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Earnings and Income Volatility in America: Evidence from Matched CPS

Abstract: In this paper we offer new evidence on earnings and income volatility in the United States over the past four decades by using matched data from the March Current Population Survey. We find that between 1973 and 2008 family income volatility rose by 38 percent, primarily as a result of higher volatility of husbands earnings and non means-tested nonlabor income. Rising family income volatility is in evidence across race, education, and family structure, and after declining sharply while young, it is increasing in the latter part of the life cycle among the skilled. The Federal tax and transfer system dampens the magnitude of volatility in any given year, but not the trends. Nonparametric tests of structural change indicate that overall family income volatility peaked in 1999, with the 2000s characterized by greater short-term volatility rather than a continued secular increase. Most of the increase in family earnings volatility occurred prior to the 1990s, which coincides with the trend volatility of male earnings. The earnings volatility of women fell dramatically through the early 1980s, and the ongoing secular decline implies male and female earnings volatility is converging. A variance decomposition suggests that the trends in earning volatility are driven both by increases in the conditional variance of earnings of continuous workers as well as the variance of the conditional mean of those workers exiting the labor force.

There is ongoing debate in economics on whether and to what extent the volatility of earnings and incomes have increased in the United States in recent decades (Gottschalk and Moffitt 1994, 2009; Dynarski and Gruber 1997; Haider 2001; Kniesner and Ziliak 2002a,b; Gundersen and Ziliak 2003; Dahl, DeLeire, and Schwabish 2008; Dynan, Elmendorf, and Sichel 2008; Hacker and Jacobs 2008; Jensen and Shore 2008; Keys 2008; Shin and Solon 2008; Winship 2009). Documenting trends in volatility is important for a host of reasons, not least of which is a better understanding of the rise in income inequality since the mid 1970s (Katz and Autor 1999; Piketty and Saez 2003; Lemieux 2006; Autor, Kearney, and Katz 2008). Higher inequality could be due to a rise in overall earnings and income instability, a shift in permanent incomes, or both (Gottschalk and Moffitt 1994; Haider 2001). However, if there is little corroborative evidence of a rise in instability then widening inequality is the likely outcome of lifetime changes in the distribution of earnings and income, the latter of which could have negative consequences for long-term economic mobility (Gottschalk and Moffitt 2009). Whereas the preponderance of evidence on inequality in the United States is based on cross-section data from the Current Population Survey (CPS), with few exceptions the evidence on earnings and income volatility comes almost exclusively from longitudinal data in the Panel Study of Income Dynamics (Gittleman and Joyce 1996; Cameron and Tracy 1998; Dahl, et al. 2008). In this paper we offer new evidence on earnings and income volatility over the past four decades by exploiting the longitudinal dimension of the CPS to match individuals across surveys.

The use of the PSID for estimates of volatility owes in part to the literature's early emphasis on decomposing volatility into its permanent and transitory components (Gottschalk and Moffitt 1994). This decomposition is illustrative because it permits identification of temporary deviations of earnings from long-term trends, as well as identification of structural

changes in long-term trends such as decadal shifts in earnings processes. This research found that transitory earnings instability rose by over 40 percent from the mid 1970s through the mid 1980s, and then more or less stabilized thereafter, while lifetime inequality rose primarily in the 1980s (Gottschalk and Moffitt 1994; Haider 2001). Although much of this research was based on samples of prime-age men, Keys (2008) finds that the basic pattern of results hold across race, gender, education, and family structure.

More recently attention has turned to broader measures of economic volatility, namely family and/or household earnings and incomes, rather than individual earnings per se, and in some cases to simpler measures of volatility such as the annual percent change. The PSID-based papers on family income tend to find a strong increase in volatility in the 30 years from the early 1970s to the early 2000s, especially in the 1990s, though there is considerable disagreement on the magnitude. The estimates range from a doubling of volatility (Hacker and Jacobs 2008) to as low as 10 percent (Winship 2009), with Gundersen and Ziliak (2003), Dynan, et al. (2008), and Gottschalk and Moffitt (2009) falling in between with reported increases of 40 to 80 percent. Part of the divergence in results emanates from treatment of the PSID redesign in 1992 and 1993, and part from the treatment of families reporting zero earnings or income. Because much of the literature reports the variance of log earnings or income, person-years with zero earnings/income are dropped from the analysis, which can understate measured volatility because labor-force dropouts are ignored. Dynan et al. (2008) proposed instead to measure volatility as the standard deviation of the arc percent change, which admits person-years with zero earnings and/or incomes. Dahl, et al. (2008) adopted a similar measure, but in lieu of the PSID they used administrative earnings records from the Social Security Administration's Continuous Work History File merged with longitudinal data in the Survey of Income Program Participation. They

found little change in measured earnings and household income volatility after the mid 1980s, underscoring that the volatility literature is far from consensus.

In this paper we extend research on the evolution of earnings and income volatility in several directions. First, we use data from matched CPS files spanning 1973-2009, which makes our results more directly informative to the CPS-based inequality research.[1] The rotating structure of the CPS permits one to match approximately 50 percent of sample respondents in one March survey to the March survey the subsequent year. A second contribution then is with two observations for each match we extend the summary measure of volatility used in Dynan, et al. (2008) and Dahl, et al. (2008) to be robust not only to those workers transitioning in and out of the labor market but also to negative earnings commonly found among the self employed. Most of the previous research measures earnings volatility in terms of the growth in log earnings, which by construction precludes those with zero or negative earnings. However, there has been trend growth in the fraction of the labor force that is self employed, as well as growth in the fraction of men out of the labor force and women into the labor force, and our measure captures this shifting composition.

A third contribution is that our use of the CPS offers much larger sample sizes compared to the PSID and thus permits more precision as well as detailed subgroup analyses by race, family structure, and cohort. With respect to the latter, we construct 48 five-year date of birth by education cohorts that permits us to examine volatility trends over the life cycle. Likewise, an advantage of the CPS over the SIPP is that the CPS dates back to the 1960s as opposed to 1984

[1] We are aware of two related studies using matched CPS. Gittleman and Joyce (1996) use matched CPS data to estimate earnings mobility and inequality from 1968-1992, focusing on shifts in permanent income differences rather than volatility. Cameron and Tracy (1998) use matched CPS data to examine earnings instability of working men, focusing on the permanent/transitory distinctions found in Gottschalk and Moffitt (1994). Our study differs from the latter in several directions, including our examination of income, rather than just earnings, our focus on men and women whether working or not, a wide array of family structures, our longer time horizon through the 2000s, and our formal testing of structural breaks and variance decomposition as described in the text.

in the case of the SIPP, and thus we can compare volatility trends in the 1970s directly to those found in the PSID.

There is much discussion in the volatility literature on if and when the trend in volatility changed in recent decades. In some cases the authors examine the series by decade, and in other cases they simply remark on whether and what year the series appears to increase, decrease, or stabilize. A fourth contribution of our study is to more formally test for structural breaks in trend volatility by employing nonparametric Quandt-Andrews tests of structural change (Quandt 1960; Andrews 1993), coupled with confidence intervals around the breakdate (Bai 1997). The Wald tests, which are common to the time-series literature, have not been utilized in the volatility literature (or inequality literature more generally) and yet offer the promise of adding precision to our understanding of when volatility trends changed, if at all.

Since 1970 there have been dramatic changes in the composition of the labor force, and this change in composition could have an important effect on earnings and income volatility. A fifth contribution of our project is to exploit the fact that the unconditional variance of earnings volatility can be decomposed into the sum of the variance of the conditional mean and the conditional variance, and because each of those two terms are a function of whether an individual is transitioning into or out of the labor force, or always in or out of work, we can examine the relative contributions of changing employment probabilities, variance of conditional means, and conditional variances on volatility.

We find that family income volatility rose by 38 percent over the past four decades, driven both by rising volatility of earnings and non means-tested nonlabor income. Rising family income volatility is in evidence across race, education, family structure, and the life cycle. Our tests of structural change indicate that overall family income volatility peaked in 1999, with the

2000s characterized by greater short-term volatility rather than a continued secular increase. Most of the 20 percent increase in family earnings volatility occurred prior to the 1990s, which coincides with the trend volatility of male earnings. The earnings volatility of women fell dramatically between 1973 and 1983, and with the continued secular decline is converging toward levels of men. The variance decomposition of earnings volatility suggests that the trends are driven both by increases in the conditional variance of earnings of continuous workers as well as the variance of the conditional mean of those workers exiting the labor force.

II. Data

The data derive from the 1973–2009 waves (1972–2008 calendar years) of the March Annual Social and Economic Study of the Current Population Survey (CPS). The unit of observation is an individual between the ages of 16 and 60. This is intentionally a wider age sample than many previous studies that focus on prime-age workers in order to take advantage of the survey design of the CPS, which continuously records earnings at the individual level and thus fosters an examination of life-cycle profiles of volatility by detailed birth cohort. The rotating design of the CPS means that a respondent is in sample for 4 months, out 8 months, and in another 4 months, and this makes it possible to match approximately one-half of the sample from one March interview to the next. Following the recommended procedure we perform an initial match of individuals on the basis of five variables—month in sample (months 1-4 for year 1, months 5-8 for year 2); gender; line number (unique person id); household identifier; household number; and state of residence. We then cross check the initial match on two additional criteria: race and age of the individual. If the race of the person changed we delete that observation. Also, if the age of the person fell, or if age increased by more than two years (owing to the staggered timing of the initial and final interviews), then we delete those observations on

the assumption that they were bad matches. These additional criteria were very important prior to the 1986 survey year, but thereafter the five base criteria matched most observations.

There was a major survey redesign both in the mid 1980s and mid 1990s so it is not possible to match across the 1985-1986 waves and the 1995-1996 waves. In addition, the line number, which is intended to uniquely identify a person in the household, was not recorded for the 1976-1978 survey years. Thus we do not attempt to match across the 1975-1976 survey years, nor is it possible to match across the 1976-1977 years because of changes in the format of matching variables. Thus, we produce an interrupted time series across 36 years with gaps in calendar years 1974-1975, 1975-1976, 1984-1985, and 1994-1995. In total we have 640,412 matches, or roughly 20,000 observations in an average year when a match is possible. Appendix Table 1 lists the number of correct matches across survey years.

Prior to matching across years, we address two issues with the CPS data. First, if the respondent refuses to supply information on earnings or nonlabor income, then the Census Bureau uses a "hotdeck" imputation method to allocate income to those with missing data. Bollinger and Hirsch (2006) argue that including allocated data generally leads to an attenuation bias on estimated regression coefficients based on imputed data. Although the implications of hot decking for moments of the distribution beyond the mean are not well known, we follow Bollinger and Hirsch (2006) and drop those observations with allocated earnings or income. Second, in a series of papers, Richard Burkhauser and varied co-authors (Burkhauser, et al. 2004; 2007; Larrimore, et al. 2008) have raised concerns about trends in income inequality because of changes in the way the Census top-codes income data for public release. Prior to 1995 the Census assigned top-coded data a common value (though this value varied across income sources, and at times, years), but starting in 1995 they assigned top-coded data the mean values

of actual income based on broad demographic groupings (age, race, gender, education). Larrimore, et al. (2008) obtained access to internal Census data, which allowed them to back-cast the post-1995 procedure to 1976 and thus provide a consistent method of top-coding from 1976 onwards. We incorporated their series into our data prior to matching across years.

Our primary variables of interest are total labor-market earnings and before-tax income. Earnings is defined as the sum of wage and salary income, non-farm self employment, and farm self employment. Before-tax income is the same as that used in official Census Bureau calculations of poverty and inequality and includes earnings, social insurance payments, means-tested transfers, and other forms of non-transfer nonlabor income. A more detailed description of the construction of income is provided in the Data Appendix. As described in the results section below we also examine volatility omitting self employment earnings and including taxes and in-kind transfers. Although we match individuals across years, and present results based on individual outcomes, much of the recent literature on volatility has focused on family or household earnings and income, and we follow suit. In the CPS a family is defined as two or more persons related by birth, marriage, or adoption and thus family earnings (income) is the sum of earnings and income of all related members. Because each member of the family is assigned the same family-level earnings and income, for the family analyses we restrict attention to the head of household in order to prevent double counting. Unless noted otherwise all earnings and income data are deflated by the Personal Consumption Expenditure Deflator with 2008 base year. Basic summary statistics are provided in Appendix Table 2.

III. Trends in Earnings and Income Volatility

We follow Dynan, et al. (2008) and measure volatility as the standard deviation of the arc percent change, defined as

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

where y_{it} is earnings or income for person *i* in time *t*. Dynan, et al. define the denominator as $\bar{y}_i = \frac{y_{it} + y_{it-1}}{2}$, which is the person-specific time mean across the matched pair of years. The key advantage of this measure over the variance of log earnings used in most of the prior literature is that it is defined even if earnings (or income) is zero in one of the two years, and that it is symmetric and bounded below by -200 percent and above by +200 percent.[2] However, the symmetry property is violated if earnings are negative one year, say due to a business loss, and positive the next, and this can lead to wild swings in measured volatility based on equation (1). As a consequence we modify the arithmetic mean in the denominator as $\bar{y}_i = \frac{abs(y_{it}) + abs(y_{it-1})}{2}$, where *abs*(.) refers to the absolute value. This modified measure at once permits negative earnings and retains the symmetry property of -200 percent and +200 percent. Because we document a rising share of the prime-age male population out of the labor force two years in a row in Section 5, we want to retain those individuals with no earnings in either year by setting volatility equal to zero.

[Figure 1 here]

We begin in Figure 1 depicting trends in year-to-year family earnings and income volatility.[3] The first panel of the figure shows that earnings volatility increased sharply through the 1970s and into the mid 1980s, rising 20 percent, which corroborates findings from the PSID.

[2] We note that it is possible for family income to be zero based on our baseline definition, which does not include in-kind transfers or income from non-family members. In an average year about 58 families report zero income, though there was a trend increase over the past decade. We examined more closely those families reporting zero income, and in a typical year after 1980, 55-60 percent received in-kind support in the form of food stamps, public housing, Medicaid, or Medicare, and of the remaining 40 percent, nearly 9 out of 10 report income from non-family household members.

[3] Dynan et al. (2008) report 3-year moving averages rather than annual changes owing to smaller samples in the PSID. The large samples in the CPS make smoothing less important, but for completeness we conducted our entire analysis with 3-year averages with little change in results.

The 1986 redesign of the CPS reset the sample to coincide with the 1980 Decennial Census, which initially resulted in a sharp decrease in the level of volatility but not the trend. By the 1996 redesign, which reset the CPS sample to coincide with the 1990 Census, much of the overall increase in family earnings volatility over the 36-year period was realized. However, the lower line in the first panel also shows that family income volatility continued to increase to the end of the century, suggesting that although nonlabor income clearly reduced the level of economic volatility facing the family, it did not reduce the trend. In fact, from 1973-2008 family income volatility rose 38 percent, almost double that of earnings.

The series in the first panel of Figure 1 does not adjust for possible changes in family size and composition from one period to the next, whether owing to changes in marital status, children in the family, or other relational changes. To account for changing needs in the family in the second panel we report the volatility of family earnings to needs and income to needs. In this case needs are determined by the family-size specific poverty threshold, which makes an adjustment for economies to scale in family consumption and changes each year according to the Consumer Price Index. Because the threshold is adjusted annually by the CPI, we construct the series as the ratio of nominal earnings (or nominal income) to needs. As the second panel indicates, adjusting for changing family needs has no discernable impact on volatility trends, and thus for the remaining analyses we do not adjust for family size when presenting family or household level data.

Many of the studies in the volatility literature exclude persons with zero or negative earnings, although there have been substantial changes in labor force participation of men and women in the past four decades. In Section 5 we provide a more complete accounting of the influence of zero earnings to trend volatility, but as a first look at the importance of non-positive

earnings or incomes, in the third panel of Figure 1 we reproduce our base-case results excluding families reporting negative or no earnings or income in either year. As all the panels in Figure 1 are on a common scale, it is readily apparent in comparing panel one to panel three that including non-positive values shifts up the level of volatility in any given year by about 10 percentage points, but the basic trends reported in the first panel hold, at least with respect to earnings. Earnings volatility increases 21 percent in panel three as opposed to 20 percent in panel one, most of which is realized by the early 1990s, but family income volatility increases a more modest 28 percent with the non-positive values omitted.

Recent research highlights the consumption-smoothing role of the Federal tax and transfer system; that is, the fact that for any given change in before-tax and transfer income, after-tax and transfer income changes by less (Gruber 1997; Auerbach and Feenberg 2000; Kniesner and Ziliak 2002a,b; Gundersen and Ziliak 2003; Blundell, Pistaferri, and Preston 2008). Our series already contains the income from major social insurance programs such as Unemployment Insurance, Social Security, as well as means-tested cash transfers. However it does not include in-kind transfers such as food stamps or public housing, or income tax payments and credits such as the Earned Income Tax Credit (EITC). To examine the potential stabilizing role of the tax system and fungible in-kind transfers we subtract tax payments from gross income and add in the cash value of food stamps, school lunch and breakfast programs, and public housing/Section 8. Tax payments are the sum of Federal, state, and payroll taxes that are estimated for each family in each year using the NBER *TAXSIM* program in conjunction with basic information on labor income, taxable nonlabor income, dependents, and certain deductions such as property tax payments and child care expenses.[4] The Federal and state taxes include the

[4] The CPS does not have information on certain inputs to the *TAXSIM* program such as annual rental payments, child care expenses, or other itemized deductions. We set these values to zero when calculating the tax liability. The

respective EITC code for each tax year and state, thus allowing for the possibility of negative tax payments after 1975. We assume that the family bears only the employee share of the payroll tax rate. The fourth panel of Figure 1 shows that in any given year the tax system reduces the level of volatility by about 10 percent, but does not alter the trend growth. Indeed the trend growth in after-tax income volatility is actually higher at 48 percent than before-tax income volatility. When restricting attention to the 1980-2008 survey years when all tax and transfer data are available, after-tax volatility increased 43 percent compared to 32 percent for before-tax income. These results are consistent with Kniesner and Ziliak (2002a) who found that the tax reforms of the 1980s, which reduced the number and magnitude of marginal tax rates, reduced the automatic stabilizer capacity of the tax system.

A. Volatility across Race, Family Structure, and Education

In this section we examine whether the trend increase in family earnings and income volatility was widely distributed across families based on race, family structure, and education of the family head. In Figure 2 we depict trends in volatility for families headed by a white or a black person. The level and pattern of earnings volatility is strikingly different; although the level of earnings volatility is nearly one-third higher among black families, the trend increase in overall family earnings volatility in Figure 1 was driven entirely by the 24 percent increase in volatility among white families. There was a strong increase in earnings volatility among black families through the mid 1980s, but starting in the early 1990s black family earnings volatility fell and the level in 2008 is the same as in 1973. At the same time, black family income volatility actually rose more than white family income volatility (48 versus 36 percent), although it is clear that overall income volatility was widely distributed across race.

EITC did not begin until the 1975 tax year, and state taxes were not included in TAXSIM until 1976. In addition, food stamps and public housing were not added to the CPS until 1980, and the early-release version of the 2009 CPS we use does not include the dollar value of ink-kind transfers.

[Figures 2-3 here]

With the secular rise of divorce and out of wedlock births, as well as cohabitation, it is possible that this has translated into marked differences in volatility across family structure. In Figure 3 we present earnings and income volatility for intact families; that is, for families with continuous marital status from one year to the next separately for married families (panel one), unmarried families (widowed, divorced, separated, never married in panel two), and single female-headed families (panel three). Figure 3 reveals that earnings and income volatility is lowest for married families as opposed to unmarried heads, or single female headed families, but the rise in family earnings volatility occurred primarily among married families. Earnings volatility was essentially constant across the 36 years among unmarried families, while it actually fell 15 percent among female heads. On the other hand, the trend rise in family income volatility was experienced across all family types, although the trend rise was least pronounced among single female heads of household. At first blush this may seem surprising given the dramatic reforms to the U.S. welfare system in the 1990s, but as noted in Bollinger and Ziliak (2008) there were substantial changes in the composition of single mothers toward a much higher educated population at the same time that might have dampened the effects of volatility.

Family income in the CPS does not include the earnings and nonlabor income of cohabitors, but their contributions are included in household-level earnings and income, and in the last panel of Figure 3 we compare family to household income volatility. The contributions of cohabitors and other non-family members dampens the level of household volatility compared to family volatility, as well as the short-term swings in family volatility in the 2000s, but the overall trend is unchanged.

[Figure 4 here]

The vast literature on income inequality seems to be in agreement that the increase in wage inequality was most pronounced in the 1980s and was likely due to a combination of skill-biased technical change favoring skilled workers, falling unionization, and a declining real wage (Katz and Autor 1999; Lemieux 2008), while the inequality growth of the 1990s was most pronounced in the upper tail of the distribution (Piketty and Saez 2003; Autor, et al. 2008). The developments suggest that the growth in earnings and income volatility should differ across education group, and be most pronounced among the least skilled in the first half of the series and most pronounced among the high skilled in the second half.. In Figure 4 we depict trends in family earnings and income volatility for family heads with less than a high school education, those with a high school diploma but not college, and those with some college. The rise in family earnings inequality cuts across education level fairly uniformly, increasing by 30 percent for dropouts, 30 percent for high school graduates, and 35 percent for those with at least some college. However, as predicted earnings volatility rose faster among the less skilled compared to high skilled from 1973-1984 (33 versus 12 percent), and then reversed from 1986-2008 (11 versus 31 percent). Likewise, total income volatility increased considerably more among high school dropouts (70 percent) compared to those with some college (41 percent), but the timing followed the earnings pattern.

B. Volatility across the Life Cycle

The timing of volatility over the life cycle can have potentially important welfare implications in terms of mobility. If volatility is largely concentrated early in the life cycle when job change is more frequent, either within or across employers, then the welfare consequences are likely attenuated relative to a situation where it is increasing with age. To examine the life cycle path of volatility we construct a pseudo panel of individuals along the lines of Deaton

(1985) and Blundell et al. (1998) by allocating each individual to one of 48 five-year birth by education cohorts, comprised of sixteen birth cohorts and three education groups (less than high school, high school graduate, and more than high school). In effect we construct an unbalanced panel because many of the cohorts are not present for all ages, but it is possible to look across cohorts to identify life cycle profiles of volatility.

[Figures 5-6 here]

In Figure 5 we present the education-group specific life cycle profile of family earnings volatility. Each panel contains the time series for sixteen birth cohorts, and in a bid to add transparency we overlay a lowess plot that smoothes the data across cohorts using a locally weighted regression method. Figure 5 shows that across education groups volatility declines rapidly until about age 35, but among those with high school or more volatility actually begins to increase at age 45 and thus is U-shaped across the life cycle. Figure 6 we present the parallel graph of family income volatility across the life cycle. As with earnings, income volatility stabilizes by age 35, but unlike earnings, income volatility is relatively constant thereafter. One reason for the U-shape in earnings volatility might be labor force entry when young and labor-force exit when old. In results not graphed we re-drew Figure 5 excluding families with zero earnings and indeed the U-shape is attenuated, with earnings volatility being fairly constant across the life cycle for less than high school educated heads, and more L-shaped for those with 12 and more years of schooling akin to total income in Figure 6.

[Figure 7-8 here]

Because it is difficult to identify birth-cohorts in Figures 5-6 owing to the overlapping of 16 series, in Figures 7-8 we present the time series of family earnings and income volatility by each of the 48 education-birth cohorts. For example, cohort 1 is a family head born between

1987 and 1992 who is a high school dropout, cohort 2 is from the same birth years but a high school graduate, cohort 3 is also the same birth cohort but with more than high school, cohort 4 is a high school dropout born between 1982 and 1986, and so on, until cohorts 46-48 who were born before 1917. This figure enables us to identify the full evolution of the life cycle profiles and to better understand whether the rising earnings volatility depicted in Figure 1 is driven by younger cohorts, older cohorts, or distributed widely across education-birth cohorts. Looking across the columns and down the rows of Figures 7-8 it is possible to trace out the U-shape found in the previous figures, but at any given age it is not obvious that volatility is concentrated more heavily on any one or set of cohorts. For example, if we focus on cohorts with less than high school, cohorts 10, 13, 16, 19, 22, 25, and 28 stand out somewhat with higher volatility at age 40, but it is subtle. Rather the rise in volatility in Figure 1 is likely due to the combination of high volatility among the young as well as increasing volatility of the old, and with an aging workforce the latter is fostering a trend increase in overall volatility.

C. Earnings and Income Volatility by Source

Our analysis to this point has focused on the family as an aggregate unit, and thus in this section we want to look within the family to examine the volatility of earnings husbands, wives, and other family members at the individual level, as well as the volatility of income by component source in addition to earnings. However, to place the volatility of husbands and wives in perspective in Figures 9 and 10 we first document trends in earnings volatility overall and by race for men and women, respectively. Figure 9 shows that from 1973 to 2008 earnings volatility of men increased about 14 percent overall, with a 16 percent increase for white men and no increase for black men, and that much of the increase occurred in the 1970s and early 1980s. For example, volatility of black men rose 15 percent from 1973-1984, but fell in the last

two decades. For women in Figure 10, on the other hand, volatility has fallen about 15 percent overall in the last four decades, and although most of the decline occurred by the mid 1980s it has continued into the 2000s. Indeed, if the volatility trends of men and women continue the levels are likely to converge in the current decade, and in fact this convergence has already taken place between black men and women.

[Figures 9 and 10 here]

In Figure 11 we document earnings volatility by status in the family—husbands, wives, and others. The latter category includes single parents (separated, divorced, never married) as well as other members of the family other than the head or wife. The figure, coupled with the results in Figure 3 which showed a decline in female-headed earnings volatility and constant for unmarried family heads in general, suggests that the overall increase in family earnings volatility is being driven primarily by volatility of husbands earnings, and with an added push from family members other than the head. Figure 11 shows that the volatility trends of husbands and wives in the last four decades mimics the trends of men and women in general.

[Figures 11 and 12 here]

We return to total income volatility in Figure 12 to examine the rise in volatility by income source. Because of the secular growth in self-employment in the U.S. in recent decades in the first panel of Figure 12 we examine the role of self-employment in earnings volatility by presenting the time series with and without self employment earnings. Although self-employment earnings are volatile from the individual perspective, from the family volatility perspective this source actually has the effect of dampening the level of volatility. The panel makes clear that self-employment earnings affect the level but not the trends. The second panel depicts trends in income volatility for means-tested transfers and credits (cash welfare, food

stamps, housing assistance, SSI, and EITC). As discussed in surveys such as Blank (2002), Hotz and Scholz (2003), and Ziliak (2008) there have been dramatic changes in the safety net in the U.S. since the 1980s, with huge expansions in cash welfare and food stamps in the early 1990s, followed by even larger declines in the late 1990s but with a concomitant increase in the EITC and SSI. However, these changes have had little effect on overall trend inequality for the American family, though in results not tabulated means-tested income volatility did increase by 15 percent for single mother families. On the other hand, as panels three and four demonstrate, there is a strong upward trend in non-welfare nonlabor income since the mid 1980s, which is being driven by higher volatility of income from rent payments, interest, and dividends.

IV. Estimating Trend Breaks in Earnings and Income Volatility

Although the family earnings volatility series appears to change in the late 1980s and family income volatility about a decade later, it is also important to determine whether the series differ in a statistical sense. In lieu of arbitrarily choosing break points in the volatility series, we instead turn to the recent time series literature on testing for structural change with an unknown change point (Andrews 1993; Bai 1997; Hansen 2001). Because these tests have not to our knowledge been applied in the volatility or inequality literatures a brief summary of the procedure is warranted.

The tests build on an idea due to Quandt (1960), who proposed splitting the sample at every possible breakdate, estimating the model parameters separately on the two sub samples, and constructing the associated Chow test statistic for all possible sample splits (any subsample must have more observations than parameters estimated). The estimated breakdate is the sample split with the largest value of the Chow test statistic. If the breakdate is known a priori then one can appeal to the usual chi-square tables for critical values. However, in many cases the

breakdate is not known and the chi-squared critical values are not valid. Andrews (1993) developed the asymptotic theory for the case of unknown change point and provided tables of critical values, and consequently the new tests are generally known as the Quandt-Andrews sup-Wald statistic. As noted by Hansen (2001), this method of least squares testing for structural change is valid for the linear regression model with homoskedastic variances, and Bai (1997) proposed a straightforward method of constructing confidence intervals around the breakdate.

To implement the tests we take our estimated univariate time series of volatility and run the following regression:

$$(2)\qquad \begin{aligned} \widehat{\sigma(t)} &= \sigma_{10} + \sigma_{11} y85 + \sigma_{12} y95 + \theta_1 t + \zeta_1, t = 1, ..., \tau \\ \widehat{\sigma(t)} &= \sigma_{20} + \sigma_{21} y85 + \sigma_{22} y95 + \theta_2 t + \zeta_2, t = \tau + 1, ..., T \end{aligned}$$

where $\widehat{\sigma(t)}$ is the estimated standard deviation of the percent change, $\sigma_{j0}, j = 1, 2$ is a constant term (reflecting the constant volatility), $\theta_j, j = 1, 2$ is the coefficient on the linear trend *t*, ζ is an iid random error term, τ is the unknown breakdate, and $T = 32$ for the calendar years 1973–2008 (including the 4 missing match years). The variable *y85* is an indicator variable that takes a value of 0 before 1985 and 1 thereafter, while *y95* takes a value of 0 before 1995 and 1 thereafter. These two variables are intended to admit an intercept shift in constant volatility associated with the survey redesigns applying to calendar years 1985 and 1995. For each possible breakdate, τ, we conduct the joint test of the null hypothesis of constant volatility, i.e. the first set of coefficients equals the second set, by constructing the following Wald test statistic

$$(3)\qquad W = (SSE_{pooled} - (SSE_1 + SSE_2)) / \left((SSE_1 + SSE_2)/(T - 2*l)\right)$$

where SSE_{pooled} is the sum of squared errors for the pooled regression with no break, SSE_1 and SSE_2 are the sum of squared errors for the pre- and post-break periods, respectively, and *l* is the

number of parameters in each subsample. The estimated breakdate is the $\hat{\tau}$ with the maximum test statistic, $\hat{W}$, i.e. the supWald statistic. The associated Bai (1997) confidence interval for $\hat{\tau}$ with trending regressors is $\left[\hat{\tau} \pm (\frac{c}{\hat{L}} + 1)\right]$. The term *c* is the critical value for a test of size α and $\hat{L}$ is the outer product of the fitted valued of the regression standardized by the estimated error variance, $\hat{L} = \frac{\hat{\gamma}' Z Z' \hat{\gamma}'}{\hat{\sigma}^2}$, with $\hat{\gamma} = [\hat{\sigma}_j, \hat{\theta}_j]$ and $Z = [1, y85, y95, t]$ and where *t* is set at the estimated breakdate $\hat{\tau}$ (See Bai (p. 555) for additional details).

In Table 1 we report the Quandt-Andrews supWald test statistics for earnings volatility, along with the estimated breakdate, and the associated 95 percent confidence interval. Our tests contain four variables—a constant term, trend, and the two indicator variables, which reflects the fact that by construction the tests allow for structural change in the coefficients of all included regressors. The corresponding critical values for the $l = 4$ case are 13.82, 15.84, and 20.24 for the 10 percent, 5 percent, and 1 percent levels of significance, respectively (Andrews 1993). Because the determinants of earnings, and thus earnings volatility, are affected by the business cycle (Solon, et al. 1994; Ziliak, et al. 1999), we also conduct our Quandt-Andrews tests controlling for the aggregate unemployment rate and report those results in Table 2. The corresponding critical values when unemployment is included are 15.63, 17.88, and 21.90, respectively.[5]

[Tables 1 and 2 here]

In the first row of Table 1 the supWald statistic of 32.3 clearly rejects at the 1 percent level the null hypothesis of no structural change for family earnings. As initially indicated in

[5] In choosing asymptotic critical values there are three parameters of interest, the size of the test, the number of parameters, and the date change parameter that lies on the unit interval. Andrews (1993) recommends restricting the date change interval to [0.15, 0.85] when there is no information on the possible structural break date. We chose 0.20 for our critical values.

Figure 1 where it appeared the break date occurred before the 1990s, the Quandt-Andrews test suggests a breakdate in 1992, plus or minus four years. The somewhat wide confidence interval is not too surprising given how the series gradually plateaus from the late 1980s to mid 1990s. The last column indicates that the coefficient on the linear trend is positive and statistically significant, but it is statistically zero after the break. This result is robust to the inclusion of the unemployment rate in Table 2. When broken down by race the breakdate for white families is pushed back to 2001, and to 1997 for black families when controlling for unemployment. Interestingly, the 1992 breakdate in family earnings appears to be a weighted average across education levels of the family head, with the break toward higher volatility occurring for high school graduates in 1980, and in the 1990s for dropouts and those with at least some college. Table 2 shows, however, the differential influence of the business cycle on family volatility as the breakdate for graduates rises to 1992, albeit with a very wide confidence interval. Whether controlling for the business cycle or not there are marked differences in the structural break point between whites and blacks within gender, but controlling for the cycle in Table 2 leads to similar breakdates across gender overall, and within racial groups. White men and women have an earnings breakdate in 1979, though the trends are declining for women and rising for men, but for both black men and women the early 1990s trend break is toward lower volatility.

[Tables 3 and 4 here]

In Tables 3 and 4 we present the structural break test results for income volatility, with and without controls for the business cycle. Consistent with our priors based on Figure 1, family income volatility increases until 1999 before stabilizing. The 5-year confidence interval around the breakdate appears to be due in part to the heterogeneity in breakdates across race, education, family structure, and income source. For example, the trend toward higher volatility among

female headed families and black families is traced back to the late 1970s. Collectively the Quandt-Andrews tests of structural change on matched CPS data broadly coincide with the consensus findings from studies using the PSID that most of the increase in earnings volatility in the U.S. took place in the 1970s and 1980s, and that income volatility continued through the 1990s, but the tests are also at odds with the conclusion from Dahl, et al. (2008) who found in SIPP data matched to administrative earnings records that overall income volatility was little changed from the 1980s.

V. Decomposing the Volatility of Earnings

With the influx of large numbers of women into the labor force in recent decades, coupled with labor-force withdrawal of men, the increase in family earnings volatility may be due to a compositional change of the workforce, or it may simply reflect increased earnings dispersion of workers (Lemieux 2006). That is, the volatility of earnings depends on the relative role of changes in the extensive margin of entry and exit into employment and the intensive margin of earnings conditional on being a worker. Because we define volatility as the variance of the percent change from one period to the next, there are four possible states of labor-force participation: (0,0), (0,1), (1,0), and (1,1), where 0 means out of the labor force and 1 means participation. In Figure 13 we depict trends in employment rates for men and women, and husbands and wives, for each of the four states, and where employment refers to earnings at any point in time during the past year. The figure reveals that among men there is a secular trend increase in the (0,0) state, and trend decrease in the (1,1) case, but relatively constant and symmetric transition employment rates. These trends hold for husbands as well, though they are less distinct. For women, on the other hand, the trend increase in the (1,1) state, and concomitant

decrease in (0,0), plateaued in the mid 1990s and actually reversed slightly in the 2000s. This was true for wives as well.

[Figure 13 here]

To see the possible interaction between the extensive and intensive margins on the unconditional volatility of earnings note that we can write the variance as

(4) $V(q) = E\{V(q|P)\} + V(E\{q|P\})$,

where q is the arc percent change in earnings, P is an indicator variable equal to one if an individual participates in the labor force, and E is the expectations operator. Equation (4), which expresses volatility as the unconditional variance of the percent change of earnings instead of the standard deviation, is the sum of the expected conditional variance of the percent change and the variance of the conditional mean of the percent change.

With four possible states of labor-force participation, this implies that the first term on the right hand side of equation (4) can be expressed as

(5) $E\{V(q|P)\} = V(q|P = 0,0) * \Pr(P = 0,0) + V(q|P = 0,1) * \Pr(P = 0,1) +$

$V(q|P = 1,0) * \Pr(P = 1,0) + V(q|P = 1,1) * \Pr(P = 1,1)$.

However, the volatility of nonworkers is zero, and thus the first term of (5) is zero. Also, because the arc percent change from equation (1) equals 200 for all workers in the (0,1) state, and equals -200 for all workers in the (1,0) state, this means the variance of these two subsamples are also zero since the percent change is a constant. Consequently, the only term remaining in (5) is the fourth term, which is the volatility of two-period workers weighted by the probability of working both periods.

Likewise, we can express the variance of the conditional mean in equation (4) as follows

(6) $V(E\{q|P\}) = (E\{q|P = 0,0\} - E\{q\})^2 * \Pr(P = 0,0) + (E\{q|P = 0,1\} - E\{q\})^2 * \Pr(P = 0,1) + (E\{q|P = 1,0\} - E\{q\})^2 * \Pr(P = 1,0) + (E\{q|P = 1,1\} - E\{q\})^2 * \Pr(P = 1,1),$

where $E\{q|P = 0,0\} = 0$, i.e. the conditional mean of two-period non-workers is zero. This implies that the unconditional variance in (4) is a function of five terms—the weighted conditional variance in equation (5) plus the four weighted variances of the conditional mean in two-period non-workers, the two transition states, and two-period workers from (6).

[Figures 14-20 here]

In Figures 14-20 we depict the time series of each of the five components in the volatility variance decomposition for family earnings, husbands, wives, white men, black men, white women, and black women. In the top panel of each figure we depict the conditional variance of two-period workers from equation (5) on the right axis and on the left axis we present the variance of the conditional mean for the two transition states (0,1) and (1,0). Because the scales are markedly different the trends for the conditional mean variances for the two period work (1,1) and non-work (0,0) states are in the bottom panel. Across all samples the contribution of the variances of the conditional means from the continuous work and non-work states to overall volatility is negligible, and thus we restrict attention to the top panels. At the family level in Figure 14 most volatility comes from the conditional variance, though after the mid 1990s the contribution of the conditional mean variance of families transitioning from work to non-work (1,0) increases. Thus even though the probability of such a transition is small, and stable over the period, the contribution to volatility is not. The trends affecting the family track strongly those of husbands in Figure 15. In Figure 16 for wives, however, in the early part of the sample volatility is dominated by labor-force transitions, both (0,1) and (1,0), but as volatility of wives

earnings declined over time the three variance terms in the top panel were roughly equal in magnitude. At the individual level, among white men in Figure 17, the conditional variance dominates the variance of the conditional mean in any given year, though clearly in the past decade the conditional mean variance of exiters increases as the conditional variance of continuous workers declines. For black men in Figure 18, and white and black women in Figures 19 and 20, respectively, the last four decades are characterized by a declining contribution of the variance of the conditional mean of labor-force transitions such that by the 2000s the three terms were roughly each in magnitude.

VI. Conclusion

We found strong evidence from matched data from the CPS that income volatility increased substantially from the 1970s through the 1990s, and that this increase was distributed widely across the American family in terms of race, education, and family structure. The primary source of rising income volatility was an increase in earnings volatility of men and an increase in non-transfer nonlabor income volatility, especially income from rent, interest, and dividends. Although much of the rise in earnings volatility stems from higher conditional variance of earnings among continuous workers, an increasing fraction comes from higher variance of the conditional mean among workers exiting the labor force from one period to the next. With the aging of the labor force these trends are likely to continue to exert upward pressure on volatility overall.

Our results broadly corroborate those from studies based on the PSID, namely that most of the increase in earnings volatility occurred prior to the 1990s but that income volatility continued to rise through the 1990s. With the change to every other year survey design after 1997, Gottschalk and Moffitt (2009) urge caution in interpreting volatility trends from the PSID

in the 2000s. This makes data from matched CPS a potentially more appealing source for future research on this topic. Along these lines, our cohort analysis indicates that earnings volatility is U-shaped across the life cycle, especially for skilled workers. Future research should examine in more detail life cycle patterns of volatility, especially the role of labor-force exits. Related, with broad trends now established across several major survey and administrative data sets new research is needed on underlying causal factors such as whether the labor force transitions leading to higher volatility are voluntary or involuntary, as well as to research on the effects of volatility on family and child well being.

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Data Appendix

Earnings is the sum of wage and salary income, non-farm self employment, and farm self employment. Individual earnings before 1977 are calculated using the sum of income from wages, self employment income, and farm income. For 1977 and beyond the CPS has its own composite definition of individual earnings that incorporates the same components we use before 1977.

Income is includes earnings, Social Security (retirement, disability, and survivors benefits), Supplemental Security Income, Unemployment Insurance, workers' compensation, AFDC/TANF and other forms of public cash welfare, veterans' payments, pension income, rent/interest/dividend income, royalties, income from estates, trusts, educational assistance, alimony, child support, assistance from outside the household, and other income sources. Data on AFDC/TANF cash assistance, social security payments, and social security disability payments are available in the CPS after 1974; the monetary value of food stamps, earned income tax credits, and housing subsidies do not become available in the CPS until 1979. This means that our income category for "Means Tested Transfers and Credits" excludes these variables before 1979. When we decompose "Other Income" into its respective subcategories, note that the CPS combines two distinct variables, (1) alimony and (2) child support, to create "Alimony and Child Support" between 1975 and 1986. After 1986 alimony and child support are separate variables that we combine to create a uniform measure across the panel. The income categories "Unemployment (UI), Worker's Compensation (WC), and Veteran's benefits" and "Rent, Interest, and Dividends" are structured similarly, so that each of the three distinct subcategories are combined after 1986 to create one variable for use across the panel. As with "Alimony and Child Support", these last two categories' components were combined in the CPS prior to 1987.

Appendix Table 1: Number of Merges Per Year by 2nd Year of CPS Panel
Calendar Year 1973-2008

Year	Number of Merges
1973	10,116
1974	14618
1975	-
1976	-
1977	26,063
1978	23,661
1979	21,800
1980	23,421
1981	21,404
1982	23,379
1983	23,303
1984	21,313
1985	-
1986	19,129
1987	21,114
1988	22,436
1989	22,810
1990	24,330
1991	24,131
1992	23,792
1993	22,580
1994	19,883
1995	-
1996	18,462
1997	18,140
1998	16,976
1999	16,223
2000	15,449
2001	18,538
2002	18,161
2003	19,085
2004	16,260
2005	17,470
2006	18,431
2007	18,873
2008	19,061
Average Number of Matches	20,013

Appendix Table 2. Summary Statistics by 2nd Year Adjusted for Inflation (2008 Dollars)

Variables	Mean	Standard Deviation
Earnings and Income		
Family Earnings ($)	62,709.95	53,678.91
% Change in Family Earnings	0.65	107.19
Family Income ($)	69,280.60	55,925.64
% Change in Family Income	1.82	190.83
Disposable Income ($)	52,561.31	35,583.78
Self Employment Income ($)	3,489.32	18,142.65
Demographics		
Age	37.63	12.21
% Female	53.53	49.87
No. of Persons in Family	3.28	1.49
% Less Than High School	20.37	39.82
% High School	35.55	47.60
% More Than High School	44.08	48.73
% White	86.07	34.52
% Black	9.50	29.32
% Other	4.42	19.96
% Married	62.70	48.20

Figure 1. Family Earnings and Income Volatility

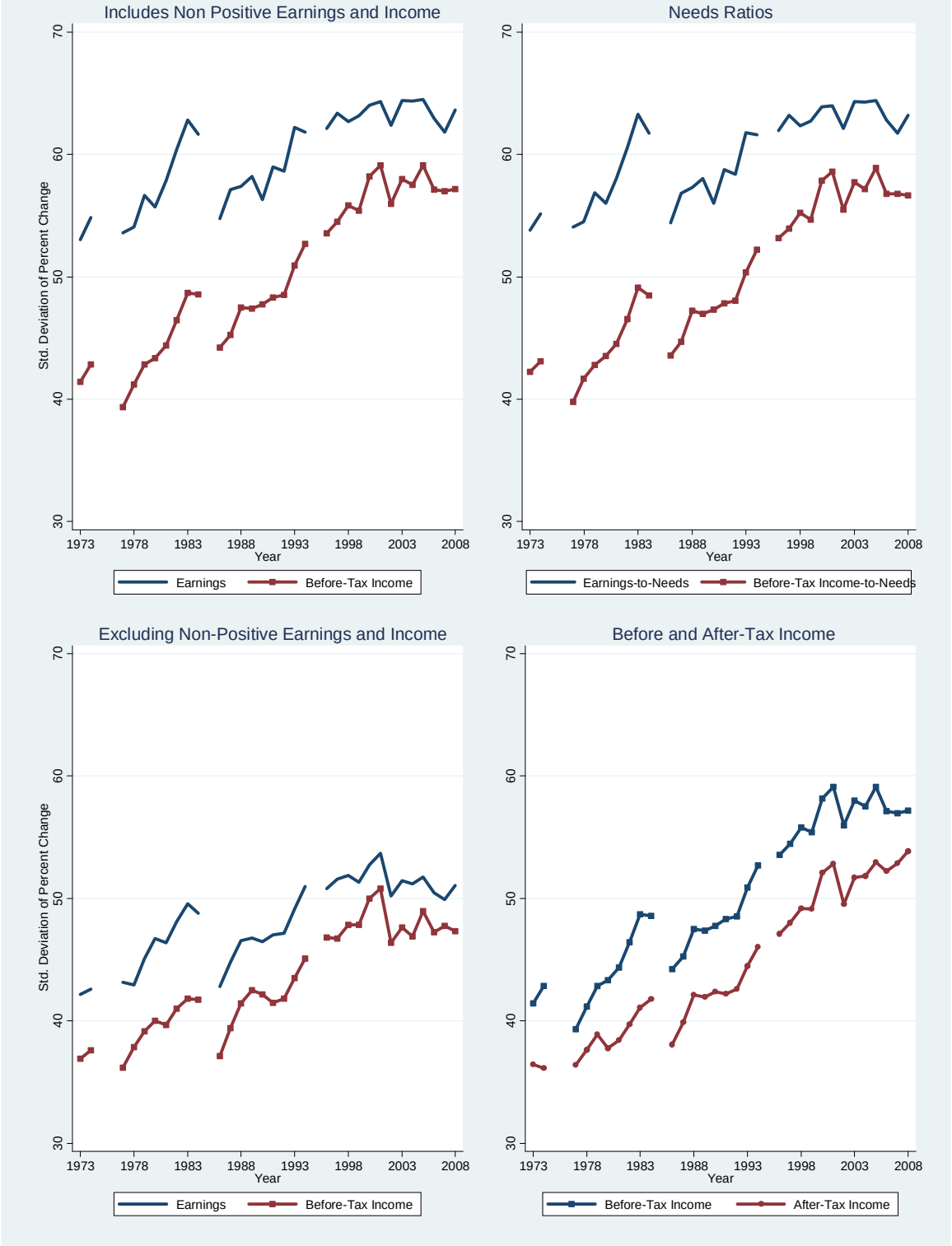


Figure 2. Family Earnings and Income Volatility

By Race of Head

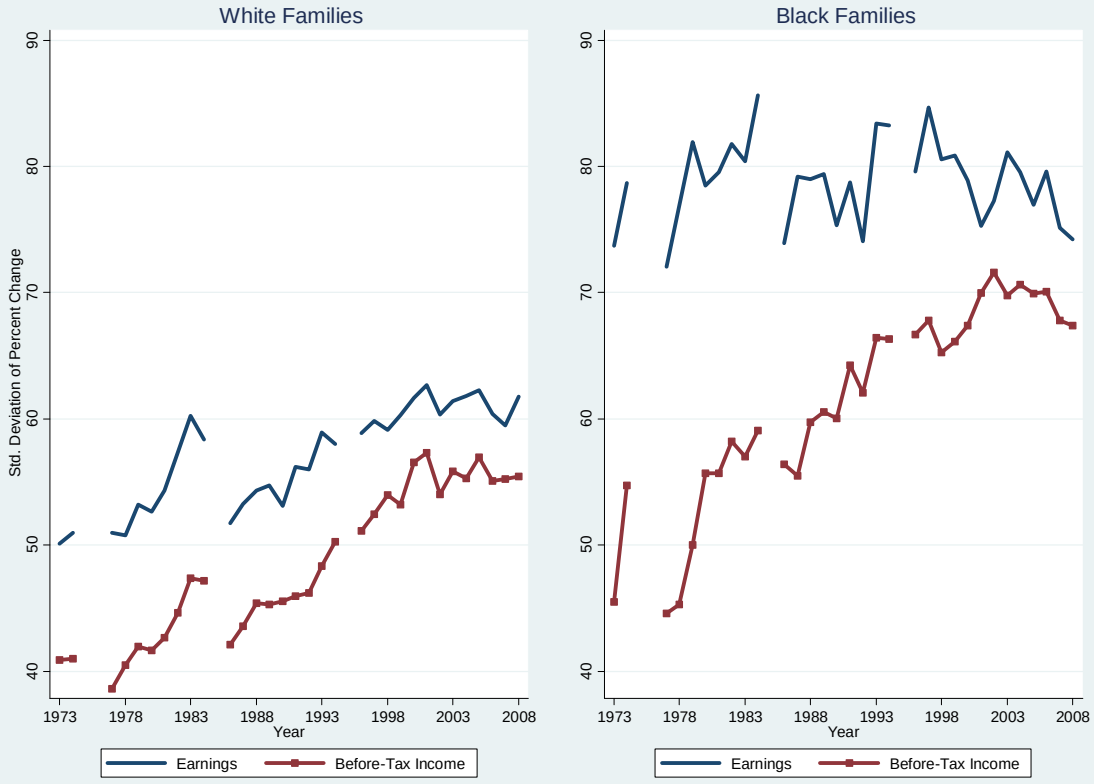


Figure 3. Family Earnings and Income Volatility

By Family Structure

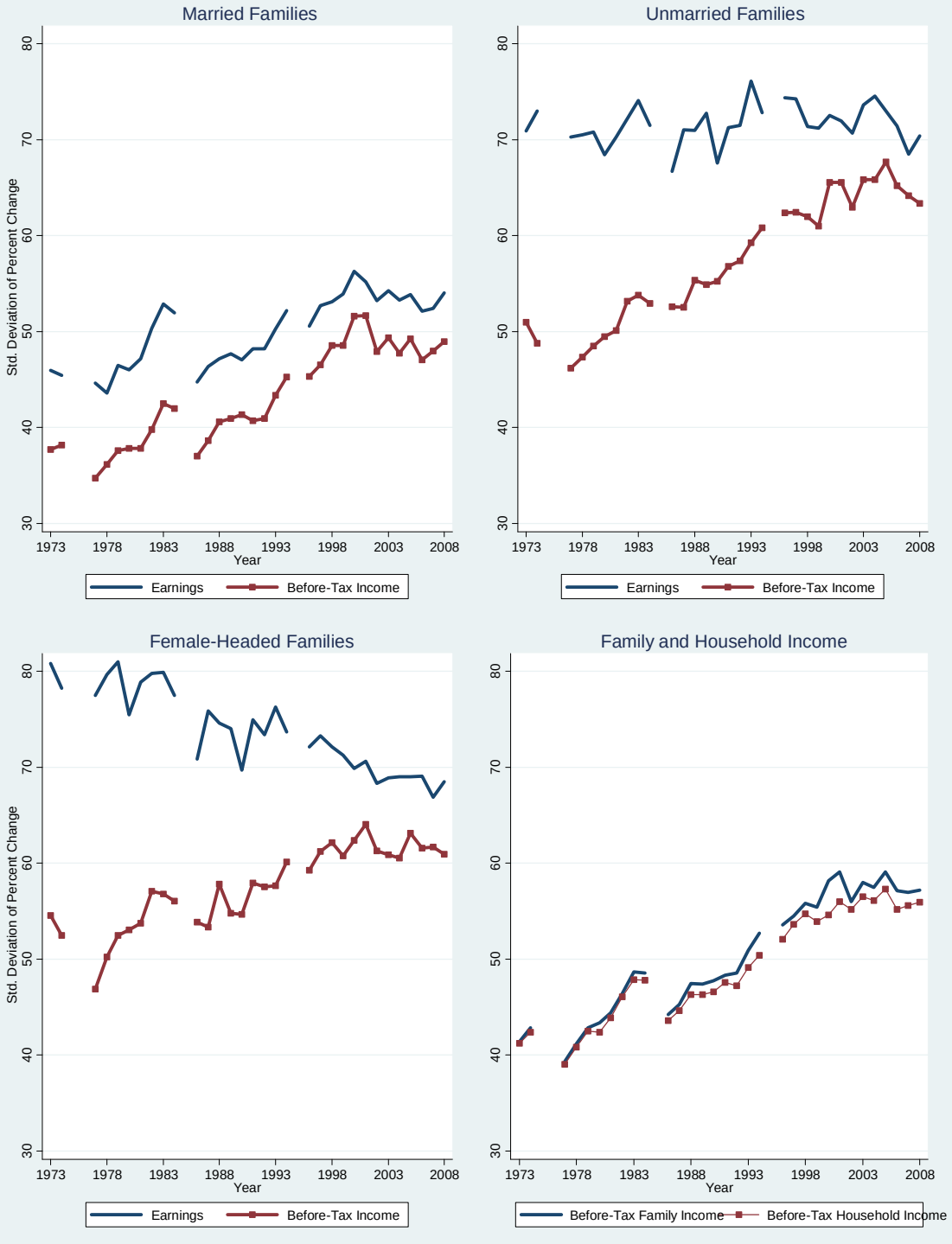


Figure 4. Family Earnings and Income Volatility

By Education

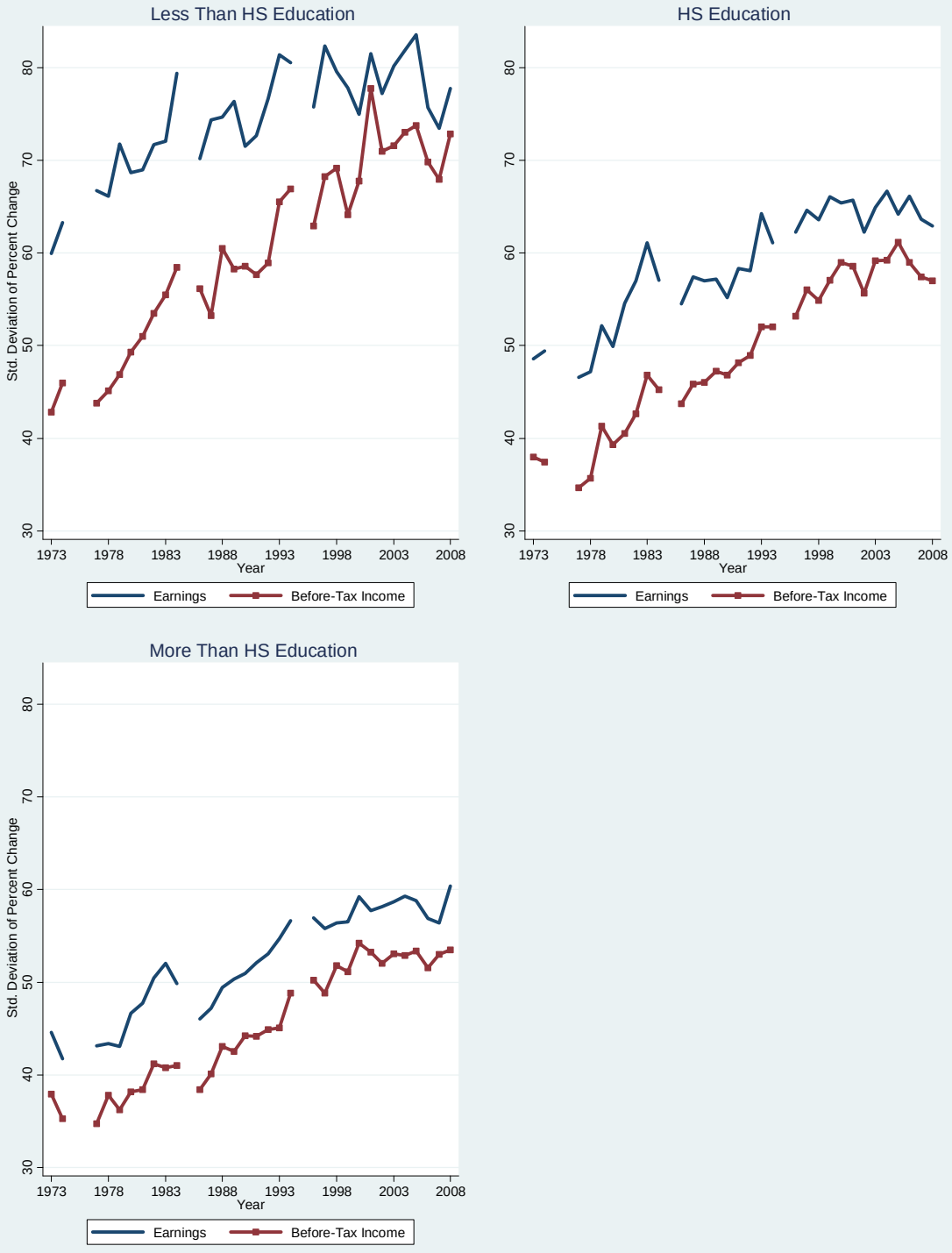


Figure 5. Earnings Volatility Across the Lifecycle

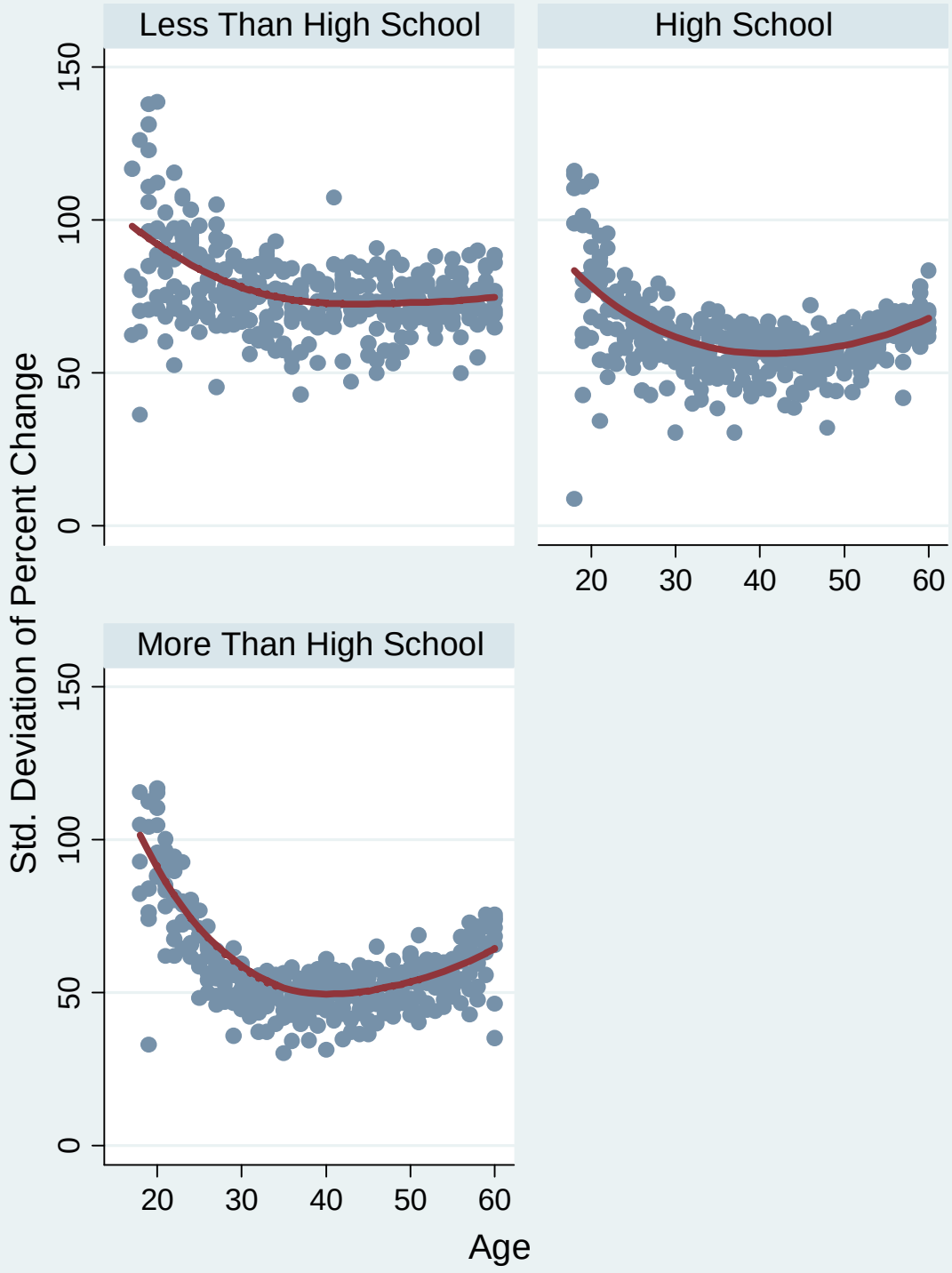


Figure 6. Income Volatility Across the Lifecycle

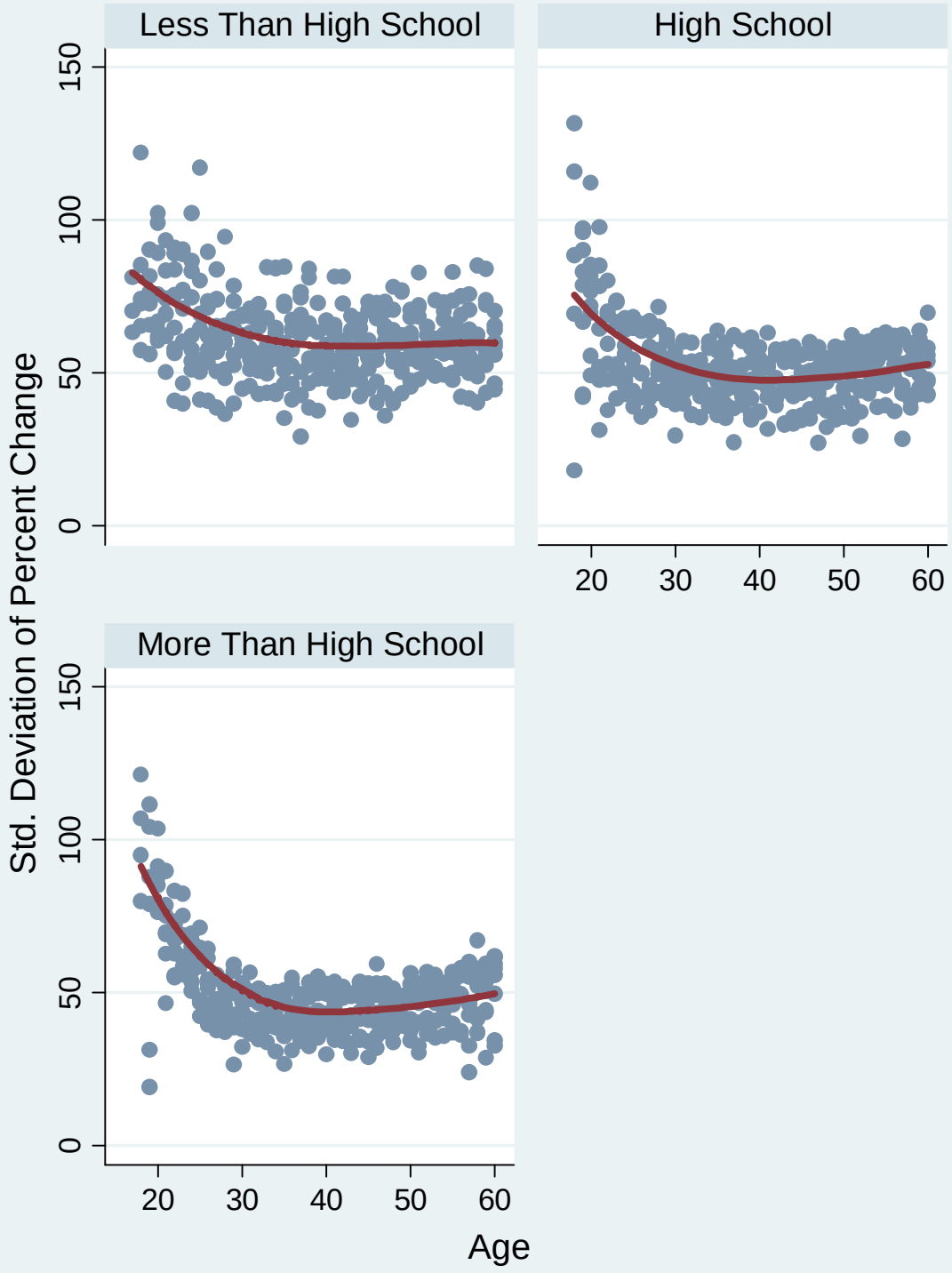


Figure 7. Earnings Volatility by Education-Birth Cohort

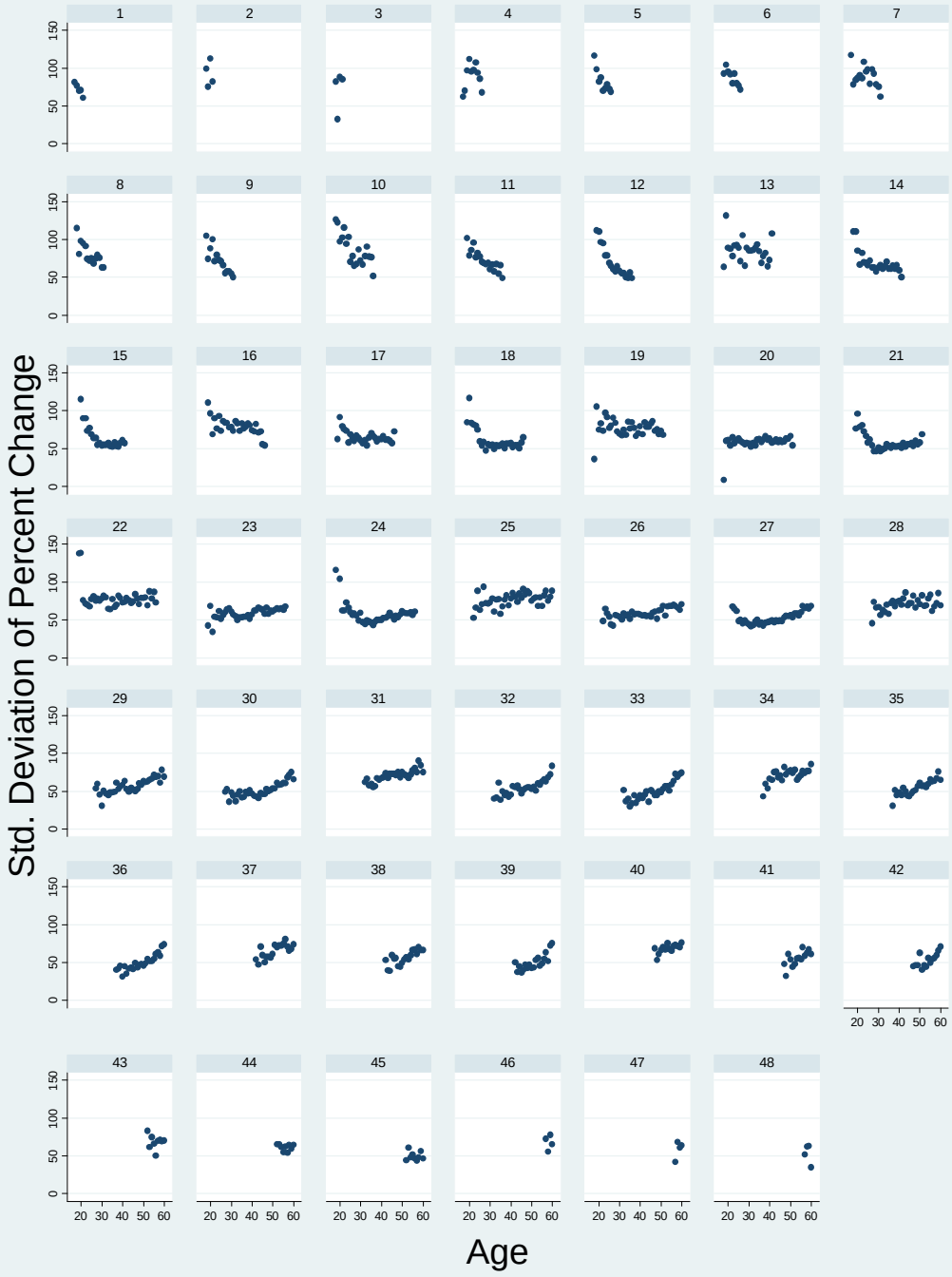


Figure 8. Income Volatility by Education-Birth Cohort

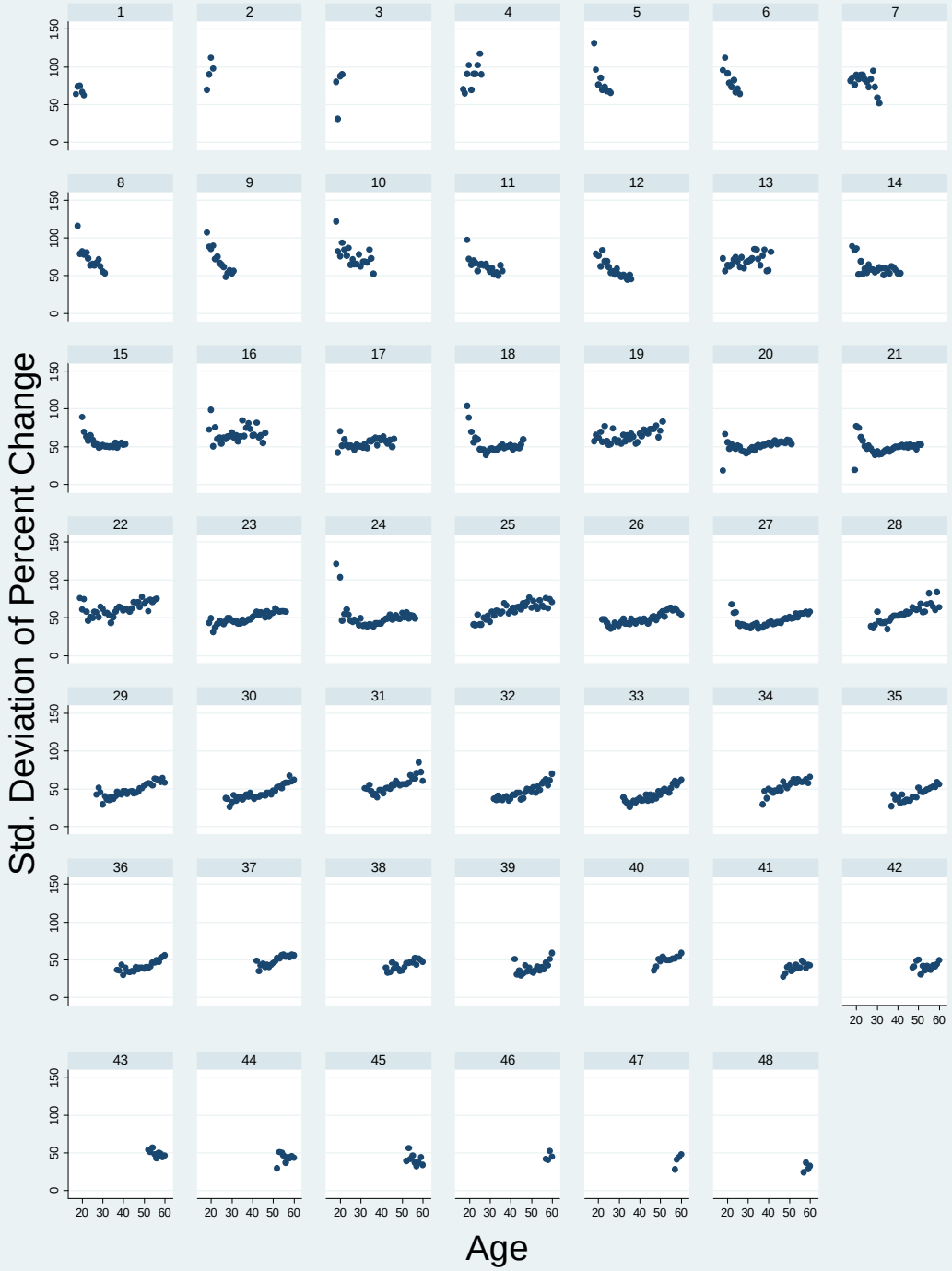


Figure 9. Individual Earnings Volatility

All Men and By Race

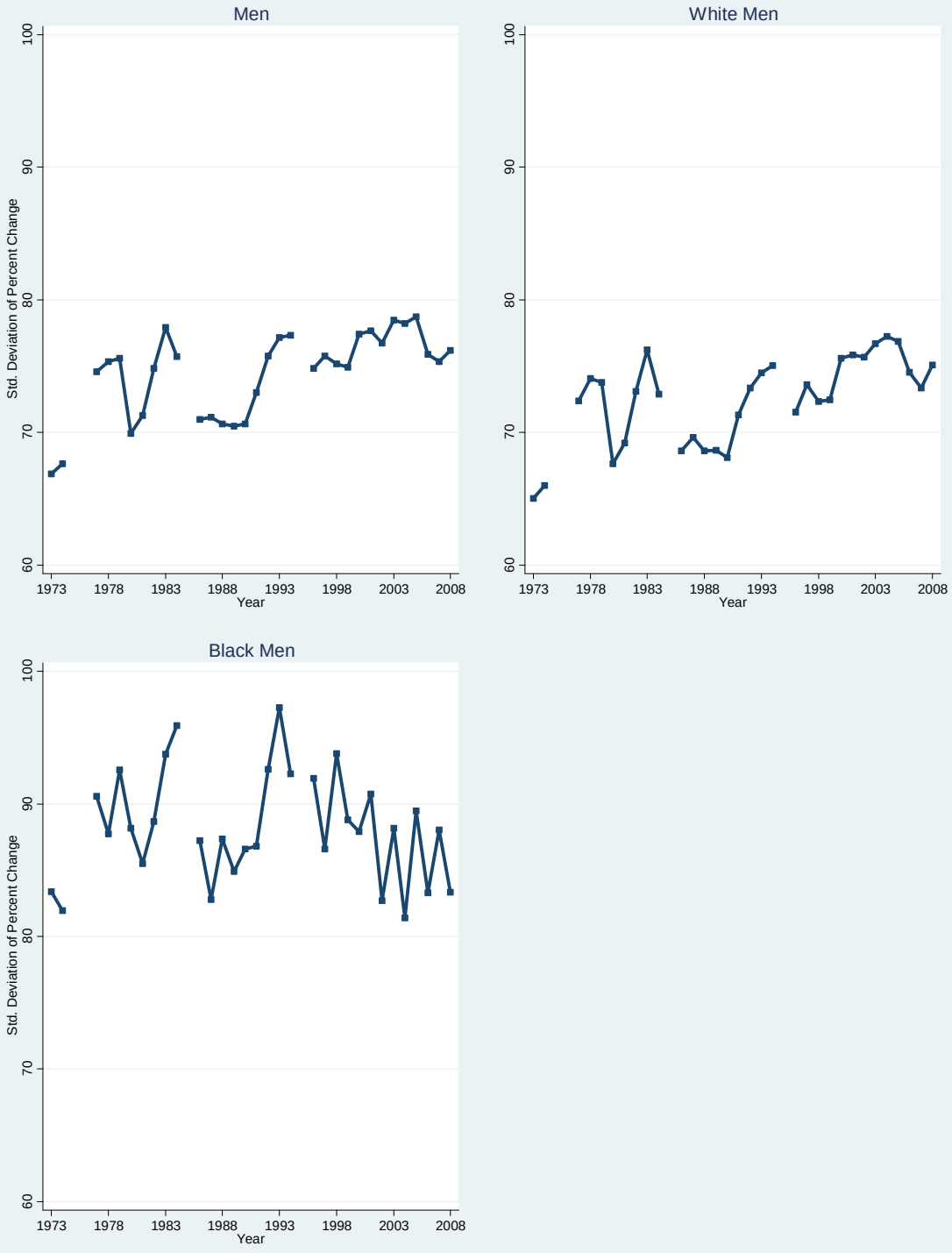


Figure 10. Individual Earnings Volatility

All Women and By Race

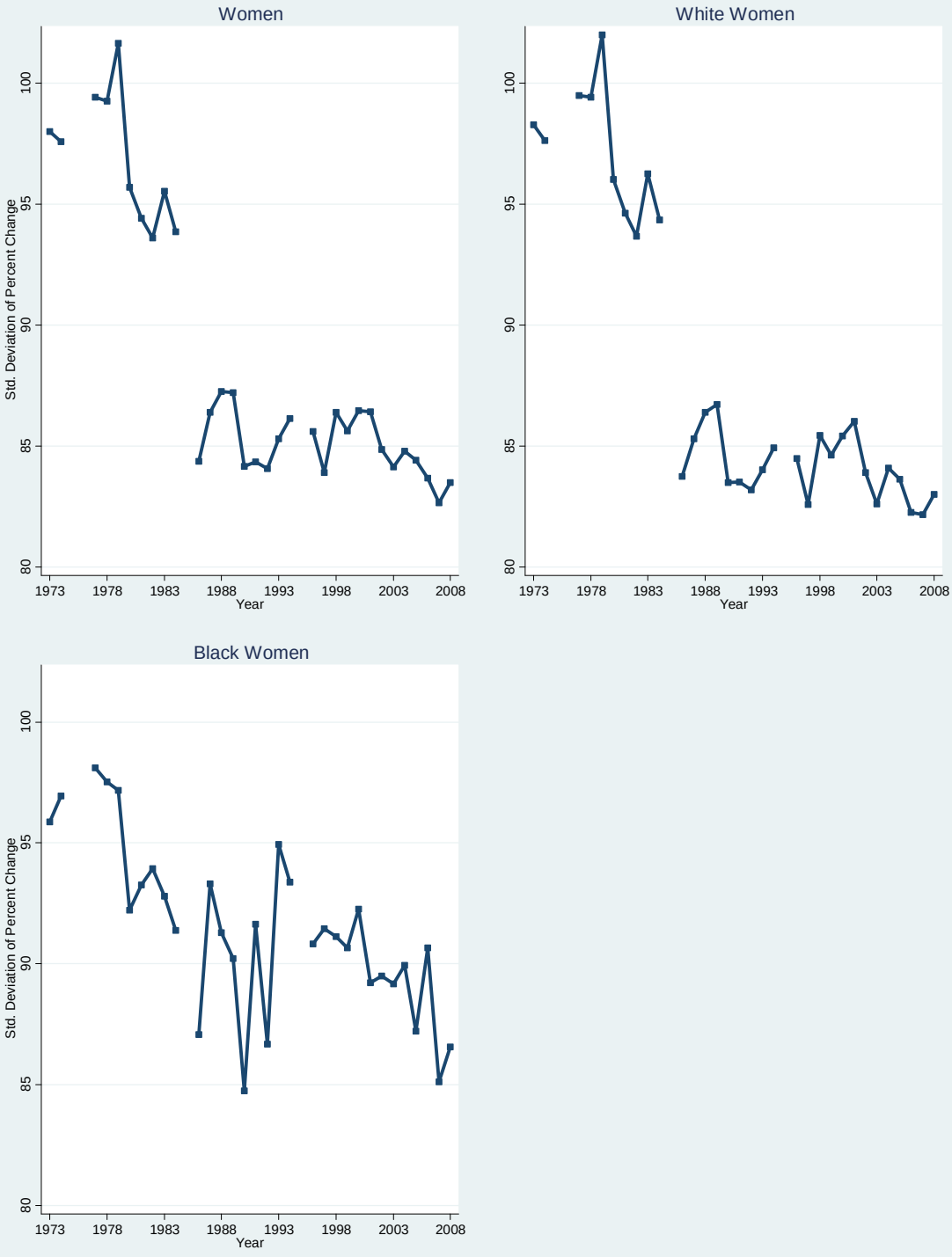


Figure 11. Individual Earnings Volatility

By Status in Families

Figure 12. Income Volatility By Source of Income

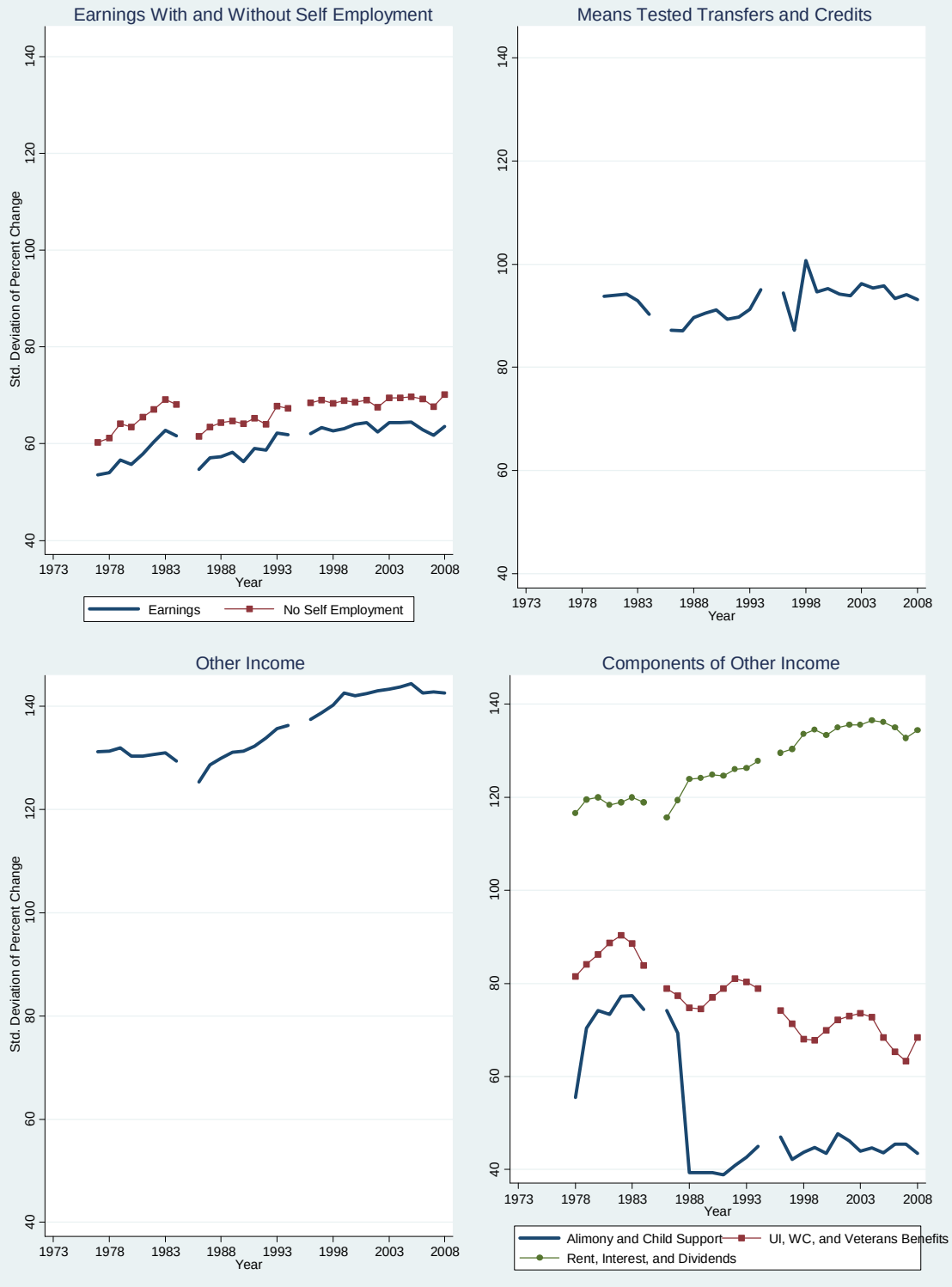
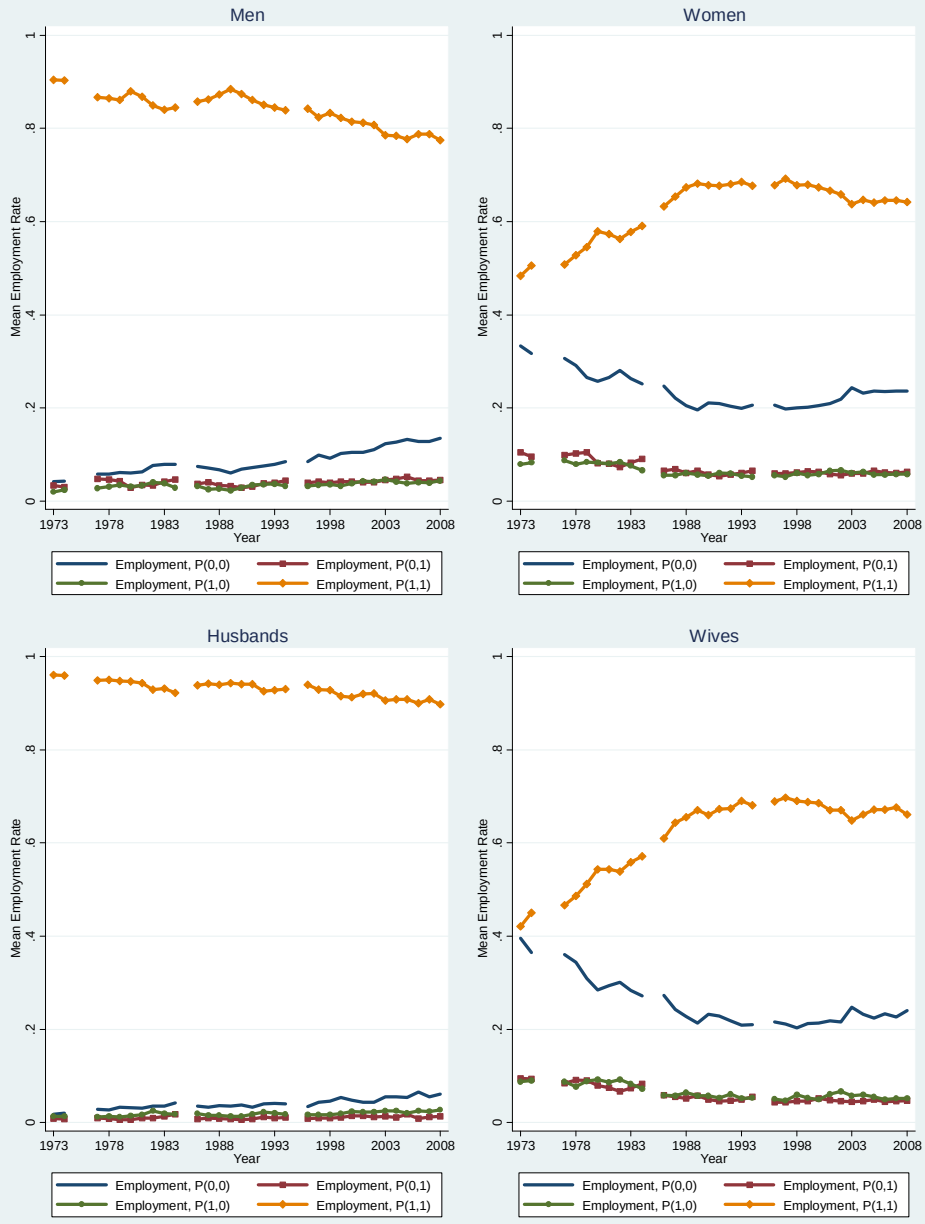
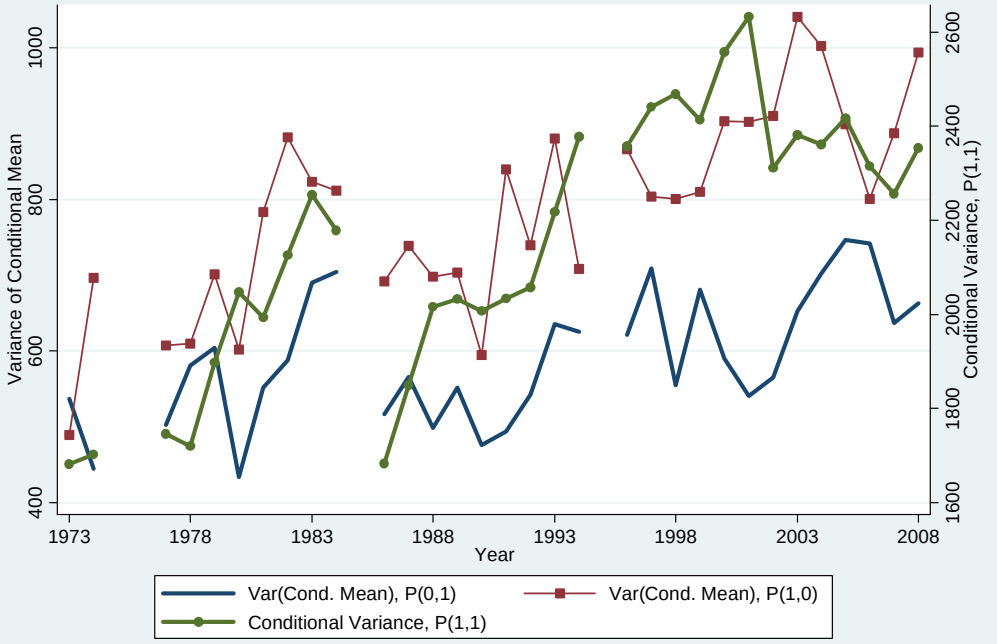


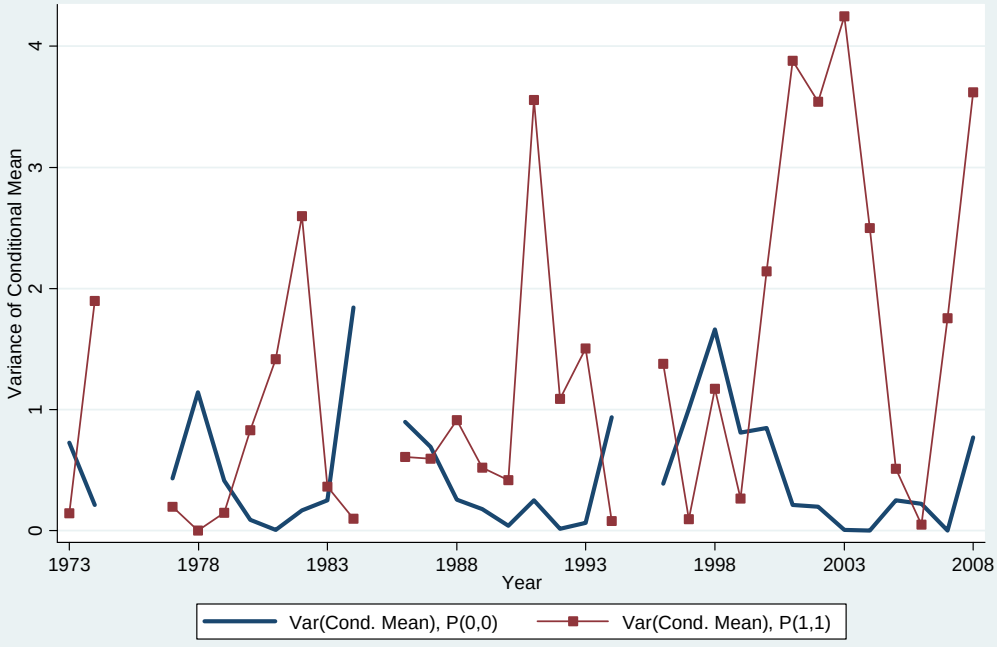
Figure 13. Mean Employment Rate by Entry and Exit Status



Note: Includes zeros

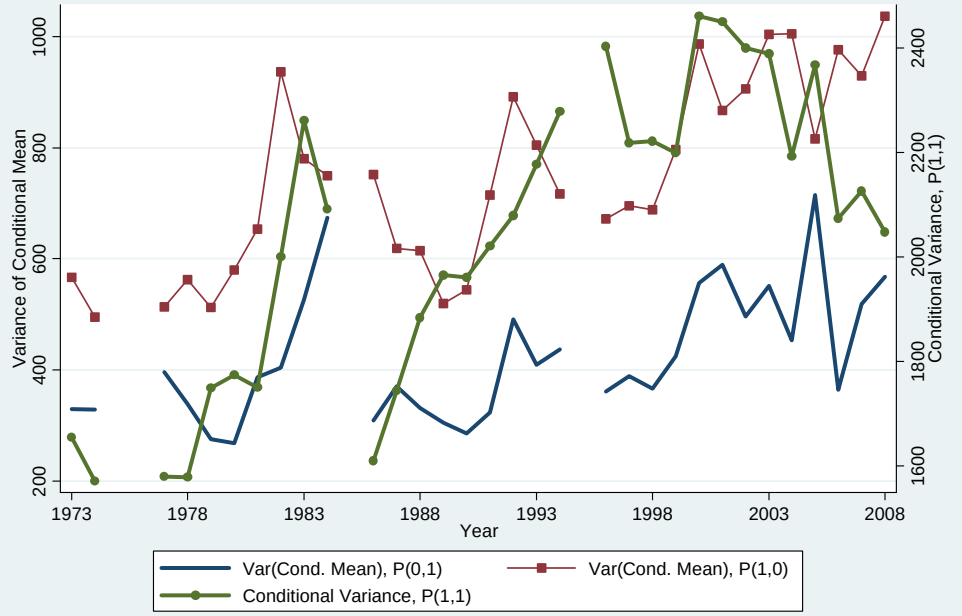
Figure 14. Variance Decomposition of Family Earnings

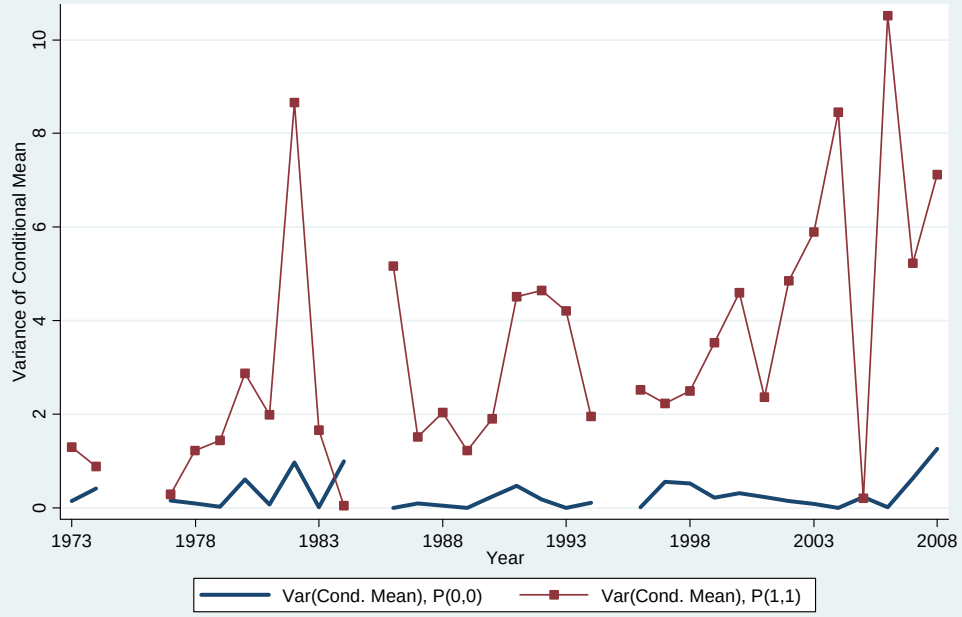




Note: Includes zeros

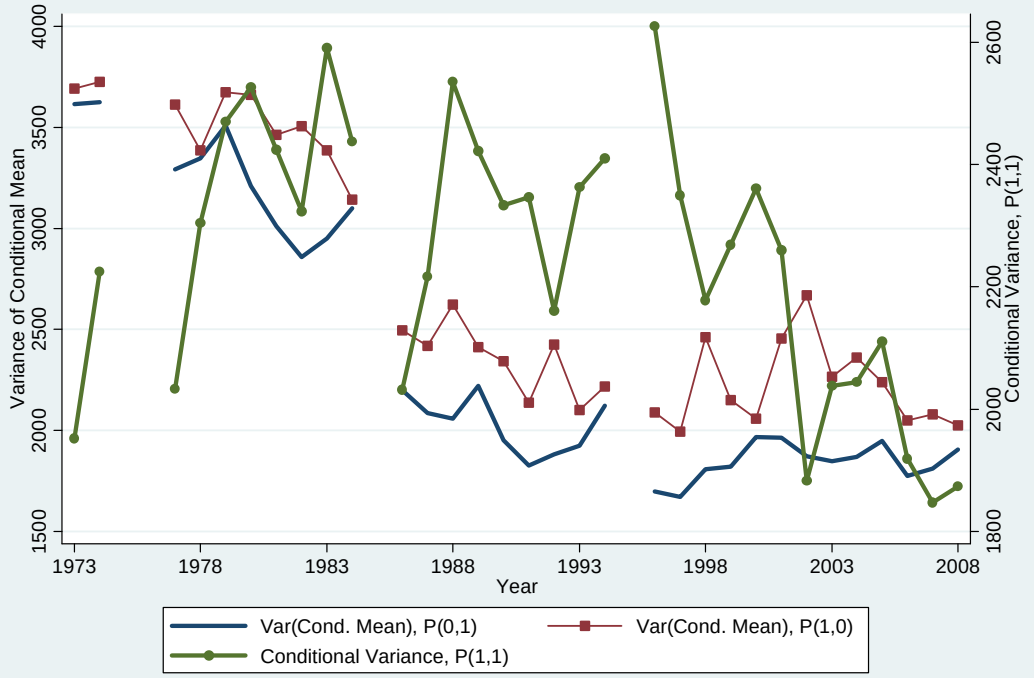
Figure 15. Variance Decomposition of Husband Earnings

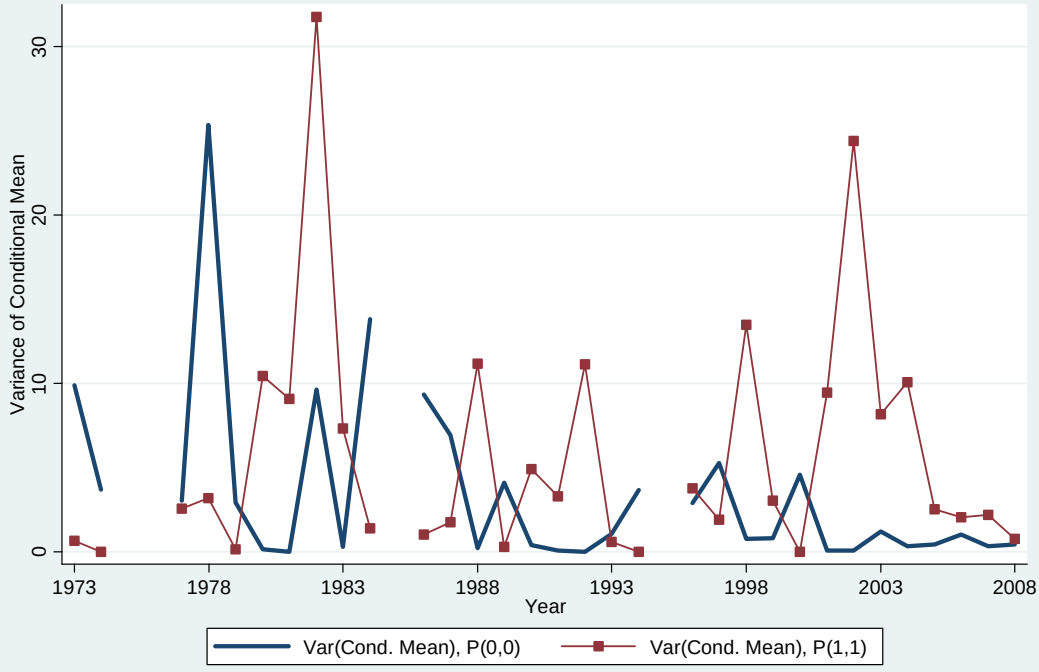




Note: Includes zeros

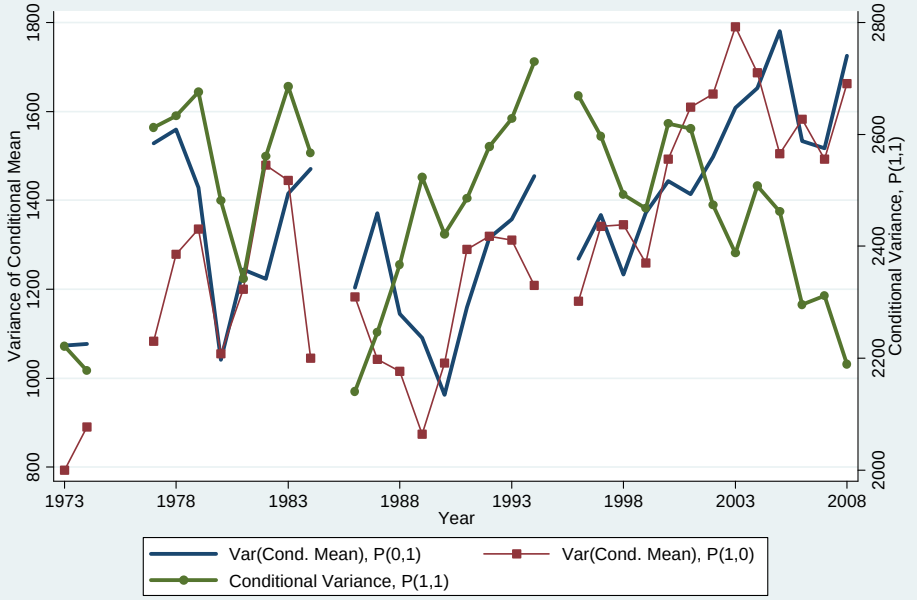
Figure 16. Variance Decomposition of Wife Earnings

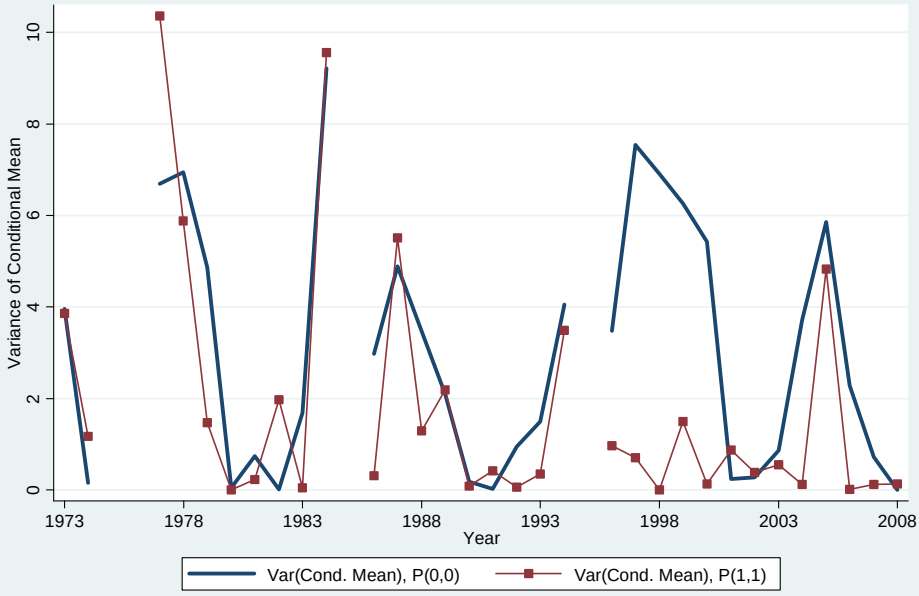




Note: Includes zeros

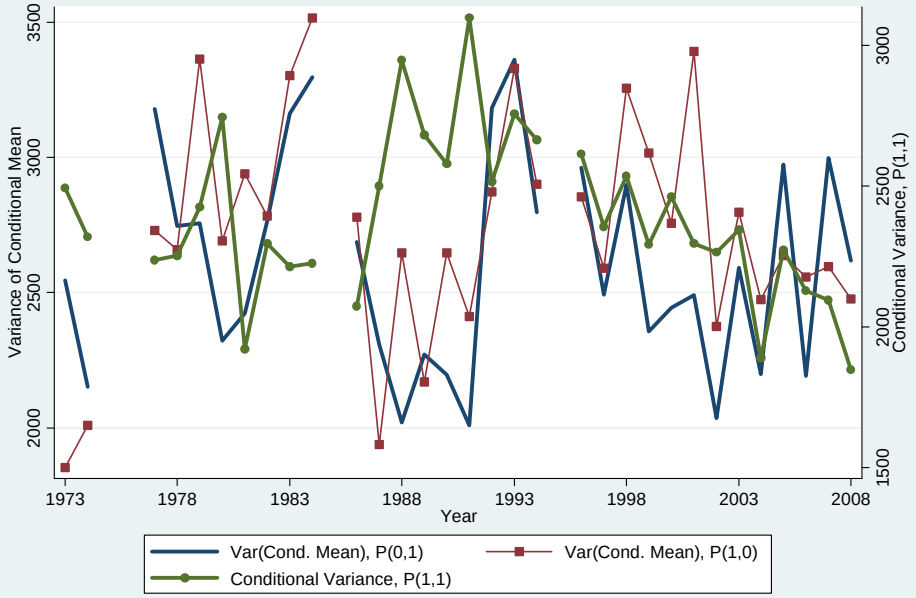
Figure 17. Variance Decomposition of White Male Earnings

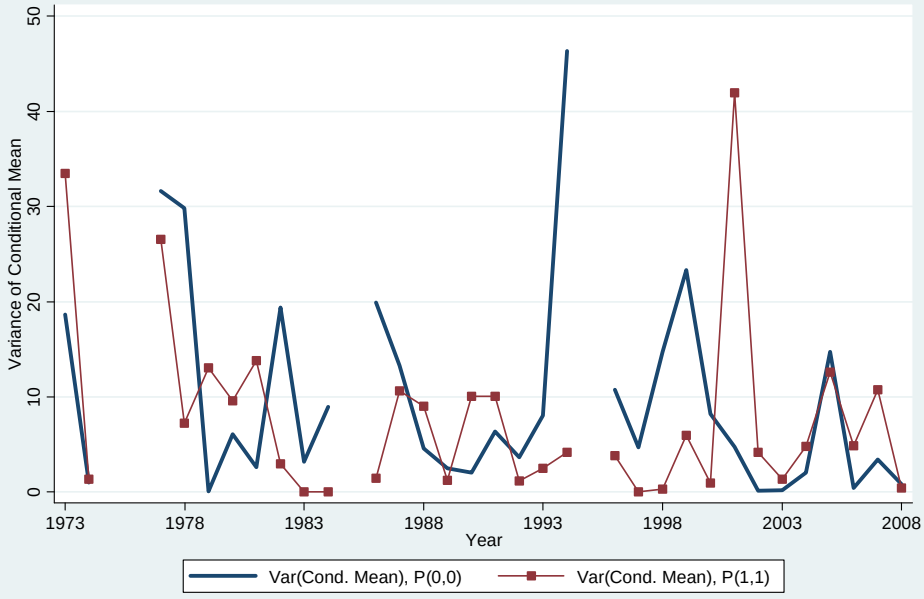




Note: Includes zeros

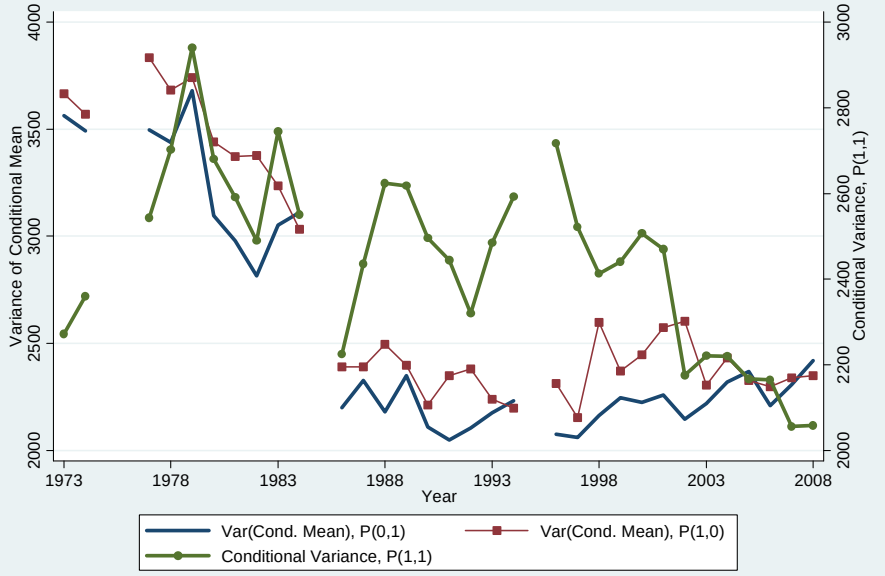
Figure 18. Variance Decomposition of Black Male Earnings

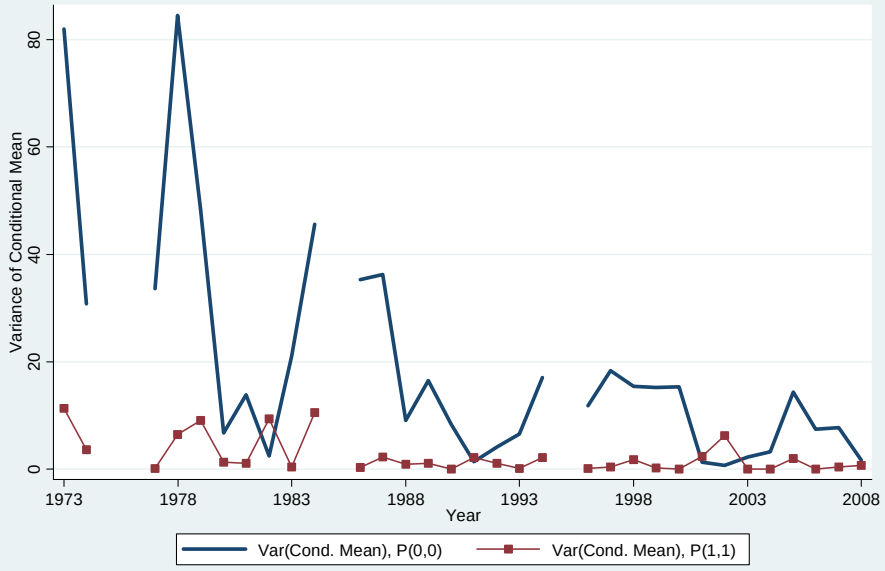




Note: Includes zeros

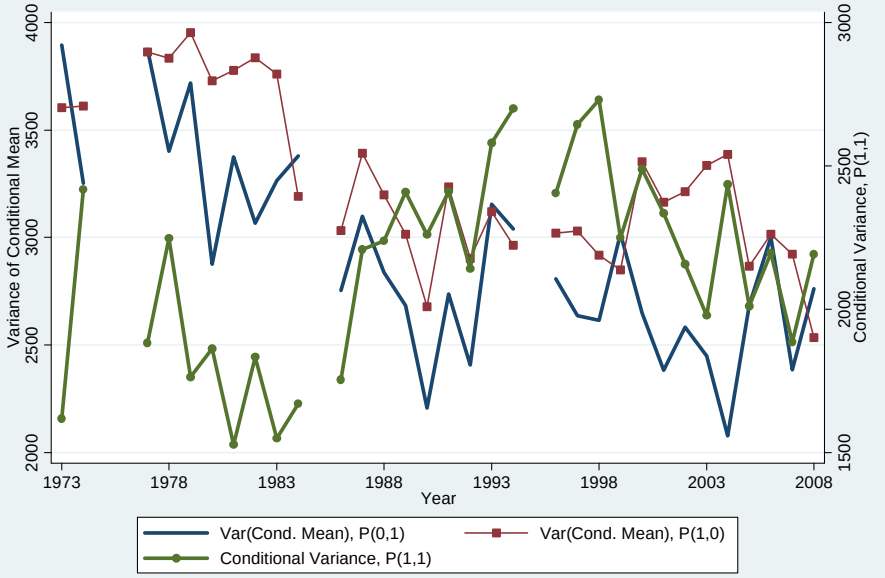
Figure 19. Variance Decomposition of White Female Earnings

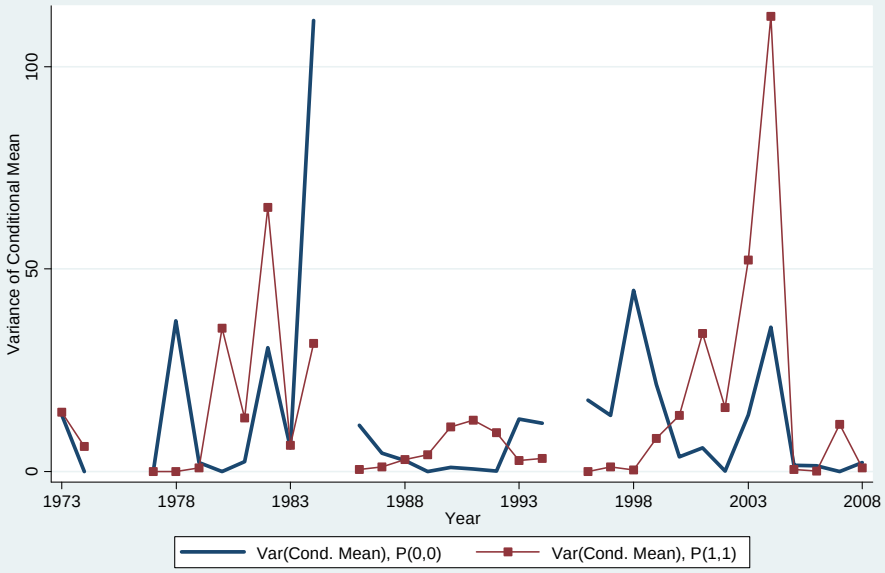




Note: Includes zeros

Figure 20. Variance Decomposition of Black Female Earnings





Note: Includes zeros

Table 1: Quandt-Andrews Tests of Structural Change in Earnings Volatility

Series	supWald Statistic	Break Year	CI-width (Years)	Sign of Trend Coefficient (pre-break, post-break)
Family Earnings	32.26***	1992	+/- 4	+/0
White Families	28.99***	2001	---	+/0
Black Families	20.37***	1992	+/- 4	+/-
Less than H.S.	21.74***	1996	+/- 5	+/0
H.S.	18.45**	1980	+/- 2	0/+
More than H.S.	22.97***	1993	+/- 4	+/+
Married Heads	24.61***	2001	+/- 8	+/0
Single Heads	11.31	1992	+/- 3	0/-
Female Heads	8.12	1990	+/- 4	0/-
Men	13.99*	2002	---	+/-
White Men	10.79	2003	---	+/0
Black Men	26.77***	1991	+/- 3	+/-
Women	34.78***	1979	+/- 1	+/-
White Women	28.23***	1979	+/- 1	+/-
Black Women	15.77*	1992	+/- 1	-/-
Husbands	26.75***	1981	+/- 1	0/+
Wives	8.11	2000	+/- 2	-/-
Not Husbands or Wives	19.93**	1979	+/- 2	+/0
Earnings without Self Employment Income	48.32***	1988	---	+/0

Note: The 0 in the last column indicates that the coefficient on the trend variable is statistically zero at least at the 10% level. For the Wald statistics *** = reject at the 1% level; ** = reject at the 5% level; *=reject at the 10% level. --- refers to a confidence interval that lies out of sample.

Table 2: Quandt-Andrews Tests of Structural Change in Earnings Volatility Controlling for Unemployment

Series	supWald Statistic	Break Year	CI-width (Years)	Sign of Trend Coefficient (pre-break, post-break)
Family Earnings	23.78***	1992	+/- 4	+/0
White Families	23.17***	2001	+/- 4	+/0
Black Families	21.54***	1997	---	+/-
Less than H.S.	25.48***	1996	+/- 2	+/0
H.S.	15.59*	1992	+/- 15	+/+
More than H.S.	17.93**	2000	+/- 4	+/0
Married Heads	22.20***	2001	+/- 3	+/0
Single Heads	12.40	1992	+/- 2	0/-
Female Heads	7.70	1986	+/- 2	0/-
Men	14.50	1979	+/- 1	+/+
White Men	18.58**	1979	+/- 1	+/+
Black Men	24.73***	1991	+/- 3	+/-
Women	25.02***	1979	+/- 1	+/-
White Women	20.18**	1979	+/- 1	0/-
Black Women	13.87	1992	+/- 2	0/-
Husbands	16.96*	1999	+/- 2	+/-
Wives	12.29	2000	+/- 4	0/-
Not Husbands or Wives	18.74**	1979	+/- 1	0/0
Earnings without Self Employment Income	37.45***	1989	---	+/0

Note: The 0 in the last column indicates that the coefficient on the trend variable is statistically zero at least at the 10% level. For the Wald statistics *** = reject at the 1% level; ** = reject at the 5% level; *=reject at the 10% level. --- refers to a confidence interval that lies out of sample.

Table 3: Quandt-Andrews Tests of Structural Change in Income Volatility

Series	supWald Statistic	Break Year	CI-width (Years)	Sign of Trend Coefficient (pre-break, post-break)
Family Income	17.77**	1999	+/- 5	+/0
White Families	16.69**	1999	+/- 3	+/0
Black Families	13.21	1979	+/- 2	0/+
Less than H.S. (family)	17.35**	2000	+/- 3	+/0
H.S.	12.43	2003	---	+/0
More than H.S.	12.48	1993	+/- 2	+/+
Married (family)	17.16**	1999	+/- 4	+/-
Single	8.11	1978	+/- 4	0/+
Female Head (family)	14.52*	1978	+/- 2	0/+
Household	15.51*	1981	+/- 2	0/+
Means Tested Income (1980-)	11.13	1997	+/- 2	0/-
Other Income (1977-)	21.78***	1986	+/- 1	-/+

Note: The 0 in the last column indicates that the coefficient on the trend variable is statistically zero at least at the 10% level. For the Wald statistics *** = reject at the 1% level; ** = reject at the 5% level; *=reject at the 10% level. --- refers to a confidence interval that lies out of sample.

Table 4: Quandt-Andrews Tests of Structural Change in Income Volatility Controlling for Unemployment

Series	supWald Statistic	Break Year	CI-width (Years)	Sign of Trend Coefficient (pre-break, post-break)
Family Income	16.79*	1999	+/- 4	+/0
White Families	17.31*	1999	+/- 3	+/0
Black Families	10.00	1979	+/- 3	0/+
Less than H.S. (family)	14.31	2000	+/- 3	+/0
H.S.	11.19	1999	+/- 8	+/0
More than H.S.	13.99	2001	+/- 6	+/0
Married (family)	22.85***	2001	+/- 3	+/0
Single	10.60	1979	---	0/+
Female Head (family)	21.21**	1979	+/- 7	0/+
Household	14.30	1981	+/- 1	0/+
Means Tested Income (1980-)	9.91	1997	+/- 2	0/-
Other Income (1977-)	17.16*	1986	+/- 1	0/+

Note: The 0 in the last column indicates that the coefficient on the trend variable is statistically zero at least at the 10% level. For the Wald statistics *** = reject at the 1% level; ** = reject at the 5% level; *=reject at the 10% level. --- refers to a confidence interval that lies out of sample.