Great Micro Moderation or Great Risk Shift? The Role of Low Earnings in Differing Trends in Earnings Volatility

Michael D. Carr*and Emily E. Wiemers†

July 30, 2019

Abstract

Trends in earnings volatility appear to differ between survey and administrative data with volatility flat or increasing in survey data but falling in administrative data. This paper uses Survey of Income and Program Participation data linked to administrative earnings histories from the Detailed Earnings Records to investigate the effect of the treatment of low earnings on earnings volatility. We show that when low earnings are treated as is typically done with survey data, volatility is flat or increasing, but when low earnings are treated as is typically done with administrative earnings data, volatility declines.

*Department of Economics, University of Massachusetts Boston. Email: michael.carr@umb.edu

†Department of Public Administration and International Affairs, Syracuse University. Email: eewiemer@syr.edu.

We thank Robert Moffitt and Sisi Zhang and participants in the Washington Center for Equitable Growth Volatility Trends Meeting for their helpful comments. We gratefully acknowledge funding from the Russell Sage Foundation for this project (award #83-15-09).

Evidence from survey and administrative data appear to tell different stories about trends in earnings volatility since the 1980s. Evidence from the Panel Study of Income Dynamics (PSID) suggests that earnings volatility rose substantially during the 1970s and has been highly cyclical since 1980 with declines through the expansion of the 1990s and large increases during the Great Recession. In more recent years, volatility in the PSID appears to be declining toward its 1980 levels (Shin and Solon, 2011; Gottschalk et al., 1994; Moffitt and Gottschalk, 2002, 2012; Celik et al., 2012; Moffitt and Zhang, 2018; Dynan, Elmendorf, and Sichel, 2012; Carr and Wiemers, 2018). Evidence from the Current Population Survey (CPS) and Survey of Income and Program Participation (SIPP) shows flatter trends in volatility than the PSID though with considerable cyclicality (Ziliak, Hardy, and Bollinger, 2011; Dahl, DeLeire, and Schwabish, 2011; Celik et al., 2012). In contrast, evidence from administrative data suggests that as the macro economy has become more stable, so too have earnings at the micro level with declining earnings volatility since 1980 (Sabelhaus and Song, 2009, 2010; Guvenen, Ozkan, and Song, 2014).

While attention has been paid to methodological choices about how to estimate earnings volatility, and the role that zero earnings plays in trends in earnings volatility, comparatively little focus has been paid to the treatment of low earnings. However, when estimating trends in earnings volatility, the typical treatment of low earnings in survey data differs from that in administrative data. Studies using survey data typically trim the lowest and highest percentiles of the earnings distribution in each year, while studies using administrative data typically exclude earnings below a threshold linked to either the minimum earnings to qualify for a covered quarter for Social Security or to the real value of the minimum wage.

In this paper we use Survey of Income and Program Participation data linked to administrative earnings histories from the Detailed Earnings Records (DER) to investigate the effect of choices about the treatment of low earnings on trends in earnings volatility. Our estimates use a single dataset that contains administrative earnings histories drawn from the same universe as typically used in the administrative data literature, but has compositional characteristics of survey data. We estimate trends in earnings volatility under five different assumptions about how to treat low earnings, two of which trim low earnings based on percentile points of the annual earnings distribution and three of which trim low earnings based on the minimum wage or the threshold for coverage by Social Security. We estimate trends in earnings volatility using three measures each of which is directly comparable to other studies: the standard deviation of log earnings changes, the standard deviation of the arc change in earnings, and the spread of percentile points of log earnings changes.

Differences in the treatment of low earnings across studies has the potential to alter the levels and trends in earnings instability for several reasons. First, differences in the treatment of low earnings alter trends in total inequality. Since earnings volatility is a function of earnings inequality, different levels and trends in earnings inequality may yield different levels and trends of earnings volatility. Second, volatility is typically estimated using earnings growth rates and these percent changes can be large at low levels of earnings. Moreover, because administrative earnings data tend to have a higher density of low earnings that may also be growing over time, the treatment of low earnings may be a potentially important source of differences in levels and trends in volatility across studies using survey and administrative data. Using a pooled sample of men and women, Sabelhaus and Song (2010) show that the standard deviation of one-year earnings growth rates is less than half as large when excluding individuals with annual earnings below the threshold required to receive four quarters of coverage towards Social Security, and Guvenen, Ozkan, and Song (2014) and Hardy and Ziliak (2014) both show that volatility is higher at the top and bottom of the earnings distribution than in the middle. But, although the literature is in general agreement that very low earners should be excluded, no one has systematically investigated the impact of differences in the treatment of low earnings on trends over time in earnings volatility.

We show that different choices on the treatment of low earnings produces quite large differences in trends in earnings volatility. Our findings show that when earnings are trimmed in the way that is typically done in studies using survey data, the trends in the SIPP-linked administrative earnings data are similar to those found in other studies using survey data. However, when earnings are trimmed in the way that is typically done by studies using administrative earnings data, the trends in the SIPP-linked administrative earnings are similar to those found in studies using administrative data. Namely, when earnings are trimmed based on percentile points of the earnings distribution, earnings volatility is broadly u-shaped from the 1980s through the Great Recession with volatility trending toward its 1980 level by 2014. When earnings are trimmed using a threshold linked to either the minimum wage or to Social Security qualification, earnings volatility is broadly declining since the 1980s.

While our results are based on only one source of administrative earnings data, they suggest that the differences in trends in the literature may be influenced by choices about the treatment of low earnings. Deciding which method of handling low earnings is more appropriate is beyond the scope of this paper, but, our results show that across all methods of treating low earnings, the majority of individuals excluded from the sample are those who bounce into or out of low earnings, not those who have low earnings in two consecutive periods. This observation implies that all methods of excluding low earners have the effect of excluding individuals who have low earnings because of a negative earnings shock, not just workers who have persistently low attachment to the labor market.

1 Data, Measures, and Sample

The data for this project come from Survey of Income and Program Participation data linked to administrative earnings histories from the Detailed Earnings Records.[1] The SIPP is a nationally representative sample of the civilian noninstitutionalized population of the U.S. that began in 1984. There have been 14 SIPP panels since 1984 with each panel lasting between two and six years. Each panel draws a new nationally representative sample of 14,000 to 52,000 households. SIPP panels after 1990 include a small oversample of low-income geographic areas that increases the number of households in and near poverty by 15% - 20% over what would be observed otherwise. In the SIPP-linked administrative data, each individual in a SIPP household (including both children and adults) in the 1984, and 1990 – 2008 SIPP panels are linked to the DER, which is co-maintained by the SSA and the IRS and contains administrative earnings histories. These administrative earnings records are linked prospectively and retrospectively and contain non top-coded earnings from 1978 - 2014.

Administrative earnings histories are only available for individuals who are successfully matched to the DER. Match rates for these data are generally high. In the panels from the 1980s and 1990s, the match rate was about 80%. In the 2001 panel, the match rate dropped to 47% because many SIPP participants refused to provide Social Security numbers. Beginning with the 2004 panel, the match rate increased to around 90% because individuals were no longer required to provide a Social Security number for their survey data to be linked to

[1] This analysis was first performed using the SIPP Synthetic Beta (SSB) on the Synthetic Data Server housed at Cornell University which is funded by NSF Grant #SES-1042181. These data are public use and may be accessed by researchers outside secure Census facilities. For more information, visit https://www.census.gov/programs-surveys/sipp/methodology/sipp-synthetic-beta-data-product.html. Final results for this paper were obtained from a validation analysis conducted by Census Bureau staff using the SIPP Completed Gold Standard Files and the programs written by these authors and originally run on the SSB. The validation analysis does not imply endorsement by the Census Bureau of any methods, results, opinions, or views presented in this paper. See Benedetto, Stinson, and Abowd (2013) for more information on the creation of these data and how to access them.

their DER records. Data for any given year come from pooling all panels together, so no individual year is affected by the lower match rate in the 2001 panel. Overall, in the pooled data, about 80% of our sample are successfully matched to their respective administrative earnings histories.

The measure of earnings that we use represents total earnings from all FICA-covered and non-FICA covered jobs with a W-2 or Schedule C (self-employment) filing. W-2 earnings are the sum of amounts from Box 1 (Total Wages, Tips, and Bonuses) and Box 12 (earnings deferred to a 401(k) type account). Earnings are not top coded after 1978. These earnings histories are drawn from the same universe of earnings histories–the Master Earnings File– that is used in most other analyses of administrative data, though the sampling frame is potentially different as the SIPP-linked data reflect the sampling procedure of the SIPP.

We pool data from all the panels so each year contains individuals from several SIPP panels. We use years between 1979 and 2014. We include in the sample men age 25 to 59 who are successfully matched to the DER and who have positive earnings in two consecutive years. This yields annual sample sizes between 95,125 and 155,591.

2 Treatment of Low Earnings

Our primary interest is the effect of differences in the treatment of low earnings on trends in earnings volatility. The primary motivation for excluding low earnings in this context is the fact that small absolute changes in earnings for individuals with very low earnings can have an outsized impact on earnings volatility. This problem has been addressed differently across the literature, with users of survey data excluding earnings based on percentile points in the annual earnings distribution and users of administrative data excluding earnings below a threshold linked to either Social Security coverage or the minimum wage. Here we implement multiple versions of each approach.

We consider two approaches to the treatment of low earnings based on percentile points of the annual earnings distribution. When we exclude low earnings based on percentile points, we trim the bottom 1% (P1) and 5% (P5) of positive earnings, respectively, separately by year. This approach to the treatment of low earnings follows that taken by Shin and Solon (2011) who trim the top and bottom 1% of earnings in the PSID. Shin and Solon (2011) trim the bottom 1% of earnings to address the effect of low earnings on earnings volatility and trim the top 1% to address the topcode in earnings in the PSID. Because we do no have any topcoding in earnings in our data, we only exclude the bottom percentiles of earnings. We additionally implement the 5% trim because the first percentile of earnings in our data is quite low relative to that in the PSID (Carr and Wiemers, 2018).

We also consider three approaches to the treatment of low earnings that are not based on percentile points of the earnings distribution. First, we implement an approach analogous to Kopczuk, Saez, and Song (2010) and Debacker et al. (2013) and exclude in each year individuals with real earnings that are below one-quarter of full-time, full-year employment at the minimum wage in 2011.[2] That is, we exclude real earnings below \$3770 in each year in 2011 Personal Consumption Expenditures (PCE) adjusted dollars. We refer to this approach as the \$3770 trim. Second, we implement a different version of excluding low earnings based on the minimum wage that is used in Guvenen, Ozkan, and Song (2014). Here we exclude earnings below one-quarter of full-time, full-year employment at one-half of the minimum wage in each year, a trim that allows the real value of the minimum wage to evolve as observed resulting in a trim that varies in real terms through time. We refer to this approach as the minimum wage trim. Finally, we implement an approach used in Sabelhaus and Song (2009, 2010), which excludes earnings in each year below that needed to have four quarters of credit towards Social Security coverage in that calendar year. The

[2]Kopczuk, Saez, and Song (2010); Debacker et al. (2013) use a similar dollar amount tied to the real value of the minimum wage in 2004.

SSA covered quarters earnings threshold varies by year but is linked to average wages and tends to increase over time in real terms. We refer to this approach as the SSA trim.

The primary difference between these methods is whether the year to year changes in the trim are driven by observed changes in the earnings distribution. When we exclude low earnings based on percentile points, the cut points are determined by the cross-sectional earnings distribution in a given year. When we exclude low earnings based on non-percentile point thresholds, they are not: the $3770 trim is fixed in real dollars through time, the SSA trim increases in real terms through time, and the minimum wage trim increases and decreases in real terms as the minimum wage is adjusted.

3 Methods

We rely on three simple measures of earnings volatility that have previously been used in the literature. First, we follow Shin and Solon (2011) and estimate the standard deviation of the change in log earnings over short time horizons:

$$\text{Vol}_t = \text{SD}(y_{it} - y_{it-\tau}) \tag{1}$$

where y_{it} ($y_{it-\tau}$) is log annual earnings of individual i at time t ($t-\tau$). Following the literature, we age adjust log earnings changes separately by year, reporting the standard deviation of the age-adjusted residuals as our estimate of volatility. Here we use $\tau = 1$ which is consistent with most work using administrative data, while work on the PSID uses $\tau = 2$. This measure of earnings volatility has the benefit of having been estimated frequently in the literature using numerous sources of data and samples.

An alternative measure of volatility uses the standard deviation of the arc change in earnings (Ziliak, Hardy, and Bollinger, 2011; Dahl, DeLeire, and Schwabish, 2011), given in

Equation 2.

$$\text{ArcChange}_t = \text{SD}\left\{\frac{Y_{it} - Y_{it-\tau}}{\frac{|Y_{it}|+|Y_{it-\tau}|}{2}}\right\} \tag{2}$$

where Y_{it} ($Y_{it-\tau}$) is annual earnings of individual i at time t ($t-\tau$) and $\tau = 1$. We age adjust the arc change in earnings separately by year. The arc change method reduces the impact of outlier earnings changes by bounding changes between -2 and 2. Because considering the role of individuals with zero earnings is not the focus of this paper, we exclude men with zero earnings in either t or $t - \tau$, though this measure allows for the inclusion of men with zero earnings in either year.

Finally, we measure earnings instability using the spread of percentile points of the distribution of earnings growth rates. We take the age-adjusted earnings growth rates that we calculate in Equation 1 and, instead of measuring the standard deviation of these growth rates, we measure the spread between the 90th and the 10th percentile of earnings growth rates.

$$9010_t = P90(y_{it} - y_{it-\tau}) - P10(y_{it} - y_{it-\tau}) \tag{3}$$

where y_{it} is log annual earnings of individual i at time t ($t - \tau$) with $\tau = 1$. As with our other measures of volatility, we age adjust log earnings changes separately by year, reporting the 90-10 spread of the age-adjusted residuals as our estimate of volatility. Note that, while the estimated levels of volatility using Equations 1 and 2 are directly comparable, the levels using Equation 3 are not.

3.1 Descriptive Statistics on Alternative Restrictions on Low Earnings

Table 1 shows the value in 2011$ of the threshold below which earnings are excluded for each of our five restrictions on low earnings. Earnings are adjusted for inflation using the PCE

Index. It also shows the distribution in year t of the sample of men age 25 - 59 with positive earnings in t and $t - \tau$ in terms of whether their earnings are above the threshold in both years, below the threshold in both years, or below in t $(t-1)$ and above in $t-1$ (t), which we refer to as "switch."

Table 1 shows that both the first and fifth percentile point cut points generally fall over time as inequality has increased, and, though somewhat difficult to discern in Table 1, the cut point tends to fall during recessions. In contrast, the non-percentile point earnings restrictions are not cyclical and the restriction based on the Social Security earnings qualification threshold rises in real terms over time. The SSA trim includes 97.22% of the men age 25 - 59 with positive earnings in t and $t - \tau$ in 1980, and only 93.66% of these men in 2014. The $3770 trim also increases in bite over time, including 96.28% of the baseline sample in 1980 and a low of 93.82% in 2010. The fraction of the sample included with of the minimum wage trim also decreases over time, but by less than either the SSA or the $3770 trim.

For all of the restrictions, the majority of individuals excluded from the sample are individuals who have earnings above the threshold in one year and below the threshold in the other. With the percentile point trims, the fraction of the excluded sample that "switches" falls slightly over time, while it rises for the non-percentile point trims. This result highlights the fact that trimming not only removes the impact of individuals with persistently low earnings – earnings below the trim in t and $t - \tau$ – but also the transitory instability of individuals who are above the trim in either t or $t - \tau$, but not both.

Table 1 clearly shows the trade-offs in excluding low earnings based on percentile points versus thresholds that are not explicitly tied to the observed distribution of earnings. Excluding low earnings based on percentile points preserves the rise in earnings inequality due to increasing density of low earnings. The real dollar value of percentile-point based exclusion rules declines over time as earnings inequality rises, but this comes at the expense of allowing a larger number of increasingly small earnings to influence estimates of earnings

Table 1: Threshold and Distribution of Sample Under Alternative Restrictions on Low-Earnings

	P1 Trim				P5 Trim			
Year	$ Trim	Above	Below	Switch	$ Trim	Above	Below	Switch
1980	951.30	98.73	0.15	1.12	5693.00	93.64	1.61	4.74
1985	682.80	98.80	0.15	1.05	4359.00	93.84	1.57	4.58
1990	704.70	98.80	0.15	1.05	4523.00	93.88	1.69	4.44
1995	586.90	98.87	0.21	0.93	4272.00	94.03	1.69	4.28
2000	656.80	98.84	0.21	0.95	5110.00	94.02	1.79	4.18
2005	531.20	98.88	0.23	0.89	4270.00	94.16	1.69	4.15
2010	359.00	98.94	0.19	0.88	3285.00	94.29	1.42	4.29
2014	476.30	98.91	0.16	0.93	3831.00	94.33	1.57	4.10
	SSA Trim				$3770 Trim			
Year	$ Trim	Above	Below	Switch	$ Trim	Above	Below	Switch
1980	3166.62	97.22	0.47	2.30	3770.00	96.28	0.73	2.98
1985	3428.44	95.82	0.90	3.29	3770.00	94.62	1.31	4.06
1990	3579.75	95.60	1.03	3.37	3770.00	94.90	1.30	3.80
1995	3719.46	95.05	1.29	3.65	3770.00	94.60	1.47	3.93
2000	4075.55	95.49	1.20	3.32	3770.00	95.48	1.20	3.33
2005	4238.48	94.42	1.59	3.99	3770.00	94.73	1.47	3.81
2010	4621.41	92.91	1.94	5.15	3770.00	93.82	1.58	4.61
2014	4560.81	93.66	1.83	4.51	3770.00	94.41	1.54	4.05
	Min Wage Trim							
Year	$ Trim	Above	Below	Switch				
1980	2200.25	97.93	0.29	0.71				
1985	1820.84	97.46	0.44	1.14				
1990	1700.38	97.75	0.36	0.86				
1995	1630.96	97.52	0.50	0.96				
2000	1749.09	97.70	0.47	0.87				
2005	1542.21	97.48	0.56	0.94				
2010	1944.50	96.36	0.76	1.32				
2014	1791.07	96.92	0.62	1.29				

Author's calculations using SIPP linked data for selected years from 1980 to 2014. "Above" is above the threshold in t and $t-1$. "Below" is below threshold in t and $t-1$. "Switch" is above (below) threshold in t and below (above) in $t-1$. Shares are out of untrimmed volatility sample. Dollars are in 2011$ using PCE.

volatility. Excluding low earnings based on thresholds linked to either the minimum wage or Social Security eligibility does not preserve the observed increase in inequality that comes from an increasing density of low earnings, but also does not allow the increasingly large number of small earnings to drive trends in earnings volatility. Neither the SSA nor the minimum wage trim are fixed through time, and so also vary through time in the extent to which low earnings may influence volatility. Of course, the overwhelming majority of men age 25 to 59 with positive earnings in years t and $t - \tau$ are included in all of the trims. In the next section we investigate the extent to which these differences in the treatment of low earnings influence levels and trends in volatility.

4 Results

4.1 Volatility in Untrimmed Earnings

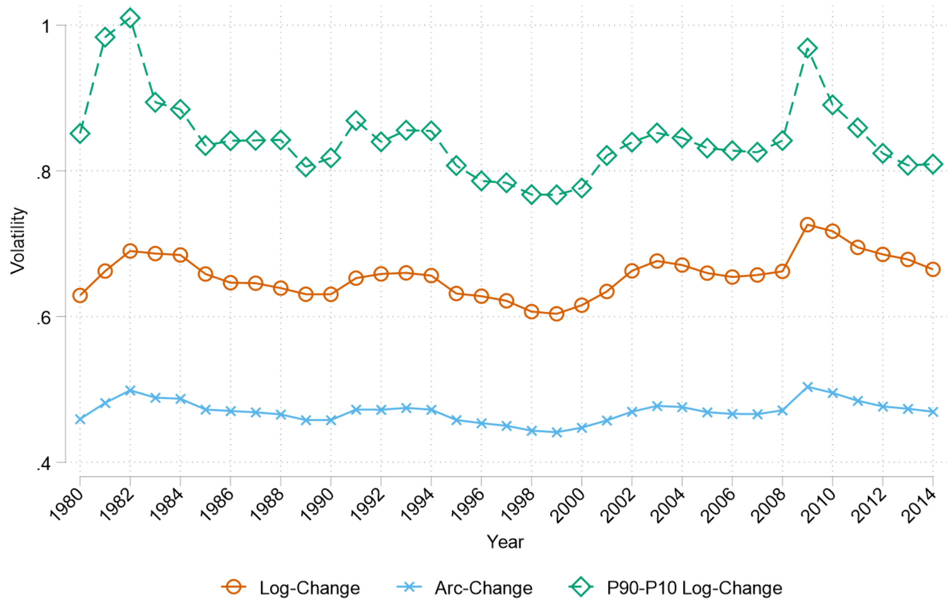
We begin by showing volatility of total untrimmed earnings in Figure 1a, using each of our three measures of volatility. Figure 1b shows the same series where the levels of volatility are normalized to equal 1 in 1980. This normalization facilitates an easier comparison of trends over time across methods. These figures set a baseline against which we can assess the impact of each trimming method. We are unaware of any analysis using administrative data that presents untrimmed results for men alone, so we cannot assess how our untrimmed results compare to other estimates using administrative data.[3]

Figure 1a shows that the level of volatility is lower using the arc change than the log change and lower using the log change than the P90 - P10 spread. Figure 1b shows clear similarities in the trends over time with all three series showing declining volatility from 1982 to 1998, increasing volatility from 1998 to 2009 and declining volatility thereafter. With all

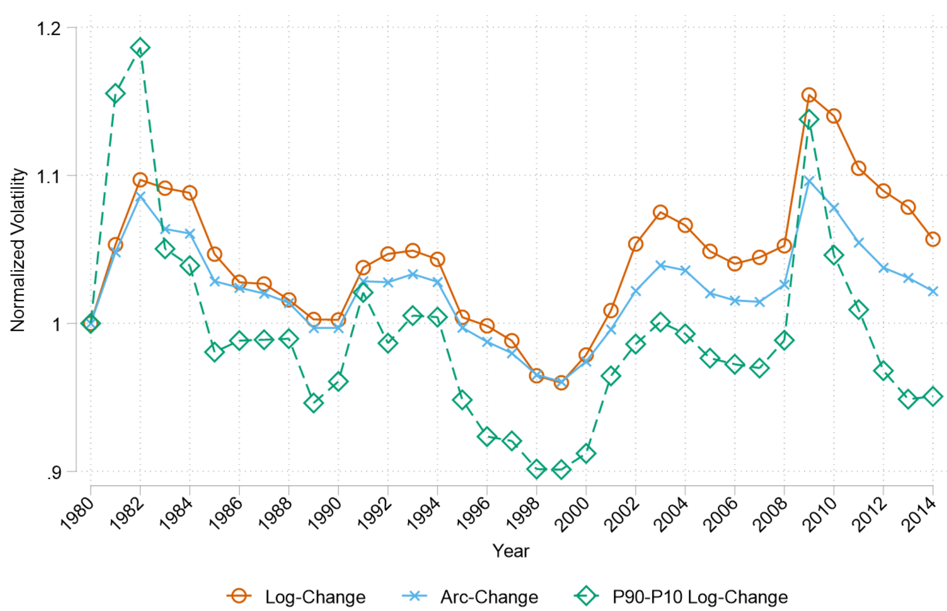
[3]As noted above, Sabelhaus and Song (2010) show trimmed and untrimmed estimates, but they pool men and women together. Ziliak, Hardy, and Bollinger (2011) show that, in survey data, trends in volatility differ between men and women.

Figure 1: Untrimmed Volatility

(a) Volatility by Method



(b) Normalized Volatility by Method



Author's calculations using SIPP linked data for 1980 to 2014. Figure a shows the level of volatility using the three measures described in section 3 while figure b shows these trends normalized to equal 1 in 1980.

three methods, volatility in 2014 is within 6% of its 1980 level. The change in volatility over time is the largest for the log earnings change measure, where volatility increases by 6%, and the smallest for the 90-10 spread where volatility declines by about 5%. In only the 90-10 spread measure is the level of volatility in 2014 lower than in 1980. However, the 90-10 measure shows the largest relative decline from the peak in 1983 to the low in 1999, and the largest relative increase from 1999 to 2009, suggesting a higher degree of sensitivity to both secular trends and cyclical changes.

Because Figures 1a and 1b use the same sample and do not restrict low earnings, the small differences in trends of volatility across these three measures is the result of the part of the distribution of earnings changes that each measure weights most heavily. Volatility in log earnings changes allows for a larger role for large percent changes, which are more likely among those with low earnings. The arc change measure is less heavily weighted toward large changes because percent changes are bounded between -2 and 2. The percentile point measure uses only the tails of the distribution of earnings changes. While this reduces sensitivity to outliers earnings changes, it also introduces the possibility that volatility is based on earnings changes that do not represent the full earnings distribution, since large changes (both positive and negative) may be more likely to come from low or high earnings, and less likely to come from the middle of the earnings distribution.

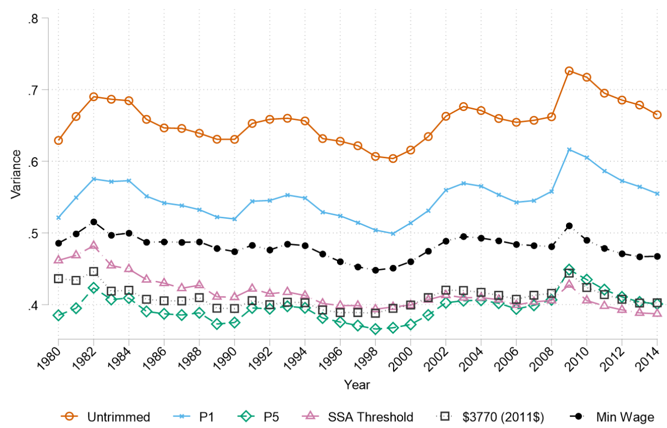
4.2 Volatility under Alternative Restrictions on Low Earnings

Figure 2 shows trends in volatility for each of the three methods using untrimmed earnings and using each of our five alternative restrictions on low earnings. Figure 3 shows these trends normalized to equal one in 1980.

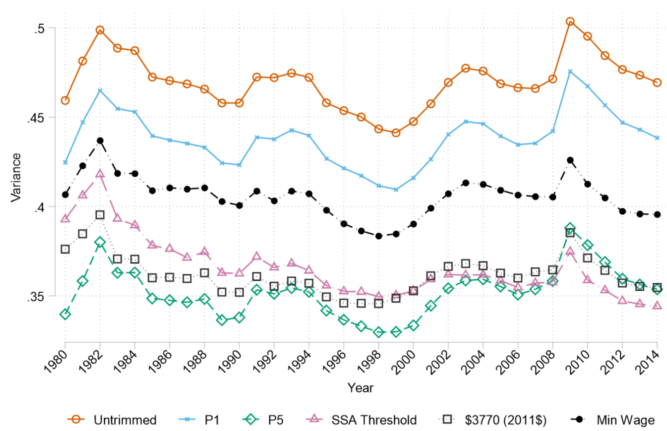
Starting with restrictions on low earnings based on percentile points, Figure 2 shows that for each measure of volatility, the level of volatility declines as a greater number of low earners are excluded from the sample. For the log earnings change method, Figure 2a

Figure 2: Volatility by Method and Trim

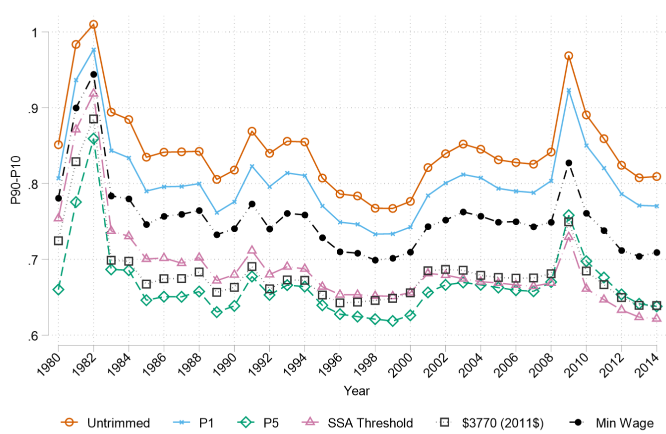
(a) Log Change



(b) Arc Percent Change



(c) P90-P10 Spread of Log Change



Author's calculations using SIPP linked data for 1980 to 2014.

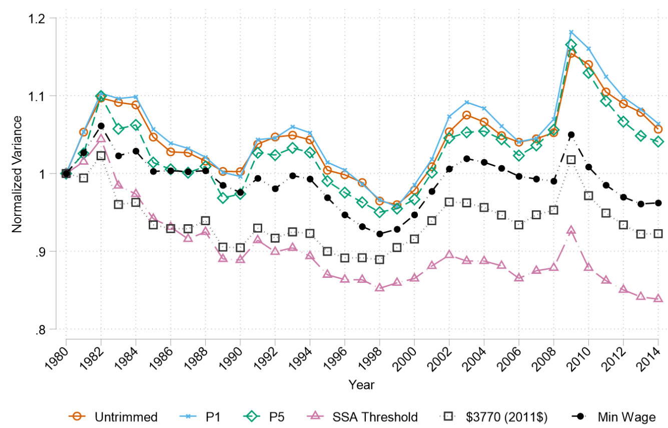
shows that excluding earnings below the first percentile decreases volatility by roughly 20% compared with volatility of the untrimmed earnings distribution, and excluding earnings below the fifth percentile again decreases the level of volatility by around 20% relative to the first percentile restriction. Figure 3a shows that these alternative restrictions for treating low earnings leave the overall trend largely unchanged. Figure 3a shows that using the untrimmed earnings distribution or excluding either earnings below the first or fifth percentiles, results in a 5% to 6% increase in volatility since 1980. In sum, trimming on percentile points of the earnings distribution alters the level of volatility in log earnings changes, but has little impact on the trend. Trimming on percentile points also results in a trend in volatility in log earnings changes that is qualitatively similar to that seen in the PSID when the PSID is also trimmed on annual percentile points (Carr and Wiemers, 2016; Shin and Solon, 2011; Carr and Wiemers, 2018).

For the two other measures of volatility that we consider, Figures 2b and 2c show that excluding a larger number of low earnings also reduces the level of volatility, but Figures 3b and 3c show that the trends in volatility in the untrimmed data are preserved when we exclude the bottom 1% and 5% of earnings. The arc change measure results in lower levels of volatility relative to the log earnings change method but still yields a 5% to 6% increase in volatility over the period using untrimmed earnings and when excluding the bottom 1% and 5% of earnings. Estimating volatility using the 90-10 method results in a decline in volatility of about 4% over the entire period. However, this decline is consistent when using the untrimmed earnings distribution and each of the percentile-point based restrictions on low earnings.

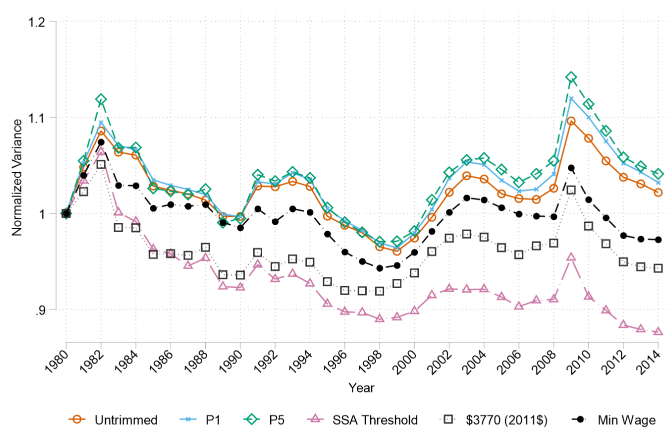
When earnings are excluded based on minimum wage or Social Security eligibility thresholds, both the level and the trends in volatility change relative to trends in the untrimmed earnings distribution. Starting with the log earnings change measure in Figure 3a, excluding individuals with earnings below a threshold based on Social Security eligibility results in

Figure 3: Normalized Volatility by Method and Trim

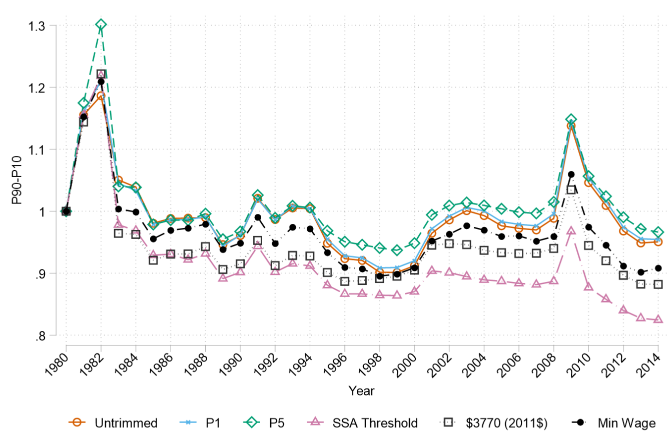
(a) Normalized Log Change



(b) Normalized Arc Percent Change



(c) Normalized P90-P10 Spread of Log Change



Author's calculations using SIPP linked data for 1980 to 2014.

volatility falling by about 17% since 1980. Excluding individuals with earnings below $3770 results in volatility falling about 9% since 1980 and excluding earnings using the annual minimum wage threshold results in volatility falling about 5%.[4] When using the arc change measure there are declines in earnings volatility of similar magnitudes for each of the non-percentile point earnings exclusions. Using the 90-10 spread in log earnings changes as a measure of volatility results in larger declines in earning volatility, but again the declines are largest when using a non-percentile point earnings exclusion.

Figures 2 and 3 point to three important features of estimating volatility. First, it is possible for a single source of administrative earnings data to produce different trends in volatility simply by changing how low earnings are treated. These differences in trends come from differences in how the treatment of low earnings binds on the earnings distribution over time, and the different levels and/or trends in volatility among low earners. This result implies that direct comparison of existing estimates of volatility in administrative and survey data is impossible because of systematic variation in the treatment of low earnings across studies. Second, the level of volatility is sensitive to how the earnings distribution is trimmed. This observation is consistent with Hardy and Ziliak (2014) and Guvenen, Ozkan, and Song (2014) who show that earnings volatility is higher at the tails of the earnings distribution. Third, the method used to calculate volatility may interact with the method used to exclude low earners. Volatility based on the spread of the distribution of earnings changes is more likely to yield declining volatility after 1980, which, if combined with a non-percentile point method of excluding low earnings would reinforce declines in volatility.

[4]The level of volatility in log earnings changes in Figure 2 when trimming using one-quarter of full-time, full-year employment at one-half of the minimum wage is about 15% lower in our sample than in Guvenen, Ozkan, and Song (2014), but the slight downward trend found here is qualitatively similar to their results.

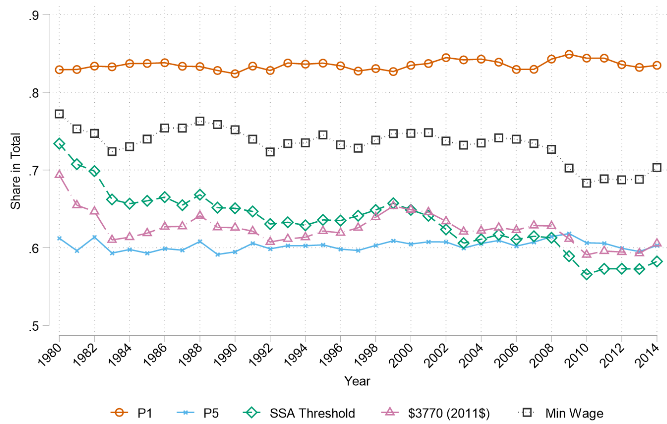
4.3 Reductions in Volatility under Alternative Restrictions on Low Earnings

An alternative method for illustrating how trends in volatility vary across different restrictions on low earnings is to calculate the fraction of untrimmed earnings volatility captured by each method in each year for each of our five restrictions on low earnings. We use this way of understanding the trends in volatility rather than a variance decomposition method because the 90-10 spread in log earnings changes in earnings is not decomposable in the same way as a variance. However, the logic behind the measure we use is the same: for each measure, we calculate how much of the volatility in the untrimmed earnings distribution is accounted for with each of our five alternative restrictions on low earnings by dividing volatility under each earnings restriction by untrimmed volatility for each year. This exercise produces results for the log earnings change and arc change methods that are nearly identical to a variance decomposition model because, as Table 1 shows, the subsample above the trim is a large percent of the untrimmed sample. Figure 4 shows the result of this calculation.

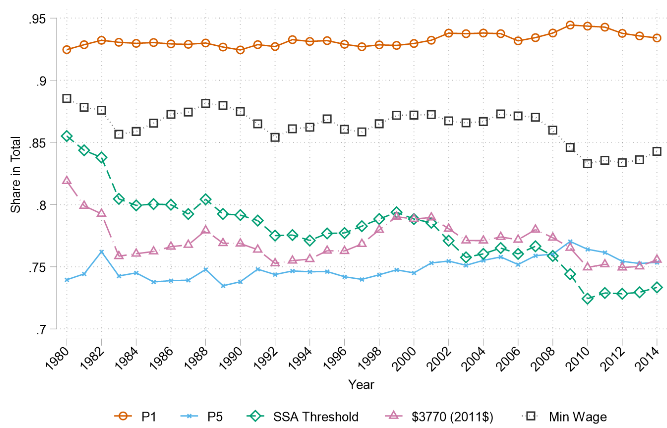
Figure 4 shows two consistent trends across the three methods of calculating volatility. For each method, the percentile-point restrictions on low earnings represent a constant fraction of total volatility over time. The exclusion of earnings below the 1st percentile of the earnings distribution captures between 80% and 95% of the volatility in untrimmed earnings depending on the method of calculating volatility, while the exclusion of earnings below the 5th percentile of the earnings distribution captures between 60% and 80% of volatility in untrimmed earnings across methods. But in each case, the percent of volatility captured is constant over time. In contrast, the restrictions on low earnings that are based on minimum wage thresholds or Social Security eligibility exclude an increasing fraction of total earnings volatility over time. For example, when we measure volatility in log-earnings changes, the SSA trim captures 75% of total volatility in 1980 but 58% of total volatility in 2014. The min-

Figure 4: Shares

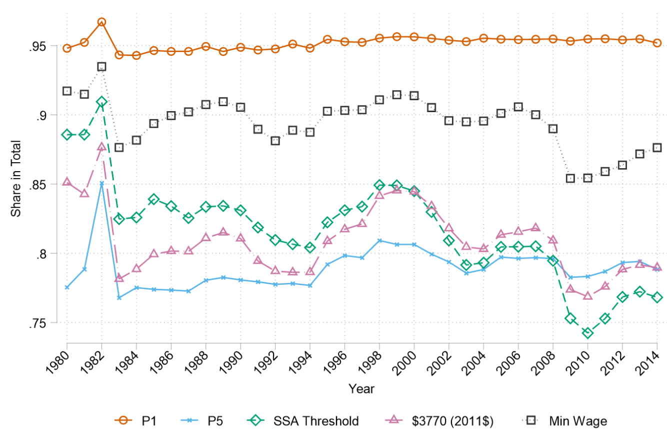
(a) Log Change



(b) Arc Percent Change



(c) P90-P10 of Log Change



Author's calculations using SIPP linked data for 1980 to 2014. Figures display volatility for each trim divided by volatility for untrimmed earnings, separately by method.

imum wage trim, which excludes a smaller and more stable fraction of the sample, captures 78% of volatility in 1980 falling to 70% in 2014. These trends are consistent across methods, though the 90-10 methods shows considerably more cyclicality in the share of volatility captured by each non-percentile point trim. In particular, the share of volatility captured during the Great Recession using the 90-10 method dips for each of the non-percentile point trims.

5 Conclusion

Our results show that the same set of administrative earnings data can show distinctly different trends in volatility simply by changing how low earnings are treated. Using the percentile point restrictions on low earnings, common in the literature estimating volatility on survey data, we find that earnings volatility declines from 1980 to the mid-1990s, increases through 2009, and falls through 2014. Whether the level of volatility is higher in 2014 than in 1980 depends on the measure of volatility that we use, but all three measures show a u-shape in earnings volatility between 1982 and 2009 with volatility in 2014 within 6% of its level in 1980. In contrast, using restrictions on low earnings based on minimum wages or Social Security earnings eligibility that are common in the literature using administrative data, we find declining earnings volatility regardless of the measure used, though declines are larger using the 90-10 measure of volatility than when volatility is measured with the standard deviation of log changes or arc changes. We further show that the decline in earnings volatility using non-percentile point trims is the result of these restrictions capturing a decreasing fraction of individuals and total earnings volatility over time. This is due to earnings restrictions that either increase in real dollars, as is the case with the restriction based on Social Security eligibility, or remain constant over time in real dollars as with the $3770 trim, while the density of low earnings increases.

The results have several implications. The first is that basic decisions about samples may explain some of the discrepancies in the literature on trends in earnings instability estimated with survey and administrative data. Because administrative data contain a larger density of low earners, differences in the treatment of low earners is likely to be particularly important in these data. However, we have only investigated the sensitivity of trends in volatility to the treatment of low earnings in one administrative data set. We encourage authors to explore the sensitivity of results using other administrative data to the treatment of low earnings, especially those investigating short-run outcomes such as transitory instability. Although earnings histories used here are drawn from the same universe of earnings as many other estimates of volatility, differences in sampling procedures across extracts from the Master Earnings File may influence trends in volatility. That said, our estimates are quite similar to other estimates of volatility using earnings from the Master Earnings File when similar methods and samples are used (Guvenen, Ozkan, and Song, 2014).

Second, while alternative rules for excluding low earnings have a similar impact on trends in earnings volatility for each of the three measures of volatility we consider, overall levels and trends in volatility vary by the measure of volatility. In particular, the 90-10 spread in log earnings changes as a measure of earnings volatility exhibits larger relative cyclical swings than the other two measures. As a result, relative to peak volatility in 2009, it declines more through 2014 and is thus more likely to show declines in earnings volatility over time across all trims.

Third, our results show that the number of people with very low earnings is increasing over time, even among prime-age men, and point to high levels of earnings volatility among individuals with low earnings in at least one year. It is unknown whether this increase in the number of men with low earnings is a “real” phenomenon. It is also not known whether earnings levels are persistently low but sometimes above a given earnings cut point, or whether this trend reflects a rising prevalence of large but transitory downward earnings shocks, even in non-recession years. The growing number of prime-age men with low earnings is consistent with declining and less stable labor force participation among prime age men. But, it may also be the result of changes in the extent to which earnings are reported to the federal government; perhaps there has been an increase in under-the-table earnings over time or an increase in small amounts of earnings reported to the IRS among workers who in the past may have had only under-the-table earnings. Because men with low earnings in at least one of two years appear to have high levels of earnings instability, further investigation of this group is warranted.

Finally, the results imply that volatility has indeed been declining for the majority of men. In one sense, this represents a decline in earnings "risk." But, inequality has grown substantially since 1980. This growth in inequality must come from either rising transitory earnings instability or rising permanent earnings inequality. We have shown that the level of transitory earnings instability is falling for most men which implies that rising inequality has come from increases in permanent earnings inequality. These results suggest that the main "risk" that most workers face comes in the form of their place in the permanent earnings distribution rather than in the transitory earnings shocks that they face. All told the results imply that, from the perspective of micro earnings volatility, the picture is more nuanced than the monikers of Great Micro Moderation or Great Risk Shift would suggest.

References

Benedetto, Gary, Martha H Stinson, and John M Abowd. 2013. "The Creation and Use of the SIPP Synthetic Beta." US Census Bureau.

Carr, Michael D. and Emily E. Wiemers. 2016. "Recent Trends in the Variability of Men's Earnings: Evidence from Administrative and Survey Data." *University of Massachusetts Boston Working Paper* .

———. 2018. "New Evidence on Earnings Volatility in Survey and Administrative Data." *American Economic Review Papers and Proceedings* 108.

Celik, Sule, Chinhui Juhn, Kristin McCue, and Jesse Thompson. 2012. "Recent trends in earnings volatility: evidence from survey and administrative data." *BE Journal of Economic Analysis & Policy* 12 (2):1–26.

Dahl, Molly, Thomas DeLeire, and Jonathan A Schwabish. 2011. "Estimates of Year-to-Year Volatility in Earnings and in Household Incomes from Administrative, Survey, and Matched Data." *Journal of Human Resources* 46 (4):750–774.

Debacker, Jason, Bradley Heim, Vasia Panousi, Shanthi Ramnath, and Ivan Vidangos. 2013. "Rising Inequality: Transitory or Persistent? New Evidence from a Panel of U.S. Tax Returns." *Brookings Papers on Economic Activity* Spring.

Dynan, Karen, Douglas Elmendorf, and Daniel Sichel. 2012. "The evolution of household income volatility." *The BE Journal of Economic Analysis & Policy* 12 (2).

Gottschalk, Peter, Robert Moffitt, Lawrence F Katz, and William T Dickens. 1994. "The Growth of Earnings Instability in the US Labor Market." *Brookings Papers on Economic Activity* 1994 (2):217–272.

Guvenen, Fatih, Serdar Ozkan, and Jae Song. 2014. "The Nature of Countercyclical Income Risk." *Journal of Polical Economy* 22 (3):621–660.

Hardy, Bradley and James P Ziliak. 2014. "Decomposing Trends In Income Volatility: The "Wild Ride" At The Top And Bottom." *Economic Inquiry* 52 (1):459–476.

Kopczuk, Wojciech, Emmanuel Saez, and Jae Song. 2010. "Earnings Inequality and Mobility in the United States: Evidence from Social Security Data Since 1937." *Quarterly Journal of Economics* 125 (1):91–128.

Moffitt, Robert and Sisi Zhang. 2018. "Income Volatility and the PSID: Past Research and New Results." *American Economic Review Papers and Proceedings* 108.

Moffitt, Robert A and Peter Gottschalk. 2002. "Trends in the Transitory Variance of Earnings in the United States." *Economic Journal* 112 (478):C68–C73.

———. 2012. "Trends in the Transitory Variance of Male Earnings Methods and Evidence." *Journal of Human Resources* 47 (1):204–236.

Sabelhaus, John and Jae Song. 2009. "Earnings Volatility Across Groups and Time." *National Tax Journal* 2 (62):347–364.

———. 2010. "The Great Moderation in Micro Labor Earnings." *Journal of Monetary Economics* 57.

Shin, Donggyun and Gary Solon. 2011. "Trends in Men's Earnings Volatility: What does the Panel Study of Income Dynamics Show?" *Journal of Public Economics* 95 (7):973–982.

Ziliak, James P, Bradley Hardy, and Christopher Bollinger. 2011. "Earnings Volatility in America: Evidence from Matched CPS." *Labour Economics* 18 (6):742–754.