high-educated group, as $\sigma_\zeta$ increases by 50 percent, the median rate of wealth accumulation for individuals aged 25-35 almost doubles. This faster accumulation results in an earlier and faster rate of decumulation when old, alongside lower employment rates and longer unemployment durations. Table 4 also reports the implications for the standard deviation of annualized earnings growth. The changes in the permanent variance have a somewhat muted effect on the variance of earnings growth.

### 7.2 Employment Risk

The two important parameters associated directly with employment risk are job destruction and the variance of the match-specific effect. We now consider the implications of varying each of these parameters.

**Job Destruction.** Figure 7 shows the impact on welfare and output of varying job destruction, $\delta$. Increases in job destruction have large effects on output partly through increasing unemployment and partly through limiting the time that individuals are matched with the best firms. Individuals are willing to pay to avoid the increase in job destruction. There are three aspects to this willingness to pay: there is a loss of income reflected in the overall loss in output; there is an increase in employment risk; and there is an offsetting increase in leisure time. For both education groups, the effect of the increased riskiness, which otherwise would have raised the welfare loss above the loss of output, is offset by the value of increased leisure resulting from the fall in employment shown in Figure 8. More
Table 4: Comparative Statics: Varying $\sigma_\zeta$

<table>
<thead>
<tr>
<th>$\sigma_\zeta$</th>
<th>$\pi$</th>
<th>$\Delta \ln y$</th>
<th>$\sigma_y$</th>
<th>Mean Duration</th>
<th>Mean $\Delta \ln c_t$</th>
<th>Median $(\Delta \lambda/y)$</th>
<th>Age at max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>High education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.053</td>
<td>0.125</td>
<td>0.021</td>
<td>0.299</td>
<td>2.0</td>
<td>0.033</td>
<td>0.005</td>
<td>0.026</td>
</tr>
<tr>
<td>0.095</td>
<td>0.033</td>
<td>0.006</td>
<td>0.324</td>
<td>4.7</td>
<td>0.029</td>
<td>0.012</td>
<td>0.11</td>
</tr>
<tr>
<td><strong>0.106</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.332</strong></td>
<td><strong>6.0</strong></td>
<td><strong>0.029</strong></td>
<td><strong>0.013</strong></td>
<td><strong>0.14</strong></td>
</tr>
<tr>
<td>0.159</td>
<td>−0.188</td>
<td>−0.039</td>
<td>0.367</td>
<td>13.1</td>
<td>0.030</td>
<td>0.015</td>
<td>0.27</td>
</tr>
<tr>
<td><strong>Low education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.053</td>
<td>0.085</td>
<td>0.050</td>
<td>0.400</td>
<td>2.9</td>
<td>0.018</td>
<td>0.005</td>
<td>0.014</td>
</tr>
<tr>
<td><strong>0.095</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.420</strong></td>
<td><strong>8.1</strong></td>
<td><strong>0.017</strong></td>
<td><strong>0.010</strong></td>
<td><strong>0.10</strong></td>
</tr>
<tr>
<td>0.106</td>
<td>−0.027</td>
<td>−0.012</td>
<td>0.425</td>
<td>9.4</td>
<td>0.017</td>
<td>0.011</td>
<td>0.14</td>
</tr>
<tr>
<td>0.159</td>
<td>−0.161</td>
<td>−0.056</td>
<td>0.449</td>
<td>14.2</td>
<td>0.019</td>
<td>0.014</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Notes: $\sigma_y$ is the standard deviation of annual earnings growth. For the columns concerning the amount of assets, the denominator is average realized earnings (net of the fixed cost of work) in the education-specific baseline. Consumption growth is annualized consumption growth. Duration is measured in quarters. The baseline case is in bold.

Figure 7: Welfare Costs and Output Effects of Varying Job Destruction

Details of the effects of varying $\delta$ on behavior are provided in Table 11 in Appendix C. There it is shown that increasing $\delta$ from 0.1 to 0.7 causes the standard deviation of earnings growth to double for both education groups. A large part of this change in variability of earnings occurs because of the periods of non-employment that job destruction induces.

Durations of unemployment are shorter when $\delta$ is higher because of a composition effect: more of the unemployed are out of work because of job destruction than because of low productivity, and so are more likely to receive job offers above their reservation wage. The rate of wealth accumulation decreases with a higher value of $\delta$ because the increase in time unemployed reduces opportunities for accumulation.
Firm Heterogeneity. Figure 9 shows the impact on welfare and output of varying firm heterogeneity, $\sigma_a$. Increasing firm heterogeneity implies a greater variety of firms in terms of their productivity. However, because of on-the-job search the best firms tend to be overrepresented in terms of accepted offers, which pushes output up, as clearly seen in the figure. This effect of selection into the best firms leads to greater employment among older individuals when heterogeneity is increased, as shown in Figure 10. Increased heterogeneity therefore pushes welfare up, but not as much as output: increasing heterogeneity implies an increase in the cost of job loss because workers are in danger of losing a more coveted job. Interestingly the effect is not symmetric around our baseline estimates: decreasing firm heterogeneity decreases welfare as much as it does output.

More details of the effects of varying $\sigma_a$ on behavior are provided in Table 12 in Appendix C. For those aged 25-35, greater firm heterogeneity leads to faster wealth accumulation for the high-education group, but to slower wealth accumulation for the low-education group. This reflects the offsetting incentives caused on the one hand by greater risk inducing faster accumulation, while on
the other hand, the greater expected future income induces slower accumulation.

**Offer Arrival Rates.** The overall impact of varying the arrival rate of job offers when unemployed is shown in Table 13 in Appendix C, and described in more detail here. The faster arrival rate of offers reduces involuntary unemployment, but may increase voluntary unemployment, as the opportunity cost of waiting for a better offer declines (as discussed in Krussell et al., 2008). Which of these effects dominates in the simulations depends on age: for those under 50, employment falls as $\lambda^n$ increases from 0.66 to 0.96, whereas for those over 50, employment rises. For the low educated, the fall among the young is less, and the rise among the old is greater, than for the high educated. The net changes are, however, very small. Further, average unemployment durations decrease by about 1 month. Overall, these changes in employment, alongside the improved matching, lead to output increasing for the low educated by 2 percent, and for the high educated by 1 percent.

These effects translate into welfare gains of 1.6 percent and 1.2 percent, respectively. Compared to the output change, this suggests the high educated value the increased arrival rate more highly. This is because the opportunity cost of being unemployed is greater for the high educated: the high educated receive higher wage offers and are not as well insured as the low educated by the Unemployment Insurance and Food Stamps programs. For both groups, rates of wealth accumulation are hardly affected by the changing arrival rate.
7.3 Comparing Wage Risk and Job Destruction

In this section we carry out the following simple experiment as one way of comparing the relative importance of wage risk with the risk of job destruction.\footnote{We thank Richard Rogerson for this suggestion.} For each education group, we compute the unconditional variance of annual income growth ($\Delta \ln y_{it}$) as implied by our model (and which matches the data closely). We then consider the welfare effects of decreasing this variance by 5 percent, first by decreasing the job destruction rate and then by decreasing the variance of the permanent shock to wages. This provides a metric for comparing the two types of risk. The required change in the parameter to achieve this is presented in Table 5 with the other results of this experiment.

For both education groups, the willingness to pay for lowering of the variance of annual income growth by 5 percent via a reduction in the variance of productivity shocks is substantially higher than when this is achieved based on a reduction in the rate of job destruction. The output effect of these reductions is different for the two education groups: for the low-education group a reduction in job destruction leads to a higher increase in output than does a reduction in the variance of the productivity shocks. The reverse is true for the higher education group. This however does not change the fact that both groups would rather see a reduction in the variance of productivity shocks. Based on this metric productivity risk is more costly than employment risk. Part of the reason for this is that productivity risk tends to increase the variance of the permanent component of earnings, whereas job destruction has less persistent effects on income.

7.4 Implications of Government Insurance

Our framework is well suited for evaluating the welfare effects of the various programs. Such an evaluation requires a life-cycle model where risk plays an important role, and where labor supply is endogenous in order to capture the key source of moral hazard and a further mechanism of self-insurance over and above savings. The Food Stamps program tends to provide partial insurance for income loss whatever the source of the loss, while UI offers compensation when income loss is associated with job destruction. As such each program can be thought of as targeting different
Table 5: Welfare Loss Comparing Productivity Risk and Job Destruction

<table>
<thead>
<tr>
<th>Scenario</th>
<th>∆Parameter</th>
<th>Willingness to pay percent</th>
<th>Δ ln y</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(π × 100)</td>
<td>(×100)</td>
</tr>
<tr>
<td>High education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job destruction, δ</td>
<td>0.028 → 0.026</td>
<td>0.49 percent</td>
<td>0.95 percent</td>
</tr>
<tr>
<td>Productivity shocks, σζ</td>
<td>0.106 → 0.094</td>
<td>3.48 percent</td>
<td>0.66 percent</td>
</tr>
<tr>
<td>Low education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Job destruction, δ</td>
<td>0.049 → 0.045</td>
<td>0.74 percent</td>
<td>1.67 percent</td>
</tr>
<tr>
<td>Productivity shocks, σζ</td>
<td>0.095 → 0.077</td>
<td>4.05 percent</td>
<td>2.73 percent</td>
</tr>
</tbody>
</table>

Note: The table shows the implications of a reduction in the job destruction rate and in the standard deviation of the innovations to wages that each, respectively, lead to a decrease in the variance of annual income growth by 5 percent. The standard deviation of income growth decreases from 0.332 to 0.324 for the low educated and from 0.420 to 0.409 for the high educated.

We consider a small (1 percent) increase in the government spending on social insurance and compare the welfare effects of channeling this change, in turn, into UI and into the Food Stamps-type program. This calculation focuses on the insurance benefit of these programs because there is no cross-group redistribution. The results are presented in rows 1 and 2 of Table 6. Row 3 considers the

Table 6: Welfare Effects of Government Programmes

<table>
<thead>
<tr>
<th>Scenario</th>
<th>High education</th>
<th>Low education</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Willingness to pay percent</td>
<td>Willingness to pay percent</td>
</tr>
<tr>
<td></td>
<td>(π × 100)</td>
<td>(π × 100)</td>
</tr>
<tr>
<td>Unemployment Insurance</td>
<td>0.19</td>
<td>0.24</td>
</tr>
<tr>
<td>Food Stamps</td>
<td>0.25</td>
<td>0.30</td>
</tr>
<tr>
<td>Tax change</td>
<td>0.08</td>
<td>0.15</td>
</tr>
</tbody>
</table>

48 There are two caveats to these comments: first, these calculations ignore the interactions that may arise between increases in the tax rate needed to fund increased generosity of a program and the take-up of that program: the increased tax rate will make programs more valuable by reducing the benefit of being at work. Second, in practice these programs are funded by taxing the general population and consequently involve a large component of cross-group insurance.
welfare benefit of using the extra spending to reduce the proportional tax rate. For both education
groups the most valuable program is the means-tested program because it provides some insurance
against large negative (and permanent) shocks. In considering the tax cut, the two groups are willing
to pay 0.08 percent and 0.15 percent of consumption, respectively, to see the 1 percent increase in
expenditure going to a tax cut. This implies that both groups prefer the money to be spent on UI
or the means-tested program, rather than on a decrease in taxation within their own group.49

8 Conclusions

The nature and sources of risk are particularly important in understanding how to design public
insurance programs such as unemployment and disability insurance, Food Stamps and other income
support programs found across many countries. In this paper we take the first step in understanding
and quantifying different sources of risk that we broadly define as productivity and employment risk.
In our model productivity risk is identified by permanent shocks to wage rates, while employment
risk is generated by job destruction and by the fact that matches are heterogeneous and so the nature
of the job obtained has a random component to it. We demonstrate the welfare effects of varying
each type of risk and show the output implications of these changes. Varying productivity risk has
relatively low impact on output, because low draws are counteracted by high productivity outcomes
for other people. However the welfare effects of changing productivity risk are very high. On the
other hand, increasing job destruction rates has a large impact on output through the increased
periods of non-employment, as well as increasing the variance of income. The effect on welfare is
relatively low, however, because its impact is transitory. Finally, the large heterogeneity in match
quality is highly valued for the possibilities it offers for wage growth over the life cycle.

Our paper is clearly only a step in understanding the role of risk and the way it interacts with
welfare programs. One important avenue for further research, taken up by Low and Pistaferri (2009)
is that of modeling the nature of different shocks (such as health shocks) using direct information.
This will allow modeling in a more complete setting the participation and entitlement to programs
such as Disability Insurance.

49 We do not present numbers for increasing the spending on the Disability Insurance program. In our model,
spending on the Disability Insurance and Social Security program is valued less than the tax cut. However, our model
of DI in effect abstracts from the impact of large or catastrophic health shocks against which insurance is likely to be
very valuable and which is provided mainly by DI in reality.
We have also highlighted the importance of modeling the wage process and disentangling the impact of exogenous fluctuations to that of fluctuations resulting from responses to shocks, such as moving jobs or quitting work. Indeed we show that our approach leads to a much lower estimate for the variance of the productivity shock than that implied by the usual modeling of the stochastic process for income. The next step in this research agenda is to model explicitly the sources of these shocks, derive the implications for equilibrium pay setting, and link these to the match-specific effect and its stochastic properties. This will allow one to model explicitly how pay would change as risk parameters are modified or in response to welfare programs. Some first steps in this direction are the models of Jeremy Lise, Meghir, and Robin (2008). However, these models still do not allow for risk aversion, which would be a crucial component for applying them in this setting. Finally, allowing for macroeconomic shocks would allow us to revisit their relative importance to idiosyncratic shocks as in Lucas (1987), in a richer setting and to examine the way that micro and macro shocks interact.
Appendix: Numerical Solution

Households have a finite horizon and so the model is solved numerically by backward recursion from the terminal period. At each age we solve the value function and optimal policy rule, given the current state variables and the solution to the value function in the next period. This approach is standard. The complication in our model arises from the combination of a discrete choice (to work or not) and a continuous choice (over saving). This combination means that the value function will not necessarily be concave. The discrete choice about whether to move or not is less problematic because we assume that there is no cost of moving. This means that the decision to move depends only on the relative size of the match effect in the current and new firm.

There are five state variables in this problem: age, employment status, the asset stock, the permanent component of earnings, $u_{it}$, and the match component, $a_{ij(t_0)}$. Age and employment status are both discrete. We also discretize both the permanent component of earnings and the distribution of possible matches, leaving the asset stock as the only continuous state variable. Since the permanent component of earnings is non-stationary, we are able to approximate this by a stationary, discrete process only because of the finite horizon of the process. We select the discrete nodes in this process to match the paths of the mean shock and the unconditional variance over the life cycle. In particular, the unconditional variance of the permanent component must increase linearly with age, with the slope given by the conditional variance of the permanent shock. Our estimates of the wage variance are for annual shocks, but the model period is one quarter. We reconcile this difference by imposing that each quarter an individual receives a productivity shock with probability 0.25, and this implies that productivity shocks occur on average once a year. This timing means that individuals who stay with the same firm expect pay to be constant over a year.

Value functions are increasing in assets $A_t$ but they are not necessarily concave, even if we condition on labor market status in $t$. The non-concavity arises because of changes in labor market status in future periods: the slope of the value function is given by the marginal utility of consumption, but this is not monotonic in the asset stock because consumption can decline as assets increase and expected labor market status in future periods changes. This problem is also discussed in Lentz and Torben Tranaes (2005). By contrast, in J. P. Danforth (1979) employment is an absorbing state and so the conditional value function will be concave. Under certainty, the number of kinks in the
conditional value function is given by the number of periods of life remaining. If there is enough uncertainty, then changes in work status in the future will be smoothed out leaving the expected value function concave: whether or not an individual will work in $t + 1$ at a given $A_t$ depends on the realization of shocks in $t + 1$. Using uncertainty to avoid non-concavities is analogous to the use of lotteries elsewhere in the literature. In the value functions (7) and (8), the choice of whether or not to work in $t + 1$ is determined by the maximum of the conditional value functions in $t + 1$.

In solving the maximization problem at a given point in the state space, we use a simple golden search method. We solve the model and do the calibration assuming this process is appropriate. We then check that the results in our baseline case are unaffected when we use a global optimizing routine, simulated annealing. It is worth stressing that there are parameter values for which the techniques we used do not work. In particular, as the variance of shocks gets sufficiently low, the non-concavities in the expected value functions become problematic.

To give a clear example of this, we show the solution without retirement and so the life cycle ends at age 62. The same qualitative pictures are observed with retirement. Figure 11 shows consumption as a function of assets in the period preceding the end of life, $T - 1$, for workers and non-workers, and for different firm types, conditioning on individual productivity. The sharp decline in consumption when working at a given firm in $T - 1$ arises at the asset stock which induces the individual not to work in the next period, $T$. Because the individual is not working in period $T$, lifetime income is
lower and consumption falls in both periods. On the other hand, since leisure is higher in the next period, overall welfare is higher: the value function is monotonically increasing in assets. The extent of the fall depends on the degree to which consumption and leisure are substitutes. If we look at the solution in earlier time periods or the solution with retirement included, these sharp drops are smoothed out. This is partly because the fall in income associated with a change in employment in one period in the future can be smoothed out over several periods. It is also partly because uncertainty smooths the discreteness: a marginal increase in asset holdings in period \( t \) will only change employment in \( t + 1 \) in particular states and so has less of an impact on consumption in period \( t \) than if employment in \( t + 1 \) changed in all states.

\section*{B Appendix: Deriving Moments for the Variance of Wages}

In our preferred model, wages are given by

\[
\ln w_{it} = d_t + x_{it}' \psi + u_{it} + e_{it} + a_{ij(t_0)}
\]

where \( u_{it} = u_{it-1} + \zeta_{it} \) is the permanent component, \( e_{it} \) the measurement error, and \( a_{ij(t_0)} \) is the match effect. Thus wage growth is

\[
\Delta \ln w_{it} = \Delta d_t + \Delta x_{it}' \psi + \zeta_{it} + \Delta e_{it} + \xi_{it} M_{it}
\]

where \( \xi_{it} = (a_{ij(t)} - a_{ij(t_0)}) \) denotes the change in the match effect for those who switched employment. The latent indices associated to working and moving are:

\[
P^\ast_{it} = z_{it}' \gamma + \pi_{it}
\]
\[
M^\ast_{it} = k_{it}' \theta + \mu_{it}
\]

for all \( t \). Define workers in period \( t \) by \((P_{it} = 1) \equiv (P^\ast_{it} > 0)\) and similarly those who have changed workplace since the previous year by \((M_{it} = 1) \equiv (M^\ast_{it} > 0)\).

Wage growth is measured annually. However, all decisions by the individual are made quarterly in the model. To make these two consistent we assume that the individual receives a wage shock each quarter with 0.25 probability. Then when we observe a wage over a year we assume it is the result of
aggregating wages over the quarters that the individual worked in this firm. Thus the employment Mills ratio we use is the average Mills ratio over the number of quarters the individual worked with the firm where he is currently observed. This effectively assumes that the employment and wage shocks are both independent over time.\footnote{We make this assumption for tractability: otherwise we would have to condition jointly on an eight-dimensional selection vector, i.e. the sequence of decisions to work in each quarter over 2 years. As we do it we still condition on each of the employment outcomes but not on the joint event.}

Denoting the number of quarters the individual worked by $Q$ and noting that the Mills ratio for a working quarter is $\lambda_{it}^P = \frac{\phi(z_{it}^q \gamma_q)}{\Phi(z_{it}^q \gamma_q)}$ (with $\phi$ and $\Phi$ being the standard normal density and probability functions, respectively), for annual wages the Mills ratio we use is the average of the quarterly Mills ratios, i.e. $\lambda_{it}^P = \frac{1}{Q} \sum_{q=1}^{Q} \frac{\phi(z_{it}^q \gamma_q)}{\Phi(z_{it}^q \gamma_q)}$. When computing higher-order moments we also construct $z_{it}^q \lambda_{it}^P = \frac{1}{Q} \sum_{q=1}^{Q} \frac{\phi(z_{it}^q \gamma_q)}{\Phi(z_{it}^q \gamma_q)} z_{it}^q$. This procedure is not exact aggregation, but an approximation because the dependent variable is the log of the average wage and the right-hand side is a model for the average log wage (both within the year).

However, the approximation error is likely to be negligible for two reasons: first, it is proportional to the difference between the arithmetic and geometric mean of wages within a year that depends on the within-year/within-firm variance of wages, which is small. Second, any systematic error in the levels is removed by taking the growth of wages and the remaining part will be absorbed by the measurement error, leaving the estimate of the variance of the permanent effect $\sigma_{\zeta}$ unaffected.

In all calculations the mobility equation is kept constant across quarters and measures the probability that an individual changes jobs between any two years, which is what we need to correct for mobility selection.

Conditioning on working in periods $t$ and $t-1$, we obtain:

$$ E (\Delta \ln w_{it} | P_{it} = P_{it-1} = 1) = E (\Delta \ln w_{it} | M_{it} = 0, P_{it} = P_{it-1} = 1) (1 - \Pr (M_{it} = 1)) + E (\Delta \ln w_{it} | M_{it} = 1, P_{it} = P_{it-1} = 1) \Pr (M_{it} = 1) $$

$$ = \Delta d_t + \Delta x_{it}^l \psi + G_{it} $$

where

$$ G_{it} = \rho_{\zeta} \sigma_{\zeta} \lambda_{it}^P + \rho_{\xi} \sigma_{\xi} \lambda_{it}^P \Phi (k_{it}^l \theta) + \rho_{\xi} \sigma_{\xi} \lambda_{it}^P \Phi (k_{it}^s \theta) + \rho_{\xi_{t-1}} \sigma_{\lambda_{it-1}} \Phi (k_{it}^l \theta) $$

The $\rho_{ls}$ are correlation coefficients between stochastic terms $l$ and $s$. Thus, $G_{it}$ is a “selection
term accounting for conditioning on multiple indices. The estimation of the equation above is standard (Heckman 2-step method).

The variances of the wage shocks are identified by the restrictions imposed on the moments of residual wage growth \( g_{it} \equiv \zeta_{it} + \Delta e_{it} + \xi_{it} M_{it} \). Using formulae from G. M. Tallis (1961), the first moment for job stayers and movers, respectively, is:

\[
E (g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 0) = -\rho_{\zeta\mu}\sigma_{\zeta}\hat{\lambda}_{it} + \rho_{\zeta\varepsilon}\sigma_{\varepsilon}\hat{\lambda}_{it} M_{it}
\]

\[
E (g_{it}|P_{it} = P_{it-1} = 1, M_{it} = 1) = \left(\rho_{\zeta\mu}\sigma_{\zeta} + \rho_{\zeta\xi}\sigma_{\xi}\right) \lambda_{it} + \left(\rho_{\zeta\varepsilon}\sigma_{\varepsilon} + \rho_{\xi\xi}\sigma_{\xi}\right) \lambda_{it} M_{it} + \rho_{\xi \varepsilon \xi \varepsilon} \sigma_{\xi} \lambda_{it} (13)
\]

where \( \lambda_{it}^M = \frac{\phi(k_{it}^M \theta)}{\Phi(k_{it}^M \theta)} \) and \( \lambda_{it} = \frac{\phi(k_{it}^\theta)}{1-\phi(k_{it}^\theta)} \). The parameters of the model are clearly not identified from the first moments alone. Consider then the second moment for workers who either stay or move:

\[
E (g_{it}^2 | P_{it} = P_{it-1} = 1, M_{it} = 0) = \sigma_e^2 \left(1 - \frac{\rho_{\zeta\varepsilon}^2 \sigma_{\varepsilon}^2 + \rho_{\zeta\mu}^2 \sigma_{\mu}^2 \theta^2 \lambda_{it}^M}{-2\rho_{\zeta\mu}\rho_{\zeta\varepsilon}\sigma_{\mu}\sigma_{\varepsilon}\lambda_{it} M_{it}}\right) + 2\sigma_e^2
\]

and

\[
E (g_{it}^2 | P_{it} = P_{it-1} = 1, M_{it} = 1) = \sigma_e^2 \left(1 - \frac{\frac{\rho_{\zeta\varepsilon}^2 \sigma_{\varepsilon}^2}{\lambda_{it}^M} - \frac{\rho_{\zeta\mu}^2 \sigma_{\mu}^2 \theta^2 \lambda_{it}^M}{-2\rho_{\zeta\mu}\rho_{\zeta\varepsilon}\sigma_{\mu}\sigma_{\varepsilon}\lambda_{it} M_{it} - 2\rho_{\zeta\mu}\rho_{\zeta\varepsilon}\sigma_{\mu}\sigma_{\varepsilon}\lambda_{it} M_{it-1}}}{-2\rho_{\zeta\mu}\rho_{\zeta\varepsilon}\sigma_{\mu}\sigma_{\varepsilon}\lambda_{it} M_{it}}\right)
\]

\[+ \sigma_e^2 \left(1 - \frac{\rho_{\zeta\varepsilon}^2 \sigma_{\varepsilon}^2}{\lambda_{it}^M} - \frac{\rho_{\zeta\mu}^2 \sigma_{\mu}^2 \theta^2 \lambda_{it}^M}{-2\rho_{\zeta\mu}\rho_{\zeta\varepsilon}\sigma_{\mu}\sigma_{\varepsilon}\lambda_{it} M_{it-1}}\right) + 2\sigma_e^2
\]

Finally, we consider the first order autocovariance \( E (g_{it} g_{it-1}) \). At least in principle, we could use information on those who work for three periods in a row and classify them on the basis of their mobility decisions. In practice, there are too few observations in the relevant categories to be able to get structural identification in this case. We thus assume \( \Pr (M_t = 1, M_{t-1} = 1) \approx 0 \) and consider only the restrictions on the unconditional autocovariance, namely

\[
E (g_{it} g_{it-1}) = -\sigma_e^2
\]

C Appendix: Tables on Employment, Mobility, Calibration
Table 7: Summary Statistics, SIPP 1993 panel

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earnings</td>
<td>6755.03</td>
<td>5209.55</td>
</tr>
<tr>
<td>Typical weekly hours</td>
<td>37.69</td>
<td>17.09</td>
</tr>
<tr>
<td>Employed</td>
<td>0.87</td>
<td>0.33</td>
</tr>
<tr>
<td>Age</td>
<td>40.19</td>
<td>9.91</td>
</tr>
<tr>
<td>White</td>
<td>0.88</td>
<td>0.32</td>
</tr>
<tr>
<td>Married</td>
<td>0.71</td>
<td>0.45</td>
</tr>
<tr>
<td>Unearned income (net of transfers)</td>
<td>1037.62</td>
<td>2205.08</td>
</tr>
<tr>
<td>High education</td>
<td>0.55</td>
<td>0.50</td>
</tr>
<tr>
<td>Public sector</td>
<td>0.07</td>
<td>0.26</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.21</td>
<td>0.41</td>
</tr>
<tr>
<td>North Central</td>
<td>0.27</td>
<td>0.45</td>
</tr>
<tr>
<td>South</td>
<td>0.26</td>
<td>0.44</td>
</tr>
</tbody>
</table>

Note: The table report quarterly averages. Earnings and unearned income are converted in real terms using the CPI (CPI=1 in 1992:10).

Table 8: The Employment Probit for each Quarter

<table>
<thead>
<tr>
<th></th>
<th>High school or less</th>
<th>College dropout or more</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1</td>
<td>Q2</td>
</tr>
<tr>
<td>Age</td>
<td>0.0129</td>
<td>0.0107</td>
</tr>
<tr>
<td>Age^2/100</td>
<td>(0.0033)</td>
<td>(0.0033)</td>
</tr>
<tr>
<td>White</td>
<td>0.1207</td>
<td>0.1153</td>
</tr>
<tr>
<td>(0.0137)</td>
<td>(0.0135)</td>
<td>(0.0134)</td>
</tr>
<tr>
<td>Married</td>
<td>0.1410</td>
<td>0.1571</td>
</tr>
<tr>
<td>(0.0103)</td>
<td>(0.0105)</td>
<td>(0.0105)</td>
</tr>
<tr>
<td>Region dummies</td>
<td>28.51</td>
<td>34.68</td>
</tr>
<tr>
<td></td>
<td>(3.0%)</td>
<td>(3.0%)</td>
</tr>
<tr>
<td>Year dummies</td>
<td>0.35</td>
<td>1.02</td>
</tr>
<tr>
<td></td>
<td>(2.84%)</td>
<td>(2.60%)</td>
</tr>
<tr>
<td>Unearned income</td>
<td>−0.0480</td>
<td>−0.0424</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0019)</td>
</tr>
<tr>
<td>UI generosity</td>
<td>−0.0010</td>
<td>−0.0009</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0004)</td>
</tr>
</tbody>
</table>

Notes: The table reports marginal effects. Asymptotic standard errors in parentheses. For region and year dummies we report the value of the χ² statistics of joint significance and, in parentheses, the degrees of freedom and the p-value of the test.
### Table 9: The Mobility Equation

<table>
<thead>
<tr>
<th></th>
<th>High school or less</th>
<th>College dropout or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.0128</td>
<td>-0.0148</td>
</tr>
<tr>
<td>(0.0031)</td>
<td>(0.0025)</td>
<td></td>
</tr>
<tr>
<td>Age(^2)/100</td>
<td>0.0112</td>
<td>0.0142</td>
</tr>
<tr>
<td>(0.0038)</td>
<td>(0.0031)</td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>-0.0300</td>
<td>0.0091</td>
</tr>
<tr>
<td>(0.0129)</td>
<td>(0.0091)</td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>-0.0096</td>
<td>-0.0177</td>
</tr>
<tr>
<td>(0.0089)</td>
<td>(0.0071)</td>
<td></td>
</tr>
<tr>
<td>Not-for-profit</td>
<td>-0.0549</td>
<td>0.0057</td>
</tr>
<tr>
<td>(0.0180)</td>
<td>(0.0144)</td>
<td></td>
</tr>
<tr>
<td>Industry dummies</td>
<td>81.20</td>
<td>65.66</td>
</tr>
<tr>
<td>(4 df; p-value (\chi^2) 0%)</td>
<td>(4 df; p-value (\chi^2) 0%)</td>
<td></td>
</tr>
<tr>
<td>Region dummies</td>
<td>6.81</td>
<td>2.35</td>
</tr>
<tr>
<td>(3 df; p-value (\chi^2) 8%)</td>
<td>(3 df; p-value (\chi^2) 50%)</td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>35.65</td>
<td>76.50</td>
</tr>
<tr>
<td>(2 df; p-value (\chi^2) 0%)</td>
<td>(2 df; p-value (\chi^2) 0%)</td>
<td></td>
</tr>
<tr>
<td>Unearned income</td>
<td>0.0027</td>
<td>0.0016</td>
</tr>
<tr>
<td>(0.0006)</td>
<td>(0.0004)</td>
<td></td>
</tr>
<tr>
<td>UI generosity</td>
<td>0.0008</td>
<td>-0.0001</td>
</tr>
<tr>
<td>(0.0004)</td>
<td>(0.0003)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table reports marginal effects. Asymptotic standard errors in parentheses. For region and year dummies we report the value of the \(\chi^2\) statistics of joint significance and, in parentheses, the degrees of freedom and the p-value of the test.

### Table 10: Observed and Matched Moments

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Age</th>
<th>High education</th>
<th>Low education</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Data</td>
<td>Model</td>
</tr>
<tr>
<td>Employment rate</td>
<td>22-31</td>
<td>0.97</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>32-41</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>Mean duration</td>
<td>42-51</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>52-61</td>
<td>0.73</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>22-26</td>
<td>1.65</td>
<td>1.65</td>
</tr>
<tr>
<td></td>
<td>37-31</td>
<td>2.08</td>
<td>2.11</td>
</tr>
<tr>
<td></td>
<td>32-36</td>
<td>1.93</td>
<td>2.30</td>
</tr>
<tr>
<td>Mean duration</td>
<td>37-41</td>
<td>2.47</td>
<td>2.34</td>
</tr>
<tr>
<td></td>
<td>42-46</td>
<td>2.84</td>
<td>2.78</td>
</tr>
<tr>
<td></td>
<td>47-51</td>
<td>5.41</td>
<td>5.96</td>
</tr>
<tr>
<td></td>
<td>52-56</td>
<td>7.45</td>
<td>6.49</td>
</tr>
<tr>
<td></td>
<td>57-61</td>
<td>5.50</td>
<td>4.09</td>
</tr>
</tbody>
</table>
Table 11: Comparative Statics: Varying the Job Destruction Rate $\delta$

<table>
<thead>
<tr>
<th>$\delta$</th>
<th>$\pi$</th>
<th>Output</th>
<th>$\sigma_y$</th>
<th>Mean Duration</th>
<th>Mean $\Delta \ln c_t$</th>
<th>Median $(\Delta A/y)$</th>
<th>Age at max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
<td>0.028</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
<td>0.049</td>
<td>-0.049</td>
<td>-0.087</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>96</td>
<td>0.07</td>
<td>-0.090</td>
<td>-0.153</td>
</tr>
</tbody>
</table>

Notes: For the columns concerning the amount of assets, the denominator is average realized earnings (net of the fixed cost of work) in the education-specific baseline. Duration is measured in quarters. The baseline case is in bold.

Table 12: Comparative Statics: Varying the Standard Deviation of the Match-Specific effect $\sigma_\alpha$

<table>
<thead>
<tr>
<th>$\sigma_\alpha$</th>
<th>$\pi$</th>
<th>Output</th>
<th>$\sigma_y$</th>
<th>Mean Duration</th>
<th>Mean $\Delta \ln c_t$</th>
<th>Median $(\Delta A/y)$</th>
<th>Age at max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
<td>0.11</td>
<td>-0.185</td>
<td>-0.185</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
<td>0.22</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
<td>0.33</td>
<td>0.130</td>
<td>0.180</td>
</tr>
</tbody>
</table>

Notes: For the columns concerning the amount of assets, the denominator is average realized earnings (net of the fixed cost of work) in the education-specific baseline. Duration is measured in quarters. The baseline case is in bold.

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Table 13: Comparative Statics: Varying the Job Arrival Rate for the Unemployed $\lambda^n$

<table>
<thead>
<tr>
<th>$\lambda^n$</th>
<th>$\pi$</th>
<th>Output</th>
<th>$\sigma_y$</th>
<th>Mean $\Delta$</th>
<th>Mean $\Delta \ln c_t$</th>
<th>Median ($\Delta A/y$)</th>
<th>Age at max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Duration</td>
<td>$\Delta \ln c_t$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>47-52</td>
<td>25-44</td>
<td>45-62</td>
<td>25-35</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>36-50</td>
<td>51-62</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### High education

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.96</td>
<td>0.005</td>
<td>0.003</td>
<td>0.331</td>
<td>6.0</td>
<td>0.029</td>
<td>0.013</td>
<td>0.14</td>
</tr>
<tr>
<td><strong>0.82</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.332</strong></td>
<td><strong>6.0</strong></td>
<td><strong>0.029</strong></td>
<td><strong>0.013</strong></td>
<td><strong>0.14</strong></td>
</tr>
<tr>
<td>0.76</td>
<td>-0.002</td>
<td>-0.002</td>
<td>0.331</td>
<td>6.0</td>
<td>0.029</td>
<td>0.013</td>
<td>0.14</td>
</tr>
<tr>
<td>0.66</td>
<td>-0.006</td>
<td>-0.006</td>
<td>0.337</td>
<td>6.3</td>
<td>0.029</td>
<td>0.013</td>
<td>0.15</td>
</tr>
</tbody>
</table>

### Low education

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.96</td>
<td>0.010</td>
<td>0.013</td>
<td>0.416</td>
<td>7.7</td>
<td>0.017</td>
<td>0.010</td>
<td>0.11</td>
</tr>
<tr>
<td>0.82</td>
<td>0.003</td>
<td>0.004</td>
<td>0.420</td>
<td>8.0</td>
<td>0.017</td>
<td>0.010</td>
<td>0.11</td>
</tr>
<tr>
<td><strong>0.76</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.0</strong></td>
<td><strong>0.420</strong></td>
<td><strong>8.1</strong></td>
<td><strong>0.017</strong></td>
<td><strong>0.010</strong></td>
<td><strong>0.10</strong></td>
</tr>
<tr>
<td>0.66</td>
<td>-0.006</td>
<td>-0.007</td>
<td>0.424</td>
<td>8.3</td>
<td>0.017</td>
<td>0.010</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Notes: For the columns concerning the amount of assets, the denominator is average realized earnings (net of the fixed cost of work) in the education-specific baseline. Duration is measured in quarters. The baseline case is in bold.
References


[39] Krusell, Per L., Toshihiko, Mukoyama, Richard, Rogerson, and Ay-


economic Shifts in Wages from Cohort Specifications." Technical report, Stanford University.


