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Trends in Earnings Volatility Using Linked Administrative and Survey Data

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ABSTRACT
We document trends in earnings volatility separately by gender using unique linked survey data from the CPS ASEC and Social Security earnings records for the tax years spanning 1995–2015. The exact data link permits us to focus on differences in measured volatility from earnings nonresponse, survey attrition, and measurement between survey and administrative earnings data reports, while holding constant the sampling frame. Our results for both men and women suggest that the level and trend in volatility is similar in the survey and administrative data, showing substantial business-cycle sensitivity among men but no overall trend among continuous workers, while women demonstrate no change in earnings volatility over the business cycle but a declining trend. A substantive difference emerges with the inclusion of imputed earnings among survey nonrespondents, suggesting that users of the ASEC drop earnings nonrespondents.

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Attrition; Business cycle; Nonresponse; Nonworkers

1. Introduction

Understanding the level and trend of earnings volatility is important both in its own right, and because of its potential contribution to rising inequality (Gottschalk and Moffitt 2009). Much of what we know about volatility in the United States has come from survey data, which is generally advantageous because it offers a broad collection of variables, a long time series, population representativeness, and widespread availability to the research community. However, survey data suffers from data quality issues such as nonresponse and measurement error, the latter of which may include response error or survey reporting policy such as topcoding (Mellow and Sider 1983; Lillard, Smith, and Welch 1986; Bollinger 1998; Bound, Brown, and Mathiowetz 2001; Roemer 2002; Hirsch and Schumacher 2004; Meijer, Rohwedder, and Wansbeek 2012; Bollinger et al. 2019). More recently, some scholars have turned to administrative data to examine volatility on the belief that it avoids some of the pitfalls of surveys (Sabelhaus and Song 2010; Bloom et al. 2018; Carr and Wiemers 2018). However, the assumption that administrative data serve as a so-called gold standard has been challenged by some (Kapteyn and Ypma 2007; Abowd and Stinson 2013), and the populations covered between the survey and administrative samples are often quite different. Indeed, as discussed in the accompanying Overview paper in this volume, the current literature has reached differing conclusions on the trend in earnings volatility in comparing survey-alone to administrative-alone estimates. It is difficult to know how much of the difference in trends is due to measurement between survey and administrative reports, as opposed to differences in samples.

In this article we offer new estimates and a direct comparison of volatility trends in survey and administrative data by using restricted-access survey data from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) linked to the same individuals in the Social Security Administration's Detailed Earnings Record (SSA DER) for the period spanning calendar years 1995–2015. The ASEC is a large, nationally representative survey that serves as the source of official statistics on poverty and inequality, and is the workhorse dataset for research on earnings determinants. The DER reflects earnings reports provided by employers and the self-employed for purposes of payroll taxation and eligibility for Social Security retirement and disability programs. While the ASEC is used primarily for repeated cross-sectional analyses, its rotating survey design permits matching a subsample of respondents from one year to the next, and thus can be used to construct simple measures of volatility as utilized in a number of prior studies (Gittleman and Joyce 1996; Cameron and Tracy 1998; Ziliak, Hardy, and Bollinger 2011; Celik et al. 2012; Koo 2016). The consensus on the ASEC-based papers was a strong increase in male earnings volatility in the 1970s, peaking in the 1980s, and stabilizing at that higher level thereafter until the Great Recession. The few papers on women find a very different pattern of a trend decline in volatility since the 1970s. The key advance of this paper over the prior ASEC literature is our exact link to the DER, permitting us to focus on differences in volatility trends emanating from measurement between survey and administrative data while holding constant any differences due to sample frames.

We begin with a baseline sample of men and women who report positive earnings in each of two consecutive years in the

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ASEC and who have a valid link to the DER in both years. This sample offers the most direct comparison of survey and administrative estimates of volatility. We then sequentially relax a number of assumptions from the baseline sample. First, we test whether volatility estimates differ in survey and administrative data with the inclusion of zero earnings, which could emanate because people are true nonworkers and thus have no earnings in either the ASEC or DER, or because some report zero earnings to the tax authorities but report positive values to the survey representative, or vice versa (Ziliak, Hardy, and Bollinger 2011; Koo 2016). Next, because imputation of missing earnings reports in the ASEC is high and has been rising over time, and previous work has shown that inclusion of such imputations can lead to significant bias in estimates of earnings inequality and regression coefficients (Hirsch and Schumacher 2004; Hokayem, Bollinger, and Ziliak 2015; Bollinger et al. 2019), we relax the requirement that ASEC participants report their earnings on the survey. The third measurement test we conduct is whether requiring the administrative data link leads to a nonrepresentative sample of the underlying population and thus possible biased estimates of volatility. Finally, because the ASEC does not follow movers from one wave to the next, we test for potential attrition bias in our ASEC volatility estimates. The supplementary materials contain further robustness checks beyond those reported herein.

Our results for both men and women show that the level and trend in volatility is similar in the ASEC and DER, suggesting no bias from use of survey reports for earnings volatility research in the ASEC. Qualitatively, we find substantial business-cycle sensitivity among men, especially during the Great Recession, but no cyclical response among women. This corroborates the prior work in Ziliak, Hardy, and Bollinger (2011) and Koo (2016), but with the longer sample period we find that the increase in male earnings volatility in the Great Recession was temporary and the level fully returned to that from two decades prior, while women continue their secular decline in earnings volatility. We do find rising male earnings volatility among men when we include persons with zero earnings, but again no substantive difference between survey and administrative data. Moreover, the volatility levels of attriters exceeds that of nonattriters, but there are no differences in trends. The one area where survey volatility estimates depart from the administrative data is when we include earnings imputations in the ASEC. This results in substantially higher levels of volatility, and an increasing trend among men, adding further evidence on the need to drop imputed values from earnings research in the ASEC.

2. Measuring Volatility

We adopt a summary measure of earnings volatility as the variance of the arc percent change, defined as

$$\mathrm{varc}_t = \mathrm{var}\left(\frac{y_{it} - y_{it-1}}{\bar{y}_i}\right) \tag{1}$$

where $\bar{y}_i$ is the average (absolute value) earnings across adjacent years, $\bar{y}_i = \frac{y_{it}+y_{it-1}}{2}$ (Ziliak, Hardy, and Bollinger 2011; Dynan, Elmendorf, and Sichel 2012; Koo 2016). Because earnings volatility can be affected by life-cycle factors (Gottschalk et al. 1994), we first regress the arc percent change on a quadratic in age year-by-year and then use the estimated residuals in Equation (1) prior to constructing the variance.

The advantages of the arc percent measure are 2-fold. First, it is bounded between ± 200%, easing interpretation. Second, the arc percent change can also be calculated if one of the earnings observations is zero, which is not possible using other common volatility measures such as the variance of the change in log earnings (Shin and Solon 2011; Moffitt and Zhang 2018). The latter restriction could be important because as highlighted recently in Blundell et al. (2018) and Abraham and Kearney (2020), employment rates have declined for men for the past 40 years, especially for low skilled males, while employment for women has declined since the peak in the late 1990s. Hence, a larger proportion of earners will have zero earnings in some years, and removing these earners likely understates true earnings volatility levels. Whether movements in and out of the labor force contribute to trends in volatility depends on whether those transitions are trending upward. Moreover, a loose attachment to the labor force may lead to misreporting of earnings in survey data, or may lead to missing earnings from uncovered or informal labor markets. Both of these factors could contribute to differences in the earnings volatility measures between survey and administrative data. However, as we demonstrate in the supplementary materials, using the difference in logs yields similar estimates as the arc percent change measure once we omit those with zero or negative earnings from the arc percent.

The data used in estimating Equation (1) are restricted-access ASEC person records linked to the DER for survey years 1996–2016 (reporting earnings for tax years 1995–2015). Our sample consists of men and women between the ages of 25 and 59 who are not full-time students in any year or that have their entire ASEC supplement allocated. Some individuals respond to the monthly core of the CPS, but are unwilling or unable to provide a response to the ASEC supplement. For these cases, Census uses a sequential hot-deck procedure to replace the individual's entire ASEC supplement with a donor's supplement (called a whole imputation). During our sample period, roughly 12% of individuals had their entire ASEC imputed and so we drop these individuals, though we explicitly adjust for this in some of our analyses below. Following the practice of the other volatility papers in this volume, we trim the top and bottom 1% of the real annual cross-sectional ASEC and DER earnings distributions prior to estimating the age-adjusted arc percent change. In the online supplement, we also present baseline estimates with a 5% trim, without trimming as advocated in Bollinger and Chandra (2005), and using volatility not adjusted for age, and find none of these alternatives to affect our estimated trends in volatility. That supplement also provides additional details on the ASEC-DER linkage process, and how we construct the two-year panels.

3. Results

The baseline sample are those men and women who have positive earnings in both years and in both the ASEC and DER, are respondents to the ASEC earnings questions and thus do not have imputed earnings, and have a link to the DER. We refer to this group as the linked respondent sample. The linked

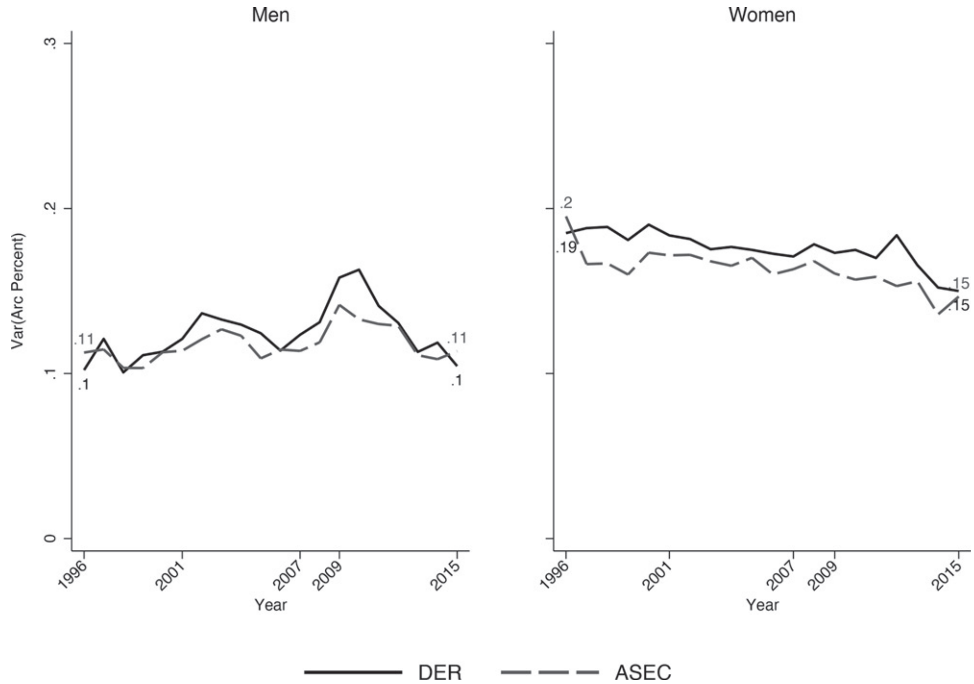

Figure 1. Trends in Earnings Volatility. The series in the figure are the variance of the arc percent change in earnings. The sample is linked respondents with positive earnings in both years. Sources: U.S. Census Bureau, Current Population Survey, 1996–2016 Annual Social and Economic Supplement; Social Security Administration, Detailed Earnings Record, 1995–2015.

respondent sample is intentionally restrictive because we wish to conduct a direct comparison of volatility estimates from survey data against administrative data with a sample and measure as similar as possible. We then broaden the sample in stages. First, we expand the sample to include those who have zero earnings in one of the two years. Second, we include those who did not respond to the ASEC earnings questions in one or both years and thus have imputed earnings, but still requiring the DER linkage in both years. Third, we then expand the sample further by including those who did not have a link. Finally, we include those who were missing from the ASEC in the second year because of attrition and examine DER volatility in that sample. The online supplement contains summary statistics for the baseline sample as well as for the other samples used in the analysis.

Figure 1 presents the baseline series of earnings volatility, with men on the left panel and women on the right panel. In addition to the first year and last year depicted on the x-axis of each panel, we also highlight the recessionary year of 2001 and the Great Recession years of 2007–2009. There is a notable uptick in male earnings volatility in the years surrounding recessions, especially the Great Recession, but there was a return to prerecession levels in the subsequent recovery. Thus, male earnings volatility among continuous workers over the last two decades is largely a business-cycle effect with no trend increase or decrease. Moreover, while there is a somewhat heightened cyclical sensitivity in the DER compared to the ASEC, there is no substantive discrepancy between the survey and administrative data in the overall level and trend.

The right panel of Figure 1 shows that women's earnings volatility differs from men's in the level, trend, and cyclicality. Women have higher levels of earnings volatility in each corresponding year compared to men, but because there is a trend decline, women's volatility is converging toward those levels found among men. The other important contrast with men is the lack of business-cycle induced volatility of women's earnings. Importantly, though, similar to men we find no substantive difference in women's earnings volatility whether we measure it in the ASEC or the DER.

3.1. Volatility with Zero Earnings

One of the aims of this research is to capture a broad measure of volatility in the labor market, including the impact of movements in and out of employment across years. The arc percent measure of volatility accommodates zero earnings in one of the two years, and as such our first robustness check on the baseline volatility estimates in Figure 1 is to relax the requirement of positive earnings in both years. The ASEC records zero earnings based on self-reports, but if the person does not work in a given year they do not receive a W-2 or 1099 tax form and do not show up in the DER. Thus, for those persons who have a link to the DER in one year, but are missing the DER in the year before or after, then we set that missing DER value to zero prior to constructing the arc percent volatility. This treats the ASEC and DER symmetrically.

Figure 2 repeats the analysis of Figure 1 but now includes those periods with zero earnings. There are several notable differences. First, for both men and women the level of volatility in any given year is at least double that in Figure 1 with zeros excluded. Second, the cyclical sensitivity of male earnings volatility is much more pronounced, especially in the years surrounding the Great Recession, and there is now some evidence of cyclicality in women's volatility. Third, male earnings volatility is trending upward when we include zero earnings—

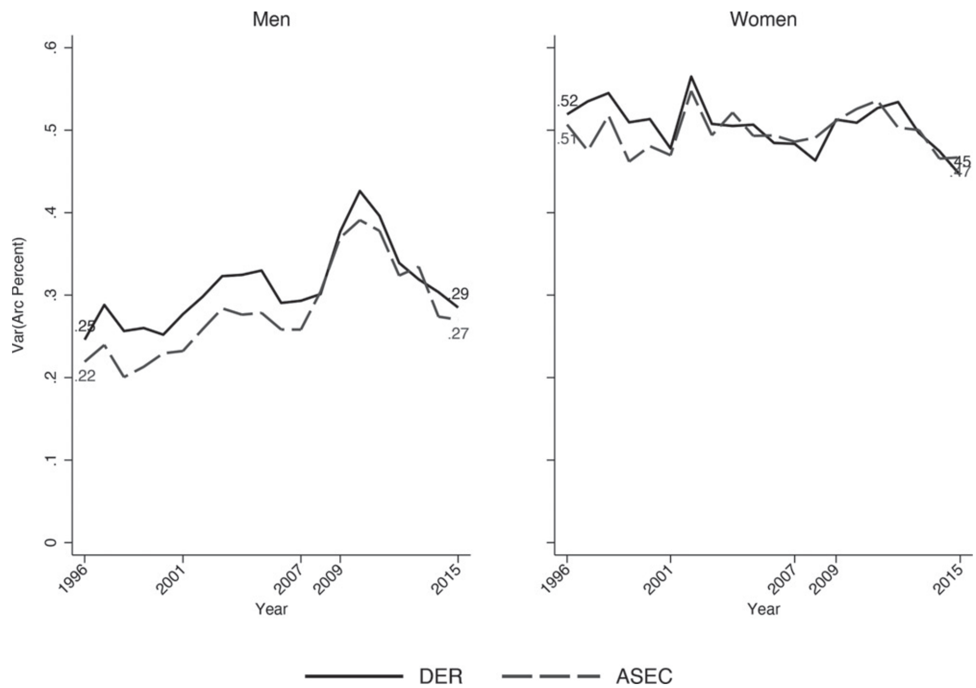

Figure 2. Earnings Volatility Including Zero Earnings. The series in the figure are the variance of the arc percent change in earnings across pairs of years. The sample is linked respondents with positive earnings in at least one of two years. Sources: U.S. Census Bureau, Current Population Survey, 1996–2016 Annual Social and Economic Supplement; Social Security Administration, Detailed Earnings Record, 1995–2015.

increasing about 20% over the sample period—suggesting that requiring positive earnings in both years is a selected sample, at least for volatility measurement. Despite these differences, similar to Figure 1 we find that inclusion of zeros in the ASEC yields the same outcome as in the DER, suggesting no discernable distinction in earnings volatility for men and women in survey and administrative reports even with the inclusion of zeros.

Notably, an earnings report of zero in the ASEC could be from nonwork, or it could be from misreporting by the respondent. That is, they could self-report zero earnings in the ASEC, but the firm could submit a positive earnings W2 that is included in the DER. There are reports of zero earnings in the DER, although this is rare, and likely reflects misreports on the part of the firm or self-employed worker. But it is possible that a worker could report earnings to the Census surveyor and not have those earnings reported to the tax authorities by the firm or self (for those self-employed). In the supplementary materials we expand the sample from Figure 2 by replacing reports of zero earnings in the ASEC with the positive values from the DER, and we replace missing DER values with earnings values from the ASEC. This change places the respective male and female earnings volatility series in between those found in Figures 1 and 2, but again we obtain qualitatively similar conclusions in both the ASEC and DER.

3.2. The Role of Nonresponse and Nonlink on Volatility

The ASEC sample is much broader than the linked respondent sample, and thus in this section we expand our analysis to a sample of individuals who may be an ASEC earnings nonrespondent in one or both years (and thus have earnings imputed) or who may not have a link to the DER in either or both years (but like Figure 1 we require positive earnings in both years). Similar to the whole imputes discussed above, Census also uses a sequential hot-deck procedure to impute earnings for individuals who otherwise responded to the ASEC, but did not provide a response to the earnings questions. The key assumption in the hot-deck procedure is missing at random (MAR). Bollinger et al. (2019) show that the economic consequences of the MAR assumption for earnings levels is primarily in the tails of the distribution, and here we extend that earlier analysis to earnings volatility.

In Figure 3 we estimate the effect of response and link status on earnings volatility of men in the top frame and women in the bottom frame. For each gender, the leftmost panel consists of the full ASEC, including those who both respond and do not respond to the earnings questions in the ASEC and those who are both linked and not linked to the DER. The ASEC and DER samples in the panel are not the same, because the ASEC lines include both linked and unlinked DER individuals, and the DER lines include those individuals who were linked in at least one year. In the middle panel we restrict the sample to two-year respondents regardless of whether they have a DER link (the ASEC and DER samples are therefore again not the same), while in the rightmost panel we impose the requirement that sample members be linked to the DER both years, but still including earnings respondents and nonrespondents. The figure makes clear that compared to Figure 1 including nonrespondents has a substantive effect on the level and trends of earnings volatility for both men and women in the ASEC. Volatility levels are double with nonrespondents included, and for men it results in an upward trend in volatility and for women no trend, which is distinct from the results in Figure 1 where men had no trend in volatility (see middle panel of Figure 3) and women have a

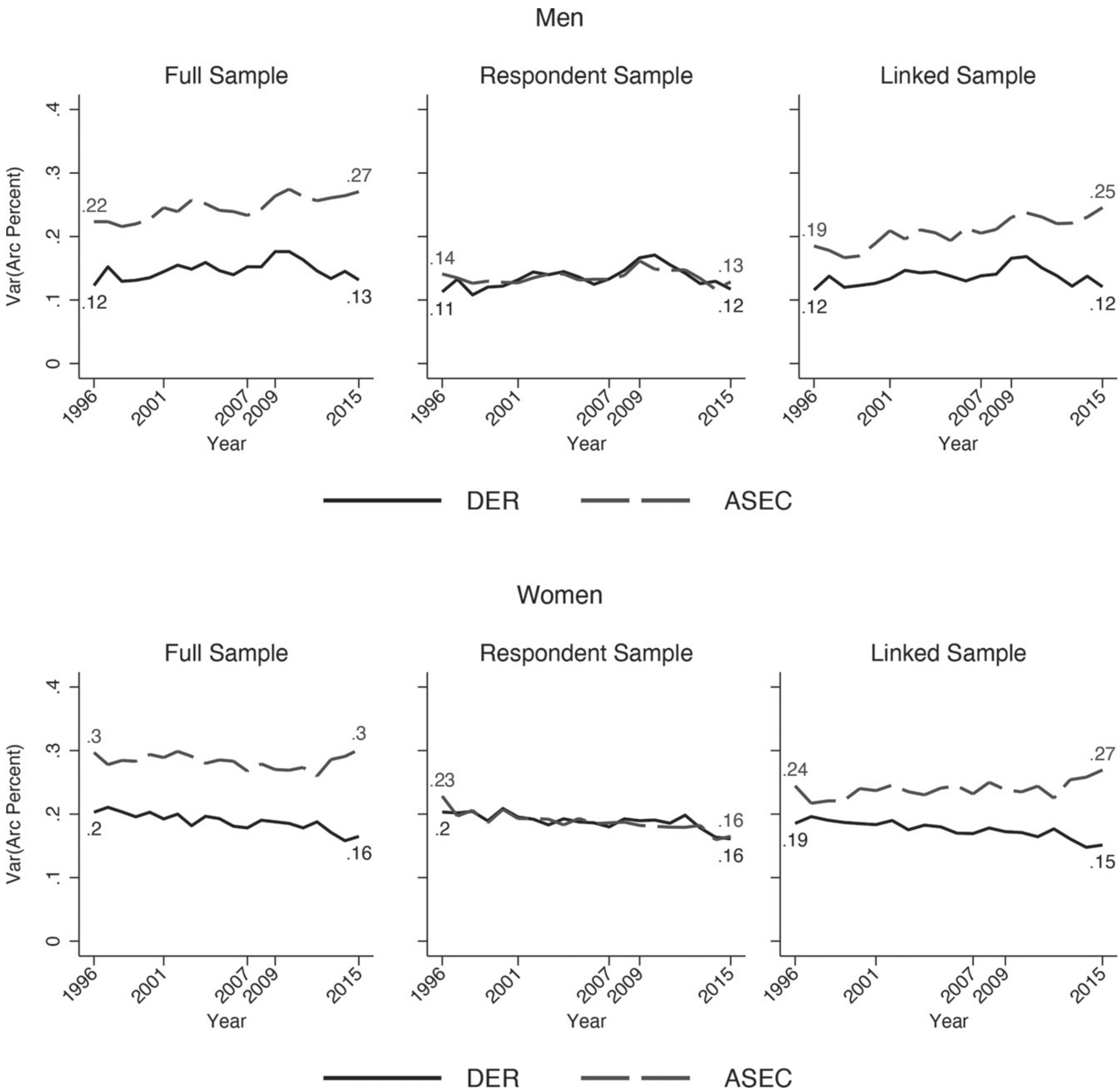

Figure 3. The Effect of Response and Link Status on Earnings Volatility. The series in the figure are the variance of the arc percent change in earnings across pairs of years among those with positive earnings in both years. The Full Sample includes those with imputed ASEC earnings or nonlink to the DER. The Respondent Sample contains only those who report earnings both years, regardless of link status. The Linked Sample contains those with an ASEC-DER link both years, regardless of earnings response status. Sources: U.S. Census Bureau, Current Population Survey, 1996–2016 Annual Social and Economic Supplement; Social Security Administration, Detailed Earnings Record, 1995–2015.

negative trend. The Census hot-deck method imparts bias much like Hirsch and Schumacher (2004) and Bollinger et al. (2019) show for wage levels, but because the imputation procedure has not changed since the late 1980s, the trend increase reflects the higher share of workers with imputed earnings. Failing to link to the DER has no effect on ASEC volatility.

3.3. Sample Attrition and Volatility

A possible concern with matched ASEC is with sample attrition affecting our earnings series. Moves are more likely among low-income families whose earnings are more volatile, which means we could understate the level and trends in volatility with our sample. Under the assumption that the probability of attrition is unobserved and time invariant (i.e., a fixed effect), or trending very slowly over time, then first differencing earnings as used in the volatility measures based on log-differences will remove the latent probability of attrition and purge estimates of possible attrition bias (Wooldridge 2001). However, because the arc percent includes mean earnings in the denominator then potential attrition bias could remain in the estimates. A conservative interpretation is that data from matched ASEC provides estimates of earnings volatility among the population of nonmovers.

To examine the potential role of attrition on volatility, we expand our dataset to include not only those matched across

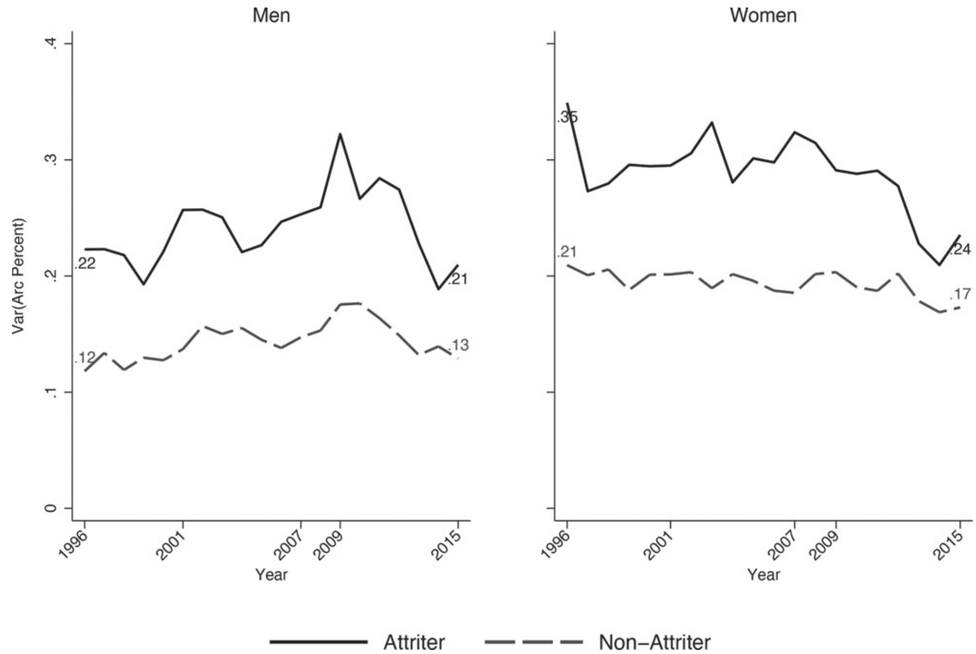

Figure 4. Earnings Volatility in the DER among Attriters and Nonattriters. The series in the figure are the variance of the arc percent change in earnings across pairs of years in the DER for those ASEC persons who attrit after year 1 and those who do not. The sample is of workers with positive earnings in both years. Sources: U.S. Census Bureau, Current Population Survey, 1996–2016 Annual Social and Economic Supplement; Social Security Administration, Detailed Earnings Record, 1995–2015.

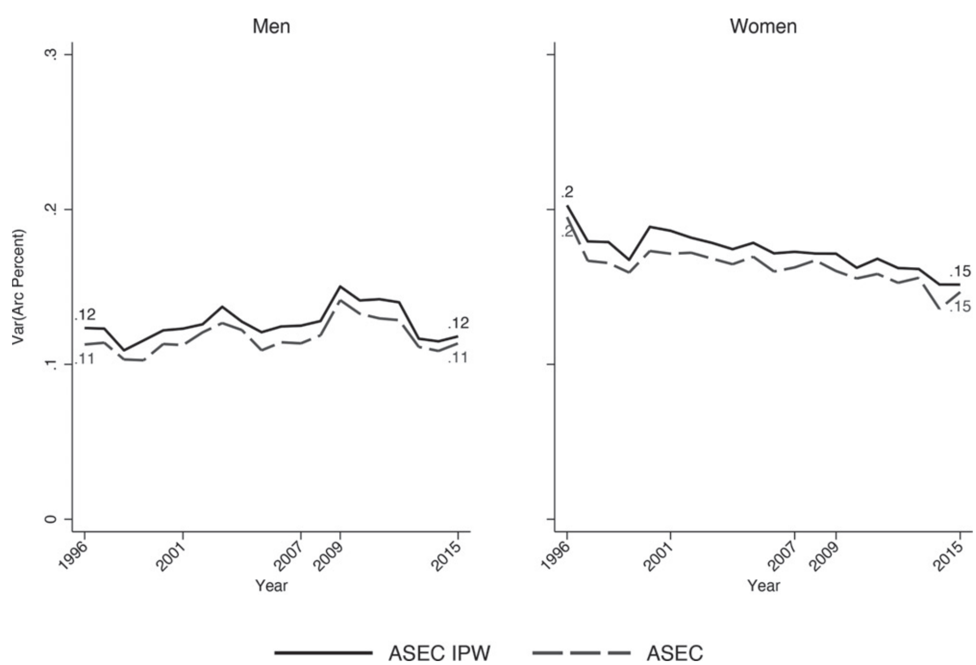

Figure 5. Reweighting the ASEC to Address Attrition. The series in the figure are the variance of the arc percent change in earnings across pairs of years in the ASEC, with one series reweighted by inverse probability weighting. The sample is linked respondents with positive earnings in both years. Source: U.S. Census Bureau, Current Population Survey, 1996–2016 Annual Social and Economic Supplement.

years in the ASEC, but also those individuals observed in year 1 of the ASEC but not year 2. The online supplement reports the year 1 socioeconomic characteristics of attriters and nonattriters, showing that attriters are younger, more likely to be a member of a minority racial group, have fewer years of school, less likely to be married (though with a higher percentage of married but with spouse absent), work fewer weeks and hours per week, have lower earnings in both the ASEC and DER, and higher rates of earnings (item) nonresponse. These patterns hold for both men and women, and suggest that volatility is likely to differ between attriters and nonattriters.

Because we have DER reports for both ASEC attriters and nonattriters, in Figure 4 we depict the volatility series for each group of men and women. The figure makes abundantly clear that volatility among attriters is substantively elevated compared to nonattriters, but the trends are similar—stable for men and declining for women. This suggests that volatility levels among ASEC stayers are too low, consistent with the results reported by Fitzgerald, Gottschalk, and Moffitt (1998) for the PSID, but the trends are unaffected by attrition.

One potential solution to address sample attrition in the ASEC is to reweight the data using inverse probability weighting (IPW). IPW is a general solution to attrition and nonresponse when the data are missing at random (Wooldridge 2007). Although there is evidence that the MAR assumption is violated in earnings levels (Bollinger et al. 2019), this does not mean it is violated for higher moments, though it is beyond the scope of this paper to formally test the MAR assumption. We proceed by estimating probit models each survey year of the probability that the person is (i) not a whole impute, (ii) is linked to the DER, (iii) is an earnings respondent, and (iv) is matched across ASEC waves as a function of a rich set of socioeconomic characteristics in both levels and interactions. We then divide the ASEC supplement weight by the fitted probability of response + link + match and estimate the IPW volatility series. The results of reweighting the ASEC are reported in Figure 5, along with original series from Figure 1. The figure shows that reweighting the ASEC does result in a higher level of volatility in each year, but likely does not fully adjust given the wide divergence between attriters and nonattriters in the DER shown in Figure 4. However, it is important to once again emphasize that attrition does not affect volatility trends of men and women.

3.4. Comparison to Common Measures and Samples in the Literature

The supplementary materials contain a number of robustness checks to the baseline estimates from the linked respondent sample depicted in Figure 1. This includes the frequently used measure of volatility in the literature of the variance of log earnings growth, comparisons to the PSID sample by restricting the analysis to household heads, nonimmigrants, not self-employed, and private sector workers, and alternative approaches to trimming the data to mitigate the influence of outliers. The key takeaway from these alternative specifications is that the volatility levels and trends in the ASEC and DER align.

4. Conclusion

This article presented new estimates of earnings volatility of men and women using unique restricted-access survey and administrative tax data for the tax years spanning 1995–2015. The linked survey-administrative sample eliminated potential differences due to overall sampling frame issues. As we varied the samples based on survey responses, we consistently found no significant trend in male earnings volatility over the last two decades, and a negative trend among women. The exception among men was when we include periods of zero earnings, where we find an upward trend in earnings volatility. However, even with zeros included, the levels and trends of volatility were qualitatively, and usually quantitatively, the same in both survey and administrative data. The one departure from this latter result was when we included Census-imputed earnings in our survey samples, which resulted in an upward trend in volatility among men and a stable trend among women. Thus, differences between survey and administrative data are dominated by earnings item response issues.

Our recommendation for users of the public versions of the ASEC for volatility research is to drop both those observations whose entire supplement is imputed, as well as those whose earnings are imputed. The remaining sample will yield estimates that align with administrative tax records.

Supplementary Materials

The supplementary materials included in the zip file ZHB_programs_supplement.zip include a PDF file as a supplementary appendix to the published paper entitled ZHB_JBES_unblinded_Supplement_Final.pdf. This supplement contains a description of the data, along with a number of robustness checks. In addition the zip file contains a series of Stata DO files for estimation of our results. The files FiguresX_clean.do (for $X = 1 - 5$) produce each of the respective Figure 1–Figure 5 in the published paper. The files FigureS-Y_clean.do (for $Y = 1 - 11$) produce the respective FigureS-1 to FigureS-11 in the Supplement. The files TableS-Z_clean.do (for $Z = 1 - 3$) produce the respective TableS-1 to TableS-3 in the Supplement.

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Disclosure Statement

The authors report there are no competing interests to declare.

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Supplement to

Trends in Earnings Volatility using Linked Administrative and Survey Data

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This supplement serves as a companion to our paper of the same title prepared for the *Journal of Business and Economic Statistics*. Below we provide additional details on the data and samples used in the analysis, including summary statistics, and we also provide a variety of different analyses from our baseline sample used in the main paper.

The results have been reviewed by the Census Bureau Disclosure Review Board to ensure that no confidential information is disclosed (DRB #2018-457, DRB #2019-322, DRB #2019-408, DRB #2019-449, DRB #2019-551, CBDRB-FY20-POP001-0076, CBDRB-FY20-POP001-0100, CBDRB-FY21-POP001-0150). Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau or any sponsoring agency.

S.1 DATA

The data used in our analysis are restricted-access Current Population Survey Annual Social and Economic Supplement (ASEC) person records linked to the Social Security Administration's Detailed Earnings Records (DER) for survey years 1996-2016, reporting earnings for tax years 1995-2015. The ASEC is a survey of roughly 90,000 households (60,000 from the usual CPS monthly rotation plus an additional 30,000 households oversampled as part of the Children's Health Insurance Program) conducted in March of each year. It serves as the source of official federal statistics on income, poverty, inequality, and health insurance coverage, and has been the primary survey dataset for earnings inequality research in the U.S. Both public-release and internal versions of the ASEC have topcoded earnings, but the internal ASEC file we use has a much higher topcode of $1.099 million for each earnings component (wage and salary, self employment), as opposed to $250,000 in the public ASEC. In the public files the Census Bureau replaces the topcoded value with a value obtained from rank proximity swapping, which is order preserving of the distribution above the topcode. Rank swapping was begun with the 2011 survey, but the Bureau released the corresponding values back to 1975.[1] Bollinger et al. (2019) recommend replacing public ASEC topcodes with rank swapped values prior to the 2011 survey for earnings research, especially that isolating the upper tail.

The DER is an extract of the Master Earnings File and includes data on total earnings as reported on a worker's Form W-2, wages and salaries and income from self-employment subject to Federal Insurance Contributions Act and/or Self-Employment Contributions Act taxation reported on Form 1099, as well as deferred wage (tax) contributions to 401(k), 403(b), 408(k), 457(b), and 501(c) retirement and trust plans, all of which we include in our earnings measure. Only positive self-employment earnings are reported in the DER because individuals do not make self-employment tax contributions if they have losses. In addition, some parts of gross compensation do not appear in the DER such as pre-tax health

[1] https://www2.census.gov/programs-surveys/demo/datasets/income-poverty/time-series/data-extracts/asec-incometopcodes-swappingmethod-corrected-110514.zip .

insurance premiums and education benefits, nor do "off-the-books" earnings appear in the DER, though they could be reported in the ASEC. Unlike the internal ASEC earnings records, DER earnings are not topcoded. This is important given substantial concerns regarding nonresponse and response bias in the tails of the distribution (Bollinger et al. 2019). Since a worker can appear multiple times per year in the DER file if they have multiple jobs, we collapse the DER file into one annual earnings observation per worker by aggregating total earnings, total self-employment earnings, and total deferred contributions across all employers. In this way, DER earnings are most compatible with ASEC earnings from all wage and salary jobs plus non-negative self-employment earnings.

The DER is linked to the ASEC using a unique Protected Identification Key (PIK) produced within the Census Bureau's Economic Reimbursable Surveys Division. The PIK is a confidentiality-protected version of the Social Security Number (SSN). Since the Census does not currently ask respondents for a Social Security Number (SSN), Census uses its own record linkage software system, the Person Validation System, to assign a SSN. This assignment relies on a probabilistic matching model based on name, address, date of birth, and gender. The SSN is then converted to a PIK in order to link the ASEC and DER. The Census Bureau changed its consent protocol to link respondents to administrative data beginning with the 2006 ASEC. Prior to this the CPS collected respondent SSNs and an affirmative agreement allowing a link to administrative data; i.e., an "opt-in" consent option. Beginning with the 2006 ASEC, respondents not wanting to be linked to administrative data had to notify the Census Bureau through the survey field representative, website or use a mail-in response in order to "opt-out". This opt-out rate is a very small 0.5 percent of the ASEC sample. If the respondent doesn't opt out, they are assigned a PIK using the Person Validation System. Once a link to the ASEC is made, we have the entire time-series of DER earnings as far back as 1978 when the DER began. However, because our focus is on the exact match for overlapping years of the ASEC and DER, we do not use this additional information in the DER.

In order to construct measures of volatility we must follow the same individual over time. Here we exploit the fact that the ASEC has a rotating sample design whereby respondents are in-sample for 4 months, out-of-sample for 8 months, and then in-sample for 4 more months. This makes it possible to match up to one-half of the sample from one ASEC interview to the next, and thus creating a series of two-year panels. The CHIP oversample in the ASEC is not eligible for the longitudinal follow-up, and thus we exclude it. Following the procedure recommended by the Census Bureau and extended by Madrian and Lefgren (1999), we initially match individuals based on four variables: month in sample (months 1–4 for year 1, months 5–8 for year 2); line number (unique person identifier); household identifier; and household number. Because the CPS sample domain is household addresses and not individuals, if a person moves between ASEC surveys then the Census Bureau interviews the new occupant at the address and does not follow the original respondent. Thus, we then do a cross check against four additional variables to make sure gender, race, and state of residence are unchanged, and that age changes by no more than two years (in case of staggered March interview, which actually spans February – April).

Table S.1 contains the annual ASEC-DER linkage rate along with the two-year panel match rate. It is clear that the link to the DER improved substantially after Census adopted the opt-out default in 2006. We match about 72 percent of persons across March surveys.

Table S.1. ASEC-DER Linkage Rate and 2-Yr Panel Match Rate

Year	Linkage Rate	Panel Match Rate
1996	79.22%	
1997	76.64	69.52%
1998	71.79	70.10
1999	66.43	69.96
2000	66.74	62.54
2001	69.20	64.20
2002	74.26	62.60
2003	71.39	74.44
2004	64.17	76.38
2005	62.48	67.26
2006	86.58	73.62
2007	86.48	74.65
2008	86.12	75.76
2009	85.73	75.73
2010	84.94	75.75
2011	85.67	76.89
2012	85.39	76.41
2013	85.14	76.05
2014	84.40	74.82
2015	84.53	62.26
2016	84.16	72.71

Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

The principal sample used for the volatility measures in the paper is people between the ages of 25-59 who have positive earnings in both years, are respondents to the ASEC earnings questions in both years, and have a link to the DER in both years. We refer to this group as the linked respondent sample. We also remove individuals who are full-time students in any year or that have their entire ASEC supplement allocated. We also present estimates for the full ASEC sample, whether they are linked or not to the DER, and whether or not they had their earnings imputed.

Table S.2 provides pooled summary statistics for the full sample and the principal sample of linked respondents, separately for men and women and weighted by the ASEC person supplement weight.

In the full sample, the average person is 43 years old, and has an average of about 14 years of education. The majority are married with spouse present (64 percent of men; 62 percent of women), native born (83 percent of men; 85 percent of women), and white non-Hispanic (72 percent). Men work for pay an average of 48 weeks per year, and 42 hours per week, while women on average work for pay 46 weeks and 36 hours per week. Inflation adjusted ASEC total earnings for men are on average $59,000 ($38,470 women), while average real DER earnings are a higher $66,290 ($41,630), likely reflecting the fact that the DER are not topcoded.[2] Among men, 84 percent have a DER link in both panel years, while 5 percent have a DER link in one but not the other panel year (85 and 7 percent, respectively, for women). For both men and women, the sample of linked respondents (linked in both panel years) is more educated, works more weeks and hours per week, is more likely to be white, and to be native born. Linked respondents have higher ASEC earnings than the full sample, but DER earnings are comparable.

Table S.2. Summary Statistics for Full ASEC and Linked Respondent Samples

	A. Men			
	Full Sample		Linked Respondent Sample	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	42.78	9.4	42.81	9.35
White	0.72	0.45	0.77	0.42
Black	0.08	0.27	0.07	0.26
Asian or American Indian	0.06	0.24	0.06	0.23
Hispanic	0.14	0.34	0.10	0.30
Years Education	13.87	2.8	14.17	2.66
Married, Spouse Present	0.64	0.48	0.67	0.47
Married, Spouse Absent	0.14	0.34	0.13	0.33
Never Married	0.22	0.42	0.20	0.40
Native	0.83	0.37	0.88	0.33
Foreign Citizen	0.07	0.26	0.07	0.25
Foreign Non-Citizen	0.09	0.29	0.06	0.23
Weeks Worked	47.65	11.93	48.97	9.60
Hours per Week	41.89	12.3	42.96	10.79
Nonrespond Yr1, Yr2	0.10	0.29		
Nonrespond Yr1, Respond Yr2	0.10	0.3		
Respond Yr1, Nonrespond Yr2	0.13	0.33		
Respond Yr1, Yr2	0.68	0.47	1.00	0.00
DER Non-Link Yr1, Yr2	0.10	0.3		
DER Non-link Yr1, Link Yr2	0.03	0.17		
DER Link Yr1, Non-link Yr2	0.02	0.15		
DER Link Yr1, Yr2	0.84	0.36	1.00	0.00
Proxy Response	0.50	0.5	0.47	0.50
Real ASEC Earnings ($2010 thou.)	59.00	74.64	64.35	75.93
Real DER Earnings ($2010 thou.)	66.29	129.00	67.42	134.00
Person-years (rounded)	381,000		222,000	

B. Women

[2] Earnings are inflation-adjusted using the personal consumption expenditure deflator with 2010 base year.

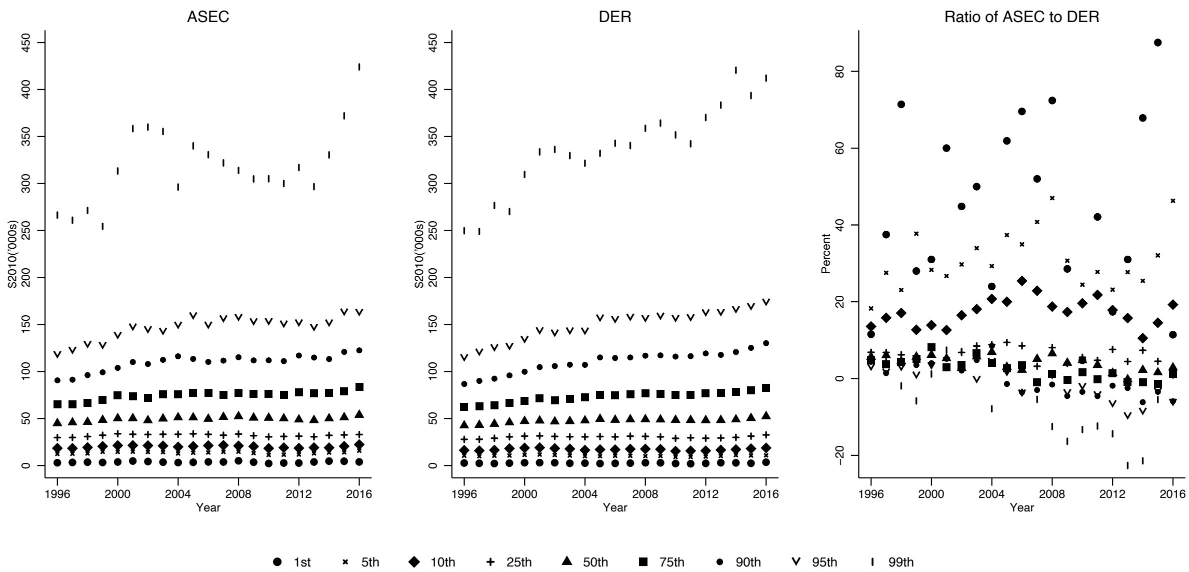
Age	43.17	9.39	43.14	9.45
White	0.72	0.45	0.74	0.44
Black	0.11	0.31	0.10	0.30
Asian or American Indian	0.06	0.24	0.06	0.24
Hispanic	0.12	0.32	0.10	0.31
Years Education	14.27	2.62	14.48	2.57
Married, Spouse Present	0.62	0.49	0.63	0.48
Married, Spouse Absent	0.19	0.39	0.19	0.39
Never Married	0.19	0.39	0.19	0.39
Native	0.85	0.35	0.88	0.33
Foreign Citizen	0.08	0.27	0.07	0.26
Foreign Non-Citizen	0.07	0.25	0.05	0.22
Weeks Worked	45.62	14.33	47.56	13.89
Hours per Week	36.17	13.26	37.60	12.99
Nonrespond Yr1, Yr2	0.09	0.28		
Nonrespond Yr1, Respond Yr2	0.09	0.29		
Respond Yr1, Nonrespond Yr2	0.11	0.32		
Respond Yr1, Yr2	0.71	0.46	1.00	0.00
DER Non-Link Yr1, Yr2	0.08	0.28		
DER Non-link Yr1, Link Yr2	0.04	0.19		
DER Link Yr1, Non-link Yr2	0.03	0.18		
DER Link Yr1, Yr2	0.85	0.36	1.00	0.00
Proxy Response	0.41	0.49	0.38	0.49
Real ASEC Earnings ($2010 thou.)	38.47	47.20	41.81	46.72
Real DER Earnings ($2010 thou.)	41.63	94.60	41.74	58.41
Person-years (rounded)	367,000		213,000	

Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

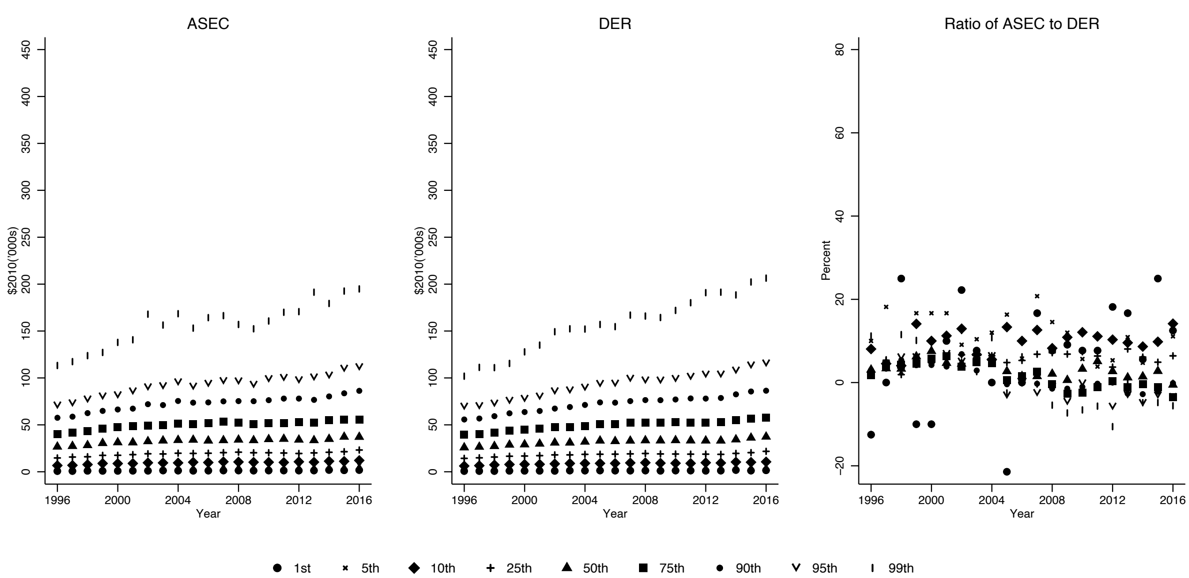
One possible reason that volatility levels and trends could differ between the ASEC and DER is differences in underlying distributions. To examine this possibility, in Figure S.1 we depict trends in selected percentiles of the male and female real earnings distributions. For this figure we require nonzero earnings and linked respondents, but do not trim the top and bottom earnings levels. The figure shows that the earnings distribution for men in the DER is shifted leftward by 20-80 percent compared to the ASEC for percentiles below the 25th, but then the DER generally has a longer right tail than the ASEC. While percent differences in the left tail are large, the absolute dollar values are not, differing by $1,000-$2,000. In the upper quantiles the DER exceeds the ASEC on average by $2,400 at the 95th percentile and just under $19,000 at the 99th, which is consistent with the lack of a topcode in the DER. There does appear to be a more substantial decline at the 99th percentile of the ASEC leading up to the Great Recession, and more rapid recovery, but overall the growth in real earnings is comparable across the ASEC and DER (e.g. 34 percent in both sources at the 1st percentile, and 59 percent and 65 percent in the ASEC and DER, respectively at the 99th percentile). The story is different for women in that across most of the distribution the ASEC and DER differ little. There is considerable noise in the lowest percentile, with the ASEC exceeding the DER in some years, and the DER exceeding the ASEC in others, but overall there is little change.

Figure S.1. Percentiles of ASEC and DER Earnings Distribution of Linked Respondents

A. Men



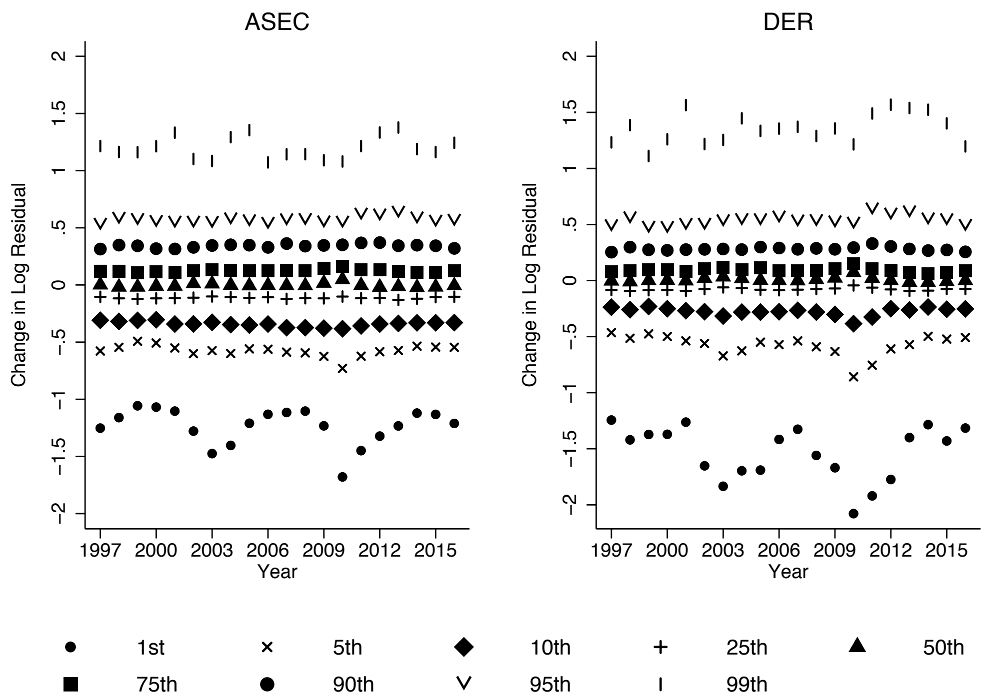
B. Women



Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

To further examine whether the differences in the survey and administrative distributions of men in the left tail might lead to different estimates in volatility, Figure S.2 shows a parallel figure for the distribution of residuals from the log difference regression (which omits 0s by construction). In this case, the ASEC series are quite comparable to the DER. Thus, based on the log changes it does not appear that there are fundamental differences in the residualized distributions in the ASEC and DER for men that prima facie point to any potential differences in volatility.

Figure S.2. Percentiles of Log Difference Residuals of Men



Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Another possible concern with matched ASEC is with sample attrition affecting our earnings series. The CPS sample domain is household addresses and not individuals, so that if a person moves between ASEC surveys then the Census Bureau interviews the new occupant at the address and does not follow the original respondent. This is why we use state of residence as one of the match criteria because if the state of residence changes for the household identifier then that signals an incorrect match across ASEC surveys. Moves are more likely among low-income families whose earnings are more volatile, which means we could understate the level and trends in volatility with our sample.

To examine the potential role of attrition on volatility, we expand our dataset to include not only those matched across years in the ASEC, but also those individuals observed in year 1 of the ASEC but not year 2. Table S.3 reports the year 1 socioeconomic characteristics of attriters and non-attriters. Attriters are younger, more likely to be a member of a minority racial group, have fewer years of school, less likely to be married (though with a higher percentage of married but with spouse absent), work fewer weeks and hours per week, have lower earnings in both the ASEC and DER, and higher rates of earnings (item) nonresponse. These patterns hold for both men and women, and suggest that volatility is likely to differ between attriters and non-attriters, which we confirm in the paper. However, attrition only affects the level and not the overall trends in volatility of male and female earnings.

Table S.3. Sample Summary Statistics by Attrition Status

	A. Men			
	Non-Attriters		Attriters	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	42.65	9.47	38.62	9.63
White	0.71	0.46	0.64	0.48
Black	0.09	0.29	0.13	0.34
Asian or American Indian	0.06	0.24	0.06	0.24
Hispanic	0.14	0.35	0.16	0.37
Years Education	13.66	2.80	13.37	2.82
Married, Spouse Present	0.61	0.49	0.44	0.50
Married, Spouse Absent	0.15	0.35	0.20	0.40
Never Married	0.25	0.43	0.36	0.48
Native	0.84	0.37	0.83	0.37
Foreign Citizen	0.07	0.26	0.06	0.23
Foreign Non-Citizen	0.09	0.29	0.11	0.31
Weeks Worked	42.95	18.12	40.27	19.44
Hours per Week	37.97	17.22	35.92	17.48
Proxy Response	0.50	0.50	0.51	0.50
Earnings Nonresponse	0.18	0.38	0.23	0.42
Real ASEC Earnings ($2010 thou.)	51.72	71.34	41.56	64.65
Real DER Earnings ($2010 thou.)	64.78	151.10	48.28	54.86
Persons in Year 1 (rounded)	204,000		79,000	
	B. Women			
Age	42.95	9.39	38.79	9.82
White	0.69	0.46	0.63	0.48
Black	0.11	0.31	0.14	0.35
Asian or American Indian	0.06	0.25	0.07	0.26
Hispanic	0.13	0.34	0.16	0.37
Years Education	13.95	2.72	13.67	2.72
Married, Spouse Present	0.62	0.49	0.46	0.50
Married, Spouse Absent	0.19	0.39	0.26	0.44
Never Married	0.19	0.39	0.29	0.45
Native	0.83	0.37	0.83	0.37
Foreign Citizen	0.08	0.27	0.06	0.24
Foreign Non-Citizen	0.09	0.28	0.11	0.31
Weeks Worked	36.43	22.28	34.94	22.67
Hours per Week	28.91	18.68	28.57	19.11
Proxy Response	0.41	0.49	0.42	0.49

Earnings Nonresponse	0.15	0.35	0.19	0.39
Real ASEC Earnings ($2010 thou.)	29.68	37.57	26.79	36.10
Real DER Earnings ($2010 thou.)	38.65	48.13	32.92	31.58
Persons in Year 1 (rounded)	223,000		81,000	

Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

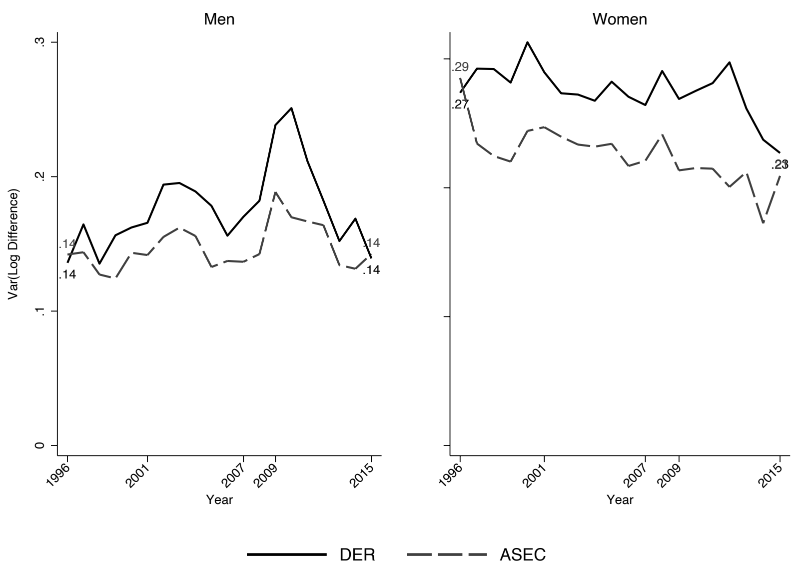
S.2 ROBUSTNESS OF VOLATILITY ESTIMATES

S.2.1 Variance of Change in Log Earnings

Our primary measure of volatility in the paper is the variance of the arc percent change. As described therein, the key advantages of the arc percent change measure of volatility are that it is bounded between ± 200% and it admits the possibility of zero earnings in one of the two years, or negative earnings. A common alternative measure is the variance of the change in log earnings (Shin and Solon 2011; Moffitt and Zhang 2018), given as $vlog_t = 100 * Var(lny_{it} - lny_{it-1})$,where lny_{it} as the natural log of earnings for individual i in time period t.

Figure S.3 presents trends in volatility estimated with the change in log earnings for the sample of male and female linked respondents with positive ASEC or DER earnings in each period with a 1% trim of top and bottom values as in the paper. As in the paper, we age-adjust the series and plot the variance of the residuals. Comparing to Figure 1 in the paper shows that there is little difference in the patterns of volatility among those with positive earnings. The left panel shows that the log difference increases the amplitude of volatility of male earnings in the DER during the Great Recession compared to the arc percent change of earnings levels, and suggests a temporary greater separation with the ASEC, but no change in long-term trends. This holds for women too in the right panel, who continue to have a negative trend in volatility.

Figure S.3. Log Difference Earnings Volatility

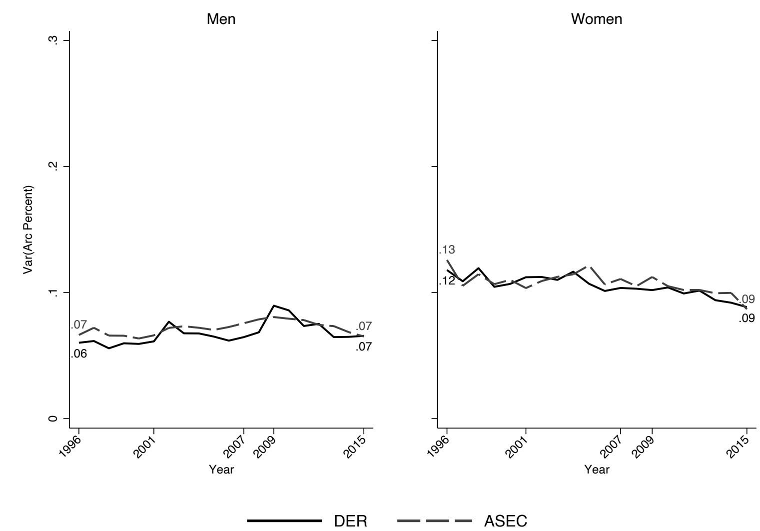


Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

S.2.2 5% Sample Trim and No Trim

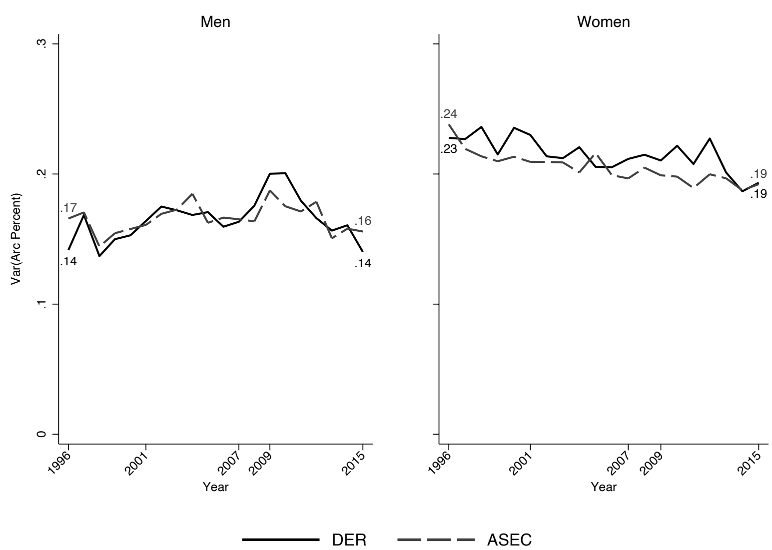
The baseline estimates involve trimming the top and bottom one percentile of the gender-specific real earnings distribution in each year prior to constructing the variance of arc percent change volatility. The hope is that by doing so we more accurately capture labor market volatility that is not unduly influenced by outliers. To test whether are results are sensitive to this choice, we consider a 5 percent trim of the top and bottom of the distribution, as well as no trimming. In the next section we consider additional trimming methods. As depicted in Figure S.4 moving to a 5% trim has the effect of bringing the ASEC and DER series closer in levels, and dampens the business-cycle amplitudes of male earnings volatility, but does not affect the central finding of no trend in male volatility or a declining trend in female earnings volatility. Figure S.5 depicts the arc percent volatility series among linked respondents with no earnings trim. This results in higher levels of volatility than the base case Figure 1 of the paper, as well as the 5 percent trim, but as with the other two figures there is no effect on the trend for men and women and the ASEC and DER deliver comparable results.

Figure S.4. Earnings Volatility with 5% Trim of Outliers



Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

Figure S.5. Earnings Volatility with No Trim of Outliers

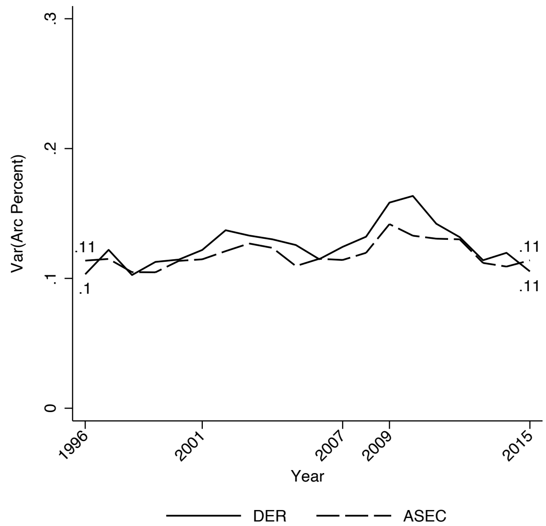


Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

S.2.3 Life Cycle Age Adjustment

The volatility estimates in the paper first residualize the volatility series before constructing the variance, under the concern that volatility estimates could differ depending on the stage of the worker's life cycle. The other papers described in the Overview paper of this volume focus on men, and to place them on a similar footing, the Overview paper presents the volatility series without age adjusting the volatility series. We reproduce that series in Figure S.6 below for men only, which shows that the baseline volatility estimates in Figure 1 of the paper are unaltered if we do not make the life cycle age adjustment.

Figure S.6. Earnings Volatility of Men without Life Cycle Age Adjustment

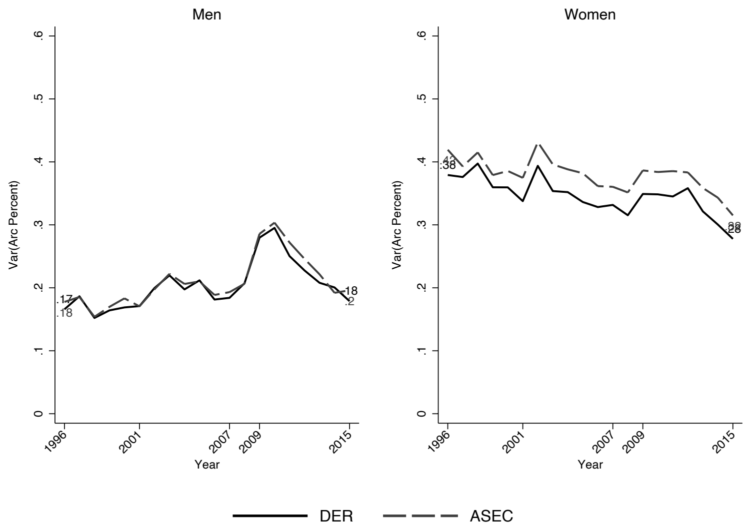


Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

S.2.4 Inclusion of Zero Earners

As discussed in the paper, an earnings report of zero in the ASEC could be from nonwork, or it could be from misreporting by the respondent. That is, they could self-report zero earnings in the ASEC, but the firm could submit a positive earnings W2 that is included in the DER. In addition, it is possible that a worker could report earnings to the Census surveyor and not have those earnings reported to the tax authorities by the firm or self (for those self-employed). In Figure S.7 we expand the sample from Figure 2 of the paper by replacing reports of zero earnings in the ASEC with the positive values from the DER, and we replace missing DER values with earnings values from the ASEC. This change places the respective male and female earnings volatility series in between those found in Figures 1 and 2, but again we obtain qualitatively similar conclusions in both the ASEC and DER.

Figure S.7. Earnings Volatility Replacing Zero ASEC with DER and Zero DER with ASEC



Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

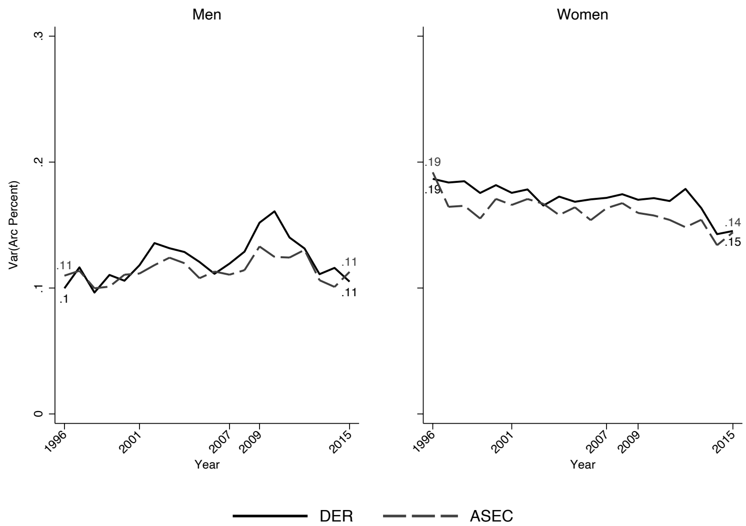
S.2.5 Comparisons to the PSID

Much of the volatility literature has been based on data from the Panel Study of Income Dynamics (PSID), as described in the Overview paper in this volume. The PSID was begun in 1968 as a survey of 4,800 American families and is the longest continuously running longitudinal survey. It has followed the children and grandchildren of original sample parents as they split off to form their own households so that today there are over 10,000 PSID families and 24,000 individuals. The original sample drew about 60 percent of the families from the nationally representative Survey Research Center (SRC) sample, and the other 40 percent from an oversample of low-income and minority families as part of the Survey of Economic Opportunity (SEO). In the subsections below we explore a number of sample restrictions on the ASEC to more closely mimic the PSID to assess what if any effect this has on our estimated volatility trends.

S.2.5.1 Non-Immigrants

The composition of the United States has dramatically changed over the last 50 years since the PSID was begun, most notably with the rise of immigrants and the share of the population that is of Hispanic ethnicity. Although the PSID has attempted to address the issue of under-representation of Hispanics with a couple of refresher samples, most researchers take the position that the PSID likely falls short on the representation of immigrant peoples. In Figure S.8 we repeat the analysis of Figure 1 from the paper, but only retain those linked-respondent continuous workers who report being a native to the United States. The figure makes clear that the basic takeaway of Figure 1 is unchanged—male volatility is cyclic but with no trend over the last two decades, while female earnings volatility is acyclic but with a declining trend, and there is no substantive difference in these results across the survey and administrative data.

Figure S.8. Earnings Volatility Excluding Immigrant Workers



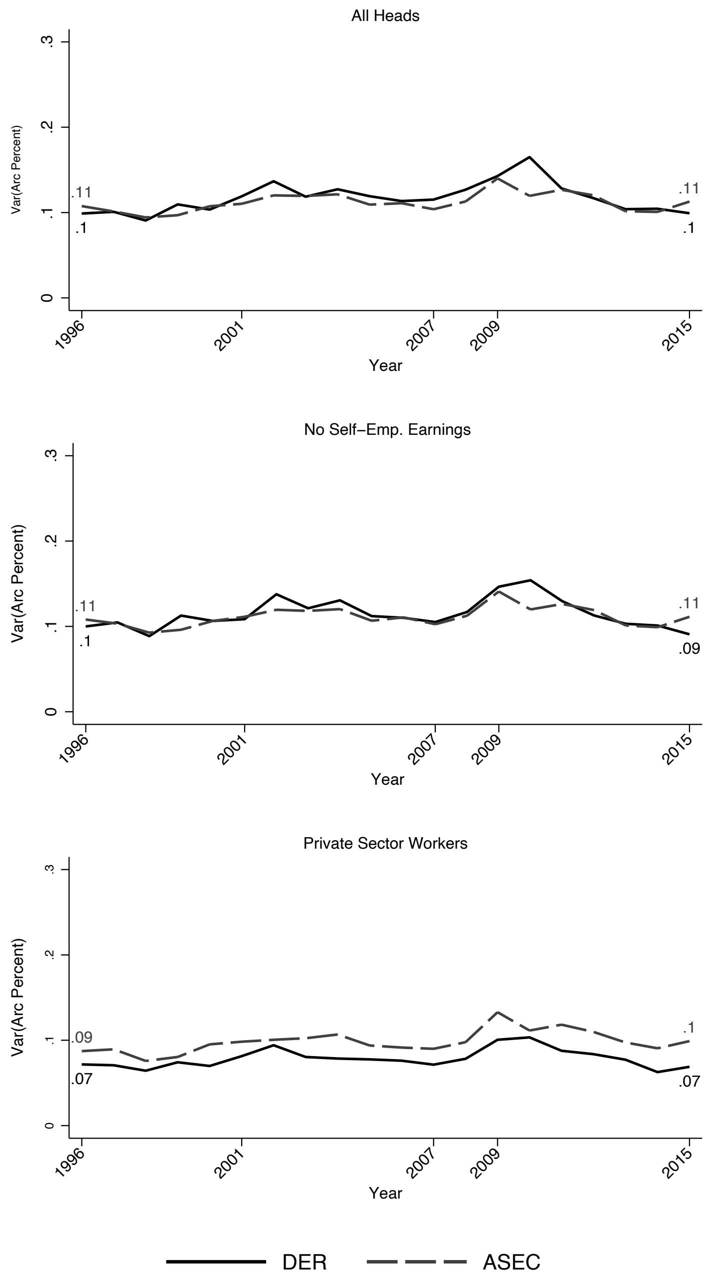
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

S.2.5.2 Household Heads

The PSID collects information on the earnings of household heads and spouses, and while there is a catch-all category for earnings of other family members, the PSID is not structured like the ASEC to collect earnings of all individuals in the household. Consequently, the PSID volatility research has focused on male heads of household, and in this subsection we return to the arc percent volatility measure of equation (1) but restrict the sample to a variety of cuts using male heads of household only in Figures S.9 and S.10.

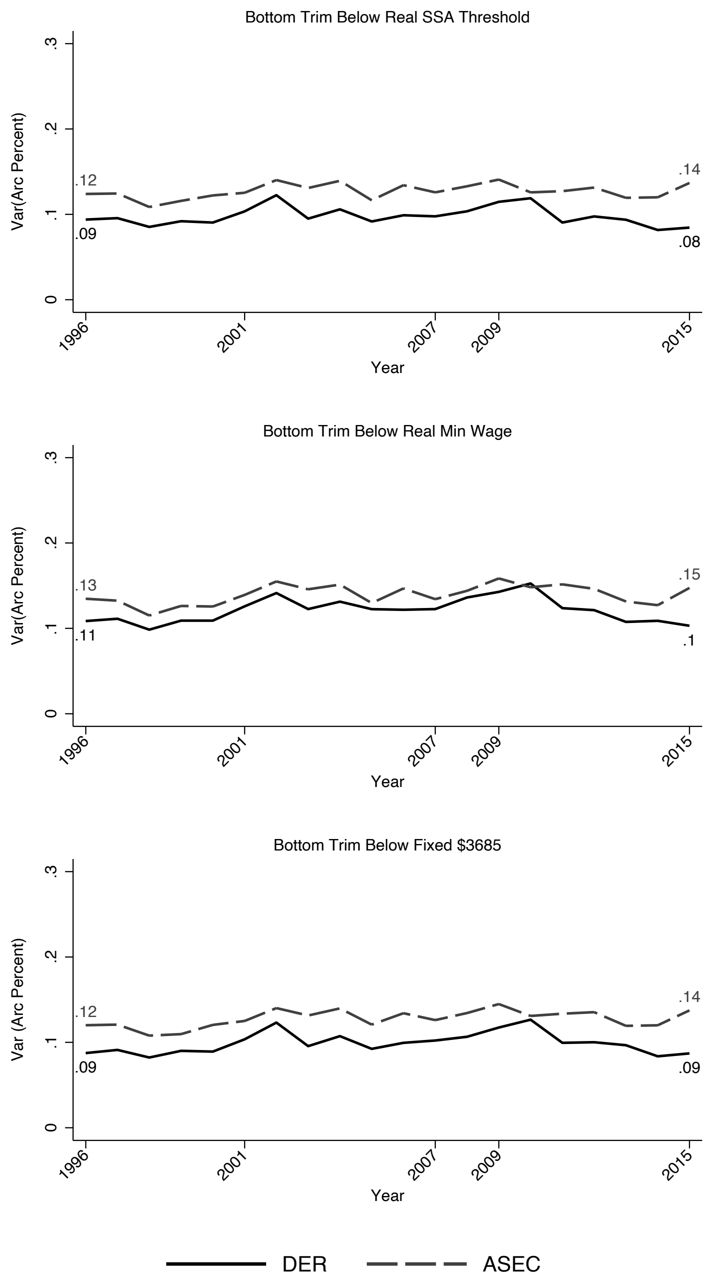
The first row of Figure S.9 replicates Figure 1 with zeros excluded, and the only difference in results is a slight reduction in volatility levels but no change in trends when restricting to heads. The second row drops those workers with any self-employment earnings, and then the third row drops public-sector workers. As the panels show, dropping self- employed or public-sector workers results in greater coincidence between survey and administrative data. Figure S.10 drops, in turn, those workers with real earnings levels below a quarter of a full-time full-year work at half the federal minimum wage, those workers with earnings below a fixed (in real terms) dollar value of $3,685, and those workers with earnings below the real value of the minimum Social Security earnings thresholds needed to qualify for retirement benefits credit, respectively. The latter three cuts have been used in various prior studies using administrative earnings records from Social Security (Sabelhaus and Song 2010; Bloom et al. 2018). The alternative bottom cutpoints do reverse the ordering of volatility levels with the ASEC now higher than the DER, but it has no effect on volatility trends, suggesting that there is nothing particularly restrictive about the PSID sample of heads of households in volatility analyses over time.

Figure S.9. Earnings Volatility of Male Household Heads



Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

Figure S.10. Earnings Volatility of Male Household Heads with Alternative Earnings Trims

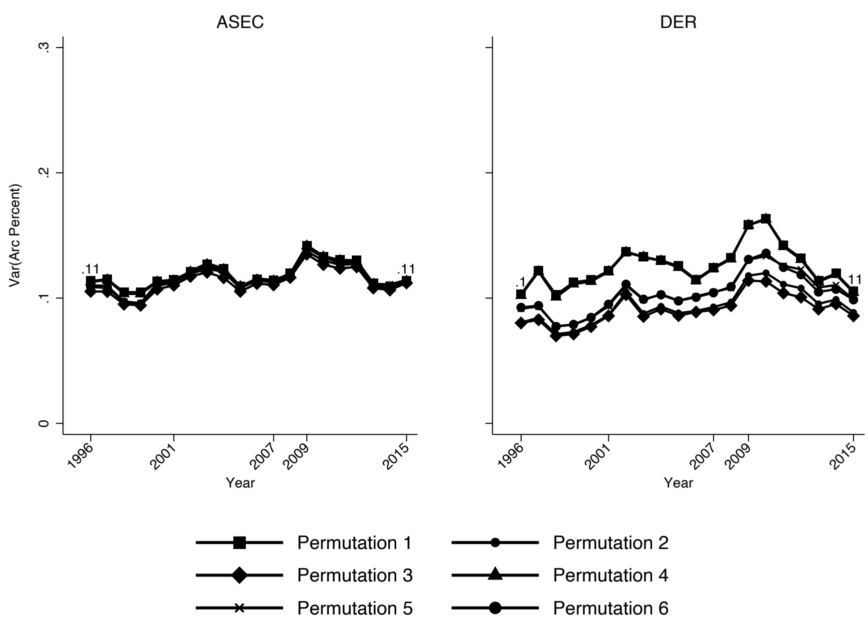


Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

S.2.5.3 Reweighting to the PSID

As discussed above in Figures S.1 and S.2, one concern in comparing our estimates with those studies using differing data sources like the PSID may be differences in the underlying distribution of earnings. These differences may arise due to sampling frame differences or measurement approaches. In order to investigate this, we adopted a uniform weighting approach across the four papers described in the accompanying Overview paper, matching the distribution of the PSID sample. Four different weighting approaches were examined. The first weighting approach takes the distribution of real (2010) earnings in each year of the PSID sample of males aged 25 to 59 working full time. The PSID data were broken into ventiles after trimming at the bottom and top 1%. We construct weights by measuring the proportion of each year's sample, p_v, which falls into the PSID ventile v. Then the weight for any observation i is given by $w_i = \sum_{v=1}^{20} 1[L_v \leq E_i < U_v]\frac{.05}{p_v}$, where E_i is the earnings (in that particular year) for observation i, $1[.]$ is the indicator function, and L_v, U_v are the lower and upper bounds of the year-specific earnings ventile. The second weighting scheme fixes the PSID distribution to the earnings distribution in the year 2000. The third and fourth approaches first regress log earnings on age and age squared. Residuals are then formed by $r_i = E_i - \eta e^{\widehat{lnE_i}}$, where $\widehat{lnE_i}$ is the predicted value from the log earnings regression. The final measure, $\widetilde{r_i} = r_i - \bar{r}$, is re-centered on zero by subtracting the mean for that year. Again, ventiles for the residuals were based upon the PSID sample (similarly treated) and weights were constructed similarly.

Figure S.11. Earnings Volatility of Men Reweighted to the PSID Earnings Distribution



Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015

The exercise resulted in six measures of the trend in earnings volatility, each of which removes imputations and zeros from the sample, as depicted in Figure S.11. Permutation 1 is the same series as that in Figure 1 of the paper, except that instead of using residuals to construct the variance, we use earnings levels. Permutation 2 uses the year-by-year weights, while Permutation 3 uses the fixed year 2000 weights. Permutation 4 does not use any weights and is comparable to our Figure 1 in the paper, in that it first regresses the arc percent change in earnings on age and age squared, and constructs the variance series from the residuals. Permutation 5 returns to the level arc percent change variance, but uses the residual weights year-by-year. Finally, Permutation 6 again uses the level arc percent change variance but with the fixed year 2000 residual weights.

As can be seen in the left panel of Figure S.11, these various permutations have no effect on the ASEC measures of volatility. The DER series, however, do show some differences. Most notably, we find that the weighting by the PSID data leads to a lower level of volatility than the ASEC compared to the benchmark in Figure 1, although similar trends, especially for the early years of the series. This could result from the longer left tail of earnings observed in the DER compared to the PSID. However, these differences are minor compared to the ones highlighted in our exercises above, and differences between the PSID and the ASEC or DER do not appear to be largely driven by the underlying distribution.

ADDITIONAL REFERENCES

Madrian, B., and Lefgren, L. (1999), "A Note on Longitudinally Matching Current Population Survey (CPS) Respondents," NBER Working Paper 247.