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*Earnings Instability and
Earnings Inequality of
Males in the United States:
1967 – 1991*

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Abstract

Although much research has focused on recent increases in annual earnings inequality in the United States, the increases could have come from either of two sources: the distribution of lifetime earnings could have become more unequal or the receipt of lifetime earnings could have become more unstable. Based on an analysis of the 1968-92 Panel Study of Income Dynamics, we find that lifetime earnings inequality increased during the early 1980s and that earnings instability increased during the 1970s. We also examine how these trends are related to changes in the distribution of wages and hours and the returns to education.

1. Introduction

A vast literature has emerged over the last decade that documents and offers explanations for the recent changes in annual earnings inequality in the United States. The changes to be explained are well-established: annual earnings inequality remained relatively stable during the 1950s, 1960s, and 1970s and then increased rapidly during the 1980s and early 1990s.¹ The proposed explanations for this increase include skill-biased technological change, changes in international trade, changes in labor market institutions, changes in worker-firm attachment, changes in labor force composition, changes in consumption patterns, and changes in family structure, to name just a few. Although many of these explanations have some empirical support, a definitive explanation (or set of explanations) has not been found for the increase in annual inequality.

Another literature recognizes that annual earnings inequality will differ from longer-run measures of earnings inequality whenever there is churning or instability in the earnings distribution. For example, Friedman and Kuznets (1945) make this distinction when examining the earnings inequality of individuals from professional practices, and Summers (1956) calculates lifetime earnings inequality with a two-year panel data set to exclude earnings instability. Lillard (1977) calculates lifetime earnings from a data set that contains earnings observations over a significantly longer period for individuals. Shorrocks (1978) provides an explicit theoretical treatment of the relationship between annual earnings inequality, longer-run measures of earnings inequality, and earnings mobility.

In this paper, we draw on both literatures by examining whether the recent increases in annual earnings inequality are associated with increases in earnings instability and/or lifetime earnings inequality. Distinguishing between the two components will

be useful in evaluating the explanations that have been put forward for the documented increase. For example, suppose the increase in annual inequality were only associated with an increase in lifetime earnings inequality. The cause of this increase must be something that widens the annual earnings distribution such that individuals with relatively high lifetime earnings systematically earn relatively even more. Consistent explanations would include skill-biased technological change and demand shifts that benefit the highly paid (perhaps due to changes in international trade). On the other hand, suppose that the increase in annual inequality were only associated with an increase in earnings instability. The cause of this increase must be something that widens the annual earnings distribution such that no individuals systematically earn more. Consistent explanations would include a secular decline in worker-firm attachment (perhaps due to increased outsourcing or reduced regulations) or increased competition (perhaps due to greater international trade).

The distinction between lifetime earnings inequality and earnings instability is also useful because it will inform the welfare evaluation of the increase in annual earnings inequality. Specifically, lifetime earnings is a measure of the long-term resources, and thus the consumption set, available to an individual; increasing inequality of consumption sets is welfare reducing for most social welfare functions.² The welfare implications for increasing earnings instability are not as straightforward. If individuals had perfect foresight and could borrow and lend freely, the consumption set of individuals would be independent of earnings instability. In such a case, increasing earnings instability (holding the distribution of lifetime earnings constant) would be welfare neutral. However, with realistic assumptions such as earnings uncertainty and the existence of liquidity

constraints, increases in earnings instability reduce welfare because earnings instability hinders individuals' ability to smooth consumption.³

In this paper, we use 25 years of the Survey Research Center (SRC) sub-sample of the Panel Study of Income Dynamics (PSID) to examine changes in lifetime earnings inequality and earnings instability for males.⁴ We first examine long-run earnings inequality by simply comparing the distribution of long-run earnings for two time periods. Such a method allows us to assess changes in long-run earnings inequality with very few assumptions. We next turn to a parametric methodology in which we model the process that determines earnings and derive the implications of the model for lifetime earnings inequality and earnings instability. The main findings of this analysis are that lifetime earnings inequality increased during the 1980s and earnings instability increased during the 1970s. Over the entire sample period, increases in an instability component and a persistent component are equally important to explaining the increases in annual inequality.

After establishing the trends in lifetime inequality and earnings instability, we explore what could have been the underlying causes. To do this, we relate the reported trends to changes in the distribution of wages and hours and changes in the returns to education. We find that the increase in lifetime inequality is associated with an increase in persistent wage inequality rather than an increase in persistent hours inequality. This finding suggests that we should look to demand shifts that bid up the relative wages of highly paid individuals, perhaps due to skill-biased technological change, changes in international trade, or changes in consumption patterns, to explain the increase in persistent earnings inequality. Furthermore, we find that about one third of the

increase in the persistent component is due to changing returns to education; this finding provides further support for a returns to skill explanation for the observed patterns.

A few other papers have similarly examined changes in annual earnings inequality, and this paper extends and improves this research along a few dimensions. First, this paper uses an innovative panel design to mitigate time inconsistencies while maximizing sample size, as well as provides direct evidence of the role of wages, hours, and education in the observed changes. Two papers also use the PSID, Gottschalk and Moffitt (1994) and Moffitt and Gottschalk (1995). The former paper uses a methodology that can identify much less with respect to temporal changes. The latter paper focuses on the parameters of the autocovariance structure of earnings; importantly, the latter paper draws substantively different conclusions than those drawn here. Two studies use data sets that are not as appropriate to distinguish between earnings instability and long-run earnings inequality. Gittleman and Joyce (1996) use matched data from the CPS, which only has two observations per person; thus, they are quite limited in drawing inferences about long-run earnings patterns. Buchinsky and Hunt (1999) use the National Longitudinal Study of Youth (NLSY) for their analysis. Importantly, they come to substantively different conclusions, presumably because of the shorter panel length (13 years) and the cohort nature of the NLSY. Baker and Solon (1998) use a large Canadian administrative data set and are able to explore more flexible models than those estimated here; however, earnings have evolved fundamentally differently between the two countries.

The rest of the paper is organized as follows. We present a tabular analysis of changes in the distribution of long-run earnings in Section 2. Section 3 provides the details of the heterogeneous growth model used for the parametric analysis and derives the implications of the model for earnings inequality and earnings instability. Section 4 provides

details of the estimation procedure and the data set construction. We present the main results of the paper in Section 5 and conclude in Section 6. Details of the estimation procedure, derivations, and sample construction are left to the appendices.

2. A Tabular Analysis of Long-Run Earnings Inequality

We first examine changes in long-run earnings inequality with a simple, tabular analysis. To do this, we construct the long-run earnings distribution for a similar cohort in two time periods, and we simply compare the distributions for evidence of increased inequality. Specifically, we calculate the present discounted value (at 5 percent) of ten years of real, total labor earnings for the periods 1969-78 and 1982-91, each with the cohort who is aged 30-44 in the first year of the periods [see Appendix C for details on variable definitions]. To describe each distribution, we calculate various quantiles, quantile ratios, the coefficient of variation, and the variance of log-earnings. In Table 1, we present the results for four samples: all males, males with positive earnings in every year, white males, and white males with positive earnings in every year.

Various trends are readily apparent in Table 1. First, the lower quantiles decline and the upper quantiles increase between the two time periods for each sample, implying that the long-run earnings distribution widened. For example, males in the top decile enjoyed a 6 percent increase in long-run earnings, but similar earners in the bottom decile suffered a 23 percent decline. However, the magnitudes of the quantiles are highly dependent on the price deflator used and thus should be interpreted with caution.⁵ Quantile ratios, direct measures of the spread of a distribution, are not as deflator dependent and increase for each sample. The other reported measures of inequality also increase

between the time periods, with the variance of log-earnings increasing 75 percent. Thus, long-run earnings inequality appears to have increased during the 1970s and 1980s.

Comparing the various samples, the restriction to positive earning males serves to dampen changes in the quantile ratios but the restriction to white positive earning males does not. Presumably, the restriction to positive earning males dampens changes in inequality because this group is selected *ex post* to have relatively stable earnings; namely, they must not have any unemployment spells which encompass an entire calendar year. Although this restriction dampens the measured change in inequality, positive earning males are the vast majority of the sample, representing 97 percent and 92 percent of all males for the periods 1969-78 and 1982-91 respectively. The restriction to white males does not change the results because there are very few non-whites in the PSID-SRC subsample. For example, only 52 of all males (6.6 percent of the sample) are non-white for the period 1982-91.

Although these results certainly suggest that at least some of the increase in annual earnings inequality is associated with an increase in lifetime earnings inequality, the results are incomplete for several reasons. Most importantly, the analysis smoothes over year-to-year earnings fluctuations, so very little can be said about earnings instability and the relationship among annual inequality, lifetime inequality, and earnings instability. It is possible that both instability and persistent inequality increased during the 1980s and this descriptive analysis ignores the instability component. In addition, the analysis ignores potentially useful information because it requires the calculation of long-run earnings for each individual. Thus, the earnings information provided by an individual observed less than the period considered (10 years in the above analysis) cannot be used. Such “partial” earnings information is important for understanding recent changes

in long-run earnings inequality. Finally, the descriptive analysis provides little information as to the timing of the increase in long-run inequality. For example, a steady increase during the entire sample period and a sudden regime shift in the middle of the sample period are consistent with the results.

3. A Parametric Model of Inequality and Instability

To overcome the disadvantages of the tabular analysis, we turn to a parametric analysis in which we model life-cycle earnings. Researchers have frequently used a heterogeneous growth model to describe the underlying process of life-cycle earnings.⁶ The intuition for the model is that each individual can have a unique life-cycle earnings profile, although the heterogeneity in profiles is limited by functional form restrictions.⁷ The functional form restrictions are usually imposed by specifying individual profiles in deviation form. For example, a standard specification for a heterogeneous growth model is,

$$\log Y_{it} = f(X_{it}, \psi_t) + (\alpha_i + \beta_i X_{it}) + \varepsilon_{it}, \quad (1)$$

where Y_{it} is real earnings for worker i in year t , X_{it} is (potential) experience, f is a polynomial function of experience with parameters ψ_t , and ε_{it} is a mean-reverting earnings shock. The inclusion of the heterogeneous growth term $(\alpha_i + \beta_i X_{it})$ allows individuals to have different intercepts, slopes, or any combination of the two, relative to the mean profile $f(X_{it}, \psi_t)$. This parameterization restricts the change in slope (the second derivative with respect to experience) to be equal across individuals. Because the model is specified with log-earnings, this assumption is equivalent to assuming that the percentage change in earnings growth is equal across individuals.

The specification in (1) is restrictive for our purposes because the distribution of individual profiles relative to the mean profile cannot change over time. This restriction precludes any systematic changes in lifetime earnings among individuals. To loosen this restriction in a straightforward manner, we include a period specific factor loading that allows an individual's deviation from the mean profile to change. If the heterogeneous growth term $(\alpha_i + \beta_i X_{it})$ is determined by skill, perhaps obtained through differential human capital investment, then the factor loading may be interpreted as the relative price of this heterogeneous skill. Specifically, suppose life-cycle earnings follow the process,

$$\log Y_{it} = f(X_{it}, \psi_t) + p_t(\alpha_i + \beta_i X_{it}) + \varepsilon_{it}. \quad (2)$$

The factor loading p_t is necessarily normalized to equal one in the first period. As p_t increases (decreases), the factor loading serves to accentuate (attenuate) any individual deviations from the mean profile. If p_t were zero, individuals would deviate from the mean profile only because of the mean-reverting error term ε_{it} .

Following most previous researchers, we assume that transitory shocks and the individual specific parameters are uncorrelated ($\text{cov}[\alpha_i, \varepsilon_{it}] = \text{cov}[\beta_i, \varepsilon_{it}] = 0$) and restrict the higher order derivatives of earnings with respect to experience to be equal across individuals.⁸ Finally, we retain the assumption of previous researchers that the variances of the individual parameters do not change over time ($\text{var}[\alpha_i] = \sigma_\alpha^2$, $\text{var}[\beta_i] = \sigma_\beta^2$, and $\text{cov}[\alpha_i, \beta_i] = \sigma_{\alpha\beta}$). However, because of the introduction of the factor loading p_t , this assumption implies that the *relative* variances of individual profiles are constant, where previously, the assumption implied that the *absolute* variance in profiles remained constant.

3.1 Lifetime Earnings Inequality

To derive the implications of a heterogeneous growth model for lifetime earnings inequality, we first define a measure of lifetime earnings. Let lifetime earnings for i in t (denoted as Y_{it}^*) be the present discounted value of earnings for individual i if he worked from experience level 0 to R (retirement) at the parameter values of year t ,

$$Y_{it}^* = \int_0^R \exp[-rX] \exp[f(X, \psi_t) + p_t(\alpha_i + \beta_i X)] dX. \quad (3)$$

Intuitively, we are simply summing over an individual's earnings profile for a given year, discounting appropriately.

There are two important aspects to this definition of lifetime earnings. First, this measure should be considered a “steady state” measure of earnings inequality because it holds the parameters constant at the level of a particular year; Y_{it}^* will only measure actual earnings if the parameters remains constant for an individual's actual work life. Second, this definition of lifetime earnings ignores the transitory component ε_{it} . Although this exclusion is made primarily for analytic convenience, it can be justified by noting that ε_{it} are mean-zero transitory shocks that do not change an individual's lifetime earnings profile and will thus have little impact on the level of lifetime earnings.⁹

Given the assumptions made thus far, the variance of the logarithm of lifetime earnings can be shown to be

$$\begin{aligned} \text{var}[\log Y_{it}^*] = & p_t^2 \left\{ \sigma_\alpha^2 + \left[\frac{\int_0^R [X \exp[f(X, \psi_t)]] dX}{\int_0^R \exp[f(X, \psi_t)] dX} \right]^2 \sigma_\beta^2 \right. \\ & \left. + 2 \left[\frac{\int_0^R [X \exp[f(X, \psi_t)]] dX}{\int_0^R \exp[f(X, \psi_t)] dX} \right] \sigma_{\alpha\beta} \right\}. \end{aligned} \quad (4)$$

To derive the expression in (4), we approximate the variance of log-lifetime earnings with the variance of a Taylor Series approximation of log-lifetime earnings in the neighborhood of $E[\beta_i] = 0$ [the derivation is in Appendix B]. Because β_i is estimated to have a small variance around its mean in many studies, this approximation should be fairly good [see Hause (1980), Baker (1997), and the results below].

A key aspect of the measure of lifetime inequality in (4) is that it is not a function of the individual specific parameters (α_i and β_i), but rather it is a function of the variance of the individual specific parameters (σ_α^2 , σ_β^2 , and $\sigma_{\alpha\beta}$). Consequently, we do not need to estimate the earnings profile for each individual, thus allowing the inclusion of individuals observed even for a single year. Furthermore, all of the parameters in (4) are directly estimable as part of the autocovariance structure of earnings. The intuition for why this is the case is that the autocovariance describes how earnings tend to evolve over time; by knowing the earnings distribution in various years and by knowing how earnings tend to evolve, we can back out estimates of lifetime earnings inequality.

3.2 Earnings Instability

We define earnings instability as temporary deviations from one's earnings profile.¹⁰ Such a definition attempts to separate systematic earnings growth, perhaps because of differential human capital investment, from transitory earnings shocks due to volatility in the labor market. Although we would want to define instability as deviations from an individual's expected earnings to obtain a "surprise" interpretation, good information on individual expectations is not generally available. In addition, if earnings were found to become more unstable with respect to an individual's expectations, the researcher could not be certain if the formation of individual expectations changed or if the instability of

earnings receipt changed. Because we form the measure of instability consistently over time, any changes we find will represent real changes in how earnings are received.

To measure the magnitude of earnings instability in year t , we use the cross-sectional variance of the idiosyncratic deviations in year t , $\sigma_{\varepsilon_t}^2$. We allow an individual's deviation from his profile to be serially correlated by modeling ε_{it} as a low-order ARMA(p,q) process. Consider the case of an ARMA(1,1),

$$\varepsilon_{it} = \rho\varepsilon_{i(t-1)} + \theta\nu_{i(t-1)} + \nu_{it}. \quad (5)$$

The primitive error term ν_{it} is the individual- and time-specific transitory shock and the variance of the primitive error term ($\sigma_{\nu_t}^2$) measures the contemporaneous volatility in the labor market. Because of the memory inherent in an ARMA process, the transitory shocks ν_{it} may build up over time in ε_{it} , the actual distance an individual is from his profile. We allow the variance of the primitive error term ($\sigma_{\nu_t}^2$) to vary over time.

One important caveat to interpreting $\sigma_{\varepsilon_t}^2$ as earnings instability is that $\sigma_{\varepsilon_t}^2$ will also capture any mean-reverting measurement error in the earnings data. Thus, $\sigma_{\varepsilon_t}^2$ will overestimate the variance of mean-reverting earnings shocks in the labor market for a given year. Although measurement error is problematic in interpreting the levels of $\sigma_{\varepsilon_t}^2$, there is little reason to believe measurement error will affect the interpretation of the *changes* in $\sigma_{\varepsilon_t}^2$.¹¹ Since the primary focus of the paper will be changes in earnings instability, measurement error will be ignored for the rest of the paper.

3.3 Decomposing Annual Earnings Inequality

The motivation for this paper is that increases in annual earnings inequality can have two sources: the distribution of lifetime earnings among individuals could become more unequal or the receipt of lifetime earnings for an individual could become more volatile. Thus, it seems natural to decompose annual earnings into a persistent component and an instability component. Consider the following expression for experience-adjusted annual earnings inequality,

$$\text{var}[\log Y_{it}|X_{it}] = p_t^2(\sigma_\alpha^2 + \sigma_\beta^2 X_{it}^2 + 2\sigma_{\alpha\beta} X_{it}) + \sigma_{\epsilon_t}^2. \quad (6)$$

The second term on the right-hand side of (6) is earnings instability and was discussed in the previous section. We will refer to the first term as the persistent component of annual earnings inequality but consider exactly what it measures. The persistent component measures the inequality of the individual specific earnings profiles *for a given level of experience*. Thus, the measured level of persistent inequality could change if the level of experience changed, even though lifetime inequality remained constant. However, it is clear from comparing (6) and (4) that changes in (6) will be approximately proportional to changes in (4): both increase multiplicatively in p_t^2 . Thus, changes in the persistent component will be related to changes in lifetime earnings inequality. How closely the quantities are related is an empirical question.

4. Estimating the Parametric Model

4.1 The Panel Construction

To construct the panel used to estimate the parametric model, we restrict the primary sample to male household heads who are white, who are not students or retirees, who have positive earnings, who are aged 25-60, and who are observed at least twice. We restrict the sample to whites because there is good reason to believe that the labor market experience was different for non-whites, but the small number of non-whites in the PSID-SRC is not sufficient for separate analysis [see Table 1]. The restriction to positive earnings observations is for two reasons. First, including the zeroes combines the dynamics associated with the extensive and intensive margins of working for a year, making the covariance matrix more difficult to interpret. Second, there exists the mechanical difficulties of using zeroes with logarithms. Because most men have positive earnings and to retain a clear interpretation of the covariance matrix, we restrict our attention to positive earnings observations. Further details about the sample definition and restrictions are in Appendix C.

With these sample restrictions, we construct a *revolving balanced panel*. In a revolving balanced panel, individuals are required to have positive earnings *only* for the years in which they satisfy the other sample restrictions (such as age, student status, retirement status, etc.). For example, a person aged 50 in 1967 will be kept in the sample until he reaches age 60, or until he retires, as long as he has positive earnings in every year. Similarly, an individual aged 25 in 1980 who is a student will be kept in the sample through 1991, as long as he has positive earnings in every year. Thus, individuals may enter and exit the sample. If an individual has zero earnings for any year he satisfies the other sample restrictions, all data for this individual are discarded.

A revolving balanced panel differs from a fully balanced panel in which an individual must satisfy all of the sample restrictions for every year. We choose a revolving balanced panel because the level of annual earnings inequality is dependent on the distribution of experience in a population [see equation (6)]. If a fully balanced panel were used, the mean level of experience and time would increase by exactly one between every year of the sample. This collinearity would make it difficult to separate time from experience effects. Allowing individuals to enter and exit, as does a revolving balanced panel, breaks this collinearity. In addition, sample sizes are much larger for a revolving balanced panel than for a fully balanced panel.

A revolving balanced panel differs from a fully unbalanced panel in which all positive earnings observations for all individuals are included in the sample, regardless of whether there are intervening years of zero earnings. The drawback to using a fully unbalanced panel is that other researchers have found important compositional changes of the labor force over the business cycle [Solon, Barsky, and Parker (1994)]. For example, if high-instability workers disproportionately enter the labor market during expansions, then measured instability could change over the business cycle in a fully unbalanced panel because of sample composition reasons rather than real, pervasive changes in the labor market. The sample composition does not change over the business cycle for a revolving balanced panel. Furthermore, the restriction to positive earning males used for a revolving balanced panel remains broadly applicable to the population of all males [see Table 1].

There still may exist sample composition inconsistencies for a revolving balanced panel. Quite simply, younger individuals need less years of positive earnings than older individuals to be kept in the sample. For example, consider an individual age 25 in 1967

who is not a student and does not retire until age 65. Such a person would need 25 years of positive earnings to be kept in the sample. On the other hand, an individual age 25 in 1990 who is not a student would need 2 years of positive earnings to be kept in the sample. Thus, individuals who are in the sample during the early years may be different from the individuals who enter the sample in later years. To examine whether such concerns are driving our conclusions, we also present results based on a secondary sample in which we impose the additional restriction that individuals must be observed for at least 10 years.

We present summary statistics in Table 2 for the primary sample in which individuals must be observed at least twice and the secondary sample in which individuals must be observed at least ten times. The restrictions leave a sample size of 3,115 individuals and 35,018 person-year observations in the primary sample. From examining the mean experience in each year, it is clear that more individuals are entering the sample than leaving the sample until the late 1970s because the mean level of experience falls initially. Although it would be ideal for there to be no drift in the mean level of experience, the important characteristic is that mean experience does not change collinearly with time. For the secondary sample, there are 1,704 individuals and 28,080 person-year observations.

4.2 The Estimation Procedure

As alluded to previously, all of the parameters of interest in (4), (5), and (6) can be estimated as part of the autocovariance structure of earnings. These parameters are estimated in two stages.¹² In the first stage, we estimate with OLS the parameters ψ_t

and the residuals of the equation

$$\log Y_{it} = f(X_{it}, \psi_t) + y_{it}. \quad (7)$$

From the residuals $\hat{y}_{it}$, we calculate an individual's contribution to the empirical covariance matrix C_i and the empirical covariance matrix $\hat{C} = n^{-1} \sum_i C_i$.

In the second stage, we estimate the parameters of the ARMA process and p_t , σ_α^2 , σ_β^2 , and $\sigma_{\alpha\beta}$ by fitting the implications of the model in (2) to the empirical covariance matrix $\hat{C}$ using a Generalized Method of Moments (GMM) framework. Equation (2) implies that the model covariance matrix $\Sigma(\mathbf{X}_i, \theta)$ has the typical diagonal element

$$\text{var}[y_{it}|\mathbf{X}_i] = p_t^2(\sigma_\alpha^2 + \sigma_\beta^2 X_{it}^2 + 2\sigma_{\alpha\beta} X_{it}) + \sigma_{\varepsilon_t}^2,$$

and the typical off-diagonal element

$$\text{cov}[y_{is}, y_{it}|\mathbf{X}_i] = p_s p_t [\sigma_\alpha^2 + \sigma_\beta^2 (X_{is} X_{it}) + \sigma_{\alpha\beta} (X_{is} + X_{it})] + \sigma_{\varepsilon_s \varepsilon_t}. \quad (8)$$

The structure of $\sigma_{\varepsilon_s \varepsilon_t}$ and $\sigma_{\varepsilon_t}^2$ will depend on the order that is specified for the ARMA process. Let the vector $\mathbf{c}_i$ be the unique elements of C_i and let the vector $\sigma(\mathbf{X}_i, \theta)$ be the unique elements of $\Sigma(\mathbf{X}_i, \theta)$, stacked conformably with $\mathbf{c}_i$. The moment conditions that identify the second stage parameters are

$$E[\mathbf{c}_i - \sigma(\mathbf{X}_i, \theta)] = 0.$$

These moment conditions imply that we are choosing the parameters of the model covariance matrix $\Sigma(\mathbf{X}_i, \theta)$ so that $\Sigma(\mathbf{X}_i, \theta)$ is as close as possible to the empirical covariance matrix $\hat{C}$. Due to the findings of other researchers, we use the identity matrix as

the weighting matrix rather than an optimal weighting matrix.¹³ Using the identity matrix will result in a consistent but generally inefficient estimator.

The results reported here are based on a specification in which the transitory earnings shock ε_{it} follows an ARMA(1,1) and the mean profile $f(X_{it}, \psi_t)$ is a quartic in experience.¹⁴ In Table 3, we present the empirical autocovariances, standard errors, and sample sizes below the diagonal and the empirical autocorrelations above the diagonal. The autocovariances reveal the expected patterns. The variances increase over time (looking down the principal diagonal) with the trend accelerating during the 1980s. The covariances are positive and significantly different from zero, implying that earnings deviations are positively, serially correlated. Furthermore, the autocovariances decline over time (looking down columns), consistent with a mean-reverting covariance process such as an ARMA(1,1).

Examining the autocorrelations provides an indication as to what should be expected from estimating the model. The autocorrelations simply measure the propensity of an individual to retain his place in the earnings distribution between two years; such persistence is exactly what we wish to measure with the formal model. For any particular order of autocorrelations (looking down a diagonal from left to right), the magnitudes tend to first decline over time and then increase. This pattern implies that individuals with earnings above the mean are more likely to remain above the mean during the earlier and later years of the sample period when compared to the middle years. Because the autocorrelations tend to increase to their previous level, one should expect that the increases in the cross-sectional earnings variance represents increases in lifetime earnings inequality: the distribution of annual earnings widened and earnings are no less stable.

The second stage parameter estimates and standard errors are presented in the first two columns of Table 4. We graph the point estimates and confidence bands for the variance of the transitory shocks ($\sigma_{\nu_t}^2$) in Figure 1 and the factor loadings (p_t) in Figure 2. All of the parameters are estimated with the expected sign and reasonably precisely, with test statistics ranging from approximately 2 to 10. Although the point-wise confidence bands are rather large, a test of the joint null hypothesis that the estimates of p_t for the early 1970s are equal to the estimates for the latter 1980s, for example, is rejected at any standard significance level.

5. Results from the Parametric Analysis and their Implications

As a benchmark to interpret the results, we first present experience-adjusted annual earnings inequality in column 1 of Table 5. The estimates are simply the principal diagonal elements from the empirical covariance matrix in Table 3. From the table, experience-adjusted annual earnings inequality increased 64 percent over the sample period.¹⁵ This result is very similar to those found by previous researchers with other data sets.¹⁶

5.1 Estimates of Lifetime Inequality and Instability

To examine changes in lifetime earnings inequality, we calculate the time series implied by equation (4). We present the calculations in Table 5, and we graph the results in Figure 3. Consistent with the findings of others, lifetime inequality is less than annual earnings inequality [e.g., see Lillard (1977)]. This finding is expected given that earnings profiles tend to cross ($\sigma_{\alpha\beta}$ is negative) and the existence of earnings instability. In addition, lifetime inequality declined slightly during the 1970s and then increased substantially during the 1980s. This trend represents an increase in lifetime inequality of 75

percent, an increase comparable to that of experience-adjusted annual inequality. The change in lifetime inequality may be interpreted as follows: an individual with lifetime earnings one standard deviation above the mean in 1967 would have had lifetime earnings 37 percent above the mean, but a similar individual in 1991 would have had lifetime earnings 50 percent above the mean. These trends are highly robust across the different specifications presented in Figure 3, as well as consistent with the tabular analysis presented in Section 2. The primary benefit of undertaking the parametric analysis is that a clearer picture of the changes is available: the increase in lifetime earnings inequality occurred almost exclusively during the first half of the 1980s.

As noted previously, there could still exist sample inconsistencies with a revolving balanced panel. In particular, the measured increase in lifetime earnings inequality may be due to many low-wage workers being drawn into the work force during the long expansion of the 1980s. To examine this possibility, we re-estimate the model for the secondary sample in which individuals must be observed for at least 10 years and include the point estimates in Figures 1 and 2. It is clear from this figure that all the conclusions remain the same.

Consider again the estimates of earnings instability presented in Figure 1 (the estimates are in Table 4). The first salient feature of the graph is the secular increase during the 1970s. Comparing the recessionary years of 1970 and 1982, the variance of the transitory shocks increased by 129 percent. Comparing the average level of transitory shocks during the 1971-73 expansion to the 1983-90 expansion, the variance of transitory shocks increased by 58 percent. In addition, it is also apparent that the variance of transitory shocks is counter-cyclical. Although declines in variance are not always present

during expansions, there are strong upward trends during each of the recessionary periods. Moreover, it appears that the increase in instability during the 1970s was due to a lack of decline during the 1970s expansion.

Although the spike in the final year in Figure 1 is due in part to the recession in the final year, there is reason to suspect that part of the spike is an artifact of the sample inconsistency possible with the panel design. Again, younger individuals who could enter the sample in later years need less successive years of positive earnings to be in the sample and could have more volatile earnings. In Figure 1, we graph estimates of transitory shocks for the primary and secondary samples. Notably, volatility in the final couple of years is systematically less in the secondary sample, and thus, the sample composition seems to matter. However, the two time series only diverge for the final three years, thus most of the measured changes appear to be real.

We present estimates of annual inequality and its components (based on equation 6) in Figure 4. The instability component ($\sigma_{\varepsilon_t}^2$) is calculated with the recursive relationship implied by equation (5). The persistent component is calculated with the expression $(p_t^2(\sigma_\alpha^2 + \sigma_\beta^2 X_{it}^2 + 2\sigma_{\alpha\beta} X_{it}))$, evaluated at the sample average of experience. Predicted annual inequality is the sum of the instability and persistent components.

In Figure 4, it is clear that actual and predicted annual earnings inequality are quite similar; thus, the model is able to capture the variation in the data quite well. Second, the modest increases in annual inequality during the 1970s were due to increases in instability. Specifically, instability increased with recessions and did not decline with the expansions during the 1970s. Although the sharp increase in annual inequality from 1979-83 was due to increases in both the persistent and instability components, annual

inequality did not decline with the 1983-90 expansion because persistent inequality continued to increase. Over the entire period, persistent inequality and earnings instability contributed fairly equally to the increases in annual earnings inequality because the relative distance between the two trend lines is very similar at the beginning and end of the sample period.

5.2 *A Comparison to Previous Studies*

The basic results for lifetime earnings inequality and earnings instability are consistent with other stylized facts on earnings. For example, the result that lifetime earnings inequality increased during the 1980s is consistent with the findings that the returns to education increased during the 1980s [see Levy and Murnane (1992)]. Because education is a persistent individual characteristic (for the ages considered here), it follows that lifetime earnings inequality should increase. Similarly, the finding that earnings instability increased during the 1970s provides further insight into the well-known increases of within-group annual earnings inequality during the 1970s, where groups are defined by such observables as age and education [see Levy and Murnane (1992) and Gottschalk (1997)]. In particular, the well-known increases in within-group inequality during the 1970s seem to be primarily driven by increases in earnings instability (“within-person inequality”) rather than by increases in the systematic differences between individuals within a group (“between-person but within-group inequality”). Such a conclusion follows from the evidence of increasing earnings instability but flat lifetime earnings inequality during the 1970s.

The results presented here encompass many of the results in previous research on changing lifetime inequality and instability, but they also highlight and illuminate important inconsistencies across previous studies. First, the result that increases in a per-

sistent component and an instability component contributed fairly equally to the increase in annual earnings inequality is consistent with the studies that can compare the components [see Gottschalk and Moffitt (1994), Moffitt and Gottschalk (1995) and Gittleman and Joyce (1996)]. Second, the result that a persistent component increased during the 1980s is consistent with Gittleman and Joyce (1996) and Buchinsky and Hunt (1999). However, Moffitt and Gottschalk (1995) find that a persistent component increased from 1974 to 1982 and then declined considerably. Third, the result that earnings instability increased during the 1970s is broadly consistent with those found in Gottschalk and Moffitt (1994) and Gittleman and Joyce (1996), although their methodologies make it difficult to observe the cyclical pattern and the timing of the changes. Our results are also consistent with the smaller literature on consumption inequality. This literature finds that the level of consumption inequality is less than the level of income inequality during the 1980s but that the growth rate for both are comparable [see Cutler and Katz (1992)]; these results accord exactly with our findings regarding the relationship between annual inequality and lifetime inequality.

One important inconsistency in the previous literature is that Buchinsky and Hunt (1999) conclude, "...mobility declined significantly over [1979 to 1991]," but Moffitt and Gottschalk (1995) conclude, "Indeed, the increase in transitory shocks was especially great in the 1980s." Buchinsky and Hunt's findings are similar to the results reported here: Figure 4 shows that instability declined during the 1980s.¹⁷ However, due to the larger panel length used here, we are able to observe that part of this decline is likely related to the business cycle.

The Moffitt and Gottschalk (1995) results are difficult to reconcile with the results presented here, as well as with the larger literature. One difference between Moffitt and

Gottschalk (1995) and the approach here is that they focus on a random walk model rather than a heterogeneous growth model.¹⁸ In their most flexible model, they specify that

$$y_{it} = p_t \mu_{it} + \varepsilon_{it}, \quad (9)$$

where y_{it} is the residual from an earnings equation for individual i in year t , μ_{it} follows a random walk, and ε_{it} follows an ARMA(1,1). To check the robustness of our results, we estimate equation (9) and use the parameter estimates to decompose annual earnings analogously to equation (6); the results are presented in Figure 5. By comparing Figures 4 and 5, it is clear that our results do not depend on the particular model of earnings dynamics used. This conclusion holds when we control for education in the first stage (the results are reported below), use a fully unbalanced panel, and include the full PSID to more closely mimic Moffitt and Gottschalk's (1995) methodology.

5.3 The Role of Wages, Hours, and Education

Whether the changes in earnings inequality reported above are associated with changes in the distribution of hours or the distribution of wages will have important implications for the hypotheses that could explain the trends. For example, two hypotheses that are consistent with the increase in persistent inequality are (a) the returns to skill increased during the 1980s and (b) the 1980s tax reforms increased the incentives for the wealthy to work. If the former were true, we would expect to see an increase in persistent wage inequality during the 1980s. If the latter were true, we would expect to see an increase in persistent hours inequality.

We first present a simple cross-sectional decomposition of the variance of log-earnings into the variance of log-wages, the variance of log-hours, and the covariance of log-wages

and log-hours.¹⁹ The decomposition is based on the identity

$$\text{var}[\log Y_{it}] \equiv \text{var}[\log w_{it}] + \text{var}[\log h_{it}] + 2\text{cov}[\log w_{it}, \log h_{it}]. \quad (10)$$

We use the same total annual labor earnings measure as well as the self-reported annual hours worked; the wage is computed from these quantities and should be interpreted as the average annual wage. We present this decomposition in Figure 6. As other researchers have found, most of the change in annual earnings inequality is due to changes in wage inequality; hours inequality is fairly constant over the time period. However, these calculations are cross-sectional in nature, thus they do not provide any direct information about persistency or instability. To examine the persistency and instability in these inequality measures, we calculate the same decomposition used for annual earnings inequality [equation (6)] but substitute in wages and hours as the dependent variable. See Table 4 for the point estimates.

We present the results of a persistent/instability decomposition in Figure 7 for the variance of log-wages (the wage inequality series in Figure 6). In Figure 7, it is possible to track how much of the changes in wage inequality is due to individuals persistently receiving a relatively higher wage versus that due to individuals receiving a relatively higher wage for a short period of time. The clear implication of the figure is that the observed increase in wage inequality during the 1980s is from a persistent component, consistent with the increase in persistent earnings inequality during the same period. In addition, the instability in wages is relatively constant during the entire period.

We present a similar persistent/instability decomposition in Figure 8 for the variance of log-hours (the hours inequality series in Figure 6). The results of the hours decomposition are much different from the previous decompositions. Namely, most of the

variance in hours is of a transitory nature. This result should not be surprising given that we have chosen a sample of males who are highly attached to the labor force and thus are likely to be working full time. The other salient features of the graph include a strong cyclical component to hours instability, a substantial increase in hours instability during the 1970s, and hours inequality increases largely because hours are becoming more unstable.

These results suggest that the explanation for the changes in the 1980s should focus on changes that persistently affect wages. Thus, hypotheses that focus on relative demand shifts, perhaps due to international trade, skill-biased technological change, or changes in consumption patterns, are supported by the results. On the other hand, explanations that focus on changes in hours are not supported. Thus, changes in the marginal tax rate, secular increases in job loss (where the subsequent unemployment spell that does not cover an entire calendar year), and increased part-time or contingent work are unlikely to explain the changes during the 1980s.

In addition, these results suggest that the increase in instability during the 1970s is something that causes more volatility in hours worked. A hypothesis consistent with this finding is that increasing inequality was associated with the increasing prevalence of the temporary or contingent workforce [see Segal and Sullivan (1997) for evidence of increased contingent employment]. However, the trend of increasing contingent employment accelerated during the 1980s, when earnings instability declined.

To further explore whether these trends can be attributed to skill, we next examine how the previous findings are related to changes in the returns to education. In particular, we remove the returns to education by including educational dummy variables

(0-8, 9-11, 12, 13-15, and 16+ years) in the first stage. We then perform the same persistent/instability decomposition to determine how much instability and inequality is left in the data. The results are reported in Figure 9.

In Figure 9, the level of annual earnings inequality is lower in every year and all of this reduction is explained by a decline in persistent inequality. This result is expected because educational attainment is a persistent individual characteristic, and thus should not explain the variance in earnings that is transitory. The interesting aspect of Figure 9 is comparing the increase in the persistent component between the two specifications. When not controlling for education (the dotted line, repeated from Figure 4), the persistent component increases 55 percent between 1967 and 1991. When controlling for education (the solid line), the persistent component increases only 40 percent. Therefore, returns to education explains about 30 percent of the increase in the persistent component. If education is an indicator of skill, than the increasing returns to skill seems to be an important component of the increase in lifetime earnings inequality. However, there is still a strong persistent component to earnings inequality that remains unexplained.

6. Conclusions

This paper examines whether the recent increases in annual earnings inequality were caused by lifetime earnings becoming more unequal or the receipt of lifetime earnings becoming more unstable. Using both a tabular and a parametric method, we find lifetime earnings inequality increased. The parametric analysis suggests that lifetime inequality increased 70 percent during the sample period, a magnitude similar to increases in annual inequality, and that most of the increase occurred during the early 1980s. In addition, we find that earnings instability increased dramatically during the sample period,

with most of the increases occurring during the 1970 s. Furthermore, we find that annual inequality increased because of fairly equal increases in the persistent and instability components.

To begin the process of understanding the changes in the labor market, we relate the trends of lifetime inequality and instability to changes in the distribution of wages and hours, changes in the returns to education, and the business cycle. These findings suggest that lifetime earnings inequality increased due to individuals receiving a persistently higher wage. These results suggest that a demand shift is likely, perhaps due to skill-biased technological change or increased international trade. An increasing returns to skill argument is further buttressed by the finding that education can explain about a third of the increase in the persistent component. Finally, we find that annual inequality is counter-cyclical largely because hours, and in turn earnings instability, is counter-cyclical.

Appendix A: The Estimation Procedure

Following other researchers, we obtain parameter estimates by using a GMM estimator [Abowd and Card (1989) and Baker (1997)]. Because the data set is unbalanced in that individuals may not be observed for every year, we use the methods described in Haider (1998).

Let $\mathbf{c}_i$ and $\sigma(X_i, \theta)$ be defined as in the text, $m^*(\mathbf{z}_i, \theta) \equiv \mathbf{c}_i - \sigma(X_i, \theta)$, and $m_l^*(\mathbf{z}_i, \theta)$ denote the l th element of $m^*(\mathbf{z}_i, \theta)$. Thus, the moment conditions in the text can be rewritten as

$$E[m^*(\mathbf{z}_i, \theta_0)] = \mathbf{0}. \quad (\text{A1})$$

In addition, let r_{il} be a random variable such that $r_{il} = 1$ if and only if i contributes to the l th moment (otherwise $r_{il} = 0$) and $\mathbf{r}_i$ be a random vector with r_{il} as the l th element. Furthermore, define the L moment functions

$$m_l(\mathbf{z}_i, r_{il}, \theta) \equiv \begin{cases} m_l^*(\mathbf{z}_i, \theta) & \text{if } r_{il} = 1, \\ 0 & \text{if } r_{il} = 0. \end{cases}$$

and let $m(\mathbf{z}_i, \mathbf{r}_i, \theta) \equiv (m_1(\mathbf{z}_i, r_{i1}, \theta), m_2(\mathbf{z}_i, r_{i2}, \theta), \dots, m_L(\mathbf{z}_i, r_{iL}, \theta))'$. Haider (1998) shows that a GMM estimator based on the moment conditions

$$E[m(\mathbf{z}_i, \mathbf{r}_i, \theta_0)] = \mathbf{0}, \quad (\text{A2})$$

is consistent for θ_0 [the same parameter identified by (A1)] and asymptotically normally distributed if certain conditions are satisfied. The primary condition needed for this result is that data must be missing randomly in the sense that $\text{Prob}[\mathbf{r}_i = 1 | \mathbf{z}_i] = \text{Prob}[\mathbf{r}_i =$

1]. For the problem considered here, $\mathbf{z}_i$ contains an individual's contribution to the empirical covariance matrix, the year, and the level of experience. Intuitively, this condition requires there to be no cohort effects.

The estimator $\hat{\theta}(A_n)$ is chosen to minimize the objective function

$$Q_n(A_n) \equiv \left(n^{-1} \sum_{i=1}^n m(\mathbf{z}_i, \mathbf{r}_i, \theta) \right)' A_n \left(n^{-1} \sum_{i=1}^n m(\mathbf{z}_i, \mathbf{r}_i, \theta) \right), \quad (\text{A3})$$

where A_n is a positive definite (possibly random) weighting matrix. From Proposition 2 of Haider (1998), $\tilde{\theta}_n(A_n)$ has the asymptotic distribution

$$\sqrt{n}(\tilde{\theta}(A_n) - \theta_0) \stackrel{A}{\sim} \mathcal{N}(0, V(A)), \quad (11)$$

where $V(A) \equiv (D'AD)^{-1}D'A\Phi AD(D'AD)^{-1}$, $\Phi \equiv E[m(\mathbf{z}, \mathbf{r}, \theta_0)m(\mathbf{z}, \mathbf{r}, \theta_0)']$, and $D \equiv E[\partial m(\mathbf{z}, \mathbf{r}, \theta)/\partial \theta|_{\theta_0}]$.

To implement the estimator, we choose $A_n = \Pi^{-1}\Pi^{-1}$, where

$$\Pi = \begin{bmatrix} \frac{n_1}{n} & 0 & \dots & 0 \\ 0 & \frac{n_2}{n} & \dots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \dots & \frac{n_L}{n} \end{bmatrix}.$$

This weighting matrix corresponds to an Equally Weighted Minimum Distance Estimator, following the suggestion of Altonji and Segal (1996). To see why this results in an Equally Weighted Minimum Distance Estimator, note that $Q_n(\Pi^{-1}\Pi^{-1})$ may be rewritten as

$$Q_n(\Pi^{-1}\Pi^{-1}) \equiv \left(n^{-1} \sum_{i=1}^n \Pi^{-1} m(\mathbf{z}_i, \mathbf{r}_i, \theta) \right)' I \left(n^{-1} \sum_{i=1}^n \Pi^{-1} m(\mathbf{z}_i, \mathbf{r}_i, \theta) \right).$$

Thus, $Q_n(\Pi^{-1}\Pi^{-1})$ is equivalent to using the identity matrix as a weighting matrix and the empirical moments that use all available observations for each element. Finally, we estimate Φ and D with their simple empirical analogs.

Appendix B: Derivations

Deriving an Expression for Lifetime Earnings Inequality

Let Y_{it}^* be the earnings i would receive if he worked from experience level 0 to R (retirement) with the parameter values present in year t ,

$$Y_{it}^* = \int_0^R \exp[-rX] \exp[f(X, \psi_t) + p_t(\alpha_i + \beta_i X)] dX, \quad (\text{B1})$$

where X is potential experience and f is a quartic in X . Equation (B1) is a restatement of (2) from the body of the paper. The discount rate r can be suppressed in (B1) without loss of generality because it simply reduces the linear coefficient in f by r . We suppress r and implicitly reduce the linear coefficient appropriately for the rest of the derivation.

As a measure of lifetime earnings inequality, we use the variance of log-lifetime earnings. Taking the logarithm of (B1),

$$\log Y_{it}^* = p_t \alpha_i + \log \left[\int_0^R \exp[f(X, \psi_t) + p_t \beta_i X] dX \right]. \quad (\text{B2})$$

Because (B2) is non-linear in β_i , we use a Taylor Series approximation to obtain an expression for the variance of (B2). We first calculate a first order Taylor Series approximation to (B2) around $E[\beta_i] = 0$,

$$\begin{aligned} \log Y_{it}^* &\doteq p_t \alpha_i + \log \left[\int_0^R \exp[f(X, \psi_t)] dX \right] + \frac{\partial}{\partial \beta_i} \log \left[\int_0^R \exp[f(X, \psi_t) + p_t \beta_i X] dX \right] \Big|_{\beta_i=0} \beta_i \\ &= p_t \alpha_i + \log \left[\int_0^R \exp[f(X, \psi_t)] dX \right] + \frac{\frac{\partial}{\partial \beta_i} \left[\int_0^R \exp[f(X, \psi_t) + p_t \beta_i X] dX \right]}{\int_0^R \exp[f(X, \psi_t) + p_t \beta_i X] dX} \Big|_{\beta_i=0} \beta_i \\ &= p_t \alpha_i + \log \left[\int_0^R \exp[f(X, \psi_t)] dX \right] + \frac{\int_0^R [p_t X \exp[f(X, \psi_t)]] dX}{\int_0^R \exp[f(X, \psi_t)] dX} \beta_i. \end{aligned} \quad (\text{B3})$$

Calculating the variance of (B3),

$$\begin{aligned} \text{var}[\log Y_{it}^*] &= p_t^2 \sigma_\alpha^2 + \left[\frac{p_t \int_0^R [X \exp[f(X, \psi_t)]] dX}{\int_0^R \exp[f(X, \psi_t)] dX} \right]^2 \sigma_\beta^2 + 2p_t \left[\frac{p_t \int_0^R [X \exp[f(X, \psi_t)]] dX}{\int_0^R \exp[f(X, \psi_t)] dX} \right] \sigma_{\alpha\beta} \\ &= p_t^2 \left\{ \sigma_\alpha^2 + \left[\frac{\int_0^R [X \exp[f(X, \psi_t)]] dX}{\int_0^R \exp[f(X, \psi_t)] dX} \right]^2 \sigma_\beta^2 + 2 \left[\frac{\int_0^R [X \exp[f(X, \psi_t)]] dX}{\int_0^R \exp[f(X, \psi_t)] dX} \right] \sigma_{\alpha\beta} \right\}. \end{aligned}$$

The expression inside the large square brackets represents the marginal impact of a change in β_i on the logarithm of lifetime earnings near $E[\beta_i] = 0$. All of these parameters are estimable and numerical methods are used to evaluate the integrals.

The Relationship between Transitory Earnings Shocks and Lifetime Earnings Inequality

Although the intuition for the claim that transitory shocks are unimportant to lifetime earnings inequality is straightforward, we provide a proof. We prove the claim for a simpler model but the method may be readily applied to the full model in (2). Consider the simple earnings model,

$$\log y_{it} = \mu_i + \varepsilon_{it} \tag{B4}$$

where y_{it} is annual earnings for i in t , μ_i is mean earnings for individual i , and ε_{it} is a mean-zero, individual-time specific error term. Assume that ε_{it} is independently and identically distributed across individuals and time and that the discount rate is zero (both assumptions may be weakened). Lifetime earnings for individual i working for R years is,

$$Y_i = \sum_{t=1}^R \exp[\mu_i + \varepsilon_{it}], \tag{B5}$$

and the variance of log-lifetime earnings is

$$\begin{aligned}
 \text{var}[\log Y_i] &= \text{var}\left[\log\left[\sum_{t=1}^R \exp[\mu_i + \varepsilon_{it}]\right]\right] \\
 &= \text{var}\left[\log[\exp[\mu_i] \sum_{t=1}^R \exp[\varepsilon_{it}]]\right] \\
 &= \text{var}[\mu_i] + \text{var}\left[\log\left[\sum_{t=1}^R \exp[\varepsilon_{it}]\right]\right]
 \end{aligned} \tag{B6}$$

To derive an expression for the final term of (B6), we use a multivariate version of the Taylor approximation method outlined in the previous section. Let ε_i be the R -vector of the error terms of individual i , then

$$\begin{aligned}
 \text{var}\left[\log\left[\sum_{t=1}^R \exp[\varepsilon_{it}]\right]\right] &= \text{var}[g(\varepsilon_i)] \\
 &\doteq \nabla g(0)' \Sigma_\varepsilon \nabla g(0)
 \end{aligned} \tag{B7},$$

where ∇ is the gradient operator and Σ_ε is the covariance matrix of ε_{it} . It is readily verifiable that $\nabla g(0)$ is a vector with $\frac{1}{R}$ as each element. If one assumes ε_{it} is independently and identically distributed with variance σ_ε^2 , then (B7) may be rewritten as

$$\nabla g(0)' \Sigma_\varepsilon \nabla g(0) = \frac{\sigma_\varepsilon^2}{R}, \tag{B8}$$

which clearly approaches zero as R tends to infinity. Including a finite discount rate will not change this result and more general covariances structures can be allowed as long as (B8) tends to zero as R tends to infinity. Thus, the contribution of the transitory variance to lifetime inequality becomes less and less important as the time horizon over which inequality is measured (R) increases.

Appendix C: Data Description

We construct the data set from Waves I to XXV of the PSID-SRC; the SRC subsample is a random sample thus weights are not needed. All individuals in the PSID-SRC are used, regardless if they are sample individuals. The data were collected in annual interviews from 1968 to 1992, and the respondents report total annual labor earnings for the preceding calendar year (the series including V21484 for 1992). Gary Solon provided the necessary data so that “top-coded” earnings values could be replaced by the actual reported values from the original interviews [see Solon, Barsky, and Parker (1994)]. However, actual reported values were unavailable for three top-coded observations. After examining the earnings histories of the three individuals, we left two observations top-coded and interpolated the earnings for the third observation. All earnings data are reported in 1994 dollars using the Bureau of Labor Statistics’ CPI-U-X1.

Age, gender, and household head status are taken each year from the individual file. We restrict our attention to male household heads, aged 25-60. The most recent report of race by an individual is used. Earnings are set to zero for an observation if the individual reports being a student in a given year or in the preceding year. Once an individual reports being retired, all subsequent observations are deleted. We define education to be the most recent report of education completed for an individual in the family file (the series including v10996 for 1984). If such a report is unavailable, we use the most recent report of education in the individual file (the series including v30748 in 1992); the years 1969 to 1978 were excluded from the individual file series, however, due to compatibility issues. We reassign a value of 18 to the category of 17 or more years of education. Potential experience is calculated as $(\text{age} - \text{education} - 6)$, recoding any negative values to be zero. Given these restrictions, we include in our sample all individuals who

are observed at least twice and who do not have zero earnings during the time-frame we observe him.

In addition, we exclude any observation in which any component of total annual labor earnings is a “major assignment” or who is determined to be an outlier, although we do retain the rest of the relevant observations for such an individual. Outliers are defined to be individuals who have an implied wage of less than \$1 or more than \$250 (1994 dollars). An earnings variable was determined to be a major assignment if either of the underlying accuracy codes indicated a major assignment (the series including V20430 and V20435 for 1992). The hours variable is the self-reported annual hours worked (the series including v20344 in 1992). Five educational categories were used when education was included in the first stage regression (0-8, 9-11, 12, 13-15, and 16-).

BIBLIOGRAPHY

- Abowd, John M., and Card, David. "On the Covariance Structure of Earnings and Hours Changes." *Econometrica* 57 (March 1989): 411-45.
- Altonji, Joseph G., and Segal, Lewis M. "Small Sample Bias in GMM Estimation of Covariance Structures." *Journal of Business and Economics Statistics* 14 (July 1996): 353-66.
- Attanasio, Orazio, and Davis, Steven J. "Relative Wage Movements and the Distribution of Consumption." *Journal of Political Economy* 104 (December 1996): 1227-62.
- Baker, Michael. "Growth Rate Heterogeneity and the Covariance Structure of Life Cycle Earnings." *Journal of Labor Economics* 15 (April 1997): 338-75.
- Baker, Michael, and Solon, Gary. "Earnings Dynamics and Inequality among Canadian Men, 1976-92: Evidence from Longitudinal Income Tax Records." March 1998 manuscript.
- Becker, Gary. *Human Capital*. Chicago, IL: University of Chicago Press, 1975.
- Bound, John, and Krueger, Alan B. "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?" *Journal of Labor Economics* 9 (January 1991): 1-24.
- Blinder, Alan. "The Level and Distribution of Economic Well-being: Introduction and Preview." In *The American Economy in Transition*, edited by Martin Feldstein. Chicago, IL: University of Chicago Press, 1980.
- Buchinsky, Moshe and Jennifer Hunt. "Wage Mobility in the United States." *Review of Economics and Statistics* 81 (August 1999): 351-68.

- Cutler, David M., and Katz, Lawrence F. "Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980s." *American Economic Review* 82 (May 1992): 546-51.
- Duncan, Greg J., Juster, F. Thomas, and Morgan, James N. "The Role of Panel Studies in a World of Scarce Research Resources." In *The Collection and Analysis of Economic and Consumer Behavior Data*, edited by S. Sudman, and M. Spaeth. Champaign, IL: Bureau of Economic and Business Research, 1984.
- Friedman, Milton. *A Theory of the Consumption Function*. Princeton, NJ: Princeton University Press, 1957.
- Friedman, Milton, and Kuznets, Simon. *Income from Independent Professional Practice*. New York, NY: National Bureau of Economic Research, 1945.
- Gittleman, Maury, and Joyce, Mary. "Earnings Mobility and Long-Run Inequality: An Analysis Using Matched CPS Data." *Industrial Relations* 35 (April 1996): 180-96.
- Gordon, Roger. *Differences in Earnings and Ability*. New York, NY: Garland Publishing, 1984.
- Gottschalk, Peter. "Inequality, Income Growth, and Mobility: The Basic Facts." *Journal of Economic Perspectives* 11 (Spring 1997): 21-40.
- Gottschalk, Peter, and Robert Moffitt. "The Growth of Earnings Instability in the U.S. Labor Market." *Brookings Papers on Economic Activity* 2 (1994): 217-72.
- Haider, Steven. "Generalized Method of Moments with Incomplete Data." March 1998 manuscript.
- _____. "The Long-Run Earnings Inequality of Families." May 1999 manuscript.

- Hause, John C. "The Fine Structure of Earnings and the On-the-Job Training Hypothesis." *Econometrica* 48 (May 1980): 1013-29.
- Juhn, Chinhui, Murphy, Kevin M., and Pierce, Brooks . "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy* 101 (June 1993): 410-42.
- Karoly, Lynn. "The Trend in Inequality Among Families, Individuals and Workers in the United States: A Twenty-Five Year Perspective." In *Uneven Tides*, edited by Sheldon Danziger and Peter Gottschalk. New York: Russell Sage Foundation, 1993.
- Lazear, Edward. "Agency, Earnings Profiles, Productivity and Hours Restrictions." *American Economic Review* 71 (September 1981) 606-20.
- Levy, Frank, and Murnane, Richard J. "Earnings Levels and Earnings Inequalities: A Review of Recent Trends and Proposed Explanations." *Journal of Economic Literature* 30 (September 1992): 1333-81.
- Lillard, Lee A. "Inequality: Earnings vs. Human Wealth." *American Economic Review* 67 (March 1977): 42-53.
- Lillard, Lee A. and Reville, Robert. "Intergenerational Mobility in Earnings and Occupational Status." March 1997 manuscript.
- Lillard, Lee A., and Weiss, Yoram. "Components of Variation in Panel Earnings Data: American Scientists 1960-70." *Econometrica* 47 (March 1979): 437-54.
- MaCurdy, Thomas E. "The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis." *Journal of Econometrics* 18 (January 1982): 83-114.

- Moffitt, Robert A. and Gottschalk, Peter. "Trends in the Autocovariance Structure of Earnings in the U.S.: 1969-1987." July 1995 manuscript.
- Murphy, Kevin M. and Welch, Finis . "Empirical Age-Earnings Profiles." *Journal of Labor Economics* 8 (April 1990): 202-29.
- Segal, Lewis M., and Sullivan, Daniel G. "The Growth of Temporary Services Work." *Journal of Economic Perspectives* 11 (Spring 1997): 117-36.
- Shorrocks, Anthony. "Income Inequality and Income Mobility." *Journal of Economic Theory* 19 (December 1978): 376-93.
- Solon, Gary, Barsky, Robert, and Parker, Jonathan A. "Measuring the Cyclicalilty of Real Wages: How Important Is Composition Bias?" *Quarterly Journal of Economics* 109 (February 1994): 1-25.
- Summers, Robert. "An Econometric Investigation of the Size Distribution of Lifetime Average Annual Income." *Econometrica* 24 (July 1956): 346-47.
- Topel, Robert H., and Ward, Michael P. "Job Mobility and the Careers of Young Men." *Quarterly Journal of Economics* 107 (May 1992) 439-79.
- Zeldes, Stephen P. "Consumption and Liquidity Constraints: An Empirical Investigation." *Journal of Political Economy* 97 (April 1989): 305-46.

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¹ See Blinder (1980) and Karoly (1993) for a historical perspective, Levy and Murnane (1992) for a literature review, and Gottschalk (1997) for recent evidence.

² Another approach to assessing the inequality of consumption sets is to examine the inequality of actual consumption [see Cutler and Katz (1992) and Attanasio and Davis (1996)]. Whether lifetime earnings or actual consumption is a better measure of an individual's consumption set will depend on (a) the quality of the respective data, (b) the existence of liquidity constraints, and (c) the relative heterogeneity in tastes and income sources [the less the heterogeneity, the easier it will be to construct a representative bundle]. *A priori*, it is not clear that one measure should be preferred to the other.

³ Friedman (1957) shows that optimizing agents will want to smooth consumption over transitory earnings fluctuations. Zeldes (1989) finds evidence of liquidity constraints affecting the ability of individuals to smooth consumption.

⁴ We restrict our analysis to males because the large changes in female labor force participation during the sample period would confound a similar analysis of female earnings. The results would be confounded because we specify a model of earnings, not of entry and exit. Appending a model of entry and exit to the current framework is beyond the scope of this paper. For results concerning husbands and wives, see Haider (1999).

⁵ In particular, if the deflator over-compensates for the rate of inflation, the real growth rate in earnings will be underestimated. Such an error will cause (1) the growth rate of long run earnings between the two periods to be biased downward and (2) too much weight to be given to the early earnings years in the PDV calculation. Focusing on a direct measure of inequality will remedy the first but not the second type of bias.

⁶ For example, see Lillard and Weiss (1979), Hause (1980), MaCurdy (1982), Moffitt and Gottschalk (1995), and Baker (1997). A common alternative model for earnings dynamics is a random walk model [MaCurdy (1982), Abowd and Card (1989) and Moffitt and Gottschalk (1995)]. This model will be discussed below.

⁷ There are many theoretical justifications for a model of heterogeneous earnings growth. In fact, appending heterogeneity to just about any model which predicts an upward sloping earnings profile will provide a compelling justification. For example, heterogeneity in human capital investment across individuals with similar ability [e.g., Becker (1975)] or heterogeneity across firms in monitoring costs [e.g., Lazear (1981)] will imply a model of heterogeneous earnings growth.

⁸ Lillard and Reville (1997) point out that the latter restriction is inconsistent with standard human capital theory. However, Baker (1997) finds that the inclusion of higher order terms does not substantially improve the fit of the model, and Baker (1997) and

Baker and Solon (1998) find that the inclusion of higher order terms does not dramatically change the other parameter estimates; thus, the restriction does not seem to be empirically important.

⁹ One can show that the variance induced in lifetime earnings by realizations of ε_{it} approaches zero as the time horizon of working becomes larger and larger. A simple proof of this claim is presented in Appendix B.

¹⁰ Because we will specify ε_{it} to follow an ARMA process, not all parameter values are compatible with a temporary interpretation. However, the parameter estimates below imply that less than 15 percent of a transitory shock remains after 3 years, thus providing support for the interpretation to follow.

¹¹ Because we find that $\sigma_{\varepsilon_t}^2$ increased over time, respondents would need to report earnings with *more* measurement error over time to cause the observed increase. Duncan, Juster, and Morgan (1984) argue that panel data will be measured with less error over time, particularly for economic phenomena, because respondents “get trained to their task, and cross-year consistency checks are applied.” Thus, the increases in instability may actually be underestimated if measurement error has declined. In addition to respondent error, measurement error could increase over time in the PSID due to reductions in the editing budget and due to increased use of proxy respondents. According to conversations with Tecla Loup of the PSID staff, significant reductions in the editing budget began with the 1993 wave, thus budgetary changes are not of concern for the sample in this paper. Bound and Krueger (1991) find that proxy-reported earnings in the CPS are comparable in accuracy to self-reported earnings; there is little reason to expect the PSID would be different.

¹² The discussion which follows implicitly assumes that a fully balanced panel is available. However, a revolving balanced panel design implies individuals may enter and exit the sample, and thus, the panel is technically unbalanced. Haider (1998), summarized in Appendix A, provides details on how the estimation procedure is extended to handle unbalanced data.

¹³ Altonji and Segal (1996) find that the feasible Optimal Minimum Distance estimator which uses the estimated covariance matrix of the moments as the weighting matrix has poor small sample properties in a similar estimation problem. Following the suggestion of Altonji and Segal (1996) and the practice of other researchers in this area, we use the identity matrix as the weighting matrix.

¹⁴ The choice of this specification is based on statistical tests, as well as the results of others. For example, Moffitt and Gottschalk (1995) and Baker (1997) find that an ARMA(1,1) is sufficient to fit the mean reverting process in earnings data and Murphy and Welch (1990) find that specifying f as a time-varying quartic fits empirical earnings profiles quite well. All of the conclusions reported here are highly robust to alternative ARMA and f specifications. For an example of this robustness, see Figure 6.

¹⁵ We calculate a 64 percent increase by comparing the first three years and last three years of estimates. Unless otherwise noted, all percentage changes will be calculated similarly so that a local outlier will not be overly influential.

¹⁶ For example, using the March CPS and a similar inequality measure (although *not* experience-adjusted), Juhn, Murphy, and Pierce (1993) report that earnings inequality increased about 80 percent for the period 1968-89.

¹⁷ Buchinsky and Hunt (1999) find larger declines in mobility than those reported here. Part of this difference is likely due to the age/cohort nature of the NLSY. In particular, we should expect some decline in instability because of life-cycle changes in earnings for the population represented in the NLSY [e.g., Gordon (1984) and Topel and Ward (1992)].

¹⁸ Conceptually, a random walk model and a heterogeneous growth model are not mutually exclusive, but practically, estimating both in the same model can be difficult with small data sets because the models are quite similar. Baker and Solon (1998) are able to include both with a much larger data set and find that the time varying parameters do not change dramatically if the random walk term or the heterogeneous growth term is excluded. We focus on the heterogeneous growth model rather than the random walk model for two reasons: conceptually it seems likely that individuals will differ from the mean profile systematically over long time periods, and empirically Baker (1997) finds that a heterogeneous growth model fits the data better than a random walk.

¹⁹ Juhn, Murphy, and Pierce (1993) perform a similar decomposition with the Current Population Surveys.

**Table 1: Long-Run Earnings Distribution
for Male Household Heads**

	All Males			Positive Earning Males**		
	1969-78 N=534	1982-91 N=791	Change	1969-78 N=519	1982-91 N=727	Change
Quantiles						
10th	\$ 173,258	\$ 132,727	-23%	\$ 177,237	\$ 161,112	-9%
20th	\$ 225,563	\$ 192,538	-15%	\$ 228,844	\$ 213,847	-7%
25th	\$ 243,403	\$ 215,766	-11%	\$ 246,373	\$ 232,222	-6%
50th	\$ 328,404	\$ 311,861	-5%	\$ 330,226	\$ 326,090	-1%
75th	\$ 437,826	\$ 436,638	0%	\$ 440,481	\$ 447,815	2%
80th	\$ 473,160	\$ 473,798	0%	\$ 477,431	\$ 484,606	2%
90th	\$ 586,823	\$ 619,256	6%	\$ 587,398	\$ 645,081	10%
Mean	\$ 370,723	\$ 365,155	-2%	\$ 375,735	\$ 384,212	2%
Inequality						
90th/10th	3.39	4.67	38%	3.31	4.00	21%
80th/20th	2.10	2.46	17%	2.09	2.27	9%
var[log]	0.24	0.42*	75%	0.23	0.31	31%
coeff var	0.62	0.79	28%	0.61	0.76	24%
	White Males			White, Positive Earning Males**		
	1969-78 N=481	1982-91 N=739	Change	1969-78 N=467	1982-91 N=677	Change
Quantiles						
10th	\$ 179,278	\$ 139,952	-22%	\$ 189,407	\$ 166,812	-12%
20th	\$ 234,624	\$ 200,285	-15%	\$ 236,644	\$ 216,462	-9%
25th	\$ 252,716	\$ 218,149	-14%	\$ 255,711	\$ 240,299	-6%
50th	\$ 330,759	\$ 316,755	-4%	\$ 334,852	\$ 333,244	0%
75th	\$ 446,955	\$ 442,990	-1%	\$ 448,489	\$ 462,237	3%
80th	\$ 483,721	\$ 481,018	-1%	\$ 489,483	\$ 491,051	0%
90th	\$ 599,172	\$ 634,939	6%	\$ 604,125	\$ 653,931	8%
Mean	\$ 379,388	\$ 373,137	-2%	\$ 384,710	\$ 393,404	2%
Inequality						
90th/10th	3.34	4.54	36%	3.19	3.92	23%
80th/20th	2.06	2.40	16%	2.07	2.27	10%
var[log]	0.23	0.42	83%	0.22	0.30	35%
coeff var	0.61	0.79	29%	0.60	0.76	25%

Note: The sample is constructed from the PSID-SRC. Calculations are based on individuals aged 30-44 during the first year of the particular time period. Long run earnings are calculated as the present discounted value (5% interest rate) of real earnings for each 10 year period, reported in CPI-U-X1 adjusted 1994 dollars. Only individuals with a complete 10 year earnings history were included, excluding the observations which were "major assignments."

*One male was excluded from this calculation because he had zero earnings for the entire 10 year period.

**Positive Earning Males refers to males who had positive earnings in every year of the given period.

Table 2: Summary Statistics for the Primary and Secondary Samples

Year	Primary Sample: 2 Year Minimum Restriction					Secondary Sample: 10 Year Minimum Restriction				
	Experience		Annual Earnings			Experience		Annual Earnings		
	Mean	Std Dev	Mean	Std Dev	N	Mean	Std Dev	Mean	Std Dev	N
1967	24.1	10.5	\$ 37,190	\$ 21,055	1,011	20.5	8.6	\$ 38,673	\$ 20,936	700
1968	24.4	10.8	\$ 38,209	\$ 22,310	1,087	20.9	8.9	\$ 40,008	\$ 21,421	757
1969	24.0	11.0	\$ 39,751	\$ 23,485	1,088	21.0	9.3	\$ 41,006	\$ 22,293	798
1970	23.4	11.0	\$ 39,955	\$ 23,095	1,088	21.3	9.6	\$ 40,869	\$ 21,478	846
1971	23.0	11.3	\$ 40,520	\$ 23,194	1,116	21.3	10.1	\$ 41,186	\$ 22,179	895
1972	22.2	11.5	\$ 42,233	\$ 26,303	1,160	21.0	10.6	\$ 42,615	\$ 23,134	971
1973	21.6	11.7	\$ 43,205	\$ 30,067	1,200	21.0	10.9	\$ 43,652	\$ 25,480	1,036
1974	21.3	11.7	\$ 42,314	\$ 30,348	1,238	21.1	11.2	\$ 43,491	\$ 31,559	1,090
1975	21.1	11.6	\$ 40,568	\$ 27,520	1,253	21.3	11.3	\$ 41,115	\$ 24,462	1,141
1976	20.8	11.5	\$ 42,500	\$ 32,605	1,314	21.3	11.6	\$ 42,742	\$ 30,293	1,213
1977	20.5	11.4	\$ 43,341	\$ 33,384	1,345	21.1	11.4	\$ 43,622	\$ 31,302	1,237
1978	20.2	11.3	\$ 43,525	\$ 30,179	1,381	20.7	11.4	\$ 44,248	\$ 30,870	1,275
1979	20.1	11.2	\$ 43,279	\$ 27,945	1,426	20.5	11.3	\$ 43,915	\$ 28,521	1,319
1980	19.8	11.1	\$ 42,516	\$ 37,129	1,459	20.3	11.1	\$ 43,199	\$ 37,990	1,355
1981	19.7	10.9	\$ 41,644	\$ 28,575	1,496	20.2	10.9	\$ 42,379	\$ 29,121	1,394
1982	19.4	10.6	\$ 40,554	\$ 29,273	1,522	20.0	10.6	\$ 41,344	\$ 29,739	1,414
1983	19.5	10.3	\$ 40,234	\$ 27,557	1,554	20.5	10.2	\$ 41,678	\$ 28,255	1,377
1984	19.4	10.0	\$ 42,575	\$ 34,752	1,590	21.0	9.8	\$ 45,072	\$ 36,716	1,330
1985	19.5	9.9	\$ 42,252	\$ 31,002	1,623	21.6	9.6	\$ 45,425	\$ 33,189	1,283
1986	19.4	9.7	\$ 43,297	\$ 32,831	1,662	22.1	9.2	\$ 47,111	\$ 34,901	1,240
1987	19.5	9.4	\$ 43,790	\$ 35,936	1,670	22.5	8.7	\$ 48,214	\$ 39,772	1,182
1988	19.6	9.2	\$ 44,565	\$ 36,048	1,687	23.1	8.3	\$ 49,317	\$ 40,363	1,135
1989	19.7	9.0	\$ 43,630	\$ 36,156	1,701	23.6	8.0	\$ 48,757	\$ 41,538	1,087
1990	19.8	8.7	\$ 43,232	\$ 37,948	1,698	24.1	7.4	\$ 48,598	\$ 43,114	1,022
1991	20.5	8.4	\$ 43,831	\$ 41,543	1,649	24.7	7.1	\$ 49,220	\$ 48,770	983
Total Observations:					35,018					28,080
Total Individuals:					3,115					1,704

Notes: Both samples are constructed from the PSID-SRC. Earnings are measured in 1994 dollars, adjusted using the CPI-U-X1. The primary sample is constructed from all individuals observed for at least 2 years. The secondary sample is constructed from all individuals observed for at least 10 years. See Appendix C for further details.

Table 3: The Empirical Covariance Matrix for the Primary Sample

	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978
1967	0.265 0.0186 1011	0.610	0.777	0.723	0.664	0.653	0.629	0.640	0.560	0.525	0.549	0.547
1968	0.216 0.0130 897	0.268 0.0178 1087	0.855	0.744	0.716	0.688	0.666	0.639	0.576	0.580	0.573	0.555
1969	0.210 0.0125 949	0.232 0.0160 1031	0.275 0.0193 1088	0.766	0.740	0.700	0.683	0.671	0.588	0.577	0.584	0.575
1970	0.200 0.0137 891	0.207 0.0133 967	0.216 0.0135 1015	0.288 0.0228 1088	0.793	0.741	0.693	0.695	0.623	0.616	0.624	0.593
1971	0.181 0.0119 849	0.190 0.0124 925	0.199 0.0126 973	0.218 0.0138 1041	0.263 0.0180 1116	0.801	0.733	0.720	0.660	0.623	0.632	0.611
1972	0.176 0.0118 804	0.186 0.0125 874	0.192 0.0127 924	0.208 0.0134 989	0.215 0.0135 1056	0.274 0.0177 1160	0.787	0.697	0.644	0.631	0.626	0.595
1973	0.159 0.0115 763	0.169 0.0122 827	0.176 0.0121 874	0.183 0.0122 936	0.185 0.0117 1002	0.202 0.0127 1103	0.242 0.0158 1200	0.770	0.697	0.664	0.677	0.613
1974	0.169 0.0124 734	0.169 0.0117 796	0.180 0.0121 841	0.191 0.0126 899	0.189 0.0123 964	0.186 0.0111 1059	0.194 0.0117 1153	0.262 0.0157 1238	0.747	0.679	0.690	0.647
1975	0.153 0.0129 690	0.158 0.0123 750	0.163 0.0118 794	0.177 0.0124 844	0.179 0.0131 907	0.178 0.0123 1000	0.181 0.0130 1088	0.202 0.0121 1169	0.281 0.0189 1253	0.734	0.687	0.630
1976	0.148 0.0125 666	0.159 0.0133 723	0.166 0.0133 765	0.181 0.0130 816	0.175 0.0140 878	0.181 0.0131 970	0.179 0.0133 1054	0.191 0.0126 1130	0.213 0.0127 1211	0.301 0.0271 1314	0.779	0.668
1977	0.158 0.0128 628	0.166 0.0125 685	0.171 0.0126 725	0.187 0.0137 775	0.181 0.0134 833	0.183 0.0135 917	0.186 0.0141 1001	0.197 0.0134 1073	0.203 0.0130 1152	0.239 0.0146 1250	0.312 0.0249 1345	0.750
1978	0.150 0.0138 594	0.153 0.0134 643	0.161 0.0130 683	0.170 0.0139 732	0.167 0.0146 788	0.166 0.0126 870	0.161 0.0126 953	0.176 0.0124 1022	0.178 0.0122 1093	0.195 0.0122 1184	0.223 0.0146 1270	0.264 0.0188 1381
1979	0.151 0.0142 562	0.153 0.0137 608	0.160 0.0136 649	0.171 0.0145 696	0.160 0.0141 748	0.159 0.0120 832	0.159 0.0124 911	0.173 0.0129 979	0.171 0.0118 1049	0.184 0.0126 1136	0.198 0.0130 1212	0.213 0.0129 1309
1980	0.147 0.0141 528	0.150 0.0139 573	0.163 0.0143 613	0.169 0.0161 661	0.164 0.0152 713	0.165 0.0138 793	0.150 0.0129 867	0.174 0.0143 932	0.167 0.0120 1001	0.193 0.0141 1082	0.202 0.0147 1156	0.210 0.0143 1249
1981	0.155 0.0147 502	0.162 0.0156 546	0.162 0.0143 584	0.167 0.0151 632	0.165 0.0153 684	0.168 0.0141 763	0.155 0.0129 835	0.171 0.0137 896	0.169 0.0127 961	0.184 0.0133 1041	0.188 0.0136 1111	0.195 0.0134 1199
1982	0.157 0.0177 459	0.163 0.0179 500	0.164 0.0167 537	0.169 0.0175 583	0.167 0.0164 634	0.170 0.0151 712	0.159 0.0150 783	0.172 0.0147 845	0.180 0.0145 905	0.190 0.0138 985	0.191 0.0141 1054	0.196 0.0133 1140
1983	0.160 0.0166 428	0.170 0.0176 468	0.171 0.0168 505	0.168 0.0157 552	0.166 0.0158 604	0.176 0.0147 678	0.159 0.0147 747	0.173 0.0140 807	0.181 0.0145 867	0.190 0.0142 941	0.190 0.0138 1009	0.197 0.0136 1092
1984	0.151 0.0172 386	0.162 0.0186 425	0.167 0.0176 461	0.166 0.0255 509	0.166 0.0157 559	0.173 0.0149 631	0.163 0.0149 696	0.177 0.0146 753	0.178 0.0144 811	0.190 0.0147 886	0.192 0.0143 954	0.187 0.0129 1032
1985	0.171 0.0220 361	0.178 0.0221 401	0.172 0.0211 436	0.180 0.0205 482	0.175 0.0185 529	0.180 0.0177 597	0.168 0.0178 659	0.187 0.0183 715	0.183 0.0181 768	0.196 0.0187 842	0.192 0.0157 904	0.192 0.0146 980
1986	0.167 0.0210 329	0.181 0.0200 365	0.170 0.0191 401	0.178 0.0196 444	0.165 0.0166 494	0.174 0.0166 561	0.158 0.0166 621	0.177 0.0168 677	0.174 0.0160 732	0.179 0.0158 804	0.187 0.0159 863	0.172 0.0136 935
1987	0.137 0.0200 283	0.147 0.0214 318	0.153 0.0201 354	0.162 0.0206 397	0.159 0.0188 445	0.166 0.0177 510	0.150 0.0178 567	0.175 0.0178 622	0.175 0.0168 673	0.186 0.0168 743	0.189 0.0182 803	0.177 0.0151 876
1988	0.136 0.0191 250	0.151 0.0206 287	0.152 0.0206 321	0.170 0.0228 363	0.157 0.0194 410	0.174 0.0208 474	0.152 0.0178 531	0.171 0.0178 584	0.179 0.0185 634	0.184 0.0183 703	0.182 0.0172 761	0.172 0.0154 834
1989	0.101 0.0193 225	0.117 0.0220 257	0.125 0.0214 292	0.148 0.0220 332	0.149 0.0199 377	0.148 0.0173 438	0.130 0.0177 495	0.148 0.0170 545	0.156 0.0174 594	0.166 0.0185 662	0.172 0.0166 717	0.165 0.0157 791
1990	0.105 0.0249 189	0.133 0.0289 220	0.140 0.0300 254	0.175 0.0276 293	0.166 0.0245 336	0.168 0.0217 396	0.152 0.0209 452	0.167 0.0200 500	0.185 0.0194 543	0.180 0.0192 609	0.180 0.0182 663	0.173 0.0171 736
1991	0.089 0.0233 166	0.125 0.0275 197	0.122 0.0270 231	0.159 0.0267 269	0.136 0.0230 313	0.149 0.0210 367	0.133 0.0199 425	0.156 0.0201 470	0.171 0.0180 514	0.163 0.0189 579	0.175 0.0188 633	0.173 0.0177 702
	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978

Note: The three numbers in each cell below the principal diagonal are the point estimate, the standard error, and the sample size. The numbers above the principal diagonals are the empirical autocorrelations.

Table 3 (cont.): The Empirical Covariance Matrix for the Primary Sample

1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	
0.561	0.505	0.519	0.479	0.471	0.478	0.511	0.495	0.423	0.413	0.315	0.310	0.244	1987
0.586	0.513	0.541	0.495	0.498	0.508	0.530	0.475	0.452	0.457	0.364	0.390	0.341	1988
0.584	0.551	0.533	0.489	0.495	0.518	0.504	0.494	0.464	0.453	0.385	0.404	0.328	1989
0.610	0.557	0.536	0.494	0.478	0.563	0.516	0.505	0.482	0.495	0.443	0.494	0.419	1970
0.599	0.587	0.554	0.511	0.499	0.532	0.525	0.493	0.494	0.481	0.467	0.490	0.375	1971
0.582	0.557	0.555	0.510	0.512	0.539	0.531	0.508	0.505	0.522	0.457	0.485	0.401	1972
0.618	0.541	0.543	0.506	0.490	0.538	0.525	0.490	0.486	0.485	0.427	0.467	0.382	1973
0.648	0.602	0.576	0.526	0.515	0.562	0.564	0.530	0.545	0.525	0.467	0.493	0.430	1974
0.617	0.557	0.549	0.532	0.520	0.546	0.532	0.502	0.526	0.531	0.475	0.530	0.455	1975
0.642	0.621	0.578	0.543	0.527	0.563	0.550	0.512	0.540	0.527	0.487	0.498	0.472	1976
0.679	0.638	0.580	0.536	0.516	0.560	0.528	0.512	0.539	0.510	0.497	0.489	0.443	1977
0.764	0.695	0.631	0.576	0.563	0.571	0.554	0.491	0.530	0.507	0.500	0.492	0.457	1978
0.273 0.0191 1426	0.771	0.704	0.626	0.560	0.616	0.587	0.531	0.579	0.544	0.533	0.514	0.472	1979
0.228 0.0137 1354	0.319 0.0199 1459	0.805	0.702	0.630	0.649	0.610	0.574	0.618	0.593	0.563	0.558	0.501	1980
0.213 0.0130 1292	0.264 0.0157 1385	0.337 0.0200 1496	0.770	0.661	0.683	0.662	0.624	0.638	0.615	0.585	0.560	0.497	1981
0.209 0.0127 1224	0.253 0.0149 1317	0.285 0.0164 1415	0.407 0.0231 1522	0.750	0.689	0.651	0.639	0.650	0.591	0.569	0.550	0.484	1982
0.192 0.0124 1178	0.234 0.0144 1264	0.252 0.0140 1357	0.315 0.0177 1442	0.433 0.0326 1554	0.757	0.679	0.665	0.647	0.601	0.582	0.550	0.513	1983
0.198 0.0131 1115	0.225 0.0142 1201	0.244 0.0141 1291	0.270 0.0149 1369	0.306 0.0168 1462	0.378 0.0202 1590	0.779	0.728	0.727	0.670	0.680	0.628	0.568	1984
0.199 0.0147 1064	0.224 0.0148 1145	0.250 0.0173 1233	0.270 0.0162 1306	0.290 0.0159 1396	0.311 0.0167 1511	0.422 0.0307 1623	0.795	0.770	0.670	0.637	0.621	0.561	1985
0.181 0.0140 1017	0.213 0.0155 1095	0.237 0.0152 1176	0.267 0.0150 1248	0.287 0.0156 1333	0.293 0.0166 1445	0.338 0.0206 1541	0.429 0.0244 1662	0.823	0.724	0.711	0.675	0.619	1986
0.190 0.0152 956	0.219 0.0165 1035	0.232 0.0148 1113	0.260 0.0154 1178	0.267 0.0158 1263	0.280 0.0154 1370	0.314 0.0204 1454	0.338 0.0178 1556	0.393 0.0199 1670	0.773	0.765	0.703	0.651	1987
0.181 0.0154 910	0.214 0.0190 983	0.228 0.0167 1058	0.241 0.0148 1123	0.252 0.0153 1204	0.263 0.0153 1306	0.278 0.0160 1389	0.302 0.0166 1482	0.309 0.0157 1569	0.407 0.0226 1687	0.826	0.753	0.692	1988
0.173 0.0151 862	0.197 0.0166 932	0.211 0.0150 1004	0.225 0.0144 1070	0.238 0.0150 1146	0.260 0.0154 1240	0.257 0.0147 1322	0.289 0.0168 1412	0.298 0.0153 1493	0.327 0.0166 1588	0.385 0.0179 1701	0.791	0.729	1989
0.177 0.0165 807	0.208 0.0195 873	0.215 0.0164 943	0.232 0.0157 1007	0.239 0.0162 1078	0.255 0.0155 1172	0.266 0.0158 1250	0.292 0.0174 1333	0.291 0.0157 1409	0.317 0.0169 1497	0.324 0.0160 1588	0.436 0.0223 1698	0.804	1990
0.175 0.0185 770	0.201 0.0188 838	0.204 0.0171 909	0.219 0.0165 966	0.239 0.0170 1035	0.248 0.0162 1129	0.259 0.0168 1204	0.287 0.0201 1290	0.289 0.0176 1366	0.313 0.0175 1455	0.321 0.0171 1538	0.376 0.0198 1616	0.502 0.0271 1649	1991
1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	

Table 4: Parameter Estimates for the Parametric Models

	Earnings		Wages		Hours	
	Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
<u>Time Invariant Parameters</u>						
var[α]	0.295	0.137	0.307	0.146	0.311	0.152
var[β]*100	0.041	0.012	0.043	0.012	0.000	0.000
cov[α, β]*100	-0.827	0.356	-0.870	0.373	-0.008	0.004
ρ	0.639	0.077	0.761	0.080	0.510	0.070
θ	-0.264	0.072	-0.422	0.072	-0.277	0.065
<u>Variance of Transitory Shocks [var(v)]</u>						
1967	0.085	0.027	0.088	0.026	0.034	0.013
1968	0.062	0.019	0.060	0.019	0.043	0.010
1969	0.057	0.017	0.026	0.013	0.046	0.013
1970	0.062	0.017	0.058	0.013	0.041	0.009
1971	0.066	0.016	0.063	0.013	0.050	0.011
1972	0.071	0.014	0.077	0.014	0.047	0.008
1973	0.074	0.014	0.086	0.012	0.034	0.004
1974	0.070	0.014	0.086	0.012	0.051	0.009
1975	0.094	0.017	0.075	0.010	0.062	0.010
1976	0.104	0.026	0.085	0.011	0.051	0.012
1977	0.102	0.023	0.075	0.011	0.053	0.011
1978	0.099	0.014	0.096	0.010	0.049	0.007
1979	0.086	0.014	0.094	0.012	0.070	0.016
1980	0.111	0.014	0.079	0.009	0.068	0.010
1981	0.111	0.016	0.082	0.011	0.067	0.011
1982	0.155	0.023	0.097	0.014	0.083	0.013
1983	0.157	0.028	0.105	0.016	0.093	0.023
1984	0.094	0.016	0.089	0.016	0.040	0.004
1985	0.123	0.023	0.069	0.016	0.069	0.016
1986	0.122	0.023	0.093	0.017	0.064	0.010
1987	0.078	0.016	0.094	0.016	0.047	0.006
1988	0.105	0.020	0.075	0.014	0.055	0.009
1989	0.101	0.016	0.092	0.014	0.043	0.006
1990	0.106	0.020	0.079	0.016	0.055	0.007
1991	0.166	0.024	0.105	0.017	0.087	0.014
<u>Factor Loadings [p]</u>						
1967	1.000		1.000		1.000	
1968	1.023	0.050	1.053	0.057	0.911	0.106
1969	1.033	0.058	1.075	0.068	0.824	0.121
1970	1.068	0.072	1.044	0.075	0.910	0.152
1971	0.997	0.074	1.005	0.082	0.736	0.131
1972	0.995	0.079	0.994	0.087	0.661	0.129
1973	0.905	0.082	0.874	0.086	0.606	0.121
1974	0.969	0.088	0.931	0.088	0.624	0.126
1975	0.953	0.086	0.924	0.086	0.671	0.131
1976	0.983	0.092	0.958	0.091	0.733	0.143
1977	1.002	0.095	0.946	0.094	0.653	0.127
1978	0.943	0.090	0.914	0.093	0.590	0.116
1979	0.955	0.091	0.934	0.095	0.582	0.117
1980	1.043	0.104	0.981	0.102	0.575	0.114
1981	1.082	0.105	1.018	0.105	0.602	0.130
1982	1.144	0.114	1.037	0.110	0.668	0.144
1983	1.173	0.112	1.062	0.110	0.593	0.127
1984	1.207	0.118	1.118	0.116	0.597	0.131
1985	1.263	0.129	1.159	0.121	0.615	0.138
1986	1.283	0.124	1.209	0.123	0.559	0.119
1987	1.301	0.130	1.175	0.121	0.548	0.117
1988	1.310	0.125	1.222	0.123	0.515	0.107
1989	1.263	0.121	1.184	0.118	0.531	0.114
1990	1.392	0.138	1.280	0.132	0.578	0.124
1991	1.404	0.140	1.319	0.134	0.589	0.128

Note: This table presents the second stage parameter estimates with annual earnings, average annual wages, and annual hours as the dependent variable. All results are for the primary sample, and ARMA(1,1) transitory shock, and a time-varying quartic.

Table 5: Earnings Inequality and Instability for Primary Sample

Year	Actual Annual Inequality $\text{var}[y(i)]$	Predicted Annual Inequality see text	Instability $\text{var}[\varepsilon(i)]$	Persistent Inequality see text	Lifetime Inequality $\text{var}[Y^*]$
1967	0.265	0.266	0.085	0.181	0.132
1968	0.268	0.268	0.074	0.193	0.138
1969	0.275	0.269	0.071	0.198	0.139
1970	0.288	0.285	0.076	0.209	0.148
1971	0.263	0.264	0.080	0.184	0.129
1972	0.274	0.270	0.087	0.184	0.129
1973	0.242	0.242	0.090	0.152	0.106
1974	0.262	0.261	0.087	0.175	0.122
1975	0.281	0.279	0.111	0.168	0.118
1976	0.301	0.302	0.124	0.178	0.125
1977	0.312	0.308	0.125	0.183	0.130
1978	0.284	0.284	0.122	0.162	0.115
1979	0.273	0.275	0.110	0.165	0.118
1980	0.319	0.328	0.132	0.195	0.141
1981	0.337	0.344	0.136	0.208	0.152
1982	0.407	0.410	0.181	0.229	0.170
1983	0.433	0.427	0.189	0.238	0.178
1984	0.378	0.378	0.129	0.248	0.188
1985	0.422	0.421	0.150	0.271	0.207
1986	0.429	0.427	0.150	0.277	0.213
1987	0.393	0.387	0.107	0.280	0.219
1988	0.407	0.409	0.128	0.281	0.222
1989	0.385	0.385	0.125	0.259	0.207
1990	0.436	0.440	0.130	0.310	0.251
1991	0.502	0.502	0.190	0.312	0.256

Note: Actual annual, experienced-adjusted inequality are calculated from the first stage residuals. Lifetime inequality is calculated as in equation (4) in the text with a career length of 35 years and a discount factor of 5%. Instability is calculated as the variance implied by equation (5). Persistent inequality is calculated as in equation (6). All calculations are with the primary sample.

Figure 1: The Variance of the Transitory Shocks

Note: The data for this figure come from Table 4. The point-wise confidence bands are calculated as two standard deviations from the primary sample results.

Figure 2: The Times Series of the Factor Loading (p_t)

Note: The data for this figure come from Table 4. The point-wise confidence bands are calculated as two standard deviations from the primary sample results.

Figure 3: Lifetime Earnings Inequality

Note: The calculations for this figure are based upon equation (4) of the text and use the primary sample. The preferred specification is the one with a time varying quartic [denoted $f(t)$] and an ARMA(1,1). $f(.)$ denotes a first-stage specification in which the parameters of the quartic are assumed to be constant (except for the intercept).

Figure 4: Decomposition of Annual Earnings Inequality

Note: The data for this figure come from Table 5 and are based on the decomposition suggested by equation (6) in the text. The recession years are marked with a rectangle.

Figure 5: Decomposition of Annual Earnings Inequality with a Random Walk Model

Note: The data for this figure come from estimating the random walk model in equation (9).

Figure 6: Cross-Sectional Decomposition of Annual Earnings Inequality

Note: This decomposition is based on equation (10).

Figure 7: Decomposition of Annual Wage Inequality

Note: This decomposition is based on equation (6) of the text but uses average wages as the dependent variable.

Figure 8: Decomposition of Annual Hours Inequality

Note: This decomposition is based on equation (6) but uses annual hours as the dependent variable.

Figure 9: Within Educational Group Inequality

Note: The decompositions in this figure are based on equation (6). The dotted lines are repeated from Figure 7. The solid line is a decomposition based on a first stage specification that controls for education.