Trends in Earnings Volatility using Linked Administrative and Survey Data*

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Abstract: We document trends in volatility separately by gender in combination with other characteristics such as race, educational attainment, and employment status using survey data linked to administrative earnings for the tax years spanning 1995-2015. We also decompose the variance of trend volatility into within- and between-group contributions, as well as transitory and permanent shocks. Our results for men suggest earnings volatility as measured by the arc percent change increased in survey data, but was stable in tax data. For women, the survey data show stable volatility, while tax data indicate a secular decline. Excluding nonworkers results in parity across survey and tax data, with stable volatility among men and declining earnings volatility among women. Importantly, for men there is a substantial procyclical component to earnings volatility that is not present among women. The variance decompositions for both men and women indicate that nonresponders, low-educated, racial minorities, and part-year workers have the greatest group specific earnings volatility, but with the exception of part-year workers, they contribute least to the level and trend of volatility owing to their small share of the population. For both men and women there is evidence of stable transitory volatility, but rising permanent volatility over the past two decades.

Keywords: CPS ASEC, earnings volatility, nonresponse, administrative tax data

JEL Codes: J31 Wage Level and Structure, C8 Data Collection and Estimation Methodology

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Understanding the level and trends of earnings volatility is important both in its own right, and because of its potential contribution to rising inequality. Much of what we know about volatility has come from survey data, which generally offers a broad collection of variables, a long time series, population representativeness, and widespread availability to the research community (Gottschalk and Moffitt 1994, 2009; Gittleman and Joyce 1996; Cameron and Tracy 1998; Haider 2001; Hacker and Jacobs 2008; Keys 2008; Dahl, DeLeire, and Schwabish 2011; Ziliak, Hardy, and Bollinger 2011; Shin and Solon 2011; Dynan, Elmendorf, and Sichel 2012; Celik, Juhn, McCue, and Thompson 2012; Moffitt and Zhang 2018). 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; Bollinger and Hirsch 2006; Kapteyn and Ypma, 2007; Meijer, Rohwedder, and Wansbeek, 2012; Abowd and Stinson, 2013; Bollinger, Hirsch, Hokayem, and Ziliak 2019). More recently, some scholars have turned to administrative data to examine volatility on the belief that it avoids some of the measurement pitfalls of surveys, and the conclusions obtained on basic facts such as trends are often at odds from survey data (Sabelhaus and Song 2010; Carr and Weimers 2018). However, the standard assumption that administrative data serve as a "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. In this paper, we aim to reconcile these differences in estimated earnings volatility.

Starting with the seminal work of Gottschalk and Moffitt (1994), the focus on volatility trends centered on identifying whether rising cross-sectional income inequality stemmed from transitory instability or from permanent shocks. The preponderance of evidence on volatility was obtained using data from the Panel Study of Income Dynamics (PSID), and the general consensus from the PSID was that transitory instability increased from the early 1970s until the mid 1980s, and stabilized until 2000, and permanent (lifetime) instability rose primarily in the 1980s (Gottschalk and Moffitt 1994, 2009;

Haider 2001; Hacker and Jacobs 2008; Keys 2008; Dynan, Elmendorf, and Sichel 2012; Shin and Solon 2013).

While there is corroborating evidence on the basic PSID trends up until 2000 from matched panels of the ASEC (Gittleman and Joyce 1996; Cameron and Tracy 1998; Ziliak, et al. 2011), and to a lesser extent from the Survey of Income and Program Participation (Dahl, DeLeire, and Schwabish 2011; Celik, Juhn, McCue, and Thompson 2012; Carr and Wiemers 2018), beginning in the 2000's there is a sharp divergence between the PSID and other survey datasets (Moffitt and Zhang 2018). More worrying is recent evidence from the Social Security Detailed Earnings Record that calls into question the basic conclusion of whether volatility increased at any point since 1980 (Sabelhaus and Song 2010; Bloom et al. 2018).

We present new estimates of earnings volatility using restricted-access survey data from the Current Population Survey Annual Social and Economic Supplement (ASEC) linked to the Detailed Earnings Record (DER) for the period spanning 1996-2016. The advantage offered by the link to administrative data is that today nearly 45 percent of survey earnings responses in the ASEC are missing due to nonresponse, and the Census Bureau uses a randomly selected "donor" with similar characteristics to replace missing earnings. This means the link to administrative data offers an independent report from the same worker to construct year-to-year volatility, and thus permits a comparison to survey estimates based on two-year responders, two-year nonresponders, and those who switch response status. Our previous research using linked ASEC-DER data has demonstrated that earnings nonresponse in the ASEC produces biased estimates of poverty and inequality (Hokayem, Bollinger, and Ziliak 2015; Bollinger et al. 2019), and in this paper we expand our analysis to the longitudinal outcome of volatility. An additional advantage, and the primary focus of this paper, is that the current literature has reached differing conclusions on the trend in volatility both across surveys and in comparing survey-alone versus administrative-alone estimates, but as these use different populations it is difficult to know how much of the difference in trends is due to differences in measurement between survey and administrative reports as opposed differences in samples. We are able to hold constant sample differences with the exact ASEC-

DER link to focus on differences in measurement between survey and administrative data reports of earnings volatility.

Our analysis begins with overall trends in earnings volatility, utilizing two measures of variance—the arc percent change and the first difference in log earnings. The arc percent change is bounded between ± 200%, and most important, it is still defined if earnings are zero in one of the two years, unlike the log growth measure which requires positive earnings in both years. Ziliak et al. (2011) found that earnings volatility was increasingly accounted for by employment transitions from the early 1970s to the mid 2000s, and these transitions are missed with the standard log-growth volatility measure. Like most of the literature, our estimates of volatility remove life-cycle factors, and we show how the series differ with a 1 percent and 5 percent trim of residual outliers. Because trimming the data can have its own pitfalls (Bollinger and Chandra 2005), we also present untrimmed estimates. We conduct detailed sensitivity checks on the effects of earnings nonresponse and survey attrition. In the second part of the paper, we move beyond the summary volatility measures to explore trends across heterogenous subgroups. We decompose the variance into within-group and between-group contributions, focusing on the roles of human capital, full-time work, race/ethnicity, and earnings response status. This is then followed with a further decomposition of the variance into trends in transitory and permanent volatility.

This work has important advantages over the recent contributions of Carr and Wiemers (2018) and Sabelhaus and Song (2010). First, Carr and Wiemers had limited access to demographic data in the SIPP-DER file they used, and were unable to isolate the potential roles of human capital and family headship on earnings volatility. The PSID research is restricted to heads of households, and the SIPP-DER file does not release family structure information, making it difficult to do a direct comparison with the PSID. In our data we have access to the full ASEC, including education attainment, marital status, race, and relationship to head to examine whether some of the divergence in trends is from workers other than the household head.[1] Second, while Sabelhaus and Song (2010) have access to a larger universe of

[1] The recent work by Carr and Wiemers (2019) does conduct analysis by education and gender.

DER workers, they have very limited demographic information, notably missing information on education, race, and family structure, which we have with the ASEC-DER link. One important difference with the Sabelhaus and Song (2010) analysis is they pool men and women together, whereas most of the survey-based research focuses only on men. Ziliak et al (2011) conducted their analyses separately for men and women, showing that volatility of women declined from the 1970s to the 2000s. This could partially account for the declining volatility reported in Sabelhaus and Song, and thus we conduct our analyses separately for men and women.

Our results for men suggest overall earnings volatility as measured by the arc percent change increased in survey data, but was stable in tax data. For women, the survey data show stable volatility, while tax data indicate a secular decline. Excluding ASEC nonworkers results in parity across survey and tax data, with stable volatility among men and declining earnings volatility among women. Importantly, for men there is a substantial procyclical component to earnings volatility that is not present among women. The variance decompositions for both men and women indicate that nonresponders, low-educated, racial minorities, and part-year workers have the greatest group specific earnings volatility, but with the exception of part-year workers, they contribute least to the level and trend of volatility owing to their small share of the population. The finding that nonresponse in the ASEC has an upward bias in estimates of volatility lends additional evidence to that in Hokayem et al. (2015) and Bollinger et al. (2019) on the perils of use of hot-deck imputations for earnings analyses. This finding seems more binding for male earnings volatility.

II. Measuring Volatility

We adopt two summary measures of earnings volatility that are typical in the literature. The first is the variance of the arc percent change (Ziliak et al. 2011; Dynan et al. 2012), defined as

(1) $$varc_t = 100 * Var\left(\frac{y_{it}-y_{it-1}}{\bar{y}_i}\right),$$

where $\bar{y}_i$ is the average (absolute value) earnings across adjacent years, $\bar{y}_i = \frac{|y_{it}|+|y_{it-1}|}{2}$. The second measure is the variance of the change in log earnings (Shin and Solon 2010; Moffitt and Zhang 2018), defined as

(2) $$vlog_t = 100 * Var(lny_{it} - lny_{it-1}) ,$$

where lny_{it} as the natural log of earnings for individual *i* in time period *t*.

A limitation of the change in logs measure of volatility is that log earnings are undefined if earnings are not positive. Employment rates, as depicted in Figure 1, 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, especially from first difference calculations, likely understates true earnings volatility. 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 would contribute to differences in the earnings volatility measures between survey and administrative data. The arc percent measure has the advantage that those with zero or even negative earnings can be included in the computation without imposing ad-hoc adjustments to the levels to allow log transformations. In addition, the arc percent change is bounded between ± 200%, which facilitates interpretation. However, the symmetry property is violated if earnings are negative one year, say due to a business loss, and positive the next, and thus we take the absolute value of earnings.

[Figure 1 here]

Because earnings volatility can be affected by life-cycle factors (Gottschalk and Moffitt 1994), we first regress the arc percent change (or log diff) on a quadratic in age year-by-year as

(3) $$\frac{y_{it}-y_{it-1}}{\bar{y}_i} = \alpha_t + \beta_t age_{it} + \gamma_t age_{it}^2 + \nu_{it}$$

and then replace the estimated residuals $\hat{\nu}_{it}$ in equation (1) (equation (2) for log diff) prior to constructing the variance. In order to mitigate the influence of outliers, we trim the top and bottom 1 percent of the annual cross-sectional ASEC and DER earnings distributions prior to estimating the age-adjustment in equation (3). For completeness, we also present baseline estimates with a 5 percent trim, and discuss the consequences of trimming.

III. Data

The data used in our analysis are restricted-access ASEC person records linked to the DER for survey years 1996-2016 (reporting earnings for calendar years 1995-2015).[2] 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. The difference between the internal ASEC and the public version is that the internal file has higher topcode values on income components.[3]

A. DER Linkage

We link the internal ASEC to the DER file, which is an extract of the Master Earnings File and includes data on total earnings as reported on a worker's W-2 form, wages and salaries and income from self-employment subject to Federal Insurance Contributions Act and/or Self-Employment Contributions Act taxation, 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 insurance premiums and education benefits, nor do "off-the-books" earnings appear

[2] The linked ASEC-DER were obtained as part of an internal-to-Census project (DSM1170) and analyzed in a secure facility at the Kentucky Research Data Center in Lexington, Ky. Researchers outside of Census interested in accessing such data must have their project approved by Census and the Social Security Administration for analysis conducted in a secure Federal Statistical Research Data Center. For more information see https://www.census.gov/fsrdc .

[3] The internal ASEC file has a 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 at https://www2.census.gov/programs-surveys/demo/datasets/income-poverty/time-series/data-extracts/asec-incometopcodes-swappingmethod-corrected-110514.zip .

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 earnings observation per worker per year 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 Center for Administrative Records Research and Applications. The PIK is a confidentiality-protected version of the Social Security Number (SSN). Since the Census does not currently ask respondents for a 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.

B. CPS ASEC Panels

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. 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). This is the approach used by Cameron and Tracy (1998) and Ziliak et al. (2011), along with many others only with access to public files. We link the ASEC to the DER prior to constructing the panel.[4] Appendix Table 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. The SCHIP oversample in the ASEC is not eligible for the longitudinal follow-up, and thus we exclude it from the denominator we match about 72 percent of persons across March surveys. Below we discuss sensitivity of estimates to adjustments for nonlink and attrition.

C. Sample Summary Statistics

The principal sample used for the volatility measures is people between the ages of 25-59 who have positive earnings in at least one year, 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 that are 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 percent of individuals had their entire ASEC imputed and so we drop these individuals, though we account for this in our attrition analysis.

[4] Because we first link the internal ASEC to the DER prior to the longitudinal match, we also have the individual's unique PIK that can be used to match from one year to the next. Results are qualitatively similar using the PIK.

In addition to the linked respondent sample, we also conduct our analyses with a sample of individuals who may be an ASEC earnings nonrespondent in one or both years or who may not have a link to the DER in either or both years, which we call the full sample. 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) calls this assumption into question. The linked respondent sample, while more selected, offers a cleaner "apples-to-apples" comparison of volatility trends from the ASEC and DER, while the full sample, and in particular the full sample of two-year respondents, provides a more comprehensive estimate of labor-market volatility because they may or may not have a DER link.[5]

[Table 1 here]

Table 1 provides summary statistics for our full sample and 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.[6] Among men, 84 percent have a DER link in both panel years, while 5 percent have a DER link in either 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.

[5] Bollinger et al (2019) show, for example, that non-citizen Hispanics have comparable response rates to native-born non-Hispanics, but are much less likely to be linked to the DER. These persons do not show up in DER volatility.
[6] Earnings are inflation-adjusted using the personal consumption expenditure deflator with 2010 base year.

[Figure 2 here]

Figure 2 depicts 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 for outliers. The figure shows that the earnings distributions in the ASEC and DER are quite comparable in terms of levels and trends. Below the 90th percentile, earnings in the ASEC tend to exceed those in the DER by $2000-3000 on average. In the upper quantiles the DER exceeds the ASEC on average by $2400 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). Appendix Figure 1 shows a parallel figure for the distribution of residuals from the log difference regression (which omits 0s by construction). The ASEC series are quite comparable to the DER. Thus, based on the levels and changes it does not appear that there are fundamental differences in the distributions in the ASEC and DER that prima facie point to differences in volatility.

IV. Results

Because most prior studies restrict attention to men only, we first present our estimates of volatility for men, both overall and by heterogeneous subgroups, and then we provide a comparison with women. We then present estimates of permanent and transitory volatility.

A. Baseline Male Volatility in the ASEC and DER

We begin by presenting the baseline volatility estimates for the linked respondent sample of men in the ASEC and DER with our preferred arc-percent change measure from equation (1) and with a 1% trim of outliers. The top panel of Figure 3 only requires men to have earnings in one of two years, while the bottom panel restricts to those with positive earnings in both years.

[Figure 3 here]

There are two key takeaways from Figure 3. First, allowing for labor-force nonparticipation has a substantive effect on the level and trend of male earnings volatility in the ASEC. The top panel shows that the level of ASEC volatility in a typical year is about double compared to the bottom panel of continuous workers. Volatility increased between 30-40 percent in the sample period with the inclusion of nonemployment, compared to no trend in volatility for the series excluding ASEC nonworkers. In both panels, there is a notable uptick in volatility in the years surrounding the Great Recession, but there was a return to pre-recession levels among the subsample of continuous workers. Second, nonemployment has little effect on the level of DER volatility, and there is no trend in DER volatility regardless of inclusion of zeros or level of trimming of residuals.[7] As with the ASEC, there is a substantial increase in volatility around the Great Recession in the DER, which is even more pronounced than the ASEC with nonworkers excluded, but it returned to pre-recession levels by 2014. Thus, volatility over the last two decades is largely a business-cycle effect, and there is no substantive discrepancy between the ASEC and DER, unless one incorporates ASEC nonworkers into the analysis. As discussed below, however, most of these nonworkers in the linked respondent ASEC sample report zero earnings in the ASEC but have a positive DER, suggesting these "0s" are reporting errors. Appendix Figure 2 repeats the analysis, but with a 5% trim of outliers instead of 1%. The story is the same, but the level of volatility is notably lower.

[Figure 4 here]

Figure 4 presents trends in volatility estimated with the change in log earnings from equation (2) for the sample of continuous working linked respondents. The log difference is the most common measure of volatility in the literature, and comparing panel B of Figure 3 to panel A of Figure 4 shows that there is little difference in the patterns of volatility among workers. The log difference increases the amplitude of volatility in the DER during the Great Recession compared to the arc percent change of earnings levels, and suggests a greater separation with the ASEC. Panel B of Figure 4 restricts the sample

[7] We communicated with two separate staff members at the Social Security Administration and received conflicting responses on whether the $0s are valid entries in the DER. As this affects only about 0.1 percent of the DER sample we have retained them as valid for completeness.

to male heads of household—the group observed in the PSID—and yields the same pattern with a sharp peak of volatility at the end of the Great Recession but flat trend over two decades. The higher volatility in the DER among workers in Figure 4 (and panel B of Figure 3) compared to the ASEC is suggestive that workers have more earnings unreported to SSA during economic downturns, whether obtained legally or off-the-books.

B. Linking and Nonresponse, and Trimming Outliers

In this section we explore how the level and trend in volatility are affected sequentially by the requirement that men be linked to the DER across two years of the ASEC and the requirement that men respond to the ASEC earnings questions in both years. We also examine the importance of trimming.

[Figure 5 here]

In Figure 5 we present the arc percent change volatility series for the full ASEC in panel A, including those linked and not linked to the DER and those who both respond and do not respond to the earnings questions in the ASEC. In panel B we impose the requirement that sample members be linked to the DER, but still include earnings nonrespondents, while in panel C we restrict the sample to two-year respondents regardless of whether they have a DER link. For each panel we present the volatility series inclusive of 0s on the left side, and exclude zero earnings on the right side. We only present the 1% trim series since only the levels and not trends are affected with the 5% trim.

The left side of panel A of Figure 5 has the same shape as panel A of the linked responders in Figure 3, the difference being the level of ASEC volatility is much higher in Figure 5 when including both the unlinked and nonresponders. Interestingly, though, the right side of Figure 5 panel A without zero earnings is much different than panel B of linked responders in Figure 3. The former shows a wide gap between the ASEC and DER volatility, with volatility higher and rising in the ASEC, whereas Figure 3 depicted no trend in volatility in either the DER or the ASEC and if anything, volatility was higher in the DER during recessionary periods. When we impose the requirement that the individual have a DER link in both periods this dampens the amplitude of volatility during the Great Recession in panel A with zero earnings included, but does not remove the trend increase in ASEC volatility with or without (right side of panel B) zeros included. Panel C, which requires the man to be an ASEC respondent in both periods, but not a DER link, shows that compared to panel A, excluding nonresponders reduces measured volatility considerably. This is particularly true for the right side with nonworkers excluded. That chart is nearly identical to panel B of Figure 3, suggesting that nonresponse amplifies volatility and that the Census hotdeck method imparts bias much like Bollinger et al. (2019) show for wage levels.[8] Notably, in the left side of panel C, the ASEC nonworkers are much more likely to be "true nonworkers" and not those who report no earnings in the ASEC but have a DER report. Thus the baseline volatility in Figure 3 is affected both by dropping nonlinked and nonresponders, and the covariance between the two groups.

[Figure 6 here]

The top panel of Figure 6 shows trends in volatility using the arc percent change for the linked respondent sample, omitting zero earnings, but no longer trimming the cross-sectional distribution. Panel B has the same sample but for the log difference volatility measure. Panel A of Figure 6 differs from the baseline trimmed volatility series in panel B of Figure 3 only in the level of volatility, but not the trends. This is not the case for log earnings. Panel B of Figure 6 makes clear that untrimmed volatility in the ASEC is quite high and different from the DER, until the Great Recession when ASEC volatility falls below that of the DER. The figure suggests that trimming earnings is much more important for the log transformation used in the log-difference volatility measure than for the levels of earnings used in the arc percent.

C. Attrition

A 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

[8] Dahl et al. (2010) report a similar upward bias from imputation in the SIPP linked to the DER.

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. 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 our estimates will be purged of possible attrition bias (Wooldridge 2001). However, if there is time-variation in the factor loading on the unobserved individual-level heterogeneity then differencing will not eliminate potential attrition bias unless the factor loading is randomly distributed across the population. A conservative interpretation is that data from matched ASEC provides estimates of earnings volatility among the population of non-movers.

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. Appendix Table 2 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.

[Figure 7 here]

Figure 7 presents trends in arc percent volatility of men by attrition status using a 1% trim at the top and bottom of the earnings distribution. In panel A we use the full sample of respondents and nonrespondents, while panel B is restricted to those who responded to the earnings questions in year 1. Panel A has four series, two for attriters and two for non-attriters. For both groups we present the DER volatility, while for attriters we also present a series that consists of the ASEC in year 1 and the DER in year 2 (for those linked to the DER). For non-attriters we present the ASEC series across both years. Focusing on the DER series, it is clear that attriters have higher earnings volatility than non-attriters, though the trends are largely similar (with a more Great Recession effect among attriters). This is also true for the subsample of year 1 earnings responders as depicted in panel B based on the DER alone. Interestingly, when we use the DER to "fill-in" for the missing year 2 ASEC among attriters in Panel A, volatility is noticeably higher in most years compared to the ASEC alone among non-attriters. Again, though, the trends are not substantively different. This suggests that our matched panels in the ASEC primarily affect the level, but not trend, in volatility.

[Figure 8 here]

To further explore the role of attrition and nonresponse on volatility, in Figure 8 we reproduce Panel A of Figures 3 (arc percent) and 4 (log difference) where we now 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 we have evidence that the MAR assumption is violated in earnings levels (Bollinger et al. 2019), it may be a valid assumption in first differences with our volatility measures. We proceed by estimating a probit model 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. Figure 8 aligns with our priors from the evidence in Figure 7; namely, when we reweight the data the original estimates of volatility with zero earnings (Figure 3, Panel A) and without (Figure 4, Panel A) the levels of volatility are higher in each year, but there is no effect on the trends.

D. Heterogeneity in Volatility

We next explore whether the changes in volatility in the ASEC and DER over the past 21 years are widespread or isolated among specific demographic groups. We focus on heterogeneity across education attainment, race and ethnicity, and intensity of work effort as full-year or part-year.[9] This is an advantage of the ASEC-DER file because of the large sample sizes. For this exercise we focus on the arc percent change measure and within the linked respondent sample to make direct comparisons between the

[9] Full year includes full-time full-year and part-time full-year workers, while part year includes full-time part-year and part-time part-year workers.

ASEC and DER. To assess the relative contributions of subgroups to total variance, we decompose the variance of volatility into within-group and between-group differences (Moffitt and Zhang 2019). Specifically, if we define $arc_{it} \equiv \frac{y_{it}-y_{it-1}}{\bar{y}_i}$, then for any time period *t* we can rewrite the variance of the arc percent change in equation (1) as

$$(4) \qquad varc_t = \frac{1}{N}\sum_{g=1}^{G}\sum_{i=1}^{N_g}\left[\left(arc_i - \overline{arc}_g\right) + \left(\overline{arc}_g - \overline{arc}\right)\right]^2 = \sum_{g=1}^{G}\frac{N_g}{N}\left[\frac{1}{N_g}\sum_{i=1}^{N_g}(arc_i - \overline{arc}_g)^2\right] + \sum_{g=1}^{G}\frac{N_g}{N}\left(\overline{arc}_g - \overline{arc}\right)^2,$$

where the first term in the second equality is the within-variance of the arc percent change at time *t* and the last term is the between-group variance, and $\frac{N_g}{N}$ is the group-specific share of the total population. Because the between-group variance accounts for less than 10 percent of the total in any given year, we focus on the within-group variance. We only show the decomposition with a 1% trim, inclusive of zeros from (one-year) ASEC nonworkers. Appendix Figures 4-6 contain the log-difference decompositions for two-year workers.

[Figure 9 here]

Figure 9 depicts trends in volatility separately in the ASEC and DER for linked-respondent men with less than high school education, high school, some college, and college or post-graduate work. The top panel contains the group-specific variances, while the bottom panel contains the variances weighted by the shares of the population. The trends in population shares are depicted in Appendix Figure 3. Volatility levels in the ASEC are much higher among high school dropouts than other education groups with the highest volatility measured by the ASEC w/0s series, as expected given the employment trends in Figure 1. The rise in ASEC volatility cuts across all education levels, except for those with a college degree or more. The bottom panel, however, shows that high-school dropouts contribute least to overall male earnings volatility, which is explained by their small and declining share of the population as depicted in panel A of Appendix Figure 3. The DER shows little difference in volatility levels or trends for those men with a high school diploma or more. There is an increase in DER volatility among dropouts around the Great Recession, but as with the ASEC, their weighted share of total variance is small and stable.

[Figures 10-11 here]

The panels of Figure 10 show trends by race and ethnicity for men in 4 groups: White Non-Hispanic, Black Non-Hispanic, Hispanic, and a combined Asian and American Indian group. Both whites and blacks experience an increase in ASEC volatility over the time period; there are no differences across race-ethnicity in DER volatility. However, once we weight by population shares, it becomes clear that White Non-Hispanic men contribute the most to volatility and their series mimics that depicted in Figure 3 for both the ASEC and DER. In Figure 11 we split the sample into whether the person is part-year in both years, part-year in year one and full-year in year two, full-year in year one and part-year in year two, and full-year in both years. As expected, men who are full-year both years have the lowest unweighted volatility, and those who are part-year in both periods have the highest unweighted volatility. Perhaps surprising, even though the two-year part-year workers are a small share of the total workforce, their weighted variance is the largest overall in the ASEC and the shape largely reflects that depicted in Figure 3. [10] Volatility in the last few years of the sample period does not fall as much as the weighted variance of two-year part-time workers, with overall volatility propped up by employment status switchers and the stability of the full-year group.

[Figure 12 here]

In Figure 12 we return to the full ASEC sample that includes both respondents and nonrespondents, and those with and without a link to the DER. Here we wish to explore how much of total volatility the standard user of the ASEC is likely to identify because of inclusion of earnings nonresponders. Panel A shows that those men who switch response status between years have the highest

[10] Note that the ASEC w/ 0s measure is defined for this sample because there are some workers who report 0 earnings in the ASEC, but they have positive earnings in the DER. These persons fall mostly in the part-part group. In general the patterns described by the variance decompositions in the text agree with the log-difference decompositions in Appendix Figures 4-6. The only difference is the weighted employment-status is now dominated by concurrent full-year workers, underscoring that the part-part group has many ASEC zeros but DER reports.

group-specific volatility, followed next by those who are ASEC nonresponders in both years. Two-year responders have the lowest volatility, but panel B shows they contribute the most to total volatility, which is consistent with their large share of the population. However, as panel D of Appendix Figure 3 shows, the latter groups share has declined in the last few years, which means total volatility did not fall as much as predicted by two-year respondents and was propped up by volatility of allocated earners. Crucially, while DER volatility among nonresponders exceeds that of responders in panel A, the differences are very small, especially in relation to the ASEC, underscoring pitfalls with the hot-deck imputation in the ASEC.

E. Comparisons with Women

We conduct a full parallel set of analyses for women, but for ease of presentation we only present a subset here. To anchor with the baseline male volatility estimates in Figure 3, in Figure 13 we use the linked respondent sample to depict the arc percent change with one-year ASEC nonworkers included in panel A and with nonworkers excluded in panel B. Unlike men, the volatility of women is stable in the ASEC when zeros are included, while in the DER (and when nonworkers are excluded in the ASEC in panel B), there is evidence of declining volatility of women. The latter continues a trend first begun in the late 1970s (Ziliak et al 2011), and contrasts with the stability of male volatility in panel B of Figure 3. The other important contrast with men is the lack of business-cycle induced volatility of women's earnings. Appendix Figure 7 presents female earnings volatility using the log difference and confirms that declining female earnings volatility is robust across measures. This holds in Appendix Figure 8 with a 5% trim of outliers, in Appendix Figure 9 with no trimming of outliers, and in Appendix Figure 10 Panel B for both attriters and non-attriters.

[Figure 13 here]

In Figure 14 we unpack the volatility of women to examine the roles of imposing a DER link and earnings response, akin to that presented in Figure 5 for men. Panel A is for the full ASEC, those with and without a DER link and those with and without allocated earnings, and with a 1% trim of annual cross-sectional earnings. When we include women with no more than one-year ASEC nonemployment, ASEC volatility is at least three times the level that in the DER, and stable, and when we exclude zero earners in the right-hand side ASEC volatility falls by half, but is still 50 percent higher than DER volatility. When we impose the two-year DER link requirement in panel B—but still include earnings responders and nonresponders—then ASEC volatility of women falls considerably (in part because many zeros fall out), but it is trending upward. In panel C we impose the requirement that earnings be reported in both years, with and without a DER link. While ASEC volatility is lower than in panel A, suggestive that nonresponse pushes volatility upward as we found with men, there is a yawning gap between the ASEC and DER when we include ASEC nonworkers, but they are coincident when we drop nonworkers in the right side of panel C. The fact that the baseline female ASEC volatility series in panel A of Figure 13 lies below the series in Figure 14 suggests important covariance in the joint imposition of having both a DER link and being a respondent.

[Figure 14]

We explore further the issue of nonresponse on women's earnings volatility in the variance decomposition based on equation (4) and presented in Figure 15. This parallels the decomposition for men in Figure 12. What is interesting here is that the group-specific volatility of two-year nonrespondents in panel A overlaps with the volatility of two-year respondents. For men the former was between 50-100 percent higher than the latter in most years, suggesting perhaps that the hot-deck may be more accurate in predicting missing earnings of women than men, or at least changes in earnings. However, as with men, once the variances are weighted by group-specific shares (panel B of Figure 15) then the volatility of two-year responders contributes most to annual volatility among women in both the ASEC and the DER, and is declining over time in both data sources.

[Figure 15 here]

Finally, in Appendix Figures 11-13 we present within-group variance decompositions (arc percent with zeros included) for women's earnings volatility by education attainment, race and ethnicity, and full-year/part-year employment status. In this case the decompositions for women are more similar to men in that the group-specific volatility of high school dropouts exceeds that of higher educated, but the weighted contribution of the less skilled is dominated by the other groups, the gross volatility of whites is less than non-whites, but the weighted variance of whites is greatest owing to their large population share, and the volatility of part-year workers dominates that of other groups, both unweighted and weighted by group shares.

F. Transitory and Permanent Volatility

Much of the early literature aimed to isolate whether earnings volatility stemmed from permanent or transitory changes in economic status. The classic model is a simple decomposition of earnings into a time-invariant permanent component, μ_i, and a time-varying transitory component, u_{it},

(5) $$y_{it} = \mu_i + u_{it}.$$

Identifying the transitory component is easily addressed in equation (5) using the arc measure or by modeling log earnings similarly (additive transitory and permanent components) because differencing removes the time-invariant permanent effect.

We note, however, that survey, y_{it}^S, and administrative, y_{it}^A, data differ in the data generating process of observed earnings. Researchers often treat administrative data as the "gold standard" or "truth", though Kapteyn and Ypma (2007) suggest that treating administrative data as error free may be unreasonable. The largest threat to treating administrative data as error free is the existence of an underground economy where workers' earnings are not reported formally. At its simplest, then, one can argue that measurement error potentially enters both the survey data and administrative data:

(6) $$y_{it}^S = \mu_i + u_{it} + \varepsilon_{it}$$

$$y_{it}^A = \mu_i + u_{it} + \upsilon_{it}.$$

Our key assumption is that while both measures may have measurement error, because the sources and causes of the measurement error differ, we assume that ε_{it} and υ_{it} are at least uncorrelated (independence seems appropriate, but is not necessary). We also assume—as is typically done—that the transitory shocks are also uncorrelated over time and uncorrelated with the two measurement error terms.

Under these two assumptions, then we can discuss various approaches to identification of the variance of the permanent component and the variance of the transitory component through autocorrelation and cross correlation terms:

(7) $Cov\left(y_{it}^{j}, y_{it-1}^{k}\right) = V(\mu_i)$,

where *j* and *k* represent either survey (*S*) or administrative (*A*) measures. This produces four possible covariance terms which identify the permanent earnings variance under the simple additive measurement error terms above: $Cov(y_{it}^{S}, y_{it-1}^{S})$, $Cov(y_{it}^{A}, y_{it-1}^{A})$, $Cov(y_{it}^{S}, y_{it-1}^{A})$, $Cov(y_{it}^{A}, y_{it-1}^{S})$.

In order to identify the transitory term, we have to remove the permanent term. Typically, this is done with first differencing as

(8) $\Delta y_{it}^{S} = (u_{it} - u_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1})$

and

(9) $\Delta y_{it}^{A} = (u_{it} - u_{it-1}) + (\upsilon_{it} - \upsilon_{it-1})$.

The corresponding variances are then

(10) $V\left(\Delta y_{it}^{S}\right) = 2V(u_{it}) + 2V(\varepsilon_{it})$

and

(11) $V\left(\Delta y_{it}^{A}\right) = 2V(u_{it}) + 2V(\upsilon_{it})$.

However, as long as the measurement error terms ε_{it} and υ_{it} are uncorrelated, then the covariance of the two series identifies the transitory variance:

(12) $Cov\left(\Delta y_{it}^{S}, \Delta y_{it}^{A}\right) = 2V(u_{it})$.

This term also provides a test of the presence of measurement error. For example, if measurement error is present in the ASEC, but not in the DER data, then $V(\Delta y_{it}^{A})$=$Cov(\Delta y_{it}^{S}, \Delta y_{it}^{A})$, and both will be less than the $V(\Delta y_{it}^{S})$. If there is no measurement error, then $V\left(\Delta y_{it}^{S}\right) = V\left(\Delta y_{it}^{A}\right) = Cov(\Delta y_{it}^{S}, \Delta y_{it}^{A})$.

[Figure 16 here]

In Figure 16 we present the three sets estimates of the transitory volatility based upon the two variances and the covariance term in equations (10) – (12), where Panel A is for men and Panel B is for women. The variances are labeled ASEC for $V(\Delta y_{it}^{S})$, DER for $V(\Delta y_{it}^{A})$, while the covariance term, $Cov(\Delta y_{it}^{S}, \Delta y_{it}^{A})$, is labelled Cov(ASEC,DER). Note, in all cases the estimated variances and covariances were divided by two to provide estimates of the underlying variance of the transitory income term.

As expected, we find that the covariance term is the lowest of the three, and thus provides evidence that there is measurement error in both the administrative and the survey data. The measurement error in the ASEC is clearly higher than in the DER, as one might expect. We note too, in comparing Panels A and B that measurement error appears largest for men both for the administrative and the survey earnings measures. The covariance-based estimate of transitory earnings variance is quite stable over the time period for both men and women. So too is the estimate of transitory earnings variance based on the administrative records. However, for men in particular, the estimates of transitory earnings variance from the ASEC records have fallen over the period, most notably around the Great Recession. However, it appears that all of this change is likely due to measurement error, rather than some significant change in the economy given the stability in the DER volatility.

[Figure 17 here]

In Figure 17 we present the four autocovariance measures of the permanent earnings volatility, with men in Panel A and women in Panel B. Here the four series are labeled Cov(ASEC(t), ASEC(t-1)), Cov(DER(t), DER(t-1)), Cov(ASEC(t), DER(t-1)), and Cov(DER(t), ASEC(t-1)). In all four cases for both men and women there is a distinct upward trend in permanent income variance. This would be consistent with an economy wide change increasing earnings variance. The upward trend is most pronounced for men, and most pronounced in the Cov(DER(t), DER(t-1)) series based only on the autocorrelation of the DER series for both men and women.

One explanation for why the Cov(DER(t), DER(t-1)) series differs from that of the ASEC series, is that the ASEC measures of earnings have measurement error which does not meet the assumptions of the simple model. A number of other authors have posited that

$$y_{it}^{S} = \rho y_{it} + \epsilon_{it} = \rho \mu_i + \rho u_{it} + \varepsilon_{it}. \quad (13)$$

If this relationship holds, with $\rho<1$, then we would expect nearly the pattern we see. Simple exploration of this suggests an estimate of ρ around .9 or higher (nearly .99 for women). Note that this would produce all the patterns we have seen. It suggests that the autocovariance series using only the DER is correct (or closest), while the Cov(ASEC,DER) series in Figure 16 is a slight understatement of the transitory earnings variance.

V. Conclusion

The paper presents 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. Our results for men suggest that when ASEC nonworkers were included, earnings volatility as measured by the arc percent change increased in survey data, but was stable in tax data. However, when ASEC nonworkers were omitted then male earnings volatility was stable over the period in both the ASEC and DER, though with a substantial business-cycle component. These “nonworkers” in the linked respondent sample are primarily those who report zero earnings in the survey, but have a positive administrative earnings report. For women, when nonworkers are included the survey data show stable volatility, while tax data indicate a secular decline. Excluding nonworkers results in parity across the ASEC and DER with declining earnings volatility among women. Importantly, for women there is no cyclical component to volatility. The variance decompositions for both men and women indicate that nonresponders, low-educated, racial minorities, and part-year workers have the greatest group specific earnings volatility, but with the exception of part-year workers, they contribute least to the level and trend of volatility owing to their small share of the population. The finding that nonresponse in the ASEC has an upward bias in estimates of volatility lends additional evidence to that in Hokayem et al. (2015) and Bollinger et al. (2019) on the perils of use of hot-deck imputations for earnings analyses. This finding seems more binding for male earnings volatility. Finally, in a decomposition of volatility into transitory and permanent components we find that measurement error is present in both administrative and survey data, though more pronounced in survey data. For both men and women there is evidence of stable transitory volatility, but rising permanent volatility over the past two decades.

Our results lead us to recommend that users of the ASEC for volatility research drop earnings nonresponders, both whole supplement imputes as well as item nonresponders. We also recommend using the arc percent change over the log difference as the former is more robust to outliers. The key advantage of the arc percent change, however, is the ability to include periods of nonwork in the measure, which helps to reveal the dynamism of the U.S. labor market that lies at the heart of volatility research.

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Table 1. Sample Summary Statistics

	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	

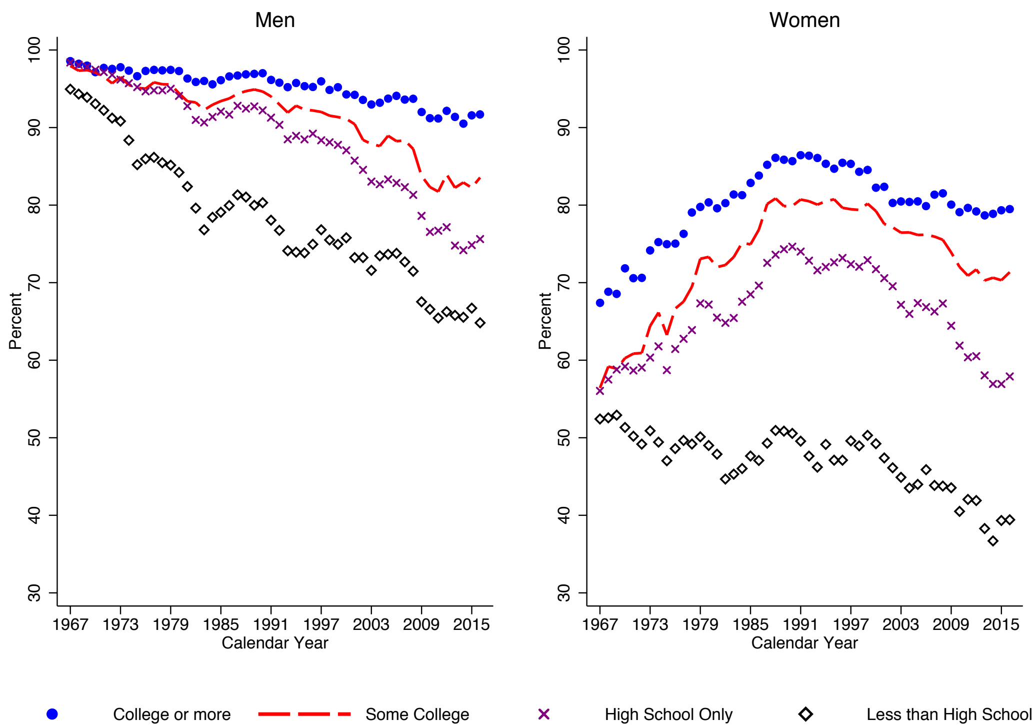
Table 1 Continued

	B. Women			
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	

Note: The full sample consists of men and women ages 25-59 who work in at least one of two years, are not full-time students in either year, and do not have their entire ASEC supplement allocated (no whole imputes). The linked respondent sample imposes the further restriction that the individual does not have allocated earnings and it is possible to link their ASEC file to the DER in both years. Earnings are deflated by the personal consumption expenditure deflator with 2010 base year.

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

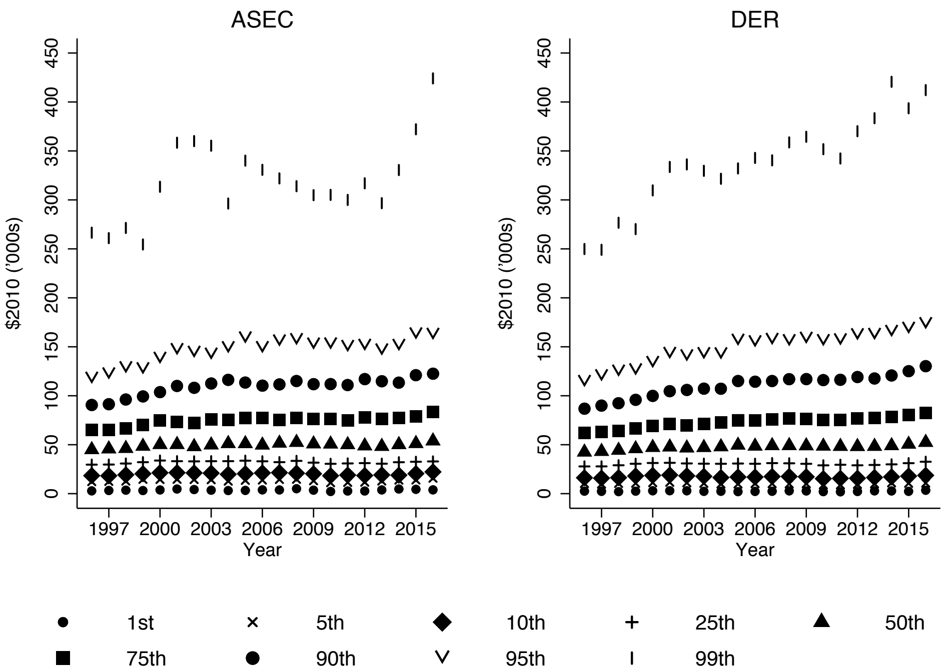
Figure 1. Trends in Employment Rates by Education Attainment



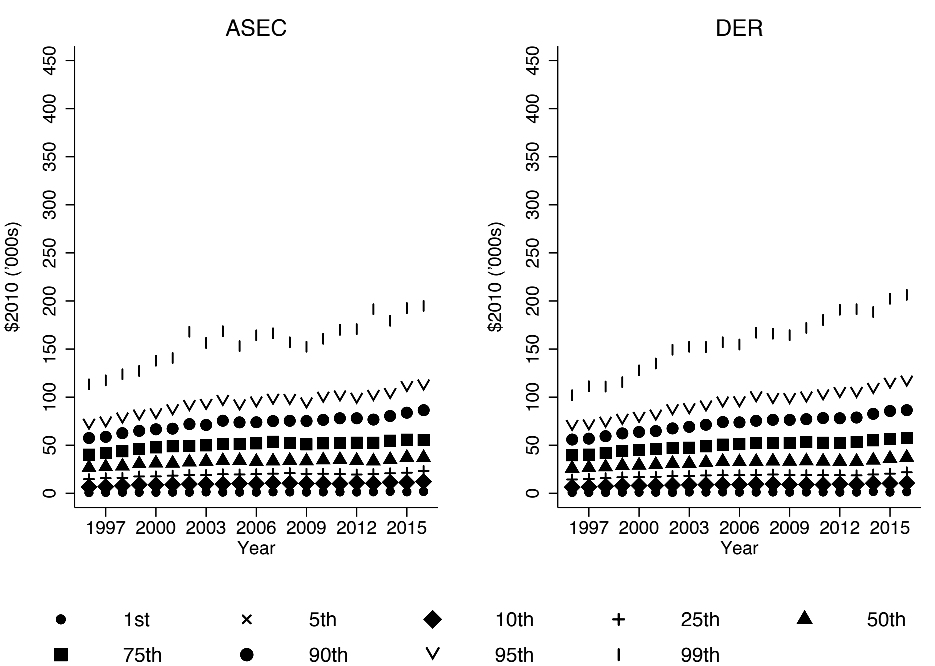
Note: Employment refers to any paid employment during the survey year.
Source: U.S. Census Bureau, Current Population Survey, 1968-2017 Annual Social and Economic Supplement.

Figure 2. Percentiles of ASEC and DER Earnings Distribution of Linked Respondents

A. Men



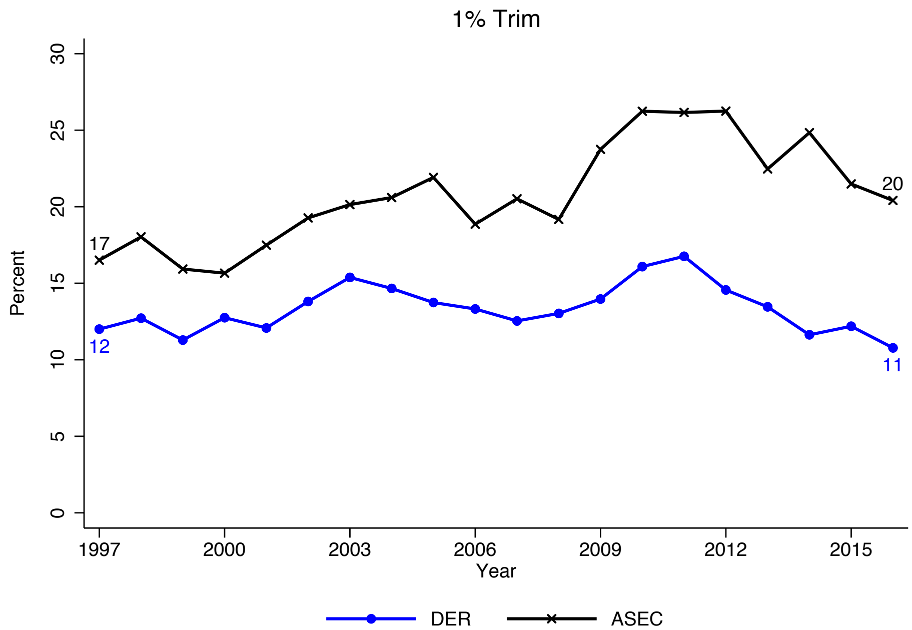
B. Women



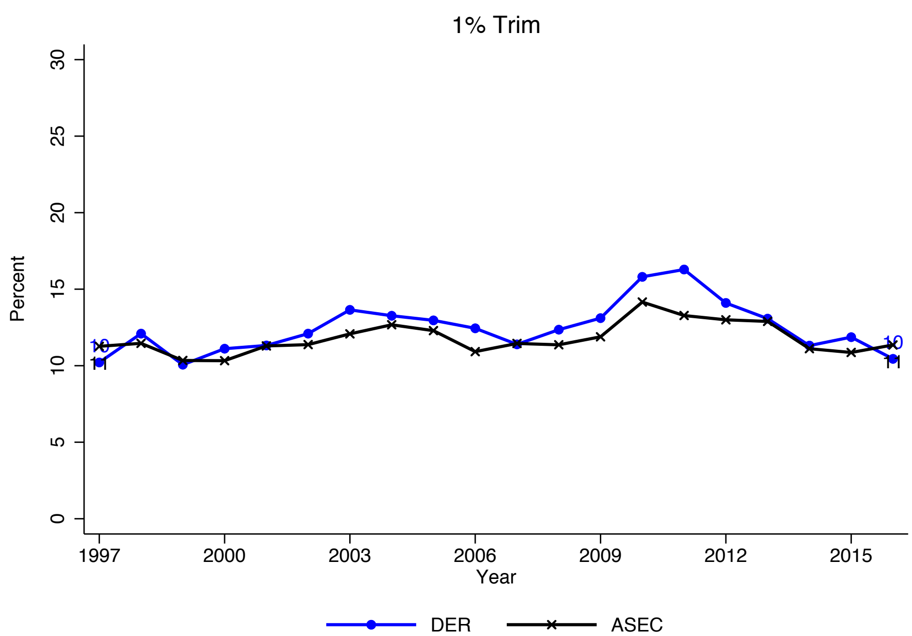
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 3. Arc Percent Earnings Volatility of Men

A. Linked Respondent Sample with Zeros



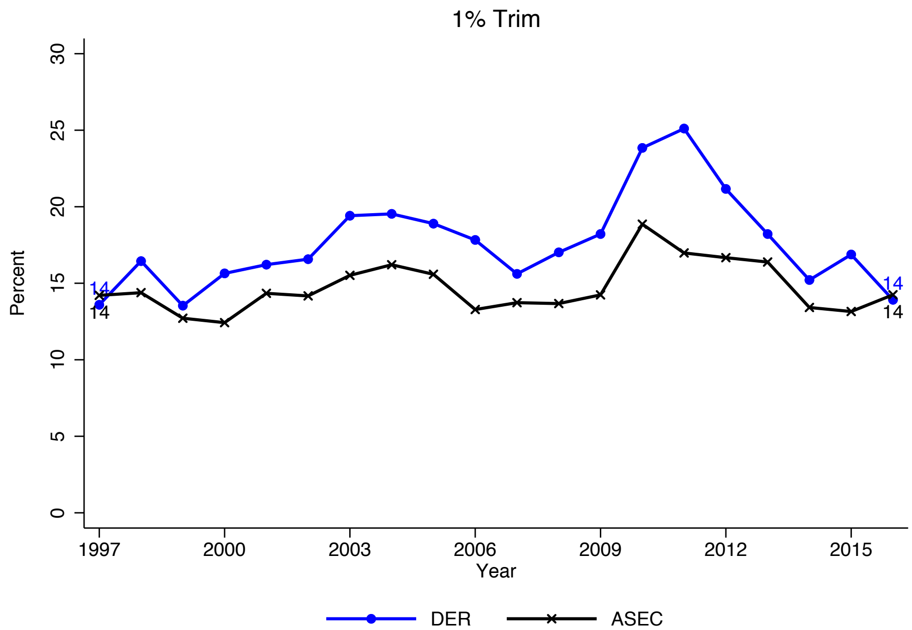
B. Linked Respondent Sample without Zeros



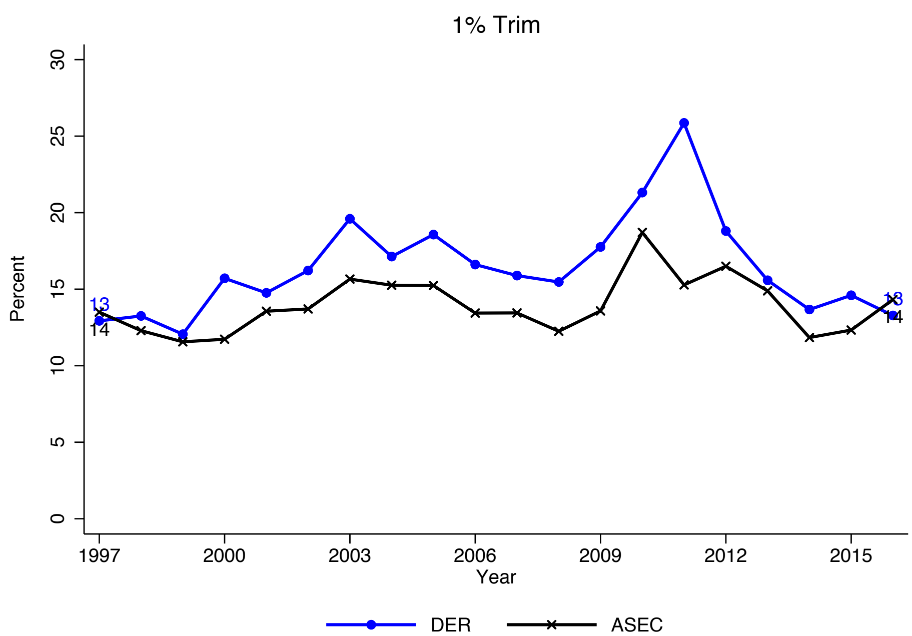
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 4. Log Difference Earnings Volatility of Men, Linked Respondents

A. All Men



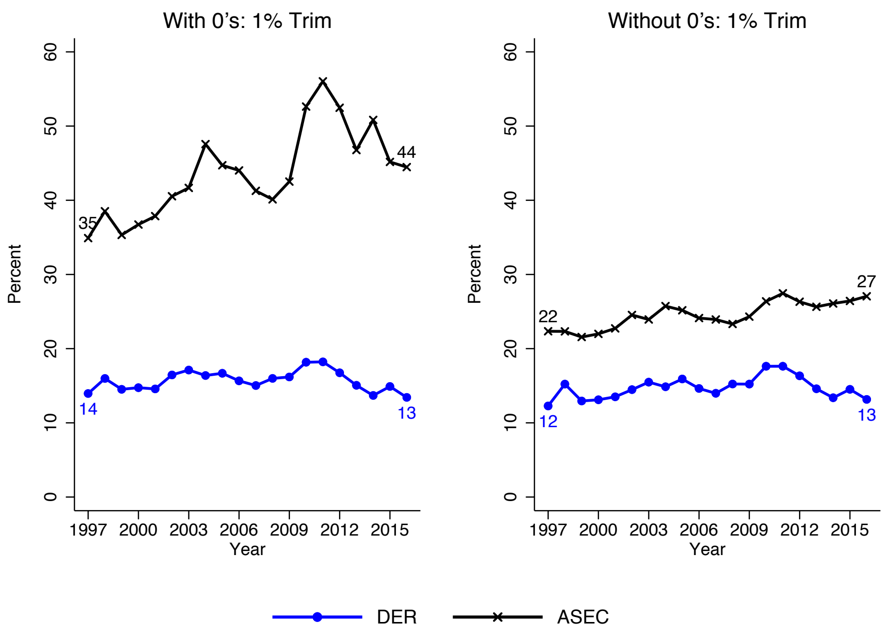
B. Heads of Household



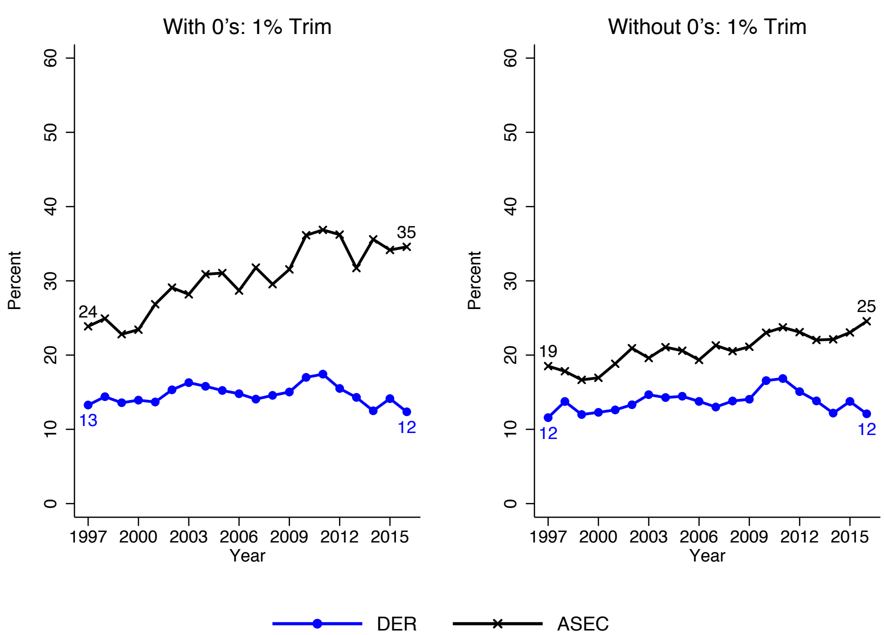
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 5. Arc Percent Earnings Volatility of Men by DER Link and ASEC Response

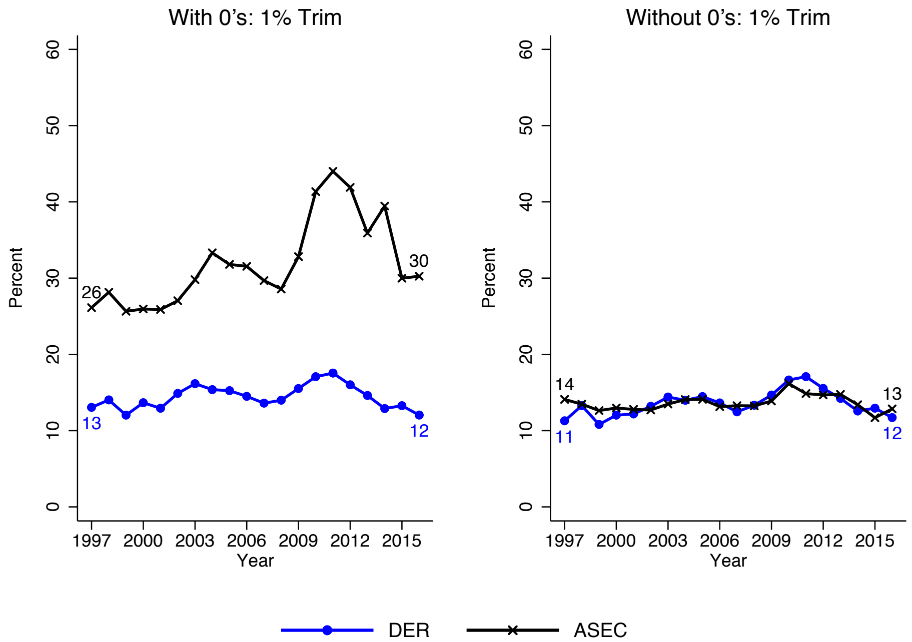
A. Full Sample with Zeros and without Zeros



B. Two-Year Linked Sample with and without Zeros



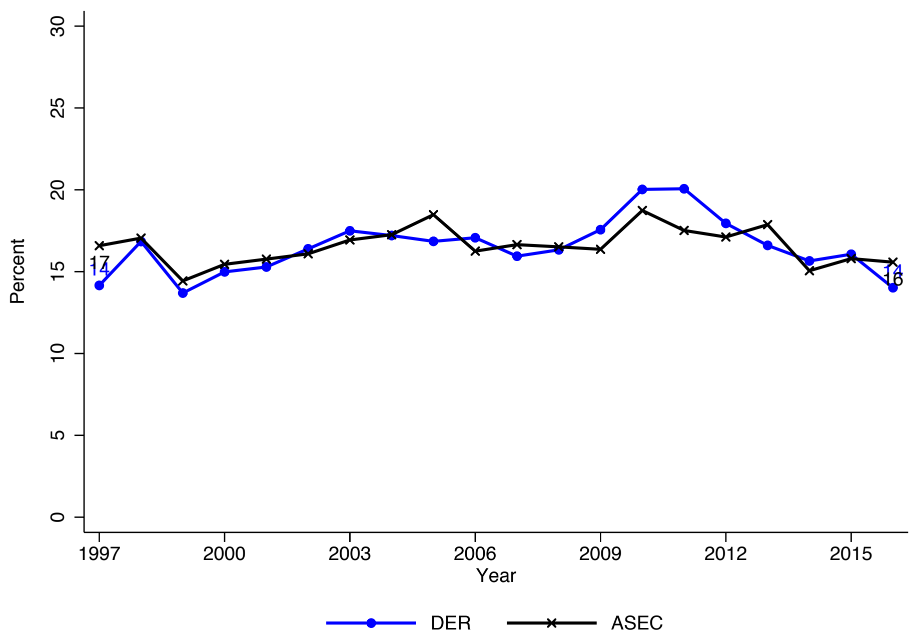
C. Two-Year Respondent Sample with and without Zeros



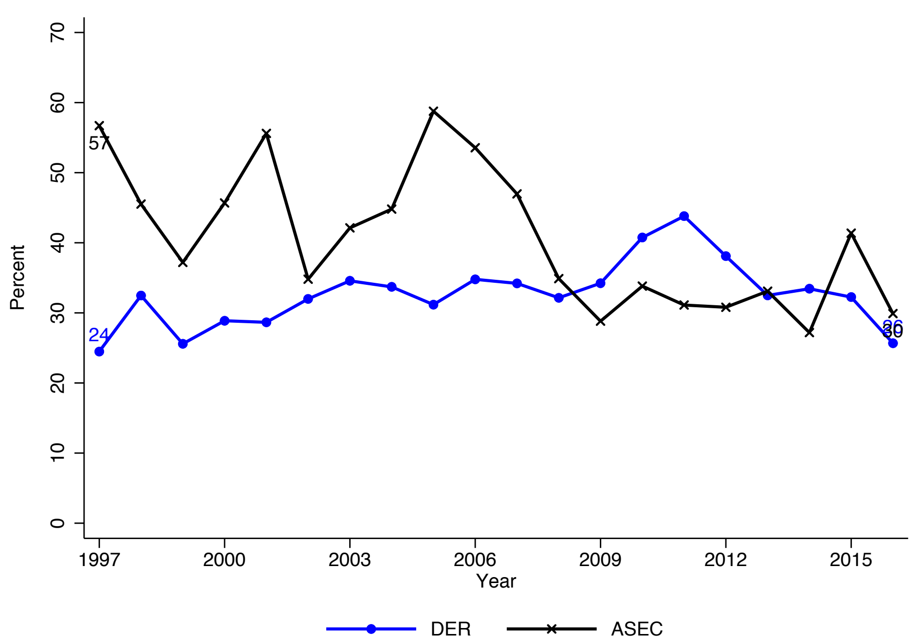
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 6. Earnings Volatility of Men without Trimming

A. Arc Percent, Linked Respondents without 0s



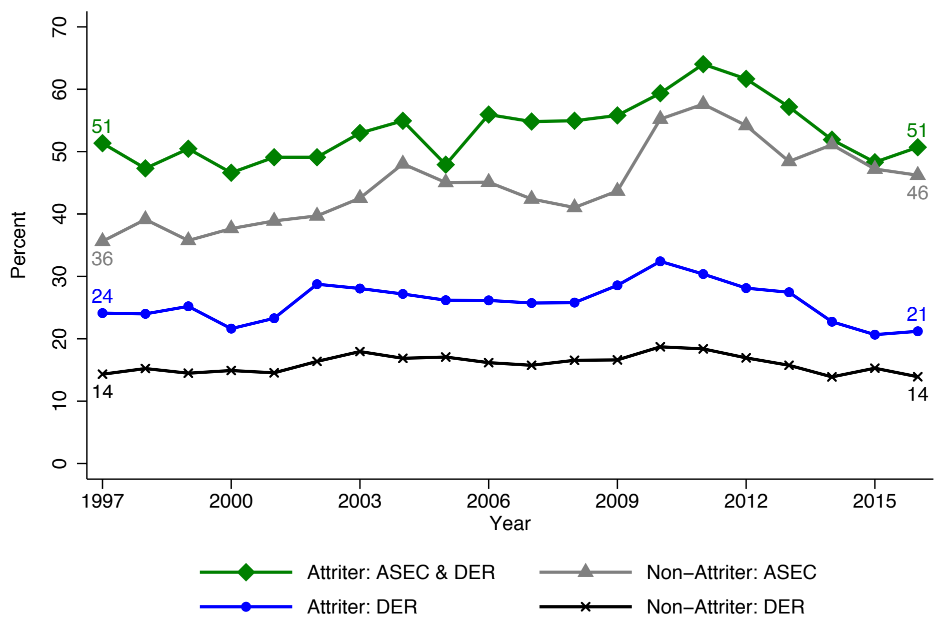
B. Log Difference and Arc Percent of Log, Linked Respondents without 0s



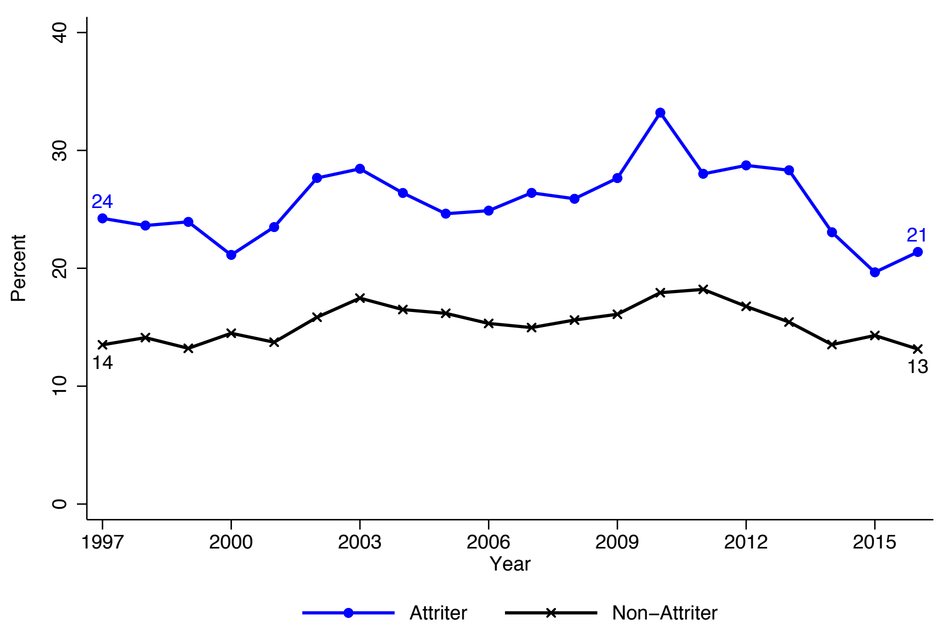
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 7. Arc Percent Earnings Volatility of Men by Attrition Status

A. Full Sample of Respondents and Nonrespondents with Zeros



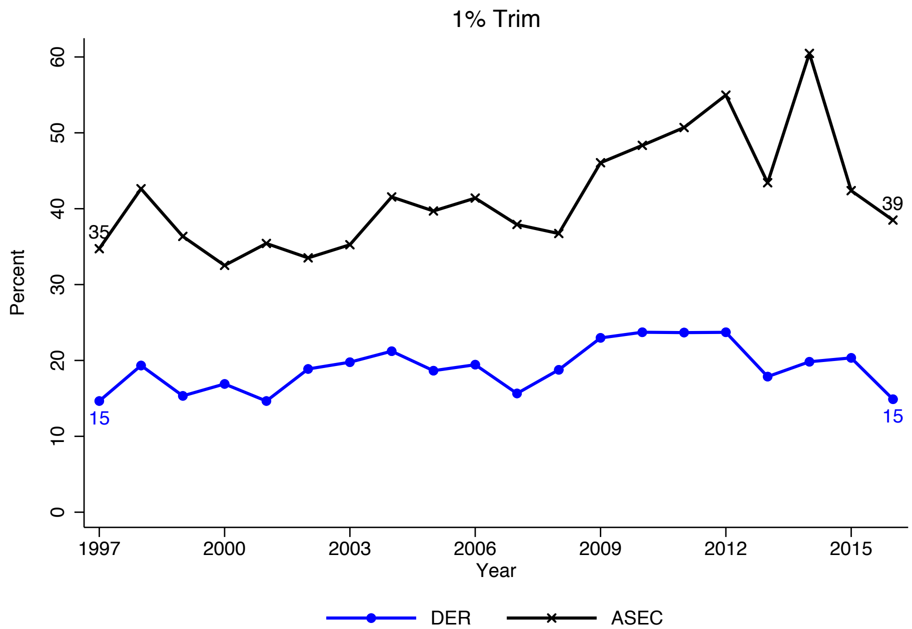
B. Sample of Year 1 Respondents with Zeros (DER only)



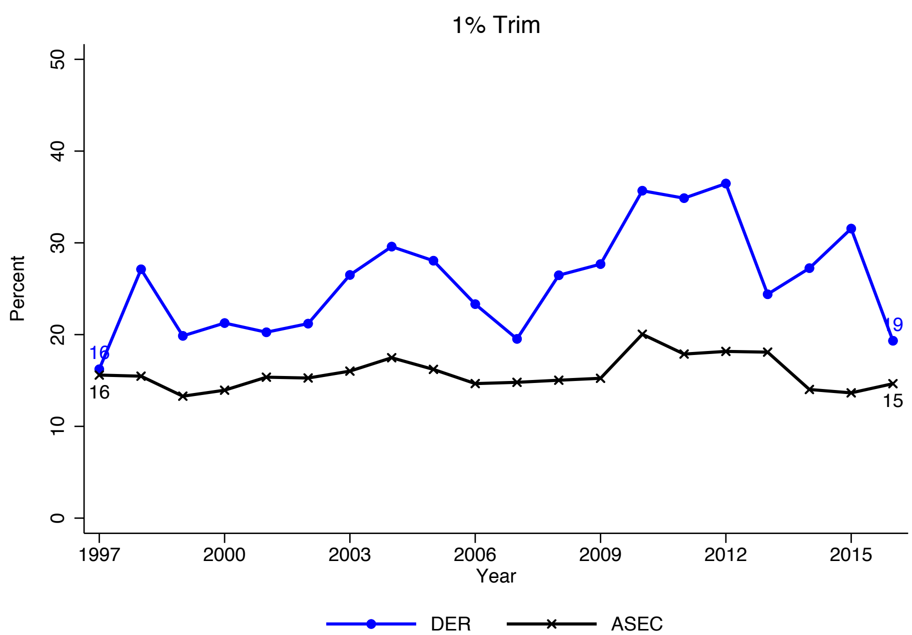
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 8. Inverse Probability Weighted Earnings Volatility of Men

A. Arc Percent with 0s



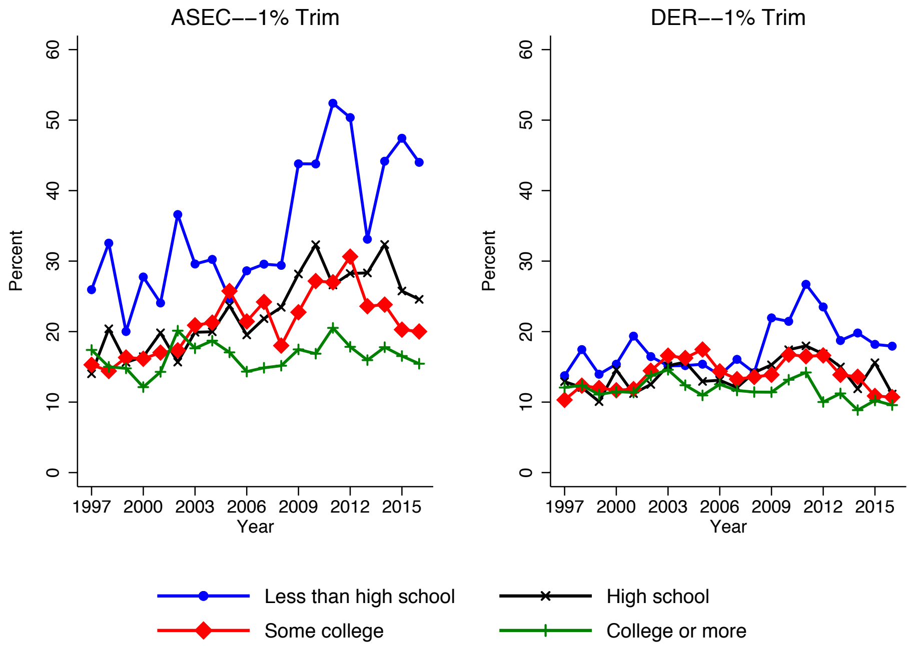
B. Log Difference



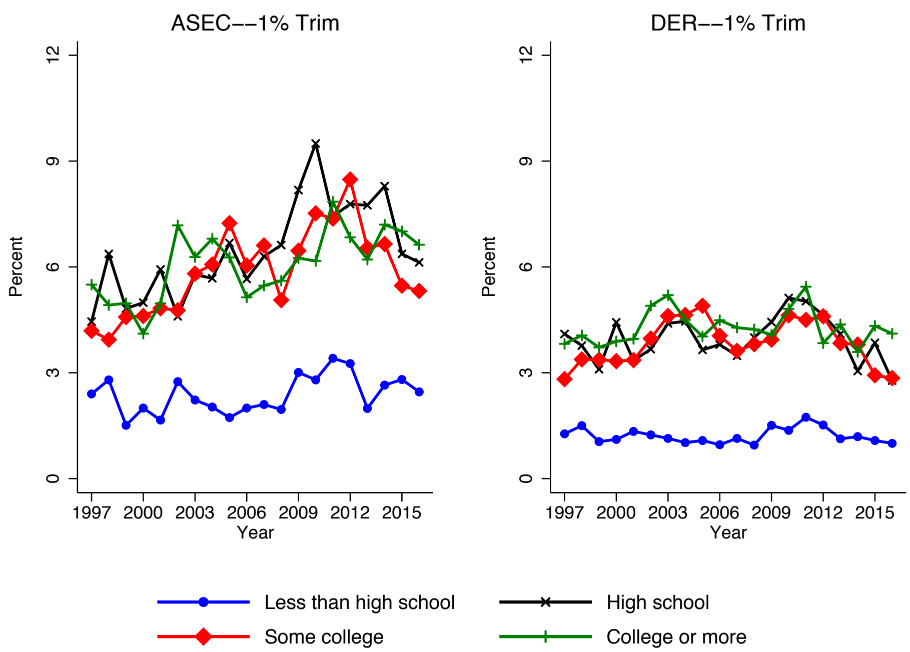
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 9. Within-Education Group Volatility of Men: Arc Percent Linked Respondents

A. Education-Specific Volatility



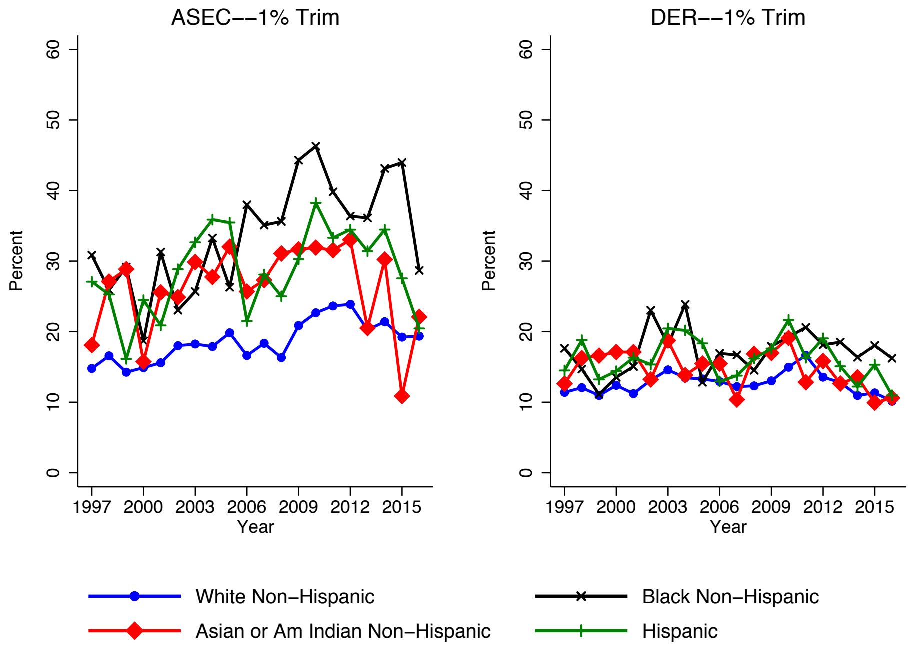
B. Weighted Education-Group Volatility



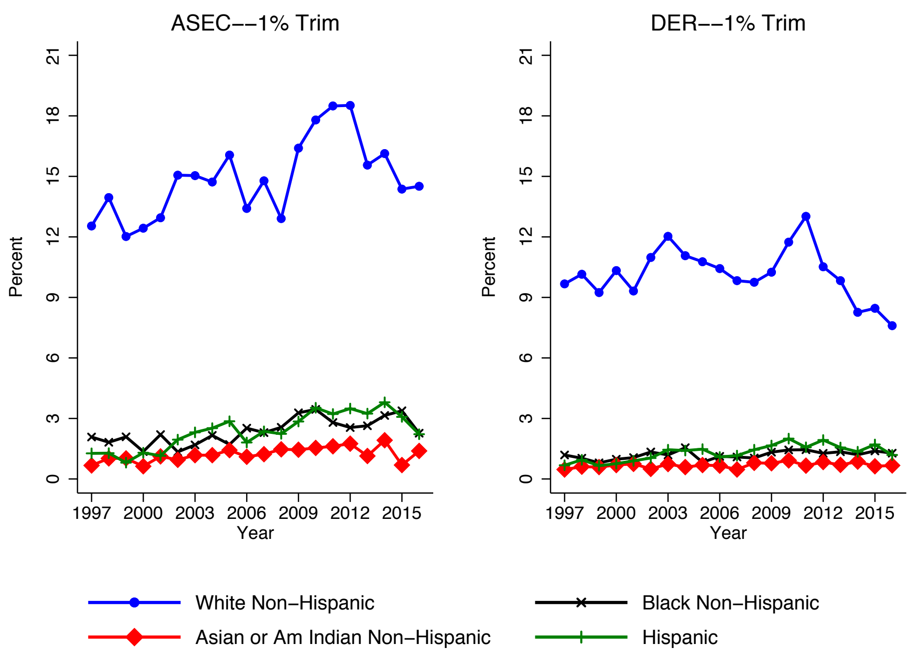
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 10. Within-Race/Ethnicity Group Volatility of Men, Arc Percent Linked Respondents

A. Race/Ethnicity-Specific Volatility



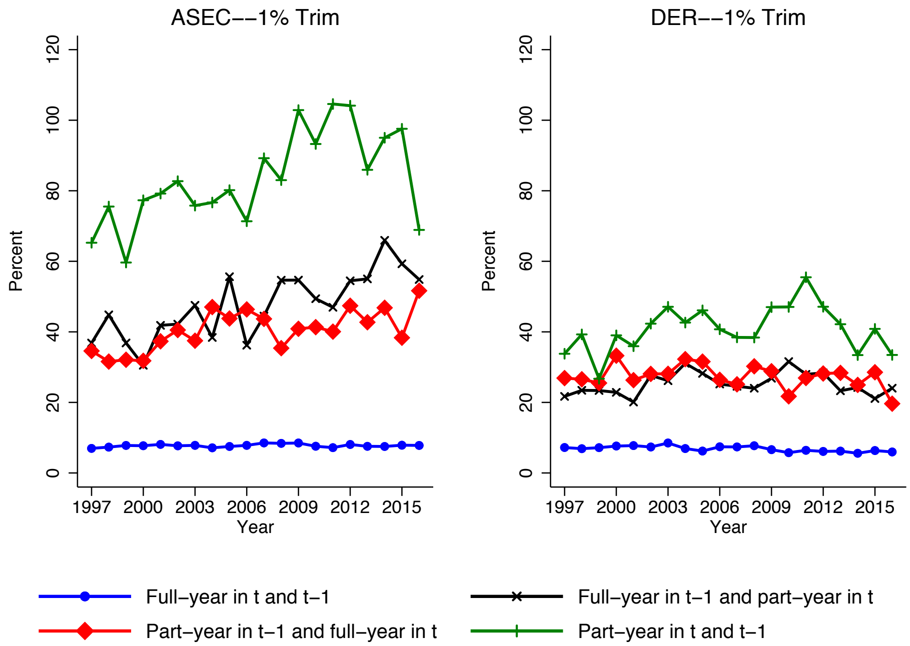
B. Weighted Race/Ethnicity-Group Volatility



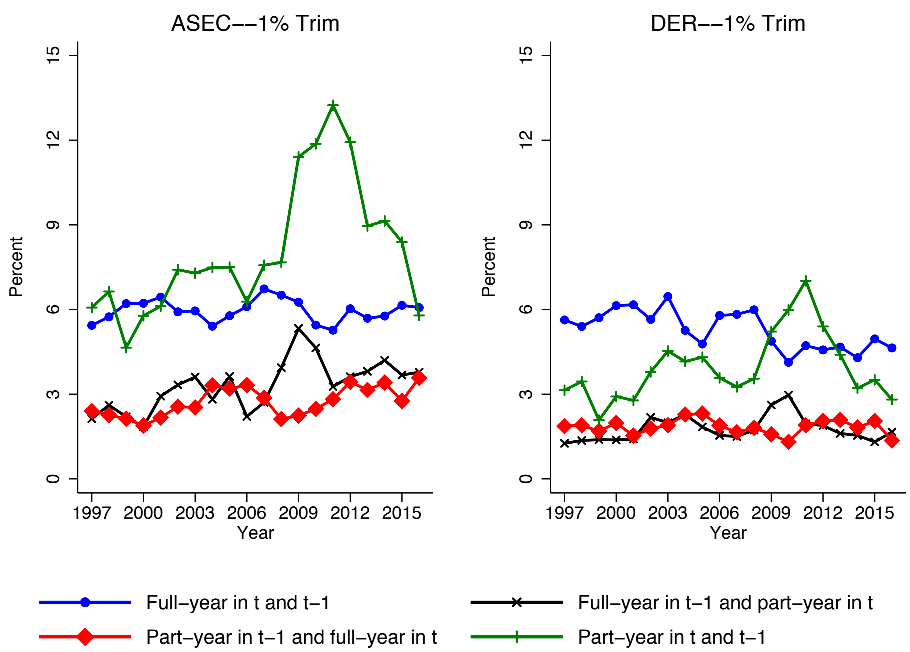
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 11. Within-Employment Status Group Volatility of Men, Arc Percent Linked Respondents

A. Employment-Specific Volatility



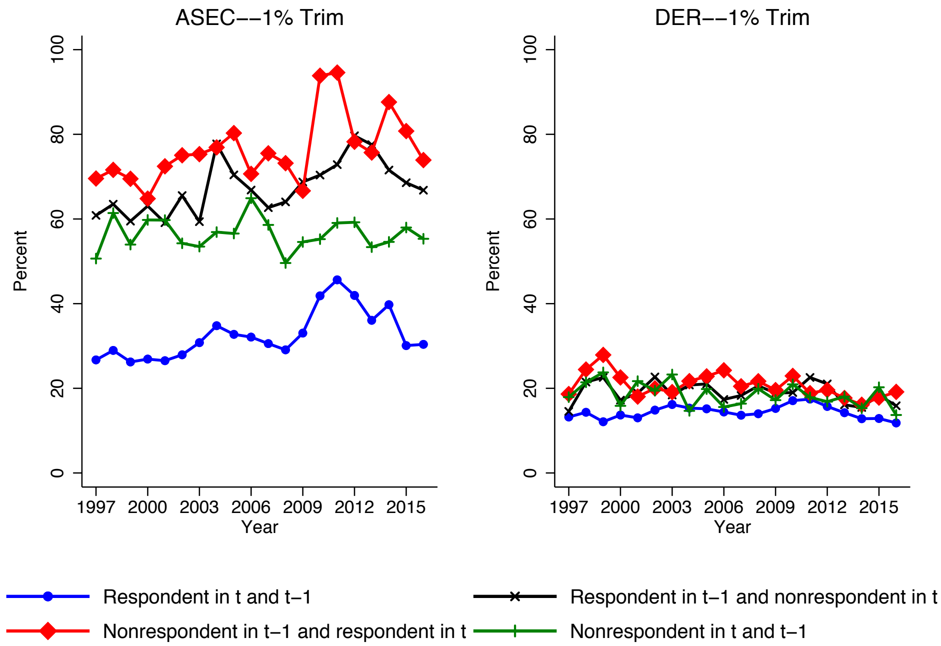
B. Weighted Employment-Group Volatility



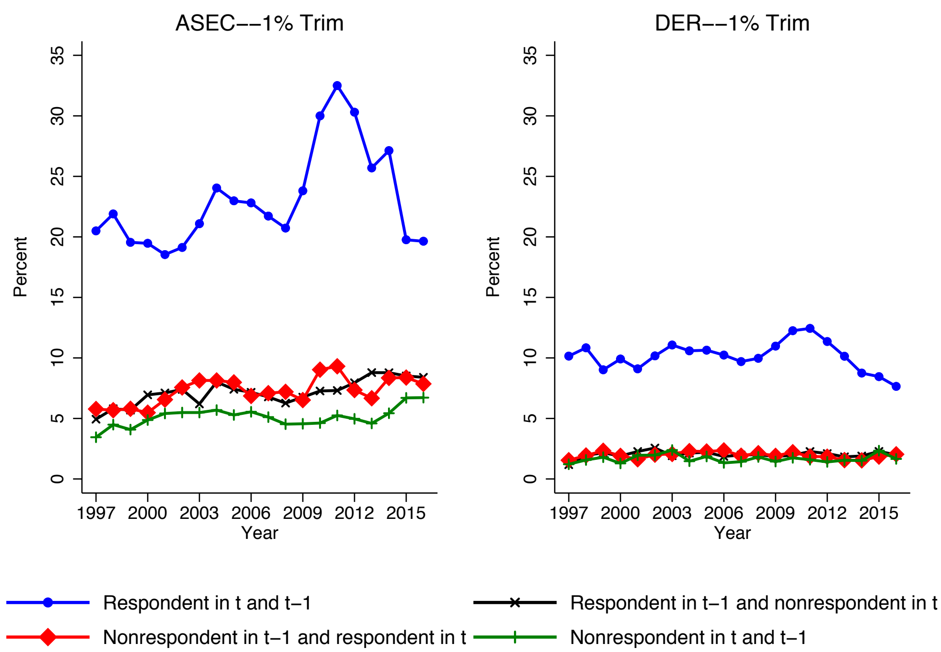
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 12. Within-Response Status Group Volatility of Men, Arc Percent Full Sample

A. Response-Specific Volatility



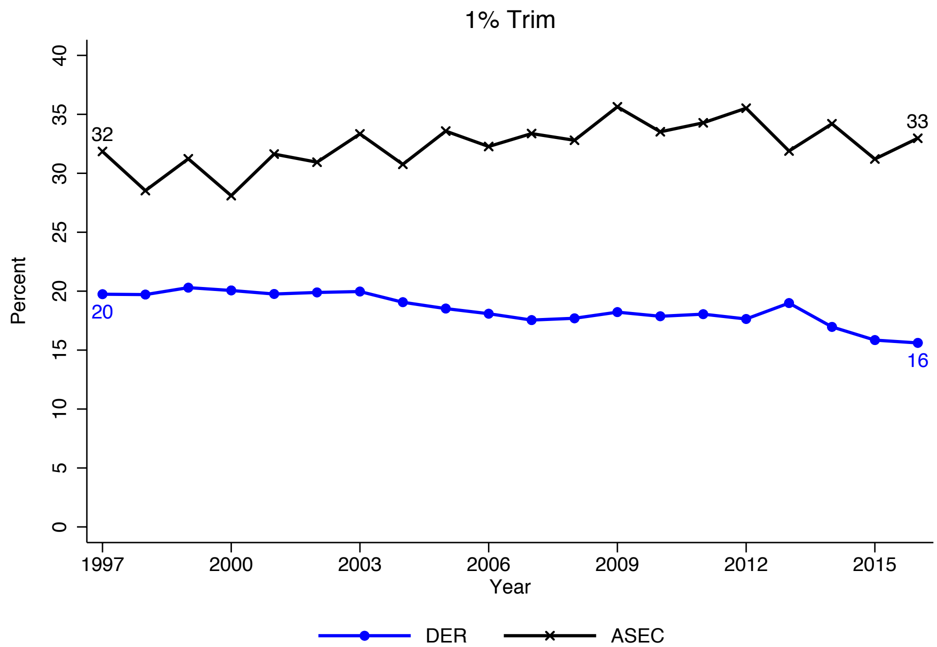
B. Weighted Response-Group Volatility



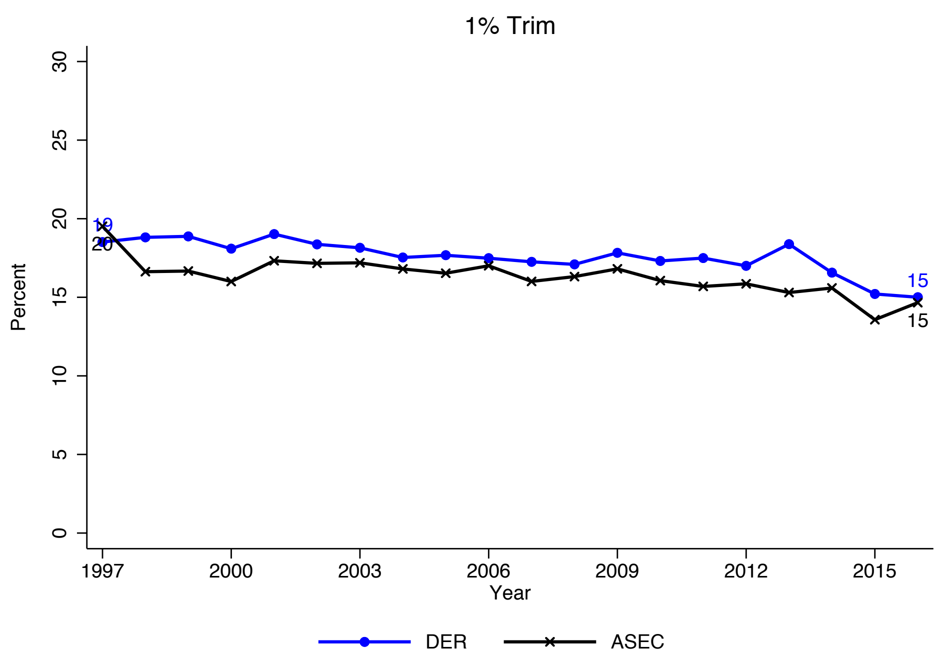
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 13. Arc Percent Earnings Volatility of Women

A. Linked Respondent Sample with Zeros



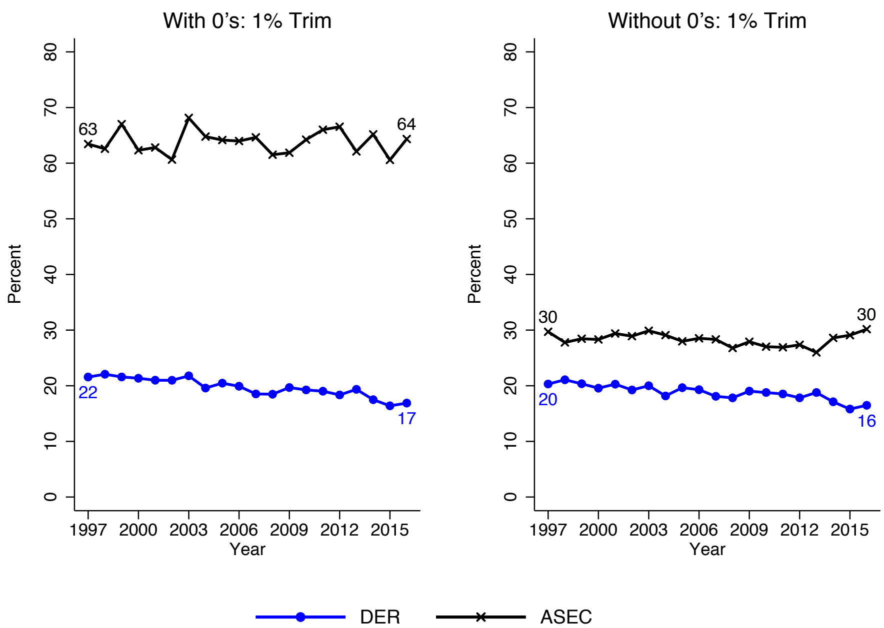
B. Linked Respondent Sample without Zeros



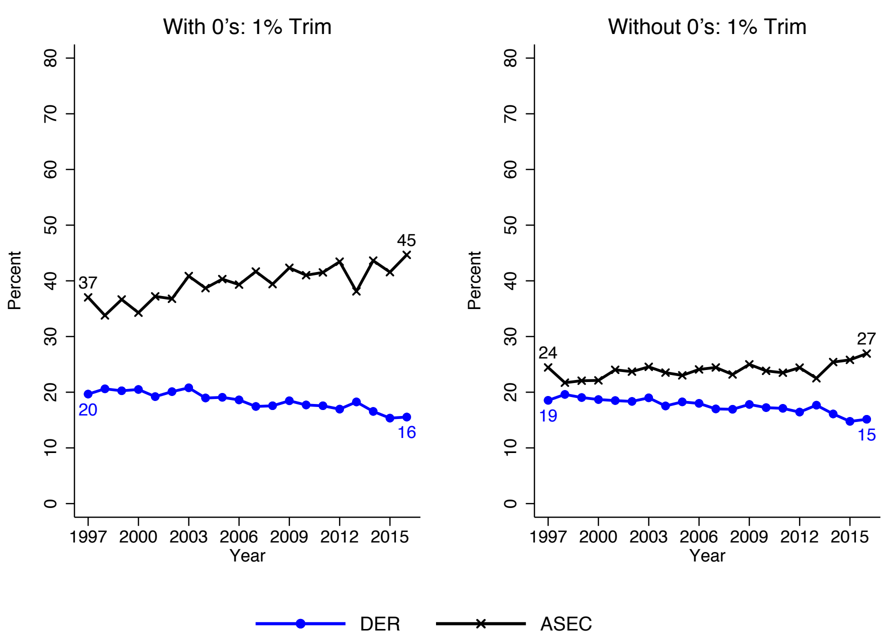
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 14. Arc Percent Earnings Volatility of Women by DER Link and ASEC Response

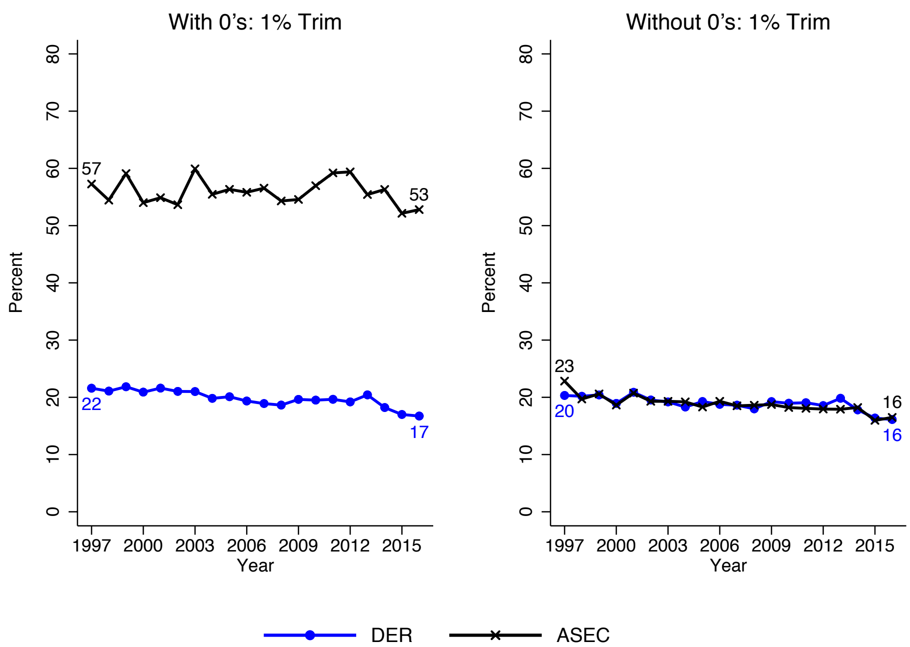
A. Full Sample with Zeros and without Zeros



B. Two-Year Linked Sample with and without Zeros



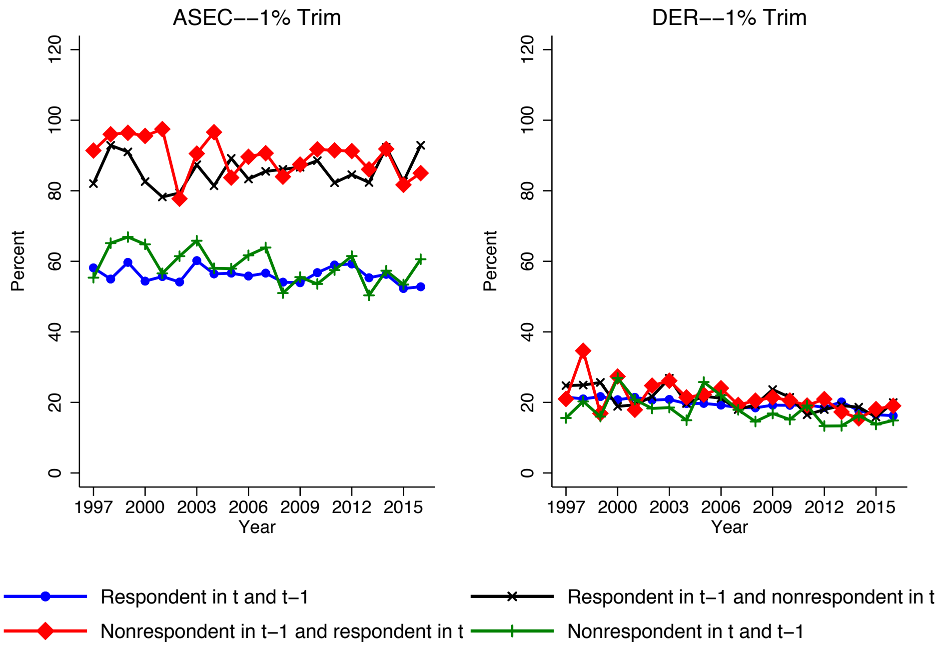
C. Two-Year Respondent Sample with and without Zeros



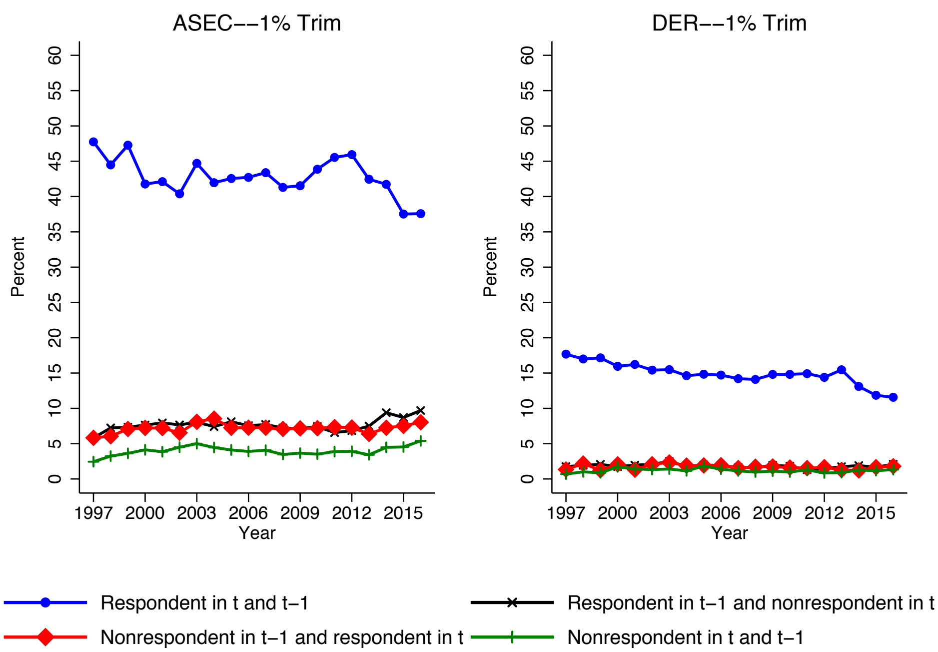
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 15. Within-Response Status Group Volatility of Women, Arc Percent Full Sample

A. Response-Specific Volatility



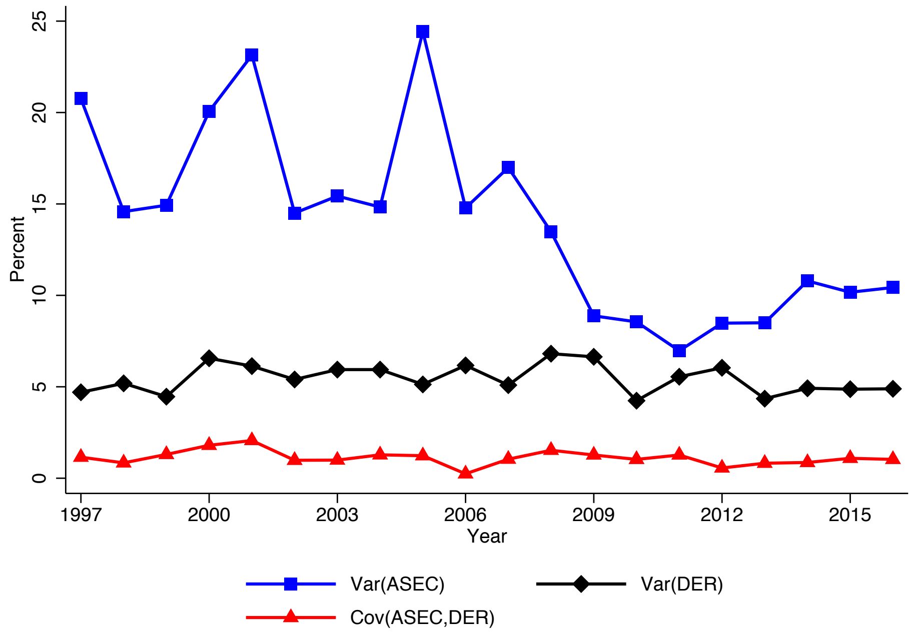
B. Weighted Response-Group Volatility



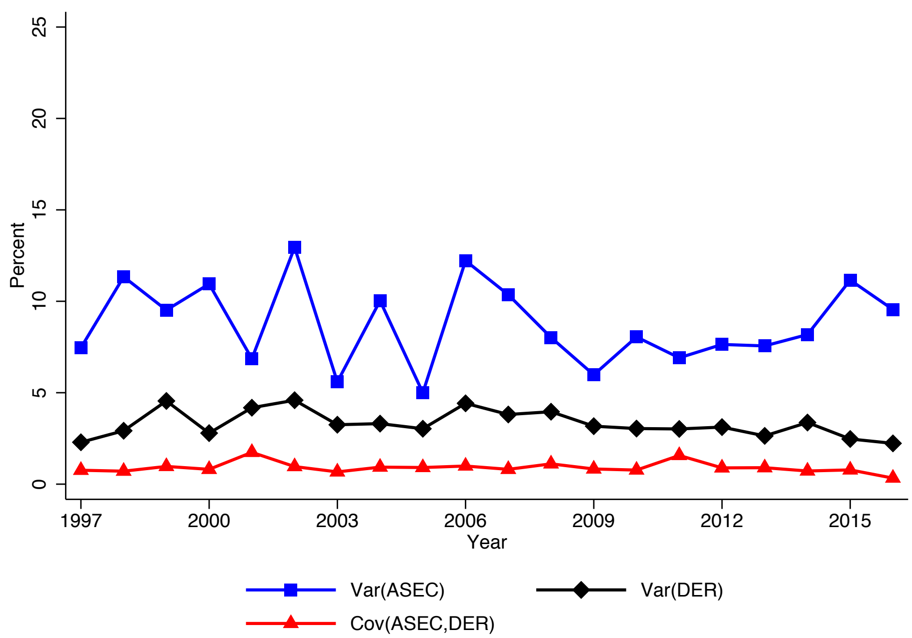
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 16. Transitory Earnings Volatility

A. Men



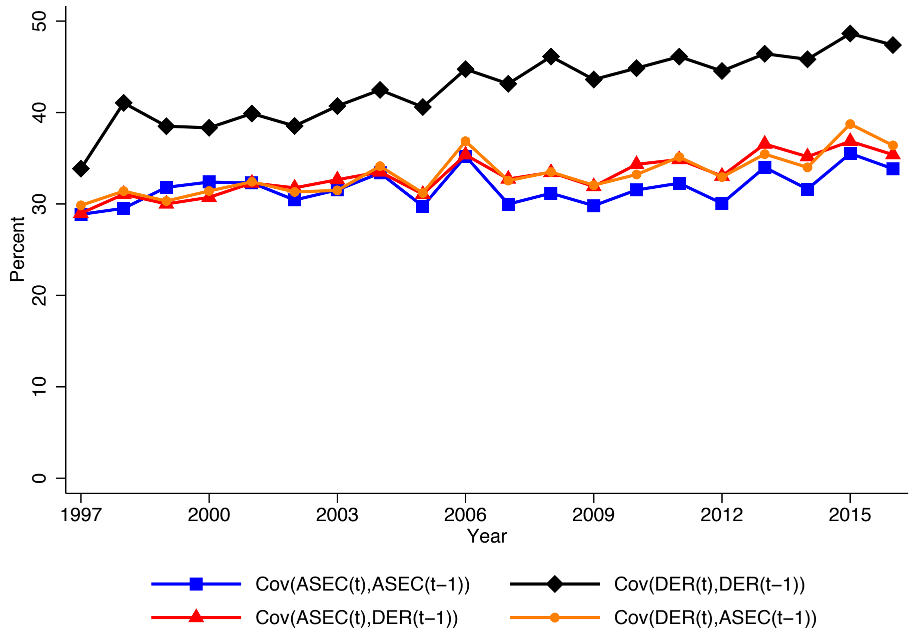
B. Women



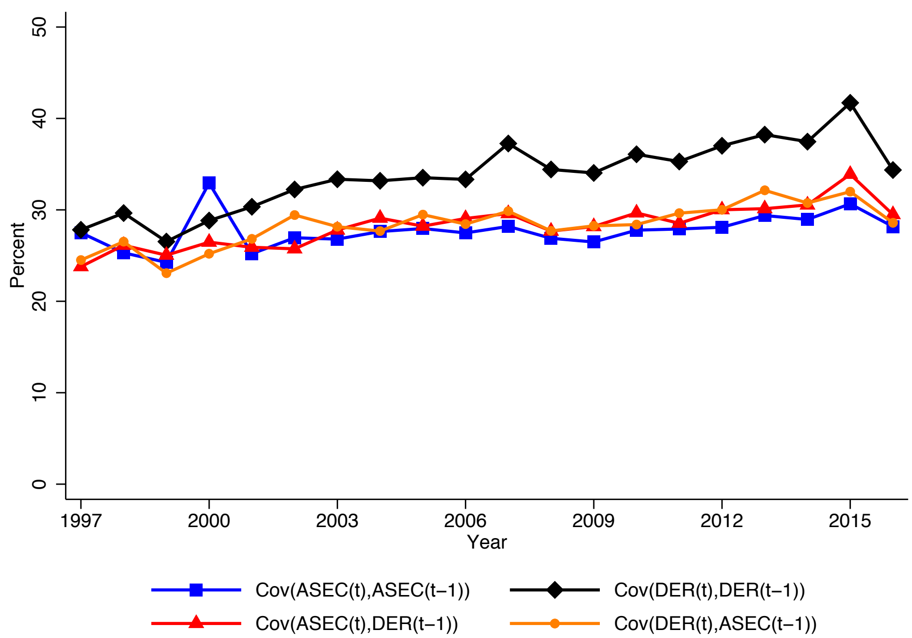
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Figure 17. Permanent Earnings Volatility

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.

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

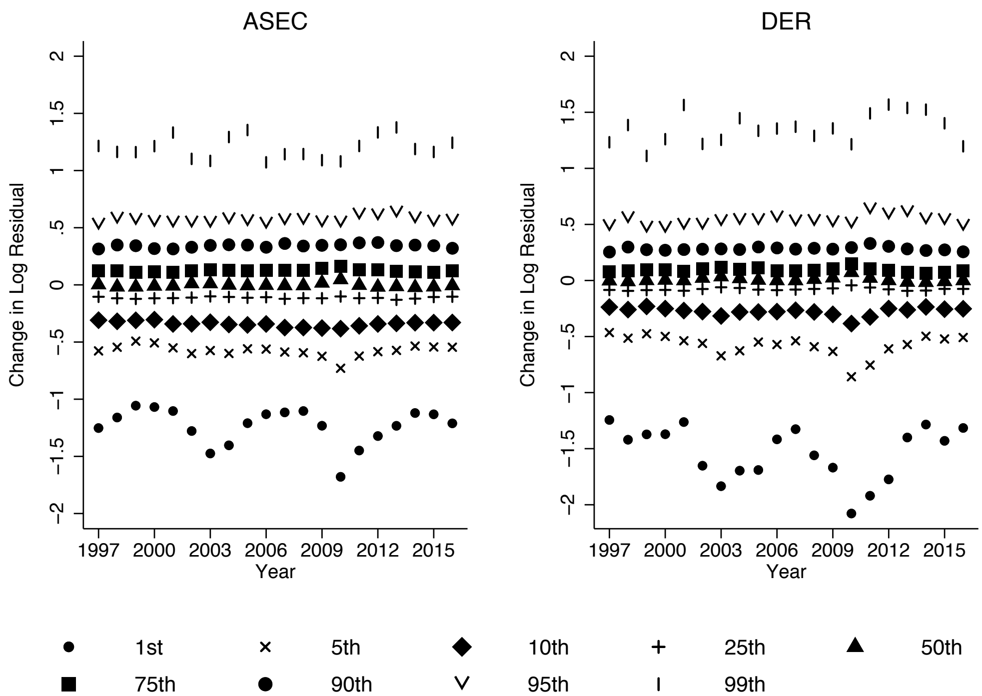
Year	Linkage Rate	Panel Match Rate
1996	79.22%	
1997	76.64	69.52%
1998	71.79	70.10
1999	66.43	69.96
2000	66.74	62.54
2001	69.20	64.20
2002	74.26	62.60
2003	71.39	74.44
2004	64.17	76.38
2005	62.48	67.26
2006	86.58	73.62
2007	86.48	74.65
2008	86.12	75.76
2009	85.73	75.73
2010	84.94	75.75
2011	85.67	76.89
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.

Appendix Table 2. 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	

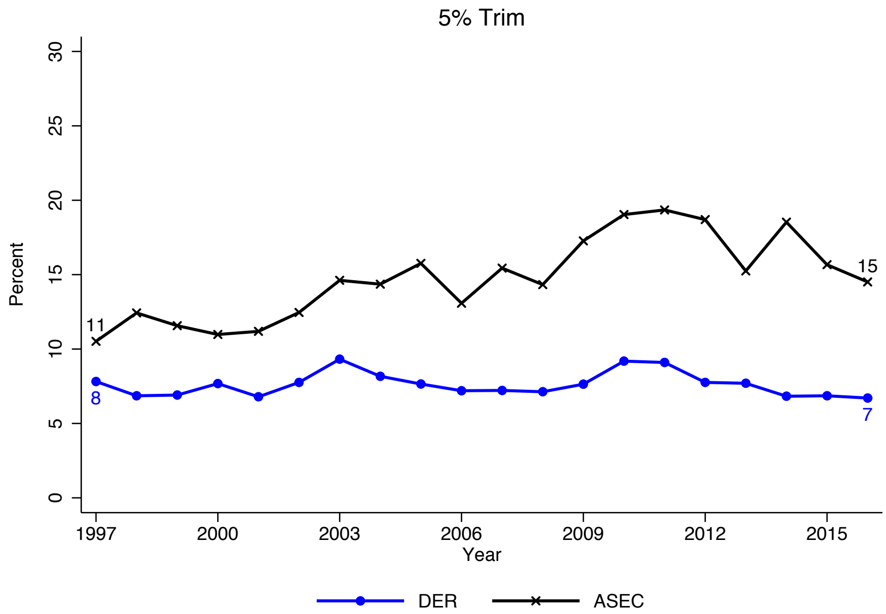
Appendix Figure 1. Percentiles of Log Difference Residuals of Men



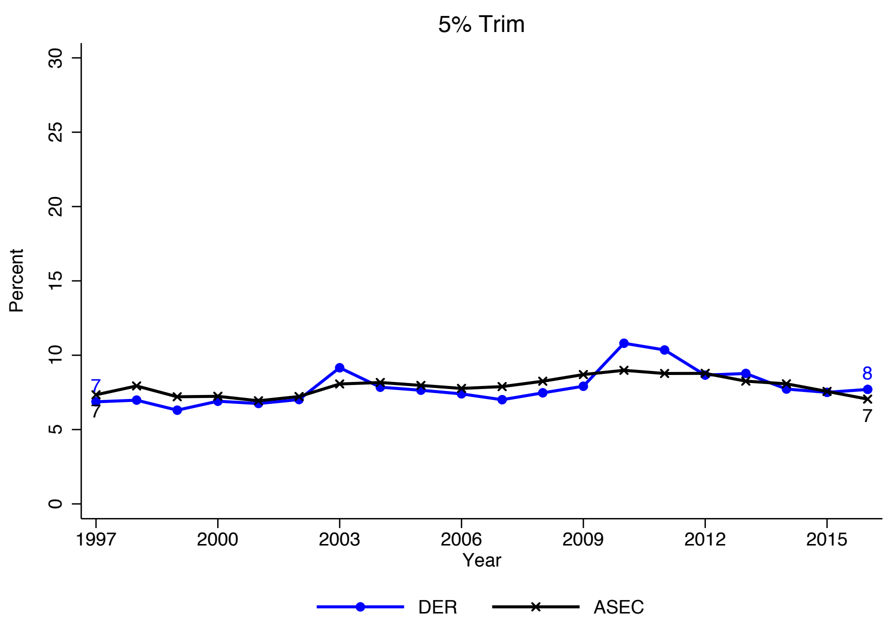
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 2. Earnings Volatility of Men, Alternative Trim

A. Arc Percent Change with 0s



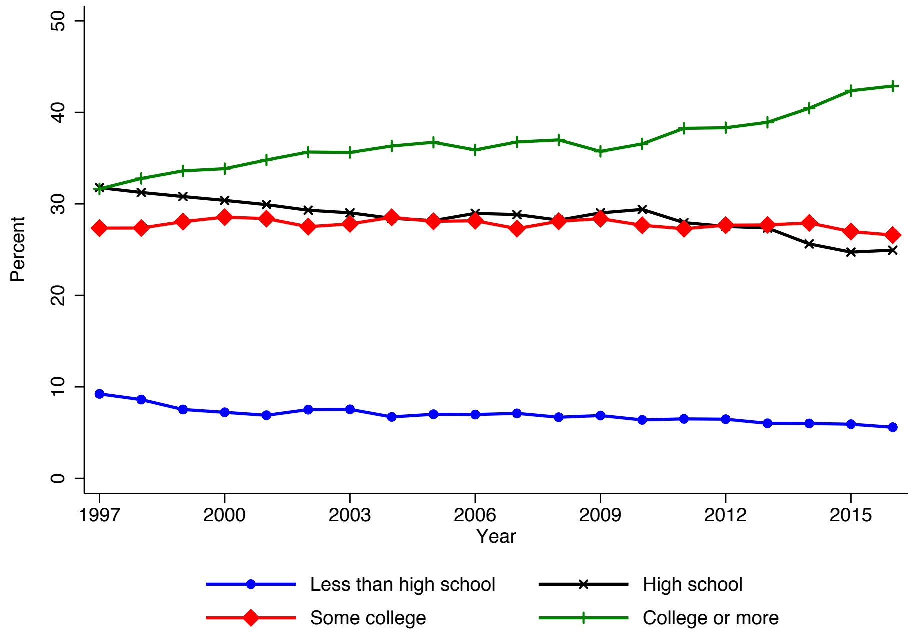
B. Log Difference



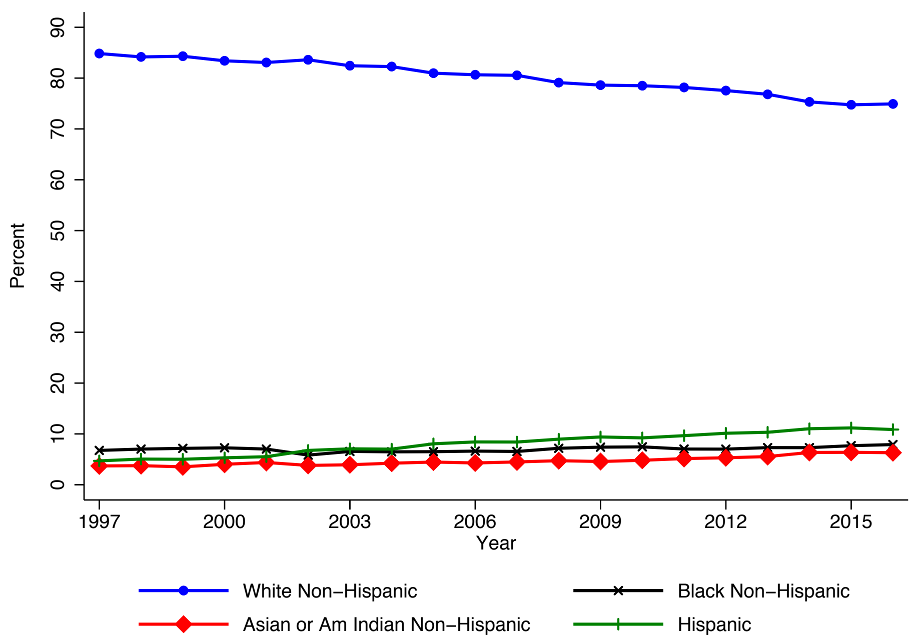
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 3. Population Shares of Men used in Variance Decompositions

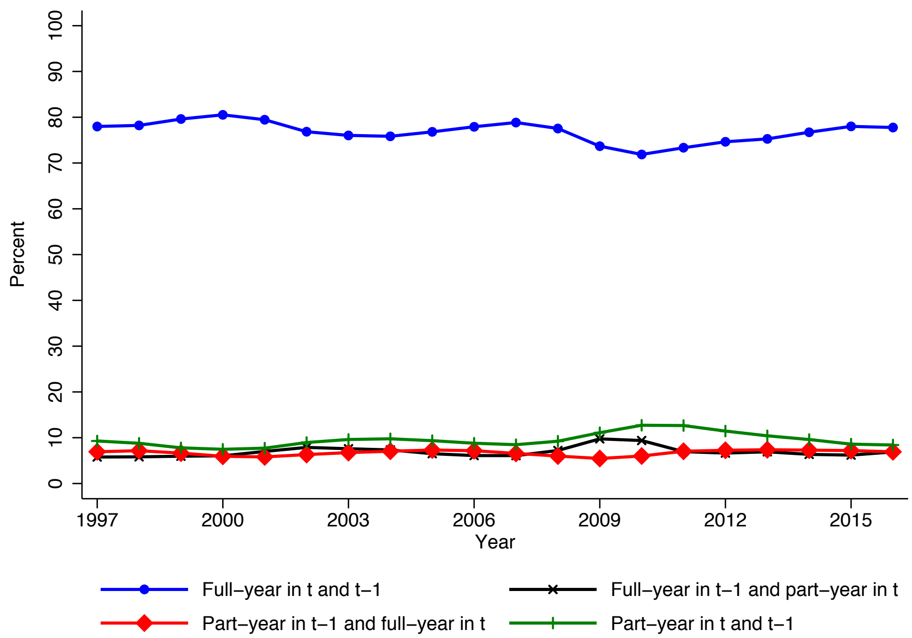
A. Education Attainment



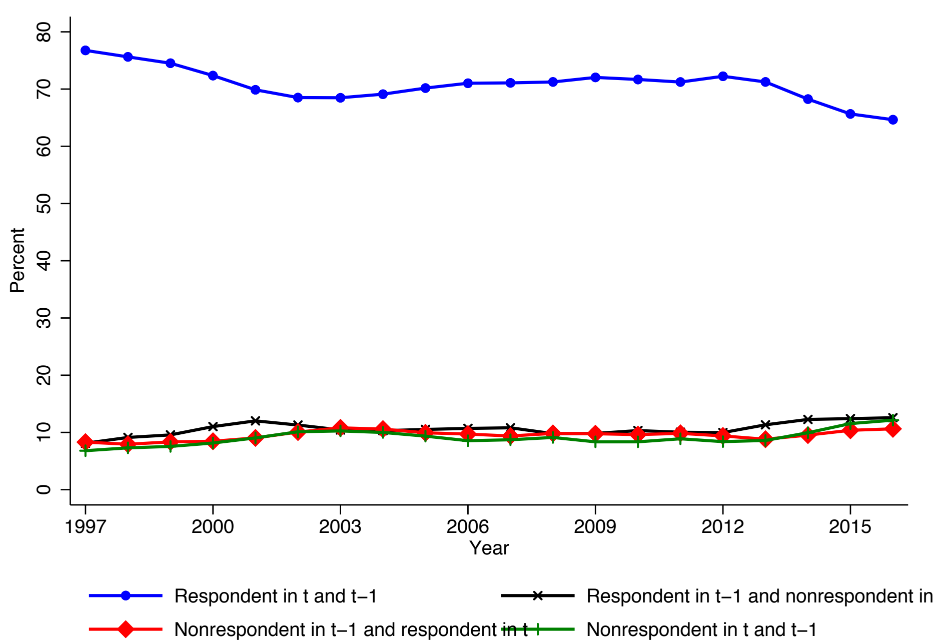
B. Race and Ethnicity



C. Full-time/Part-time Employment Status



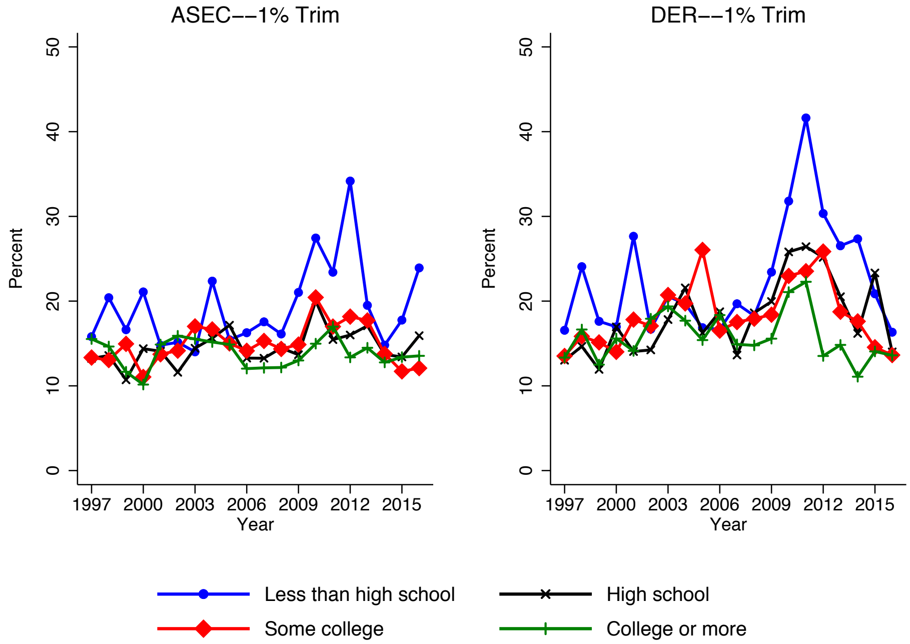
D. ASEC Earnings Response Status



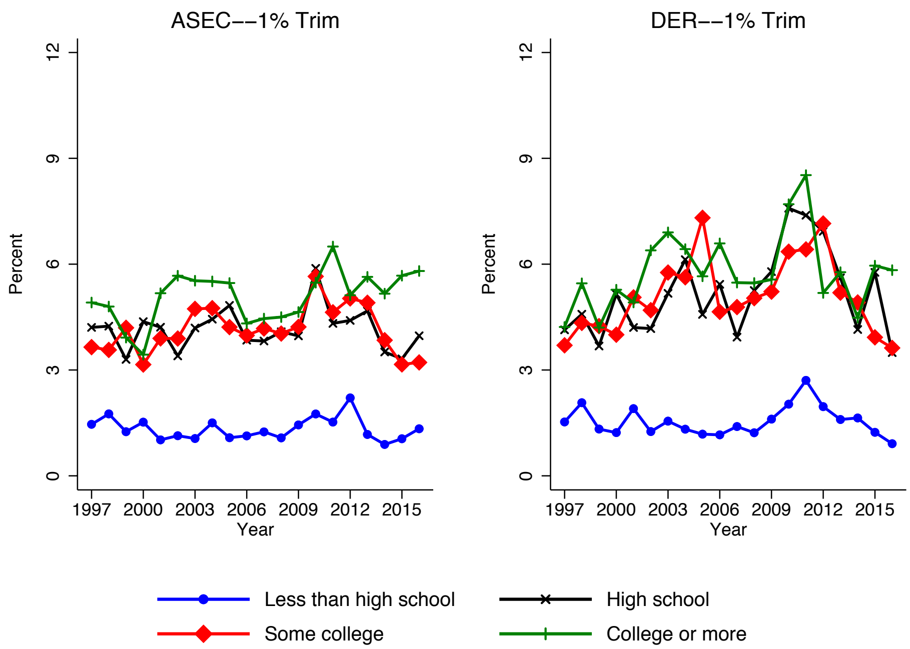
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 4. Within-Education Group Volatility of Men: Log-Difference Linked Respondents

A. Education-Specific Volatility



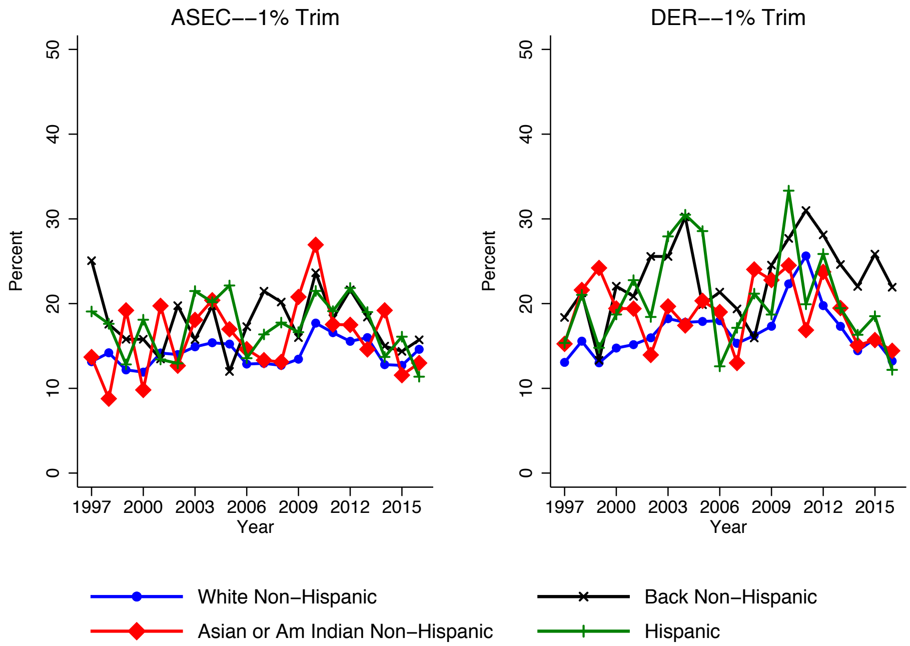
B. Weighted Education-Group Volatility



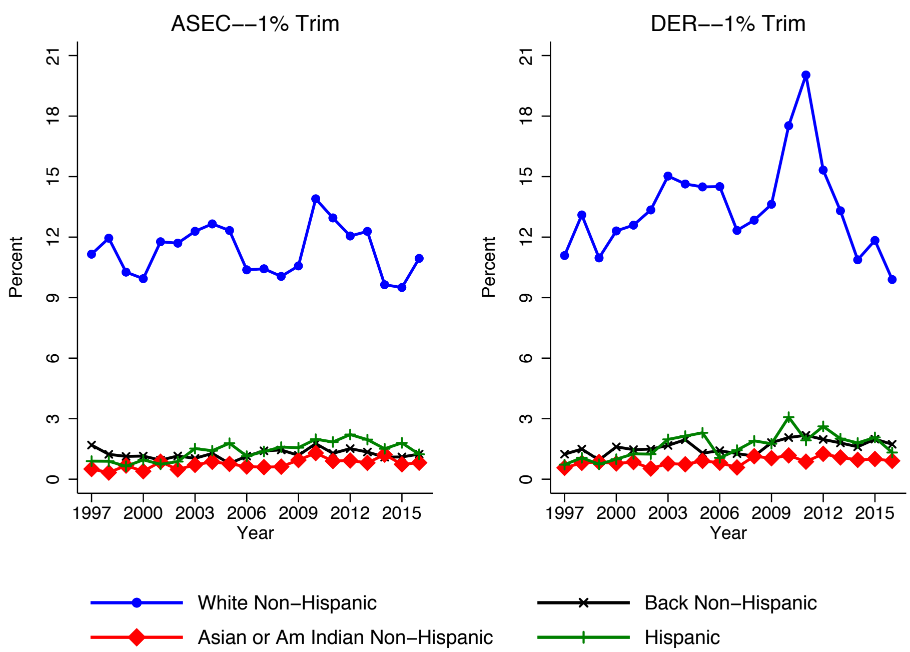
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 5. Within-Race/Ethnicity Group Volatility of Men, Log-Difference Linked Respondents

A. Race/Ethnicity-Specific Volatility



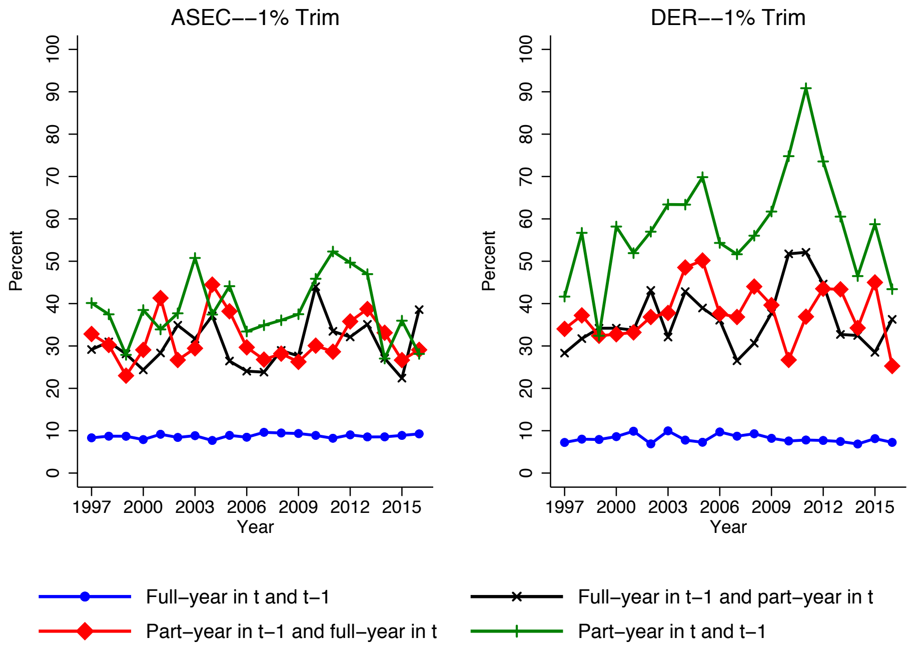
B. Weighted Race/Ethnicity-Group Volatility



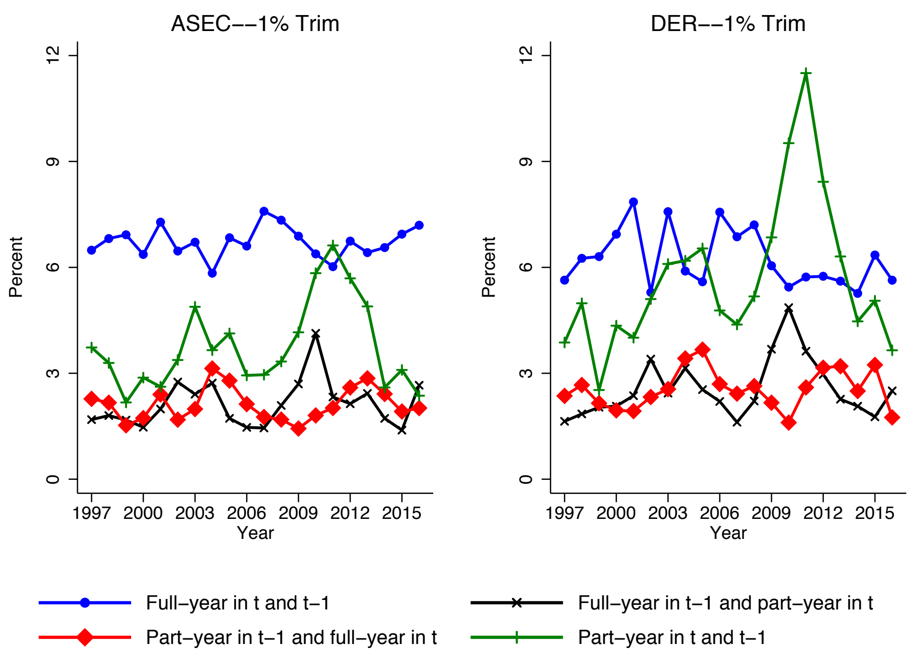
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 6. Within-Employment Status Group Volatility of Men, Log-Difference Linked Respondents

A. Employment-Specific Volatility

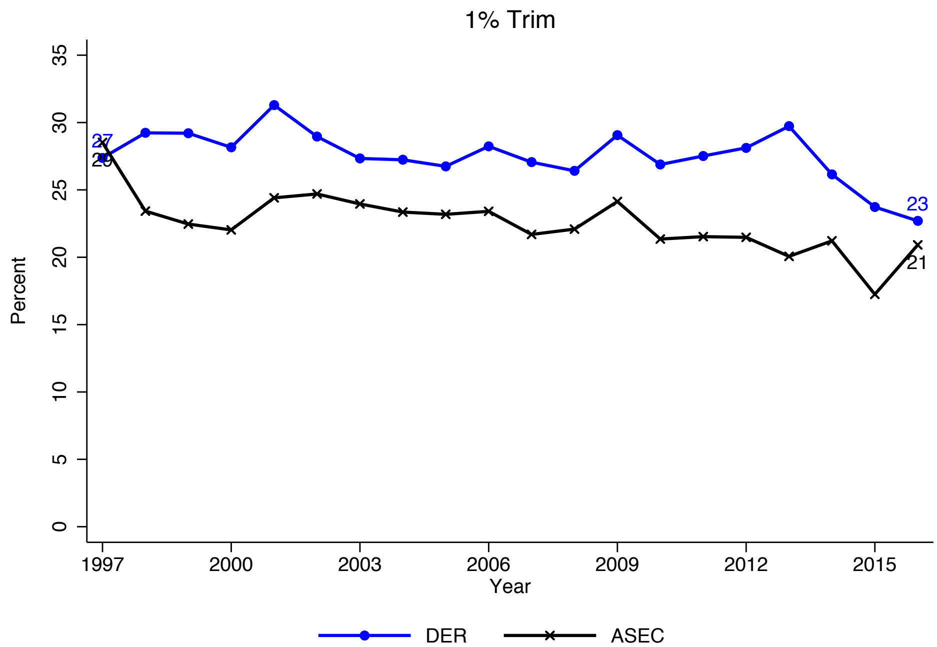


B. Weighted Employment-Group Volatility



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

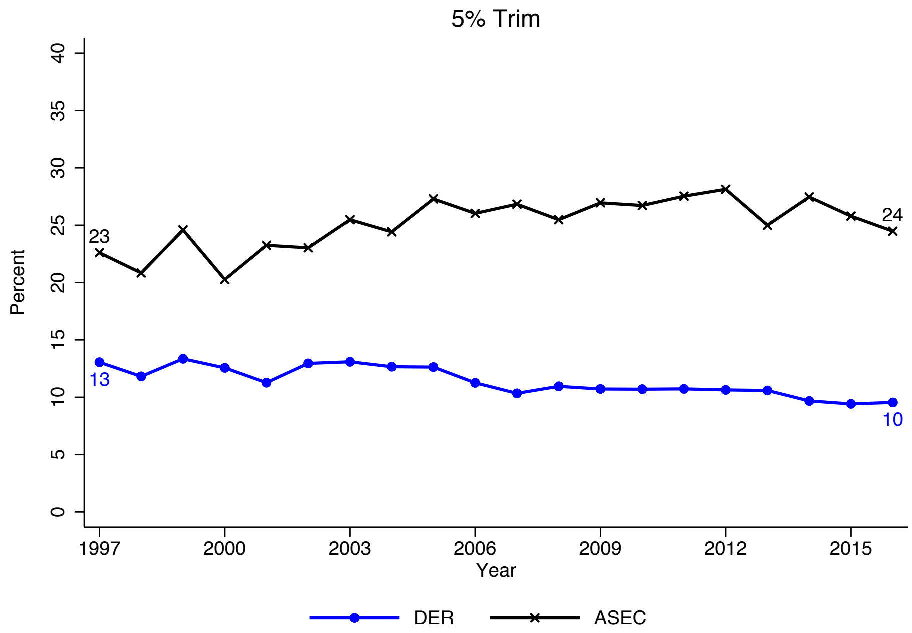
Appendix Figure 7. Log-Difference Earnings Volatility of Women



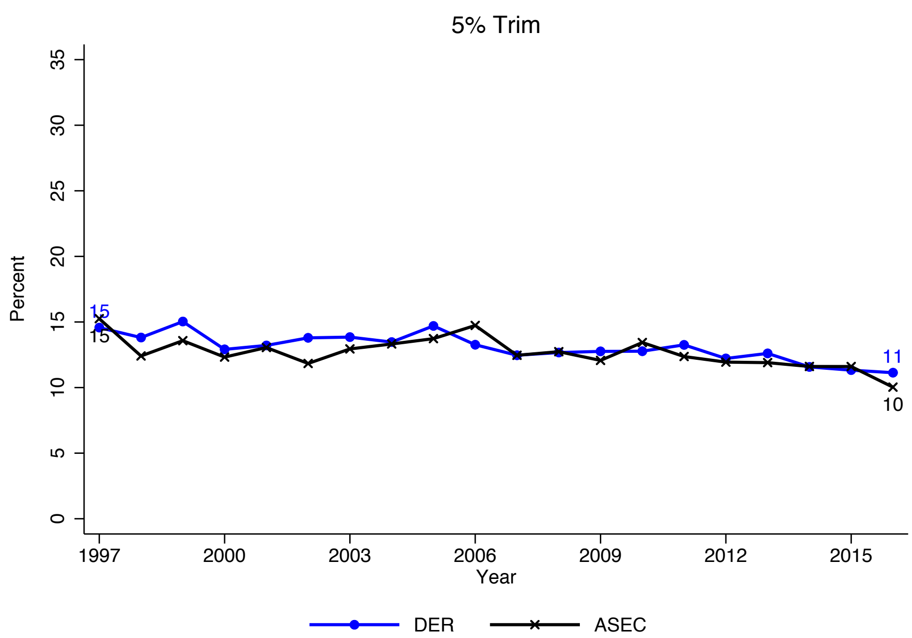
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 8. Earnings Volatility of Women, Alternative Trim

A. Arc Percent Change with 0s



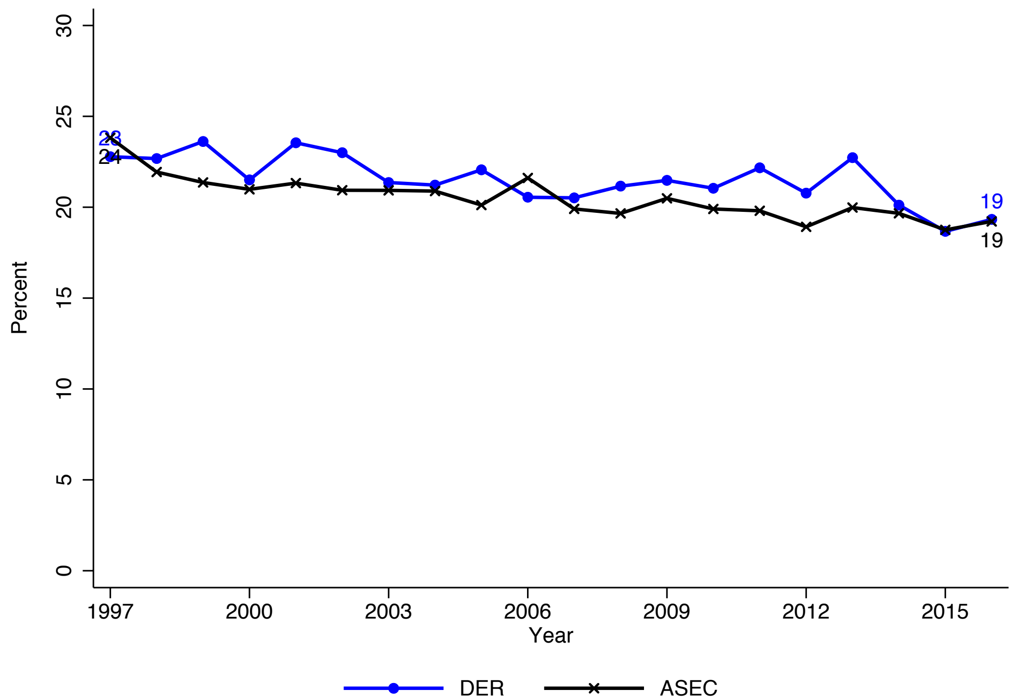
B. Log Difference



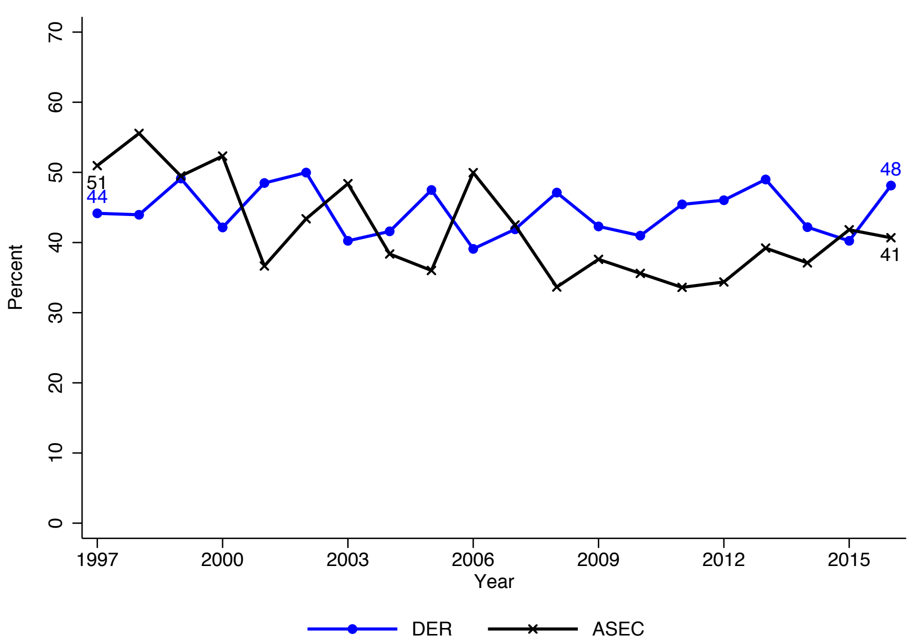
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 9. Earnings Volatility of Women, No Trim

A. Arc Percent Change without 0s



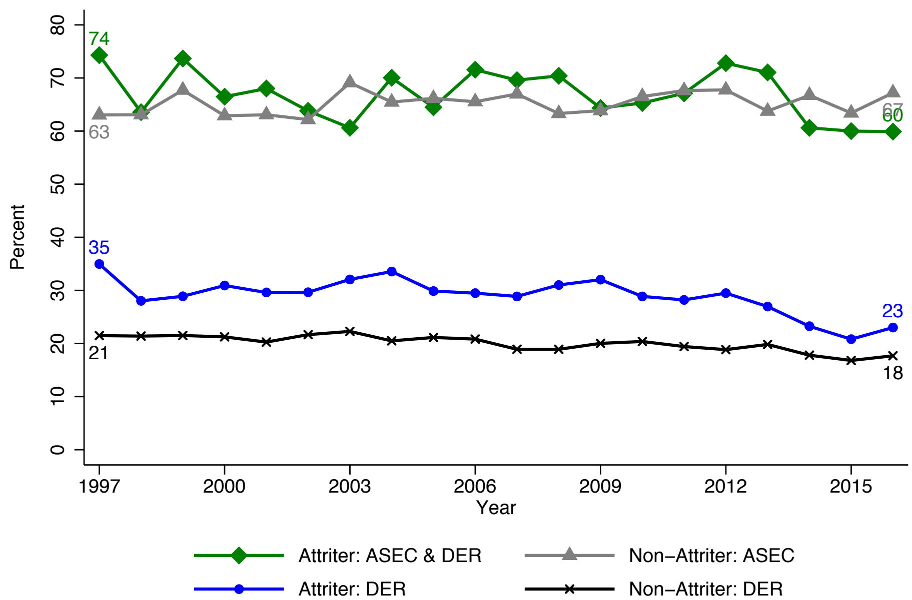
B. Log Difference



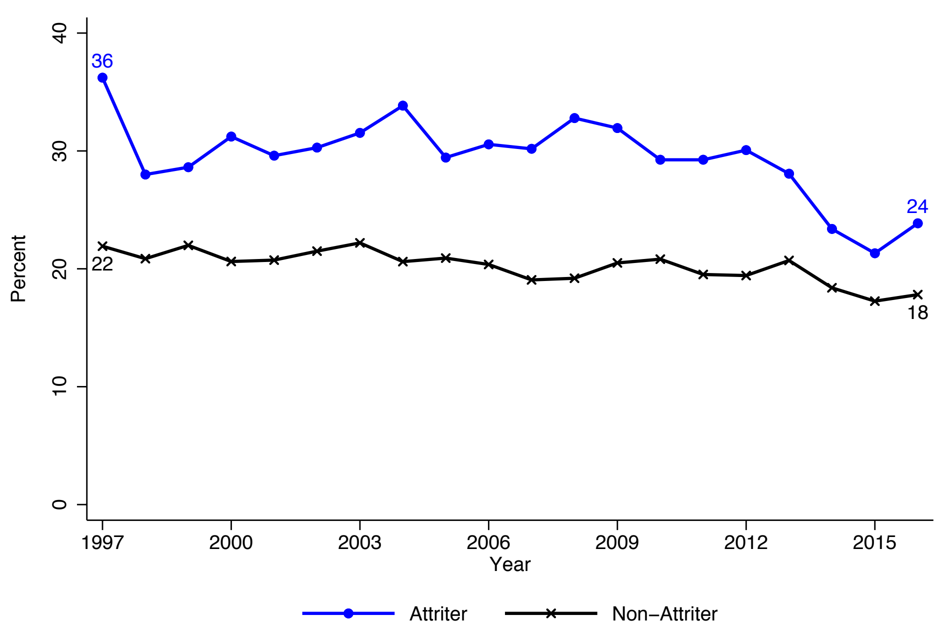
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 10. Arc Percent Volatility of Women by Attrition Status

A. Full Sample of Respondents and Nonrespondents with Zeros (1% trim)

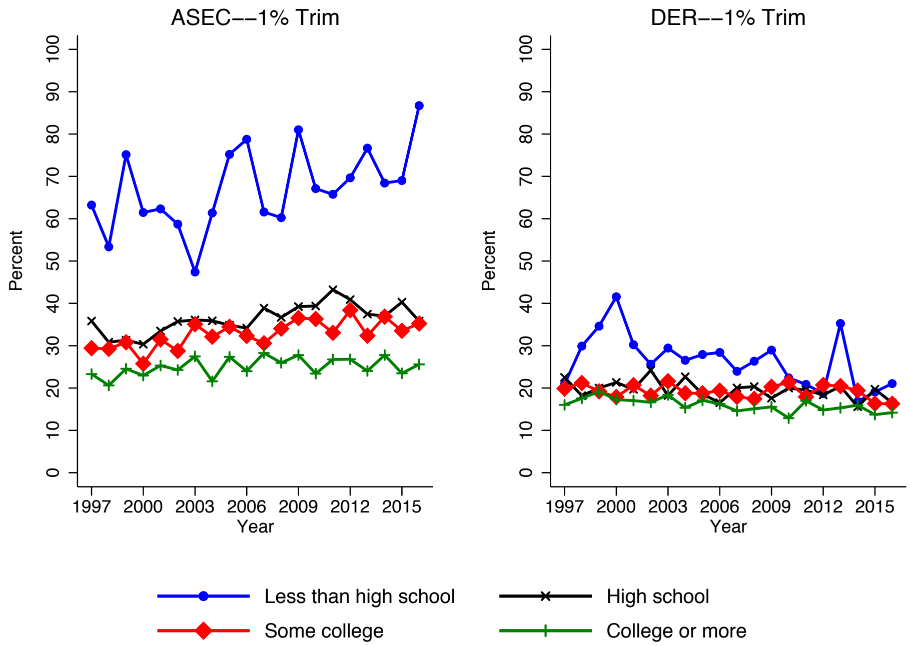


B. Sample of Year 1 Respondents with Zeros (DER only 1% trim)

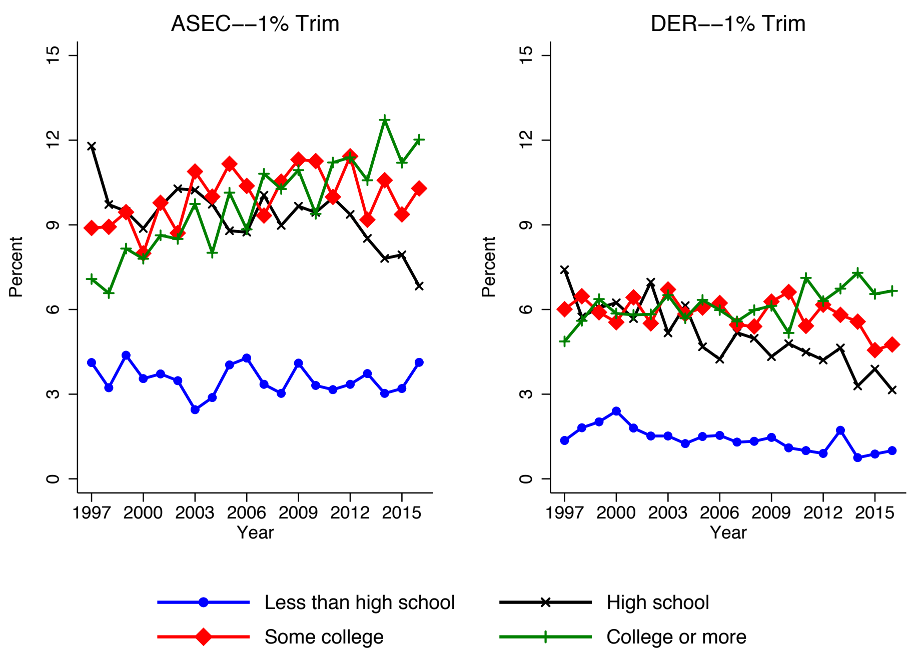


Appendix Figure 11. Within-Education Group Volatility of Women: Arc Percent Linked Respondents

A. Education-Specific Volatility



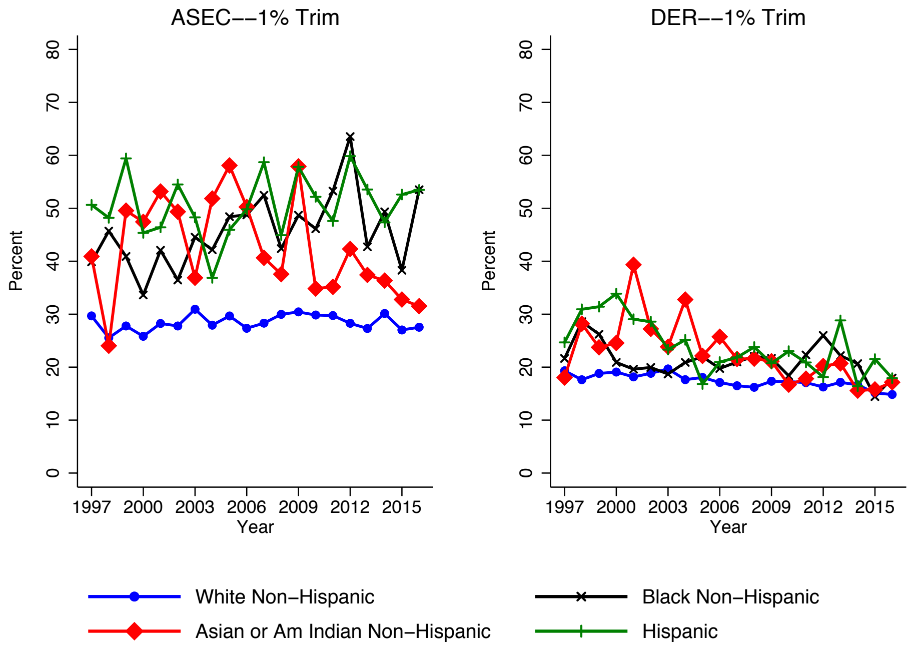
B. Weighted Education-Group Volatility



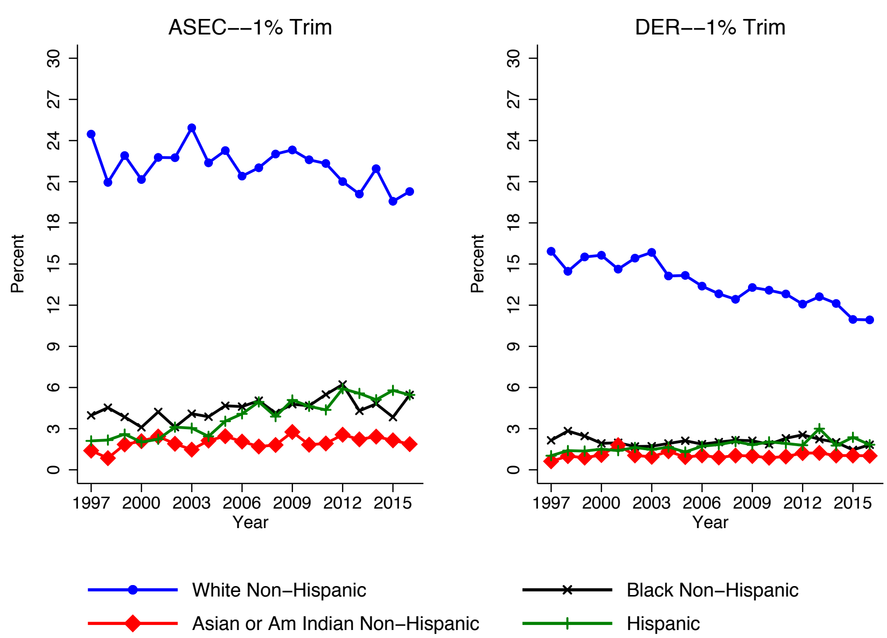
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 12. Within-Race/Ethnicity Group Volatility of Women, Arc Percent Linked Respondents

A. Race/Ethnicity-Specific Volatility



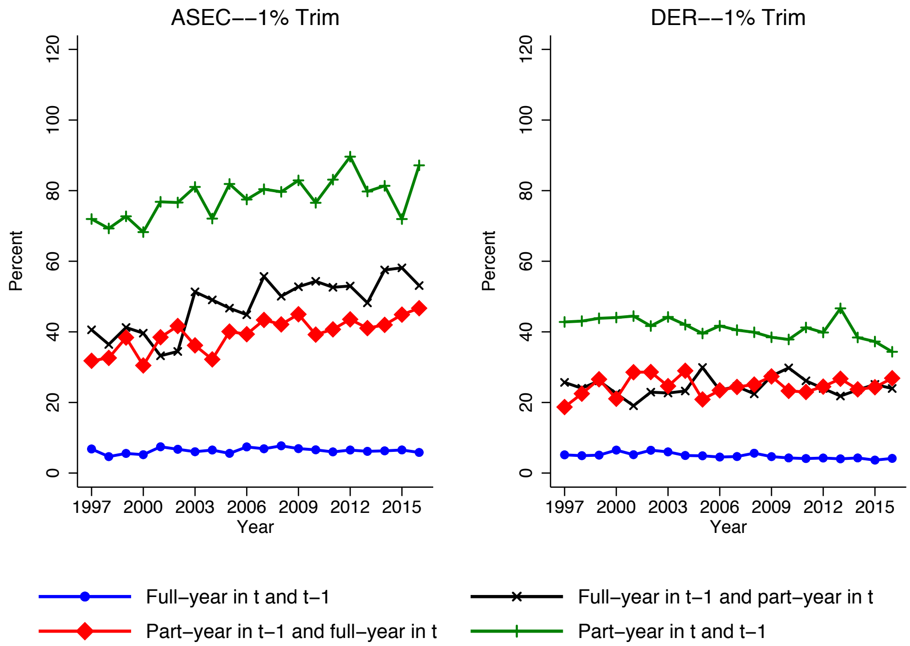
B. Weighted Race/Ethnicity-Group Volatility



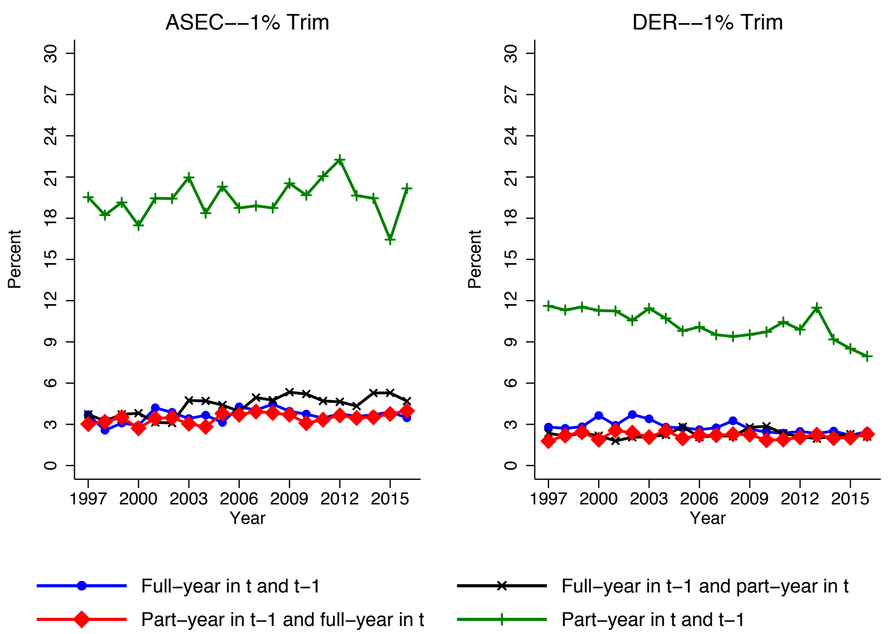
Sources: U.S. Census Bureau, Current Population Survey, 1996-2016 Annual Social and Economic Supplement. Social Security Administration, Detailed Earnings Record, 1995-2015.

Appendix Figure 13. Within-Employment Status Group Volatility of Women, Arc Percent Linked Respondents

A. Employment-Specific Volatility



B. Weighted Employment-Group Volatility



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