University of Wisconsin-Madison

Institute for Research on Poverty

Discussion Papers

Robert Moffitt
Peter Gottschalk

TRENDS IN THE COVARIANCE STRUCTURE OF EARNINGS IN THE UNITED STATES: 1969-1987

DP # 1001-93

Institute for Research on Poverty
Discussion Paper no. 1001-93

Trends in the Covariance Structure of Earnings in the United States: 1969-1987

Robert Moffitt
Brown University
Institute for Research on Poverty
University of Wisconsin-Madison

Peter Gottschalk
Boston College
Institute for Research on Poverty
University of Wisconsin-Madison

April 1993

This project was supported by grants from the U.S. Department of Health and Human Services through the Institute for Research on Poverty and from the U.S. Department of Labor through the National Bureau of Economic Research. The authors would like to thank Charles Brown, James Heckman, Gary Solon, and the members of seminars and workshops at several universities for comments on this version of the paper, as well as Thomas MaCurdy for comments on an earlier version. For assistance on the project, the authors would like to thank Amit Dar, Philip Merrigan, Reema Nayar, Renya Reed, and Robert Reville at Brown University and Alpay Filizteken at Boston College.

Abstract

We examine the increasing variance of earnings among males with similar education and age levels over the 1970s and 1980s by focusing on changes in the covariance structure of earnings. Using data from the Michigan Panel Study of Income Dynamics from 1969-1987 for white males, we find that about half of the increase arose from an increase in the variance of the permanent component of earnings and half from an increase in the variance of the transitory component, where the transitory component reflected shocks that died out within three years. We thus find that increases in transitory shocks are as important as increases in the dispersion of permanent earnings in explaining recent increases in earnings inequality. Indeed, the increase in transitory shocks was especially great in the 1980s. Our investigation of earnings mobility indicates that long-term mobility fell in the 1970s but only short-term mobility fell in the 1980s, the latter reflecting the increase in short-term covariances arising from a higher variance of serially correlated transitory shocks. The mobility declines were concentrated in the top and bottom quintiles of the earnings distribution.

Trends in the Covariance Structure of Earnings in the United States: 1969-1987

Considerable recent attention has been focused on the increase in earnings inequality in the United States over the 1970s and 1980s (see Levy and Murnane [1992] for a comprehensive list of the many studies). A growing body of research has shown that inequality in earnings grew over this period not only from an increase in returns to education and experience but also from an increase in inequality within groups of workers of similar age and education. Furthermore, the increase in inequality appears to have occurred throughout the earnings distribution, for the proportion of high-earnings workers and low-earnings workers increased during the 1970s and 1980s. In addition, the increase in dispersion occurred in wages as well as earnings.

While this literature has firmly established that an increase in the cross-sectional dispersion of earnings and wages occurred--that is, that the variance of the marginal distribution of earnings and wages went up--the research to date has not examined whether there has been any change in the joint distribution of earnings and wages over the life cycle. In this paper we ask whether the parameters of that joint distribution--that is, of the intertemporal covariance structure of earnings and wages--have also changed.

The answer to this question has two interrelated implications. First, any change in the covariance structure will affect most measures of earnings and wage mobility, such as the correlation of earnings across periods as well as movements between quantiles of the distribution. Second, any change in the covariance structure has implications for the source of the increase in the variance of the marginal distribution that has been observed in prior work. The cross-sectional dispersion in earnings could have increased either because the distribution of permanent earnings became less equal or because transitory fluctuations in earnings increased; the former implies that earnings covariances increased while the latter does not. Which of these two possibilities has generated the observed increase in cross-sectional dispersion is important to determine, for they have very different implications for the possible labor market origins of the shift as well as different normative implications.

Considering the first of these implications--those for mobility--it should be noted that nothing can be concluded about mobility from the existing evidence on increases in the marginal distribution of earnings. It has long been recognized that a fixed cross-sectional earnings distribution could arise from either a maximally mobile labor market in which individual earnings at each point in time are statistically independent of individual earnings at all other points in time, or from a perfectly immobile labor market in which individual earnings at different points in time are perfectly correlated. Thus the cross-sectional dispersion in earnings has no implication for the covariance structure of earnings.[1] Panel data are needed to derive the covariance structure of earnings.

It is also widely understood that earnings covariances or, more properly, earnings correlations, are inversely related to mobility. However, the relationship takes a special form in the canonical permanent-transitory, or "individual effects," model. In that model, the relative magnitudes of the variance of the permanent component and of the transitory component determine the degree of mobility. An increase in the variance of the permanent component (which increases the variance of lifetime earnings, for example) increases the covariance of earnings and hence lowers mobility; an increase in the variance of the transitory component increases mobility. Whether mobility has increased or decreased is, therefore, ambiguous if the variance of both components has increased (as we will find to be the case).

There is a large literature on the estimation of earnings-components models and models of earnings dynamics in general; see Lillard and Willis (1978), Lillard and Weiss (1979), Hause (1977, 1980), MaCurdy (1982), and Abowd and Card (1989), to mention only a few that have focused directly on dynamics (see Atkinson et al. [1992] for a survey). However, these studies have not considered whether there have been systematic calendar-time shifts in the covariance structure of earnings.

With regard to the second implication of an analysis of shifts in the earnings covariance structure--namely, for the possible labor market sources of increasing dispersion--the permanent-transitory model again provides the best intuition. Most hypotheses for the cause of the increasing dispersion of earnings imply that inequality must have arisen from an increase in the variance of the permanent component. Changes in the price of human capital (skill) arising from labor demand shifts (e.g., from skill-based technical change as argued by Bound and Johnson [1992]); changes in the dispersion of the quantity of human capital generated by the educational system; increases in the magnitude and dispersion of rents; and other factors all presumably have considerable persistence (see Levy and Murnane for references). Less obvious is what might have caused the variance of the transitory component to increase. Here we speculate that increases in competition both domestic and foreign; the decline of regulation, unions, and administered prices and wages generally; and increases in overall turbulence, dislocation, turnover, and "noise" in the economy and in the labor market could all, in principle, increase the variance of the transitory component without changing the variance of the permanent component. An important implication of this possibility is that, in the extreme case of only a change in the transitory variance, the variance of lifetime earnings across individuals need not have increased--in diametric opposition to the implications of an increase in the variance of the permanent component.

The paper is composed of four sections. The first presents the methods we use and the second describes our data. The third section, which forms the core of the paper, presents our main results; additional findings are discussed in Section IV. The paper ends with a summary and conclusions.

I. METHODS

We provide three alternative methods of describing the changes in the covariance structure of earnings and wages over the 1970s and 1980s.[2] Our first method imposes minimal structure and is intentionally descriptive in nature. Computing earnings covariances for age-year cells from regression residuals, we use standard regression techniques to describe how those covariances have changed over time. The advantage of this method is that it shows the patterns in the data clearly with minimal parametric assumptions. Its disadvantage is that the results cannot be interpreted in terms of a well-specified, statistical model.

Our second approach is, therefore, more parametric. We fit time-series, error-components models to the covariance matrices, allowing the key parameters to evolve with calendar time. While this parametric approach gives us a context in which to interpret the changes in the covariances, the cost is that the interpretation is conditional on our having captured the time-series process correctly.

Our third approach examines the change in the mobility structure of earnings over time by examining changes in transition rates between quantiles of the distribution. Our estimates of the formal error-components, serial-correlation structure of the earnings process imply a particular mobility structure. That is, since mobility is defined as a change in an individual's rank in the distribution from one year to the next, any error-components structure implies a probability distribution for changes in rank as well. However, just as percentile points and quantile measures of a cross-sectional distribution provide a more detailed picture of the distribution than does a summary measure like a variance, quantile transition rates can provide a more detailed picture of the mobility process than can a summary measure like a covariance. We are, for example, able to determine whether mobility has changed in different ways in different parts of the distribution (e.g., top and bottom), which would be cumbersome to do within a traditional covariance analysis.

Nonparametric Regressions

To fix ideas, let y_{ia} be a measure of earnings or wages--or a residual from a regression--for individual i at age $\underline{a}$ for a single cohort of individuals $i=1,\ldots,N$ at ages $\underline{a}=1,\ldots,T$. The TXT covariance matrix with typical element $Cov(y_{ia},y_{ia'})$ has $T(T+1)/2$ unique elements, including the diagonals of the matrix which represent the variances at each age $\underline{a}$. These unique elements can be ordered into a vector $\underline{s}$ whose jth element $(j=1,\ldots,T(T+1)/2)$ we denote as s_j. To describe the patterns in the covariance matrix, this vector can be regressed upon variables defined over j--row, column, distance off the diagonal, and so on, all of which can capture the serial-correlation structure of earnings over the life cycle (i.e., between different ages). Any formal time-series, error-components model implies restrictions on the coefficients from such a regression. To begin, however, we impose no such restrictions and simply capture the patterns of the variances and covariances with respect to age in this nonparametric fashion.

Our major interest is in determining whether the elements of the covariance matrix have shifted over time conditional on age. To that end we presume to have data on multiple cohorts. Hence we can observe each element s_j (i.e., the covariance of earnings between a particular $\underline{a}$ and a particular $\underline{a}'$) at multiple points of calendar time. We denote the jth covariance element observed at calendar-time t as s_{jt}. To determine whether s_{jt} significantly shifts with calendar time, we employ conventional linear regression procedures to estimate models of the form:

$$s_{jt} = X_{jt}\beta + \epsilon_{jt} \tag{1}$$

where X_{jt} is a row vector of regressors and β is a column vector of corresponding coefficients. X_{jt} is specified to be a flexible function of both j and t. For j, we will enter functions of both $\underline{a}$ and $\underline{a}'$--for example, variables for row, column, distance off the diagonal--and for calendar time we will enter time trends, both alone, interacted with age, and separately for different sub-time-periods. We also include a diagonal dummy variable, D_j, equal to one if element j is on the diagonal of the covariance matrix (i.e., it is a variance) and equal to zero if not. Off-diagonal elements measure persistence.[3]

The well-known permanent-transitory model provides one interpretation of the coefficient on the diagonal dummy. Ignoring year effects, if the true model is

$$y_{ia} = \mu_i + \nu_{ia} \tag{2}$$

where μ_i is a time-invariant individual component with variance σ^2_μ and ν_{ia} is a serially uncorrelated transitory component with variance σ^2_ν, then the expected value of s_{jt} is $\sigma^2_\mu + \sigma^2_\nu$ for diagonal elements of the covariance matrix and σ^2_μ for off-diagonal elements. Hence a regression of s_{jt} on D_j estimates σ^2_μ as the intercept and σ^2_ν as the slope coefficient. Since we wish to allow the elements to vary with calendar time, we allow both intercept and coefficient to change with t:

$$s_{jt} = \beta_0 + \beta_1 D_j + \beta_2 t + \beta_3 D_j t + \epsilon_{jt} \tag{3}$$

where β_2 and β_3 are, respectively, the rates of increase of the variances of the permanent and transitory components.[4]

The use of a diagonal dummy to distinguish permanent and transitory variances is incorrect if the transitory component is serially correlated, however, for in that case part of the covariances in the data arise from the transitory component rather than the permanent component. We shall determine if the transitory component is serially correlated in our error-components analysis.

Formal Models of the Error Process

Error-components models impose more structure on the covariance matrix than the nonparametric regressions but have the benefit of providing an interpretation of the trends in the elements of that matrix. The large literature on the estimation of error-components models on panel data and, in particular, on the estimation of such models for earnings and wages (cited earlier in the introduction) has established overwhelmingly the existence and importance of individual effects. But it has also established that the canonical permanent-transitory model is rejected if the transitory component is assumed to be serially uncorrelated in that model. Instead, the transitory component has been shown in most work to follow a low-order ARMA process.

Relative to this body of literature, our contribution is to permit the parameters of an error-components model to shift with calendar time. Apparently such effects have not been systematically investigated.[5] We first estimate models without such effects and confirm the findings of past work that the earnings process follows a low-order ARMA process with individual effects. Specifically, we find that log annual earnings can be modeled as a random (individual) effect that obeys a random walk, plus an ARMA(1,1) transitory effect. We then allow the parameters of this process to be a function of calendar time. To anticipate these results, the following describes the model we find to adequately describe the data:

$$y_{iat} = \alpha_t \mu_{iat} + \nu_{iat} \tag{4}$$

$$\mu_{iat} = \mu_{i,a-1,t-1} + \omega_{iat} \tag{5}$$

$$\nu_{iat} = \rho_t \nu_{i,a-1,t-1} + \xi_{iat} + \theta_t \xi_{i,a-1,t-1} \tag{6}$$

Equation (4) shows the log earnings (or earnings residual) of person i at age a in year t to be composed of an individual effect, μ_{iat}, with a time-varying factor loading α_t, and a transitory effect, ν_{iat}. The individual effect could represent latent unobservable human capital whose price (α_t) shifts with calendar time.[6] The individual effect follows a random walk as shown in (5), and the transitory effect follows the ARMA(1,1) process shown in (6). As conventional in these models, we assume the forcing variables ω_{iat}, ξ_{iat}, and the initial value of the individual effect (μ_{i1t}) to be independently distributed.

We may note that we make no attempt to explicitly identify measurement error components in (4)-(6), although such error will unquestionably enter in various places. Although classical measurement error could be captured by ξ_{iat} with $\theta_t=0$, more recent work on error in earnings reports suggests that measurement error is serially correlated (Bound et al., 1990; Bound and Krueger, 1991). Hence the parameters θ_t and ρ_t could pick up some measurement error as well.[7]

Aside from the variance of the initial individual effect, there are five parameters in the model--α_t, ρ_t, θ_t, and the variances of ω_{iat} and ξ_{iat}. We estimate a model which permits all five to vary with calendar time:

$$\alpha_t = 1 + b_1 t \tag{7}$$

$$\rho_t = c_0 + c_1 t \tag{8}$$

$$\theta_t = d_0 + d_1 t \tag{9}$$

$$\mathrm{Var}(\omega_{iat}) = e_0 + e_1 t \tag{10}$$

$$\mathrm{Var}(\xi_{iat}) = f_0 + f_1 t \tag{11}$$

The factor loading α_t is normalized to 1 at t=0 (1969 in our data), and we let $\mathrm{Var}(\mu_{i1t})=\sigma_\mu^2$ to establish the baseline variance of the individual effect.[8] We find that equations (7)-(11) are sufficient to describe the sources of the changes in variances and covariances described in the previous section.[9]

A "permanent" effect in this model is not permanent in the literal sense, since the individual effect is permitted to shift over the life cycle and with calendar time.[10] The distinction between the two components in (4) is, instead, based upon a decomposition of shocks into those that are mean-reverting and those that are not. Our decomposition defines "permanent" shocks to be those that are non-mean-reverting and "transitory" shocks to be those that are mean-reverting.

The model in (4)-(11) can be estimated with the minimum-distance method of Chamberlain (1984) (see also Abowd and Card [1989] for a prior application of the technique to panel wage data). However, our initial estimates reported below use the identity matrix for the weighting matrix, and hence the estimates are equivalent to simple nonlinear least squares applied to a model in which each element of the covariance matrix s_{jt} is a function of the underlying variances and covariances implied by (4)-(11).[11]

Mobility

Mobility, defined as a change in individual ranks within a distribution, is closely related to the covariance structure. For example, an increase in an earnings covariance between any two points in time will lower mobility because earnings in the two periods are more closely related. However, a stronger statement than this can be made. In the appendix we show that if earnings follow a joint normal distribution, the probability of a change in individual ranks between any two points in time is a function only of the correlation coefficient between earnings at those two points, and not a function of the absolute levels of either of the variances at the two points in time or the covariance.

The intuition for this result is particularly strong in the canonical permanent-transitory model, where the correlation coefficient between earnings at any two points is equal to the fraction of the variance accounted for by the permanent component, or $\sigma_\mu^2/(\sigma_\mu^2+\sigma_\nu^2)$ (see equation (2)). The degree of mobility in this model thus hinges only on the relative sizes of the permanent and transitory variances. This is because a rise in the permanent variance, which increases the average distance between the earnings of different individuals, lowers the chance of a change in rank. A rise in the transitory variance makes the chance of a change in rank more likely. A proportional increase in the permanent and transitory variances thus should have no effect on mobility; the two effects exactly cancel.

We should note that the value of the correlation coefficient in a more realistic model, such as one with serially correlated transitory components, will vary depending upon the distance between the two points under consideration. With serially correlated but mean-reverting transitory components, correlation coefficients fall with that distance, and hence mobility is likely to be greater over longer periods. In addition, if mobility is defined instead between intervals of multiple years rather than between single years, and if it is a change in the rank of mean earnings within each interval that is considered, mobility is likely to be lower since the transitory component is a smaller portion of the total variance when earnings are averaged over multiple years.[12]

Since our error-components model will provide a full accounting for the changes in correlation coefficients (i.e., over different distances and intervals) that occurred during the 1970s and 1980s, a mobility analysis may at first blush appear redundant. However, as we noted previously, transition rates between quantiles of a distribution can provide more detail on whether any changes in mobility occurred at different parts of the distribution (e.g., at top and bottom). This is the rationale for our mobility examination.

II. DATA AND VARIABLE CONSTRUCTION

We use the Panel Study of Income Dynamics (PSID), a longitudinal survey which has followed a sample of households from the civilian noninstitutional population since 1968. Approximately 5,000 households were interviewed in the initial year of the survey. The PSID has a supplementary low-income sample, the SEO, which we also include in our analysis (sample weights are used throughout). Members of the original 1968 households and their offspring have been followed through 1988, the most recent year available at the time this analysis was conducted. The primary advantage of the PSID is its long period of coverage and its conformity with cross-sectional measures of inequality.[13] A disadvantage of the PSID is that relatively little information is available on the education and earnings of individuals who are not heads of households.

Following the practice of most previous studies of inequality, we analyze only white males. There are larger sample sizes for whites than for blacks, and the problem of zero earnings is less of a problem for males than for females. We restrict our sample to heads of households aged 20 to 59 who had positive hours of work and earnings in the year prior to interview and who were not in school. We include every annual observation for each individual for which these restrictions are met;

thus the sample is not "continuous" (i.e., there are missing years for some individuals). This permits us to maximize the sample size used for the construction of each element of the covariance matrix.[14] The earnings and wage measures we examine are the log of real annual earnings (wage and salary only) in the year prior to interview and the log of real weekly earnings in that year. We exclude the first two years of the survey, 1968 and 1969, because wage and salary earnings data asked in those years were bracketed. Thus our analysis includes the years 1970-1988 and our earnings and wage measures cover the period 1969-1987. The real figures are obtained by deflating the nominal values by the GNP personal consumption expenditure deflator (base 1982).[15] Our final sample includes 2,781 individuals with a total of 25,194 person-year observations.

We work with residuals that are obtained from regressions of these earnings and wage measures on education, age, and year.[16] Regressions are estimated separately for each year and 10-year age interval (20-29, 30-39, 40-49, 50-59); each regression contains education dummies for 0-8, 9-11, 12, 13-15, and 16+ years. We choose this level of disaggregation to maintain a minimum of 250 observations per regression; there are 78 regressions altogether (4 age categories, 19 years).[17] Using the residuals from these regressions, we calculate earnings and wage variances in each year within each age interval, and we calculate covariances over the life cycle and over time by following the individuals in each age interval forward until the end of the panel or until they reach age 59, whichever comes first. The resulting covariance matrix has 553 cells, consisting of 76 variances and 477 covariances.[18]

III. RESULTS

Table 1 displays the covariances and correlations of log annual earnings in the data for the 10-year age groups pooled over all years. The covariance and correlation patterns in the data are for the most part similar to those found in other studies, falling rapidly over the first two or three lead orders

TABLE 1

Log Annual Earnings Covariances and Correlations by Age (pooled over years)

	Covariance				Correlation			
Lead Order	20-29	30-39	40-49	50-59	20-29	30-39	40-49	50-59
0	.35 (.009)	.30 (.008)	.27 (.008)	.32 (.011)	1.0	1.0	1.0	1.0
1	.17 (.005)	.18 (.005)	.18 (.005)	-	.63	.74	.80	-
2	.13 (.005)	.15 (.004)	.17 (.005)	-	.51	.64	.73	-
3	.12 (.005)	.14 (.004)	.15 (.005)	-	.43	.59	.69	-
4	.11 (.005)	.13 (.005)	.15 (.005)	-	.40	.55	.66	-
5	.11 (.006)	.12 (.005)	.15 (.006)	-	.37	.50	.65	-
6	.09 (.005)	.11 (.005)	.15 (.007)	-	.34	.49	.64	-
7	.09 (.005)	.12 (.006)	.14 (.007)	-	.32	.51	.61	-
8	.10 (.006)	.12 (.006)	.13 (.006)	-	.35	.49	.58	-
9	.09 (.006)	.11 (.006)	.12 (.006)	-	.32	.46	.53	-
10	.09 (.007)	.11 (.007)	.12 (.006)	-	.34	.47	.49	-
11	.07 (.007)	.12 (.009)	-	-	.29	.46	-	-

(table continues)

TABLE 1 (continued)

	Covariance				Correlation			
Lead Order	20-29	30-39	40-49	50-59	20-29	30-39	40-49	50-59
12	.09 (.010)	.11 (.008)	-	-	.29	.47	-	-
13	.09 (.012)	.10 (.008)	-	-	.29	.48	-	-
14	.08 (.011)	.10 (.007)	-	-	.28	.43	-	-
15	.10 (.013)	.10 (.009)	-	-	.32	.45	-	-
16	.09 (.015)	.10 (.010)	-	-	.29	.42	-	-
17	.09 (.018)	.11 (.013)	-	-	.30	.45	-	-
18	.10 (.025)	.11 (.019)	-	-	.37	.37	-	-

Source: Panel Study of Income Dynamics.

Notes: Cell sample sizes range from 183 to 7,358. Standard errors in parentheses.

and then declining at a much slower rate at higher lead orders. The covariances and correlations do not fall to zero, but appear to asymptote, consistent with the presence of an individual effect. These patterns would appear to be reasonably well fit by a model with a time-invariant individual effect (to explain the asymptote) added to a low-order ARMA error, with the MA portion explaining the rapid decline and the AR component explaining the long tail declining more slowly (see next section).

Comparing columns, earnings variances (denoted as the zero-order elements) show a slight decline, but no major change over the life cycle. Both covariances and correlations rise with age, however, a pattern that could be explained by a random walk.

Our interest is in whether these elements have shifted with calendar time. Figures 1(a)-(d) show trends in variances and in covariances at different lag orders for different age groups.[19] For all age groups the variances have been increasing, consistent with cross-sectional evidence from the CPS. However, the figures also show unmistakable evidence of an increase in covariances as well. The covariance increases are larger for the older age groups and for the low-order covariances, but are positive in almost all cases (though there is some hint of a decline in the final year or two at the older ages). It might also be recalled that the magnitude of the difference between the variance and the covariances is a rough indicator of the trend in the transitory variance in the simple permanent-transitory model. It is clear from the figures that, although the variance shows considerable fluctuation (clearly related to the business cycle), the gap between the variance and the average covariance (i.e., averaged over the lag orders) has also been growing over time. However, the gap between the variance and the low-order (order 1-4) covariances appears to be relatively constant, a finding we will return to shortly.

<u>Nonparametric Regressions</u>

To control formally for age and lag order, as well as for cyclical factors, we estimate the descriptive regressions in the manner described previously. Table 2 shows the result of fitting

Log Earnings Variances and Covariances by Year and by Lag Order

Figure 1(a): All Ages

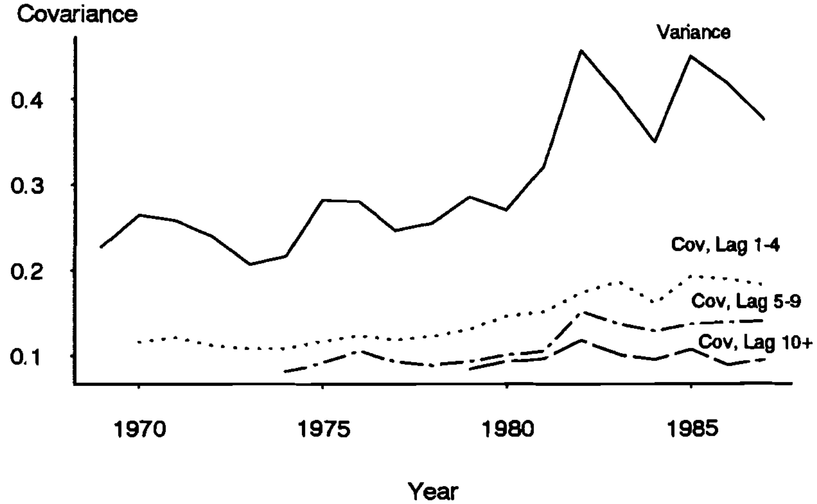


Figure 1(b): Ages 25-34

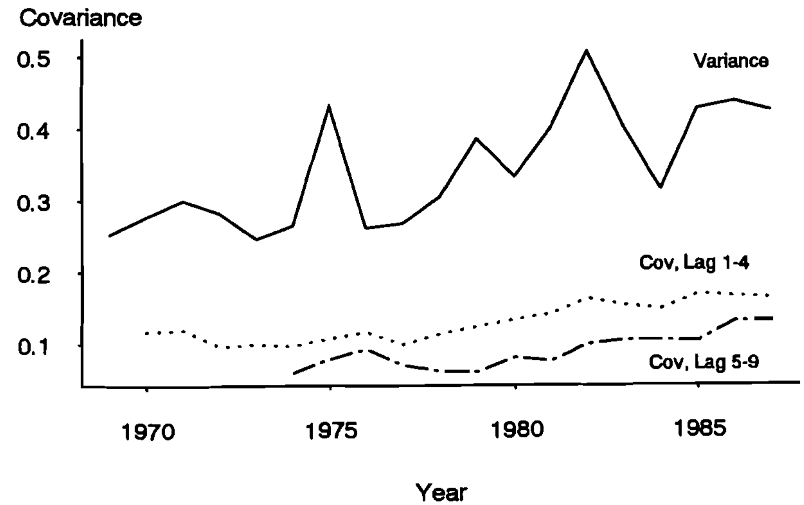


Figure 1(c): Ages 35-44

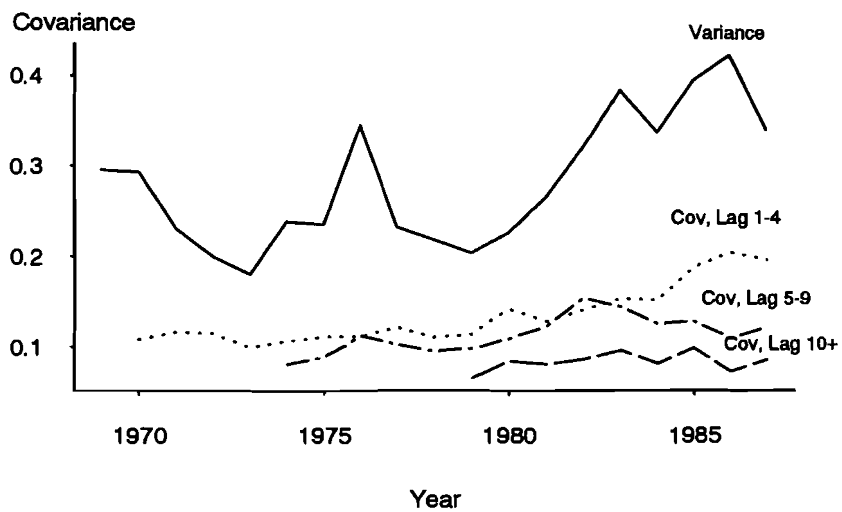


Figure 1(d): Ages 45-54

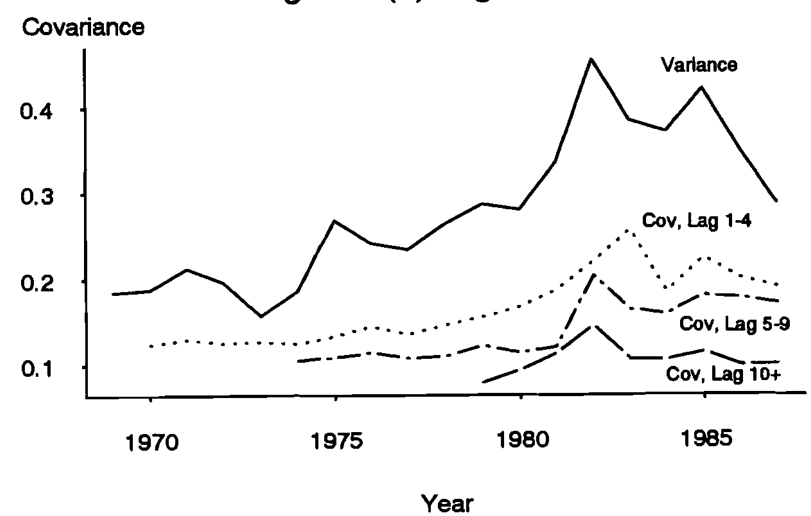


TABLE 2

Descriptive Covariance Regressions for Log Annual Earnings

	(1)	(2)	(3)	(4)
Intercept	.1253* (.0024)	.0846* (.0064)	.0823* (.0061)	.0878* (.0108)
D	.1811* (.0066)	.1296* (.0121)	.1319* (.0114)	.1656* (.0179)
t	-	.0058* (.0004)	.0061* (.0004)	.0059* (.0009)
Dt	-	.0059* (.0008)	.0056* (.0008)	.0014 (.0016)
A_2	-	.0023* (.0002)	.0023* (.0002)	.0012 (.0005)
DA_2	-	-.0029* (.0004)	-.0029* (.0004)	-.0038* (.0008)
$(A_2\text{-}A_1)$	-	-.0165* (.0014)	-.0168* (.0014)	-.0135* (.0017)
$(A_2\text{-}A_1)^2/100$	-	.0476* (.0085)	.0537* (.0080)	.0712* (.0102)
U_2	-	-	.0065* (.0011)	.0059* (.0011)
$D\ U_2$	-	-	.0097* (.0035)	.0101* (.0034)
U_1	-	-	.0020 (.0014)	.0021 (.0014)
$t\ A_2/10$	-	-	-	.0010* (.0004)

(table continues)

TABLE 2 (continued)

	(1)	(2)	(3)	(4)
t D A_2/10	-	-	-	.0012 (.0007)
t (A_2-A_1)/10	-	-	-	-.0042* (.0014)
R-squared	.58	.83	.85	.86

Source: Authors' calculations based on Panel Study of Income Dynamics.

Notes: Standard errors in parentheses. Number of observations = 553. Unemployment rate is for all U.S. male civilians 20 and over. D=diagonal dummy; A_2 = the older age minus 20; A_1 = the younger age minus 20; t = year at age A_2 minus 1969; U_2 = unemployment rate at age A_2; U_2 = unemployment rate at age A_1.

* Significant at the 10 percent level.

equation (1) to the 553 cells of the age-year covariance matrix. Column 1 shows the most restrictive model, which includes only an intercept and a slope coefficient on the dummy variable (D) equal to 1 if the cell falls on the diagonal. The results show an average covariance of approximately .13 and an average transitory variance of .18, implying a total variance of approximately .31 and a correlation coefficient of .41, which is close to other estimates of the simple random effects model.

More relevant for present purposes are the estimates in column (2), which show how these two variances have trended over the period (coefficients on "t" and "Dt"). The equation controls for age effects in the covariances and along the diagonal, as well as for declining covariances with distance off the diagonal.[20] As the results show, covariances trended at .0058 per year and the "transitory" variance trended at .0059 per year, estimates which are not significantly different from one another. Thus, at least on average, the permanent and transitory variances appear to have trended upward to an equal degree.[21]

The third column shows the effect of adding a detrended unemployment rate separately for off-diagonal and diagonal elements.[22] The coefficients on the unemployment-rate variables show that both covariances and variances are procyclical in the data. However, variances are more procyclical than are covariances (consistent with Figures 1(a)-(d)), an indirect indication that transitory variances are more procyclical than "permanent" variances.

Column (4), which shows the results of permitting the covariances to trend at different rates at different distances off the diagonal, shows strongly what was apparent in the figures, namely, that the low-order covariances have increased more rapidly than the high-order covariances. We will provide an explanation for this pattern in the next section.

The difference in trends for different time periods is explored in Table 3, which shows the trends on t and Dt for the periods 1969-1980 and 1981-1987.[23] The most striking finding in the table is the much greater relative growth of the permanent variance in the 1970s and the relatively

TABLE 3

Log Annual Earnings Covariance Regressions, by Lag Order and Time Period: Selected Coefficients

	All Years	1969-1980	1981-1987
All lag orders			
t	.0061*	.0056*	.0066*
	(.0004)	(.0008)	(.0008)
Dt	.0056*	-.0008	.0183*
	(.0008)	(.0014)	(.0022)
Lag orders 1-3			
t	.0066*	.0049*	.0093*
	(.0007)	(.0013)	(.0017)
Dt	.0051*	-.0001	.0156*
	(.0011)	(.0019)	(.0031)

Source: Authors' calculations based on Panel Study of Income Dynamics.

Notes: Standard errors in parentheses. Acronyms: see Table 2. Also included in regressions: D, A_2, DA_2, A_2-A_1, $(A_2\text{-}A_1)^2$, U_2, DU_2, U_1.

* Significant at the 10 percent level.

greater rate of growth of the transitory variance in the 1980s. Indeed, in the 1970s the transitory variance appeared to have fallen, or at least not to have changed significantly. This pattern holds both for all the elements of the covariance matrix as well as the low-order elements shown in the bottom of the table, where it is also seen that the relatively greater rate of growth of the low-order covariances relative to the high-order covariances was concentrated in the 1980s as well. Put differently, the low-order covariances almost doubled from the earlier period to the later one, whereas all covariances (and by implication the high-order ones) grew much less over the same period of time. As we shall show in the next section, this pattern is due to the same forces that caused the coefficient on Dt (i.e., the "transitory" variance) to rise faster in the 1980s than in the 1970s.

Error-Components Models

In order to compare our earnings data with data used in past studies of earnings dynamics, we begin by fitting several simple error-components models in the absence of calendar-time effects. The first column of results in Table 4 shows a significant AR(1) parameter ρ, and the second column shows both a significant AR(1) parameter and MA(1) parameter θ. Permitting the individual effect to follow a random walk, as shown in the third column, results in a significant reduction in the sum of squared residuals and also shows a significant variance parameter for ω_{iat}. Replacing the random-walk specification with a random-growth parameter, as shown in the last column, results in essentially no improvement in the fit. Simultaneously including both a random-walk and a random-growth specification (not shown in the table) results in approximately the same fit as shown in the third and fourth columns of the table. Thus, our results indicate that random-walk and random-growth models are roughly equivalent and interchangeable, which is not surprising since the main implication of both is a rising set of variances and covariances with age.[24]

In other results, we tested the ARMA(1,2) and ARMA(2,1) specifications for the transitory effect while maintaining the random-walk specification for the individual effect. In neither case was

TABLE 4

Error-Components Models for Log Real Annual Earnings
(no calendar-time effects)

	RE + AR(1) (Model I)	RE + ARMA(1,1) (Model II)	Random-Walk RE + ARMA(1,1) (Model III)	Random-Growth RE + ARMA(1,1) (Model IV)
σ_μ^2	.114 (.003)	.070 (.006)	.090 (.005)	.092 (.005)
ρ	.354 (.033)	.906 (.012)	.622 (.081)	.657 (.069)
σ_η^2	.167 (.007)	-	-	-
θ	-	-.670 (.028)	-.344 (.103)	-.362 (.092)
σ_ξ^2	-	.188 (.007)	.169 (.007)	.166 (.007)
$\sigma_\omega^2/100$	-	-	.159 (.025)	-
$\sigma_\phi^2/100$	-	-	-	.462 (.069)
Sum of squared residuals	1.381	1.321	1.248	1.240

Source: Authors' calculations based on Panel Study of Income Dynamics.
Notes: Standard errors in parentheses. All coefficients significant at 10 percent level. RE=random effect.

Model I: (1) $\epsilon_{ia} = \mu_i + \nu_{ia}$ (2) $\nu_{ia} = \rho\nu_{i,a-1} + \eta_{ia}$

Model II: (1),(2), plus (3) $\eta_{ia} = \xi_{ia} + \theta\xi_{i,a-1}$

Model III: (2),(3), plus (1') $\epsilon_{ia} = \mu_{ia} + \nu_{ia}$ (4) $\mu_{ia} = \mu_{i,a-1} + \omega_{ia}$ with $\sigma_\mu^2 = \mathrm{Var}(\mu_{i1})$

Model IV: (2),(3), plus (1") $\epsilon_{ia} = \mu_i + a\phi_i + \nu_{ia}$

the fit significantly improved, with squared residual sums of 1.247 and 1.246, respectively, and in neither case was the additional parameter (i.e., the MA(2) and the AR(2) parameters) significant.[25] An ARMA(1,1) with a random-walk individual effect hence adequately fits our data. That this specification fits the data reasonably well can be seen in Table 1, for the AR(1) component with a relatively high value of ρ accounts for the slowly falling covariances with lag length, while the (negative) MA(1) component accounts for the sharp drop in the covariance one year off the diagonal. The individual effect accounts for the fact that the high-order covariances in Table 1 do not fall to zero but instead asymptote at the variance of the individual effect, while the random walk accounts for the increasing covariances with age.

These results are fairly consistent with past work on earnings dynamics. Our model is a bit more refined than early models such as those used by Lillard and Willis (1978), who only assumed an individual effect and an AR(1) transitory effect. But more recent and flexible specifications, such as those tested by MaCurdy (1982) and Abowd and Card (1989), find strong MA components as well as random-walk components. Both MaCurdy and Abowd-Card find that an MA(2) specification adequately fits the covariance matrix of earnings differences, for example. Our random-walk-plus-ARMA(1,1) model in levels implies an ARMA(1,2) model in differences, slightly different than MaCurdy and Abowd-Card; but the first-order autoregressive component which we find fades out rapidly in differences and is close to zero beyond the second lag in any case.[26]

Table 5 shows estimates of the model in equations (4)-(11), permitting calendar-time effects in the parameters of the model. Initial testing revealed that the time trend coefficients were significant only for α_t and the variance of ξ_{iat}, so column (1) shows a specification with only these two time effects allowed. The year coefficient for α_t is .029, implying that its factor loading (or the "price of permanent unobserved human capital") increased by approximately 52 percent over the 18-year period 1969-1987 (1.52 = 1 + .029*18). Thus the model strongly confirms the suggestion from the

TABLE 5

Error-Components Models for Log Annual Earnings with Calendar-Time Effects

	(1)	(2)
α_t:		
Year	.029*	.023*
	(.003)	(.006)
$Var(\xi_{iat})$:		
Year	.005*	.005*
	(.001)	(.001)
Constant	.117*	.118*
	(.009)	(.010)
ρ_t:		
Year	-	.008
		(.015)
Constant	.641*	.578*
	(.063)	(.191)
θ_t:		
Year	-	-.003
		(.018)
Constant	-.367*	-.352*
	(.078)	(.227)
$Var(\omega_{iat})$:[a]		
Year	-	.001
		(.010)
Constant	.100*	.110*
	(.013)	(.017)

(table continues)

TABLE 5 (continued)

	(1)	(2)
σ^2_μ	.056*	.061*
	(.003)	(.006)
Sum of squared residuals	.668	.666

Source: Authors' calculations based on Panel Study of Income Dynamics.

Notes: Standard errors in parentheses. Year=0 in 1969, =1 in 1970, etc.

[a]Coefficients multiplied by 100.

* Significant at 10 percent level.

nonparametric regressions of an increase in the variance of the permanent component. At the same time, however, the variance of ξ_{iat}--which is a two-period transitory component--almost doubled over the period, increasing from .117 in 1969 to .207 in 1987 (.207 = .117 + .005*18). Thus the model also confirms that there was a strong increase in the transitory component as well. In addition, however, the autoregressive nature of the model implies that the increase in the variance of ξ_{iat} persists and increases future values of the variance of the total transitory component, ν_{iat} (see equation (6)). The persistence of the ξ_{iat} dies out at the rate ρ^2, implying that its impact is negligible after three years.

The second column in Table 5 shows that the time trends in the other three parameters of the covariance matrix are insignificant. However, the magnitude of the trend coefficient for ρ is not trivial, implying an increase from .578 to .722 (.722 = .578 + .008*18) over the period and hence a strengthening of the low-order covariances and a longer persistence of transitory shocks. However, the large standard error on the coefficient makes this result highly uncertain.[27]

One way of assessing the relative importance of the increase in the variance of the permanent component ($\alpha_t\mu_{iat}$) and the transitory component (ν_{iat}) is to calculate what the increase in the total variance would have been from 1969 to 1987 had each parameter increased separately. Table 6 shows the results of such an exercise, obtained by calculating the variance of y_{iat} assuming no change in the parameters from 1969-1987, and by then calculating what the 1987 variance would have been had each of the parameters increased by the magnitudes implied by the coefficients in the second column of Table 5.[28] The results show that the increase in the permanent variance accounted for approximately 40 percent of the increase in total variance and the increase in the transitory variance accounted for approximately 50 percent, with the remainder accounted for by changes in other parameters.[29] Thus, although the change in the transitory variance accounts for slightly more of the

TABLE 6

Effects of Parameter Changes on Log Annual Earnings Variances, 1969-1987

	Variances by Age			
	20	30	40	50
1969 values of all parameters	.179	.199	.210	.221
1987 value of α_t only	.240	.273	.296	.318
1987 values of α_t and variance of ξ_{iat}	.338	.379	.401	.423
1987 values of α_t, variance of ξ_{iat}, and θ_t	.338	.372	.394	.416
1987 values of all parameters	.338	.401	.423	.445

Source: Authors' calculations based on Panel Study of Income Dynamics.

change than that in the permanent variance, the two are roughly equal in importance for practical purposes.[30]

The estimates of this model shed light on the descriptive results found in the previous section of the paper, with implications that are of some importance. Most important is the finding that transitory (i.e., mean-reverting) shocks are serially correlated and have impacts on variances that, given our estimates of the autocorrelation parameter, last approximately three years. This implies that the association of off-diagonal components with permanent effects can be slightly misleading because the off-diagonal components, at least those within three years of one another, reflect transitory components as well as permanent components. For example, the relatively slower rate of increase of the high-order covariances as compared to the low-order covariances can now be seen to have arisen because the former measure only the upward trend in permanent variance whereas the latter capture the upward trends in transitory variance as well as permanent variance.

We next examine the differential patterns of change in the 1970s and the 1980s. To minimize the restrictiveness of the specification, we reestimate the model in the first column of Table 5 allowing α_t and $\mathrm{Var}(\xi_{iat})$ to take on different values in each year 1969-1987. As shown in Figure 2, the increase in the two parameters occurred in quite different periods. While the permanent variance grew, on average, through about 1982 or 1983, it leveled off or fell subsequently. The transitory variance, on the other hand, showed essentially no trend until 1980 or 1981, when it began to rise; further, although it showed a slight decline after 1984, it was still unambiguously higher in the late 1980s than in the early 1980s, opposite to the pattern for the permanent variance. Thus we find additional evidence indicating relatively higher growth rates of the permanent variance in the 1970s and of the transitory variance in the 1980s.

Finally, we consider whether any of the apparent increase in transitory variance we estimate could be a result of measurement error. On a priori grounds, there is no reason to expect

Figure 2: Estimated Trends in Permanent and Transitory Components

Figure 2(a)

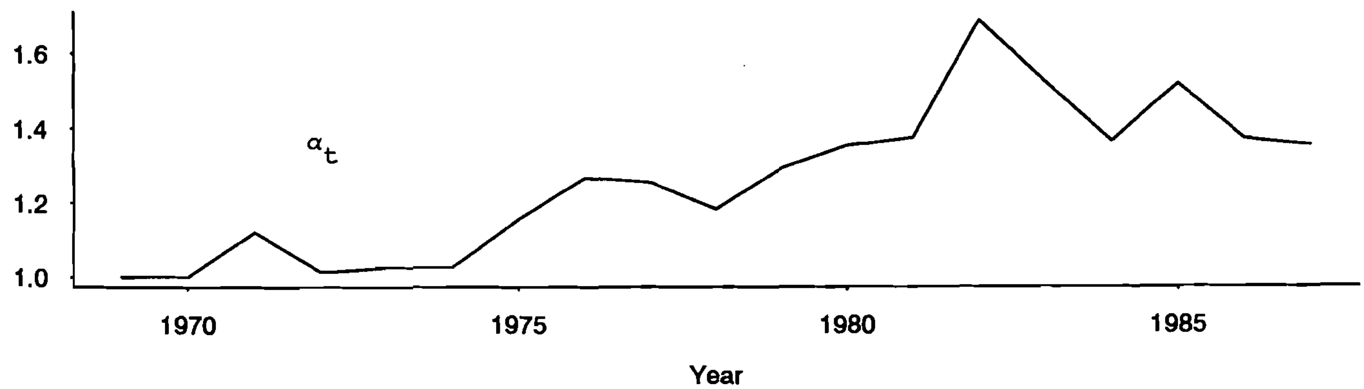
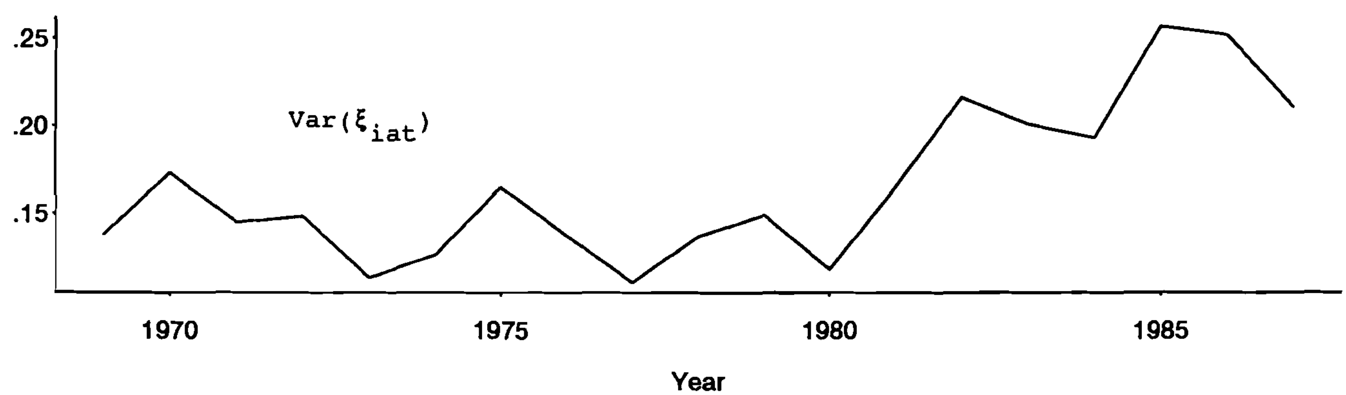


Figure 2(b)



measurement error in earnings to have changed over time, or to have changed at different rates in the 1970s and 1980s. Furthermore, the available evidence suggests that there has been no change in the accuracy of earnings data in the PSID. The fraction of earnings observations that are imputed, combining what the PSID calls "major" and "minor" imputations, is only 1.6 percent in our sample averaged over all years. This low percentage probably reflects better reporting among prime-age white males than other population groups. More important, the fraction has not changed over the period, varying only between .6 percent and 2.1 percent, with a slight downward trend over time. As a consequence, estimates of the model shown in Table 6 change only at the third or fourth decimal place when imputed earnings observations are deleted.[31]

Mobility

Our mobility analysis uses the same data structure as used in the previous analyses, and is based upon the same set of 553 cell observations of the covariance matrix of earnings. Deleting the variance elements, which are not relevant to mobility, leaves us with 477 observations, each of which represents a pair of ages at two particular points in calendar time. Instead of computing covariances for each such cell, we compute quantile mobility rates using five quantiles (i.e., quintiles).[32]

Table 7 shows the year-to-year rates of mobility in the sample between quintiles, pooled over all years and ages. Mobility at the upper and lower quintiles is less than in the middle quintiles.[33] At the upper and lower ends there is an approximate one-third chance of changing rank from one year to the next, as opposed to an approximately fifty-fifty chance for the middle quintiles. The mobility table is also remarkable for its symmetry.

Our interest is, once again, in how these mobility rates have changed over time conditional on age. As we discussed previously, the overall shape of mobility trends should follow those of the covariance analysis closely, but should depend primarily upon trends in the correlation coefficients rather than in the covariances. Figures 3(a)-(b) show the trends in both the correlation coefficient and

TABLE 7

One-Year Quintile Mobility Rates for Log Annual Earnings: All Years and Ages

		Quintile Distribution at t				
Quintile at t-1	Sum	Bottom Fifth	Next to Bottom Fifth	Middle Fifth	Next to Top Fifth	Top Fifth
Bottom fifth	100	67	21	8	3	1
Next to bottom fifth	100	20	49	22	7	2
Middle fifth	100	7	21	44	22	6
Next to top fifth	100	4	7	20	47	22
Top fifth	100	2	3	7	20	69

Source: Authors' calculations based on Panel Study of Income Dynamics.

Note: 477 observations per row.

Figure 3: Mobility Rates and Correlation Coefficients by Year and Age

Figure 3(a): Ages 35-36

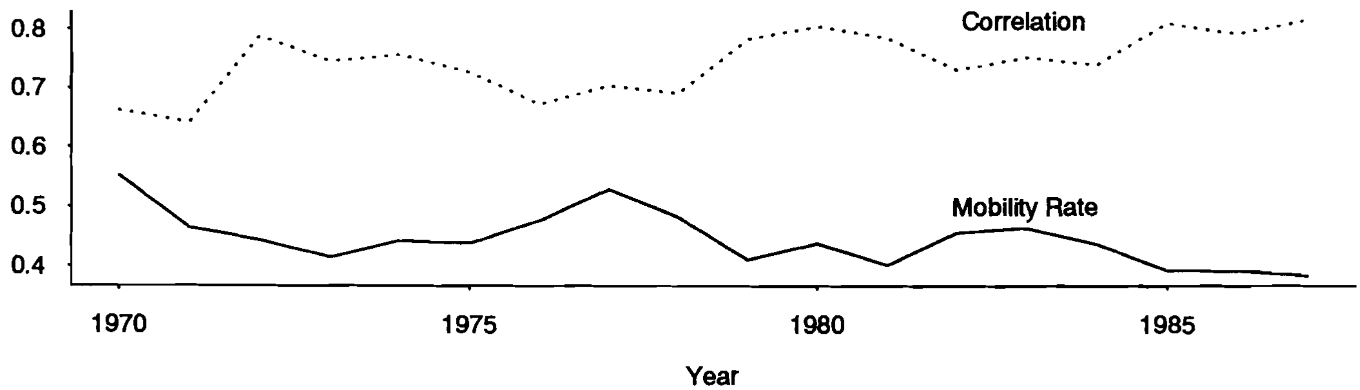
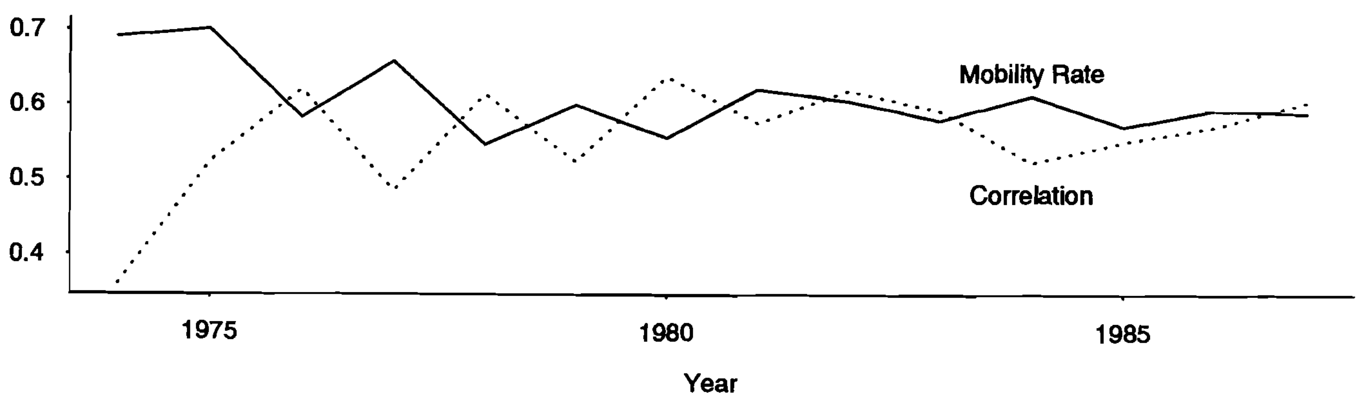


Figure 3(b): Ages 35-40



the mobility rate for two illustrative ages, 35-36 ("short") and 35-40 ("long").[34] The measure of mobility we use is the sum of the off-diagonal elements in each row of Table 7 (i.e., one minus the probability of staying in the same quintile). This measure is the inverse of what is known as the "immobility ratio" in the literature (Atkinson et al., 1992). As expected, the correlation coefficients and mobility rates in both diagrams show an extremely close inverse relationship. The one-year-apart correlation coefficient at ages 35-36 showed a slight upward trend in the 1970s but a steeper trend in the 1980s, reflecting the pattern of the transitory variance. Correspondingly, there was very little trend in one-year-apart mobility until the late 1970s, when short-term mobility dropped sharply. The five-year-apart correlation coefficient rose steadily over the late 1970s, albeit with considerable fluctuation, but leveled off in the 1980s; correspondingly, five-year mobility dropped steadily in the 1970s but leveled off in the 1980s. These patterns closely reflect the relative patterns of the transitory and permanent variances discussed previously.

Table 8 shows the results of a regression analysis of the mobility rates for all quintiles, all ages, and lag orders. The first row shows that while there was a net decline in overall mobility (over all lag orders), the magnitude of the mobility decline was greatest in the top and the bottom two quintiles. The subsequent rows of the table show overall mobility rates consistent with Figure 3, falling significantly only for short-term mobility in the 1980s and only for long-term mobility in the 1970s. However, as in the first row, the trends seem to be concentrated in the upper and lower tails of the distribution. Indeed, for the lowest fifth of earners even short-term mobility declined in the 1970s, which is an indirect indication that the variance of serially correlated transitory shocks increased for that group over the entire period, not just over the 1980s.

TABLE 8

Year Coefficients in Quantile Mobility Regressions

		Initial Quantile Location				
	All	Bottom Fifth	Next to Bottom Fifth	Middle Fifth	Next to Top Fifth	Top Fifth
All lag orders						
Year	-.0020*	-.0040*	-.0028*	-.0010	-.0007	-.0020*
	(.0004)	(.0008)	(.0008)	(.0007)	(.0007)	(.0007)
Lag orders 1-4						
1969-1980	-.0013	-.0051*	-.0008	.0001	.0006	-.0017
	(.0011)	(.0018)	(.0019)	(.0019)	(.0017)	(.0017)
1981-1987	-.0025*	-.0022	-.0038	-.0026	-.0017	-.0026
	(.0014)	(.0023)	(.0024)	(.0024)	(.0021)	(.0022)
Lag orders 5+						
1969-1980	-.0067*	-.0083*	-.0035	-.0014	-.0087*	-.0108*
	(.0017)	(.0035)	(.0034)	(.0030)	(.0034)	(.0034)
1981-1987	-.0005	-.0027	-.0044*	-.0004	.0021	.0020
	(.0009)	(.0018)	(.0018)	(.0015)	(.0018)	(.0018)

Source: Authors' calculations based on Panel Study of Income Dynamics.

Notes: Standard errors in parentheses. Sample sizes are 477 for all-lag-order sample, and 198 and 279 for the 1-4 lag-order and 5+ lag-order samples, respectively. Dependent variable: fraction of population in the relevant age-year-quantile cell that changed quantiles over the lag orders shown. Independent variables in addition to time trends: A_2, A_2-A_1, and (A_2-A_1) squared (see notes to Table 2 for definitions).

* Significant at the 10 percent level.

IV. ADDITIONAL RESULTS

Weekly Wages and Weeks of Work

An important secondary question is the extent to which the marked increase in instability in earnings profiles signified by the increase in transitory variances has been a result of increasing instability in wage rates or in employment. The literature on the overall increase in cross-sectional dispersion of earnings indicates that a majority of that increase has arisen from increases in the cross-sectional dispersion of wage rates rather than of weeks of work, hours of work, and employment in general (Levy and Murnane, 1992; Burtless, 1990, Table 7). However, there is no necessary reason for the lesser importance of dispersion in cross-sectional employment measures to follow through for the relative importance of permanent and transitory variances. In fact, the literature on life cycle labor supply analysis and on business cycle fluctuations indicates that employment fluctuates with a greater variance than wages, suggesting that transitory components in employment might be considerably stronger than permanent components.

Figures 4(a) and 4(b) show trends in the variances and covariances of log real weekly wages and the log of annual weeks worked, the two components into which log annual earnings can be decomposed (ignoring the covariance between the two), for persons aged 35 to 44. The figure clearly indicates that both variances and covariances of log weekly wages rose and in the same pattern as for log real earnings (i.e., with the same relative patterns for high-order and low-order covariances). The figure also shows clear increases in the variances and covariances of weeks of work, although the increases in covariances are much weaker than for earnings or wages. This pattern is consistent with a greater relative importance of transitory factors for weeks worked.

Table 9 shows estimates of several models for log real weekly wages and log annual weeks worked. The descriptive regressions show that the increasing variance of log real weekly wages is equally shared between diagonal and off-diagonal elements, as was the case for annual earnings.

Figure 4(a): Log Weekly Wage Variances and Covariances, Ages 35-44

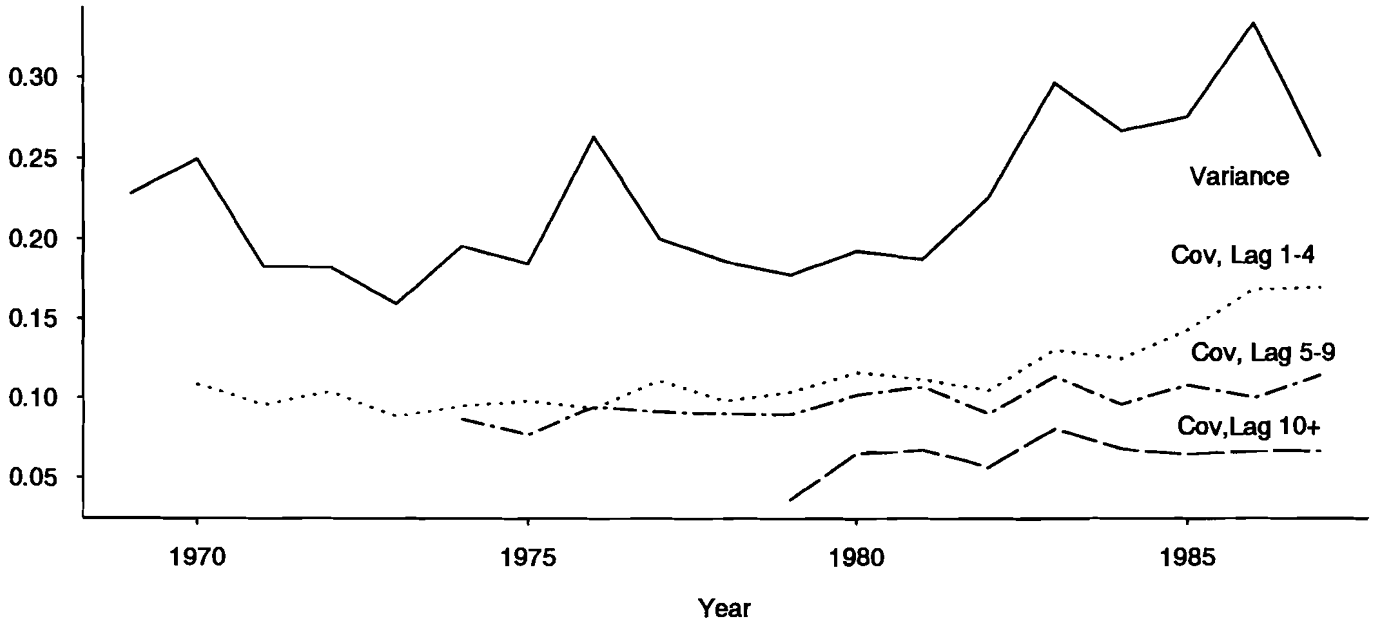


Figure 4(b): Log Weeks Worked Variances and Covariances, Ages 35-44

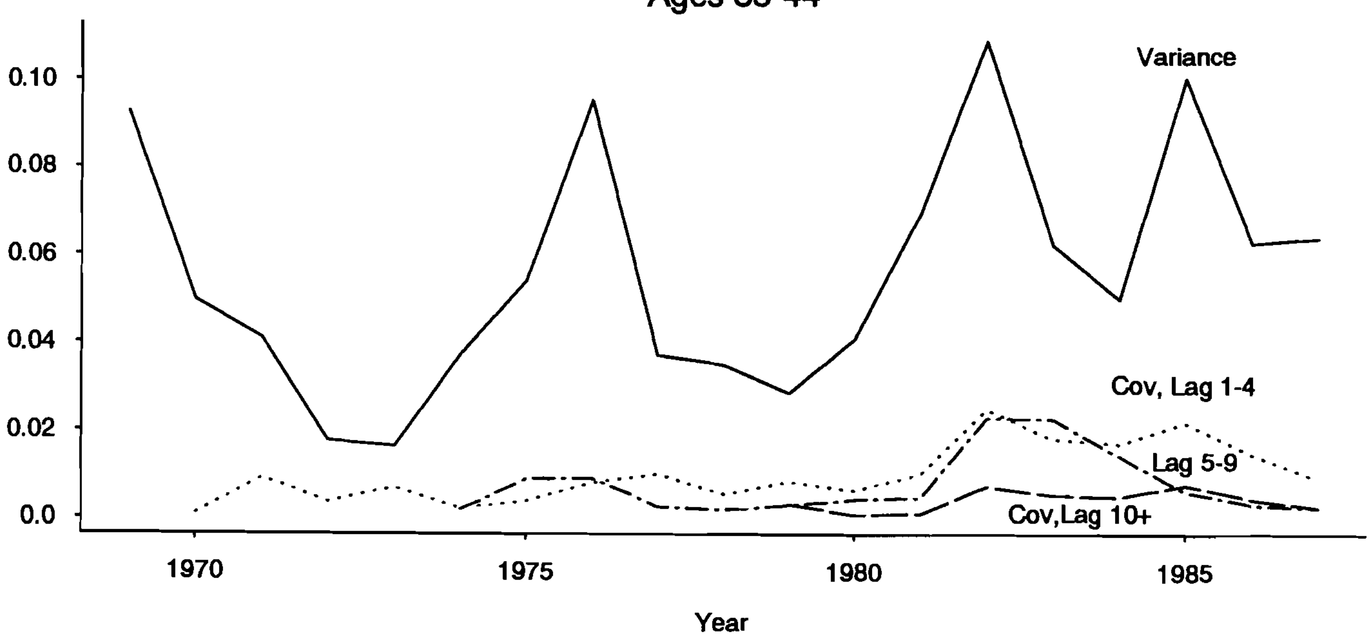


TABLE 9

Covariance Analysis of Real Weekly Wages and Annual Weeks of Work

	Log Real Weekly Wage	Log Annual Weeks Worked	Annual Weeks Worked[a]
Descriptive regressions[b]			
t	.0044*	.0008*	.485*
	(.0004)	(.0002)	(.110)
Dt	.0043*	.0021*	.846*
	(.0008)	(.0004)	(.215)
Error-components model[c]			
α_t	.024*	.075	.013
	(.002)	(.065)	(.014)
Var(ξ_{iat})	.003*	.002*	.487*
	(.001)	(.000)	(.283)

Source: Authors' calculations based on Panel Study of Income Dynamics.

Notes: Standard errors in parentheses.

[a]For positive weeks of work.
[b]For specification in third column of Table 2.
[c]Trend coefficients. For specification in first column of Table 5.

* Significant at the 10 percent level.

However, the coefficients are only approximately two-thirds the magnitude of the Table 2 results, thus confirming a role for increasing dispersion in weeks of work. This is further confirmed by the results for log and absolute weeks worked in the table, which indicate increasing diagonal and off-diagonal elements but greater relative trends for the diagonal elements. This pattern is also consistent with a greater relative importance of increases in transitory variances for weeks worked. The estimates of the error-components models shown in the lower half of the table confirm this and show that increases in transitory variances were particularly marked for weeks of work. However, it should be stressed that transitory variances have increased for real weekly wages as well.

These analyses exclude any consideration of changes in the proportion of the population with no weeks worked at all during the year. Those percentages are relatively small for our sample of prime-age white males but have increased over the period. For those aged 20 to 29, for example, the percentage without work at all during the year increased from 0.4 percent in 1969 to 2.7 percent in 1987. The corresponding percentages for those aged 30 to 39, 40 to 49, and 50 to 59 were, respectively, 0 to 1.7, 1.8 to 2.2, and 8.0 to 11.3.[35] Our results thus far already indicate increases in the variance of weeks worked in the worker subsample, and our data indicate even larger increases in that variance when nonworkers are included.

Estimates of the descriptive and error-components models for absolute weeks of work inclusive of zeros, comparable to those shown in the last column of Table 9, show stronger trends in the permanent variance and weaker trends in the transitory variance.[36] We speculate that an entire year without work may be an indication of a more serious wage or employment problem that reflects a permanent condition.

Between-Group Trends

The analysis thus far has been conducted entirely on the residuals from earnings and wage regressions, regressions containing education dummies and estimated separately by year and age interval. An important question is whether our results on the relative importance of trends in the variances of the permanent and transitory components of these within-cell earnings components apply as well to the log earnings itself. The answer depends upon the relative importance of trends in the permanent and transitory variances of the between-cell components, which in our case are the components accounted for by education and age differences in earnings.

There is a much larger literature on trends in education and age differences in earnings than in the within component, the literature showing markedly different trends in both over the 1970s and 1980s for both within and between components (see Levy and Murnane for a review). Our education and age coefficients follow the same general pattern over time as those in the past literature, which have been mainly estimated on the CPS, and therefore we will not present them.[37] Instead, we take a simpler approach to this question by reestimating the models we reported in Section III on log earnings itself rather than on the regression residuals; the difference in results will be an indirect indication of the importance of trends in the between-group variances. Thus, we work with 553 cells of a covariance matrix of log annual earnings over all years, age groups, and lag orders, constructed as described previously for the regression residuals.

The estimates of the descriptive regressions (not shown) indicate that the permanent variance is considerably more important when the between is included. Estimates of average permanent and transitory components for the specification in column (1) of Table 2 are .172 and .185, respectively, implying a correlation coefficient of approximately .48, as opposed to our prior estimate of .41. This is to be expected since education levels in our sample are essentially constant for each individual and, therefore, will mainly contribute to the permanent component of earnings. Estimates of the specifications shown in columns (2) and (3) of Table 2 show, moreover, coefficients on Dt of .0057 and .0056 in the two specifications (approximately the same as those in Table 2) but coefficients on t (the average covariance) of .0066 and .0068 (somewhat higher than those in Table 2). This higher value reflects a net increase in educational differentials over the period. Estimates of column (4) for the new covariance matrix reveal, however, the same pattern of greater increases of high-order covariances than low-order covariances as found previously.

In order to contrast the within-group and total results, we estimate the error-components model on both and simulate the implied permanent and transitory variances. The steady-state values in 1969 and 1987 are shown in Table 10.[38] As suggested by the descriptive analysis, the results show a higher level of the permanent variance for total log earnings. In addition, there was a slightly greater rate of increase in the permanent variance when the between is included. However, the magnitudes of the changes induced by including trends in the between are not large, and hence none of our substantive findings (e.g., that upward trends in transitory variance are important) are affected.[39]

V. SUMMARY AND CONCLUSIONS

In this paper we have examined the source of the increasing cross-sectional variance of male earnings in the United States over the 1970s and 1980s by determining its origins in the covariance structure of earnings. Using data from the Michigan Panel Study of Income Dynamics from 1969-1987 for white males, we found that about half of the increase in variance within education and age groups arose from an increase in the variance of the permanent component of earnings and half from an increase in the variance of the transitory component, where the transitory component reflected shocks that died out within three years. We thus found that increases in transitory shocks were of equal importance to increases in the dispersion of permanent earnings in explaining recent increases in earnings inequality. Indeed, the increase in transitory shocks was especially great in the 1980s. Other results showed that the increase in transitory shocks appeared in weekly wages as well as annual earnings, although even greater in annual weeks of work. We also found that transitory

TABLE 10

Steady-State Variance Components
Implied by the Estimated Error-Components Models

	Within			Total		
	Permanent	Transitory	Rho	Permanent	Transitory	Rho
Age 20						
1969	.061	.118	.34	.088	.118	.43
1987	.122	.216	.36	.154	.212	.42
Age 30						
1969	.072	.127	.36	.109	.127	.46
1987	.144	.258	.36	.192	.256	.43

Source: Authors' calculations based on Panel Study of Income Dynamics.

Notes: The permanent variance is the estimated value of Var(μ_{iat}) at 1969 and 1987 values. The transitory variance is the estimated value of Var(ν_{iat}) at 1969 and 1987 values of the parameters. The model estimates in column (1) of Table 5 and the analogous estimates for total log earnings are used.

shocks were still very important when trends in the variance across education and age groups were considered.

Our investigation of earnings mobility indicates that long-term mobility fell in the 1970s but only short-term mobility fell in the 1980s, the latter reflecting the increase in short-term covariances arising from a higher variance of serially correlated transitory shocks. The mobility declines were concentrated in the top and bottom quintile of the earnings distribution.

Our study suggests that research on increasing earnings and wage variances should explore a set of new hypotheses which could explain the increase in short-term transitory shocks we observed, especially those in the 1980s. Among these are increases in short-term unemployment and job mobility, an increased rate of layoffs and rehires, increased rates of job promotion and demotion within the firm, and greater instability in wage contracts. Positive indications of any of these trends would confirm as well as explain our findings.

APPENDIX

Relation of Mobility to Covariance Structure

Assume we have a random sample of n individuals with earnings observed at two points in time. We denote the earnings of individual i at time t as y_{it} $(i=1,\ldots,n;\ t=1,2)$. Although earnings are independent across individuals, we assume that they are correlated over time for the same individual. We also assume that the two earnings observations for each individual follow a bivariate normal distribution, with means zero and with $\mathrm{Var}(y_{it}) = \sigma_y^2$ and $\mathrm{Cov}(y_{it},y_{it'}) = \rho\sigma_y^2$ $(t \neq t')$. Let P denote the probability that there are no changes in rank in the distribution from t=1 to t=2. We shall demonstrate that $\partial P/\partial \rho > 0$ and that P is independent of σ_y^2.

Ordering the individuals from i=1 to i=n by rank, we have:

$$P = n!\ \mathrm{Prob}(y_{11}<y_{21}<y_{31}<\ldots<y_{n1}\ ,\ y_{12}<y_{22}<y_{32}<\ldots<y_{n2}) \tag{A1}$$

since there are n! possible orderings of the n individuals, each ordering with the same probability.

It is sufficient to compare only the change in relative rank for any given pair of individuals i and j, since the result will generalize to all pairs. Let

$$\begin{aligned} P' &= \mathrm{Prob}(y_{i1}<y_{j1}\ ,\ y_{i2}<y_{j2}) + \mathrm{Prob}(y_{i1}>y_{j1}\ ,\ y_{i2}>y_{j2}) \\ &= 2*\mathrm{Prob}(y_{i1}<y_{j1}\ ,\ y_{i2}<y_{j2}) \end{aligned} \tag{A2}$$

Defining

$$w_1 = y_{i1} - y_{j1} \tag{A3}$$

$$w_2 = y_{i2} - y_{j2} \tag{A4}$$

we have that w_1 and w_2 are distributed bivariate normal with means zero and with $\mathrm{Var}(w_t) = 2\sigma_y^2$ and $\mathrm{Cov}(w_1,w_2) = 2\sigma_y^2\rho$. Hence

$$P' = \int_{-\infty}^{0}\int_{-\infty}^{0} (2\sigma_y^2)^{-1}\, b(w_1,w_2;\rho)\, dw_1\, dw_2 \tag{A5}$$

$$= \int_{-\infty}^{0}\int_{-\infty}^{0} b(\hat{w}_1,\hat{w}_2;\rho)\, d\hat{w}_1\, d\hat{w}_2 \tag{A6}$$

where b is the unit bivariate normal density and where $\hat{w}_j = w_j/\sqrt{2\sigma_y}$. Thus P' is only a function of ρ and not a function of σ_y^2.

The partial derivative of a bivariate normal cumulative distribution function w.r.t. ρ is equal to the bivariate density evaluated at the upper limits. Hence $\partial P'/\partial\rho = b(0,0;\rho) > 0$.

Notes

[1] Put differently, the marginals of a transition matrix are not sufficient to identify transition rates between cells.

[2] Although the covariances we study are more formally termed autocovariances, we use the simpler term for brevity since all the covariances we consider are autocovariances.

[3] This approach is closely related to that outlined by Chamberlain (1984) for fitting the elements of a covariance matrix in a more general context. Chamberlain also showed the optimal weighting matrix for the problem. We use the identity matrix (i.e., OLS) instead for computational simplicity. Empirical standard errors can be calculated by applying the GLS formula for them suggested by Chamberlain, which is based on the fourth moments of earnings; the standard errors presented below have not been so adjusted.

[4] Since we allow the variance of μ to change, describing it as a "permanent" component is a bit of a misnomer (better would be "persistent" since it is simply a covariance). However, we retain the "permanent" label for intuition. Our formal error-components specifications will make this clear.

[5] MaCurdy (1982) and Abowd and Card (1989) examine whether the earnings process is or is not stationary, but they do not model calendar-time effects in detail.

[6] A proportional time-shift coefficient on an individual-specific effect was also considered explicitly by MaCurdy (1982, p.88), although he interpreted t as age instead of calendar time.

[7] The Bound-Krueger and Bound et al. studies only had two periods of validated earnings data, and hence serial correlations more than one period apart could not be examined.

[8] This variance is the variance of the individual effect at the beginning of the life cycle. It could also be allowed to shift with calendar time.

[9] We also test for different time trends in different periods as well as for cyclical effects.

[10] Indeed, an individual effect that varies freely with age and year is not identifiable from a transitory effect.

[11] The mapping of (4)-(11) into the covariance elements s_{jt} is available upon request from the authors.

[12] Over the entire lifetime, for example, an increase in the permanent variance must both increase the variance of lifetime earnings and lower mobility between average earnings between the first part of the life cycle and over the second part, at least as long as transitory components die out within those intervals.

[13] In prior work, we have treated each wave of the PSID as an independent cross section and we have compared trends in earnings differentials to those in the CPS (Gottschalk and Moffitt, 1992). We found overall conformity of the direction of the trends in the two data sets in both within-group and between-group earnings differentials.

[14] Attrition in the PSID had reached approximately 50 percent by 1988, and therefore a continuous-sample restriction would severely reduce the sample size and hinder the analysis. Fortunately, despite this heavy attrition, there is little evidence of significant attrition bias in the PSID in the studies that have examined it to date (Becketti et al., 1988; Gottschalk and Moffitt, 1992).

[15] We delete the top and bottom one-percent of the earnings and wage observations within each age-year covariance cell. These outliers introduce noise into the trends in variances and covariances. This trimming also eliminates the top-coded earnings observations in the PSID. Results on untrimmed data show the same patterns as those we present below but with larger standard errors.

[16] However, we also conduct a secondary analysis on the raw earnings data. See Section IV.

[17] The regression coefficients are available upon request.

[18] To compute the covariances between those who were, say, between 20 and 29 in 1970 and (hence) 30 and 39 in 1980, we use only those who were present in both years.

[19] The variances and covariances are averaged over the age groups in question and over the single-order lags (e.g., over the first, second, third, and fourth-order lags for the plot "lag 1-4").

[20] We also tested more flexible age specifications (e.g., categorical age dummies) with no change in the results.

[21] The estimates imply a stationary or slightly rising correlation coefficient.

[22] We use detrended unemployment rates in order to measure only cyclical effects. Since the unemployment rate trended up over the period, including a non-detrended rate would naturally lower the coefficients on t and Dt and raise their standard errors.

[23] The break point was not chosen formally and, hence, is not intended to be precise. It was chosen to be 1980 only because the prior work on trends in cross-sectional variances has shown marked differences in the 1970s and 1980s.

[24] Early examinations of the random-growth model can be found in Hause (1977, 1980) and Lillard and Weiss (1979). The random-growth model implies variances rising over the life cycle with the square of age whereas the random-walk model implies linearly increasing variances. There is relatively little curvature in the life cycle profile of variances in our data, which is no doubt the reason for the similarity of fit. We should note that our comparison does not make use of the fourth moments of the data, which are quite different in the two models. See Abowd and Card (1989) and Baker (1992).

[25] The chi-squared statistics for the specifications in the table are all much higher than the critical values at conventional significance levels, implying rejection of the model (see Chamberlain [1984] and Abowd and Card [1989] for the test-statistic formulas). This is not surprising given the large number of covariance elements (553). Models which allow time-varying parameters have much lower chi-squared statistics (see below).

[26] At the third lag, for example, the covariance of differences is reduced by ρ raised to the sixth power, which in our case ($\rho = .662$) is .084. It falls further at higher lags. Although it is clear from Table 1 that our data require a first-order autoregressive parameter to explain the decline in autocovariances after the second lag, the magnitude may be too small for statistical significance when estimation is conducted in differences. Another possible explanation for this minor difference is that we have a panel of 19 periods, whereas MaCurdy and Abowd-Card only had panels of 10 and 11, respectively; our longer panel may give us more power in detecting small autoregressive influences at longer lags.

[27] The chi-squared statistics for both specifications are approximately 950, much larger than the five-percent critical value of 605. However, the specifications discussed momentarily, which allow year dummies, generate chi-squared statistics of approximately 650, much closer to the critical value.

[28] The order of parameter change in Table 6 does not materially affect these conclusions because the permanent and transitory components are additive in the total variance and hence do not interact. For example, introducing the change in the variance of ξ first increases the four variances from their 1969 values to .277, .305, .317, and .328 for the four respective ages shown in the table.

[29] The change induced by the trend coefficient for the variance of the random walk is negligible in magnitude and hence is not broken out separately; the changes in the last row are entirely due to the change in ρ.

[30] An alternative computation is to compute the "steady-state" variances implied by the values of the parameters in 1987, and to compare these to the 1969 steady-state variances shown in the first row of Table 6. The 1987 variances in Table 6 reflect the historical experience of the shocks from 1969 to 1987 and, because of the autoregressive structure of the model, do not represent the steady-state values. However, because the autoregressive lag in the variances is so short--of negligible

importance after three years--the 1987 steady-state variances differ from those in the last row of Table 6 only at the second decimal place.

[31] In addition, there has been no change in the coding procedures used to detect "erroneous" earnings. Those procedures are documented for coders, and the same documents have been used for the entire PSID.

[32] The limited number of observations in the sample prevents us from disaggregating the quantiles further. Some prior analyses in the literature have been able to use a finer set of quantiles by pooling the data across years and across ages. However, not only have we found pooling across years to be incorrect, but both our descriptive and error-components analysis showed the necessity of conditioning on age.

[33] This is to some extent to be expected since persons in the upper (lower) quintiles can only move down (up), whereas persons in the middle quintiles can move in either direction.

[34] Given our age grouping, "35" stands for 30-39, "36" stands for 31-40, and "40" stands for 35-44.

[35] These trends by themselves have no necessary implication for our prior results. Mean weeks of work have fallen in our sample whether these zero-week observations are included or not (although they have fallen more when the zeros were included than when they were not). More important, a change in mean weeks worked, negative or positive, has no necessary implication for changes in variances.

[36] For the descriptive regressions, the off-diagonal and diagonal coefficients are 1.296 and 1.109, respectively, both significant at the 10 percent level. The magnitudes are considerably larger than those for conditional weeks worked because variances and covariances showed larger absolute increases over the period. Estimates of the error-components model reduce the magnitude and

significance level of the trend in the transitory component, and increase them for the permanent component.

[37] A detailed comparison of the PSID and CPS in this dimension can be found in our prior benchmarking exercise (Gottschalk and Moffitt, 1992).

[38] The sum of the permanent and transitory components of the within values are almost identical to the values given in Table 6. As noted previously, the steady-state predicted values from the model are essentially identical to the values predicted historically because the latter only include the influence of "history"--that is, the fact that variances have been growing over time and hence have not been at their steady-state value for the whole period--but history is unimportant after approximately three years.

[39] To some extent the small magnitude of the change induced by including the between simply reflects the relatively small R-squareds in all log earnings regressions when only education and age are the explanators; hence trends in the covariance structure of total log earnings are dominated by trends in the covariance structure of the residuals. Note as well that the correlation coefficients in Table 10 imply even less reduction in mobility than was found for the within analysis. The trends in the correlation coefficients arise from the size of the proportionate increase in the permanent variance, not its absolute size, and the proportionate increase in that variance is smaller for the between than for the within.

References

Abowd, J. and D. Card. "On the Covariance Structure of Earnings and Hours Changes." Econometrica 57 (March 1989): 411-445.

Atkinson, A.B.; F. Bourguignon; and C. Morrison. Empirical Studies of Earnings Mobility. Harwood Publishers, 1992.

Baker, M. "Growth Rate Heterogeneity and the Covariance Structure of Life Cycle Earnings." Working Paper 9209, Institute for Policy Analysis, University of Toronto, 1992.

Becketti, S.; W. Gould; L. Lillard; and F. Welch. "The Panel Study after Fourteen Years: An Evaluation." Journal of Labor Economics 6 (October 1988): 472-492.

Bound, J.; C. Brown; G. Duncan; and W. Rodgers. "Measurement Error in Cross-Sectional and Longitudinal Labor Market Surveys: Validation Study Evidence." In Panel Data and Labor Market Studies, eds. J. Hartog, G. Ridder, and J. Theeuwes. New York and Amsterdam: North-Holland, 1990.

Bound, J. and G. Johnson. "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations." American Economic Review 82 (June 1992): 371-392.

Bound, J. and A. Krueger. "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?" Journal of Labor Economics 9 (January 1991): 1-24.

Burtless, G. "Earnings Inequality over the Business and Demographic Cycles." In A Future of Lousy Jobs, ed. G. Burtless. Washington: Brookings, 1990.

Chamberlain, G. "Panel Data." In Handbook of Econometrics, eds. Z. Griliches and M. Intriligator. Amsterdam: North-Holland, 1984.

Gottschalk, P. and R. Moffitt. "Earnings and Wage Distributions in the NLS, CPS, and PSID." Part I of Final Report to the U.S. Department of Labor. Providence: Brown University, 1992.

Hause, J. "The Covariance Structure of Earnings and the On-the-Job Training Hypothesis." Annals of Economic and Social Measurement 6 (1977): 335-365.

Hause, J. "The Fine Structure of Earnings and the On-the-Job Training Hypothesis." Econometrica 48 (1980): 1013-1029.

Levy, F. and R. Murnane. "Earnings Levels and Earnings Inequalities: A Review of Recent Trends and Proposed Explanations." Journal of Economic Literature 30 (September 1992): 1333-1381.

Lillard, L. and Y. Weiss. "Components of Variation in Panel Earnings Data: American Scientists, 1960-1970." Econometrica 47 (March 1979): 437-454.

Lillard, L. and R. Willis. "Dynamic Aspects of Earnings Mobility." Econometrica 46 (September 1978): 985-1012.

MaCurdy, T. "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.