Twenty Years of Rising Inequality
in US Lifetime Labor Income Values

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ABSTRACT

In this paper we study the evolution of lifetime labor income inequality by constructing present value life cycle measures that incorporate both earnings and employment risk. We find that, even though lifetime income inequality is 40% less than earnings inequality, the total increase in lifetime income inequality over the past 20 years is the same as earnings inequality. While the total increase is the same, the pathways there differ with earnings inequality experiencing a steady increase and lifetime income inequality increasing in spurts particularly in the latter half of the 1990s. Finally, we find the changes in lifetime income inequality are primarily driven by changes in earnings mobility and changes in the earnings distribution itself, changes employment risk and the composition of the sample, such as the shift toward attaining more education and the aging population, do not play a large role.

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1 Introduction

The historical study of earnings inequality and the search for an explanation of the sharp acceleration in the growth of earnings inequality in the eighties in the U.S. has generated a large empirical literature (see Levy and Murnane, 1992, Gottschalk, 1997, and Katz and Autor, 1998, for surveys). This literature has primarily focussed on measuring inequality using cross-section data on wages, earnings, and income. The increase in earnings inequality over the 1980s and 1990s can be seen in panel (c) of Figure 1 which shows the earnings distribution for full-time male workers aged 16-65 from the U.S. Current Population Survey (CPS). While such contemporaneous measures of inequality are important, it has long been recognized that individual welfare not only depends on an individual’s current employment position, described by whether the individual is employed or not and if employed at which wage, but also on the expected evolution of this position.

This dynamic dimension of income inequality has been addressed in the literature via three approaches. The first approach aims at studying the stability of an individual’s position in the wage distribution over time, either by decomposing wages into permanent and transitory components (e.g. Lillard and Willis, 1978, MaCurdy, 1982, Gottschalk and Moffitt, 1994, or more recently Geweke and Keane, 2000, and Moffitt and Gottschalk, 2002) or by estimating wage mobility across different wage quantiles over time (e.g. Gottschalk, 1997, Buchinsky and Hunt, 1999).

The second approach analyzes consumption behavior. Consumption models are relevant in this context, because they provide a basis for examining whether individuals benefit from mechanisms designed to share consumption risk in the face of fluctuating income, health hazards, etc. (e.g. Attanasio and Davis, 1996 and Storesletten et al, 2000) The consumption literature ranges from descriptive work that compares and contrasts consumption and wage inequality (e.g. Cutler and Katz, 1992) to work that uses consumption models to identify changes in the variance of permanent and transitory income shocks and study how different types of shocks are transmitted to consumption (e.g. Blundell and Preston, 1998). These studies have been somewhat hindered by the lack of panel data on consumption and a means to properly treat durables. Despite these limitations, the consumption literature has highlighted the important point that between-group insurance exists but is imperfect. For example, Attanasio and Davis (1996) find that year-to-year changes in consumption are uncorrelated with yearly changes in relative wages, whereas ten-year differences exhibit a correlation coefficient near one.

The third approach to studying the dynamics of income inequality uses models of wage mobility and employment transitions to construct individual measures of lifetime income. It then applies the
same methodologies used to analyze earnings and income inequality (ninety-ten percentile ratios, Gini coefficients, etc.) to the distributions of these long-run income aggregates. We are aware of only two papers, Flinn (2002) and Cohen (1999), that use this approach. Both papers examine cross-country differences in inequality and find that examining lifetime inequality measures changes the perception regarding relative levels of inequality across countries. For example, Flinn (2002) constructs lifetime welfare measures for young Americans and Italians and finds striking differences across the two countries in the distributions of wages and lifetime welfare. The U.S. has higher wage inequality but lower lifetime earnings inequality than Italy. Cohen (1999) compares labor market inequality levels in France and the U.S. and finds that wage inequality is about 60% greater in the U.S. than in France, but using lifetime welfare measures reduces the gap to 15%. These results indicate that the degree of wage and employment mobility varies significantly across countries and is an important component when measuring long-run inequality.

There is a clear link between lifetime income-based inequality measures and welfare (or consumption) inequality. Lifetime income inequality analyses are only informative about welfare if the degree of insurance is large enough. If the degree of insurance is large enough, expected lifetime income measures permanent income which determines consumption. In such a case, the analyses of consumption inequality and lifetime income inequality should be equivalent. However, if consumers are liquidity constrained and consumption tracks current income, then it is the structure of current labor earnings that better matches the distribution of individual welfare. In any case, studies of current and lifetime earnings inequality provide two useful benchmarks for the analysis of the distribution of individual welfare. Regardless of the limitations of lifetime income analyses with respect to welfare analysis, there is indeed a definite gain in moving from analyzing employment and wage mobility separately to the construction of a lifetime labor income measure. The latter allows for the aggregation of individual data on employment, wage levels and risk into a single synthetic measure, which in turn allows one to make unequivocal statements about changes over time in the cross-sectional dispersion of individual wage trajectories or inter-country comparisons.

In this paper we develop a methodology based on the lifetime labor income approach using a wage mobility and employment transition model to study the evolution of inequality in expected and realized lifetime earnings. Specifically, for each individual in each year, we compute the discounted sum of expected (remaining) lifetime earnings and the discounted sum of a possible (remaining) lifetime earnings trajectory, assuming that each individual is subjected in the future to the same distribution of shocks as older workers face today. We then calculate the annuity values of these
future streams to allow for comparisons across different age groups. Finally, we compare and contrast standard inequality measures of lifetime income and earnings over time. Our focus on the evolution of lifetime inequality over time is a departure from Flinn (2002) and Cohen (1999) who analyze inequality levels across countries at a point in time. Importantly our approach allows us to study the nature of the increase in inequality in the U.S. over the last two decades. In particular, we can decompose the changes in lifetime income inequality levels over time into the relative importance of changes in wage and employment risk, as well changes in the overall distribution of wages and sample composition. In addition, the analysis also provides evidence on the role of permanent and transitory variance components.

The main innovation in our study, with respect to the studies of Flinn (2002) and Cohen (1999), is that we allow for nonstationarity in individual labor trajectories and build our analysis on a much more flexible econometric framework. With regard to the former, individuals age deterministically and all parameters, including wage distributions and wage mobility processes, are allowed to change as the individuals age and increase their potential experience levels. This is in contrast to models that allow for aging via a stochastic process or not at all, and allows us to match the actual aging process observed in the data. It also provides a means to incorporate the fact that individuals face both transitory and permanent changes in their earnings process.

With regard to our econometric framework, we let the cross-sectional distribution of earnings be unspecified and utilize a non-parametric approach to estimation. Our wage mobility process is forced to be consistent with the estimated marginal earnings distribution, yet it is flexible enough to match the mobility data well. To estimate the model parameters and construct our lifetime values we use data from the March US CPS (full and matched samples). Here we deviate from other long run inequality studies that have used longer panel data sets such as the Panel Study of Income Dynamics (PSID). Use of the CPS gives us the advantage of being able to reproduce well known patterns and allows for a direct comparison of our results with other inequality studies. In addition the CPS provides us with large, nationally representative samples covering both the 1980s and the 1990s.

Our main results include the following. First, as in Cohen (1999) and Flinn (2002), the high degree of wage and employment mobility in the US translates into lifetime income inequality levels that are 40% lower than those for wages. This is primarily because young workers profit more than other workers from wage mobility. Returns to education are not high enough, when one takes into account the dynamics of future wages, to compensate for the effect of experience via wage
mobility. Second, while employment and wage mobility rates fluctuate over the sample period, by 1997 they have returned to their 1977 levels. This pattern helps explain why both wages and lifetime income exhibit the same increase in inequality over the past 20 years. Taking a closer look at the respective evolutions of earnings and lifetime income inequality, we find that earnings inequality tends to increase steadily from the mid 1970s to the late 1990s without interruption. In contrast, the dynamics of lifetime income inequality exhibit three different short-run trends: in the late 1970s the evolution of lifetime income inequality is parallel to that of earnings; from 1982 to 1993 it remains stable as the top of the distribution tended to move in tandem with the bottom; finally, the post-1993 period is characterized by a greater return to education in lifetime income than in wages with lifetime income inequality increasing at a faster rate than earnings inequality. These results thus shed a somewhat different light on the dynamics of income inequality. The story here is not so much the bottom falling as it is with wages, but rather the top increasing with differences in educational returns and mobility playing a large role. Decomposing these changes we find the changes in lifetime income inequality are primarily driven by changes in earnings mobility and changes in the earnings distribution itself, changes employment risk and the composition of the sample, such as the shift toward attaining more education and the aging population, do not play a large role. Lastly, in terms of permanent and transitory variance components we show that the results of our analysis are consistent with Moffitt and Gottschalk's (2002) findings from the Panel Study of Income Dynamics (PSID) for the 1980s, but not for the 1990s. In particular, our measure shows an important increase in the permanent variance component in the late 1990s that is not evident in the PSID data.

The plan of the paper is as follows. The next section develops a theoretical framework for computing lifetime values. Data and estimation are discussed in Section 3. Section 4 analyzes the results. The last section concludes.

2 The model

In this section we develop our model of labor income dynamics and explain how we construct the present value of an individual’s labor market position under static expectations. At the end of the section we discuss how to aggregate the individual values into a welfare measure.
2.1 Individual trajectories

Consider a worker with potential experience $a$ (age minus age at the end of school). For simplicity we assume discrete time and $a$ is thus any integer in $\{1, \ldots, A\}$, where $A$ is the (exogenous) length of a working lifetime. At any given point in time, the worker can be either employed or unemployed. We model employment status transitions as follows. A worker who is employed (unemployed) at the beginning of period $t$ has a probability $\delta_{a,t}$ ($\lambda_{a,t}^0$) of becoming unemployed (employed) by the end of the period. These parameters, and those defined hereafter, may depend on a set of predetermined variables like education, gender, race, etc. However, for expositional simplicity, we present the model for a population of workers that differ only with respect to potential experience, which naturally changes over calendar time as individuals age, because different individuals are born at different dates.

Income levels in the two employment states are characterized as follows, where by convention all payments are received at the end of the period. An unemployed worker of experience level $a$ at the beginning of period $t$ receives non-employment income $b_{a,t}$, net of search costs. If the worker is lucky enough to find a job in period $t$, he will receive wage, $w_{t+1}$ drawn from the sampling distribution $F_{a,t}$.

Modelling the wage mobility process of workers who remain employed over two subsequent periods is more complicated. In choosing a model we face the following dilemma. It seems natural to proceed with lifetime labor incomes, as with cross-sectional wages, and use the same battery of inequality indices for the distribution of lifetime values as for earnings distributions, e.g. Gini coefficients. But in order for all inequality indices to be applicable, the distribution of present values needs to have the same standard properties as earnings distributions. Continuity, in particular, is required. The past work on modelling wage mobility process has either used extensions of ARMA models or mixtures of ARMA models (e.g. Lillard and Willis, 1978, McCurdy, 1982, Gottschalk and Moffitt, 1994, Geweke and Keane, 2000 and Moffitt and Gottschalk, 2002), or has adopted less constrained parametric approaches of the wage mobility process using by Markov chains over a discrete wage space (e.g. Shorrocks, 1976, 1978, Buchinsky and Hunt, 1996). Discrete-space Markov chains have the advantage of providing a more precise and more flexible description of wage dynamics than standard AR(1)MA models. However, they generate (approximately) continuous present values only if the discretization of the earnings support is sufficiently precise. Unfortunately, the estimation of large transition probability matrices is unreasonable given the size of most available data sets. Moreover, in our framework the assumed wage mobility process must be sufficiently
simple for the computation of lifetime value functions to remain tractable.

To solve this dilemma we develop a new—and hopefully innovative—wage mobility model by borrowing features from the search literature. In search theory it is assumed that job offers arrive randomly over time and workers accept offers only if they satisfy a lower bound constraint determined by the current state. Thus, the probability of acceptance depends on the worker’s employment state and, if employed, on his location in the wage offer distribution. It is this feature that we build on below.¹

Consider an employed worker with experience level \(a\) in period \(t\) who is currently paid a wage \(w_t\). At the end of period \(t\), the employment spell is either terminated with probability \(\delta_{a,t}\) or it is not. In the latter case a new wage \(w_{t+1}\) is paid at the end of period \(t + 1\). We postulate the following probability density measure for the conditional distribution of \(w_{t+1}\) given \(w_t\):

- the density at \(w_{t+1} > w_t\) is \(\lambda_{a,t}^+(w_t) \cdot dF_{a,t}(w_{t+1})\),
- the density at \(w_{t+1} < w_t\) is \(\lambda_{a,t}^-(w_t) \cdot dF_{a,t}(w_{t+1})\),
- and the probability that \(w_{t+1} = w_t\) is \(1 - \lambda_{a,t}^+(w_t) \cdot [1 - F_{a,t}(w_t)] - \lambda_{a,t}^-(w_t) F_{a,t}(w_t)\),

where \(dF_{a,t}(\cdot)\) refers to the sampling probability measure that is assumed to be common to unemployed and employed workers. Note that the distribution of \(w_{t+1}\) given \(w_t\) is thus absolutely continuous with respect to the sampling measure \(dF_{a,t}(\cdot)\) except at \(w_t\) where it displays a mass. This specification of the transition probabilities is reminiscent of regime switching models. With a certain probability that depends on the current wage (specifically, \(\lambda_{a,t}^+(w_t) [1 - F_{a,t}(w_t)]\)) the wage process goes up and with another probability \((\lambda_{a,t}^-(w_t) F_{a,t}(w_t))\) it goes down. There is also a positive probability that the wage does not change.²

This simple wage mobility model displays the usual characteristics of probability transition matrices. It is easier to move up when one is at the bottom of the wage distribution, since \(1 - F_{a,t}(w_t)\) decreases with \(w_t\), and to move down when one is at the top. Moreover, by allowing for the additional factors \(\lambda_{a,t}^+(\cdot)\) and \(\lambda_{a,t}^-(\cdot)\), upward mobility can be more or less frequent than downward mobility, and by making their levels conditional on current wages, future wages can be made more or less inert.

¹While we are partial to the search interpretation, the above framework can stand alone without search as the basis of the mobility processes. One may then use the search interpretation purely as a descriptive device. In fact, the only place where “behavior” plays a role is when we compute the values of non-labor time \((b_{a,t})\) by relating them to the observed lower bounds of the sampling distributions \((F_{a,t})\).

²See Gottschalk (2001) for recent evidence pointing to the importance of modelling wage decreases as well as wage increases.
Another justification for the presence of factors $\lambda_{a,t}^+(\cdot)$ and $\lambda_{a,t}^-(\cdot)$ can be found in the search interpretation of this model. With probability $\lambda_{a,t}^+(\cdot)$ the worker draws an alternative job offer from the wage offer distribution $F_{a,t}$ that he accepts only if the wage offer is greater than his current wage, and with probability $\lambda_{a,t}^-(\cdot)$ he is laid off but is given a chance of drawing an offer within the same period without going through unemployment.

In order to better see the difference between our model and standard, quantile-based Markov chains, suppose that $\lambda_{a,t}^+(\cdot)$ and $\lambda_{a,t}^-(\cdot)$ take at most three different values according to which third of the cross-sectional (marginal) distribution of wages (at time $t$ and for employees with experience level $a$) the current wage $w_t$ belongs to. Now compare our wage mobility model with the $3 \times 3$ Markov chain defined on the same thirds of the distribution. The probability of moving to the upper third in the Markov chain model resembles $\lambda_{a,t}^+(\cdot)$, while the probability of moving to the lower third resembles $\lambda_{a,t}^-(\cdot)$. However, one advantage to proceeding as we do is that the Markov chain framework necessarily imposes that the probability of a wage increase (decrease) for those individuals with a wage in the top (bottom) third is zero, whereas in our model such a restriction only holds for the highest (lowest) observed wages. Lastly, by allowing the wage offer distribution $F_{a,t}$ to be continuous, we have constructed a Markov chain with a continuous state space. Therefore, our approach avoids the problems mentioned above without restricting flexibility.

2.2 Expectations

In order to calculate lifetime values we must decide how to treat future parameter values. In the real world workers’ future labor trajectories are uncertain. They value their current state and take decisions based on what they believe the structural parameters, denoted $\theta_t = \{\lambda_{a,t}^0, \delta_{a,t}, b_{a,t}, F_{a,t}, \lambda_{a,t}^+, \lambda_{a,t}^-, a = 1, \ldots, A\}$, will be in the future. One natural expectations hypothesis to adopt when modelling such behavior is rational expectations (RE). Unfortunately, computing expected lifetime labor income under the RE hypothesis requires the econometrician to fully model how the structural parameters evolve over time, including the effects of growth and business cycle conditions on the parameters. That is, the model should specify $\theta_t = h(\theta^{t-1}, u_t; \beta)$, where $\theta^{t-1}$ denotes past realizations of $\theta_t$, $u_t$ is a stochastic component and $\beta$ is a parameter. An alternative is adaptive expectations, which a priori complicates the econometrician’s task even more because, in addition to specifying a model for $\theta_t$, one must also specify how agents learn the value of $\beta$. We are aware of only one attempt at using such a complicated expectations hypothesis in the context of a dynamic choice model (see Buchinsky and Leslie, 1997).

There are two main approaches to the above problem. The first puts forth a model structure
that is simple enough (linear or approximately linear) for the RE hypothesis to be tractable. For
example, Hall and Mishkin (1982) derive the true individual mobility process in a life-cycle model
under the assumption of quadratic utility functions and a (rather) simple hypothesis on the structure
of the income process (linear with a deterministic trend, a stochastic trend and a transitory shock).
The second has a model structure that is too complicated (non linear) for it to be tractable with
time-varying structural parameters and RE expectations. In this case, the structural parameters
are usually assumed to be constant over time (see Hotz and Miller, 1993, or Keane and Wolpin,
1994, for two well cited examples).

We also adopt this latter assumption of static expectations. At time $t$, workers observe a value
of $\theta_t$ and expect $\theta_{t+1}, \theta_{t+2},$ etc., to remain constant and equal to $\theta_t$. That is, they use the wage
mobility process they observe individuals ten years older facing today to predict the wage mobility
process they will face ten years from now. Note that static expectations can be thought of as
an extreme case of RE, when there exists no better guess about the future values of $\theta_{t+1}, \theta_{t+2}, \ldots$
but the current value $\theta_t$. We show in the empirical analysis that the transition rate parameters
exhibit untrended, smooth dynamics that are characteristic of random walks. Therefore, static
expectations appear to be a good approximation of individuals’ true expectations process. The
static expectations hypothesis also allows us to make the following thought experiment that we
think is useful. Take two time periods, $t_0$ and $t_1$ with two sets of parameter values, $\theta_{t_0}$ and $\theta_{t_1}$,
respectively. Then compute the distribution of lifetime income for time $t_0$ and time $t_1$ that would
be observed if the structural parameters $\theta_{t_0}$ and $\theta_{t_1}$ remained constant for ever. Comparing the
implied lifetime income inequality for $\theta_{t_0}$ to the implied lifetime income inequality for $\theta_{t_1}$ is like a
comparative statics analysis and is useful as such.

2.3 Present values

Under the assumption of static expectations, let $\mathcal{E}_{a,t}(w)$ denote the present value of employment
at wage $w$ in period $t$ when experience is $a$. Let $\mathcal{U}_{a,t}$ be the present value of unemployment and $r$
be the discount rate. We make the simplifying assumption with regard to terminal values that

$$\mathcal{E}_{A,t} = \mathcal{U}_{A,t} = 0.$$ 

(1)

This assumption is justified if retirement income results only from savings (voluntary or involuntary)
and is therefore already counted in the gross wage summation.

The following Bellman equation holds true for the unemployment value

$$(1 + r)\mathcal{U}_{a,t} = b_{a,t} + \lambda_{a,t}^0 \int_{w_{a,t}}^{w_{a+1,t}} \mathcal{E}_{a+1,t}(x)dF_{a,t}(x) + \left[1 - \lambda_{a,t}^0\right] \mathcal{U}_{a+1,t}.$$ 

(2)
Similarly, for employment values

\[(1 + r)E_{a,t}(w) = w + \delta_{a,t}U_{a+1,t} + \lambda_{a,t}^+(w)\int_{w}^{\pi_{a,t}} E_{a+1,t}(x) dF_{a,t}(x) + \lambda_{a,t}^-(w)\int_{w}^{w} E_{a+1,t}(x) dF_{a,t}(x) + \left[1 - \delta_{a,t} - \lambda_{a,t}^+(w)\bar{F}_{a,t}(w) - \lambda_{a,t}^-(w)\bar{F}_{a,t}(w)\right] E_{a+1,t}(w).\] (3)

In the above Bellman equations we have used the static expectations hypothesis to substitute \(E_{a+1,t}(\cdot)\) and \(U_{a+1,t}\) for the future value functions \(E_{a+1,t+1}(\cdot)\) and \(U_{a+1,t+1}\) which are uncertain because they depend on \(\theta_{t+1}\). Thus, the only nonstationarity that remains comes from the aging process.

In the above equations the lowest wage \(w_{a,t}\) was allowed to vary by experience level. However, because there is a positive probability of keeping the same wage across years, the minimum wage given experience should be independent of the level of experience (but not of calendar time and education), i.e. \(w_{a,t} = w_t\). We impose this assumption which also has the advantage of simplifying the numerical computation of values. We do, however, allow the average wage to vary across experience levels.

We also make the assumption that employers have enough monopsony power to force the minimum wage \(w_t\) to be such that \(U_{a,t} = E_{a}(w_t)\). This assumption enables us to identify non-labor income \(b_{a,t}\) from wage data. It can be justified by the following equilibrium argument. If firms have enough monopsony power, the minimum wage offer in the market must be equal to the workers’ reservation wage, which equates the values of employment and unemployment.

It follows from these two arguments that evaluating equation (3) at \(w = w_t\) implies

\[(1 + r)U_{a,t} = w_t + \lambda_{a,t}^+(w_t)\int_{w_t}^{\pi_{a,t}} E_{a+1,t}(x) dF_{a,t}(x) + \left[1 - \lambda_{a,t}^+(w_t)\right] U_{a+1,t}.\] (4)

Equations (2) and (4) together then yield the following restriction on \(b_{a,t}\):

\[b_{a,t} = w_t + \left[\lambda_{a,t}^+(w_t) - \lambda_{a,t}^0\right] \int_{w_t}^{\pi_{a,t}} E_{a+1,t}(x) dF_{a,t}(x) - U_{a} \]. (5)

Equations (3) and (4) provide a set of forward recursive equations that together can be solved backward given the terminal condition \(E_{A,t} = U_{A,t} = 0\).

We end this section by considering one final problem with computing and comparing employment values across individuals with different life expectancies. In order to compare present values across all individuals, not only those within the same cohort, we compute the annuity value of
employment rather than the stock value. To convert stock values into annuity values we use the standard formula for an annuity:

\[ \frac{E_{a,t}(w)}{\sum_{t=0}^{A-1-a} \frac{1}{(1+r)^t}} = rE_{a,t}(w) \frac{(1 + r)^{A-1-a}}{(1 + r)^A - 1}. \] 

(6)

2.4 Ex-ante versus Ex-post Welfare Analysis

The empirical strategy we put forward in this paper consists of the following steps. For each pair of subsequent survey periods, we

1. estimate the year-to-year probability transition matrix of the individual labor trajectories conditional on education and experience;

2. construct the distribution of individual present values of future trajectories under static expectations about employment and wage mobility; and

3. compute the series of inequality measures for each cross-section of annuitized present values.

Step 2 of the preceding empirical strategy implies drawing for each individual of the survey (with a given education level, age, etc.) a set of potential future employment trajectories and averaging over them. If instead of drawing many individual trajectories to compute expectations we draw only one and compute the corresponding lifetime earnings, we can parallel step 3 by computing the series of inequality measures for each cross-section of annuitized “realized” future values.

The issue of whether one should characterize the inequality of individual labor trajectories ex ante or ex post is essentially arbitrary and axiomatic. In a recent paper Gottschalk and Spolaore (2002) remark that most welfare analyses refer to Atkinson and Bourguignon (1982) who specify the social welfare function as the average value of a concave transformation of individual utilities of uncertain income trajectories. They point out that a feature of this type of social welfare function is that intertemporal independence between earnings plays no special role. They go on to propose replacing realized future income values by certainty equivalents in the construction of the social welfare function. Time independence is then valued if aversion to risk in the second period is low enough. It is easy to see that the study of inequality in realized lifetime income is equivalent to an Atkinson-Bourguignon type of welfare analysis, whereas the study of inequality in expected lifetime income can be understood as a particular materialization of a Gottschalk-Spolaore type of welfare analysis.

3 Note that, if instead one chooses a convex transformation of the utility function, one obtains an inequality index. Maximizing social welfare or minimizing inequality are essentially the two sides of the same coin.
However, as arbitrary as the choice of welfare function is, there is little chance that looking at inequality levels in realized or expected lifetime income will make a significant qualitative difference. Of course, the dispersion of realized lifetime income across individuals will be necessarily bigger than the dispersion of expected lifetime income, but the way they depend on the structural parameters governing income mobility and cross-sectional income distributions is likely to be the same. Nevertheless, in the empirical analysis we present results for both.\footnote{A detailed discussion of these claims exists in the working paper version of this paper and is available upon request.}

3 Estimation

In this section we present the estimation methodology we use to estimate the underlying parameters of the model and to calculate the annuitized present and realized values. We wish to keep the estimation method as simple as possible, as we use many years of data containing large samples. For this reason we do not resort to time consuming non-linear estimation methods such as maximum likelihood but instead apply the method of moments. Below we discuss the estimators for a generic experience level. In the actual estimation of the model we compute the flow rates, and subsequent parameter estimates, for four different experience groups conditional on the year and education level. The Appendix presents the estimation method for data grouped by experience levels. First, we proceed to a description of the data.

3.1 Data

The data we use come from the 1978-1999 March CPS. To calculate the flow rates we need longitudinal data and therefore we use the matched March CPS files. For each year a portion of the March sample can be matched back to the previous March. By using information on current employment status and the prior year’s wages we can calculate transitions between employment and unemployment as well as wage mobility measures such as promotion and demotion rates. The first available matched March CPS file is the 1977-1978 file and we have data up to 1998-1999. We are unable to construct values for 1984, 1985, 1994 and 1995 because there are no matched CPS files for 1985-86 and 1995-96.\footnote{Peracchi and Welch (1995) examine the representativeness of the matched files and find attrition is highest among young people. Matched men (women) tend to exhibit higher (lower) participation rates and mean and median wages are higher amongst full year and full time matched workers. However, despite the differences in participation rates, they find no major bias in the estimates of the transitions between labor force states.} While we need the matched files to calculate the flows, to measure inequality levels we use the full March samples. In this way we ensure a more representative sample and more than double
our sample size. We restrict the samples to white males between the ages of 16 and 65 who work full-time (35 hours per week or more) or, if unemployed, are looking for full-time work. To standardize all annual earnings values we use a full-year earnings measure. Because we restrict the sample to full-time workers, our annualized earnings measure is not affected by the high degree of measurement error in hours worked. This restriction also brings our earnings measure closer to a wage measure and mitigates labor supply responses. Because our lifetime measure incorporates only year-to-year changes in earnings, we do not attempt to incorporate potential within year changes in wages. For a description of how we handle part-year workers see section A.3 in the Appendix.

Our use of full-time workers leads us to exclude females who are more likely to work part-time and to transition between part-time and full-time jobs. We also exclude blacks because their small sample sizes limit our ability to estimate some parameters within our defined skill groups. Full-time white males are a common focus of inequality studies and thus these restrictions also allow for direct comparisons with many other studies.

We exclude those who are self-employed, work without pay, are enrolled in school, or are retired. As stated above to standardize all earnings values we use a full-year earnings measure. Earnings are converted to full-year earnings by dividing annual wages and salaries by the number of weeks worked in the past year and multiplying by 52. Real annual earnings are then calculated using the CPI with 1983 as the base year. Top-coded values were multiplied by the year-specific constants in Liu (1998). These constants were calculated to ensure that mean earnings levels after correcting for top-coding were consistent with the means predicted by a regression model that assumed a normal error distribution and properly incorporated top-coded values in the log likelihood function. They range from 1 to 1.5 and therefore are close to the 1.33 value used by Juhn, Murphy and Pierce (1993). Finally, we weight all calculations by the March supplemental weights given in the CPS.

We note that in the 1995 CPS (1994 earnings) the question regarding past earnings was changed so as to make sure individuals included taxes in their earnings before all deductions calculation. There is some evidence that this resulted in higher reported levels of earnings (Lerman, 1997). This slight change in the question may be enough to cause a break in the series, but trends before and after 1994 should still be reflective of changes in inequality. We return to this issue in the discussion of the results.

We stratify the US data further to account for observed heterogeneity. We are able to retain reasonable sample sizes by stratifying on four education and four experience categories. The education categories are less than high school, high school, some college, and university. Experience is
computed as age minus years of education minus 6 and is categorized as follows: 0-9 years, 10-19 years, 20-29 years, and 30 plus years. We use Jaeger’s (1997) definition for years of education to maintain consistency across the sample period, and define less than high school to be less than 12 years of education, high school to be 12 years, some college to be 13 to 15 years, and university to be greater than or equal to 16 years. To then maintain consistency in terms of experience levels within an education group we set years of education equal to 10 if less than high school, 12 if high school graduate, 14 if some college and 16 if university.

The composition of the resulting sample is shown in panels (a) and (b) of Figure 2. The shift toward attaining more education is apparent as the fraction with some college or university is growing while the fraction with less than high school is declining. With respect to experience the largest increase has been in the 20-29 year range. In contrast, the lowest and highest levels of experience show significant declines.

To deal with outliers in the data we determine minimum and maximum earnings levels for each education group. This is necessary because our calculations of the employment values include mean and lowest wage calculations that are sensitive to extreme outliers. The trimming values are determined using the full March samples. At the bottom we trim earnings below the third percentile for each education group. This results in lowest earnings values that vary appropriately across groups reflecting each group’s relative position in the market. For the top end we trim earnings above the ninety-ninth percentile. Results from sensitivity analysis with respect to the amount of trimming at the bottom of the distributions are discussed in section 4.1.

3.2 Estimation

Let $M_{a,t}(w)$ be the number of employed workers in period $t$ with potential experience $a$ and a current wage less than $w$, and let $U_{a,t}$ be the number of unemployed workers in period $t$ with potential experience $a$. Next, define

$$
\Delta M_{a,t}(w) \equiv [M_{a+1,t+1}(w) - M_{a,t}(w)]
= \left[ \lambda_{a,t}^0 U_{a,t} + \int_w \lambda_{a,t}^{-}(x) dM_{a,t}(x) \right] F_{a,t}(w)
- \left[ \delta_{a,t} M_{a,t}(w) + \overline{F}_{a,t}(w) \int_w \lambda_{a,t}^{+}(x) dM_{a,t}(x) \right],
$$

where $\overline{F}_{a,t}(w) = 1 - F_{a,t}(w)$. That is, the change in the number of workers earning less than $w$ who had potential experience level $a$ in period $t$ and now have level $a + 1$ in period $t + 1$ is equal to the inflow of new hires, i.e. the number of formerly unemployed workers who found a job paying less
than \( w \) plus the number of formerly employed workers at a wage greater than \( w \) who experienced a wage decrease to a wage level below \( w \), minus the outflow, i.e. the number of workers with experience level \( a \) paid less than \( w \) last year who were laid off or who obtained a wage increase to a wage level above \( w \).

Rearranging the above equation and solving for \( F_{a,t}(w) \) yields

\[
F_{a,t}(w) = \frac{\Delta M_{a,t}(w) + \delta_{a,t} M_{a,t}(w) + \int_{w}^{w_{a,t}} \lambda_{a,t}^{+}(x) dM_{a,t}(x)}{\lambda_{a,t}^{0} U_{a,t} + \int_{w_{a,t}}^{w} \lambda_{a,t}^{-}(x) dM_{a,t}(x) + \int_{w}^{w_{a,t}} \lambda_{a,t}^{+}(x) dM_{a,t}(x)}. \tag{7}
\]

Conditional on \( \lambda_{a,t}^{0}, \delta_{a,t}, \lambda_{a,t}^{+}(x), \lambda_{a,t}^{-}(x) \), a non-parametric estimator of \( F_{a,t} \) can be constructed using equation (7) and non-parametric estimates of the earnings distributions in two adjacent periods that explicitly take into account the aging of the sample.

To recover the transition rate parameters from the data we use the method of moments. The reemployment rate, \( \lambda_{a,t}^{0} \), is estimated by the proportion of unemployed with experience level \( a \) in year \( t \) who transit to employment in \( t+1 \). The job destruction rate, \( \delta_{a,t} \), is estimated by the proportion of employees with experience level \( a \) in year \( t \) who are unemployed in year \( t+1 \). Let \( UM_{a,t} \) denote the number of unemployed workers with experience \( a \) at time \( t \) who are employed at \( t+1 \) and let \( MU_{a,t} \) be the number of employees at \( t \) with experience \( a \) who are unemployed at \( t+1 \). Our estimates are, therefore,

\[
\lambda_{a,t}^{0} = \frac{UM_{a,t}}{U_{a,t}}, \tag{8}
\]

\[
\delta_{a,t} = \frac{MU_{a,t}}{M_{a,t}}. \tag{9}
\]

The wage mobility rates \( \lambda_{a,t}^{+}(w) \) and \( \lambda_{a,t}^{-}(w) \) are estimated from promotion and demotion rates between year \( t \) and year \( t+1 \) observed in the data. Let \( M_{a,t}^{+}(w) \) \((M_{a,t}^{-}(w)) \) denote the number of employees with experience \( a \) and a wage less than \( w \) at time \( t \) who get promoted (demoted) to a higher (lower) wage at time \( t+1 \). Next, define

\[
p_{a,t}^{+}(w) \equiv \frac{dM_{a,t}^{+}(w)}{dM_{a,t}(w)},
\]

\[
p_{a,t}^{-}(w) \equiv \frac{dM_{a,t}^{-}(w)}{dM_{a,t}(w)},
\]

as the corresponding promotion and demotion rates, i.e. the proportions of employees with a year \( t \) wage equal to \( w \) who obtain a wage increase or decrease. From section 2.1 we have that

\[
\lambda_{a,t}^{+}(w) = \frac{p_{a,t}^{+}(w)}{F_{a}^{+}(w)}, \tag{10}
\]

\[
\lambda_{a,t}^{-}(w) = \frac{p_{a,t}^{-}(w)}{F_{a}^{-}(w)}. \tag{11}
\]
These equations show that the unknown rates $\lambda_{a,t}^+(w)$ and $\lambda_{a,t}^-(w)$ can be estimated with observations on promotion and demotion rates and an estimate of $F_{a,t}(w)$.

Returning to equation (7) and using the above definitions for $\lambda_{a,t}^+(w)$ and $\lambda_{a,t}^-(w)$, we now have a fixed-point functional equation for $F_{a,t}(\cdot)$:

$$F_{a,t}(w) = \frac{\Delta M_{a,t}(w) + \frac{MU_{a,t}}{M_{a,t}} M_{a,t}(w) + \int_w \frac{dM_{a,t}^+(w)}{F_{a,t}(w)}}{UM_{a,t} + \int_w \frac{dM_{a,t}^-(w)}{F_{a,t}(w)}}.$$  

An estimate of $F_{a,t}(\cdot)$ can, therefore, be obtained from observed mobility flows by iterating this equation until numerical convergence occurs.\(^6\) For implementation replace the above components with their empirical counterparts and approximate the integrals with sample sums. Once $F_{a,t}(\cdot)$ is estimated, equations (10) and (11) deliver estimates of $\lambda_{a,t}^+(w)$ and $\lambda_{a,t}^-(w)$.

We observe that almost everyone in our sample experiences a real wage change over two consecutive years. Given that CPS wages are measured with error, it seems sensible to acknowledge a wage change only if it is greater in absolute value than a certain threshold. Rather than using an arbitrary percentage as our threshold, we use a value that is related to the optimal width values associated with kernel density estimates of the corresponding log wage distribution for each education*experience group. These values range from 6.3 to 13.2 with an average of 9.3 over the 16 groups and 21 years. We, therefore, set the value at 5% (10% width) for every education*experience group.\(^7\)

In order to reduce the cost of computing the non-stationary employment and unemployment present values with experience taking on all of the possible integer values, we modified the above estimation procedure by constraining the structural parameters to be stepwise constant with respect to the experience variable. That is, $(\lambda_{0,t}^0, \delta_{a,t}, b_{a,t}, F_{a,t}, \lambda_{a,t}^+, \lambda_{a,t}^-) \equiv (\lambda_{i,t}^0, \delta_{i,t}, b_{i,t}, F_{i,t}, \lambda_{i,t}^+, \lambda_{i,t}^-)$, for all $a \in [a_i, a_{i+1}]$, where $i$ indicates one of the four experience groups ($i = 1, \ldots, 4$). Moreover, we further reduced the dimensionality of the problem by assuming $\lambda_{i,t}^+(\cdot)$ and $\lambda_{i,t}^-\cdot$ are constant over each third of the time $t$ cross-sectional distribution of earnings for workers with experience level $a \in [a_i, a_{i+1}]$. See the Appendix for further details on the exact way that we implement the estimation procedure.

\(^6\) We did not try to show that the right-hand-side functional was indeed contracting, hence guaranteeing the numerical convergence of this iterative procedure. Nevertheless, we never encountered any convergence problems with this procedure.

\(^7\) We experimented with other values to determine the sensitivity of the results. As expected, lower (higher) thresholds led to higher (lower) promotion and demotion rates and therefore less (more) inequality amongst the lifetime employment values. However, the differences were not substantial and the long run trends were not affected. In addition, the results are not sensitive to excluding promotions greater than 100% and demotions greater than 50% as is sometimes done to remove obvious outliers.
3.3 Value Annuities

To compute unemployment and employment values we use the estimated parameters from above, equations (3) and (4), and a value of $r = 0.05$.\footnote{We tested different values of the discount rate without noticing a marked difference in the final results.} We start with individuals who are age 65 and work backwards to those who are 16 replacing the theoretical integrals with their empirical counterparts. When computing the value functions we assume that the structural parameters do not change over time and that as individuals move through the experience groups they take on the structural parameters estimated for each group in that year. In this way the computed present value annuities from equation (6) can be viewed as a measure reflecting current market conditions with respect to wages and mobility.

For comparison we also compute a simulated realized labor income trajectory for each individual starting at their current age and wage and moving forward until they reach 65. Again we assume individuals face the same mobility rates and earnings distributions in the future as older workers face today. Finally we compute the annuity value of this realized stream for comparison with the present value annuities and wages. We expect inequality levels to be higher for the realized value annuities as they contain the randomness of transitory shocks. However, the mean values should be the same.

4 Results

4.1 Parameter Estimates

We now turn to the results of our analysis. First, we present evidence concerning the estimates of the underlying parameters used in computing the employment and unemployment values. We start with the estimates of $\lambda_{a,t}^0$, $\delta_{a,t}$, $\lambda_{a,t}^+(w_t)$ and $\lambda_{a,t}^-(w_t)$. Since the parameter estimates of these flow rates follow directly from their empirical counterparts, we focus on the flow rates found in the data. Figure 3 shows the calculated flow rates in and out of unemployment, while Figure 4 shows how average promotion and demotion rates vary across education and experience categories. Job destruction rates exhibit a countercyclical pattern, while re-employment rates are procyclical. In terms of education highly educated workers have the lowest job destruction rates and the highest re-employment rates. Similarly, highly experienced (older) workers exhibit a low job destruction rate. With regard to promotion and demotion rates we find that younger workers have the highest promotion rates, and, as expected, there is an inverse relationship between education levels and demotion rates. All groups experience a high degree of wage mobility (promotion+demotion) with
the greatest mobility exhibited by low educated (high demotion rates) and young (high promotion rates) workers.

In this application we have constrained the parameter functions $\lambda_{a,t}^+(w_t)$ and $\lambda_{a,t}^-(w_t)$ to be constant for all values of current wages in the same third of the current earnings distribution. In principle the unrestricted model would allow for a perfect match of the promotion and demotion data (see equations (10) and (11)). However, numerical tractability led us to constrain the parameters. Figure 5 provides an interesting evaluation of the capacity of the constrained model to reproduce the degree of wage mobility conditional on the initial wage observed in the data. Panels (a) and (c) show the actual promotion and demotion rates, respectively, in the data by wage cell, where P10 (P90) refers to the bottom (top) decile and P33, P33-P67 and P67 refer to the bottom, middle and top third of the distribution, respectively. Panels (b) and (d) confront these patterns using equations (14) and (15) and the transition rate estimates. A comparison of the two panels indicates that the model is able to reproduce the pattern found in the data of declining (rising) promotion (demotion) rates as the wage increases. The model also matches the level of upward wage mobility among the poorest workers relatively well, but underestimates it among the richest workers. With respect to downward wage mobility, the model does well in matching the middle and upper third of the distribution, but tends to underestimate it among the bottom.

Before calculating the present and realized values, we need estimates of the minimum wage, $w_t$, for each education group. These estimates are sensitive to the choice of trim level used to remove outliers. As noted in Section 3.1, we trimmed the bottom of each educational earnings distribution 3%. This yields estimates of $w_t$ that ranged from $3,115 to $9,933 with an average of $6,303 over the 16 groups and 21 years. At a legislated minimum wage of $3.35/hour a full-time, full-year worker would have earned approximately $6,000. Thus our trim level produces lowest wage estimates that are within 50% of the earnings of a typical minimum wage worker. In conjunction with equation (5) these estimates of the lowest wage yield estimates of $b_{a,t}$, the value of non-labor time. In general the estimates of $b_{a,t}$ cover a greater range than the $w_t$ estimates, but have a similar mean. For example, in 1977 the mean of $w_t$ is $7,004 while the mean of $b_{a,t}$ is $7,370.

We conducted two forms of sensitivity analysis with regard to the choice of trim level and the value of non-labour time. The first analysis examined two other trim levels, 1% and 5%, while the second re-calculated the annuity values with the value of non-labor time set equal to zero. As expected, lowering (raising) the trim level lowered (raised) the minimum wage estimates and, consequently, lowered (raised) the estimates of the non-labour time values and the average earnings.
and annuity value. In terms of inequality levels lowering (raising) the trim level slightly increased (decreased) wage inequality levels, but had little effect on annuity value inequality levels. Setting the value of non-labour time to zero also had the effect of lowering the calculated annuity values slightly. In this case the inequality level amongst the annuity values increased slightly, but the change over time was the same as that presented below. This latter effect is to be expected given unemployment is a fairly transient state.

4.2 Present and Realized Value Annuities

Using the parameter estimates we now construct the present and realized value annuities. Figure 6 exhibits the trends in means by education and experience which can be compared to those in Figure 1 for earnings. As expected the mean levels are similar across the two value measures. In comparing earnings and value annuities we find that both decline until the mid- to late 1990s with some increase in the last few years. University graduates see the largest gains in the last years in both earnings and value annuities, surpassing the levels at the beginning of the sample period. Across the education groups we find that, as with earnings, more education yields higher value annuities. The return to experience is also positive, with the exception of older workers. As expected, mean value annuities are much larger than mean earnings for workers with little experience, while they are lower for those with high levels of experience.

Returning to the main issue of inequality Figure 7 compares the distributions of present and realized value annuities and earnings. The level of the 90th percentile over most of the period is lower for both value annuity measures than for earnings, while the 10th percentile is much higher. Table 1 indicates these differences translate into inequality levels that are 40% lower for the annuity value measures. Comparing the two value measures Table 1 also shows that the level of inequality amongst realized value annuities is indeed higher than that for present value annuities. Figure 8 shows the growth in inequality measures for both earnings and value annuities over time. The total increase in inequality was fairly similar for both earnings and the value annuities over the sample period. Using the 90/10 ratio we find that wage inequality increased more than value annuity inequality, except in 1997, while the Gini coefficient puts the increase in value annuity inequality higher throughout the period.

The fact that the increase in inequality from 1977 to 1997 is the same for earnings and value annuities suggests that the increase in earnings inequality is the dominant factor in explaining the increase in value annuity inequality. Alternatively, one could conclude that the flow rates must have been at similar levels in the two years. In fact, Figures 3 and 4 indicate only small changes
between the average flow rates in 1977 and 1997. To formalize this idea further we decompose the increase in present value annuity inequality into various components. The decomposition results comparing 1977 to 1997 are presented in the top panel of Table 2. The first row shows the 90/10 ratio and Gini coefficient for 1977. The second row indicates the change in both if the 1977 sample faces the same wage offer distribution and the same promotion and demotion parameters ($\lambda^+$ and $\lambda^-$), but face the employment and unemployment flow parameters ($\lambda^0$ and $\delta$) for 1997. Here we see that inequality levels change very little when moving between the 1977 and 1997 flow rates. In the third row we continue the process by now changing the parameters that govern promotion and demotion rates to those in 1997 in addition to the (un)employment parameters. The wage mobility process did contribute to the increase in inequality albeit not substantially. In the fourth row we face the 1977 sample with the 1997 transition rate parameters plus the 1997 wage offer distribution. This is where the greatest action is and confirms our above intuition. The final step is to move to the 1997 inequality levels by allowing the composition of the sample and current wages to change to 1997 levels. Again this contribution is small.

4.3 Education and Experience Premiums

Much in the inequality literature has been made of the rising education premium. Here too differential patterns across education and experience groups contribute to the observed patterns in value annuities. Table 3 presents various education and experience differentials. A rising education premium, especially for a university education, is found for both earnings and value annuities. This increase is higher for value annuities even though the educational returns for value annuities are quite a bit higher in 1977 than for earnings. Overall for lower levels of education we find that the returns are higher when measured using value annuities than earnings. This is especially true for the return to finishing high school. The return to university over attending some college is similar for the two measures. Thus the returns to increasing education (especially at the low end of the skill distribution) are greater when one takes into account the dynamics of future wages and employment.

In terms of experience we find much smaller experience differentials with respect to value annuities than earnings, especially for the young. Thus taking into account future wage and employment opportunities brings younger workers much closer to older workers than their current earnings would indicate. In fact allowing for permanent changes in the transition rates and earnings distributions as individuals age is important on two dimensions. First, as discussed above, it increases the mean level of the annuity values of young workers far above their mean earnings, and, second, it causes
inequality in lifetime measures to be greater than if only transitory changes based on the current distributions for young workers were incorporated. To provide evidence on the extent this matters we calculated the present value annuities for the youngest experience group assuming no change in their transition rates or earnings distribution. The mean of the annuity values in 1977 under this calculation is $18,962 compared to a mean earnings of $19,861. In contrast, incorporating changes in the rates and distributions as one ages yields a mean annuity value of $25,516. Since the relative improvement in the rates and distributions is greater the more education one has as well, the permanent changes also increase inequality. For example, the standard deviation of youth annuity values assuming no permanent changes is 4899, while it is 6364 once the changes are incorporated. Both are substantially lower than the 9560 level for earnings, but it is clear that excluding permanent changes due to experience in lifetime calculations underestimates the degree of lifetime income inequality.

The main effect then of accounting for future employment and wage prospects in the evaluation of employment values has been shown to be a large reduction in inequality (in 1993, the 90-10 percentile ratio is 4.6 for wages and 2.4 for present value annuities). This is thus essentially due to young workers profiting more than older workers from wage mobility. Returns to education do not increase enough, when one takes into account the dynamics of future wages, to compensate for the effect of experience on wage mobility.

4.4 Within Education*Experience Cell Inequality

It is also interesting to examine the trends in inequality levels within education and experience groups. Figures 9 and 10 repeat the ordering found for the full sample of higher inequality levels for earnings, then realized values and then present values. Inequality is trending upward for all groups although university graduates exhibit the most pronounced growth in inequality. It is interesting to note that the reduction in inequality levels from a current to a lifetime measure is greater, at 60% for the 90/10 ratios and more for the Gini coefficient, for the within education measures than the 40% reduction found for the entire sample. In addition, over time the annuity inequality levels are quite stable within the education groups, while earnings inequality increases steadily. This is not true for experience as seen in Figure 10. These patterns are consistent with the rising education premiums being permanent in nature and the increase in inequality within education groups being more transitory in nature.

Figures 9 and 10 indicate that there is a significant amount of within group inequality. Using variance decomposition analysis, Table 4 examines the amount of inequality within and between
the education*experience cells for both earnings and value annuities. The variance decomposition indicates that the rising inequality is a result of increases in both between and within cell inequality. For both earnings and value annuities, between cell inequality increases at a faster rate than within cell inequality. A comparison of the $R^2$ values shows that education and experience explain about two times more of the variation in realized value annuities than wages and about three times more of the variation in present value annuities. This ordering mirrors the role of within-cell inequality as compared to between-cell inequality. For earnings, 65-70% of the variation is due to within-cell variation; the relevant figure is only 5-10% for present value annuities. As expected, within-cell variation plays a larger role for realized values than for present values with 30% of the variation due to within-cell variation. However, the realized value figure is still substantially lower than that for earnings.

Intuitively one would expect the amount of within cell variation to increase with experience. That is, as the remaining lifetime shortens, the current wage becomes more important. While this intuition is not apparent in Figure 10, it is born out in the data as the standard deviation of both present and realized value annuities for the oldest members of the sample can be two to three times higher than that for the youngest. This is consistent with the Deaton and Paxson’s (1994) finding that consumption inequality increases with age.

4.5 Three Distinct Episodes

Returning to Figure 8 we note that looking only at 1977 and 1997 obscures that fact that earnings and annuity values have not always followed the same path over this period. In fact, three distinct time episodes emerge from these graphs. From 1977-1981 value annuity inequality increased with earnings inequality but at a greater rate with a particularly large increase in 1981. From 1982 to 1993 the value distributions are relatively stable, while inequality amongst earnings steadily increases. Finally in the late 1990s the inequality amongst values increases again by about 25% in contrast to the earnings distribution for which inequality increases by much less. The patterns in the late 1990s, however, differ dramatically from those in the late 1970s. In the earlier period earnings and values were falling for everyone with higher incomes being slightly less affected. In the 1990s the return of growth generated higher incomes for most everyone, but especially those with higher levels of education. This latter affect appears to be more pronounced for values than for earnings.

Before decomposing the changes in annuity value inequality over these three periods it is important to note three key facts. First, only about half of the workers in the top and bottom deciles of
the earnings distribution are in the top and bottom decile of the value distribution and vice versa. That is, one’s position in one distribution is not a perfect predictor of one’s position in the other distribution. Second, the role of education is important for the extremes of the value distribution. In 1977 about half of the workers in the top decile of the earnings distribution had a university degree, by 1997 that figure had grown to over 70%. In contrast over the entire time period over 98% of the workers in the top decile of the value distribution have a university degree. A similar pattern can be found for the bottom decile with respect to those having less than a high school degree. High school dropouts made up 46% of the bottom decile of the earnings distribution in 1977 and 97% of the value distribution. Interestingly in 1997 the percentage for the earnings distribution fell to 36%, while that for the value distribution increased to 99%. Thus any explanation for the patterns observed in the tails of the value distribution must incorporate the wage levels and mobility patterns across education categories. Third, as mentioned in Section 3.1, a change occurred in the 1995 CPS questionnaire that may have induced higher earnings responses causing a break in the series. In fact some evidence from other data series suggests that this may be the case. Both Lerman (1997) using the Survey of Income and Program Participation (SIPP) and Moffitt and Gottschalk (2002) using the PSID find evidence of declining or stable trends in inequality over the mid 1990s, while the CPS exhibits increasing inequality levels. Thus, we caution readers that some of the increase in inequality between 1993-1996 may be due to this change. However, post-1994 trends in the CPS should once again reflect actual increases in inequality. An important question is whether other data series will reveal the same strong increase in inequality levels in the latter half of the 1990s as in the CPS.

Turning to the decomposition analysis, we present the same type of decomposition analysis as described above for 1977 to 1997 in the bottom three panels of Table 2, one panel for each sub-period. The panel for 1977 to 1981 indicates that the increase in inequality amongst annuity values was driven primarily by changes in the parameters governing the (un)employment flow rates and the promotion and demotion rates. To bring about an increase in inequality some flow rates must have decreased lowering mobility. In fact, from 1977 to 1981 both the re-employment rate and the promotion rate fell. Interestingly the decomposition analysis indicates that the change in the wage offer distribution was a countervailing force in the presence of the changing flow rates, as the level of inequality increase is reduced by a half, going from a 22-31% increase (depending on which measure is used) to 11-17%. Finally, the large jump up in inequality amongst values in 1981 appears to be due to university graduates. While their average wage did not increase, they did see
better re-employment rates, higher promotion rates and lower demotion rates causing their future prospects to increase taking the top of the value distribution with them.

From 1982-1993 a different regime ensued. In this period the top of the wage distribution was stable while the bottom continued to decline. In contrast the top of the value distribution tended to move more in tandem with the bottom. Table 2 shows that, apparently, neither flow rates nor the wage offer distribution were generating ample movements (this is particularly visible with the Gini coefficient). Nevertheless, mobility rates across groups move together and, while the earnings levels for those with less education were falling, their mobility rates did not exhibit a similar decline. In fact, the decomposition analysis reveals that during this period mobility rates were (slightly) moving in a direction to counter the increase in wage inequality and were helping to hold increases in value annuity inequality down. This appears to have been driven by small increases in many of the (un)employment and wage mobility rates over this period.

Finally in the late 1990s most of the action is at the top of the distributions. Here the improvement in the labor market for university graduates in terms of earnings is compounded in the value measures with improvements in re-employment rates, job destruction rates, and promotion and demotion rates. Again the mobility rates seem to be moving in a way to counter the increase in wage inequality, but during this period the increases are not enough to overcome the large increases in wage inequality and so inequality amongst annuity values increases dramatically as well.

Overall and over each of these three periods, after changing the transition rates and the wage offer distributions, changing the composition of the sample never makes a large difference. It is quite remarkable that, although significant, the sample composition changes, including the shift toward attaining more education and the aging population, do not play a large role in explaining the recorded changes in lifetime income inequality.

4.6 Permanent Versus Transitory

As a final exercise we compare our results to those found in Moffitt and Gottschalk’s (2002) permanent and transitory variance component exercise. We note that one can make a link between our measure and the notion of permanent and transitory components. If a change in inequality is fully reflected in current wage inequality, then the change is likely to be transitory in nature, while if it is reflected in both current and lifetime inequality measures then it is likely permanent.

Using data from the PSID, Moffitt and Gottschalk (2002) decompose the variance of earnings into permanent and transitory components and then examine which factors have increased over time contributing to the overall observed increase in earnings inequality. They find that increases
in both components contributed to the overall increase in inequality from 1977-1987. After 1987 they found that both variance measures were fairly stable until 1991 when both took a large jump only to both fall in 1993. Since 1993 the PSID data show a downward to stable trend in the overall variance of earnings with a stable permanent component accompanied by a sharply declining transitory component. Since PSID data for the late 1990s are not available, Moffitt and Gottschalk’s analysis ends at 1996.

Our results coincide with Moffitt and Gottschalk’s (2002) for the early period. From 1977-1981 our measures show that the earnings inequality increases are also reflected in lifetime inequality increases suggesting both permanent and transitory components are present. From 1981-1987 the transitory component appears to dominate as earnings inequality continues to increase but is no longer reflected in lifetime inequality. Our results start to depart from Moffitt and Gottschalk’s in the late 1980s and early 1990s. The CPS data show fairly stable inequality levels over this period with no large increase in 1991 or decline in 1993. Between 1993 and 1996 we see an increase in inequality, while the PSID data revealed a declining or stable trend. As noted this difference may be due to the change in the CPS questionnaire. Interestingly our measure shows a significant increase in the permanent component from 1996-1997 as lifetime inequality increased but wage inequality did not suggesting a counter decline in the transitory component. Reconciling these various trends in overall inequality as well as the permanent and transitory components across the CPS and PSID is an important avenue for further research.

5 Conclusions

In this paper we characterize the current position of a worker in the labor market by three components: current earnings, employability (probability of losing job when employed, probability of finding job when unemployed), and wage mobility (magnitude and likelihood of wage changes). Each of these components varies across workers according to their accumulated human capital, here characterized by education and experience. Using CPS data, we construct life cycle values that incorporate both wage and employment risk. Using these measures we show that lifetime income inequality is 40% less than earnings inequality, essentially due to young workers profiting more than other workers from wage mobility, and that it exhibits the same increase as earnings inequality. We characterize and contrast the different patterns in inequality amongst earnings and lifetime income over time and also show that lifetime income exhibits far less within-cell inequality than earnings.
To our knowledge, this paper is the first to consider changes in the inequality level of lifetime values using a labor market transition framework. Closely related work includes Flinn (2002) and Cohen (1999) who also use models of labor market transitions to compare inequality levels in lifetime values across countries. Our methodology, however, differs from theirs in that it requires much shorter panels to implement and is far less computer intensive. Both of these features are important given the type of data available and the time frame we study. In addition, our model is nonstationary as it allows for experience accumulation. Aging workers face different parameter values, i.e., different state transition rates and different wage offer distributions. In that sense, they are submitted to both transitory (mobility for a given value of experience) and permanent shocks (mobility governed by new parameter values as one ages). While our methodologies differ, the result that lifetime income exhibits far less inequality than current earnings is consistent across all three studies.

This latter finding is also consistent with the consumption literature which finds much lower levels of inequality amongst consumption than income (Cutler and Katz, 1992). The consumption literature also contains results concerning the change in consumption inequality over time that can be compared to ours. For example, Cutler and Katz show that consumption and income inequality exhibit similar trends over the 1980s. For the 1990s Kreuger and Perri (2001) find that consumption inequality levels remained stable despite rising income inequality levels. As our lifetime income inequality levels increase over both decades, they match the consumption inequality pattern in the 1980s but diverge away from it in the 1990s. This development of stabilized consumption inequality in the face of continued increases in earnings and lifetime income inequality is interesting and worthy of further study.

While we are able to demonstrate the importance of both transitory and permanent future components as allowed by our measure, the main limitation of our study is certainly the lack of unobserved heterogeneity. Without incorporation unobserved heterogeneity, we can not directly address the question of whether the widening of the (lifetime) income distribution reflects a growing short-term instability in wages or an increase in the variability of the individual-specific component of individual wages. We were able to conduct some rudimentary comparisons between implications from our measures and Moffitt and Gottschalk’s (2002) findings. Interestingly, we find a divergence in the results in the 1990s. However, such an extension is beyond the scope of this project as estimating our model with unobserved heterogeneity would require using longer panels than the CPS and allowing for unobserved heterogeneity is not a trivial extension of the model. We therefore
leave this important extension for further study.

APPENDIX

Details on the estimation procedure

We here describe the estimation procedure and data used in detail.

A.1 The wage offer distribution

We assume that the structural parameters are stepwise constant with respect to potential experience, i.e. \((\lambda^0_{a,t}, b_{a,t}, F_{a,t}, \lambda^+_a, \lambda^-_a) \equiv (\lambda^0_{i,t}, b_{i,t}, F_{i,t}, \lambda^+_i, \lambda^-_i)\), for all \(a \in [a_i, a_{i+1}]\), where \(i\) indicates one of the four experience groups \((i = 1, \ldots, 4)\).

Let \(U_{a,t}\) and \(M_{a,t}\) denote the number of unemployed and employed workers, respectively, with experience level \(a\) and time \(t\), and let \(U_{i,t} \equiv \sum_{a=a_i}^{a_{i+1}} U_{a,t}\) and \(M_{i,t} \equiv \sum_{a=a_i}^{a_{i+1}} M_{a,t}\) denote the number of unemployed and employed workers, respectively, with an experience level within the \(i\)th experience interval \([a_i, a_{i+1}]\). Let \(G_{a,t}\) be the cross-sectional earnings distribution for all employed workers with experience \(a\) in period \(t\). Let \(G_{i,t}(w) = \sum_{a=a_i}^{a_{i+1}} G_{a,t}(w) M_{a,t}/M_{i,t}\) denote the cumulative distribution function (cdf) of the distribution of earnings of all employed workers with experience level \(a \in [a_i, a_{i+1}]\).

Consider the stock \(G_{i,t}(w) M_{i,t}\) of employees with experience \(a \in [a_i, a_{i+1}]\) paid less than a wage \(w\) at time \(t\). All of these workers will have aged one year in year \(t + 1\). Let \(\Delta G_{i,t}(w) M_{i,t}\) denote the difference between the stock of employees with experience \(a \in [a_i + 1, a_{i+1} + 1]\) paid less than wage \(w\) at time \(t + 1\), and \(G_{i,t}(w) M_{i,t}\), i.e.

\[
\Delta G_{i,t}(w) M_{i,t} = \sum_{a=a_i}^{a_{i+1}-1} G_{a+1,t+1}(w) M_{a+1,t+1} - \sum_{a=a_i}^{a_{i+1}-1} G_{a,t}(w) M_{a,t} \\
= G_{i,t+1}(w) M_{i,t+1} + G_{a_i+1,t+1}(w) M_{a_i+1,t+1} - G_{a_i,t+1}(w) M_{a_i,t+1} - G_{i,t}(w) M_{i,t}.
\]

In addition \(\Delta G_{i,t}(w) M_{i,t}\) can be written as

\[
\Delta G_{i,t}(w) M_{i,t} = \left[ \lambda^0_{i,t} U_{i,t} + \int_{w}^{\infty} \lambda^+_i(x) dG_{i,t}(x) M_{i,t} \right] F_{i,t}(w) \\
- \left[ \delta_{i,t} G_{i,t}(w) + F_{i,t}(w) \int_{w}^{\infty} \lambda^+_i(x) dG_{i,t}(x) \right] M_{i,t}.
\]

That is, the change in the number of workers earning less than \(w\) who were in experience group \(i\) in period \(t\) and now are in period \(t + 1\) is equal to the inflow of new hires, i.e. the number of formerly
unemployed workers who found a job paying less than \( w \) plus the number of formerly employed workers at a wage greater than \( w \) who experienced a wage decrease to a wage level below \( w \), minus the outflow, i.e. the number of workers in experience group \( i \) paid less than \( w \) last year who were laid off or who obtained a wage increase to a wage level above \( w \).

Solving for \( F_{i,t}(w) \) we obtain the following expression for \( F_{i,t}(w) \):

\[
F_{i,t}(w) = \frac{\Delta G_{i,t}(w)M_{i,t}}{\lambda_{i,t}^0M_{i,t}} + \delta_{i,t}G_{i,t}(w) + \int_w^\infty \lambda_{i,t}^+(x)dG_{i,t}(x).
\]

Finally, a more useful equation can be derived by imposing \( \lambda_{i,t}^+(w) \equiv \lambda_{i,t}^{+(j)} \) and \( \lambda_{i,t}^-(w) \equiv \lambda_{i,t}^{-(j)} \), \( j = 1, 2, 3 \), to take on only three values according to which third of the distribution \( G_{i,t} \) the current wage \( w \) belongs to. We thus assume that the wage offer distributions \( F_{i,t} \) are related to the earnings distributions \( G_{i,t} \) by a parametric relationship indexed by eight parameters \( \delta_{i,t} \), \( \lambda_{i,t}^0 \) and \( \lambda_{i,t} = (\lambda_{i,t}^{-(1)}, \lambda_{i,t}^{+(1)}, \lambda_{i,t}^{-(2)}, \lambda_{i,t}^{+(2)}, \lambda_{i,t}^{-(3)}, \lambda_{i,t}^{+(3)}) \):

\[
F_{i,t}(w) = \begin{cases} 
\frac{\Delta G_{i,t}(w)M_{i,t}}{\lambda_{i,t}^0M_{i,t}} + \delta_{i,t}G_{i,t}(w) + \frac{1}{3}\lambda_{i,t}^{+(1)} + \frac{1}{3}\lambda_{i,t}^{+(2)} + \lambda_{i,t}^{+(3)}(G_{i,t}(w) - \frac{2}{3}), & \forall w > q_{i,t}^{(2)} \\
\frac{\Delta G_{i,t}(w)M_{i,t}}{\lambda_{i,t}^0M_{i,t}} + \delta_{i,t}G_{i,t}(w) + \frac{1}{3}\lambda_{i,t}^{-(3)} + \frac{1}{3}\lambda_{i,t}^{+(1)} + \lambda_{i,t}^{+(2)}(G_{i,t}(w) - \frac{2}{3}), & \forall q_{i,t}^{(1)} < w \leq q_{i,t}^{(2)} \\
\frac{\Delta G_{i,t}(w)M_{i,t}}{\lambda_{i,t}^0M_{i,t}} + \delta_{i,t}G_{i,t}(w) + (\delta_{i,t} + \lambda_{i,t}^{+(1)})G_{i,t}(w), & \forall w \leq q_{i,t}^{(1)} 
\end{cases}
\]

where \( q_{i,t}^{(1)} \) and \( q_{i,t}^{(2)} \) are the 1/3 and 2/3 percentiles of the distribution \( G_{i,t} \), i.e. \( G_{i,t}(q_{i,t}^{(1)}) = 1/3 \) and \( G_{i,t}(q_{i,t}^{(2)}) = 2/3 \).

To calculate the employment and unemployment values we need to calculate \( F_{i,t}(w) \). This is done using the above formula along with estimates of \( G_{i,t}(w) \), \( \frac{\Delta G_{i,t}(w)M_{i,t}}{\lambda_{i,t}^0} \) and the transition rate parameters. Our estimation strategy for these components is discussed in the next section.

### A.2 Transition rates

We estimate the re-employment rate, \( \lambda_{i,t}^0 \), as the ratio of the number of unemployed workers in experience group \( i \) of one year who are employed in the next year, \( UM_{i,t} \), to the number of unemployed workers in the first year, \( U_{i,t} \). Similarly, we estimate the job destruction rate, \( \delta_{i,t} \), as the ratio of the number of employees in experience group \( i \) in one year who are unemployed in the next year, \( MU_{i,t} \), to the number employed in the first year, \( M_{i,t} \).
Our estimation of rates \( \lambda_{i,t}^{+}(w) \) and \( \lambda_{i,t}^{-}(w) \) is based on counting how many workers display a wage increase from one year to the next and how many display a wage decrease, respectively. Let \( p_{i,t}^{+}([a, b]) \) denote the proportion of employees with a year \( t \) wage \( w \) in quantile \( G_{i,t}^{-1}([a, b]) \), for \( a \) and \( b \) in \([0, 1]\), who get promoted between year \( t \) and year \( t + 1 \). Then, the promotion rate in quantile \( G_{i,t}^{-1}([a, b]) \) is

\[
p_{i,t}^{+}([a, b]) = \frac{1}{b - a} \int_{G_{i,t}^{-1}(a)}^{G_{i,t}^{-1}(b)} \lambda_{i,t}^{+}(w) F_{i,t}(w) dG_{i,t}(w).
\]

Using the fact that \( \lambda_{i,t}^{+}(w) \) takes on only three values, one easily obtains

\[
p_{i,t}^{+}(3) \equiv p_{i,t}^{+}([2/3, 1]) = \lambda_{i,t}^{+}(3) \cdot 3 \int_{q_{i,t}^{(3)}}^{q_{i,t}^{(2)}} F_{i,t}(w) dG_{i,t}(w),
\]

\[
p_{i,t}^{+}(2) \equiv p_{i,t}^{+}([1/3, 2/3]) = \lambda_{i,t}^{+}(2) \cdot 3 \int_{q_{i,t}^{(1)}}^{q_{i,t}^{(2)}} F_{i,t}(w) dG_{i,t}(w),
\]

\[
p_{i,t}^{+}(1) \equiv p_{i,t}^{+}([0, 1/3]) = \lambda_{i,t}^{+}(1) \cdot 3 \int_{q_{i,t}^{(1)}}^{q_{i,t}^{(2)}} F_{i,t}(w) dG_{i,t}(w).
\]

Let \( p_{i,t}^{-}([a, b]) \) denote the proportion of employees with a year \( t \) wage \( w \) in quantile \( G_{i,t}^{-1}([a, b]) \), for \( a \) and \( b \) in \([0, 1]\), who get demoted between year \( t \) and year \( t + 1 \). Then, the demotion rate in quantile \( G_{i,t}^{-1}([a, b]) \) is

\[
p_{i,t}^{-}([a, b]) = \frac{1}{b - a} \int_{G_{i,t}^{-1}(a)}^{G_{i,t}^{-1}(b)} \lambda_{i,t}^{-}(w) F_{i,t}(w) dG_{i,t}(w).
\]

For any wage interval \( G_{i,t}^{-1}([a, b]) \) over which \( \lambda_{i,t}^{-}(w) \) and \( \lambda_{i,t}^{+}(w) \) are constant, we have

\[
\frac{1}{\lambda_{i,t}^{+}} p_{i,t}^{+}(a_{i,t}, a_{i,t+1}) + \frac{1}{\lambda_{i,t}^{-}} p_{i,t}^{-}(a_{i}, a_{i+1}) = 1,
\]

which provides a simple equation for computing demotion rates given corresponding promotion rates.

We obtain an estimate of the rates in \( \lambda_{i,t} \) by minimizing the Euclidian distance between \( p_{i,t} = (p_{i,t}^{(1)}, p_{i,t}^{+}(1), p_{i,t}^{+}(2), p_{i,t}^{+}(3), p_{i,t}^{+}(3)) \) and \( \lambda_{i,t} \) subject to the constraint

\[
0 \leq \lambda_{i,t}^{+}(w) F_{i,t}(w) + \lambda_{i,t}^{-}(w) F_{i,t}(w) \leq 1 - \delta_{i,t},
\]

i.e.

\[
\begin{align*}
0 & \leq \lambda_{i,t}^{+}(1) \leq 1 - \delta_{i,t}, \\
0 & \leq \frac{2}{3} \lambda_{i,t}^{+}(1) + \frac{1}{3} \lambda_{i,t}^{-}(1) \leq 1 - \delta_{i,t}, \\
0 & \leq \frac{2}{3} \lambda_{i,t}^{+}(2) + \frac{1}{3} \lambda_{i,t}^{-}(2) \leq 1 - \delta_{i,t}, \\
0 & \leq \frac{1}{3} \lambda_{i,t}^{+}(2) + \frac{2}{3} \lambda_{i,t}^{-}(2) \leq 1 - \delta_{i,t}, \\
0 & \leq \frac{1}{3} \lambda_{i,t}^{+}(3) + \frac{2}{3} \lambda_{i,t}^{-}(3) \leq 1 - \delta_{i,t}, \\
0 & \leq \lambda_{i,t}^{-}(3) \leq 1 - \delta_{i,t}.
\end{align*}
\]
To reduce the number of different regimes to consider within that constrained minimization problem, we impose a slightly more stringent restriction that each rate must be less than $1 - \delta_{i,t}$. We thus estimate the rates in $\lambda_{i,t}$ by solving the following fixed point system of equations:

$$
\begin{align*}
\lambda_{i,t}^{+(3)} &= \max \{ 0, \min \{ 1 - \delta_{i,t}, \frac{\lambda_{i,t}^{+(3)} + P_{i,t}^{+(3)} - 1}{f_i^{(3)} G_{i,t}(w)} \} \} \\
\lambda_{i,t}^{+(2)} &= \max \{ 0, \min \{ 1 - \delta_{i,t}, \frac{\lambda_{i,t}^{+(2)} + P_{i,t}^{+(2)} - 1}{f_i^{(2)} G_{i,t}(w)} \} \} \\
\lambda_{i,t}^{+(1)} &= \max \{ 0, \min \{ 1 - \delta_{i,t}, \frac{\lambda_{i,t}^{+(1)} + P_{i,t}^{+(1)} - 1}{f_i^{(1)} G_{i,t}(w)} \} \} \\
\lambda_{i,t}^{-(3)} &= \max \{ 0, \min \{ 1 - \delta_{i,t}, \frac{\lambda_{i,t}^{-(3)} + P_{i,t}^{-(3)} - 1}{f_i^{(3)} G_{i,t}(w)} \} \} \\
\lambda_{i,t}^{-(2)} &= \max \{ 0, \min \{ 1 - \delta_{i,t}, \frac{\lambda_{i,t}^{-(2)} + P_{i,t}^{-(2)} - 1}{f_i^{(2)} G_{i,t}(w)} \} \} \\
\lambda_{i,t}^{-(1)} &= \max \{ 0, \min \{ 1 - \delta_{i,t}, \frac{\lambda_{i,t}^{-(1)} + P_{i,t}^{-(1)} - 1}{f_i^{(1)} G_{i,t}(w)} \} \} 
\end{align*}
$$

(17)

A.3 Practical details about estimation

The fixed-point nature of this system is due to the fact that $F_{i,t}$ is a function of the unknown rates $\lambda_{i,t}$. We solve this fixed-point equation for $\lambda_{i,t}$ by iterating the following simple procedure until convergence. For an initial value of $\lambda_{i,t}$, we compute an initial value for $F_{i,t}$ using equation (13). We then update $\lambda_{i,t}$ using equation (17) and repeat.

To estimate the earnings distributions, $G_{i,t}(w)$, we use the full March CPS samples and calculate the empirical cdfs for each education*experience group. To formulate an estimate of $\frac{\Delta G_{i,t}(w) M_{i,t}}{M_{i,t}}$, we note that we need to take into account the aging of the population. Therefore, for the $i$th experience group’s change between year $t$ and $t+1$, we use the preceding estimate of $G_{i}(w)$ for the estimate of the distribution of earnings in year $t$, but for the $t+1$ distribution we use the empirical cdf of the $i$th experience group aged one year in $t+1$. That is, for the lowest experience group we calculate the empirical cdf for those with experience level 0-9 years in the full March CPS sample in year $t$ and the empirical cdf for those with experience level 1-10 years in the full March CPS sample in year $t+1$ and so on for each experience group. The same aging system is used for the
calculations of the employment levels in $t$ and $t+1$. However, in this case, to maintain consistency with our estimated flows in and out of employment, we estimate the changes in the employment levels using the same data that we use to estimate the re-employment and job destruction rates. These data are from the matched March CPS files and are described next.

To calculate the flow rates between unemployment and employment we use the March labor force states in the matched files to determine the labor force states in each year. Individuals without a labor force state, those who are not in the labor force and those who are either employed part-time or unemployed and looking for part-time work in either year are dropped from the sample. Thus we do not consider transitions between out of the labor force and the other states or between part-time and full-time employment.

To calculate the promotion and demotion rates for each third of the earnings distribution we use annualized earnings from the previous years in the matched CPS files. Given we are looking at annual earnings there is a concern as to how to treat part-year workers. Those who are employed for the full year in the first year as well as employed or unemployed for the full year in the second year are easy to classify. In the first case a comparison of the annualized earnings will reveal if the individual had a promotion, demotion or no change; while in the second the individual will be classified as moving from employment to unemployment and therefore will not be counted in the promotion and demotion calculations except as a member of the employment pool in the first year. Individuals employed part-year in either year are more difficult to classify as the timing of the unemployment spell is unknown. The inclusion of earnings changes associated with part-year workers in the calculation of the promotion and demotion rates results in an overestimate of the promotion and demotion rates, while excluding them results in an underestimate. In the first case one implicitly assumes that the weeks of unemployment in the first (second) year occurred at the beginning (end) of the year so that all of the observed earnings changes occurred without an intervening period of unemployment. In the second case the assumption is that the unemployed weeks occurred at the end (beginning) of the first (second) year so that all of the observed earnings changes occurred with an intervening spell of unemployment and thus the individual should be coded as moving from employment to unemployment. Because one feature of our analysis is to determine whether or not mobility trends in the U.S. can reverse the increase in earnings inequality, we chose to work under the first assumption where we generate an upper bound on promotion and demotion rates. In practice this choice had very little effect on the results. While the lower bound rates did result, as expected, in more inequality amongst our annuitized value measures, the increase
was slight and the trend was unchanged.

Therefore, for the promotion and demotion rate calculations we exclude those individuals who work part-time (full or part-year) in either year or who were unemployed in the first year. We also exclude all working respondents with real annual earnings that fall outside the minimum and maximum earnings bounds. For the first year we use the minimum and maximum earnings bounds for that year calculated after trimming the data. For the second year we use as the minimum (maximum) bound the lowest (highest) bound between the two years. In this way we ensure that all individuals in year one have a positive probability of incurring no change. Finally, because we cannot determine the actual earnings change for individuals with top-coded values, we eliminate respondents with top-coded earnings in either year. In order to divide the first year of the matched sample into each third of the distribution we calculate \( q_{i,t}^{(1)} \), \( q_{i,t}^{(2)} \), and \( q_{i,t}^{(3)} \) using earnings data from the full March sample.

**References**


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Table 3: Education and Experience Differentials

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Figure 1: Earnings - Means and Quantiles ($1000)

(a) Mean Earnings by Education

(b) Mean Earnings by Experience

(c) Earnings Distribution
Figure 2: Composition of the Samples

(a) Fraction of Education Groups

(b) Fraction of Experience Groups
Figure 3: Employment-Unemployment Transition Rates

(1) By Education

(a) Job Destruction Rates

(b) Re-employment Rates

(2) By Experience

(c) Job Destruction Rates

(d) Re-employment Rates
Figure 4: Promotion and Demotion Rates

(1) By Education

(a) Promotion Rates

(b) Demotion Rates

(2) By Experience

(c) Promotion Rates

(d) Demotion Rates
Figure 5: Observed and Predicted Mobility Rates by Earnings Cell

(a) Actual Promotion Rates

(b) Predicted Promotion Rates

(c) Actual Demotion Rates

(d) Predicted Demotion Rates
Figure 6: Mean Present and Realized Value Annuities ($1000)

(1) By Education

(a) Present Value Annuities

(b) Realized Value Annuities

(2) By Experience

(c) Present Value Annuities

(d) Realized Value Annuities
Figure 7: Earnings and Value Annuity Distributions ($1000)

(a) Earnings

(b) Present Value Annuities

(c) Realized Value Annuities
Figure 8: Earnings and Value Annuities - Inequality Indices

(a) 90/10 Ratios

(b) Gini Coefficients
Figure 9: Level of Inequality Indices by Education

(1) Less Than High School

(a) 90/10 Ratios

(b) Gini Coefficients

(2) High School

(d) 90/10 Ratios

(d) Gini Coefficients
Figure 9: Level of Inequality Indices by Education

(3) Some College

(e) 90/10 Ratios

(f) Gini Coefficients

(4) University

(g) 90/10 Ratios

(h) Gini Coefficients
Figure 10: Level of Inequality Indices by Experience

(1) 0-9 Years

(a) 90/10 Ratios

(b) Gini Coefficients

(2) 10-19 Years

(d) 90/10 Ratios

(d) Gini Coefficients
Figure 10: Level of Inequality Indices by Experience

(3) 20-29 Years

(e) 90/10 Ratios

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(f) Gini Coefficients

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(4) 30 Plus Years

(g) 90/10 Ratios

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(h) Gini Coefficients

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