Twenty Years of Rising Inequality in US Lifetime Labor Income Values

Audra J. Bowlus
University of Western Ontario

Jean-Marc Robin
University of Paris 1 - Panthéon Sorbonne, Paris,
CREST-INSEE, Malakoff,
and CEPR, London

October 2002

ABSTRACT

In this paper we characterize the current position of workers in the labor market by three components: wages, employability, and wage mobility. Each varies across workers according to their education and experience levels. 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 profitting more than other workers from wage mobility. We also show that, although the total increase in lifetime income inequality over the past 20 years is the same as earnings inequality, their particular evolutions differ. The total increase is the same because, while employment and wage mobility rates fluctuate over the sample period, by 1997 they have essentially returned to their 1977 levels. However, while earnings inequality tends to increase more or less steadily from the mid 1970's to the late 1990's without interruption, the dynamics of lifetime income inequality exhibit three different short-run trends: in the late 1970's the evolution of lifetime income inequality is parallel to that of earnings; from 1982 to 1993 it remains stable as the top of the value distribution tended to move in tandem with the bottom; finally, the post-1993 period is characterized by a greater return to education in values than in wages and value inequality increases at a faster rate than earnings inequality. Our last important result is that composition changes, although significant (the shift toward attaining more education and the aging population), do not play a large role in explaining the changes in lifetime inequality.

JEL classification numbers: D30, D63, J22, J64.

Keywords: Inequality, mobility, search theory, labor markets

Acknowlegements: We greatly benefited from comments by participants at the Conference on Inequality and Labor Markets, 21-22 May 1999, organized by P. Aghion at the Institute for Fiscal Studies in London, and sponsored by ELSE, IFS and the McArthur Foundation Research Network on Inequality and Economic Performance. We have also benefited from comments made by A. Shorrocks, Zvi Eckstein and Fabien Postel-Vinay, and seminar participants at the Institute for Fiscal Studies (London), at the University of Western Ontario, Queen's University, University of Toronto, Århus University, FED Minneapolis and the Journées Jourdan (Paris).

RESUME

Trois composantes essentielles caractérisent les trajectoires individuelles sur le marché du travail : le niveau des salaires, l'employabilité et la mobilité salariale. Chacune varie d'un travailleur à l'autre selon son éducation et son expérience. A partir des données du Current Population Survey (CPS), de 1977 à 1997, nous construisons pour cet échantillon d'individus, à toute date, un indice de revenu permanent, somme espérée des revenus futurs, qui tient compte des risques de perte d'emploi et de variation de salaire. Nous montrons alors que l'inégalité de revenu permanent est 40% moindre que l'inégalité des salaires en coupe, ceci essentiellement parce que les jeunes travailleurs peuvent espérer des trajectoires salariales plus pentues que leurs ainés. Nous montrons aussi que l'accroissement total des inégalités de revenu permanent est le même que celui des inégalités de salaires. Ceci est dû au fait qu'entre 1977 et 1997, les taux de mobilité emploi-chômage et de mobilité salariale ont fluctué avec le cycle économique sans marquer de tendance. Ce taux d'accroissement identique cache cependant des évolutions sensiblement différentes. De 1970 à 1981, les évolutions des deux indicateurs sont parallèles. De 1982 à 1993, les inégalités de revenu permanent stagnent alors que les inégalités salariales continuent de croître. Enfin, les années 90 voient les inégalités de revenu permanent augmenter à un rythme plus vif que les inégalités salariales, du fait d'un rendement accru de l'éducation dans la dernière décennie. Notre dernier résultat important est que les changements de composition de la population par niveau d'éducation et niveau d'expérience (âge) n'ont que peu d'effet sur les évolution d'inégalité.

Classification JEL: D30, D63, J22, J64.

Mots-clés: Inegalité, mobilité, emploi, salaires, recherche d'emploi

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).[1] While such contemporaneous measures of inequality are important, it has long been recognized that individual welfare not only depends on the individual's current employment position (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 essentially been addressed in the literature via three approaches. The first approach aims at studying the stability of each 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) or by estimating wage mobility across different wage quantiles over various periods of time (e.g. Gottshalk, 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.[2] 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). The dynamic study of individual consumption is rendered difficult by the lack of panel data and a proper treatment of durables. In particular, health and housing seem for the moment out of reach.[3] Despite how disputable these consumption analyses can be, they teach us the reasonable neither-nor story that between-group insurance exists but is imperfect. For example, Attanasio and Davis (1996) find that year-to-year changes in consumption are basically uncorrelated with yearly changes in relative wages, whereas ten-year differences exhibit a correlation coefficient near one.

The last approach uses models of wage mobility and employment transitions to construct individual measures of lifetime income, and applies to the distributions of these long-run income aggregates the same methodologies used to analyze earnings and income inequality (ninety-ten

[1] Panel (c) of Figure 1 shows the earnings distribution for males and documents the increase in earnings inequality over the 1980s. Inequality levels continued to increase in the nineties, especially in the latter half of the decade. The earnings data depicted in Figure 1 come from the US Current Population Survey. The sample includes full-time working males, 16-65, and is described in detail in section 3.1.

[2] See e.g. Attanasio and Davis (1996) and Storesletten et al (2000) for references and recent evidence, or more precisely the *lack* of evidence, on the degree of between-group consumption risk sharing.

[3] Yet, see Krueger and Perri (2001) for an analysis of consumption data that includes imputed services from some durables.

percentile ratios, Gini coefficients, etc.). We are aware of only two papers, Flinn (1997) and Cohen (1998), that use estimates from labor market transition models to make inferences about lifetime earnings inequality. 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 (1997) 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 (1998) compares labor market inequality levels in France and the U.S. His main finding is that wage inequality is about 60% greater in the U.S. than in France, but using lifetime welfare measures reduces the gap to 15%.

With regard to the last two approaches, we note that the analysis of lifetime income inequality is only informative about welfare if the degree of insurance is large enough. Otherwise, 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. Thus, studies of current and lifetime earnings inequality provide two useful benchmarks for the analysis of the distribution of individual welfare. Regardless of how unsatisfactory the analysis of lifetime inequality can be with regard 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, as it allows for the aggregation of individual data on employment and wage levels and risk into a single synthetic measure. This in turn allows one to make unequivocal statements about changes over time in the cross-sectional dispersion of individual wage trajectories or to make 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.[4] 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 values and earnings over the last twenty years. An important feature of our approach is that using the model we can decompose the changes in lifetime inequality levels into the relative importance of changes in wage and employment risk, as well changes in the overall distribution of wages and sample composition, over the sample period.

The main innovation in our study, with respect to the studies of Flinn (1997) and Cohen (1998),

[4] This is a common assumption in these studies (for example, see Hotz and Miller, 1993). Extending the model to allow individuals to form expectations over future parameters would be useful but is beyond the scope of this paper.

is that we allow for non-stationarity in individual labor trajectories and build our analysis on a much more flexible econometric framework. In particular, 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. We also allow all parameters, including wage distributions and wage mobility processes, to change with potential experience (analogously age). In this way individuals face both transitory and permanent changes in their earnings process. To estimate the model parameters and construct our lifetime values we use data from the March US Current Population Surveys (CPS) (full and matched samples). This is in contrast to other long run inequality studies which 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. It also, unlike the PSID, provides us with large, nationally representative samples covering both the 1980s and the 1990s.

Our main results include the following. First, as in Cohen (1998) and Flinn (1997), the high degree of wage and employment mobility in the US translates into lower levels of inequality for employment annuity values than for wages, 40% lower.[5] This is essentially due to the fact that 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 essentially returned to their 1977 levels. This pattern aids in explaining why both wages and employment annuity values show similar long-run trends in means and inequality measures over the past 20 years. Taking a closer look at the respective evolutions of earnings and values inequality, we find that earnings inequality tends to increase more or less steadily from the mid 1970's to the late 1990's without interruption. In contrast, the dynamics of lifetime income inequality exhibit three different short-run trends: in the late 1970's the evolution of lifetime income inequality is parallel to that of earnings; from 1982 to 1993 it remains stable as the top of the value distribution tended to move in tandem with the bottom; finally, the post-1993 period is characterized by a greater return to education in values than in wages and value inequality increases at a faster rate than earnings inequality. Lastly, composition changes, although significant (the shift toward attaining more education and the aging population), do not play a large role in explaining the changes in lifetime inequality.

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

[5] Buchinsky and Hunt (1999) find a similar result using a different model.

results. The last section concludes.

2 The model

In this section we develop our model of individual dynamics and explain how we construct the present value of a particular labor market position under static expectations. At the end 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 $\{1, ..., A\}$, 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 $\delta_{a,t}$ ($\lambda^0_{a,t}$) 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 homogeneous population of workers except for potential experience which naturally changes over calendar time as individuals age and differs across individuals born at different dates.

An unemployed worker of experience level a at the beginning of period t receives non-employment income $b_{a,t}$, net of search costs. By convention, all revenues are received at the end of the period. If the worker is lucky enough to find a job in period t (with probability $\lambda^0_{a,t}$), he will receive wage, w_{t+1}, paid at the end of period $t+1$, that is drawn from the *sampling* distribution $F_{a,t}$.[6]

Modelling the wage mobility process of workers who remain employed over two subsequent periods is more complicated. There is a long literature on wage, earnings and income mobility that attests to the interest in and the variety of approaches to this subject. Some of these models are 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)). Other authors prefer less constrained parametric approaches of the wage mobility process and use Markov chains over a discrete wage space (e.g. Shorrocks (1976, 1978), Buchinsky and Hunt (1996)).

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

[6] We do not make any semantic distinction between wages and earnings, because we only consider full-time employment spells and an annualized earnings measure when we estimate the model. We return to this point in section 3.1.

same standard properties as earnings distributions. Continuity, in particular, is required. With discrete-space Markov chains, which provide a more precise description of wage dynamics than standard AR(I)MA models, (approximately) continuous present values can only be generated 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 datasets. Moreover, 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, innovative wage mobility model by borrowing features from the search literature. In the search framework it is assumed that job offers arrive randomly over time and that a worker accepts an offer only if it satisfies 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.[7]

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 $1 - \lambda^+_{a,t}(w_t)\,[1 - F_{a,t}(w_t)] - \lambda^-_{a,t}(w_t)F_{a,t}(w_t)$,

where $dF_{a,t}(\cdot)$ refers to the sampling probability measure, which 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 switching regime 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.[8]

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 $1-F_{a,t}(w_t)$

[7] While we are partial to the search interpretation, the above framework can stand alone without it 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 ($F_{a,t}$).

[8] See Gottschalk (2001) for recent evidence pointing to the importance of modelling wage decreases as well as wage increases.

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.

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 $\lambda^+_{a,t} - \lambda^-_{a,t}$ 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. With probability $\lambda^-_{a,t}$ he is laid off but is given a chance of drawing an offer within the same period without going through unemployment.[9]

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 3×3 Markov chain defined on the same thirds of the distribution. The probability of moving to the upper third 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.

2.2 Expectations

In the real world workers' future labor trajectories are uncertain. They value current projects and take contemporary decisions based on what they believe the structural parameters, denoted $\theta_t = \left\{\lambda^0_{a,t}, \delta_{a,t}, b_{a,t}, F_{a,t}, \lambda^+_{a,t}, \lambda^-_{a,t},\ a = 1, ..., A\right\}$, will be in the future. One natural expectations hypothesis to adopt when modelling such behaviour is rational expectations (RE). Unfortunately, computing expected lifetime labor income (or consumption) 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 $\theta_t = h(\boldsymbol{\theta}^{t-1}, u_t; \beta)$, where $\boldsymbol{\theta}^{t-1}$ denotes past realizations of θ_t, u_t is a possible stochastic component and β is a parameter.[10] An alternative is adaptive expectations, which *a priori* complicates the

[9] To see this write $\lambda^+ \cdot \mathbf{1}\{w' > w\} + \lambda^- \cdot \mathbf{1}\{w' < w\} = \left(\lambda^+ - \lambda^-\right) \cdot \mathbf{1}\{w' > w\} + \lambda^-$.

[10] The consumption literature seems to bypass this difficulty by looking only at Euler equations. Yet, the studies of consumption inequality based on Euler equations draw their conclusions from partial structures as the random shocks to consumption are generally only approximately related to exogenous income shocks. For example, these

econometrician's task even more because, in addition to specifying a model for θ_t, one must also specify how the agents learn the value of β. 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 θ_t and expect θ_{t+1}, θ_{t+2}, etc., to remain constant and equal to θ_t forever. 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 $\theta_{t+1}, \theta_{t+2}, ...$ but the current value θ_t. We show in the empirical analysis that the transition rate parameters exhibit untrended, smooth dynamics that are characteristic of random walks.[11] Therefore, static expectations may not be such a bad approximation of individuals' true expectations process after all.

Whatever the acurateness of the static expectations hypothesis, it allows us to make the following thought experiment that we think is useful. Take two time periods, t_0 and t_1. We observe two sets of parameter values, θ_{t_0} and θ_{t_1}, corresponding to these two periods. Then compute the distribution of lifetime income for time t_0 and time t_1 that *would* be observed if the structural parameters θ_{t_0} and θ_{t_1} remained constant for ever. Comparing the implied lifetime income inequality for θ_{t_0} to the implied lifetime income inequality for θ_{t_1} is like a comparative statics analysis and is useful as such.

studies often assume log-normality or make first-order linear Taylor expansions.

[11] There is some definite evidence that random walks are a cheap way of modelling time-series with changing trends. See Reichlin and Rappaport (1989) for a demonstration that a model with a unit root is always preferred to a model with segmented deterministic trends unless the exact number and timing of trend changes are known beforehand.

2.3 Present values

Under the assumption of static expectations, let $\mathcal{E}_{a,t}(w)$ denote the time t present value of employment at wage w 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

$$\mathcal{E}_{A,t} = \mathcal{U}_{A,t} = 0. \tag{1}$$

We justify this assumption by claiming that 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

$$(1+r)\mathcal{U}_{a,t} = b_{a,t} + \lambda^0_{a,t} \int_{\underline{w}_{a,t}}^{\overline{w}_{a,t}} \mathcal{E}_{a+1,t}(x) dF_{a,t}(x) + \left[1 - \lambda^0_{a,t}\right] \mathcal{U}_{a+1,t}. \tag{2}$$

Similarly, for employment values

$$\begin{aligned}(1+r)\mathcal{E}_{a,t}(w) &= w + \delta_{a,t}\mathcal{U}_{a+1,t} \\ &+ \lambda^+_{a,t}(w) \int_{w}^{\overline{w}_{a,t}} \mathcal{E}_{a+1,t}(x) dF_{a,t}(x) + \lambda^-_{a,t}(w) \int_{\underline{w}_{a,t}}^{w} \mathcal{E}_{a+1,t}(x) dF_{a,t}(x) \\ &+ \left[1 - \delta_{a,t} - \lambda^+_{a,t}(w)\overline{F}_{a,t}(w) - \lambda^-_{a,t}(w) F_{a,t}(w)\right] \mathcal{E}_{a+1,t}(w). \end{aligned} \tag{3}$$

In those Bellman equations we have used the static expectations hypothesis to substitute $\mathcal{E}_{a+1,t}(\cdot)$ and $\mathcal{U}_{a+1,t}$ for the uncertain future value functions $\mathcal{E}_{a+1,t+1}(\cdot)$ and $\mathcal{U}_{a+1,t+1}$ (uncertain because they depend on θ_{t+1} which is unknown at time t). The only nonstationarity that remains thus comes from the aging process.

Although we allow the average wage to increase with seniority as it does in the data, we note that, because there is a positive probability of keeping the same wage between years, the minimum wage given experience should be independent of the level of experience (but not of calendar time and education), i.e. $\underline{w}_{a,t} = \underline{w}_t$. We impose this assumption which also has the advantage of simplifying the numerical computation of values.

In addition, we make the assumption that employers have enough monopsony power to force the minimum wage offer $\underline{w}_t$ to be such that $\mathcal{U}_{a,t} = \mathcal{E}_a(\underline{w}_t)$. 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 $w = \underline{w}_t$ implies

$$(1+r)\,\mathcal{U}_{a,t} = \underline{w}_t + \lambda^+_{a,t}(\underline{w}_t) \int_{\underline{w}_t}^{\overline{w}_{a,t}} \mathcal{E}_{a+1,t}(x) dF_{a,t}(x) + \left[1 - \lambda^+_{a,t}(\underline{w}_t)\right] \mathcal{U}_{a+1,t}. \tag{4}$$

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

$$b_{a,t} = \underline{w}_t + \left[\lambda^{+}_{a,t}(\underline{w}_t) - \lambda^{0}_{a,t}\right] \left[\int_{\underline{w}_t}^{\overline{w}_{a,t}} \mathcal{E}_{a+1,t}(x) dF_{a,t}(x) - \mathcal{U}_{a,t}\right]. \qquad (5)$$

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

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:

$$\frac{\mathcal{E}_{a,t}(w)}{\sum_{t=0}^{A-1-a} \frac{1}{(1+r)^t}} = r\mathcal{E}_{a,t}(w) \frac{(1+r)^{A-1-a}}{(1+r)^{A-a} - 1}. \qquad (6)$$

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 available couple 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[12] 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.

Whether one should characterize the inequality of individual labor trajectories *ex ante* or *ex post*, by reference to expected or realized lifetime earnings is an issue that must be addressed before proceeding further. In addressing this issue we first claim that choosing between these two alternatives is arbitrary in our setting. At the end, we temper this assertion by showing with an

[12] In fact we do not draw many trajectories to average them but compute mathematical expectations given distribution estimates.

example why both approaches are likely to yield similar results. In the empirical analysis we present results for both.

To make the first point, we use an argument recently put forward by Gottschalk and Spolaore (2001). Suppose that workers live two periods. Let (w_{i1}, w_{i2}) denote worker i's income trajectory. Assume that future uncertainty and worker heterogeneity are consistent with the description of individual trajectories as realizations of a particular stochastic process. Atkinson and Bourguignon (1982) propose to weigh workers' intertemporal outcome valuations $U(w_{i1}, w_{i2})$ according to a social welfare function of the form

$$W = \mathrm{E}\left[U(w_{i1}, w_{i2})^{1-\varepsilon}\right], \tag{7}$$

where $\varepsilon > 0$ is the degree of aversion to inequality.[13] In equation (7) the expectation operator applies to the distribution of any measurable function of (w_{i1}, w_{i2}) in the population of workers. Any source of individual heterogeneity that would condition individual trajectories is thus averaged out.

Assume, for example, that

$$U(w_{i1}, w_{i2}) = \left(w_{i1}^{1-\rho} + w_{i2}^{1-\rho}\right)^{\frac{1}{1-\rho}}. \tag{8}$$

Gottschalk and Spolaore (2001) remark that in the Atkinson-Bourguignon setting, if $\varepsilon > \rho$, the aversion to inequality offsets the aversion to intertemporal fluctuations and a mobile society is preferred to a static one. The optimal level of wage mobility is "complete reversal," whereby the poor in period 1 have a probability equal to one of becoming rich in period 2 and the rich in period 1 have a probability equal to one of becoming poor.[14]

Gottschalk and Spolaore then point out that intertemporal independence between earnings (w_{i2} independent of w_{i1}) plays no special role in this context. They claim that this is because of the choice of Von Neuman-Morgenstern (VNM) utility functions which confuse risk aversion and intertemporal substitution. Claiming that origin independence might be of value to the society (see also Fields and Ok, 2001) Gottschalk and Spolaore propose to replace VNM utility functions by utility functions *à la* Kreps and Porteus (1978) or Epstein and Zin (1991). Specifically, they consider social welfare functions of the form

$$\widehat{W} = \mathrm{E}\left(w_{i1}^{1-\rho} + \mathrm{E}\left(w_{i2}^{1-\gamma}|w_{i1}\right)^{\frac{1-\rho}{1-\gamma}}\right)^{\frac{1-\varepsilon}{1-\rho}}. \tag{9}$$

[13] 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.

[14] In order to make this statement precise, suppose that wages follow a simple two-state Markov chain with a single parameter p, where the probability of w_{i2} being high conditional on w_{i1} being low is p and the probability of w_{i2} being low conditional on w_{i1} being high is also p. It is easy to show that when $\varepsilon > \rho$ the value of p that maximizes W is one.

That is, they replace w_{i2} in (8) by its certainty equivalent: $\widehat{w}_{i2} = \mathrm{E}\left(w_{i2}^{1-\gamma}|w_{i1}\right)^{\frac{1}{1-\gamma}}$.[15] They show that time independence is then valued if aversion to risk in the second period is low enough, i.e. $\varepsilon \geq \gamma$ and $\rho \geq \gamma$ with one of these two inequalities being strict. In this case, some reversal (a negative correlation between w_1 and w_2) is preferred if and only if $\varepsilon > \rho$.

As a benchmark examine the case of $\rho = \gamma = 0$ to see the link between Gottschalk and Spolare and our analysis. In this case W and $\widehat{W}$ become

$$\begin{aligned} W &= \mathrm{E}\left[(w_{i1} + w_{i2})^{1-\varepsilon}\right], \\ \widehat{W} &= \mathrm{E}\left[(w_{i1} + \mathrm{E}\left(w_{i2}|w_{i1}\right))^{1-\varepsilon}\right]. \end{aligned}$$

We note that the Atkinson-Bourguignon welfare function is now obtained by averaging a concave function of *realized* lifetime earnings, while the Gottshalk-Spolaore welfare function is obtained by averaging a concave function of individual *present values* of lifetime earnings. In both cases, complete reversal is always the preferred wage mobility pattern and the choice of which welfare measure to choose is arbitrary. This discussion shows that the choice between studying inequality in realized values or in present values is entirely axiomatic. In our empirical study, we do not choose between the two alternatives, but rather present results for both. Moreover, although we only consider the benchmark case $\rho = \gamma = 0$, we note that the empirical analysis conducted in this paper could be applied to any choice of values for the parameters ρ, γ and ε.

We end this subsection by showing that in the end both approaches are likely to yield similar results. Assume that individuals can earn in each period either $\underline{w}$ or $\overline{w}$ and that the probability of $\overline{w}$ in period 2 given $\underline{w}$ in period 1 and the probability of $\underline{w}$ in period 2 given $\overline{w}$ in period 1 are both equal to p. The wage mobility process can therefore be described by a simple Markov chain with the following transition probability matrix

$$P = \begin{pmatrix} 1-p & p \\ p & 1-p \end{pmatrix}.$$

The equilibrium marginal probability of each wage is 1/2.

The present value of earnings, $w_{i1} + \mathrm{E}\left(w_{i2}|w_{i1}\right)$, has the following steady-state distribution in the population of workers

$$w_{i1} + \mathrm{E}\left(w_{i2}|w_{i1}\right) = \left| \begin{array}{ll} \underline{w} + p\overline{w} + (1-p)\underline{w}, & \text{with probability } \frac{1}{2} \\ \overline{w} + p\underline{w} + (1-p)\overline{w}, & \text{with probability } \frac{1}{2} \end{array} \right., \tag{10}$$

[15] In (9) the conditional expectation operator refers to individual i's earnings trajectory, whereas the first expectation operator refers to the population.

whereas the steady-state distribution of realized lifetime earnings is

$$w_{i1} + w_{i2} = \left| \begin{array}{ll} \underline{w} + \overline{w}, & \text{with probability } \frac{p}{2} \\ \underline{w} + \underline{w}, & \text{with probability } \frac{1-p}{2} \\ \overline{w} + \underline{w}, & \text{with probability } \frac{p}{2} \\ \overline{w} + \overline{w}, & \text{with probability } \frac{1-p}{2} \end{array} \right. . \tag{11}$$

Note that

$$\begin{aligned} \mathrm{E}\left[w_{i1} + \mathrm{E}\left(w_{i2}|w_{i1}\right)\right] &= \mathrm{E}\left[w_{i1} + w_{i2}\right] \\ &= \underline{w} + \overline{w}, \end{aligned}$$

is independent of the mobility parameter p.

Because it fits better with our subsequent empirical analysis, instead of choosing a positive value for ε and computing W and $\widehat{W}$ for that value of ε, we choose $1 - \varepsilon = 2$ and compute population variances as welfare indicators. In our empirical work, we use other measures of dispersion (Gini, 90-10 percentile ratios) but this should not affect the qualitative results derived below.

Computing the population variance of present values in equation (10), we find

$$\mathrm{Var}\left[w_{i1} + \mathrm{E}\left(w_{i2}|w_{i1}\right)\right] = (1-p)^2 \left(\overline{w} - \underline{w}\right)^2 .$$

Increases in mobility reduce inequality. Moreover, the lowest level of inequality in present values is attained for the case of complete reversal ($p = 1$). Lastly, more inequality in the marginal wage distribution (the cross-sectional variance of earnings is equal to $\left(\overline{w} - \underline{w}\right)^2 / 2$) generates more inequality in the marginal distribution of present values, and any increase in wage inequality can be partly offset by a simultaneous increase in mobility.

By comparison, the population variance of realized lifetime income $w_{i1} + w_{i2}$ is

$$\mathrm{Var}(w_{i1} + w_{i2}) = (1-p)\left(\overline{w} - \underline{w}\right)^2 \geq \mathrm{Var}\left[w_{i1} + \mathrm{E}\left(w_{i2}|w_{i1}\right)\right].$$

This expression shows a similar aggregation of the mobility parameter (p) and cross-sectional dispersion ($\left(\overline{w} - \underline{w}\right)^2$). *Ex-post* lifetime income inequality is, of course, greater than *ex ante*, and the offsetting effect of wage mobility is greater *ex ante* than *ex post* relative to cross-sectional wage inequality (except for the two extreme cases of $p = 0$ or 1). This is because the *ex-ante* measure cancels out the contribution to inequality of any future transitory sources of wage fluctuations.

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.[16]

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.[17]

[16] 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.

[17] One alternative is to include part-time workers and examine the weekly wage without correcting for hours

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 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. This coincides with the aging of the baby boom. 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.

---

differentiation. For white males this alternative approach results in higher levels of inequality, as expected, but the trends in inequality - both earnings and employment values - are similar to those in the restricted sample.

3.2 Estimation

For ease of exposition we present here a brief outline of the estimation procedure. Details can be found in the Appendix.

To start, 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

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

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

$$F_{a,t}(w) = \frac{\Delta M_{a,t}(w) + \delta_{a,t} M_{a,t}(w) + \int_{\underline{w}_{a,t}}^{w} \lambda_{a,t}^+(x) dM_{a,t}(x)}{\lambda_{a,t}^0 U_{a,t} + \int_w^{\overline{w}_{a,t}} \lambda_{a,t}^-(x) dM_{a,t}(x) + \int_{\underline{w}_{a,t}}^{w} \lambda_{a,t}^+(x) dM_{a,t}(x)}. \tag{12}$$

Conditional on $\lambda_{a,t}^0$, $\delta_{a,t}$, $\lambda_{a,t}^+(x)$, $\lambda_{a,t}^-(x)$ being known, a non-parametric estimator of $F_{a,t}$ can be constructed using equation (12) 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 are observed to have a job the year after. The job destruction rate, $\delta_{a,t}$, is estimated by the proportion of employees with experience level a in year t who are unemployed the year after. 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 experence a who are unemployed at

$t+1$. Our estimates are, therefore,

$$\lambda_{a,t}^{0} = \frac{UM_{a,t}}{U_{a,t}}, \tag{13}$$

$$\delta_{a,t} = \frac{MU_{a,t}}{M_{a,t}}. \tag{14}$$

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 subsection 2.1 we have that

$$\lambda_{a,t}^{+}(w) = \frac{p_{a,t}^{+}(w)}{\overline{F}_{a}(w)}, \tag{15}$$

$$\lambda_{a,t}^{-}(w) = \frac{p_{a,t}^{-}(w)}{F_{a,t}(w)}. \tag{16}$$

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

$$F_{a,t}(w) = \frac{\Delta M_{a,t}(w) + \frac{MU_{a,t}}{M_{a,t}} M_{a,t}(w) + \int_{\underline{w}_{a,t}}^{w} \frac{dM_{a,t}^{+}(w)}{\overline{F}_{a,t}(w)}}{UM_{a,t} + \int_{w}^{\overline{w}_{a,t}} \frac{dM_{a,t}^{-}(w)}{\overline{F}_{a,t}(w)} + \int_{\underline{w}_{a,t}}^{w} \frac{dM_{a,t}^{+}(w)}{\overline{F}_{a,t}(w)}}.$$

An estimate of $F_{a,t}(\cdot)$ can, therefore, be obtained from observed mobility flows by iterating this equation until numerical convergence occurs.[18] 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 (15) and (16) deliver estimates of $\lambda_{a,t}^{+}(w)$ and $\lambda_{a,t}^{-}(w)$.

Before this last step, however, we need to consider the practical problem of determining the size of a wage increase (decrease) needed to be labelled a promotion (demotion) for estimation

[18] 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.

purposes. 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.[19]

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, $(\lambda^0_{a,t}, \delta_{a,t}, b_{a,t}, F_{a,t}, \lambda^+_{a,t}, \lambda^-_{a,t}) \equiv (\lambda^0_{i,t}, \delta_{i,t}, b_{i,t}, F_{i,t}, \lambda^+_{i,t}, \lambda^-_{i,t})$, for all $a \in [a_i, a_{i+1}[$, where i indicates one of the four experience groups ($i = 1, ..., 4$). 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 our estimation procedure and the data used.

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 $r = .05$.[20] 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 their 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

[19] 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 commonly done to remove obvious outliers.

[20] We tested different values of the discount rate without noticing a marked difference in the final results.

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 $\lambda^0_{a,t}$ and $\delta_{a,t}$. 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 for the different education and experience groups. Panels (a) and (c) present job destruction rates (probability of entering unemployment) for the education and experience categories, respectively, while panels (b) and (d) present the re-employment rates (probability of exiting unemployment) for each group. The job destruction rates exhibit a countercyclical pattern while the 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. Surprisingly, except for the job destruction rates of young workers which are clearly above the average, both job destruction and re-employment rates vary little with experience. In general the panels in Figure 3 do not exhibit any marked trends over the sample period.

The wage mobility parameters, $\lambda^+_{a,t}(w_t)$ and $\lambda^-_{a,t}(w_t)$, follow from the promotion and demotion rates found in the data. Figure 4 shows how average promotion and demotion rates vary across education and experience categories. Promotion rates tend to be similar across education categories, while differing across experience groups. Younger workers have the highest promotion rates. Demotion rates tend to be similar across experience categories, while education groups exhibit more variation. 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 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 (16) and (15)). However, numerical tractability led us to constrain the parameters. Figure 5 then 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. Here P10 (P90) refers to the bottom (top) decile of the full wage distribution, while P33, P33-P67 and P67, respectively, refer to the bottom, middle and top third of the distribution. Panels (b) and (d) confront these patterns using equations (19) and (20) 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. In terms of the levels the model matches upward wage mobility among the poorest workers relatively well, but underestimates upward wage mobility 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 of the distribution. Given the parsimonious parameter specification of the model and the dependence of the promotion and demotion probabilities on the placement in the wage offer distribution, we conclude that the model does a good job of matching the patterns found in the data.

Before calculating the present and realized values, we need estimates of the minimum wage, $\underline{w}_t$, 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 gave use estimates of $\underline{w}_t$ 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 conjuction with equation (5) these estimates of the lowest wage yield estimates of $b_{a,t}$, the value of non-labour time. In general the estimates of $b_{a,t}$ cover a greater range than the $\underline{w}_t$ estimates, but have a similar mean.[21] For example, in 1977 the mean of $\underline{w}_t$ is \$7,004 while the mean of $b_{a,t}$ is \$7,370.

We conducted two forms of sensitivity analysis to determine how sensitive the results are to the choice of trim level and the value of non-labour time. The first examined two other trim levels, 1% and 5%, while the second re-calculated the annuity values with the value of non-labour time set to zero for everyone. 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. The average minimum wage estimates over the sample period dropped to \$3,737 under a 1% trim level and increased to \$7,720 under a 5% trim level. This in turn also moved the average salary and annuity value in the same directions, albeit by only a few hundred dollars. In terms of inequality levels lowering (raising) the trim level slightly increased (decreased) wage inequality levels, but in both cases had very little effect on the inequality levels of the annuity values. Setting the value of

[21] In some cases the estimates of b_a are negative. This happens when the future value of employment is particularly high and the only way to explain a low reservation wage ($\underline{w}$) is with a very low value of non-labour time.

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 1990's 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, but older workers with 30 years or more of experience display a lower average value annuity than workers with 20-29 years of experience. 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. Even though the realized and present value annuity distributions look quite similar in Figure 7, Table 1 does indicate, as expected, that the level of inequality amongst realized value annuities is indeed higher than that for present value annuities. Importantly, both are much lower, about 40%, than that for earnings.[22] It is also interesting to note that the inequality differences between the realized and present value annuity distributions are greater when viewed through the Gini coefficient or the coefficient of variation than the 90/10 ratio.

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. This tells us something about what is happening in the tails of the distributions versus the middle. Table 1 provides the levels of the inequality measures for various years including more percentile ratios. For value annuities most of the increase in inequality

[22] We note that this reduction in inequality due to wage mobility is in line with Buchinsky and Hunt (1999) who find that inequality is cut by 12 to 26 percent when measured over a four year horizon.

occurs in the third quartile - the middle of the distribution, as opposed to the larger changes in the tails of the earnings distribution.

The fact that the increase in inequality from 1977 to 1997 is the same 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 and thus do not contribute to holding inequality down or increasing inequality amongst the annuity values. In fact, Figures 3 and 4 do indicate only small changes between the average flow rates in 1977 and 1997. To formalize this idea further we decomposed 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 line shows the 90/10 ratio and Gini coefficient for 1977. The second line indicates the change in both if the 1977 sample faces the same wage offer distribution and the same promotion and demotion parameters (λ^+ and λ^-), but face the employment and unemployment flow parameters (λ^0 and δ) for 1997. Here we see that inequality levels change very little when moving between the 1977 and 1997 flow rates. In the third line 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. Here we see that the wage mobility process did contribute to the increase in inequality albeit not substantially. In the fourth line we faced 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.[23] 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 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 the 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 90/10 ratios are more for Gini 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

[23] This exercise is actually similar to the calculations that Flinn (1997) made as his lifetime measures are based on parameters estimated from youth samples which are assumed to remain constant as the individual's age.

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 both between and within cell inequality increasing. 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, while 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 1990's 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 1990's, however, differ dramatically from those in the late 1970's. In the earlier period earnings and values were falling for everyone with higher incomes being slightly less affected. In the 1990's 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 two 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 extremely 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 incorportate the wage levels and mobility patterns across education categories.

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 1990's 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 increases in 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. It will be interesting to see if the large jump in inequality during the late 1990's is sustained in the coming years or is purely a temporary phenomenon.

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 inequality.

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 three 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 profitting 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 (1997) and Cohen (1998) 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.[24] Both of these features are

[24] Flinn (1997) and Cohen (1998) resort to parametric maximum likelihood, while we use a combination of moment

important given the types of data available and the time frame we study. In addition, our model is non-stationary 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 values exhibit 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 1980's. For the 1990's Kreuger and Perri (2001) find that consumption inequality levels remained stable despite rising income inequality levels. As our lifetime inequality levels increase over both decades, they match the consumption inequality pattern in the 1980's but diverge away from it in the 1990's. This development of stabilized consumption inequality in the face of continued increases in earnings and lifetime labor market 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 in our measure, the main limitation of our study is certainly the lack of unobserved heterogeneity. We can not 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 note that Gottschalk and Moffitt (1994) find that earnings instability explains about one-third to one-half of the noted increase in the variance of earnings from the 1970's to the 1980's, and that both transitory and individual-specific variances increased by the same percentage, about 40%. It would certainly be interesting to know what happened in this respect in the 1990's and whether lifetime income inequality shows a similar dependence on unobserved heterogeneity. 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.

---

and non-parametric estimators.

APPENDIX

A 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. $(\lambda_{a,t}^0, b_{a,t}, F_{a,t}, \lambda_{a,t}^+, \lambda_{a,t}^-) \equiv (\lambda_{i,t}^0, b_{i,t}, F_{i,t}, \lambda_{i,t}^+, \lambda_{i,t}^-)$, for all $a \in [a_i, a_{i+1}[$, where i indicates one of the four experience groups ($i = 1, ..., 4$).

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 $U_{i,t} \equiv \sum_{a=a_i}^{a_{i+1}-1} U_{a,t}$ and $M_{i,t} \equiv \sum_{a=a_i}^{a_{i+1}-1} M_{a,t}$ denote the number of unemployed and employed workers, respectively, with an experience level within the ith 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 $G_{i,t}(w) = \sum_{a=a_i}^{a_{i+1}-1} G_{a,t}(w)M_{a,t}/M_{i,t}$ denote the cummulative distribution function (cdf) of the distribution of earnings of all employed workers with experience level $a \, \epsilon \, [a_i, a_{i+1}[$.

Consider the stock $G_{i,t}(w)M_{i,t} = \sum_{a=a_i}^{a_{i+1}-1} G_{a,t}(w)M_{a,t}$ of employees with experience $a \, \epsilon \, [a_i, a_{i+1}[$ 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 $a \, \epsilon \, [a_i+1, a_{i+1}+1[$ paid less than wage w at time $t+1$, and $G_{i,t}(w)M_{i,t}$, i.e.

$$\begin{aligned}\Delta G_{i,t}(w)M_{i,t} &= \sum_{a=a_i}^{a_{i+1}-1} G_{a+1,t+1}(w)M_{a+1,t+1} - \sum_{a=a_i}^{a_{i+1}-1} G_{a,t}(w)M_{a,t} \\ &= G_{i,t+1}(w)M_{i,t+1} + G_{a_{i+1},t+1}(w)M_{a_{i+1},t+1} - G_{a_i,t+1}(w)M_{a_i,t+1} - G_{i,t}(w)M_{i,t}.\end{aligned}$$

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

$$\begin{aligned}\Delta G_{i,t}(w)M_{i,t} = \left[\lambda_{i,t}^0 U_{i,t} + \int_w^{\overline{w}_{i,t}} \lambda_{i,t}^-(x)dG_{i,t}(x)M_{i,t}\right] F_{i,t}(w) \\ - \left[\delta_{i,t}G_{i,t}(w) + \overline{F}_{i,t}(w)\int_{\underline{w}_{i,t}}^{w} \lambda_{i,t}^+(x)dG_{i,t}(x)\right] M_{i,t}.\end{aligned}$$

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 $F_{i,t}(w)$:

$$F_{i,t}(w) = \frac{\frac{\Delta G_{i,t}(w) M_{i,t}}{M_{i,t}} + \delta_{i,t} G_{i,t}(w) + \int_{\underline{w}}^{w} \lambda_{i,t}^{+}(x) dG_{i,t}(x)}{\lambda_{i,t}^{0} \frac{U_{i,t}}{M_{i,t}} + \int_{w}^{\overline{w}_{i,t}} \lambda_{i,t}^{-}(x) dG_{i,t}(x) + \int_{\underline{w}}^{w} \lambda_{i,t}^{+}(x) dG_{i,t}(x)}. \tag{17}$$

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 $\boldsymbol{\lambda}_{i,t} = \left(\lambda_{i,t}^{-(1)}, \lambda_{i,t}^{+(1)}, \lambda_{i,t}^{-(2)}, \lambda_{i,t}^{+(2)}, \lambda_{i,t}^{-(3)}, \lambda_{i,t}^{+(3)}\right)$:

$$F_{i,t}(w) = \begin{cases} \dfrac{\frac{\Delta G_{i,t}(w) M_{i,t}}{M_{i,t}} + \delta_{i,t} G_{i,t}(w) + \frac{1}{3}\lambda_{i,t}^{+(1)} + \frac{1}{3}\lambda_{i,t}^{+(2)} + \lambda_{i,t}^{+(3)}\left(G_{i,t}(w) - \frac{2}{3}\right)}{\lambda_{i,t}^{0}\frac{U_{i,t}}{M_{i,t}} + \lambda_{i,t}^{-(3)}\left(1 - G_{i,t}(w)\right) + \frac{1}{3}\lambda_{i,t}^{+(1)} + \frac{1}{3}\lambda_{i,t}^{+(2)} + \lambda_{i,t}^{+(3)}\left(G_{i,t}(w) - \frac{2}{3}\right)}, & \forall w > q_{i,t}^{(2)} \\ \dfrac{\frac{\Delta G_{i,t}(w) M_{i,t}}{M_{i,t}} + \delta_{i,t} G_{i,t}(w) + \frac{1}{3}\lambda_{i,t}^{+(1)} + \lambda_{i,t}^{+(2)}\left(G_{i,t}(w) - \frac{1}{3}\right)}{\lambda_{i,t}^{0}\frac{U_{i,t}}{M_{i,t}} + \lambda_{i,t}^{-(2)}\left(\frac{2}{3} - G_{i,t}(w)\right) + \frac{1}{3}\lambda_{i,t}^{-(3)} + \frac{1}{3}\lambda_{i,t}^{+(1)} + \lambda_{i,t}^{+(2)}\left(G_{i,t}(w) - \frac{1}{3}\right)}, & \forall q_{i,t}^{(1)} < w \leq q_{i,t}^{(2)} \\ \dfrac{\frac{\Delta G_{i,t}(w) M_{i,t}}{M_{i,t}} + \left(\delta_{i,t} + \lambda_{i,t}^{+(1)}\right) G_{i,t}(w)}{\lambda_{i,t}^{0}\frac{U_{i,t}}{M_{i,t}} + \lambda_{i,t}^{-(1)}\left(\frac{1}{3} - G_{i,t}(w)\right) + \frac{1}{3}\lambda_{i,t}^{-(2)} + \frac{1}{3}\lambda_{i,t}^{-(3)} + \lambda_{i,t}^{+(1)} G_{i,t}(w)}, & \forall w \leq q_{i,t}^{(1)} \end{cases} \tag{18}$$

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 $G_{i,t}(w)$, $\frac{\Delta G_{i,t}(w) M_{i,t}}{M_{i,t}}$ 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

$$p_{i,t}^{+}([a, b]) = \frac{1}{b - a} \int_{G_{i,t}^{-1}(a)}^{G_{i,t}^{-1}(b)} \lambda_{i,t}^{+}(w) \overline{F}_{i,t}(w) dG_{i,t}(w). \tag{19}$$

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

$$\begin{aligned}
p_{i,t}^{+(3)} &\equiv p_{i,t}^{+}\left([2/3,1[\right) = \lambda_{i,t}^{+(3)} \cdot 3\int_{q_{i,t}^{(2)}}^{\overline{w}_{i,t}} \overline{F}_{i,t}(w)dG_{i,t}(w),\\
p_{i,t}^{+(2)} &\equiv p_{i,t}^{+}\left([1/3,2/3[\right) = \lambda_{i,t}^{+(2)} \cdot 3\int_{q_{i,t}^{(1)}}^{q_{i,t}^{(2)}} \overline{F}_{i,t}(w)dG_{i,t}(w),\\
p_{i,t}^{+(1)} &\equiv p_{i,t}^{+}\left([0,1/3[\right) = \lambda_{i,t}^{+(1)} \cdot 3\int_{\underline{w}_{i,t}}^{q_{i,t}^{(1)}} \overline{F}_{i,t}(w)dG_{i,t}(w).
\end{aligned}$$

Let $p_{i,t}^{-}\left([a,b[\right)$ 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

$$p_{i,t}^{-}([a,b[) = \frac{1}{b-a}\int_{G_{i,t}^{-1}(a)}^{G_{i,t}^{-1}(b)} \lambda_{i,t}^{-}(w)F_{i,t}(w)dG_{i,t}(w). \tag{20}$$

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

$$\frac{1}{\lambda_{i,t}^{+}}p_{i,t}^{+}\left([a_{i,t},a_{i,t+1}[\right) + \frac{1}{\lambda_{i,t}^{-}}p_{i,t}^{-}([a_i,a_{i+1}[) = 1, \tag{21}$$

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

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

$$0 \leq \lambda_{i,t}^{+}(w)\overline{F}_{i,t}(w) + \lambda_{i,t}^{-}(w)F_{i,t}(w) \leq 1-\delta_{i,t},$$

i.e.

$$\begin{cases}
0 \leq \lambda_{i,t}^{+(1)} \leq 1-\delta_{i,t},\\
0 \leq \frac{2}{3}\lambda_{i,t}^{+(1)} + \frac{1}{3}\lambda_{i,t}^{-(1)} \leq 1-\delta_{i,t},\\
0 \leq \frac{2}{3}\lambda_{i,t}^{+(2)} + \frac{1}{3}\lambda_{i,t}^{-(2)} \leq 1-\delta_{i,t},\\
0 \leq \frac{1}{3}\lambda_{i,t}^{+(2)} + \frac{2}{3}\lambda_{i,t}^{-(2)} \leq 1-\delta_{i,t},\\
0 \leq \frac{1}{3}\lambda_{i,t}^{+(3)} + \frac{2}{3}\lambda_{i,t}^{-(3)} \leq 1-\delta_{i,t},\\
0 \leq \lambda_{i,t}^{-(3)} \leq 1-\delta_{i,t}.
\end{cases}$$

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 $\boldsymbol{\lambda}_{i,t}$ by solving the following fixed point system of equations:

$$\left\{\begin{array}{l}
\lambda_{i,t}^{+(3)} = \max\left\{0, \min\left\{1-\delta_{i,t}, \dfrac{p_{i,t}^{+(3)}}{3\int_{q_{i,t}^{(2)}}^{\overline{w}_{i,t}} \overline{F}_{i,t}(w)dG_{i,t}(w)}\right\}\right\} \\
\lambda_{i,t}^{+(2)} = \max\left\{0, \min\left\{1-\delta_{i,t}, \dfrac{p_{i,t}^{+(2)}}{3\int_{q_{i,t}^{(1)}}^{q_{i,t}^{(2)}} \overline{F}_{i,t}(w)dG_{i,t}(w)}\right\}\right\} \\
\lambda_{i,t}^{+(1)} = \max\left\{0, \min\left\{1-\delta_{i,t}, \dfrac{p_{i,t}^{+(1)}}{3\int_{\underline{w}_t}^{q_{i,t}^{(1)}} \overline{F}_{i,t}(w)dG_{i,t}(w)}\right\}\right\} \\
\lambda_{i,t}^{-(3)} = \max\left\{0, \min\left\{1-\delta_{i,t}, \dfrac{p_{i,t}^{-(3)}}{1-3\int_{q_{i,t}^{(2)}}^{\overline{w}_{i,t}} \overline{F}_{i,t}(w)dG_{i,t}(w)}\right\}\right\} \\
\lambda_{i,t}^{-(2)} = \max\left\{0, \min\left\{1-\delta_{i,t}, \dfrac{p_{i,t}^{-(2)}}{1-3\int_{q_{i,t}^{(1)}}^{q_{i,t}^{(2)}} \overline{F}_{i,t}(w)dG_{i,t}(w)}\right\}\right\} \\
\lambda_{i,t}^{-(1)} = \max\left\{0, \min\left\{1-\delta_{i,t}, \dfrac{p_{i,t}^{-(1)}}{1-3\int_{\underline{w}_t}^{q_{i}^{(1)}} \overline{F}_{i,t}(w)dG_{i,t}(w)}\right\}\right\}
\end{array}\right. . \tag{22}$$

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 $\boldsymbol{\lambda}_{i,t}$. We solve this fixed-point equation for $\boldsymbol{\lambda}_{i,t}$ by iterating the following simple procedure until convergence. For an initial value of $\boldsymbol{\lambda}_{i,t}$, we compute an initial value for $F_{i,t}$ using equation (18). We then update $\boldsymbol{\lambda}_{i,t}$ using equation (22) 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 ith 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 ith 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.[25] 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

[1] Atkinson, Anthony B. and Francois Bourguignon (1982) "The Comparison of Multi-Dimensioned Distributions of Economic Status," *Review of Economic Studies*, 49(2), 183-201.

[2] Attanasio, Orazio and Steven Davis (1996) "Relative Wage Movements and the Distribution of Consumption," *Journal of Political Economy*, 104(6) , 1227-1262.

[3] Blundell, Richard and Ian Preston (1998) "Consumption Inequality and Income Uncertainty," *Quarterly Journal of Economics* 113 (2), 603-640.

[4] Buchinsky, Moshe and Jennifer Hunt (1999) "Wage Mobility in the United States," *Review of Economics and Statistics*, 81 (3), 351-368.

[5] Buchinsky, Moshe and Phillip Leslie (1997) "Education Attainment and the Changing U.S. Wage Structure: Some Dynamic Implications," Brown University, Department of Economics Working Paper: 97/13.

[6] Cohen, Daniel (1998), "Welfare Differentials across French and US Labor Markets," mimeo.

[7] Cutler, David M. and Lawrence F. Katz (1992) "Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980's," *American Economic Review* 82 (3), 546-551.

[8] Deaton, Angus and Christina Paxson (1994) "Intertemporal Choice and Inequality," *Journal of Poltical Economy* 102(3), 437-467.

[9] Epstein, Larry and Stanley Zin (1991) "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework," *Econometrica*, 57, 937-969.

[10] Fields,G.S.and E.A. Ok (2001), "The Measurement of Income Mobility:An Introduction to the Literature," in J.Silber (ed.), *Handbook on Income Inequality Measurement*, Boston, Kluwer Academic Press, 557-596, forthcoming.

[25] 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.

[11] Flinn, Christopher J. (1997) "Labor Market Structure and Welfare: A Comparison of Italy and the U.S.," New York University, forthcoming in *The Review of Economic Studies*.

[12] Geweke, J. and M. Keane (2000), "An empirical analysis of earnings dynamics among men in the PSID: 1968-1989," *Journal of Econometrics* 96, 293-356.

[13] Gottschalk, Peter (1997) "Inequality, Income Growth and Mobility: The Basic Facts," *Journal of Economic Perspectives* 11(2), 21-40.

[14] Gottshalk, Peter (2001) "Wage Mobility Within and Between Jobs," mimeo.

[15] Gottshalk, Peter and Robert Moffitt (1994), 'The Growth of Earnings Instability in the US Labor Market.' *Brookings Papers on Economic Activity*, 2: 217-273.

[16] Gottshalk, Peter and Enrico Spolaore (2001), "On the evaluation of economic mobility," mimeo.

[17] Hall, Robert E. and Frederic S. Mishkin (1982) "The Sensitivity of Consumption to Transitory Income: Estimates from Panel Data on Households", *Econometrica* 50(2), 461-482.

[18] Hotz, J. and R. A.Miller (1993) "Conditional Choice Probabilities and Estimation of Dynamic Models," *Review of Economic Studies*, 60, 497-529.

[19] Jaeger, David A. (1997) "Reconciling the Old and New Census Bureau Education Questions: Recommendations for Researchers," *Journal of Business and Economic Statistics* 15 (3), 300-309.

[20] Juhn, Chinhui, Kevin M. Murphy and Brooks Pierce (1993) "Wage Inequality and the Rise in the Returns to Skill," *Journal of Political Economy* 101 (3), 410-42.

[21] Katz, Lawrence F. and David H. Autor (1998) "Changes in the Wage Structure and Earnings Inequality," forthcoming in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*.

[22] Keane, M.P. and K. I. Wolpin (1994), "The Career of Young Men," *Journal of Political Economy*, 105, 473-522.

[23] Kreps, David and E. Porteus (1979) "Dynamic Choice Theory and Dynamic Programming," *Econometrica*, 47, 91–100.

[24] Krueger, Dirk and Fabrizio Perri (2001) "Does Income Inequality Lead to Consumption Inequality? Empirical Findings and a Theoretical Explanation," mimeo.

[25] Levy, Frank and Richard J. Murnane (1992) “U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations,” *Journal of Economic Literature* 30(3), 1333-81.

[26] Lillard, L. and R. Willis (1978), “Dynamic Aspects of Earnings Mobility,” *Econometrica,* 46, 985-1012.

[27] Liu, Haoming (1998) “Labor Quality and the Cyclicality of Real Wages,” University of Western Ontario Department of Economics Research Report 9712.

[28] MaCurdy, T. (1982), “The use of time series processes to model the error structure of earnings in a longitudinal data analysis,” *Journal of Econometrics* 18, 83-114.

[29] Peracchi, Franco and Finis Welch (1995) “How Representative are Matched Cross-Sections? Evidence from the Current Population Survey,” *Journal of Econometrics* 68(1), 153-80.

[30] Reichlin, L. and P. Rappaport (1989), “Segmented Trends and Nonstationary Time-Series,” *The Economic Journal*, 99.

[31] Shorrocks, Anthony F. (1976), “Income mobility and the Markov assumption,” *Economic Journal* 86, 566-578.

[32] Shorrocks, Anthony F. (1978) “The Measurement of Mobility,” *Econometrica*, 46, p. 1013-1024.

[33] Stoereslettern, Kjetil, Chris Telmer and Amir Yaron (2000) ”Consumption and Risk Sharing Over the Life Cycle,” mimeo.

Table 1: Inequality Measures for Earnings and Value Annuities

	1977	1981	1987	1993	1996	1997
A. Earnings						
90-10 Ratio	3.470	3.678	4.371	4.615	4.808	4.867
90-75 Ratio	1.282	1.328	1.386	1.395	1.429	1.460
75-50 Ratio	1.345	1.356	1.443	1.433	1.531	1.457
50-25 Ratio	1.435	1.481	1.471	1.546	1.524	1.525
25-10 Ratio	1.402	1.379	1.486	1.492	1.442	1.500
Gini Coefficient	0.271	0.287	0.318	0.313	0.360	0.359
Coefficient of Variation	0.540	0.584	0.666	0.587	0.901	0.885
Standard Deviation (log earnings)	0.494	0.523	0.580	0.582	0.628	0.628
B. Present Value Annuities						
90-10 Ratio	2.047	2.293	2.357	2.352	2.673	3.069
90-75 Ratio	1.348	1.335	1.206	1.218	1.167	1.185
75-50 Ratio	1.150	1.230	1.388	1.312	1.532	1.682
50-25 Ratio	1.150	1.192	1.138	1.143	1.187	1.158
25-10 Ratio	1.146	1.171	1.238	1.287	1.260	1.33
Gini Coefficient	0.147	0.175	0.183	0.170	0.210	0.233
Coefficient of Variation	0.275	0.324	0.341	0.306	0.398	0.444
Standard Deviation (log values)	0.259	0.305	0.321	0.306	0.369	0.411
C. Realized Value Annuities						
90-10 Ratio	2.042	2.421	2.481	2.526	2.758	3.068
90-75 Ratio	1.243	1.315	1.298	1.258	1.336	1.385
75-50 Ratio	1.203	1.260	1.304	1.323	1.383	1.443
50-25 Ratio	1.173	1.201	1.202	1.220	1.222	1.217
25-10 Ratio	1.165	1.216	1.220	1.244	1.221	1.261
Gini Coefficient	0.157	0.192	0.201	0.195	0.232	0.250
Coefficient of Variation	0.294	0.366	0.386	0.353	0.465	0.497
Standard Deviation (log values)	0.277	0.336	0.352	0.350	0.398	0.432

Table 2: Decomposition of Change in Present Value Annuity Inequality

	90/10 Ratio	Relative to Base	Gini	Relative to Base
A. 1977 to 1997				
1977 Inequality Levels	2.047	100	0.147	100
Change (un)employment rates	2.037	100	0.147	100
Change promotion/demotion rates	2.208	108	0.161	110
Change earnings distribution	3.154	154	0.230	156
1997 Inequality Levels	3.069	150	0.233	159
B. 1977 to 1981				
1977 Inequality Levels	2.047	100	0.147	100
Change (un)employment rates	2.131	104	0.155	105
Change promotion/demotion rates	2.494	122	0.192	131
Change earnings distribution	2.268	111	0.172	117
1981 Inequality Levels	2.293	112	0.175	119
B. 1981 to 1993				
1981 Inequality Levels	2.293	100	0.175	100
Change (un)employment rates	2.266	99	0.171	98
Change promotion/demotion rates	2.230	97	0.170	97
Change earnings distribution	2.423	106	0.174	99
1993 Inequality Levels	2.352	103	0.170	97
C. 1993 to 1997				
1993 Inequality Levels	2.352	100	0.170	100
Change (un)employment rates	2.262	96	0.169	99
Change promotion/demotion rates	2.020	86	0.145	85
Change earnings distribution	3.170	135	0.225	132
1997 Inequality Levels	3.069	130	0.233	137

Table 3: Education and Experience Differentials

	1977	1981	1987	1993	1996	1997
A. Earnings						
Education:						
Univ/HS Differential	1.505	1.564	1.748	1.766	2.039	2.057
<HS Level ($1,000)	20.389	17.937	17.038	13.797	13.745	14.208
Univ Level ($1,000)	36.291	34.014	37.861	33.931	40.377	41.166
HS/<HS	1.182	1.213	1.271	1.392	1.441	1.408
Some College/HS	1.074	1.111	1.150	1.192	1.186	1.202
Univ/Some College	1.402	1.407	1.520	1.483	1.719	1.711
Experience:						
0-9 Level ($1,000)	19.861	18.003	18.682	16.620	17.373	18.143
30+ Level ($1,000)	27.733	27.079	28.721	25.848	28.408	29.628
30+/20-29	0.902	0.949	0.930	0.940	0.964	0.988
20-29/10-19	1.097	1.116	1.175	1.171	1.127	1.150
10-19/0-9	1.411	1.420	1.406	1.412	1.505	1.438
B. Present Value Annuities						
Education:						
Univ/HS Differential	1.588	1.745	1.798	1.711	2.058	2.241
<HS Level ($1,000)	19.355	16.308	16.598	13.825	14.537	13.987
Univ Level ($1,000)	39.025	37.111	39.985	34.834	42.473	46.595
HS/<HS	1.270	1.304	1.340	1.473	1.420	1.487
Some College/HS	1.109	1.169	1.180	1.148	1.229	1.201
Univ/Some College	1.432	1.493	1.524	1.490	1.675	1.866
Experience:						
0-9 Level ($1,000)	25.516	22.133	24.201	21.400	24.165	24.858
30+ Level ($1,000)	25.713	24.570	26.388	24.336	27.264	28.855
30+/20-29	0.900	0.927	0.904	0.927	0.931	0.947
20-29/10-19	1.002	1.006	1.057	1.073	1.070	1.070
10-19/0-9	1.118	1.190	1.142	1.143	1.134	1.146

Table 4: Between and Within Cell Inequality

	1977	1981	1987	1993	1996	1997
A. Earnings						
Variance Decomposition (log earnings):						
Total	0.244	0.274	0.336	0.338	0.394	0.394
Within	0.173	0.192	0.223	0.216	0.262	0.260
Between	0.072	0.082	0.113	0.122	0.133	0.134
R-squared	0.29	0.30	0.34	0.36	0.34	0.34
B. Present Value Annuities						
Variance Decomposition (log values):						
Total	0.067	0.092	0.103	0.094	0.136	0.169
Within	0.006	0.007	0.008	0.005	0.008	0.008
Between	0.061	0.086	0.095	0.088	0.128	0.161
R-squared	0.91	0.93	0.93	0.94	0.94	0.95
C. Realized Value Annuities						
Variance Decomposition (log values):						
Total	0.077	0.113	0.124	0.122	0.159	0.187
Within	0.026	0.028	0.036	0.029	0.041	0.039
Between	0.051	0.084	0.088	0.094	0.117	0.147
R-squared	0.67	0.75	0.71	0.76	0.74	0.79

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

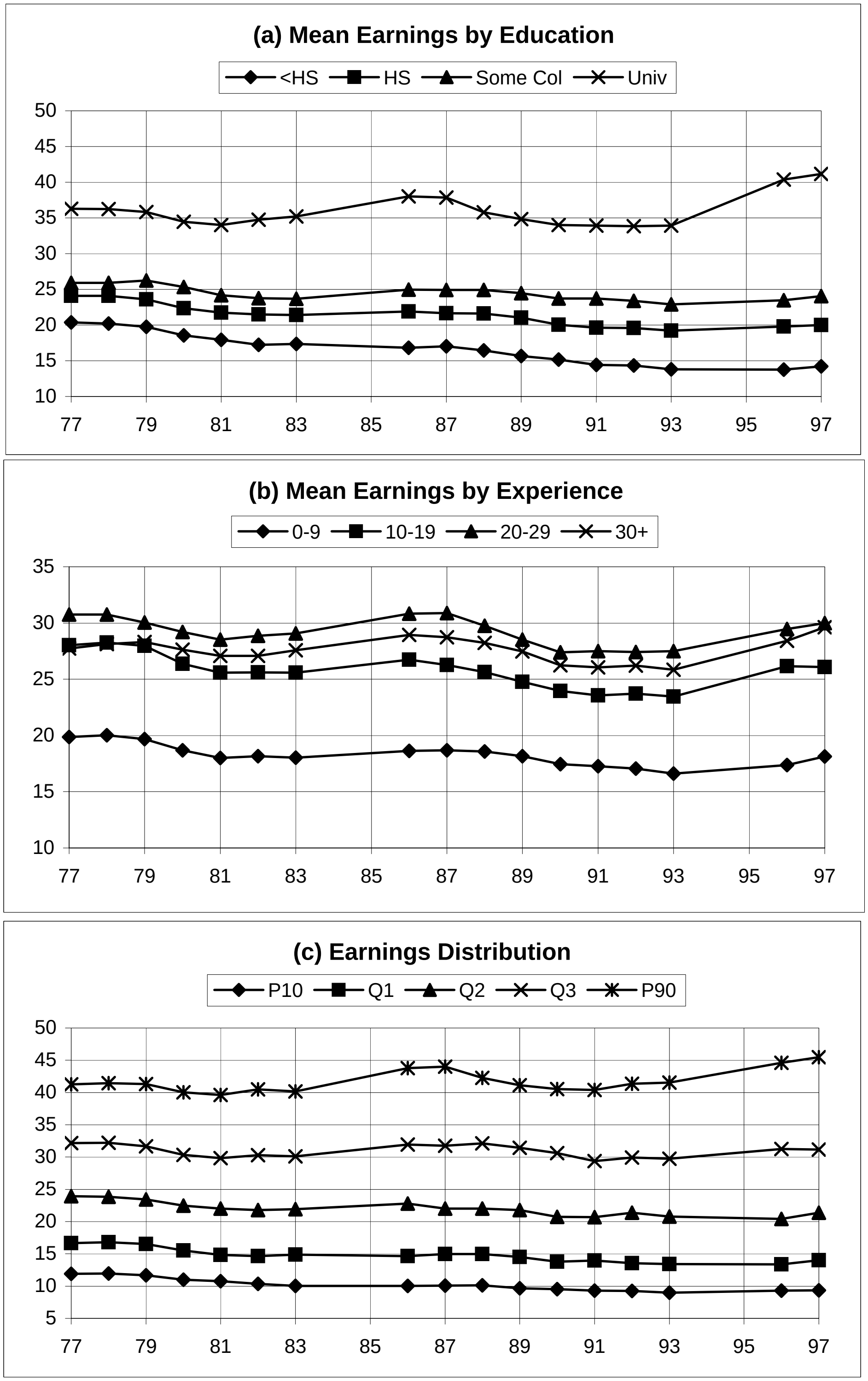


Figure 2: Composition of the Samples

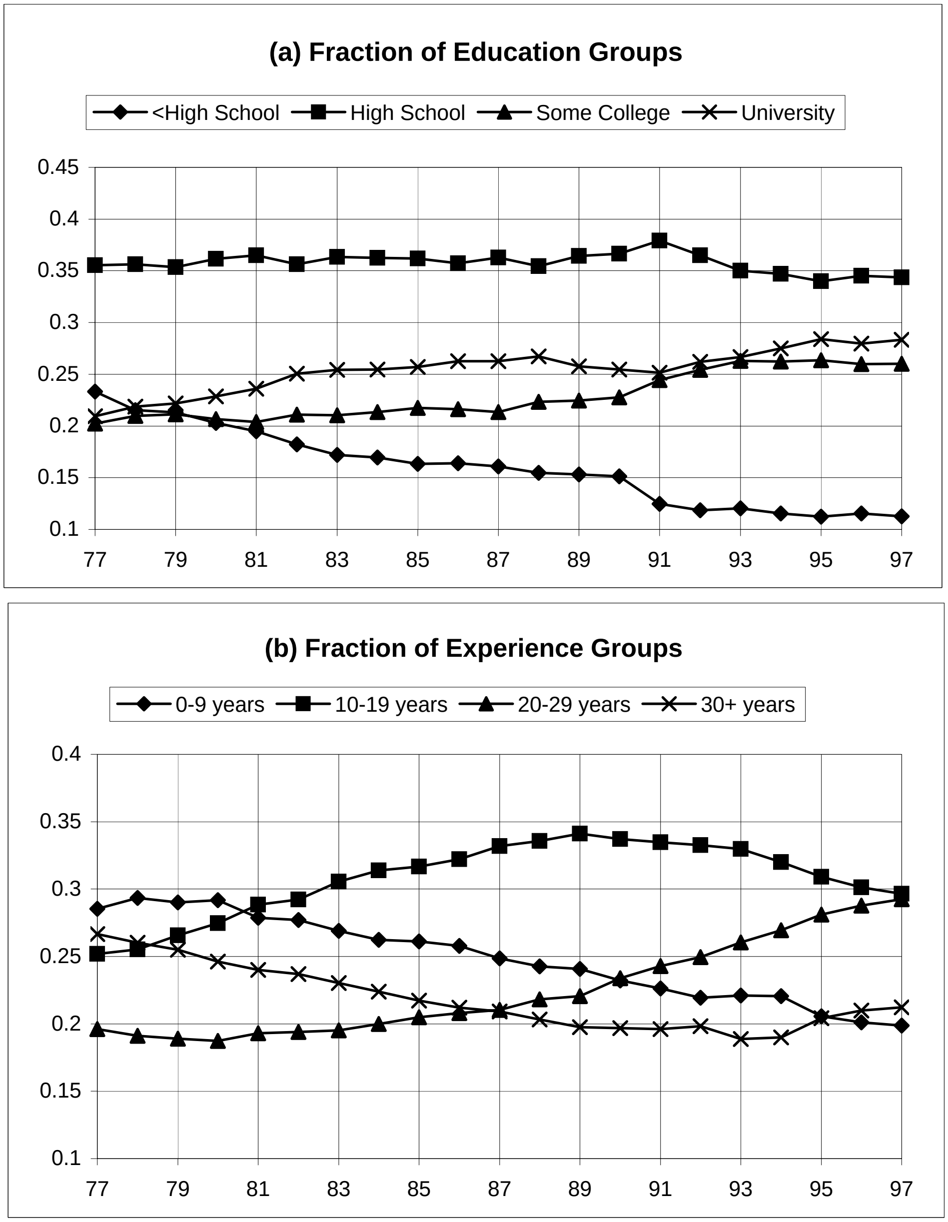
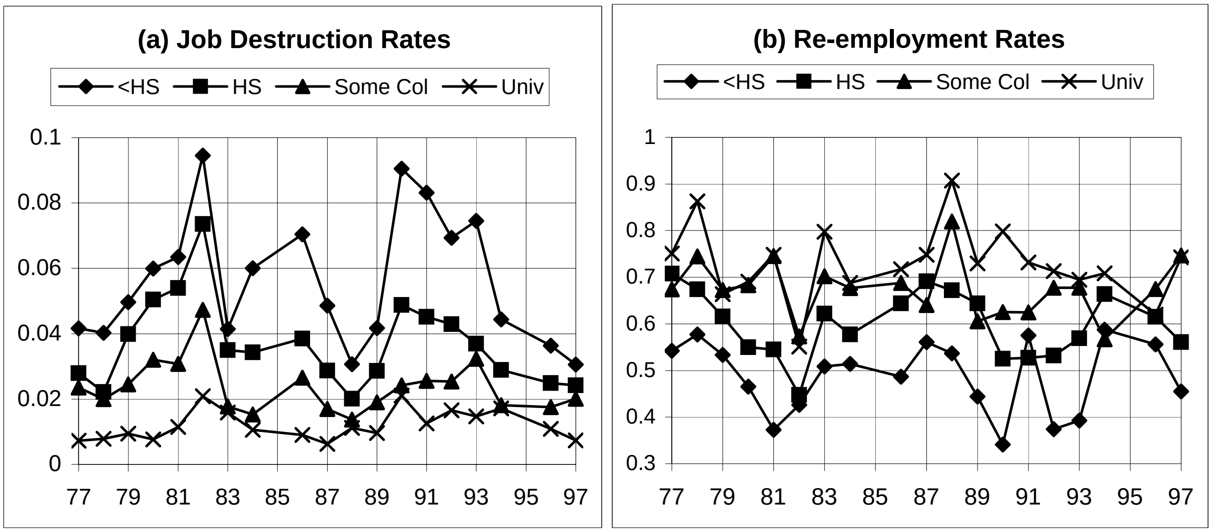


Figure 3: Employment-Unemployment Transition Rates

(1) By Education



(2) By Experience

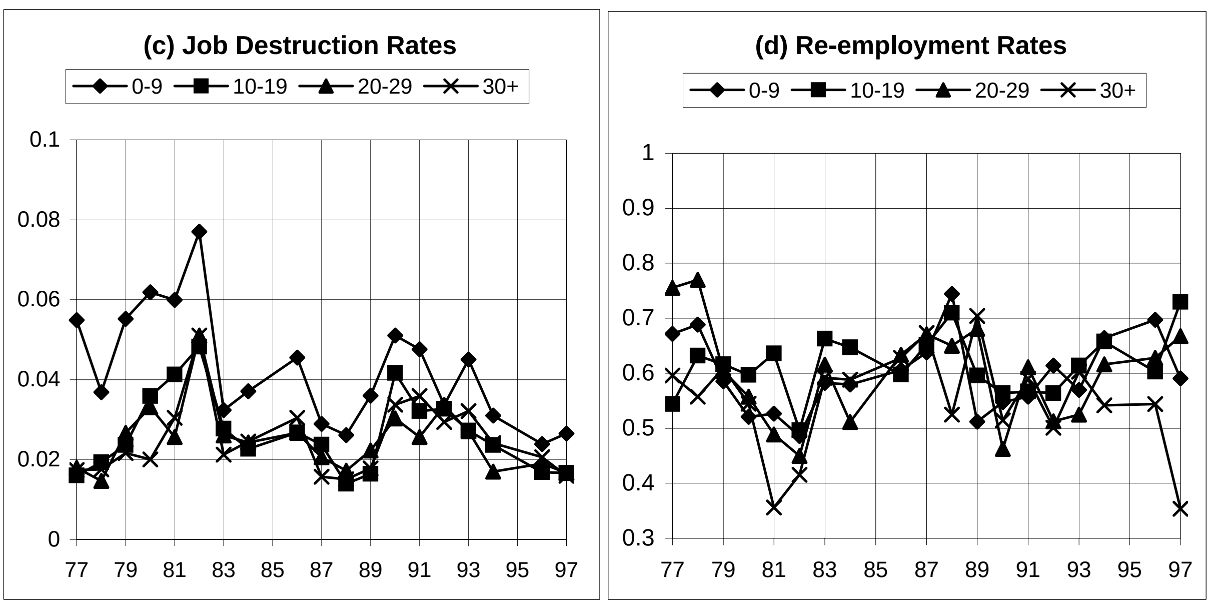
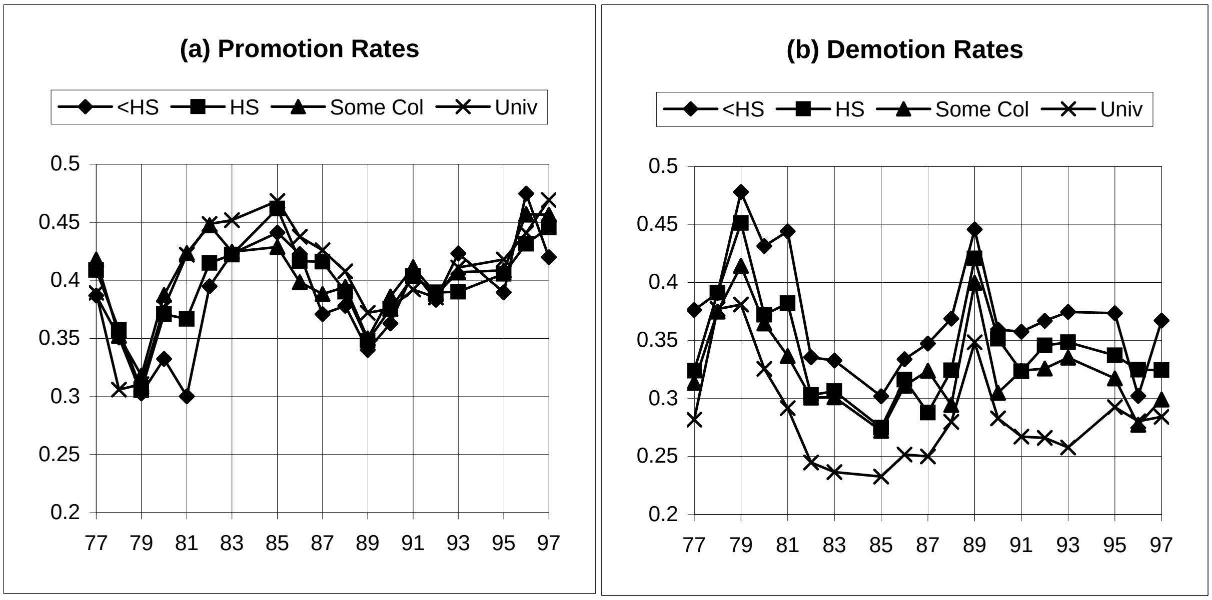


Figure 4: Promotion and Demotion Rates

(1) By Education



(2) By Experience

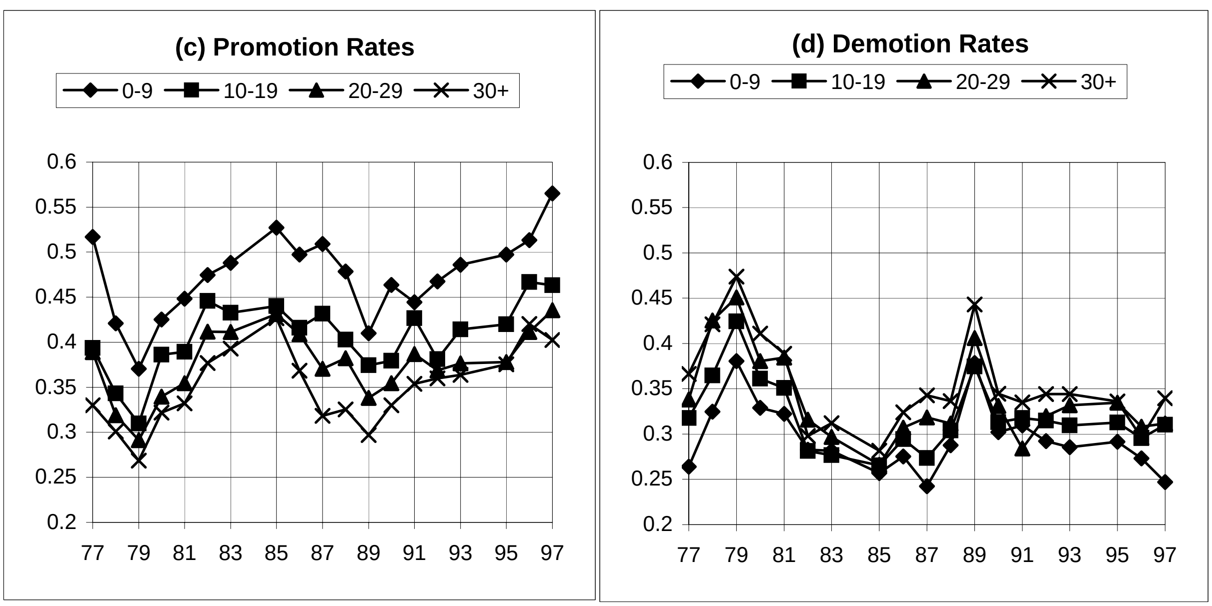


Figure 5: Observed and Predicted Mobility Rates by Earnings Cell

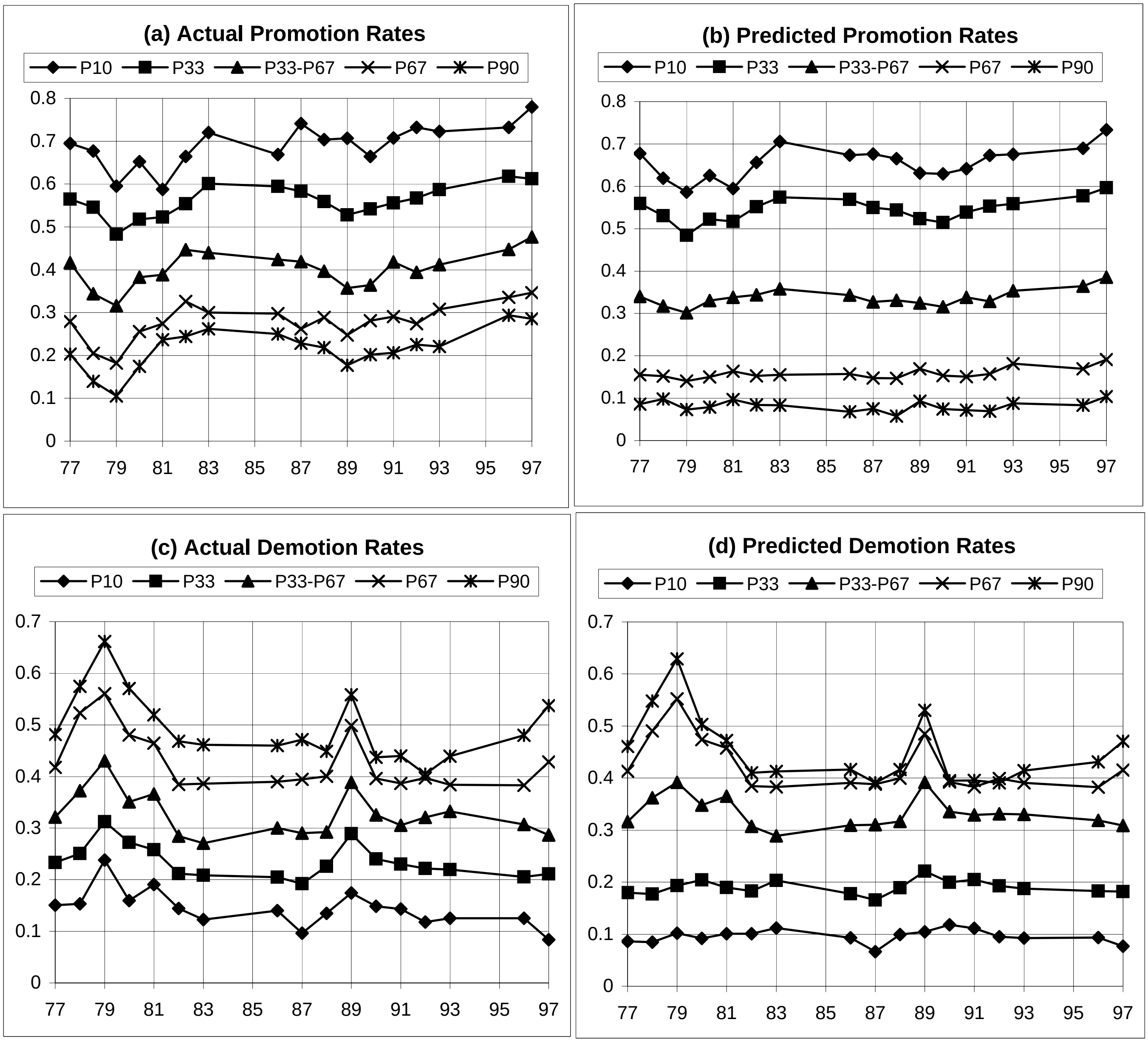
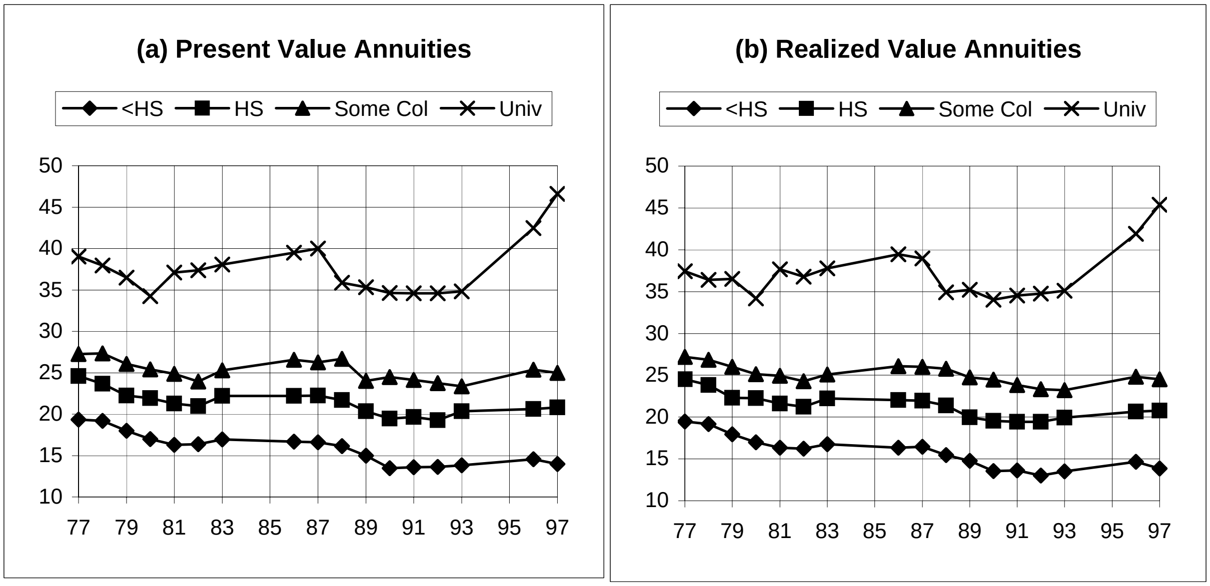


Figure 6: Mean Present and Realized Value Annuities ($1000)

(1) By Education



(2) By Experience

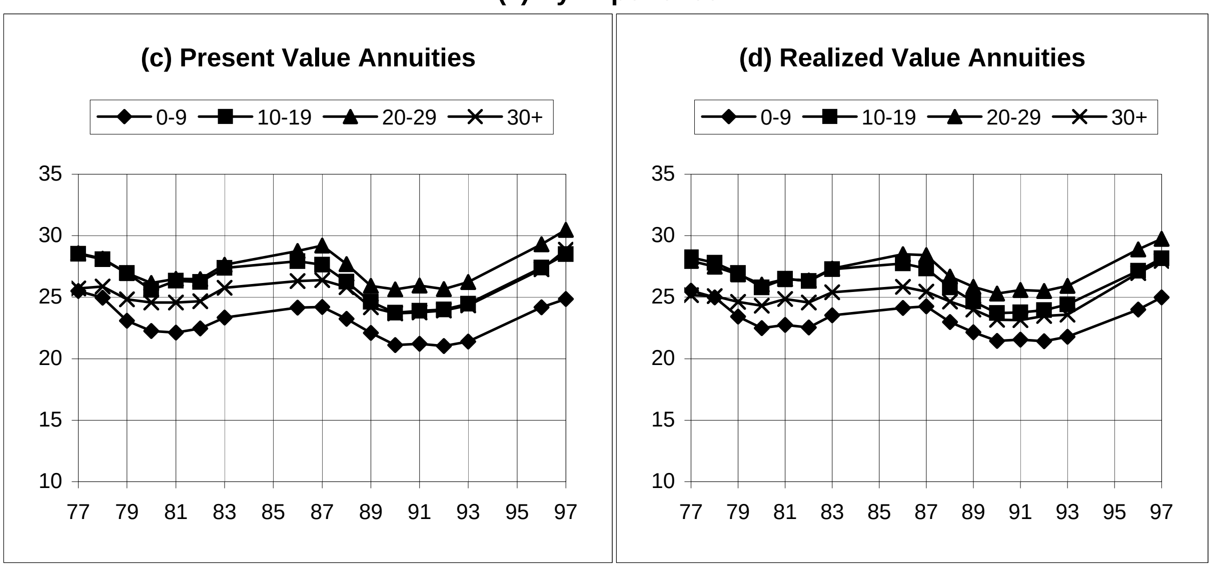


Figure 7: Earnings and Value Annuity Distributions ($1000)

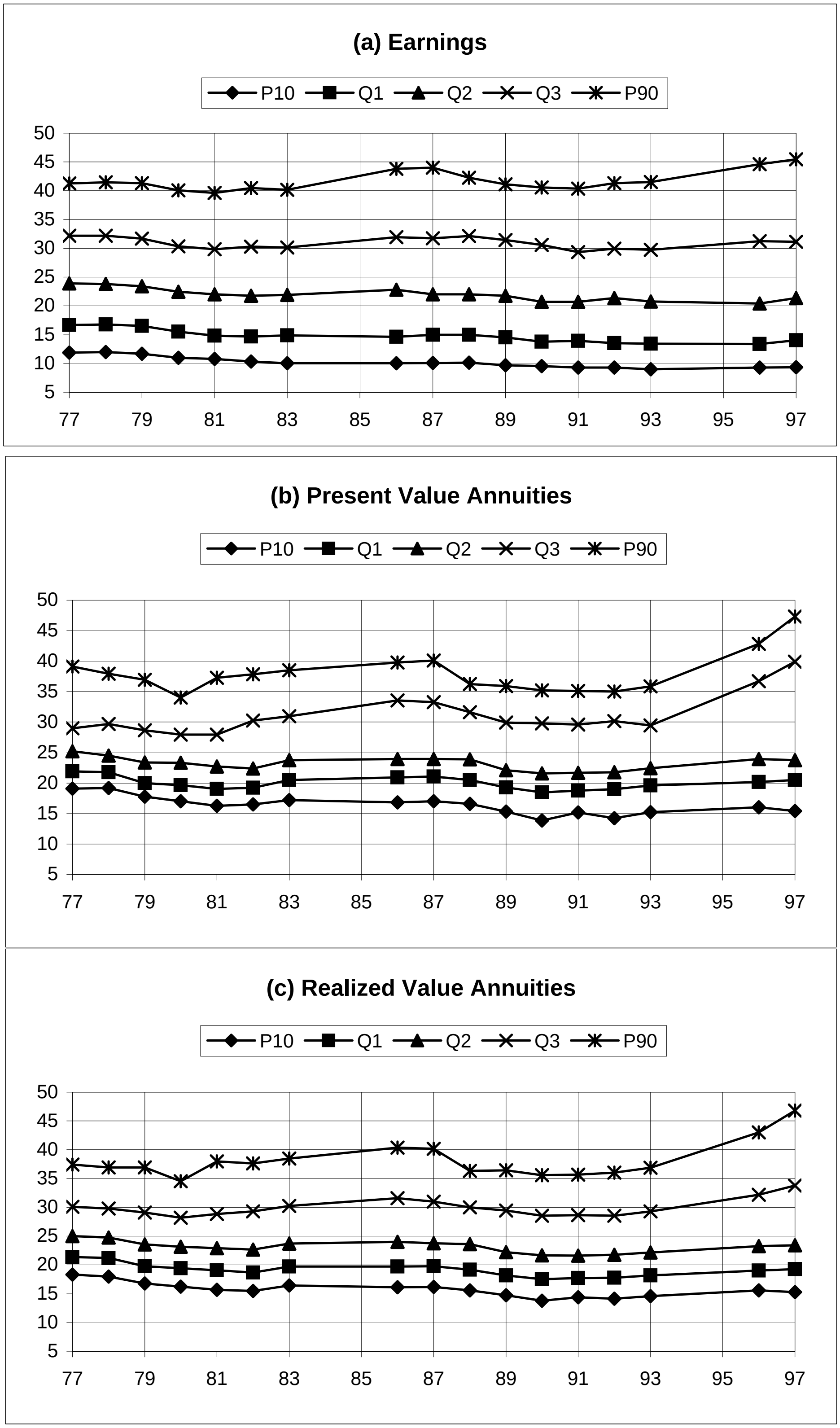
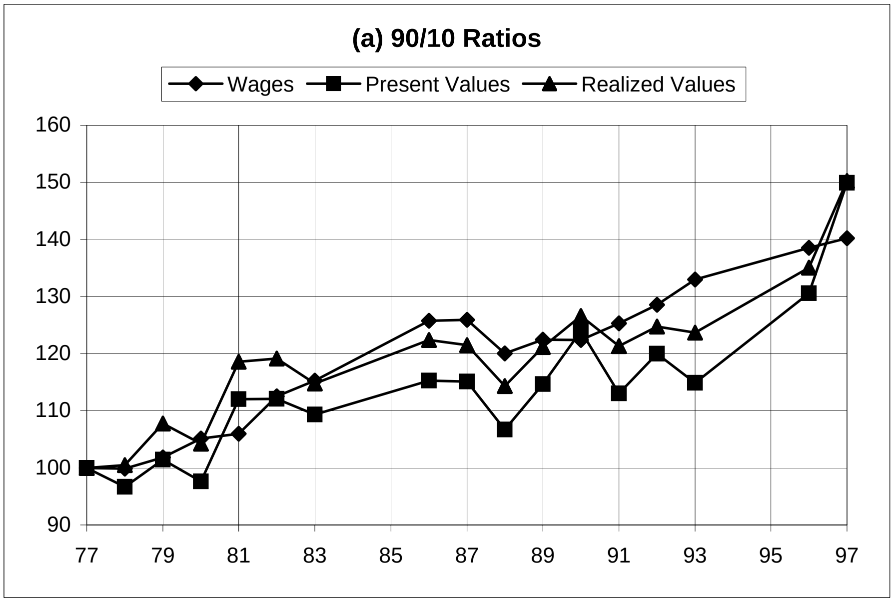


Figure 8: Earnings and Value Annuities - Inequality Indices



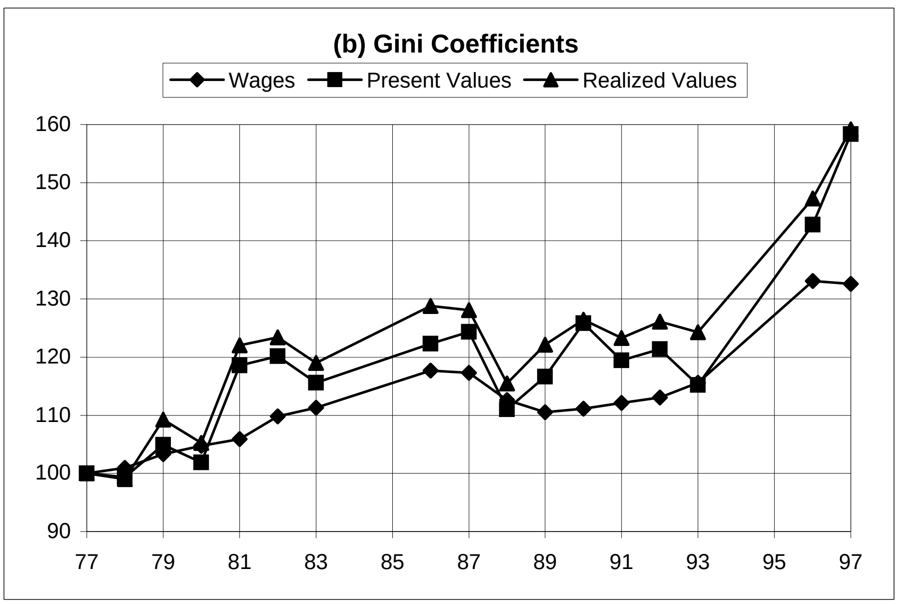
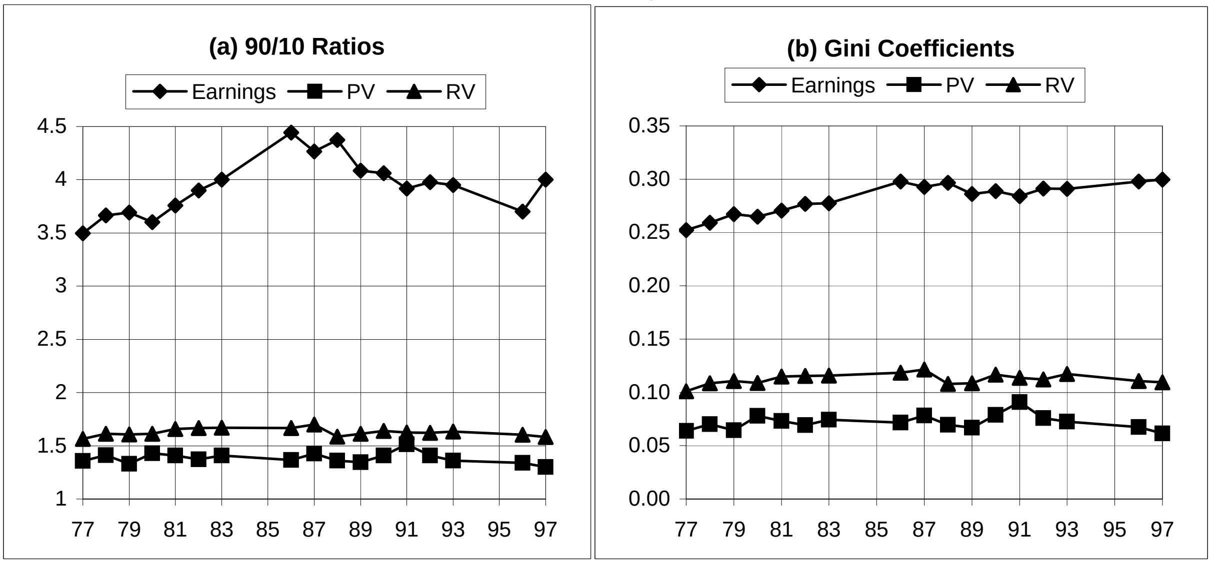


Figure 9: Level of Inequality Indices by Education

(1) Less Than High School



(2) High School

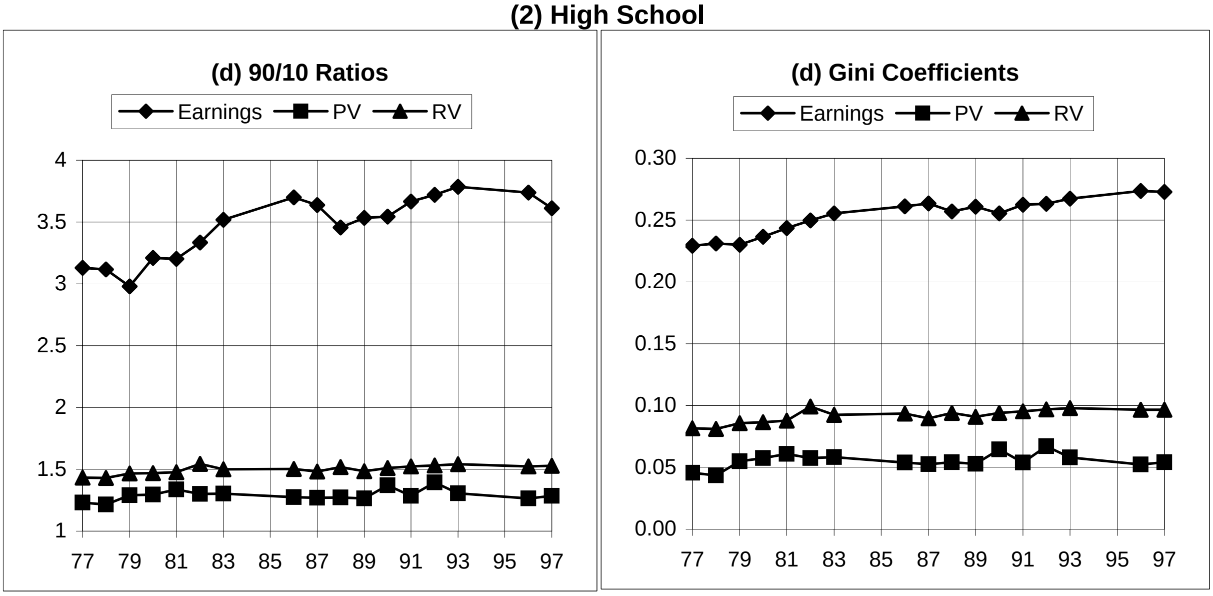
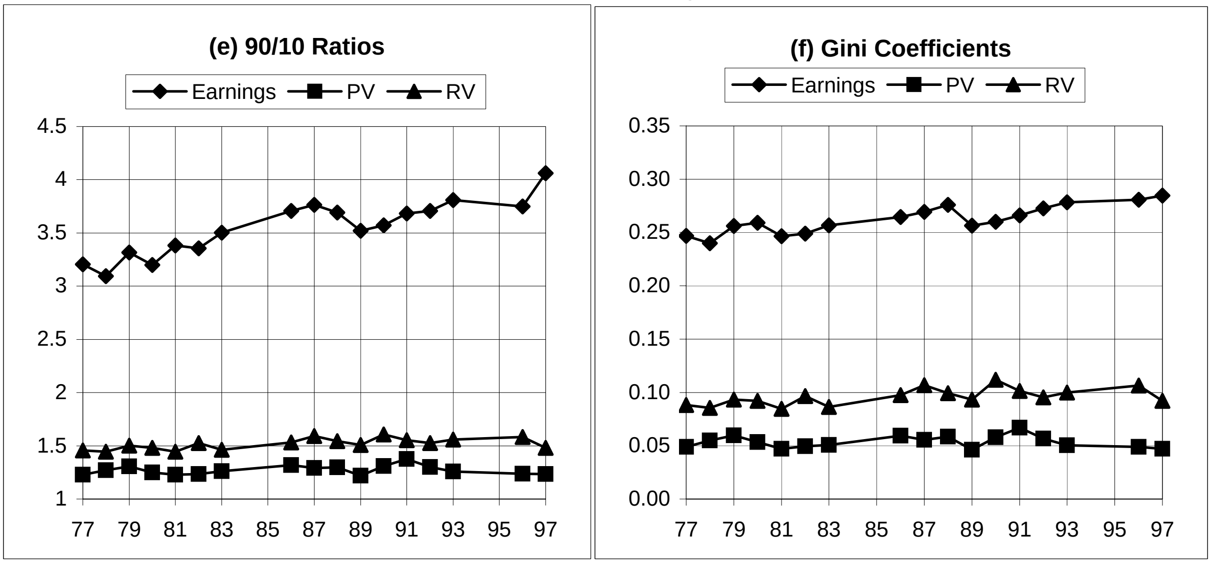


Figure 9: Level of Inequality Indices by Education

(3) Some College



(4) University

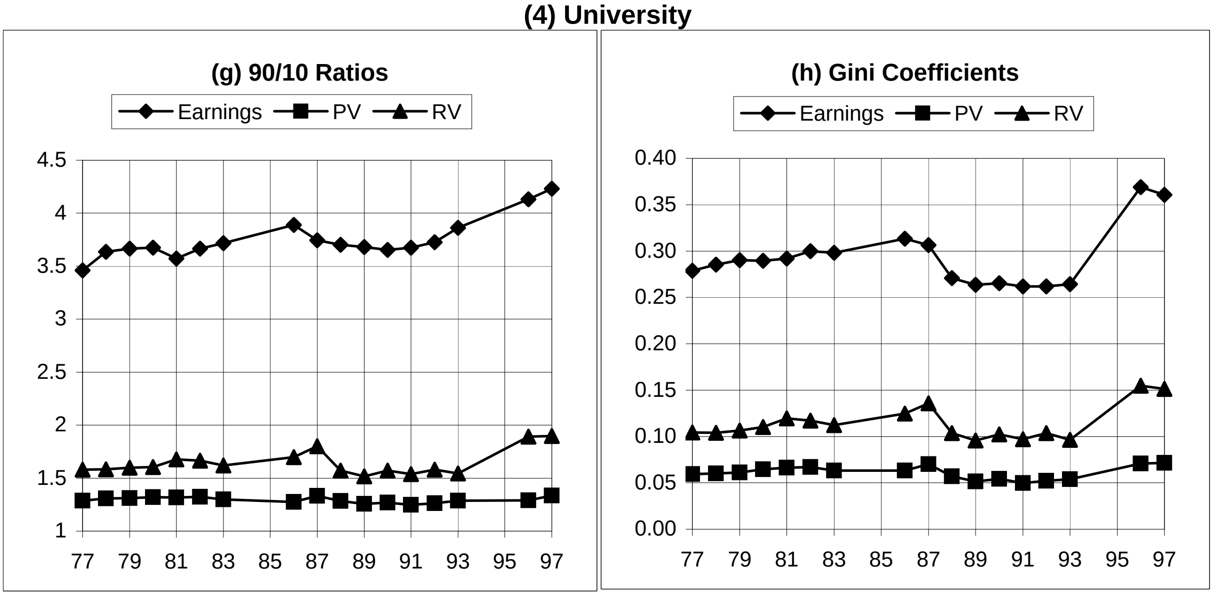
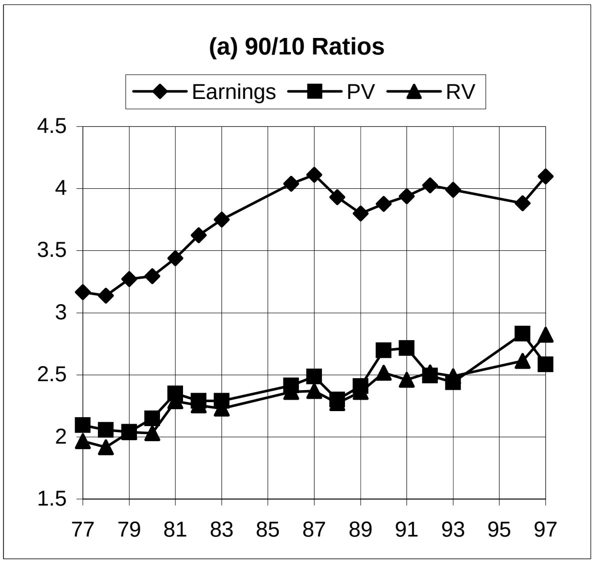
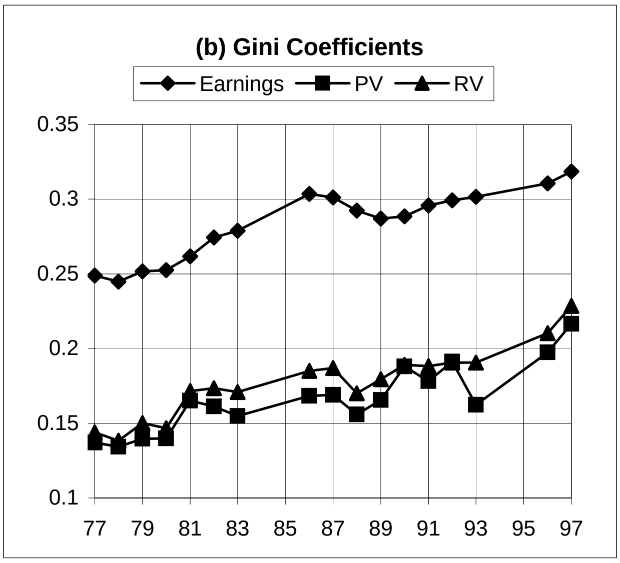


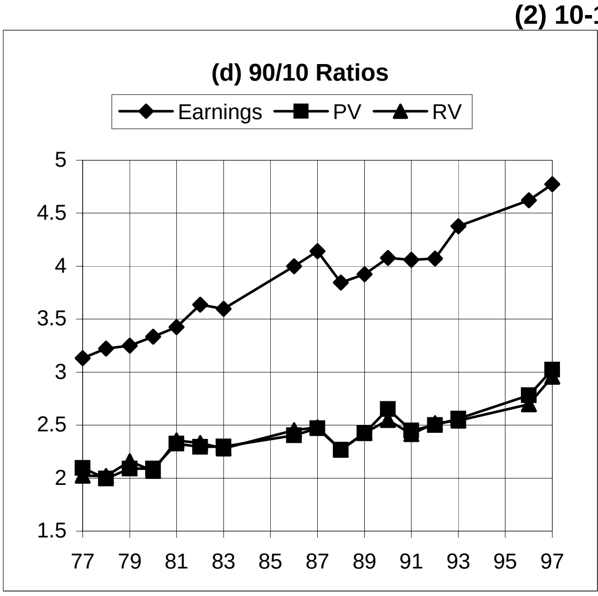
Figure 10: Level of Inequality Indices by Experience

(1) 0-9 Years





(2) 10-19 Years



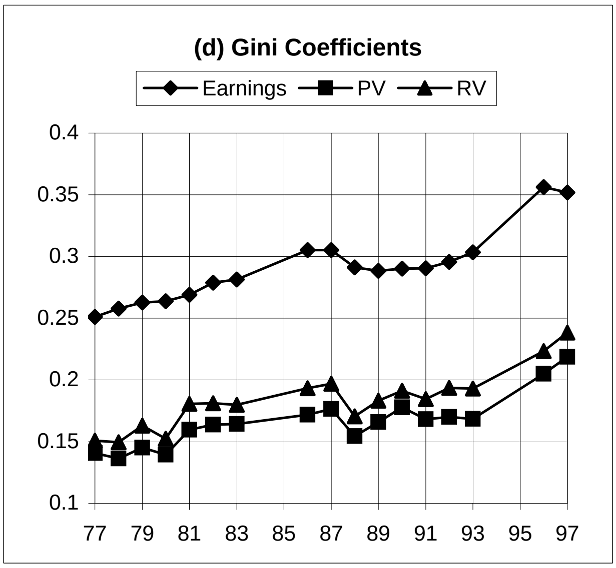
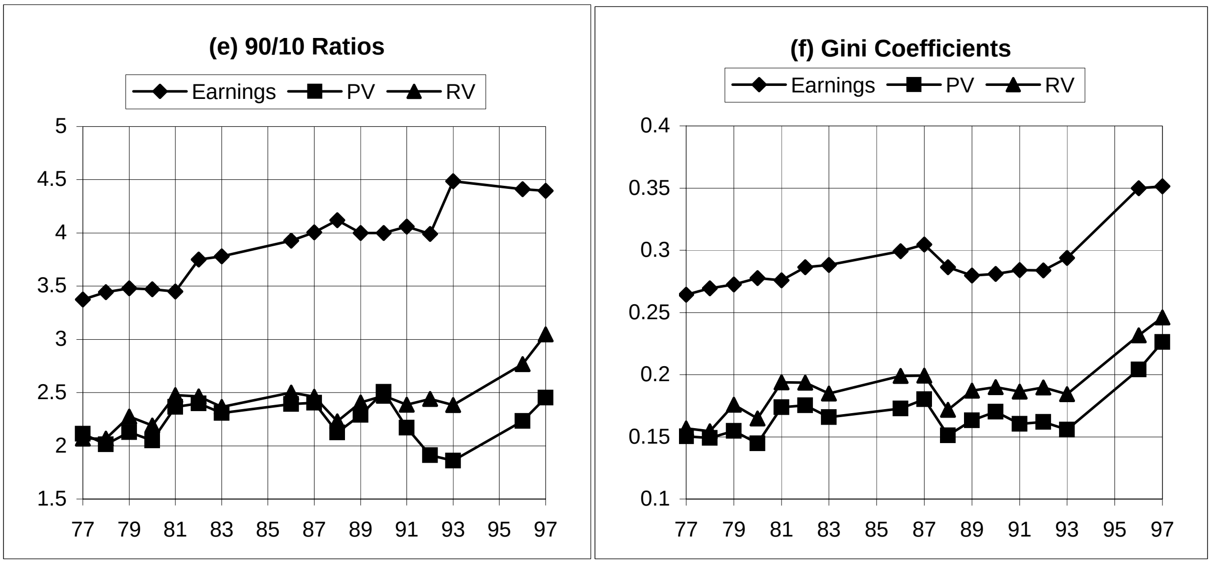


Figure 10: Level of Inequality Indices by Experience

(3) 20-29 Years



(4) 30 Plus Years