Trends in Within- and Across-Job Earnings Variability

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PRELIMINARY AND INCOMPLETE

Abstract

Estimates of earnings growth variability based on annual wages and salaries suggest that individuals may face great uncertainty, with year to year variances on the order of twenty percent. These estimates combine earnings fluctuations for the majority of workers who remain in their jobs from one year to the next with workers who experience a job change and/or labor force entry or exit. Earnings growth variability for “stable” workers is much more muted, at less than half the overall sample average. Much of the overall drop in earnings variability since the late 1980s is due to a decline in variability for the stable worker group, and the composition of workers across entry/exit and job-change categories may also help explain the trends and pronounced left skewness of earnings changes in bad labor markets.

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1. Introduction

Estimates of earnings variability based on Social Security administrative data suggest that workers face substantial uncertainty about their future income (Guvenen, Ozkan, and Song, 2012; Sabelhaus and Song, 2010). The benefit of using administrative earnings data is large sample sizes and minimal measurement error, but the downside is that measured annual earnings reflects variability in hours worked (voluntary or not) as well as variability in the rate of compensation. In this paper we take steps towards disentangling these confounding factors by decomposing overall earnings variability across labor force entry/exit and job-change groups.

The overall variance of annual real earnings changes in the Social Security data is on the order of 20 percent, so the standard deviation is about 45 percent. Growth rate variances increase linearly as one measures earnings changes over longer and longer frequencies (year-gaps), which is consistent with a stochastic earnings process that has both transitory and slowly evolving permanent components. A standard decomposition (Carroll, 1992, Carroll and Samwick, 1997) suggests that transitory variability dominates, with variance estimates on the order of 15 percent. The estimated variance of permanent innovations is just over 2 percent per year.

A standard deviation of 45 percent is not a useful measure of the uncertainty that most wage and salary earners face in most situations. Annual earnings vary over time because of changes in labor supply intensity, changes in labor demand, and changes in

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1 Reasons for modeling earnings dynamics and variability include analyzing consumption behavior under uncertainty (Friedman, 1957; Carroll, 1997; Gourinchas and Parker, 2002; many others) and building micro-level policy simulation models (Schwabish and Topoleski, 2013).
2 Low, Meghir, and Pistaferri (2010) emphasize the importance of wage versus employment risk, and focus on the importance of employer matching premiums and costly search when modeling earnings dynamics.
3 These estimates are based on tabulating earnings above the Social Security qualifying threshold only; the values are much larger when tabulating the variance of all positive earnings.
worker productivity. Productivity is used generally here to include factors like employer-match premiums (Low, Meghir, and Pistaferri, 2010). Although the Social Security data we use here does not make it possible to completely disentangle all of the contributing factors, we take steps in that direction by identifying labor market entry/exit and job change, then considering how overall earnings variability is associated with those events.

The main findings from this investigation so far are based on comparing earnings variability of “stable” workers to other groups. Stable workers are those who do not enter or exit the labor market and do not change jobs during the window over which we are measuring earnings changes. The variability of earnings growth for the stable worker group is less than half of the variance for the entire sample. Workers who change jobs during the window over which we are measuring earnings change have somewhat higher than average variances, and the (relatively small) group entering and exiting the labor market have much higher variances and account for much of the overall average variance.

In addition to differences in levels of earnings variability at every point in time, there is a substantial trend component to stable worker earnings variability, but less so for the other groups (job changers and entry/exits). Overall average earnings variability fell 6.6 log points between 1988 and 2010, for a decrease of nearly 30 percent. Earnings variability for stable workers fell 4 log points, which is 40 percent of the 1988 level. However, earnings variability of job changers fell 3.7 log points, which is only 12 percent below the 1988 value. Some of this divergence is because the end point (2010) is a relatively bad labor market, and the data suggest that job staying has risen and within-job earnings variability has fallen, both of which may help explain the countercyclical left skewness of earnings changes observed by Guvenen, Ozkan, and Song (2012).
2. Social Security 1% Master Earnings File (MEF)

The analysis here is based on a one percent random sample from the Social Security Administration one percent Master Earnings File (MEF) sample for 1988 through 2011. The MEF contains most of the information one finds on the annual W2 information return. Our measure of labor earnings used throughout is total wage and salary compensation, which is reported without any limitations (in particular, the Social Security or Medicare taxable maximums) for every year in our sample. The analysis excludes self-employment earnings because (until 1994) the values from the Form SE information return were limited to the taxable maximum—only after Medicare began taxing all self-employment is non-topcoded data available. The base sample used for any given estimate is every observation with earnings (above a minimum threshold) in the two time periods between which the earnings change is being measured.

All of the calculations here involve variances of log residual earnings growth, where the residual is solved for by subtracting the average growth rate for each (single-year) age and sex group for the entire period. This amounts to subtracting individual growth rates from average slopes for sex-specific age-earnings profiles estimated over the entire time period. Thus the reference point for measuring earnings growth variability is the individual’s level of earnings relative to the year-specific average for their age-sex group. Although there are a few different ways to compute residuals for the purpose of measuring variability, it turns out not to affect the average variance estimates greatly.5

4 Sabelhaus and Song (2010) is based on a slightly different one percent sample derived from the Continuous Work History Sample (CWHS) sample frame. For more details about the MEF see Kopczuk, Saez, and Song (2007).
5 Celic, Juhn, McCue, and Thompson (2012) make a similar point in their comparison of earnings variability estimates from various data sources.
The sample of earners used here (and in similar work) is limited to individuals in their prime working years, which we take to be ages 25 through 55. Thus, birth cohorts between 1934 and 1985 all contribute at least one observation to the measure earnings changes in our 1988 through 2011 time period. The results are based on both men and women, and although some differences between the groups are evident in some measures and shifting composition towards more women is part of the story, the overall conclusions are not affected by restricting (as in other work on the topic) to only men.

Variance measures constructed using any positive earnings in both of the years for which the change is being calculated are inherently problematic because some relatively small dollar changes may dominate the estimates if those changes are measured relative to a very low initial earnings. There are a number of ways to deal with that issue. For example, many studies restrict analysis of earnings growth variability to employed heads of household or prime-age males. The approach taken here is more direct—people with earnings below the amount needed to qualify for a year towards Social Security eligibility are excluded, meaning their earnings are effectively set to zero. That threshold value was $4,480 in 2010. As with several other key Social Security parameters the threshold grows over time with average wages, and year-specific values are used to set the inclusion criteria.  

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6 This threshold is the same as in Sabelhaus and Song (2010) and is consistent with the approach used in Kopczuk, Saez, and Song (2007). One way to think about the Social Security coverage threshold is this: a person crossed the coverage threshold if they worked 617 hours at the federal minimum wage, which was $7.25 in 2010. That is either about 12 hours per week for a full year, or 15 weeks full time. One alternative involved estimating the variance trend using a threshold consistent with a minimum wage/full time/full year salary, which (in 2000 dollars) works out to $10,494. The estimated variance of earnings growth above this threshold shows the same relative decline as indicated here, and in Sabelhaus and Song (2010). However, the much higher threshold has a big impact on the sample (excluding 20 to 25 percent in any given year, as opposed to a steady 9 percent in the Social Security qualifying case) and (given the goal of capturing unemployment-related transitory shocks) the higher threshold is excluding observations that should be in the sample.
In any given year, about ten percent of the observations in the administrative data with positive earnings are below the qualifying threshold, and there is no trend in that ratio over time. However, including those observations doubles the estimated variance at every point in time (Sabelhaus and Song, 2009). The disproportionate effect of low earners stems directly from the nature of the statistics we are dealing with: a change from $100 to $200 of earnings has the same impact on the average variance as a change from $10,000 to $20,000, yet the former is much less economically meaningful.

3. Earnings Variability over Time and Across Multiple Frequencies

Variances of earnings growth at all frequencies are quite large in the Social Security 1% MEF, even after removing low earnings and restricting the sample to prime-age workers. Figure 1 shows the variance of the annual, three year, and five year changes in log earnings for all wage and salary earners ages 25 to 55 between (base years) 1988 and 2010. The variance of one year earnings growth averages about 20 percent over the sample period. The variances at three and five year gaps are—consistent with both transitory shocks and cumulative persistent shocks being operative—systematically higher. Earnings variability at all three frequencies is declining over time. The patterns are consistent with Sabelhaus and Song (2010), and in fact, the trend toward smaller earnings variability continues (perhaps unexpectedly) beyond the end of the sample period (which was 2005) in that earlier paper.

Some of the decline in earnings variability between 1988 and 2011 occurred because the population we are studying became older.7 Although the sample is all

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7 Jaimovich and Siu (2009) focus on the role of demographics in helping to explain the decrease in business cycle volatility over the past few decades.
workers age 25 through 55 in every year, the aging of the disproportionately large Baby Boom cohort changes the composition of the sample greatly during this time period. The simplest way to show the demographic effect is to fix population weights at the base year level, which is done in Figure 1A. The change in the pattern is consistent with demographics having a dampening effect on earnings variability, but the trends over time are not greatly changed.

Differences in the variability of earnings growth at multiple frequencies is the basis for disentangling permanent and transitory components to earnings growth. Figure 2 shows that variances increase systematically and nearly linearly as one considers one year to twelve year earnings growth rates. The variance profile across frequencies 1 to 12 shifts depending on the base period for which the average variances are computed, but the shifts are relatively small compared to the averages across all periods. Figure 2A fixes the population weights at the 1988 age-sex composition, and the effect on variance profiles is not substantial.

Figure 2B illustrates how these variance profiles are used to disentangle transitory and permanent variability, using a simple method suggested by Carroll (1992). The key principle underlying that approach is that any given frequency over which earnings change is measured (1 through 12 periods here) always has two transitory innovation terms, and a number of permanent innovation terms equal to the frequency itself. This approach would work for every period if autocovariances between transitory innovations for the first few years over which earnings changes are zero, but the data clearly rejects

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8 Sabelhaus and Song (2010) show that permanent and transitory variances do fall with age, especially over the younger half of the sample relatively early in their careers.
9 See Appendix for details on the standard variance decomposition approach used here.
that very simple specification. However, Carroll (1992) showed that under standard estimates for the underlying stochastic process, one can safely ignore autocovariances for year-gap earnings changes of three and higher.

The principle of two transitory terms and number of permanent terms equal to the gap leads to the simple regression approach illustrated in Figure 2B. For two of the base periods considered in Figure 2, we fit regression lines through variances of earnings changes at frequencies three through twelve. The intercept of this line is twice the variance of the transitory innovations, while the slope is the variance of the permanent innovations (see Appendix). For the two base periods 1988-93 and 1994-1999, these fitted lines are somewhat similar, though the decrease in variability at longer frequencies for the second base period twist the regression line down, so the estimated variance of permanent innovations is slight lower (2.1 versus 2.6 percent) while the estimated variance of transitory innovations is slight higher (15.0 versus 13.6 percent).

One could certainly fit a regression line for the earnings growth variance profile for the 2000 and later period—there is no principle that says twelve periods is a magic number—but the shape of the profile speaks to the main point of this paper as well as recent work on countercyclical left skewness in earnings growth (Guvenen, Ozkan, and Song, 2012). Earnings growth variability does not simply increase in bad labor markets, as some have hypothesized. Rather, the mean of the distribution for earnings changes shifts left and the distribution itself also become more skewed, meaning the possibility of large earnings losses is higher while the possibility of large earnings increases is diminished. Whatever mechanical processes are underlying this empirical observation, it is pretty clear that the effect is dominating earnings growth variances towards the end of

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10 See, for example, Meghir and Pistaferri (2004).
our sample when labor markets have been especially bad, and thus the entire variance profile is rotated down.

The remainder of this paper explores what has been happening to earnings growth variability over time and across the business cycle (including the observed left skewness) by dividing the sample into groups with different labor market experiences. Before turning to that, however, the last two sets of charts in this section confirm (from a mean-variance perspective) two of the fundamental elements in the Guvenen, Ozkan, and Song (2012) observations about earnings growth over the business cycle.

There are four sets of years in our sample period during which overall average real earnings decreased: 1990-91, 2001-2002, 2007-2008, and 2008-2009. Figure 3 shows that average earnings growth rate for all age groups shifts systematically during these bad labor market years, so we can say clearly that not all age groups were affected. Figures 3A and 3B also show that, although there are differences in the slopes of age-earnings profiles by sex in all years, the drop in average earnings growth for all years is systematic and widespread.

The second part of the countercyclical principle is reflected in Figure 4. Although earnings growth variability has a strong age component in all years (Sabelhaus and Song, 2010), the average variance does not increase during the bad labor market years. Figures 4A and 4B confirm that the same pattern holds within sex groups as well. These observations about earnings variability over the business cycle confound interpretations about what is happening to earnings variability in recent years, and thus our next step is looking across and within various groups defined by job change and labor force entry and exit.
4. Identifying Job Change and Labor Market Entry and Exit

The administrative Social Security earnings data used to describe variability above and in earlier papers is very high-quality, derived from employer-provided W2s. However, there is a downside to using administrative data instead of self-reported earnings, because we can’t discern whether earnings changed because of changes in rates of compensation versus changes in annual hours worked (whether voluntary or involuntary). In this section we describe the approach used to divide the population we are studying into stable workers, job changers, labor force entrants, and labor force exits.

Consider the following schematic that captures relevant aspects of each individual’s labor force participation and job characteristics for studying the earnings change between periods t and t+1:¹¹

<table>
<thead>
<tr>
<th>Period t-1</th>
<th>Period t</th>
<th>Period t+1</th>
<th>Period t+2</th>
</tr>
</thead>
<tbody>
<tr>
<td>In Labor Force in Period t-1</td>
<td>No Job Change in Period t</td>
<td>No Job Change in Period t+1</td>
<td>In Labor Force in Period t+2</td>
</tr>
<tr>
<td>Not in Labor Force in Period t-1</td>
<td>Job Change in Period t</td>
<td>Job Change in Period t+1</td>
<td>Not in Labor Force in Period t+2</td>
</tr>
</tbody>
</table>

The schematic illustrates two key principles for what follows. First, we need data for the period before and after the period for which we are measuring earnings change, because we can only be sure about certain things happening in a given year by considering years

¹¹ The discussion of timing here is based on one-year earnings growth computations, and thus focused on years “t-1”, “t”, “t+1”, and “t+2”. The same principles hold over longer frequencies, of course, and the notation for the two end periods simply becomes “t+r” and “t+r+1”.
on either side. Second, there are two relevant aspects of the individual’s earnings and job attachment across the four years, so there are a total of sixteen \(2^4\) possible pathways that any given individual can follow. For the variance decomposition that follows we collapse individuals into one of four groups. Stable workers are those who move along the top row only. Entrants and exits are defined by labor force participation in the t-1 and t+2 periods respectively, regardless of whether they changed jobs. The remaining group—job changers—is defined as those who changed jobs in either period across which the earnings change is being measured, conditional on not having entered and exited.

Why do we care about entry and exit? One reason is that the population of individuals moving in and out of the labor force may be inherently more volatile, but there is a more practical concern involving distinguishing part- and full-year workers. Previous work on earnings variability was generally based on pairwise combinations of earnings, and those pairs can be based on any positive earnings or (as in Sabelhaus and Song, 2010) earnings above a pre-set threshold. Therefore, if an individual entered the labor force during the base period (t), they will show up in the sample if their earnings cross the threshold for inclusion, even though they may only be in the labor force part-year. Transitions from part-year (period t) to full-year (period t+1) status should (and do) involve higher average earnings growth and higher average earnings variability. Similarly, if exits during year t+1 are also generally mid-year, we expect to see (and do see) larger declines in earnings between t and t+1, along with a higher variance.

The possibility that part-year earnings might be dramatically affecting average variances motivates our identifying entrants and exits, which requires controlling for
earnings in the year prior to and the year subsequent to the period for computing the earnings change itself. In order to be sure an individual did not enter in period t, we need to check that they had earnings in t-1. The same principle holds for exits, because the lack of earnings in period t+2 suggests they exited during period t+1, the end year for which we are measuring earnings change.

Identifying job changes in period t or period t+1 also involves looking outside the window for which we are computing earnings growth, because we need to check whether a given job identified in a particular period is still observed in the subsequent period in order to decide whether a job change occurred. The Social Security MEF data includes a record for every W2 received by the individual in a given year. Individuals who hold only one job over the course of the year will only receive one (unique) W2, with one associated Employer Identification Number (EIN). Individuals who receive income from multiple jobs in a given year will be issued multiple W2s, and we will observe two or more distinct EINs associated with each earnings stream, but we know nothing about when during the year the earnings were received.

The principle used to identify job changes is very simple. If we observe a given EIN for an individual in a particular year t, but that EIN does not appear again in year t+1, then we say that person left that particular job sometime during year t.12 In the usual transition from one job (at a time) to a different job, we will observe two EINs in the year in which the transition occurred, and only one of those in the subsequent year. In situations where (say) the individual works a full- and a part-time job in a given year,

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12 One key potential bias is still under investigation. Some of the group we identify as job changers are really just individuals working for companies that changed their EINs, which can occur for various tax and/or other legal reasons. In the next version of the paper we will identify and control for false job changes by looking at large groups of individuals who change from one EIN to another en masse.
they will be classified as a job changer if either of those jobs is not observed in the subsequent year.

Figure 5 shows that about 70 percent of individuals with positive earnings have only one EIN in any given year. Another 20 percent have two unique EINs in any given year, about 6 percent have 3 unique EINs, and the remaining 4 percent or so have 4 or more EINs.\textsuperscript{13} There is no obvious trend in the distribution of EIN counts during our sample period, but there is evidence of cyclicality in the distribution, as confirmed in Table 1. The fraction of individuals with only one unique EIN is 69.8 percent during the majority of years in our sample in which average real earnings are rising, and jumps to 72.7 percent in the four years identified above (1991, 2002, 2008, and 2009) during which overall average earnings fell in real terms. This cyclicality in EIN distribution helps motivate the approach to decomposing overall average earnings variability in the next section.

5. Decomposing Variability in Earnings Growth

The schematic showing relevant labor force entry and exit as well as job change activity indicate there are 16 possible paths any given individual can follow over the four periods. In what follows we divide the sample into four groups. The first is the most stable group that does not enter in $t$, exit in $t+1$, or change jobs in either $t$ or $t+1$. For simplicity we refer to that group as “job stayers.” The second group is “job changers,” and they do not enter or exit, but do change jobs (meaning any EIN observed in $t$ is not

\textsuperscript{13} In what follows we identify job changes by focusing on the two EINs in any given year with the highest earnings. Thus, the exact criteria for “no job change” in year $t$ is that both of those EINs (if two exist) continue to be observed in year $t+1.$
observed in t+1, or any EIN observed in t+1 is not observed in t+2). The last two groups are those who enter in t (no earnings in t-1) or exit in t+1 (no earnings in t+2).

Figure 6 shows the sample composition in each year for these four groups. Stable workers account for just over half of the sample in any given year, and there is a clear cyclical (and possibly trend) component, which is not surprising given the observations about the distribution of EIN counts above. Job changes account for about a third of the sample in every year, with exits just over 5 percent and entrants just under 5 percent, on average.

Table 2 shows how composition across the four labor force groups differs between good and bad labor markets, and speaks the point about countercyclical left skewness observed in the data. The share of job stayers rises several percentage points in the four years in our sample during which average real earnings fell, and that is completely accounted for by a decrease in the job changer group, because a modest (relative to the overall population) increase in exits is offset by a modest decrease in entrants. The patterns one sees is that of a labor market shutting down in bad years: job staying increases, inflows decrease, and outflows increase.

The overall average variances shown earlier in the paper are obviously just weighted averages across the four groups, and are thus affected by both within- and across-group (compositional) changes. Figure 7 shows the within group variances for the four labor force groups. The first thing to note about Figure 7 is the scale: the vertical axis goes up to 80 percent in order to accommodate the very large variances for individuals entering and exiting the labor market, both greater than 50 percent. The
average variance for job changers is about 27 percent over the sample period, and for stable workers the average is about 9 percent.

Figure 7 shows the dramatic differences in levels of earnings variability across the four groups, but the scale somewhat obscures differences in trends. All four groups exhibit declining within-group variability over the sample period, but the proportional drop for the job stayers is much larger. Overall average earnings variability fell 6.6 log points between 1988 and 2010, for a decrease of nearly 30 percent. Earnings variability for stable workers fell 4 log points, which is 40 percent of the 1988 level. However, earnings variability of job changers fell 3.7 log points, which is only 12 percent below the 1988 value.

Figure 8 takes the within-group analysis one step further, implementing an overall decomposition for trend variability over time. The top (blue) line is the overall average variance for the entire sample. The second (green) line is the result of removing job changers, the third (red) line is the result of removing entrants, and the fourth (black) line is the result of removing exits, which is the same as the black line for stable workers in Figure 7.

The first important message of Figure 8 is that entry and exit are contributing much more to overall average variability than job changing. Keep in mind that job changing here is conditional on not entering or exiting. The second message ties back to the overall trend in earnings variability discussed above. The fact that the four lines are roughly parallel suggests that within-group decreases for job stayers is the dominant trend. The shift towards more job stayers towards the end of the sample period is also pulling down the overall average variance.
Some of the divergence in trend-variability across the four groups is due to the end point (2010) being a relatively bad labor market, and the data suggest that job staying has risen and within-job earnings variability has fallen, both of which may help explain the countercyclical left skewness of earnings changes observed by Guvenen, Ozkan, and Song (2012). This leads us to conclude with two final questions. First, is there a cyclical component to earnings changes within one or more groups, or is counter-cyclical left-skewness in earnings change attributable to composition? Second, is the recent decrease in overall average earnings variability just a really big cyclical effect, or is there a trend?

Figure 9 shows the fraction of workers in each group experiencing real year over year earnings losses. The experiences of people entering and exiting the labor force confirm the (practical) part-year earnings concern described above: about 75 percent of people exiting during t+1 experience an earnings loss between t and t+1, while only 25 percent of people entering in t experience a loss. The fraction of job stayers and job changers experiencing real earnings losses is (not unexpectedly) below but near 50 percent, and although there is some evidence of increased loss rates in bad labor markets, the differences in levels or trends between job changers and job stayers is not first order.

In terms of countercyclical left-skewness, Figure 9 seems more consistent with a story about changing composition across groups, rather than changes within groups. Increases in the share of exits (whose earnings are falling) and decreases in the share of entrants (whose earnings are rising) may be important contributors to countercyclical left skewness. There is some increase in job loss rates for the job-stayer and job-changer groups that is contributing to the overall shift in the distribution of earnings losses in bad
labor markets, but there is no evidence (based on these simple gain/loss ratios) that a particular process is operating differently on one group versus the other. That is, there is no evidence that job stayers are protected from earnings losses relative to job changers, but the extent of the differences between the groups awaits further investigation for the entire distribution of earnings changes.

Given the extent to which the labor market deteriorated during (and subsequent to) the Great Recession, it is not clear that we will be able to discern trend from cyclical effects using annual data that ends in 2010. Figure 10 provides some evidence that some trend differences in overall average earnings variability may be operative, however. The figure shows job survival rates at frequencies of one, three, and five years. The increase in job staying at high frequencies is consistent with the compositional patterns show in Figure 6 and in Table 2: job staying rises in bad labor markets. But there is also an apparent differential in job staying rates in recent “good” years relative to past “good” years. Job staying went up after the 2001 recession and then stayed higher, with job changing rates never (at least not yet) returning to the boom years of the mid to late 1990s. This pattern seems to hold at three and five year frequencies as well.

The impressions given by Figures 9 and 10 are intriguing, but clearly more rigorous analysis is warranted. The most obvious place to turn is the shapes of the within-group earnings change distributions. In particular, how do the earnings change distributions for job stayers and job changers vary over the business cycle? Are increased exits and decreased entrants a quantitatively important part of countercyclical left-skewness? Finally, are there trend components, or do the most recent data just reflect a really bad labor market?
6. Conclusions and Next Steps

The results presented here are based on preliminary analysis of a new data set currently being developed for analyzing earnings dynamics. The innovations relative to earlier work using administrative earnings data include using employer identification numbers (EINs) to identify job changes, and controlling for labor market entry and exit. Not unexpectedly, the variability of earnings growth for “stable” workers is much lower than the overall sample average, but job changers who do not enter or leave the labor market during the period for which we are measuring earnings change account for a relatively small share of the gap between the overall average and stable workers. Controlling for entry and exit has a much larger impact on average variability estimates.

Much of the overall drop in average earnings variability since the late 1980s is due to a decline in variability for the stable worker group, though variability of earnings growth fell for all groups to some extent. The composition of workers across entry/exit and job-change categories may also help explain the trends and pronounced left skewness of earnings changes in bad labor markets, in part because there is a marked increase in job-staying and exiting, and decrease in entry, when average earnings are falling.

Plans for future work on this project include extending the analysis to the 10 percent MEF data, which will make it possible to control for evolving EINs and allow us to investigate skewness across- and within-job change categories. The estimated labor force and job transitions generated in this analysis will also be benchmarked against employment flows in the Current Population Survey CPS and Census firm-level data. Given the enhanced and validated data, the goal is then evaluating the impact of job and labor market transitions in a permanent versus transitory variance decomposition.
6. References


Appendix: Permanent and Transitory Variance Components

The simple decomposition of labor earnings variability into permanent and transitory components used here begins by subtracting observable earnings determinants ($\beta x_{it}$) and focusing on residual log earnings ($y_{it}$),

(A1) \[ y_{it} = \mu_{it} + \epsilon_{it} \]

where $\mu_{it}$ is the slowly-evolving permanent component of earnings, and $\epsilon_{it}$ is the transitory component. The permanent component evolves over time according to,

(A2) \[ \mu_{it} = \mu_{it-1} + \eta_{it} \]

The usual assumption is that $\epsilon_{it}$ and $\eta_{it}$ are distributed normally with variances $\sigma^2_\epsilon$ and $\sigma^2_\eta$, respectively. Ignoring the observables, the variance of the change in log earnings is,

(A3) \[ \text{var}(y_{t} - y_{t-1}) = \text{var}(\epsilon_{t}) + \text{var}(\epsilon_{t-1}) - 2 \cdot \text{cov}(\epsilon_{t}, \epsilon_{t-1}) + \text{var}(\eta_{t}) \]

In the simplest case where the variances for the permanent shocks are constant across groups and time, this becomes,

(A4) \[ \text{var}(y_{t} - y_{t-1}) = 2 \cdot \sigma^2_\epsilon - 2 \cdot \text{cov}(\epsilon_{t}, \epsilon_{t-1}) + \sigma^2_\eta \]

The key insight from in Carroll (1992) and Carroll and Samwick (1997) is that every expansion of the “gap” over which the variance of the log earnings change is measured adds one permanent component, but the number of transitory components is unchanged. For example, the variance of the two-year change is given by,

(A5) \[ \text{var}(y_{t} - y_{t-2}) = \text{var}(\epsilon_{t}) + \text{var}(\epsilon_{t-2}) - 2 \cdot \text{cov}(\epsilon_{t}, \epsilon_{t-2}) + \text{var}(\eta_{t}) + \text{var}(\eta_{t-1}) \]

Again, in the simplest case where the variances for the permanent shocks are constant across groups and time, this becomes,

(A6) \[ \text{var}(y_{t} - y_{t-2}) = 2 \cdot \sigma^2_\epsilon - 2 \cdot \text{cov}(\epsilon_{t}, \epsilon_{t-2}) + 2 \cdot \sigma^2_\eta \]

Extending the logic to the r-th gap and assuming that the covariance term becomes zero,

(A7) \[ \text{var}(\Delta^r y_{t}) = 2 \cdot \sigma^2_\epsilon + r \cdot \sigma^2_\eta \]

The Carroll (1992) decomposition strategy involves assuming (based on results from empirical autocovariance studies) that the covariance for gaps greater than r=2 are small. Thus, one can run a regression of the variance at each frequency on the length of the gap for observations where r>2, and the slope is the estimate of the permanent shock variance, while the intercept is two-times the transitory shock variance.
Table 1. Counts of Employer Identification Numbers (EINs)

<table>
<thead>
<tr>
<th>Number of EINs</th>
<th>Percent of Sample</th>
<th>Average Earnings Decrease Years</th>
<th>Average Earnings Increase Years</th>
<th>Change Between Year Prior and Earnings Decrease Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>70.3%</td>
<td>72.7%</td>
<td>69.8%</td>
<td>2.3%</td>
</tr>
<tr>
<td>Two</td>
<td>20.0%</td>
<td>19.2%</td>
<td>20.2%</td>
<td>-1.0%</td>
</tr>
<tr>
<td>Three</td>
<td>6.1%</td>
<td>5.3%</td>
<td>6.2%</td>
<td>-0.6%</td>
</tr>
<tr>
<td>Four or More</td>
<td>3.6%</td>
<td>2.7%</td>
<td>3.8%</td>
<td>-0.7%</td>
</tr>
</tbody>
</table>


Table 2. Distribution by Job Change and Entry/Exit Status

<table>
<thead>
<tr>
<th>Job Change and Entry/Exit Status</th>
<th>Percent of Sample</th>
<th>Average Earnings Decrease Years</th>
<th>Average Earnings Increase Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>No entry, exit, or job change</td>
<td>54.2%</td>
<td>57.7%</td>
<td>53.5%</td>
</tr>
<tr>
<td>Exit during t+1</td>
<td>5.6%</td>
<td>6.1%</td>
<td>5.5%</td>
</tr>
<tr>
<td>Enter during t</td>
<td>4.6%</td>
<td>4.0%</td>
<td>4.7%</td>
</tr>
<tr>
<td>Job change period t or t+1</td>
<td>35.6%</td>
<td>32.3%</td>
<td>36.4%</td>
</tr>
</tbody>
</table>

Notes: Sample is all 1% MEF earnings records with positive earnings, 1988 through 2010. Average earnings decrease years are 1991, 2002, 2008, and 2009, and refer to the end period (t+1).
Figure 1. Variance of Change in Real Log Earnings at Various Frequencies

Source: Social Security 1% MEF Data
Figure 1A. Effect of Age and Sex on Variance of Change in Real Log Earnings

Source: Social Security 1% MEF Data

Solid lines repeated from Figure 1. Dashed lines
Figure 2. Variance of Change in Real Log Earnings, Various Base Years

Source: Social Security 1% MEF Data
Figure 2A. Effect of Age and Sex on the Variance of Change in Real Log Earnings

Same as Figure 2, but actual population weights

Source: Social Security 1% MEF Data
Figure 2B. Identifying Transitory and Permanent Innovation Variances


Slopes are estimated variances for permanent innovations: .026 in

Omit r=1,2 from regression because of auto-covariances not accounted for in simple decomposition.

Source: Social Security 1% MEF Data.
Figure 3. Average Percent Change in Real Annual Earnings by Age

- All Years 1988-2010

Source: Social Security 1% MEF Data
Figure 3A. Average Percent Change in Real Annual Earnings by Age, Males

Source: Social Security 1% MEF Data
Figure 3B. Average Percent Change in Real Annual Earnings by Age, Females

Source: Social Security 1% MEF Data
Figure 4. Variance of Percent Change in Real Annual Earnings by Age

Source: Social Security 1% MEF Data
Figure 4A. Variance of Percent Change in Real Annual Earnings by Age, Males

Source: Social Security 1% MEF Data
Figure 4B. Variance of Percent Change in Real Annual Earnings by Age, Females

Source: Social Security 1% MEF Data
Figure 5. Distribution of Workers by Number of Unique EINs
Figure 6. Sample Composition by Job Change and Entry/Exit

- No Changes (Stable Workers)
- Enter in year t
- Exit in year t+1
- Job Change in year t or t+1
Figure 7. Variance of Annual Earnings Growth Across Groups

Source: Social Security 1% MEF Data
Figure 8. Contributions of Various Groups to Var(Annual Earnings Growth)

Source: Social Security 1% MEF Data
Figure 9. Percent Experiencing Real Earnings Loss, by Job Change and Entry/Exit

- No job change or entry/exit (stable workers)
- Enter during year t
- Exit during year t+1
- Change jobs years t or t+1

Source: Social Security 1% MEF Data
Figure 10. Survival Rates (No Job Change) by Base Year

Source: Social Security 1% MEF Data