Trends in Men's Earnings Volatility:
What Does the Panel Study of Income Dynamics Show?

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Abstract

Using Panel Study of Income Dynamics data for 1969 through 2004, we examine movements in men's earnings volatility. Like many previous studies, we find that earnings volatility is substantially countercyclical. As for secular trends, we find that men's earnings volatility increased during the 1970s, but did not show a clear trend afterwards until a new upward trend appeared in the last few years. These patterns are broadly consistent with the findings of recent studies based on other data sets.

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"… the volatility of family incomes has gone up – way, way up…. In fact, over the past generation the economic *instability* of American families has actually risen much faster than economic *inequality*…."

-- Jacob S. Hacker (2006, p. 2)

"The variance of transitory earnings … rose in the 1980s but declined in the 1990s."

-- Robert A. Moffitt and Peter Gottschalk (2002, p. C68)

"While earnings instability today is higher than the late 1960s and early 1970s, it has declined more or less steadily, aside from business-cycle effects, from a peak in the early 1980s."

-- Stephen Cameron and Joseph Tracy (1998, p. 2)

"CBO's analysis of the CWHS administrative data indicates that, since 1980, the trend in year-to-year earnings variability has been roughly flat."

-- Congressional Budget Office (2007, p. 3)

I. Introduction

The seminal study by Gottschalk and Moffitt (1994) used 1970-1987 data from the Panel Study of Income Dynamics (PSID) to document that the well-known increase in men's earnings inequality during that period stemmed partly from an increase in earnings volatility. Several subsequent studies corroborated the general finding and filled in additional details about the trend. Haider (2001), for example, analyzed PSID data for 1967-1991 and concluded that "earnings instability increased dramatically during the sample period, with most of the increases occurring during the 1970s" (p. 829). Haider also found that the rise in earnings volatility during the 1970s was associated mainly with increased volatility in annual hours of work, not average hourly earnings.[1]

As indicated by the quotations at the top of this page, a few researchers have extended the analysis of men's earnings volatility trends to more recent years. Cameron

[1] Because the permanent component of earnings variation also increased, the rise in earnings volatility need not have reduced autocorrelations in earnings nor increased transition rates across quintiles of the earnings distribution. The evidence that earnings volatility increased therefore is altogether consistent with studies – such as Kopczuk, Saez, and Song (2007) and Acs and Zimmerman (2008) – that have found relative stability in such measures of economic mobility.

and Tracy (1998) studied longitudinally matched Current Population Survey (CPS) data for 1967-1996. They replicated Haider's PSID-based finding that earnings volatility trended upwards during the 1970s and, after a large cyclical increase during the recession of the early 1980s, came back down for the rest of the 1980s to about the same level as in the late 1970s. Cameron and Tracy also found that this relatively flat trend continued through the end of their sample period in 1996. The Congressional Budget Office (2007) study by Dahl, DeLeire, and Schwabish used Social Security earnings histories for 1980-2003. The parts of their analysis that focused on men's age-adjusted earnings (especially figure A-15) found trends similar to those previously reported by Haider and by Cameron and Tracy. In addition, their results showed some indication of a rise in men's earnings volatility in the early 2000s.

In contrast, Moffitt and Gottschalk's (2002) analysis of 1969-1996 PSID data reported that the transitory variance of men's log earnings "rose dramatically in the 1980s, leveled off in the late 1980s, and fell after 1991" (p. C70).[2] And Hacker's (2006) analysis of 1974-2002 PSID data on family income, rather than men's earnings, also reported a volatility increase in the 1980s, but found an even larger increase in the early 1990s, followed by a decline later in the 1990s and another increase in the early 2000s. These new PSID analyses appear to be at odds both with each other and with the other recent studies based on other data sets.

The question is which results are accurate and which are not. If the answer were to be found mainly in differences among data sets, then we would need to ascertain which data are more reliable. That would be difficult because each data set has strengths and weaknesses relative to the others. Compared to the PSID, the data from the CPS and Social Security feature much larger sample sizes, and the administrative data from Social Security avoid the problem of survey response error. But the longitudinally matched CPS data also have the relative disadvantage of systematically excluding individuals who changed residences, which must make the sample at least somewhat unrepresentative with respect to earnings changes. Limitations of the Social Security data are that they

[2] In an incomplete draft, Gottschalk and Moffitt (2006) extend their analysis through 2002 and find that earnings volatility began rising again in the late 1990s.

include only those earnings reported by employers on W-2 forms, and they are not publicly available for replication and further analysis.

On the other hand, if a reanalysis of the PSID data were to find that the trends revealed in the PSID actually are qualitatively similar to those reported for the CPS and the Social Security data, then we could be more confident in the common patterns observed in all three data sets. That is just what our study does find.

Our results are previewed in figure 1, which shows the standard deviation of age-adjusted year-to-year changes in log earnings for men in the PSID. The data, which are described in detail below in section III, are from interviews in 1970 through 2005 and pertain to annual wage and salary income in the preceding calendar years. Because the PSID has conducted interviews only in odd years since 1997, we look at *two*-year changes in log earnings: 1969-1971 (based on the 1970 and 1972 interviews), 1970-1972 (based on the 1971 and 1973 interviews), 1971-1973, …, 1994-1996, 1996-1998, 1998-2000, 2000-2002, and 2002-2004. The time axis in the figure labels observations by the second year in the two-year difference; e.g., the observation for 1969-1971 is labeled as 1971. The figure also marks the timing and severity of recessions by plotting the annual civilian unemployment rate.

One striking pattern in the figure, familiar from many previous studies, is that the dispersion in log earnings changes is greater during recessions,[3] especially the severe recession in the early 1980s. As for secular trends, the figure is fairly consistent with the trends previously described by Haider, Cameron and Tracy, and the Congressional Budget Office. Men's earnings volatility appears to have trended upwards during the 1970s, but it is not clear that there was much further secular trend between the late 1970s and late 1990s. Finally, a new upward trend in earnings volatility starts appearing by 2000. This last finding is consistent with some of the Social Security evidence reported in the Congressional Budget Office study.[4]

[3] See, for example, Haider (2001), Cameron and Tracy (1998), Baker and Solon (2003), Gottschalk and Moffitt (2006), and Congressional Budget Office (2007).

[4] At the same time we began reanalyzing the PSID data, so did Dynan, Elmendorf, and Sichel (2008). Their study focuses on family income rather than men's earnings, but the last panel of their figure 1 includes a plot of the standard deviation of two-year percentage changes in men's earnings. Their plot is not exactly comparable to our figure 1 for several reasons. First, they use a more comprehensive PSID earnings measure, "total labor income." The difficulty with this measure, which we discuss below in section III, is that it is not measured consistently over time. Second, they do not adjust their earnings

The remainder of our paper fleshes out these findings. In section II, we use a simple canonical model of earnings dynamics to assess a Moffitt-Gottschalk method for estimating volatility and to interpret our own measures, including the standard deviation of age-adjusted change in log earnings. In section III, we first describe our data, and we then present a variety of analyses of men's earnings volatility trends in the PSID. Section IV summarizes and discusses our findings.

II. Measuring Earnings Volatility

Some previous studies of earnings volatility trends – such as Moffitt and Gottschalk (1995, 2002), Haider (2001), Baker and Solon (2003), and Gottschalk and Moffitt (2006) – have couched their analyses in terms of complicated parametric models of earnings dynamics. The drawback of this approach is that the parametric models used in the literature are arbitrary mechanical constructs and the resulting estimates of trends can be sensitive to arbitrary variations in model specification. For example, using a large sample of Canadian income tax records, which enabled more thorough specification checking than is possible with smaller U.S. data sets, Baker and Solon strongly rejected the restrictions of Moffitt and Gottschalk's preferred model and found that imposing those restrictions substantially biased the estimation of Canadian trends in components of earnings variation.

We therefore sympathize with the inclination of several other researchers – such as Dynarski and Gruber (1997), Cameron and Tracy (1998), Congressional Budget Office (2007), and Dynan, Elmendorf, and Sichel (2008) – to eschew complex earnings dynamics models and focus instead on simple statistics that might be reasonable indexes of earnings volatility under a wide range of data-generating processes. The series we just previewed in section I – the standard deviation of year-to-year change in log earnings – is meant to serve as such a statistic. The simple idea is that, if earnings volatility increases a lot, one might reasonably expect that development to be reflected in increased dispersion of earnings changes.

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growth variable for age or experience. Third, their figure plots three-year rolling averages of the standard deviation, which makes it difficult to discern cyclical versus secular changes. Notwithstanding these and other differences, Dynan, Elmendorf, and Sichel reach the same broad-brush conclusion that we and others do – that men's earnings volatility has increased substantially since the early 1970s.

Similar concerns presumably are what motivated Moffitt and Gottschalk – in their 1995, 2002, and 2006 papers – to supplement their analyses based on earnings dynamics models with what, in the 2006 paper, is called their "descriptive" approach. The particular descriptive statistic they use to measure earnings volatility in year t is the variance of log earnings in that year minus the fifth-order autocovariance[5] between years t and $t-5$. Although Moffitt and Gottschalk clearly express a preference for their analyses based on parametric earnings dynamics models, they also prominently feature their descriptive approach in all three papers. Thanks to Moffitt and Gottschalk's well-deserved stature in the field, their descriptive approach has been quite influential; for example, Hacker (2006) adopted it for his own analysis of trends in family income volatility. We therefore need to explain why we do not adopt it as well.

Although we do not wish to commit to any particular model of the earnings dynamics process, we will begin to illustrate our concerns in terms of a simple version of the often-used variance components model that splits log earnings (after adjustment for life-cycle/cohort effects) into two orthogonal factors – a permanent component and a transitory component. Expressed in a way that allows for trends in the dispersion of either component, the model is

(1) $$y_{it} = p_t \alpha_i + \varepsilon_{it}$$

where y_{it} is the age-adjusted log earnings of individual i in year t, α_i is an individual-specific "fixed effect" with population variance σ_α^2, p_t is a year-specific factor loading (which might reflect, for example, year-specific returns to human capital), and ε_{it} is a transitory component with time-varying variance σ_t^2 and negligible serial correlation. Then cross-sectional earnings inequality in year t, as measured by $Var(y_{it})$, is simply

(2) $$Var(y_{it}) = p_t^2 \sigma_\alpha^2 + \sigma_t^2 .$$

[5] In the 2006 paper, Moffitt and Gottschalk switch to using the fourth-order autocovariance.

According to this model, an increase in earnings inequality could stem from an increase in either the permanent variance component (represented as an increase in p_t) or the transitory variance component σ_t^2.

Like most researchers who have used parametric models to study volatility trends, Moffitt and Gottschalk define earnings volatility as the transitory variance component σ_t^2. The question then becomes how well their descriptive statistic measures that component. It is easy to show that

(3) $$Var(y_{it}) - Cov(y_{it}, y_{i,t-5}) = \sigma_t^2 + p_t(p_t - p_{t-5})\sigma_\alpha^2 .$$

Thus, Moffitt and Gottschalk's descriptive statistic correctly identifies the transitory variance component σ_t^2 only when $p_t = p_{t-5}$; that is, only when the permanent component is unchanged and earnings inequality has changed solely because of a change in the transitory component. More generally, when both variance components are changing, their descriptive statistic conflates the two.

More importantly, their statistic can be way off the mark not only for estimating the level of the transitory variance, but also for estimating its change over time. Consider this simple example. Suppose that, up through year $t-5$, $\sigma_\alpha^2 = \sigma_{t-5}^2 = p_{t-5} = 1$. Then $Var(y_{i,t-5}) = 1+1 = 2$; that is, cross-sectional earnings inequality as of year $t-5$ divides evenly between permanent and transitory variation. Given stationarity up through time $t-5$, Moffitt and Gottschalk's descriptive statistic would correctly identify σ_{t-5}^2 as 1.

But now suppose that, in every year from $t-5$ through t, the permanent factor loading p increases at an annual rate of 0.1. Then, by year t, cross-sectional inequality has grown to $Var(y_{it}) = (1.5)^2 + 1 = 3.25$ with no increase whatsoever in the transitory variance component, which still equals 1. Nevertheless, if one applies Moffitt and Gottschalk's descriptive method for estimating σ_t^2, one overestimates it as 1.75. The method incorrectly concludes that the transitory variance has increased by 75 percent over the five years, and it incorrectly ascribes 60 percent of the increase in inequality to change in the transitory component. The lesson is that, in a non-stationary environment (which, after all, is entirely what this trends literature is about), this descriptive statistic does not actually describe what anyone wants it to. And this is not an artifact of the simple illustrative model from equation (1). Readers can verify for themselves that adding complications – heterogeneity in earnings growth, serial correlation of the transitory component, or whatever – does not set things right.

Accordingly, we look elsewhere for our descriptive statistics. In particular, we will use measures of the dispersion in year-to-year earnings changes, such as the standard deviation of change in log earnings. It seems reasonable to guess that trends in earnings volatility would be reflected in such measures, but we should check that guess. To begin with, consider the variance of the age-adjusted change in log earnings between years $t-2$ and t (the square of the standard deviation measure previewed in section I). Under the model in equation (1), this variance is

$$(4) \qquad Var(y_{it} - y_{i,t-2}) = (p_t - p_{t-2})^2 \sigma_\alpha^2 + \sigma_t^2 + \sigma_{t-2}^2 .$$

As conjectured, this dispersion measure tends to be higher when the transitory variance is higher in years t and $t-2$. The bad news is that, like Moffitt and Gottschalk's statistic, this measure also is affected by changes in p. The good news is that, if p's closer together in time tend to be more similar, this measure tends to be less distorted than the Moffitt-Gottschalk statistic in equation (3), which is contaminated by the *five*-year difference $p_t - p_{t-5}$. (Of course, this good news gets better still when one has access to a data set in which one can use the variance of one-year changes instead of two-year changes.) Additional good news for the measure in equation (4) is that it squares the typically fractional change in the p's, leading to a smaller fraction multiplying σ_α^2.

Now consider again the numerical example above. In year $t-5$, our statistic in equation (4) correctly identifies $\sigma_{t-5}^2 + \sigma_{t-7}^2$ as 1+1=2.[6] In year t, our statistic estimates

[6] Some readers of previous drafts have asked what happens if the transitory component is serially correlated. If the second-order autocorrelation is stable and denoted by ρ, then the statistic in equation (4) would identify $2(1-\rho)$ instead of 2, and hence would still be proportional to the level of the transitory variances. Of course, if the serial correlation parameter changes over time, matters become much more complicated. Indeed, it would become less clear what we even mean by changes in earnings volatility.

$\sigma_t^2 + \sigma_{t-2}^2$ as $(0.2)^2 + 1 + 1 = 2.04$, instead of the correct value of 2. This illustrates our claim that, although our statistic is affected by changes in the variance of the permanent component, it is much less sensitive to them than Moffitt and Gottschalk's statistic is.

We can gain further insight into the behavior of our statistic by generalizing the earnings dynamics model in equation (1) to encompass permanent as well as transitory earnings shocks. The extended model is

(5) $$y_{it} = p_t(\alpha_i + u_{it}) + \varepsilon_{it}$$

where u_{it} follows a random walk

(6) $$u_{it} = u_{i,t-1} + v_{it}$$

with innovation variance σ_v^2. This extension makes the earnings dynamics model more realistic by allowing for long-lasting shocks such as the persistent earnings losses often suffered by workers displaced from their jobs.[7] With this addition to the model, the variance measure in equation (4) now gets modified to

(7) $$Var(y_{it} - y_{i,t-2}) = (p_t - p_{t-2})^2 Var(\alpha_i + u_{i,t-2}) + \sigma_t^2 + \sigma_{t-2}^2 + 2p_t^2\sigma_v^2$$

where $\alpha_i + u_{i,t-2}$ might be thought of as worker i's permanent human capital as of time $t-2$. The important change relative to equation (4) is the addition of the last term $2p_t^2\sigma_v^2$, the component of the variance in earnings change that comes from permanent shocks.

The key lesson is that an earnings volatility measure based on dispersion in year-to-year earnings change reflects permanent shocks in addition to transitory ones. Thus, in contrast to model-based studies that attempt to identify the transitory variance, our study and others using similar methods include permanent shocks in the measurement of

[7] Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997).

earnings volatility. There is something to be said for that. Interest in earnings volatility trends stems in large part from a concern about whether earnings risk has increased. Because permanent shocks, such as those experienced by many displaced workers, are even more consequential than transitory ones, it makes good sense to include them in the measurement of earnings volatility.

Having said that, however, we should be very clear that measures like the standard deviation of change in log earnings muddle together permanent shocks and transitory shocks without making any distinction between them. Furthermore, as discussed by Blundell, Pistaferri, and Preston (forthcoming) and Cunha, Heckman, and Navarro (2005), even if one could separate permanent and transitory variation, identifying the associated risk still would require further information on whether the shocks were or were not anticipated and whether the affected individuals were or were not insured against the shocks. These important questions constitute a crucial (and daunting) agenda for future research.[8] Our empirical analysis in the next section is just a preliminary step directed at the simpler question of what are the basic facts regarding overall trends in men's earnings variability.

III. Evidence from the Panel Study of Income Dynamics

A. Data

Our data are from the Panel Study of Income Dynamics, a longitudinal survey administered by the University of Michigan's Survey Research Center every year from 1968 through 1997 and every other year since then. We use the data from the nationally representative Survey Research Center component of the PSID sample.[9]

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[8] Blundell, Pistaferri, and Preston (forthcoming), for example, begin to tackle these issues by using consumption data along with income data.

[9] We do not use the Survey of Economic Opportunity component (the so-called "poverty sample") mainly because of the serious irregularities in that sample's selection. The problems recounted in Brown (1996) are too numerous to repeat here in their entirety. The problem we find most disturbing is that, for reasons that remain unknown to this day, the computer consulting firm in Washington, DC that the Office of Economic Opportunity hired to select low-income households from the Census Bureau's 1967 Survey of Economic Opportunity sample failed to include most of the eligible households in the lists it transmitted to the Survey Research Center. Worse yet, the omissions clearly were not random. Brown's memo notes a racial pattern – the transmission rate was 55 percent for non-whites and 21 percent for whites. A passage he quotes from the Survey Research Center's 1984 PSID *User Guide* also refers to "substantial" variation across geographic areas. That passage concludes, "By the time we realized that not all the addresses of the 'signers' had been forwarded, the Census personnel knowledgeable about the process had moved on to

Like Moffitt and Gottschalk, we first analyze the wage and salary income of male household heads because it is the earnings variable that the PSID has measured most consistently over time. We exclude imputations for missing values, the inclusion of which would distort measured earnings variability.[10] The wage and salary income variable is available only in "bracketed" (i.e., interval) form for the PSID's 1968 and 1969 interviews, so our data set begins with the 1970 survey, which collected income information for the 1969 calendar year. Because the PSID was administered annually through 1997 and every other year since, our earnings data are for every year from 1969 through 1996 plus 1998, 2000, 2002, and 2004. Accordingly, our analyses of earnings changes will pertain to two-year differences for 1969-1971, 1970-1972, 1971-1973, …, 1994-1996, 1996-1998, 1998-2000, 2000-2002, and 2002-2004.

We restrict our sample of earnings observations to calendar years when the male head of household is between the ages of 25 and 59. For a two-year change to be included in our analysis, the worker must be within that age range in *both* years. At the outset of each analysis in section III.B, we will provide information on the available sample sizes. Each of those analyses of earnings changes begins with a regression adjustment for mean effects of year (such as inflation in nominal wages), life-cycle stage, and cohort. In particular, we apply least squares (separately for each year) to a regression of the earnings change variable on age and age squared, and then use the residual as the object of the subsequent analysis of dispersion in earnings changes.[11]

B. Analyses of PSID Earnings Changes

We begin by describing in detail the analysis previewed in our introductory section. That analysis looks at the trend in the standard deviation of change in log earnings. For this particular analysis, in addition to the sample restrictions listed above, we exclude observations of zero earnings. We also exclude the top and bottom 1 percent

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designing the 1970 Census, and OEO personnel were not able to provide us any information. Our repeated efforts to secure more information about the lost cases were not successful."

[10] On the advice of PSID staff, we interpret the several instances from 1994 on in which wage and salary income is coded as 1 as missing values that require imputation.

[11] We stop at a quadratic because going to a cubic specification typically resulted in coefficient estimates for the cubed terms that were small and statistically insignificant. In any case, given the restricted age range in our sample, variations on our age controls (including using none at all) turn out to have very minor effects on our results concerning volatility trends.

of positive observations in each year. Besides the usual reasons for excluding outliers, dropping the top 1 percent eliminates all the top-coded observations and thereby sidesteps the question of whether and how to adjust them. We recognize, however, that excluding zeros and other extreme observations in a study of earnings volatility is not entirely a good thing. Accordingly, in an alternative analysis described later in this section, we take a different approach to the extreme observations.

In combination, all the sample restrictions applied in the present analysis leave us with a total of 43,346 observations over our 30 years of data on two-year differences. The average sample size per year is thus 1,445. The smallest sample size is 1,005 for 1969-1971, and the largest is 2,016 for 2000-2002.

Our preliminary regression of change in log earnings on a quadratic in age each year causes our residualized measure of change in log earnings to have zero sample mean in every year. Accordingly, we estimate the variance of each year's change in log earnings with that year's sample mean squared residual. The estimated standard deviation plotted in figure 1 is the square root of the estimated variance.[12]

As already discussed in our introductory section, figure 1 displays the familiar finding that earnings volatility is strongly countercyclical. Like Haider (2001) and Cameron and Tracy (1998), we find that earnings volatility trended upwards during the 1970s. Like those studies and the Congressional Budget Office (2007) study, which began with 1980 data, we do not see much evidence of increasing volatility during the 1980s or most of the 1990s (apart from temporary bulges during the recessions of the early 1980s and early 1990s). This impression of the 1990s is all the stronger if one discounts the observations for 1990-1992 through 1993-1995, i.e., the observations that come at least partly from the 1993 and 1994 PSID interviews. Kim et al. (2000) explain that the data from those interviews should be viewed cautiously because the continuity of the PSID data in those years was disrupted by a major overhaul of the survey that included, among other things, a switch to computer-assisted telephone interviewing, a shift from human to automated editing of the data, and changes in the structure of the income questions. Finally, like the Congressional Budget Office results for men's age-

[12] The associated 95 percent confidence band, shown in light blue, is based on the textbook result on the asymptotic distribution of the sample mean squared residual under the classical regression assumptions (Schmidt, 1976).

adjusted earnings, our results suggest that men's earnings volatility started to increase by 2000.

In figure 2, we check the sensitivity of our results to several variations in the analysis. First, although the wage-and-salary-income variable we use is defined almost consistently over time, there is an exception. Starting in the 1993 survey year (which inquired about 1992 income), a new earnings category called "income from extra jobs" was separated out, and it is possible that some of this income might previously have been included in the PSID's measure of wage and salary income. In figure 2, the blue line connecting the dashed data points shows what happens to our earnings volatility series from figure 1 (shown in figure 2 as purple diamonds) when we add income from extra jobs in with wage and salary income. Up through the data for 1991, of course, the two series are identical. Even afterwards, the differences are trivial, so this comparability issue appears to be of no consequence.

Second, several previous studies (e.g., Baker and Solon, 2003) have documented greater year-to-year earnings variation for workers in their twenties and as they approach retirement age. If the representation of those age groups in the population changed over time, this could produce the appearance of a trend in earnings volatility even if the life-cycle profile of earnings volatility did not shift at all. We therefore check what happens if we restrict our sample's age range to 30-54 instead of 25-59. As expected, the resulting yellow line connecting the triangular data points in figure 2 is lower, but it displays a time pattern quite similar to that for the larger sample.

Third, as already discussed in footnote 4, one difference between our main analysis and the earnings analysis by Dynan, Elmendorf, and Sichel (2008) is that they use a more comprehensive earnings measure, "total labor income," which includes bonuses, overtime, tips, commissions, and the labor parts of business, farm, market gardening, and roomers/boarders income in addition to wage and salary income. The difficulty is that the PSID's treatment of business and farm income in total labor income has varied over the years, and it is not possible to construct a consistent series over time. One approach we have tried is to use total labor income excluding business and farm income. The resulting series is shown in figure 2 as the black line connecting the rectangular data points. This series starts with the 1975-1977 observation because, prior to 1975, business and farm income were measured in bracketed form. We also have followed Dynan, Elmendorf, and Sichel's approach of using the PSID's total labor income variable up through 1992, adding in the "labor part of business income" after 1992 (when the PSID stopped counting it in "total labor income"), and excluding all observations with positive farm income. (Unfortunately, this approach remains inconsistent over time because, starting with the 1993 survey's measurement of 1992 income, the PSID changed the way it calculates the labor part of business income.) The resulting series is shown in figure 2 as the green line connecting the circular data points. The volatility measures for these more comprehensive earnings variables track quite similarly to our series for wage and salary income until the early 1990s, when they start diverging upwards, especially the series that includes business income. It is unclear how to interpret the divergence. On one hand, the pattern with the more comprehensive earnings variables may signify that earnings components besides wage and salary income really did contribute to rising earnings volatility throughout most of the 1990s. On the other hand, the divergence coincides with the timing of the major overhaul of the PSID's data collection and editing procedures, and might be merely an artifact of the changes in survey procedures. In any case, all the alternative series show rising volatility in the early 2000s, long after the changes in the survey had occurred.

One limitation of all our analyses so far is that the standard deviation is just one arbitrary measure of dispersion in earnings changes. A second limitation is the exclusion of zeros and other extreme earnings observations. One way of addressing the first limitation is to present a more complete picture of changes in the distribution of log earnings changes by plotting various quantiles of the distribution. Returning to the wage-and-salary-income variable used in figure 1, figure 3 displays the 10th, 25th, 50th, 75th, and 90th sample percentiles of the log earnings changes for each year. The 50th percentiles are always close to zero because the preliminary regression adjustments force the sample means to be zero. In figure 3, the cyclical increases in the dispersion of earnings changes in the severe recessions of the mid 1970s and early 1980s are manifested mainly as a lowering of the relative position of the 10th percentile. In contrast, the secular increases in the spread of the distribution during the 1970s and after 1998 are more symmetric.

Bringing the zeros into the analysis requires us to stop using logarithms and to measure relative dispersion in earnings changes in another way. We begin by taking two-year differences in the level (not log) of real earnings. We use the CPI-U-RS to put earnings into real terms. Again we account for mean effects of year, age, and cohort by estimating a separate regression in each year of the change in real earnings on a quadratic in age, and then we proceed to study the residualized version of the earnings change. We rescale the residualized real earnings change between years $t-2$ and t into relative terms by dividing it by the simple average of the sample means of real earnings in the two years. Initially using the same sample as before, figure 4 plots the quantiles of this alternative measure of earnings change. A comparison to figure 3 shows that, holding the sample constant, the two alternative measures show qualitatively similar time patterns.

Next, using the new measure of earnings change, we repeat the entire procedure with an expanded sample that includes zeros and other extreme earnings observations. The new sample contains a total of 53,840 observations over our 30 years of data on two-year differences. The sample size per year averages 1,795 and ranges from a low of 1,230 in 1969-1971 to a high of 2,500 in 2000-2002. Figure 5 plots the quantiles of the measured earnings changes for the expanded sample. Naturally, with outliers added to the sample, dispersion is greater than in the previous figures. Again, however, the temporal patterns are greater dispersion in severe recession years and secularly increasing dispersion in the 1970s and after 1998. The most striking difference from the earlier figures is that the post-1998 increase in dispersion is even greater.[13]

Finally, as a check on our eyeball impressions of our figures, we apply least squares to regressions of the earnings volatility time series plotted in the figures on the unemployment rate and a piecewise linear time trend. For figure 1, the volatility variable is the estimated standard deviation of the age-adjusted change in log earnings. For figures 3-5, the dispersion variable we use is the difference between the 90th and 10th percentiles. Using Y_t to denote each measure of the dispersion of earnings changes between years $t-2$ and t, we estimate the regression of each Y_t on the civilian unemployment rates in years t and $t-2$ (to account for business cycle effects) and a

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[13] Dynan, Elmendorf, and Sichel (2008) observe a similar pattern and express a concern that it may be driven by an increase in erroneous observations of zero earnings in the PSID.

spline function in time that allows for distinct time trends in three parts of our sample period: 1969-1971 through 1979-1981, 1979-1981 through 1990-1992, and 1990-1992 through 2002-2004. The results are shown in table 1. As expected from our visual impressions of the figures, the coefficient estimates for the unemployment variables are almost always significantly positive, and the estimated time trends are significantly positive in the first and third time periods, but not in the second.

IV. Summary and Discussion

Our reanalysis of the Panel Study of Income Dynamics has found that, apart from business cycle fluctuations, men's earnings volatility trended upwards during the 1970s, but did not show a clear secular trend after that until climbing again after 1998. These patterns are broadly consistent with those that Cameron and Tracy (1998) found in the Current Population Survey and that the Congressional Budget Office (2007) found in Social Security administrative data.

We are well aware that our results raise more questions than they answer, and so we conclude with several suggestions for further research. First, we believe that the finding that increasing earnings volatility for men has resumed in recent years is potentially very important, and we think it should be checked with other data. In particular, despite the inability to follow residential movers in the CPS, a study that updates Cameron and Tracy's analysis beyond 1996 would be valuable. If the CPS results turn out to corroborate the patterns we have observed in the PSID, the much larger sample size of the CPS would then enable more finely detailed analyses, such as Cameron and Tracy's disaggregations by age, education, and industry.

Second, the growing literature on earnings volatility trends should be connected to the growing literature on trends in job tenure and turnover (see Farber, 2007, and the references therein). Further research along the lines of Stevens (2001) that explores the earnings implications of changing job stability would illuminate both literatures.

Third, results in Congressional Budget Office (2007) and Dynan, Elmendorf, and Sichel (2008) suggest that, at the same time that earnings volatility has risen for men, it has decreased for women, which is not surprising in light of women's increasingly stable attachment to the labor market. Future research should combine the patterns by gender into a more complete picture and should give particular attention to the covariation of spouses' earnings.

Finally, we wish to reemphasize the point we made at the end of section II – that translating measured trends in dispersion of earnings change into conclusions about earnings risk will require additional information about whether the observed earnings changes were or were not anticipated and whether the affected individuals were or were not insured against the earnings changes.

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Table 1. Estimated Coefficients (and Standard Errors) for Regressions of Measures of Dispersion in Earnings Changes, 1969-1971 to 2002-2004

	(1) Standard Deviation of Change in Log Earnings	(2) 90-10 Difference for Change in Log Earnings	(3) 90-10 Difference for Relative Change in Real Earnings (Zeros and Outliers Excluded)	(4) 90-10 Difference for Relative Change in Real Earnings (Zeros and Outliers Included)
Intercept	0.1678	0.3985	0.3905	0.4609
	(0.0341)	(0.0425)	(0.0286)	(0.0466)
Piecewise-linear time trend:				
1969-1971 to 1979-1981	0.0059	0.0094	0.0075	0.0088
	(0.0027)	(0.0034)	(0.0023)	(0.0038)
1979-1981 to 1990-1992	0.0019	-0.0012	-0.0026	-0.0031
	(0.0018)	(0.0023)	(0.0015)	(0.0025)
1990-1992 to 2002-2004	0.0055	0.0122	0.0100	0.0265
	(0.0019)	(0.0024)	(0.0016)	(0.0027)
Unemployment rates:				
Year t	0.0152	0.0168	0.0153	0.0222
	(0.0045)	(0.0057)	(0.0038)	(0.0062)
Year $t-2$	0.0122	0.0128	0.0039	0.0118
	(0.0043)	(0.0053)	(0.0036)	(0.0058)
Number of time-series observations	30	30	30	30
$\hat{\rho}_1$	0.5508	0.0816	0.0825	-0.1169
$\hat{\rho}_2$	0.3668	-0.1358	-0.3476	-0.1036

Note: $\hat{\rho}_1$ and $\hat{\rho}_2$, the estimates of the first- and second-order autocorrelations of the error term, are calculated from least squares estimation of autoregressions (without intercepts) of the residuals. The regressions to calculate $\hat{\rho}_1$ stop with the 1994-1996 observation because, after that, the PSID interviews occur every other year.

Figure 1. Standard Deviation of Age-Adjusted Change in Log Earnings, 1969-1971 to 2002-2004

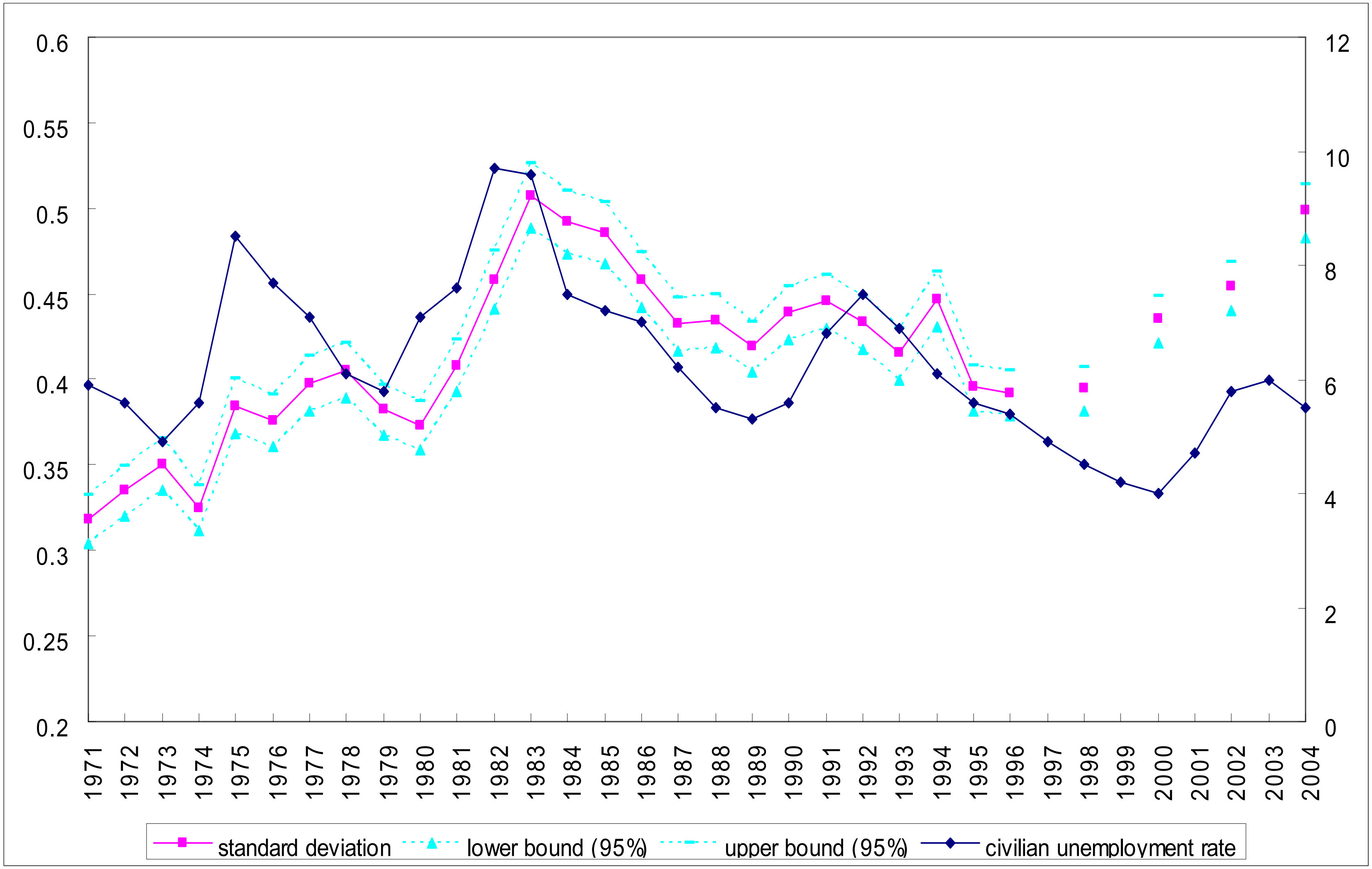

Figure 2. Standard Deviation of Age-Adjusted Change in Log Earnings with Various Earnings Measures

Figure 3. Quantiles of Age-Adjusted Change in Log Earnings, 1969-1971 to 2002-2004

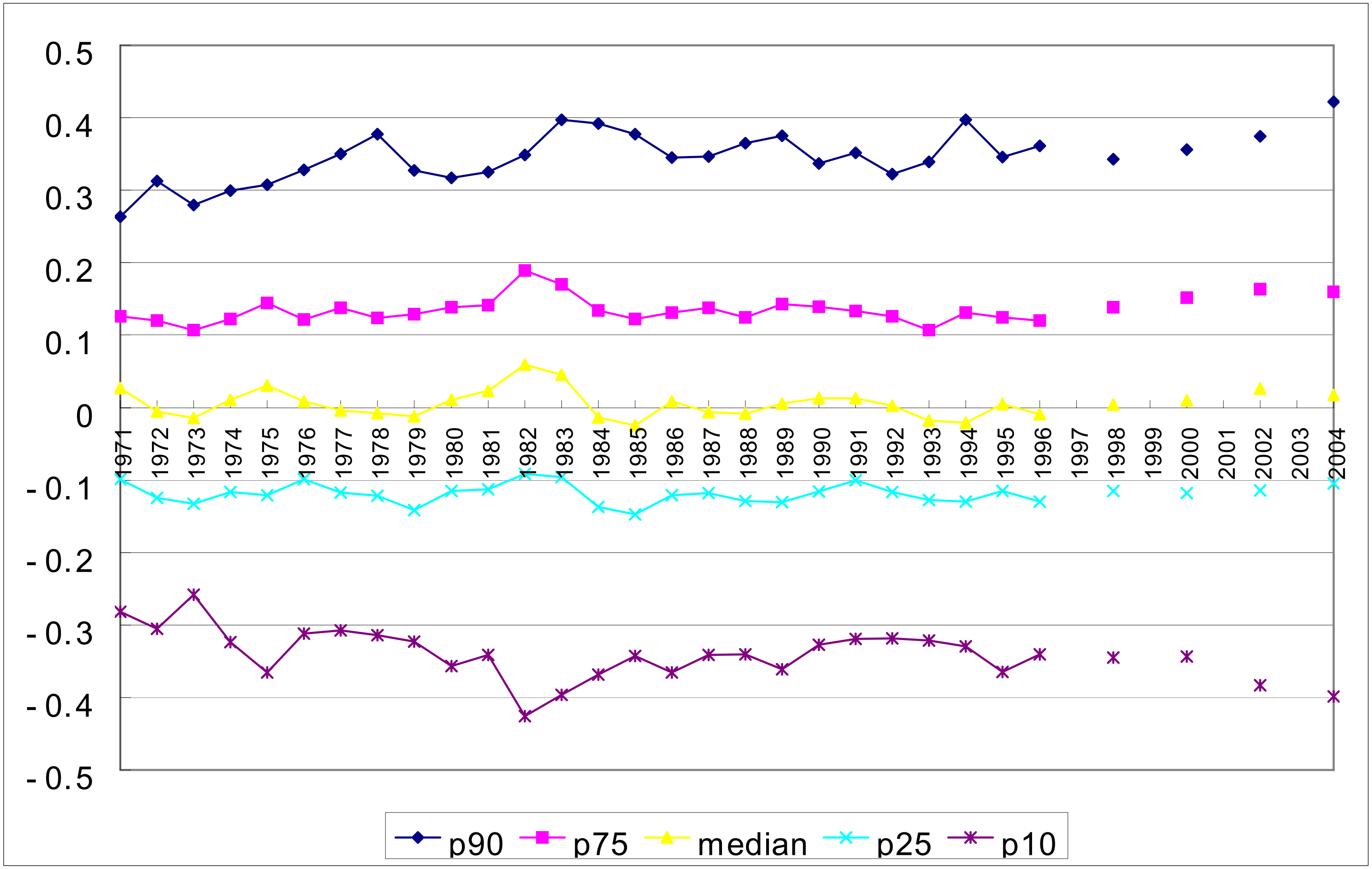

Figure 4. Quantiles of Relative Age-Adjusted Change in Real Earnings (Zeros and Outliers Excluded), 1969-1971 to 2002-2004

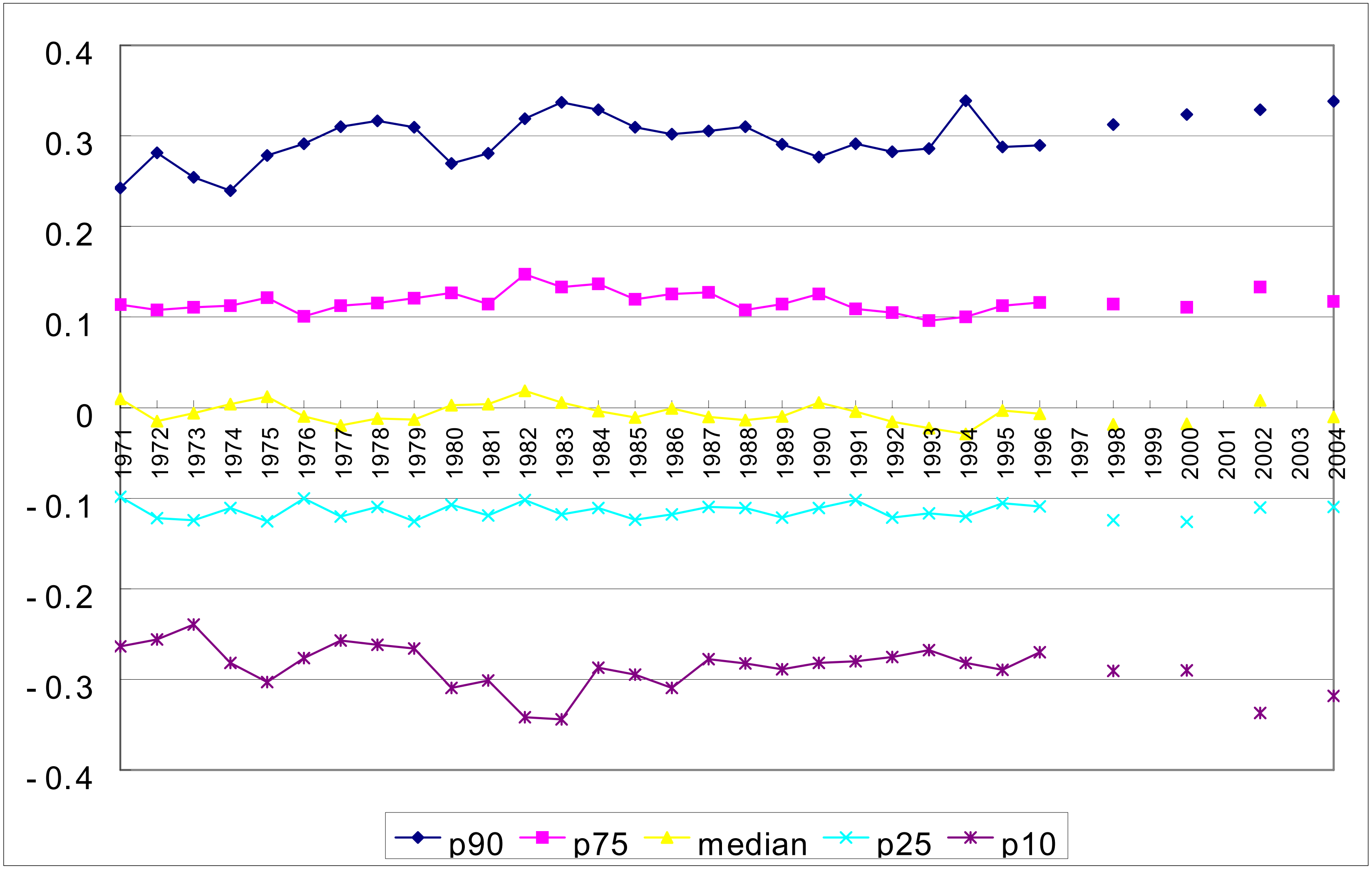

Figure 5. Quantiles of Relative Age-Adjusted Change in Real Earnings (Zeros and Outliers Included), 1969-1971 to 2002-2004