2011

ESSAYS ON INCOME VOLATILITY AND INDIVIDUAL WELL-BEING

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ABSTRACT OF DISSERTATION

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The Graduate School

University of Kentucky

2011

ESSAYS ON INCOME VOLATILITY AND INDIVIDUAL WELL-BEING

ABSTRACT OF DISSERTATION

A dissertation submitted in partial fulfillment of the
Requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
at the University of Kentucky

By
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Lexington, Kentucky

Director: Dr. James P. Ziliak, Carol Martin Gatton Chair in Microeconomics
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My dissertation consists of three essays in which I document trends in earnings and income volatility, estimate potential causal mechanisms for changing volatility, and examine the long-term consequences of parental income volatility for children. In essay 2 I document trends in earnings and income volatility of individuals and families using matched data in the March Current Population survey from 1973 to 2009. Essay 3 advances the literature on volatility, using matched data from the CPS to identify demographic and labor market correlates of earnings volatility within education-birth year cohorts. This study collapses the cross-sectional CPS into a pseudo-panel and then estimates the association between earnings volatility and race, local economic activity, and industry, accounting for endogeneity and sample selection bias. In essay 4 I use data linked across generations in the Panel Study of Income Dynamics to estimate the relationship between exposure to volatile income during childhood and a set of socioeconomic outcomes in adulthood. The empirical framework is an augmented intergenerational income mobility model that includes controls for income volatility.

I find that family income volatility rose by 38 percent over the past four decades, likely driven both by rising volatility of earnings and non means-tested non-labor income. Rising family income volatility occurs across race, education, and family structure. From essay 3, I find that individuals with lower mean earnings have higher earnings volatility. Earnings volatility is also weakly related to race, decreases when young and then rises while workers are still within prime working years. Industry and local economic conditions are significantly related to the occurrence of earnings volatility after accounting for education, though these links differ between men and women. Finally, when examining the intergenerational consequences of volatility, a weak negative association occurs between family income instability during childhood and adult educational outcomes in essay 4.

KEYWORDS: Intergenerational Mobility; Volatility; Instability; Labor Force Non-Participation; Economic Risk.

Bradley L. Hardy

July 27, 2011

Date

THREE ESSAYS ON INCOME VOLATILITY AND INDIVIDUAL WELL-BEING

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For my parents, Leon and Nellie Hardy, and my grandfather, B.B. Hardy

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1 INTRODUCTION

Several economic studies have documented a rise in earnings and income volatility throughout the United States over the past 40 years. This phenomenon may or may not warrant concern in an economy with functioning credit markets and individuals consuming on permanent income. When volatility derives from uncharacteristically low earnings relative to the previous year, this implies consumption on accumulated savings or accessing loanable funds. Such volatility could have far reaching consequences for well-being among individuals and families unable to absorb these changes through traditional consumption smoothing channels. If volatility has negative consequences and occurs unequally across demographic groups, this introduces additional concerns regarding inequality and economic mobility. Because some volatility derives from income changes that are involuntary, such as the loss of employment, unanticipated health problems, or other events resulting in transitions into and out of the labor force, the occurrence of such unanticipated volatility is a concern for policymakers. The social safety net is designed to insure against such events by intervening for individuals and families with limited access to the consumption smoothing benefits of savings and credit markets. In other instances, volatility can result from voluntary decisions or positive growth in earnings and income over time, neither of which connote the same individual or family welfare concerns as unexpected volatility.

With these important implications for individual well-being and the social safety net in mind, this dissertation consists of three essays in which I document trends in earnings and income volatility, estimate potential causal mechanisms for changing volatility, and examine the long-term consequences of parental income volatility for children. The first essay of the dissertation, essay 2, examines historical trends in earnings and income volatility among families. These historical trends focus on family volatility trends occurring across race, education, and family structure type.   Essay 2 provides documentation of volatility trends across a variety of demographic characteristics and also shows how trends are sensitive to labor force transitions. Essay 3 then examines correlates of exposure to earnings volatility. Here, explanatory variables include race, earnings level, education, local economic performance, and industry classification. This essay estimates individual and local economic variables, along with industrial correlates of earnings volatility, adding to knowledge from essay 2 to understand where volatility is likely to occur within the population. Finally, essay 4 estimates an augmented intergenerational mobility model to examine the relationship between income volatility during childhood and adult outcomes.

2 FAMILY EARNINGS AND INCOME VOLATILITY IN AMERICA

2.1 Introduction

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 facilitates 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 evidence of a rise in instability then widening inequality is the likely outcome of lifetime changes in the distribution of earnings and income, which could have negative consequences for long-term economic mobility (Gottschalk and Moffitt 2009). 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 essay I offer new evidence on earnings and income volatility using data from matched Current Population Survey (CPS) files spanning 1973-2009, which makes the results more informative to the CPS-based inequality research.[1] The rotating structure

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[1] 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

of the CPS permits one to match approximately 50 percent of sample respondents in one March survey to the March survey the subsequent year. I then calculate volatility by extending the summary measure used in Dynan, et al. (2008) and Dahl, et al. (2008), described in the literature section, so it is 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. This captures the 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. The results can be generalized to the U.S. population because the larger sample sizes of the CPS allow me to estimate volatility trends with precision for detailed subgroups by race, and family structure.

Essay 2 calls attention to income and earnings volatility at the family level. By doing so, I establish a better understanding of the total earnings and incomes available to individuals; this is a helpful step towards determining if and how volatility affects the economic well-being of adults and dependent children within the family unit. Family earnings and income volatility trends account for labor market earnings but also include non-labor income and government transfers. By emphasizing both earnings and income, I obtain a more complete representation of the family's total resource volatility. Because a family's economic volatility can occur from a range of voluntary and involuntary events that may not be directly related to labor market or non-labor income instability, this essay cannot lend predictions of welfare consequences from volatile earnings or incomes. Instead, this essay identifies heterogeneity in family earnings and income

(1998) use matched CPS data to examine earnings instability of working men, focusing on the permanent/transitory distinctions found in Gottschalk and Moffitt (1994).

volatility trends across race, family structure, education, gender, and by income source that motivates additional inquiry into volatility's causes and consequences.

I 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 non-labor income. Rising family income volatility occurs across race, education, family structure, and the life cycle. 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, with the continued secular decline converging toward the levels of men. The variance decomposition of earnings volatility suggests that trends are driven by increases in the conditional variance of earnings of continuous workers and the variance of the conditional mean of those workers exiting the labor force.

2.2 Literature

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). The original motivation in this decomposition was to gain a deeper understanding of the observed increase in earnings variability throughout the 1970s and 1980s and to gain a better understanding of what factors drove this dispersion. The variance decompositions are illustrative because they permit identification of temporary deviations of earnings from long-term trends, as well as identification of structural changes in long-term trends. This characterization of earnings variance helps to fit a range of labor market events as possible causes of short term instability, including job loss, which might drive the transitory component and larger shifts in the economy that would show up as permanent volatility. To connect these and other measures employed throughout the dissertation, I describe the major volatility definitions from the literature. First, income y_{it} can be decomposed into a permanent component μ_i and a transitory component v_{it}:

(1) $y_{it} = \mu_i + v_{it}$.

Like total income or earnings, total volatility can be decomposed into its permanent and transitory components (Gottschalk and Moffitt 1994):

(2) $lny_{it} = \alpha_t \mu_i + \varphi_t \varepsilon_{it}$,

where μ_i is permanent earnings, ε_{it} is transitory earnings, and α_t and φ_t are time-varying factor loadings on the permanent and transitory components, respectively. Assuming that the factor loadings are equal to 1 in all periods, and that the permanent and transitory components are independent, then the variance of log earnings in (2) is simply

(3) $Var(lny_{it}) = \sigma_\mu^2 + \sigma_\varepsilon^2$.

This decomposition in (3) prevails in discussions of how the cross-sectional distribution of earnings has been affected by permanent and transitory volatility in recent decades. One reason for the dominance of this approach is the intuition by which permanent and transitory volatility might occur among individuals and within the population. Transitory volatility, deviations from some individual-specific mean, could represent temporary increases in economic hardship or risk, but could equally result from positive events including bonus or incentive pay. Permanent volatility, measured as the variance of earnings (or incomes) between individuals, could be more indicative of larger shifts throughout society and the economy. Changes in permanent volatility could indicate larger shifts in the degree of mobility within and across generations, a topic taken up in more detail within essay 4. A leading, though somewhat controversial explanation for permanent volatility is skill biased technological change (Autor, Kearney, and Katz 2008), whereby changes in the functioning of the economy put a higher premium on skilled labor, with this premium being reflected by greater income and earnings inequality throughout society (Gottschalk and Moffitt 2009). Dynan et al. (2008) posit that part of volatility originates from involuntary job loss and wage cuts, as well as a voluntary component. Forecasting the risks related to earnings instability requires determining if the observed instability was voluntary or involuntary, anticipated or unanticipated, and whether or not individuals have access to public or private insurance mechanisms to absorb such instability (Shin and Solon 2010).

Historical trends in volatility suggest many adults in the PSID experienced high levels of family income volatility as a child. Gottschalk and Moffitt (1994) find that transitory earnings volatility was approximately 1/3rd of the overall volatility observed, and that this trend increased throughout the 1970's and 1980's. Additional evidence generally confirms the rise in volatility that Gottschalk and Moffitt (1994) describe during the 1970's and 1980's, with a flattening out in the 2000's. Alternatives to Gottschalk and Moffitt's (1994) log earnings decompositions are proposed for the measurement of volatility.

Dahl et al. (2008) analyze prime-age earnings using Social Security administrative earnings records matched to longitudinal data in the Survey of Income and Program Participation. Looking at year to year changes in earnings and income, using the percent change to measure volatility, they conclude earnings volatility is cyclical, though the trend is flat since the mid 1980's. Dynan et al. (2008) use a similar approach to Dahl et al. (2008), and are a bridge between Gottschalk and Moffitt (1994) and Dahl et al. (2008). Their relatively transparent measure of total volatility - the standard deviation of the arc percent change, admits person-years with zero earnings and/or incomes:

(4) $$Total\ Volatility = \sqrt{Var\left\{100 * \frac{y_{it}-y_{it-2}}{Y_{average}}\right\}},$$

where $Y_{average} = (Y_t+Y_{t-2})/2$.

Like Gottschalk and Moffitt (1994), they examine a PSID sample. From 1967-2004, they estimate that household earnings and transfer payments are more volatile and conclude income volatility rose 40 percent. This rise in volatility is concentrated at the lower end of the household income distribution. A key advantage of this approach is that it is relatively transparent when compared to the volatility decomposition described in equations (1) – (3). While a shortcoming of this approach is that persistent changes in overall volatility are not estimated, the total volatility measure relies on fewer distributional assumptions, particularly that the components are both additive and independent. This assumption is especially rigid, and it is plausible to envision transitory and permanent volatility components being related. As a result, by capturing both components, the total measure is relatively transparent and flexible when compared to Gottschalk and Moffitt (1994).

Another approach, one closer to the total measure I adopt, is to take first differences over equation (2) and then compute variances so that

(5) $$Var(lny_{it} - lny_{it-1}) = (\alpha_t - \alpha_{t-1})^2\sigma_\mu^2 + \varphi_t^2\sigma_\varepsilon^2(t) + \varphi_{t-1}^2\sigma_\varepsilon^2(t-1),$$

a measure of total or summary volatility adopted by Shin and Solon (2010). The time-difference in log earnings in the left hand side of (5) is approximately the percent change in earnings levels, an approach similar to the summary volatility measure introduced in equation (4). The important distinction is that in (4) the arc percent change is computed, while in (5) Shin and Solon (2010) measure the point percent change. If the denominator in (4) is not too different from the initial earnings level (y_{it-1}), then the expressions in (4) and (5) are roughly equal. This demonstrates the summary nature of (4), which captures changes to permanent variances via changes in the permanent factor loadings as well as changes in transitory variances from either transitory factor loadings or shocks (Shin and Solon 2010).

Most papers in the volatility literature are based on samples of prime-age white men, and Keys (2008) verifies that findings of rising volatility over the past 30 years generalize across race, gender, education, and family structure. He finds that the least skilled, the young, and racial and ethnic minorities have relatively high transitory volatility. 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, though there is considerable disagreement on the magnitude. Regarding the components of volatility, a common result was that transitory earnings instability rose by over 40 percent 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). The estimates on increases in volatility range from a doubling (Hacker and Jacobs 2008) to a low of 10 percent (Winship 2009). 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. Because much of the literature reports the variance of log earnings, person-years with zero earnings are dropped, which can understate measured volatility because labor-force dropouts are ignored.

2.3 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. The rotating design of the CPS makes it possible to match approximately one-half of the sample from one March interview to the next. 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. I therefore do not match across the 1975-1976 survey years, and it is not possible to match across the 1976-1977 years because of changes in the format of matching variables. Thus, I produce an interrupted time series across 36 years with gaps in calendar years 1974-1975, 1975-1976, 1984-1985, and 1994-1995. In total there are 640,412 matches, or roughly 20,000 observations in an average year when a match is possible. Table 2.3 lists the number of correct matches across survey years.

The primary variables of interest are total family labor-market earnings and before-tax family income. I test the robustness of the volatility trends to after-tax income in figure 2.1. Family earnings is defined as the sum of wage and salary income, non-farm self-employment, and farm self-employment among family householders. Before-tax income is the same as that used in official Census estimates of poverty and inequality and includes earnings, social insurance payments, means-tested transfers, and other forms of non-transfer non-labor income of all members within the family household. Because the CPS surveys home addresses and does not follow families as in the PSID, adults are counted as family members if they are related and living within the same household.

2.3.1 Matching Procedure

The process of using matched CPS is adopted by at least two other studies (Cameron and Tracy 1998; Celik, Juhn, McCue, and Thompson 2009). The basic ideas is as follows: The CPS surveys respondents within U.S. household locations, and the rotating design of the survey creates a schedule whereby respondents are in the sample for four months, out for eight months, and then they re-enter the sample for four months. This results in a large share of respondents, almost one-half, being observed in two consecutive March CPS surveys. To ensure I observe the same individuals over time, I utilize a matching procedure recommended by the Census Bureau that matches individuals along five variables. These are month in sample (months 1-4 for year 1, months 5-8 for year 2); gender; line number (unique person id); household identifier; and household number. I also restrict the sample by dropping individuals if their self-identified race or age changes by more than two years, or if state of residence changes.

Prior to matching the CPS cross sections, I address two issues with the data. First, if a respondent is missing information on earnings or nonlabor income, then the Census Bureau uses a "hotdeck" imputation method that allocates income to those with such missing data. Bollinger and Hirsch (2006) show that an attenuation bias oftentimes occurs when allocated CPS data is used, which can then lead to a related attenuation bias on estimated regression coefficients based on this imputed data. Per the recommendation of Bollinger and Hirsch (2006), I drop observations with allocated earnings or income prior to matching. A second issue concerns inconsistent topcoding procedures from the Census (Burkhauser, et al. 2004; 2007; Larrimore, et al. 2008), which have raised concerns about the accuracy of reported trends in income inequality due to changes over time in the methods the Census uses to top-code 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). A fix to this inconsistency comes from Larrimore, et al. (2008), who back-cast the post-1995 procedure using demographic means from internal CPS data to 1976 and thus provide a consistent method of top-coding from 1976 onwards. I incorporate this series of consistent topcodes into the data prior to matching across years. 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, and in 1977 there were changes in the format of matching variables. This yields an interrupted time series across 36 years with gaps in *calendar* years 1974-1975, 1975-1976, 1984-1985, and 1994-1995. As indicated in table 2.3, the resulting data set contains roughly 20,000 observations in an average year when a match is possible. It also summarizes the number and rate of matches for each year, indicating I am able to match approximately 52 percent across survey years on average. The declining match rate after the mid 1990s reflects in part a rise in allocation within the CPS after adoption of CATI-CAPI computer-assisted interviewing techniques.

Comparing summary statistics before (table 2.2) and after (table 2.1) the match procedure, the final data set appears to suffer from some attrition. Prior to matching, the sample respondents have lower earnings and income. Smaller differences emerge when comparing demographic characteristics before and after the procedure. The respondents are slightly younger, less educated, more likely to be female, more racially and ethnically diverse, and less likely to be married prior to matching. The observed impact of matching CPS observations on earnings, income, and demographic characteristics may also be borne out in the final volatility levels and trends.

2.4 Model

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

$$(6) \qquad volatility = \sqrt{Var\left\{100 * \frac{y_{it}-y_{it-1}}{\bar{y}_i}\right\}},$$

where y_{it} is earnings or income for person *i* in time *t*. Dynan, et al. (2008) 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. However, the symmetry property is violated if earnings are negative one year, say due to a business loss, and positive the next. I 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. In addition, there is a rising share of the male population out of the labor force two years in a row, and after declining through the mid 1990s it has been rising among women as well. By definition earnings volatility of these individuals is zero, but because I am interested in a population measure of volatility I retain these individuals and set earnings volatility to zero in the baseline series. This is a measure of total volatility, in contrast to the variance decomposition of total volatility into its transitory and permanent components put forth by Gottschalk and Moffitt (1994; 2009). Similar measures are adopted when the primary goal is to measure volatility trends, as I do in this essay (Dynan et al. 2008; Dahl et al. 2008).

2.5 Results - Earnings and Income Volatility Levels and Trends

Figure 2.1 depicts trends in year-to-year family earnings and income volatility. 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. 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. From 1973-2008 family income volatility rose 38 percent.

The series in the first panel of Figure 2.1 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 I 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, I 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.

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 the third panel of Figure 2.1 I reproduce the base-case results excluding families reporting negative or no earnings (or income) in any year to examine the influence of zeros and negative values. It is readily apparent that including non-positive values shifts up the level of volatility in any given year by about 10 percentage points, but the basic trends 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 earnings/income 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). The 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 I 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. In panel 4 I assume that the family bears only the employee share of the payroll tax rate. The fourth panel of Figure 2.1 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 1980-2009 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.

2.6 Volatility across Race, Family Structure, and Education

In this section I examine trends in family earnings and income volatility across families based on race, family structure, and education of the family head. Figure 2.2 depicts 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 2.1 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.

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 2.3 I 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 2.3 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. 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. 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, dampening the effects of volatility. In the last panel of Figure 2.3 I compare family to household income volatility. Cohabitors and other non-family members dampen 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.

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). This suggests 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. Figure 2.4 depicts 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, 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).

2.7 Earnings and Income Volatility by Source

The analysis to this point has focused on the family as an aggregate unit, and thus in this section I want to look within families to examine the volatility of earnings, as well as the volatility of income by component source. I first document trends in earnings volatility overall for men and women in the first two panels of Figure 2.5. From 1973 to

2008 earnings volatility of men increased about 14 percent overall. In unpublished results, men's earnings volatility included a 16 percent increase for white men and no increase for black men, with much of the increase occurring in the 1970s and early 1980s. For women, volatility has fallen about 15 percent overall in the last four decades. Most of the decline occurred by the mid 1980s and has continued into the 2000s. If the volatility trends of men and women continue the levels are likely to converge in the current decade, and this convergence has already taken place between black men and women (not depicted here).

In the last two panels of Figure 2.5 I document earnings volatility for husbands and wives. Viewed with the decline in female-headed earnings volatility and constant volatility for unmarried family heads in general (Figure 2.3), panels three and four suggest that the overall increase in family earnings volatility is being driven primarily by volatility of husbands earnings. In support of this, the covariance between earnings volatility of husbands and wives over the sample period is -22.73. The volatility trends of husbands and wives in the last four decades mimics the trends of men and women in general.

I return to total income volatility in Figure 2.6 to examine the rise in volatility by income source. Because of the secular growth in self-employment in the U.S. in recent decades, I examine the role of self-employment in earnings volatility in the first panel of Figure 2.6. 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 figure 2.7 means-tested income volatility did increase by 15 percent for single mother families. On the other hand, as panels three and four of figure 2.6 demonstrate, there is a strong upward trend in non-welfare non-labor income since the mid 1980s, which is being driven by higher volatility of income from rent payments, interest, and dividends.

2.8 Decomposing the Volatility of Earnings

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 I 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 2.8 I 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.

2.9 Understanding the Importance of Labor Force Transitions

To see the possible interaction between the extensive and intensive margins on the unconditional volatility of earnings note the variance can be written as

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

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 (7), 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 (7) can be expressed as

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

However, the volatility of nonworkers is zero, and thus the first term of (8) is zero. Also, because the arc percent change from equation (6) 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 (8) is the fourth term, which is the volatility of two-period workers weighted by the probability of working both periods.

Likewise, the variance of the conditional mean in equation (7) can be expressed as follows:

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

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 (7) is a function of five terms—the weighted conditional variance in equation (8) plus the four weighted variances of the conditional mean in two-period non-workers, the two transition states, and two-period workers from (9).

In Figures 2.9-2.15 I show 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, respectively. The top panel of each figure depicts the conditional variance of two-period workers from equation (8) on the right axis and the left axis presents 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 I restrict attention to the top panels. At the family level in Figure 2.9 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 2.10. In Figure 2.11 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 2.12, 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 2.13, and white and black women in Figures 2.14 and 2.15, 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.

2.10 Conclusion and Future Work

I find 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 husbands 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. Given the attrition initially observed between tables 2.1 and 2.2, volatility trends and levels based on matched CPS data may suffer from a slight downward bias as well.

My 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.

Future research should examine in more detail life cycle patterns of volatility, which I do in essay 3. Another important extension involves a full variance decomposition of family income, to gain an even better understanding of what drives the overall income volatility rise. 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 research on the effects of volatility on family and child well-being. To that end, essay 3 also identifies demographic, economic, and industry correlates of earnings volatility, while essay 4 is an inquiry into family volatility during childhood and its relationship to adult outcomes.

Table 2.1 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

Table 2.2 Summary Statistics Prior to Merging CPS Cross Sections (2008 Dollars)

Variables	Mean	Standard Deviation
Earnings and Income		
Family Earnings ($)	57,417.33	51,899.71
Family Income ($)	63,473.16	54,293.74
Disposable Income ($)	48,674.96	34,814.52
Self Employment Income ($)	3,276.26	17,282.31
Demographics		
Age	35.48	12.41
% Female	52.73	49.92
No. of Persons in Family	3.25	1.55
% Less Than High School	24.86	42.87
% High School	34.66	47.38
% More Than High School	40.47	48.30
% White	84.82	35.68
% Black	10.30	30.36
% Other	4.88	20.81
% Married	58.44	49.13

Table 2.3 Number and Rate of Merges Per Year by 2nd Year of CPS Panel. CY 1973-2008.

Year	# Merged CPS Observations	Total # CPS Observations	Merge Rate
1973	10,116	20,863	48.5%
1974	14,618	19,612	74.5%
1975	-	-	-
1976	-	-	-
1977	26,063	36,299	71.8%
1978	23,661	33,707	70.2%
1979	21,800	38,320	56.9%
1980	23,421	38,970	60.1%
1981	21,404	36,635	58.4%
1982	23,379	37,547	62.3%
1983	23,303	36,942	63.1%
1984	21,313	36,232	58.8%
1985	-	-	-
1986	19,129	35,778	53.5%
1987	21,114	41,573	50.8%
1988	22,436	38,616	58.1%
1989	22,810	41,776	54.6%
1990	24,330	42,342	57.5%
1991	24,131	41,784	57.8%
1992	23,792	40,847	58.2%
1993	22,580	41,316	54.7%
1994	19,883	37,931	52.4%
1995	-	-	-
1996	18,462	32,466	56.9%
1997	18,140	31,812	57.0%
1998	16,976	30,761	55.2%
1999	16,223	34,942	46.4%
2000	15,449	49,155	31.4%
2001	18,538	49,586	37.4%
2002	18,161	49,650	36.6%
2003	19,085	49,243	38.8%
2004	16,260	48,466	33.5%
2005	17,470	48,572	36.0%
2006	18,431	48,611	37.9%
2007	18,873	48,640	38.8%
2008	19,061	49,679	38.4%
Average Number of Matches	20,013	Average % Matched	52.1%

FIGURE 2.1

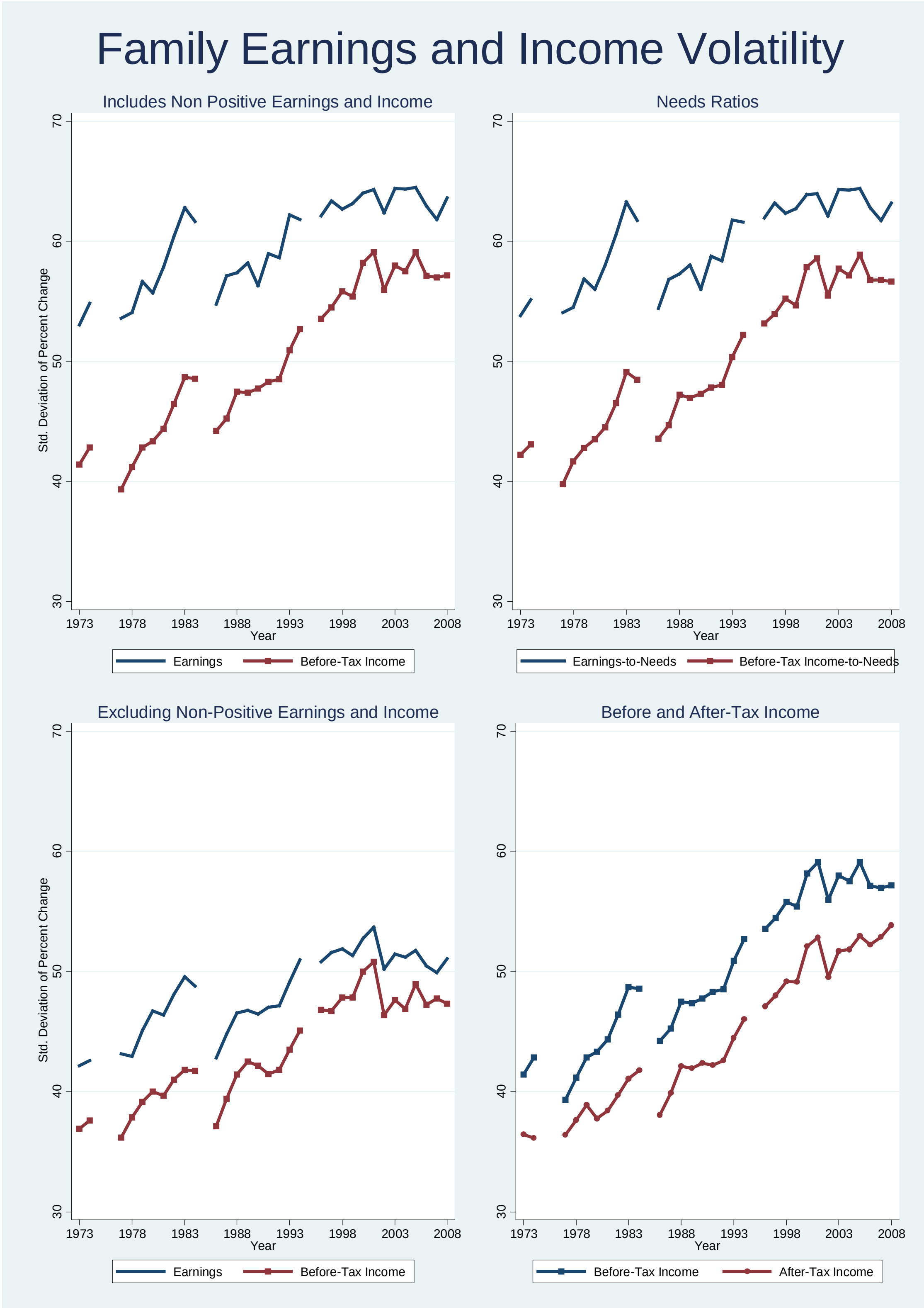
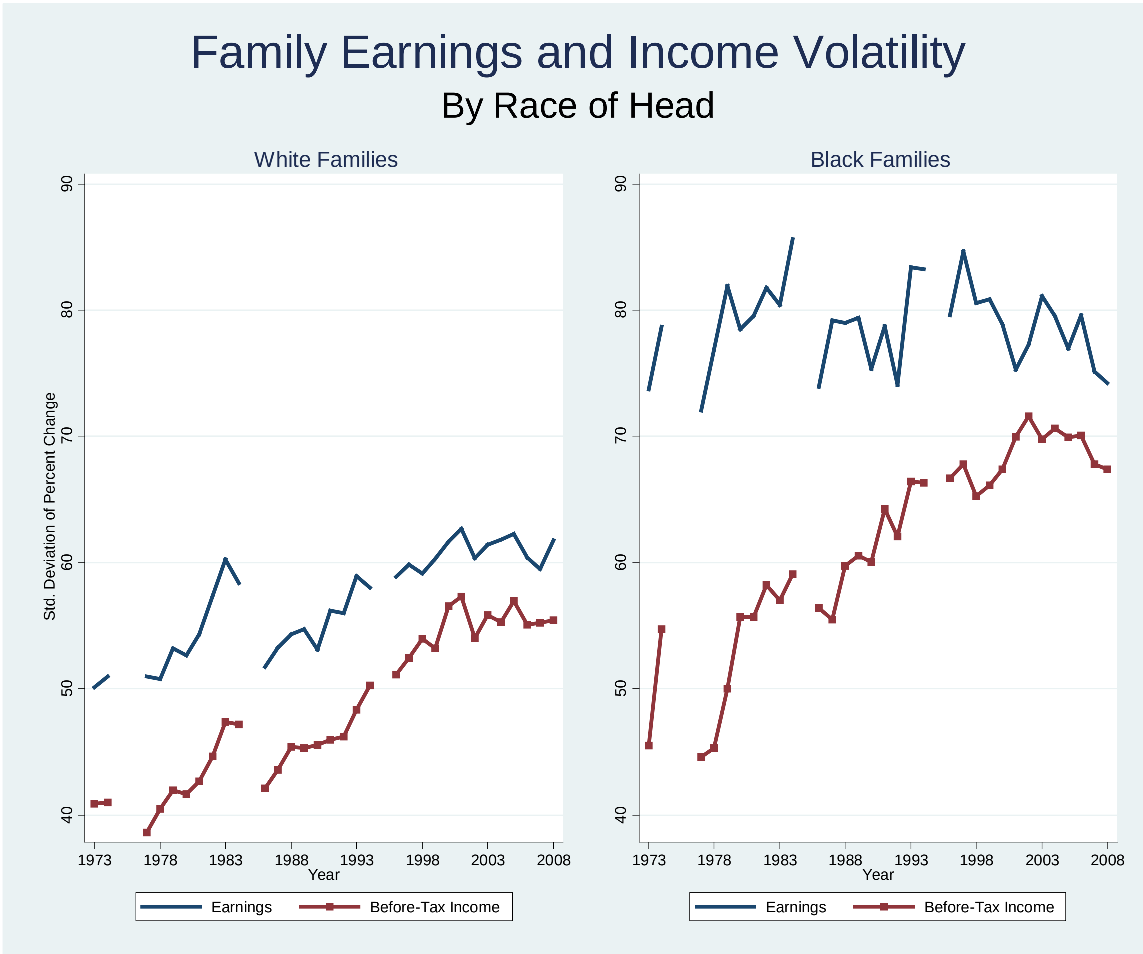
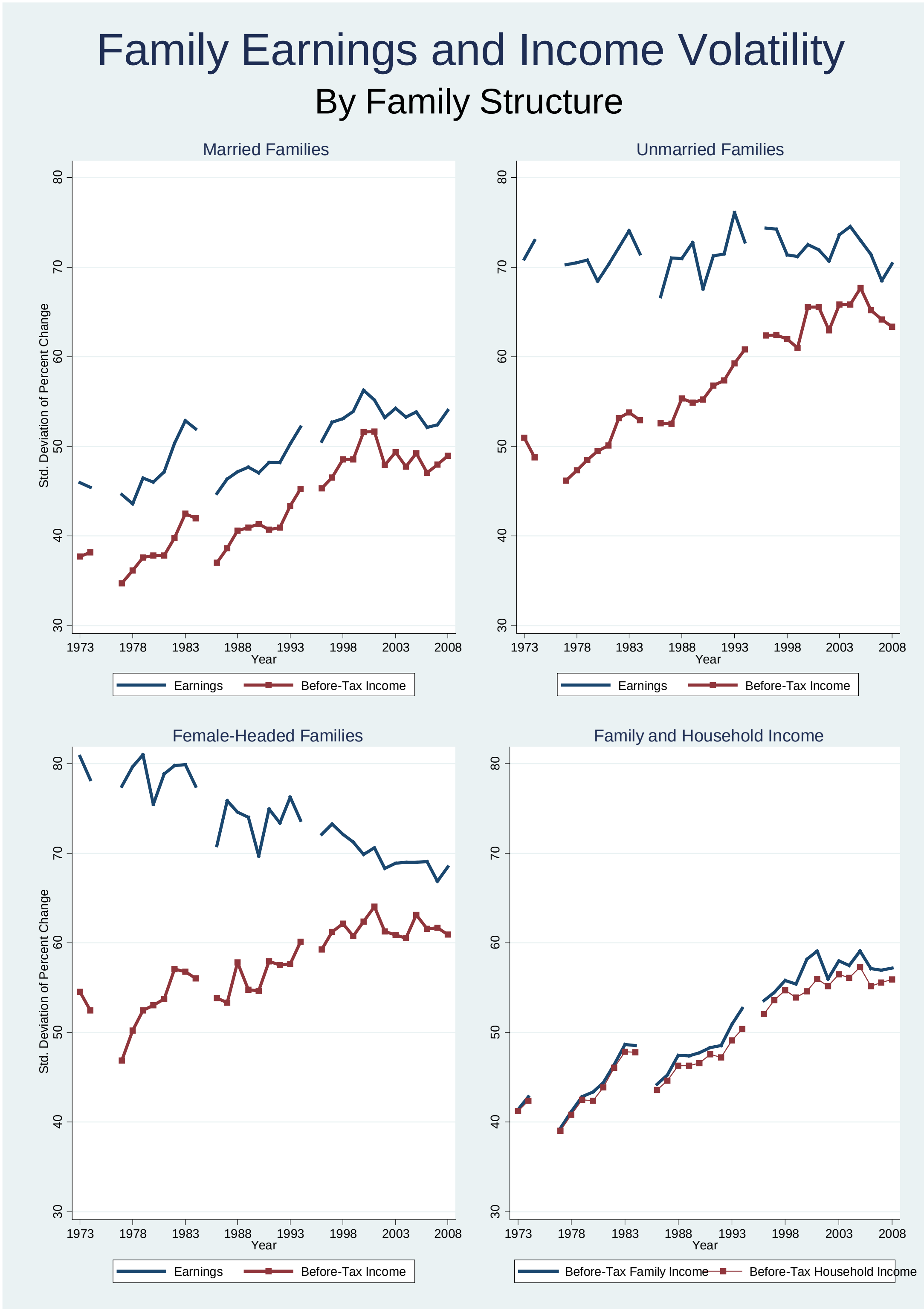

Family Earnings and Income Volatility
Includes Non Positive Earnings and Income
Needs Ratios
Excluding Non-Positive Earnings and Income
Before and After-Tax Income
Std. Deviation of Percent Change
Year
30
40
50
60
70
1973
1978
1983
1988
1993
1998
2003
2008
Earnings
Before-Tax Income
Earnings-to-Needs
Before-Tax Income-to-Needs
After-Tax Income

FIGURE 2.2



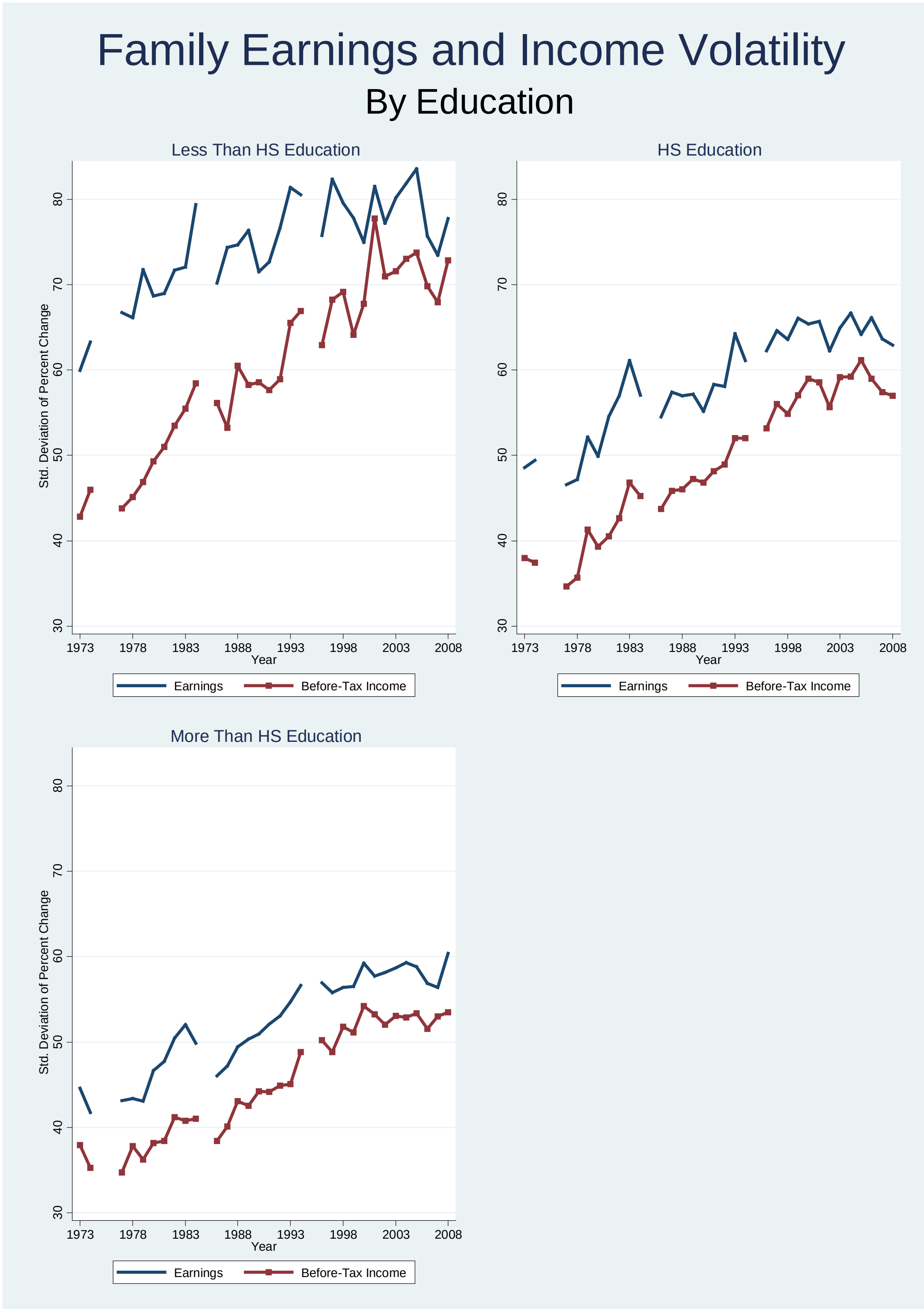
Family Earnings and Income Volatility
By Race of Head
White Families
Black Families
Std. Deviation of Percent Change
40
50
60
70
80
90
1973
1978
1983
1988
1993
1998
2003
2008
Year
Earnings
Before-Tax Income

FIGURE 2.3



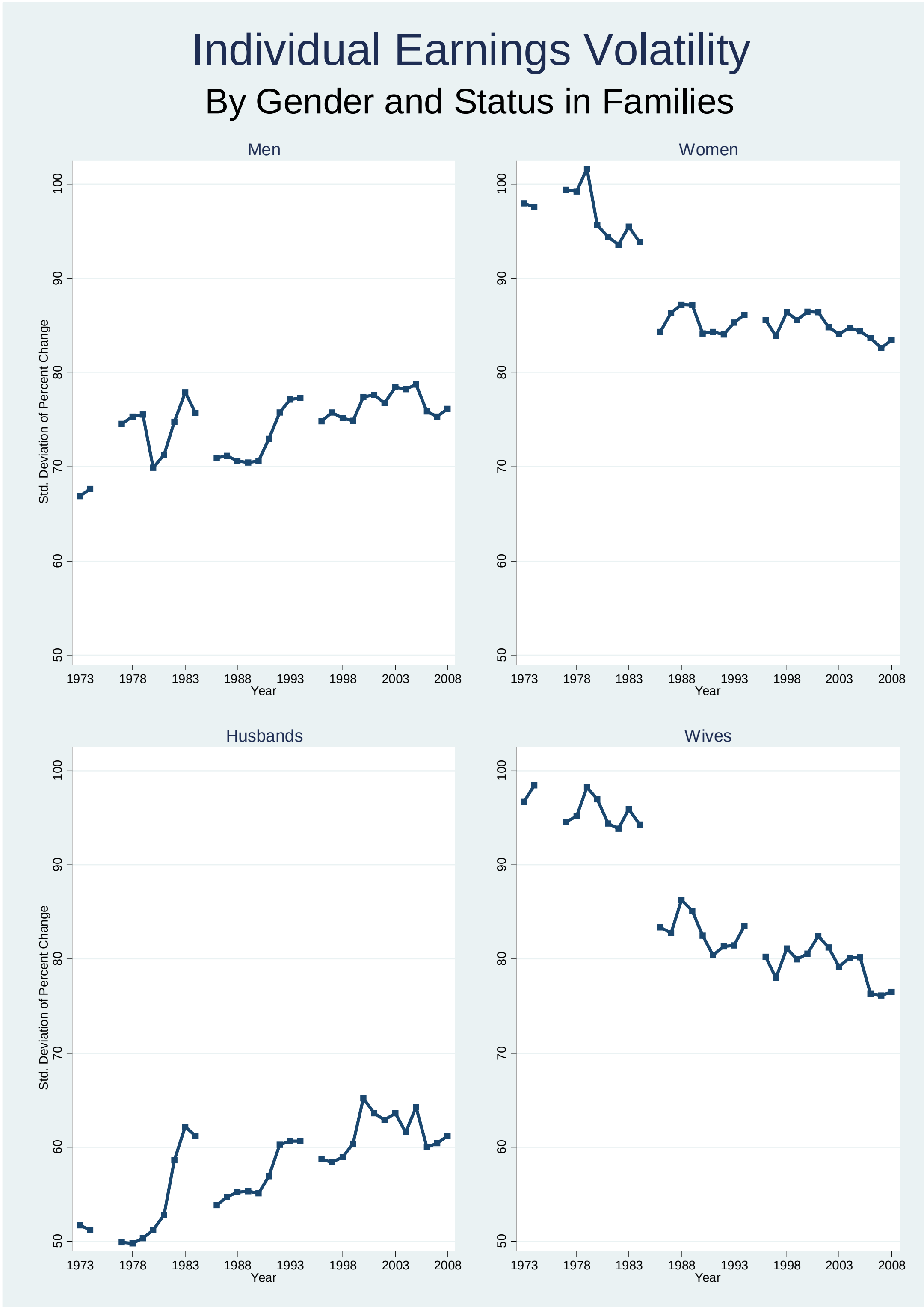
Family Earnings and Income Volatility
By Family Structure
Married Families
Unmarried Families
Female-Headed Families
Family and Household Income
Std. Deviation of Percent Change
30
40
50
60
70
80
1973
1978
1983
1988
1993
1998
2003
2008
Year
Earnings
Before-Tax Income
Before-Tax Family Income
Before-Tax Household Income

FIGURE 2.4



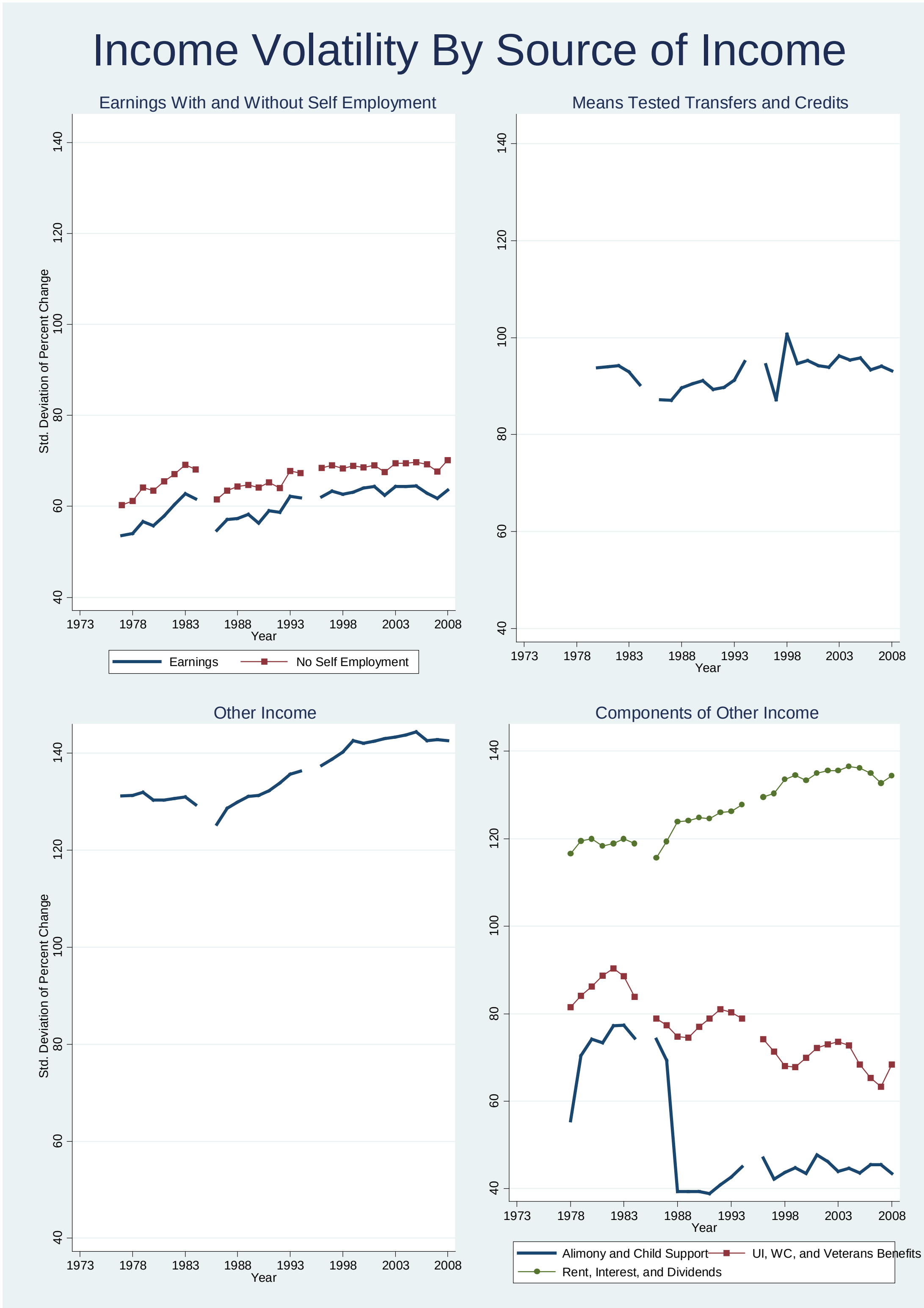
Family Earnings and Income Volatility
By Education
Less Than HS Education
HS Education
More Than HS Education
Std. Deviation of Percent Change
30
40
50
60
70
80
1973
1978
1983
1988
1993
1998
2003
2008
Year
Earnings
Before-Tax Income

FIGURE 2.5



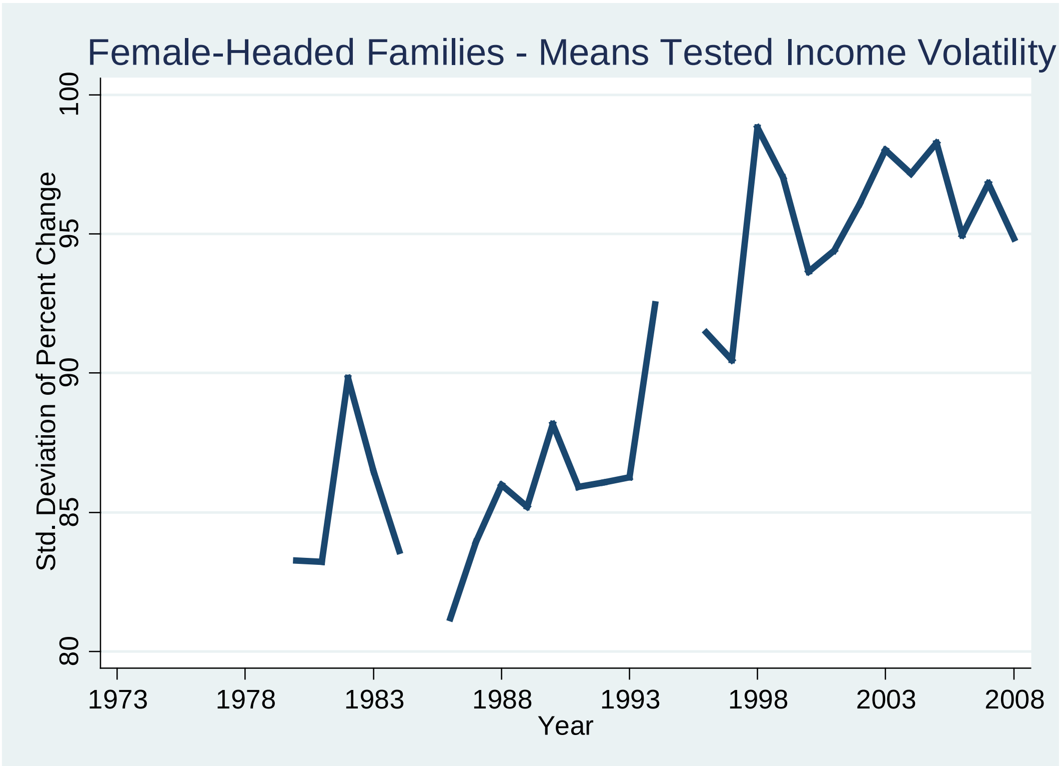
Individual Earnings Volatility
By Gender and Status in Families
Men
Women
Husbands
Wives
Std. Deviation of Percent Change
Year
50
60
70
80
90
100
1973
1978
1983
1988
1993
1998
2003
2008

FIGURE 2.6



Income Volatility By Source of Income
Earnings With and Without Self Employment
Means Tested Transfers and Credits
Other Income
Components of Other Income
Std. Deviation of Percent Change
Year
Earnings
No Self Employment
Alimony and Child Support
UI, WC, and Veterans Benefits
Rent, Interest, and Dividends

FIGURE 2.7



Female-Headed Families - Means Tested Income Volatility
Std. Deviation of Percent Change
100
95
90
85
80
1973
1978
1983
1988
1993
1998
2003
2008
Year

FIGURE 2.8

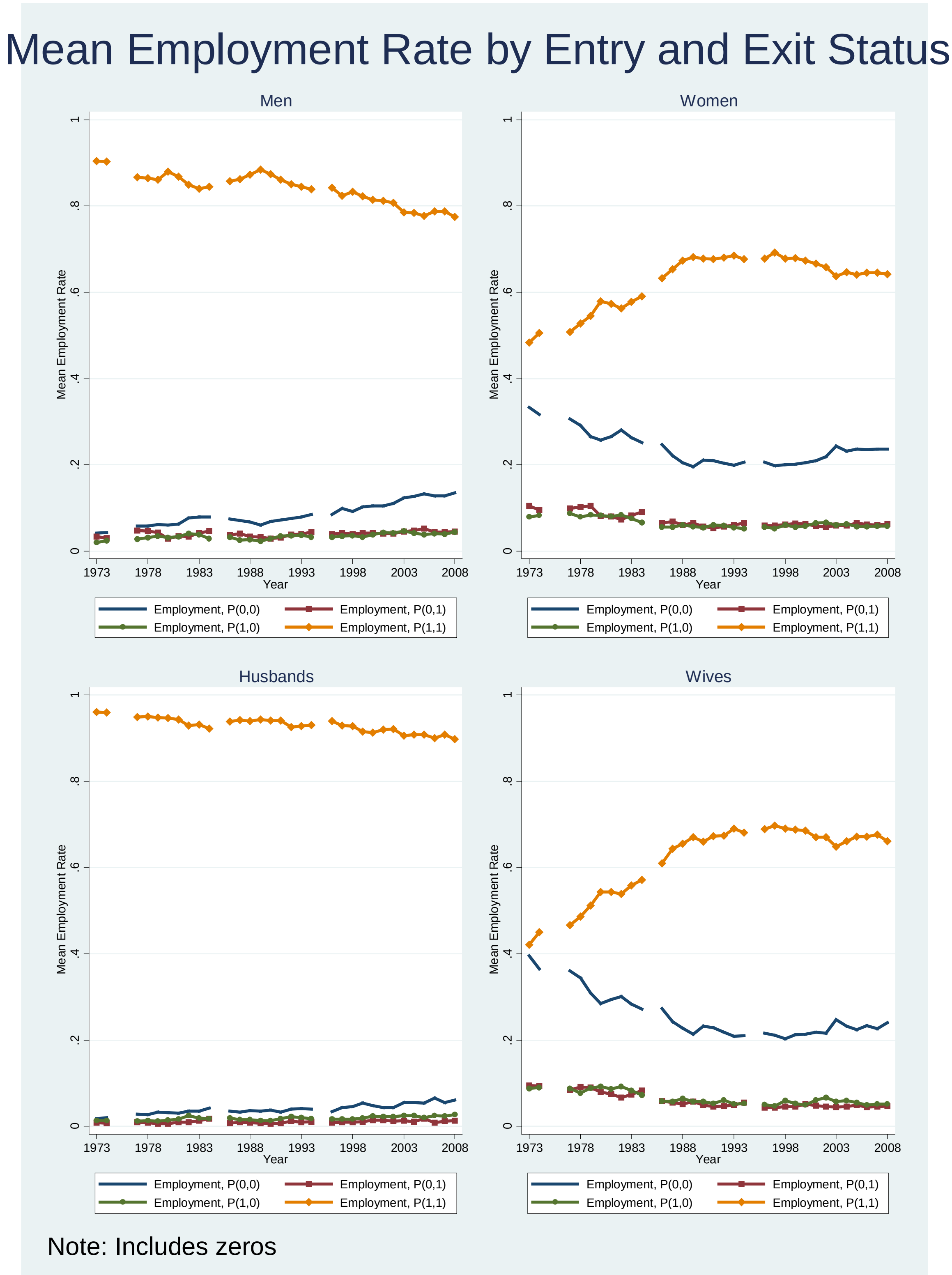
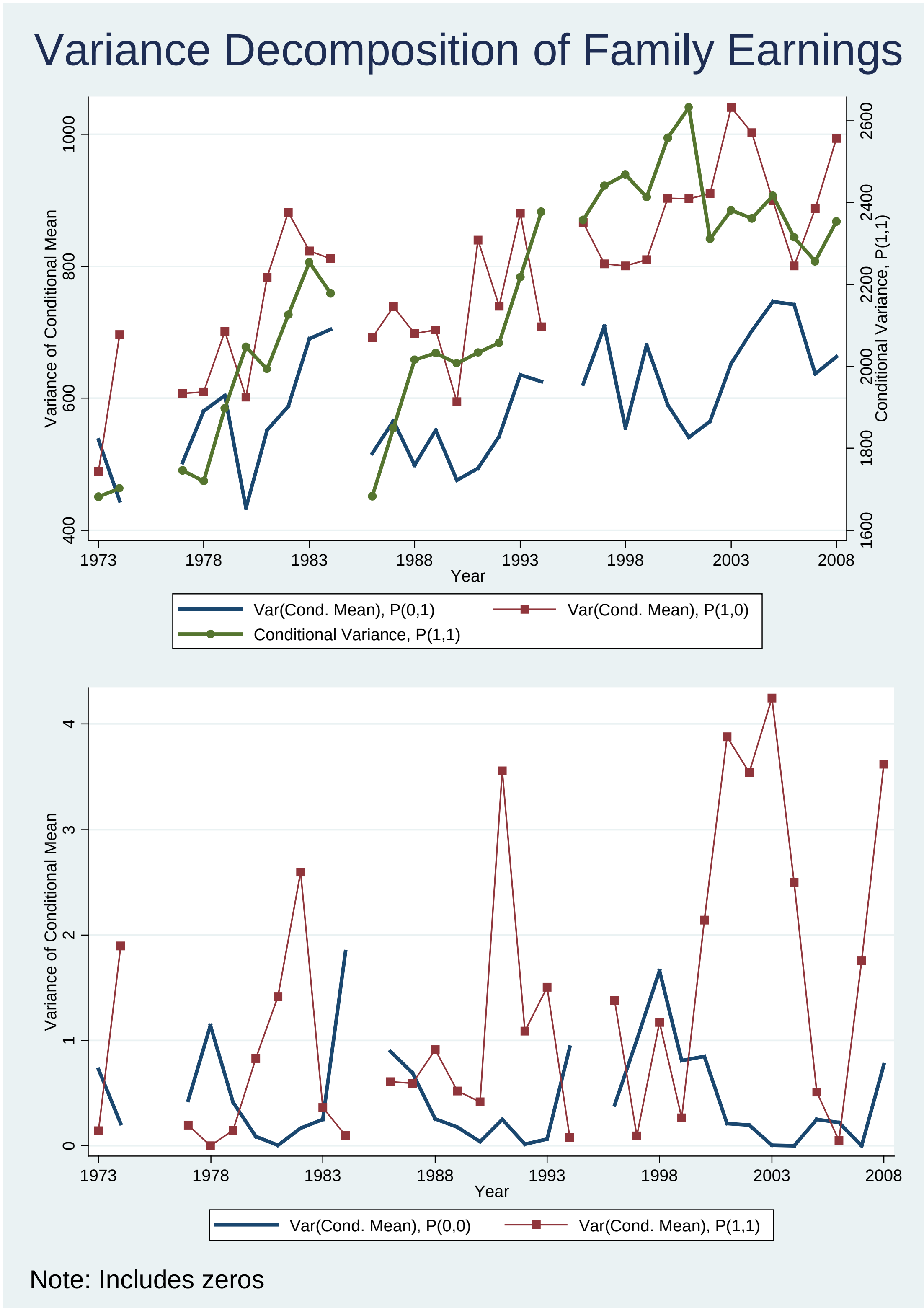

Mean Employment Rate by Entry and Exit Status
Men
Women
Husbands
Wives
Mean Employment Rate
Year
0
.2
.4
.6
.8
1
1973
1978
1983
1988
1993
1998
2003
2008
Employment, P(0,0)
Employment, P(0,1)
Employment, P(1,0)
Employment, P(1,1)
Note: Includes zeros

FIGURE 2.9



Variance Decomposition of Family Earnings
Variance of Conditional Mean
400
600
800
1000
Conditional Variance, P(1,1)
1600
1800
2000
2200
2400
2600
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,1)
Var(Cond. Mean), P(1,0)
Conditional Variance, P(1,1)
Variance of Conditional Mean
0
1
2
3
4
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,0)
Var(Cond. Mean), P(1,1)
Note: Includes zeros

FIGURE 2.10

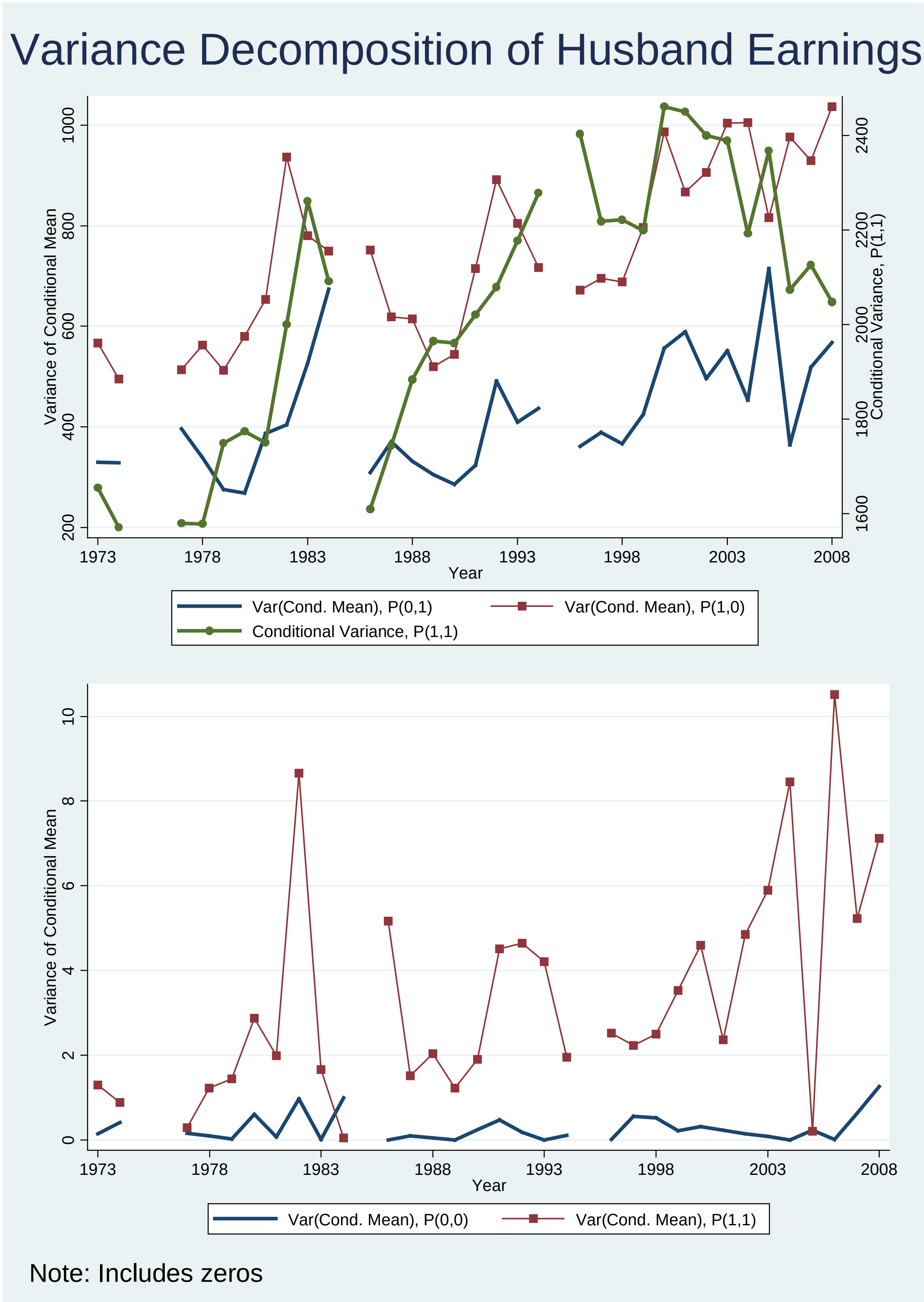
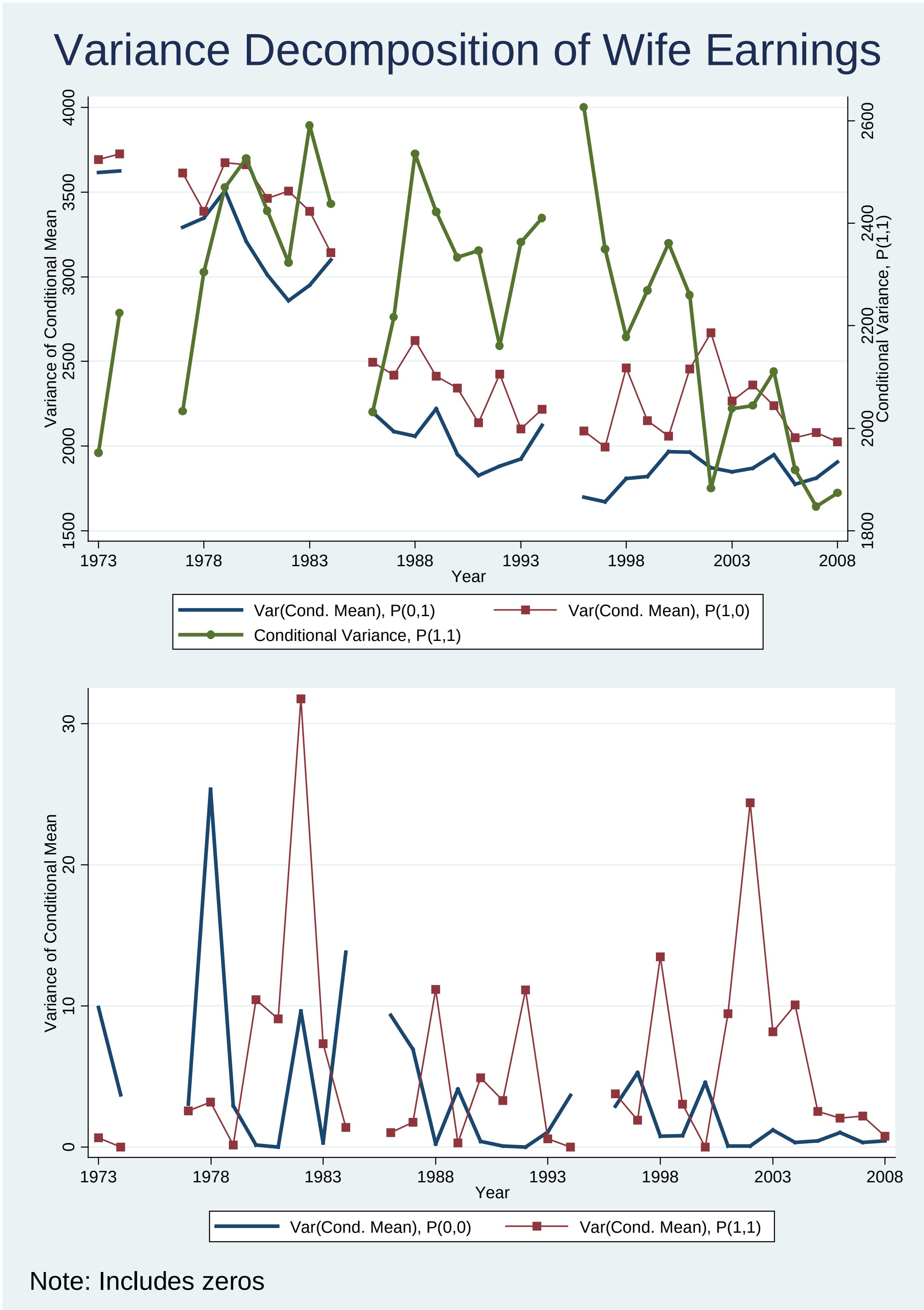

Variance Decomposition of Husband Earnings
Variance of Conditional Mean
Conditional Variance, P(1,1)
200
400
600
800
1000
1600
1800
2000
2200
2400
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,1)
Var(Cond. Mean), P(1,0)
Conditional Variance, P(1,1)
Variance of Conditional Mean
0
2
4
6
8
10
Var(Cond. Mean), P(0,0)
Var(Cond. Mean), P(1,1)
Note: Includes zeros

FIGURE 2.11



Variance Decomposition of Wife Earnings
Variance of Conditional Mean
Conditional Variance, P(1,1)
1500
2000
2500
3000
3500
4000
1800
2000
2200
2400
2600
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,1)
Var(Cond. Mean), P(1,0)
Conditional Variance, P(1,1)
Variance of Conditional Mean
0
10
20
30
Var(Cond. Mean), P(0,0)
Var(Cond. Mean), P(1,1)
Note: Includes zeros

FIGURE 2.12

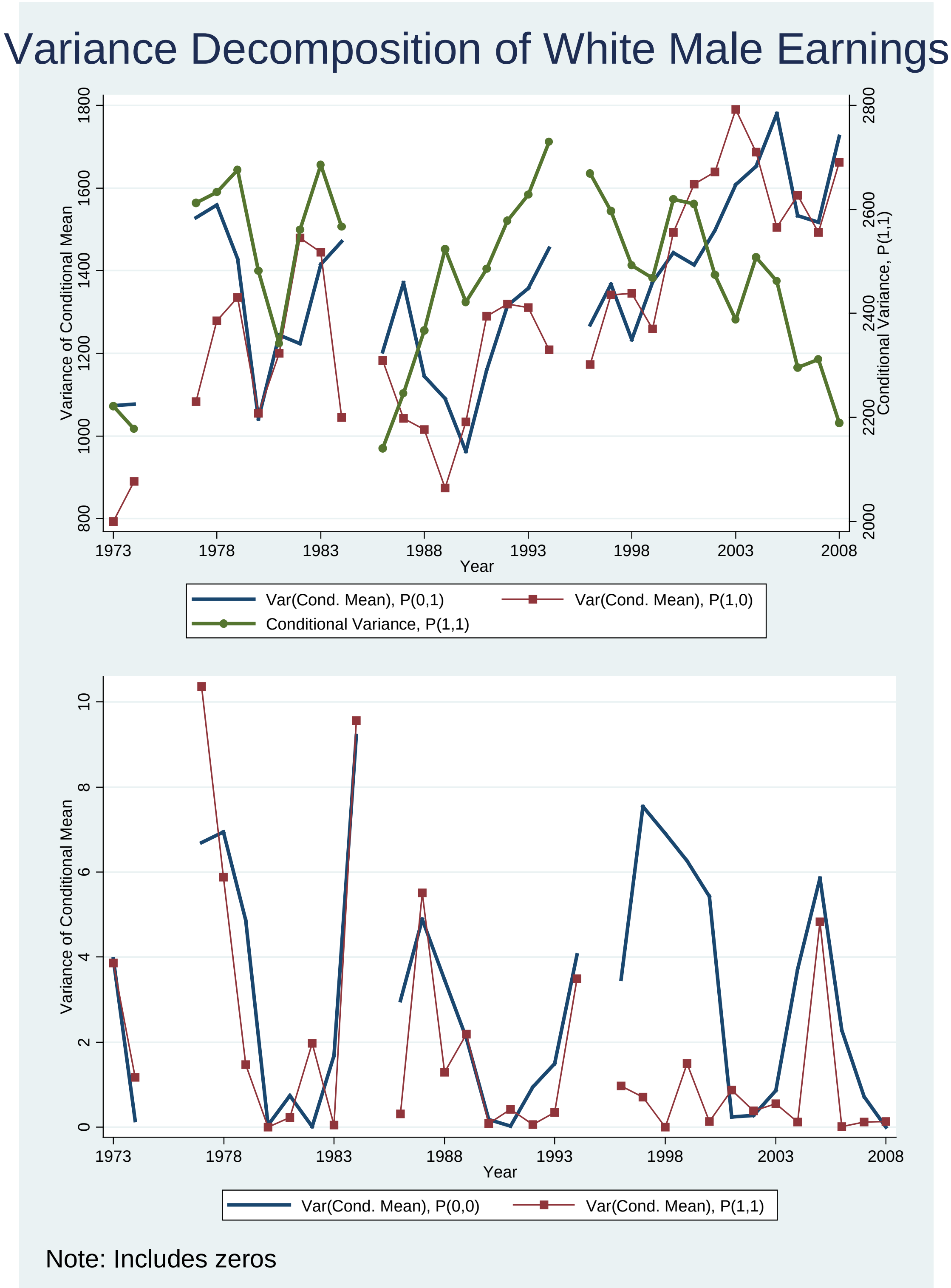
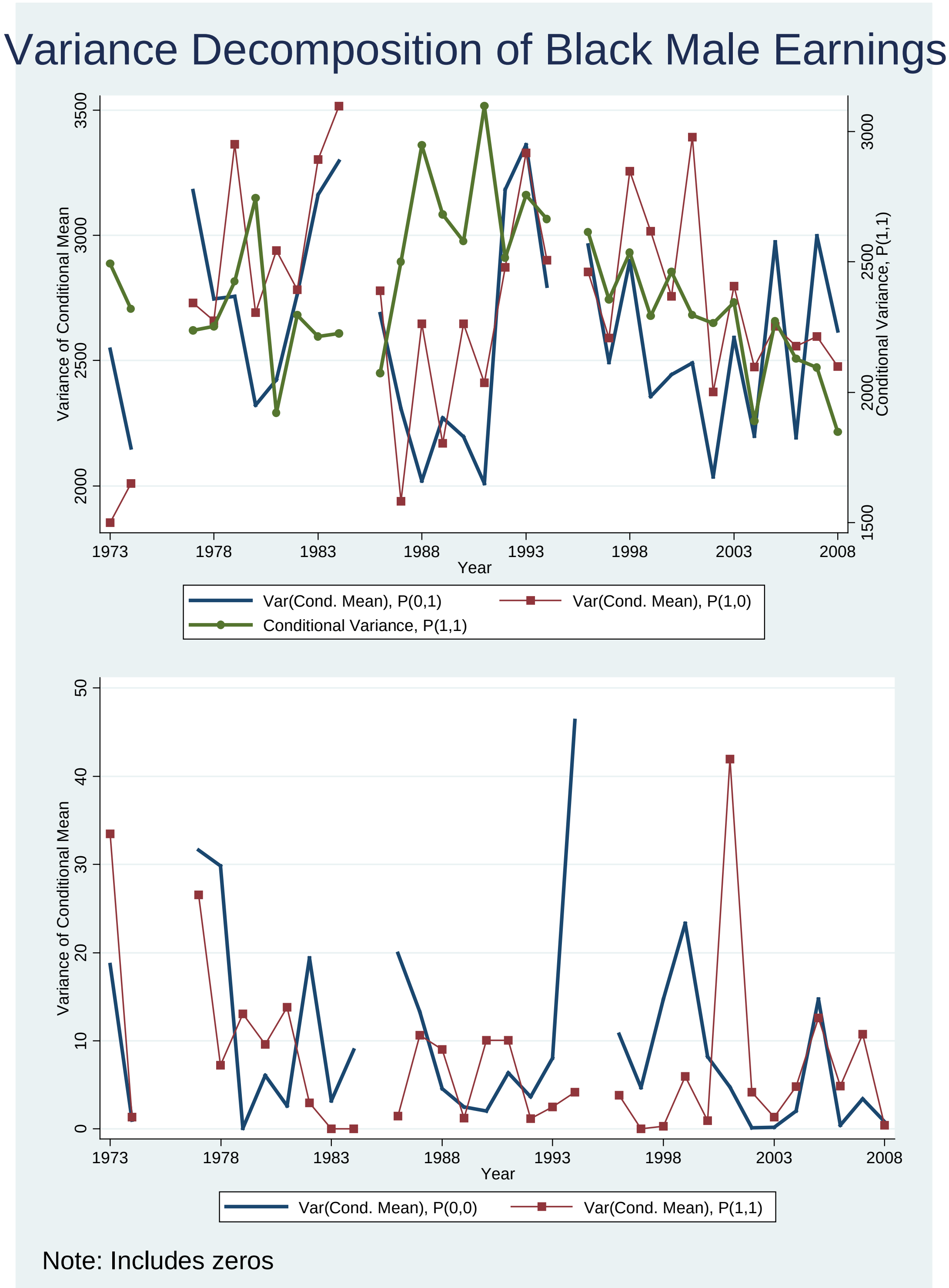
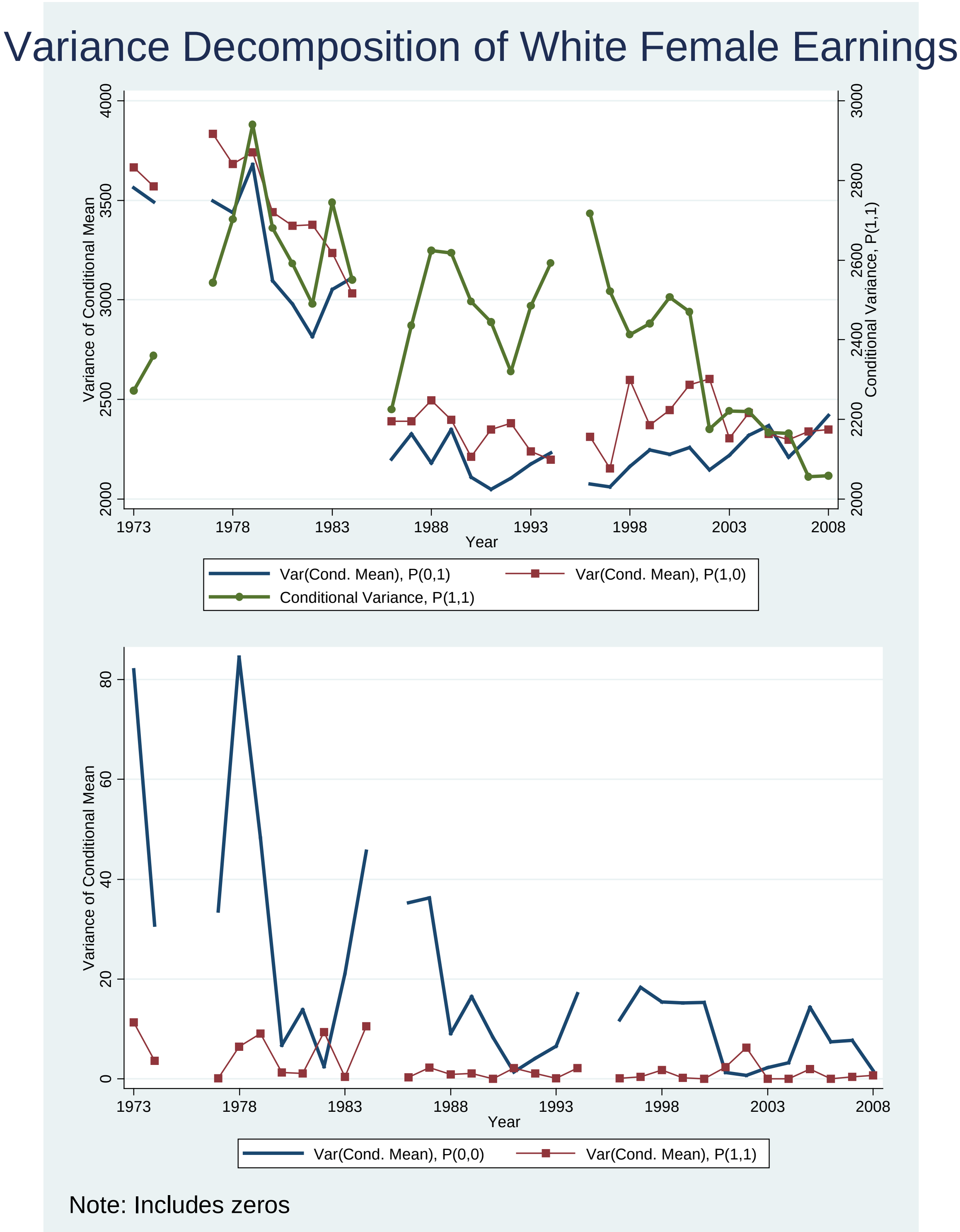

Variance Decomposition of White Male Earnings
Variance of Conditional Mean
1800
1600
1400
1200
1000
800
2800
2600
2400
2200
2000
Conditional Variance, P(1,1)
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,1)
Var(Cond. Mean), P(1,0)
Conditional Variance, P(1,1)
Variance of Conditional Mean
10
8
6
4
2
0
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,0)
Var(Cond. Mean), P(1,1)
Note: Includes zeros

FIGURE 2.13



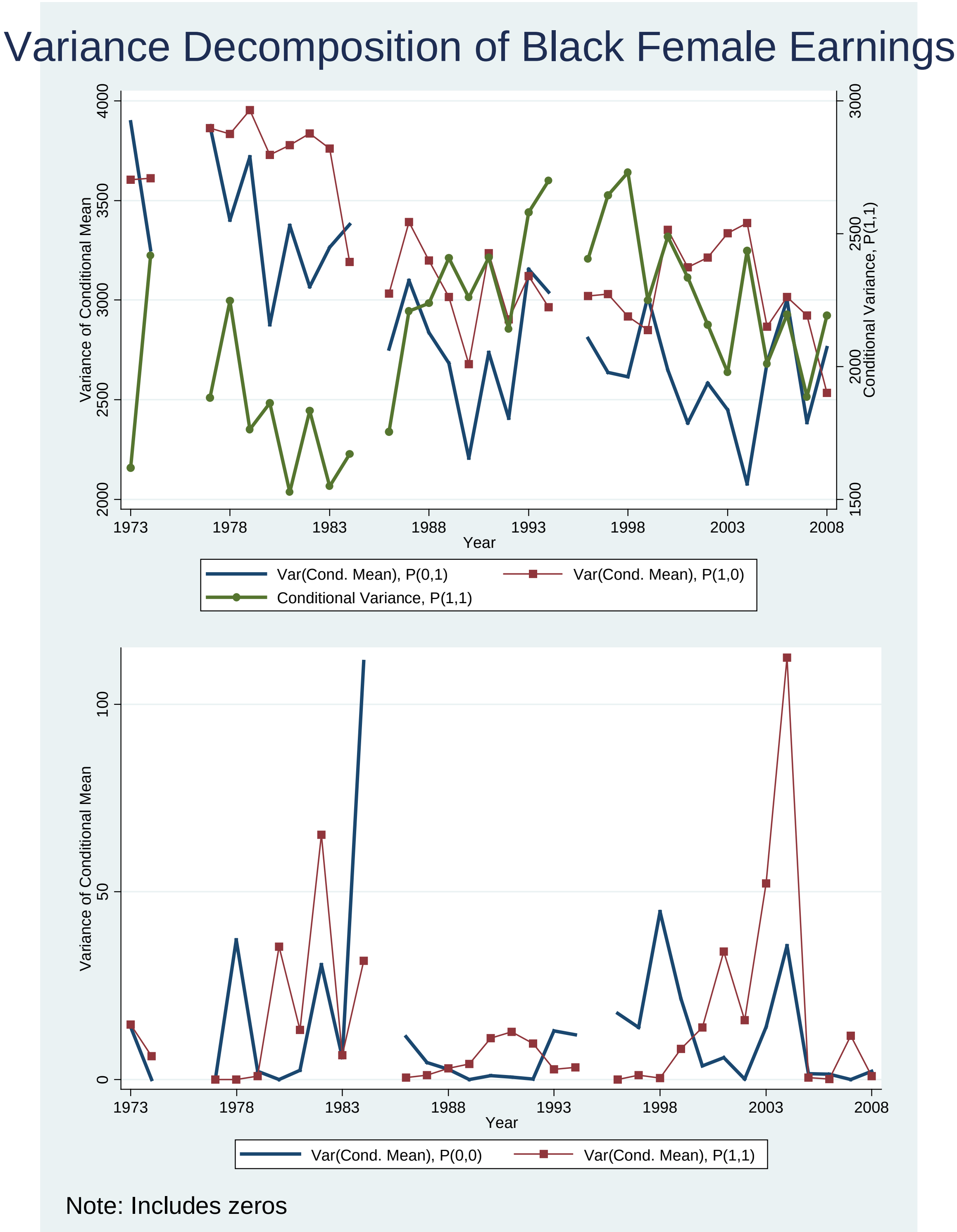
Variance Decomposition of Black Male Earnings
Variance of Conditional Mean
Conditional Variance, P(1,1)
2000
2500
3000
3500
1500
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,1)
Var(Cond. Mean), P(1,0)
Conditional Variance, P(1,1)
Variance of Conditional Mean
0
10
20
30
40
50
Var(Cond. Mean), P(0,0)
Var(Cond. Mean), P(1,1)
Note: Includes zeros

FIGURE 2.14



Variance Decomposition of White Female Earnings
Variance of Conditional Mean
Conditional Variance, P(1,1)
Year
Var(Cond. Mean), P(0,1)
Var(Cond. Mean), P(1,0)
Conditional Variance, P(1,1)
Variance of Conditional Mean
Year
Var(Cond. Mean), P(0,0)
Var(Cond. Mean), P(1,1)
Note: Includes zeros

FIGURE 2.15



Variance Decomposition of Black Female Earnings
Variance of Conditional Mean
Conditional Variance, P(1,1)
4000
3500
3000
2500
2000
3000
2500
2000
1500
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,1)
Var(Cond. Mean), P(1,0)
Conditional Variance, P(1,1)
Variance of Conditional Mean
100
50
0
1973
1978
1983
1988
1993
1998
2003
2008
Year
Var(Cond. Mean), P(0,0)
Var(Cond. Mean), P(1,1)
Note: Includes zeros

3 A COHORT ANALYSIS OF EARNINGS VOLATILITY

3.1 Introduction

Consumption smoothing among individuals and families may not occur optimally if information asymmetries or other imperfections in credit markets exist in a labor market with high levels of aggregate earnings volatility (Loury 1981; Becker and Tomes 1986; Mazumder 2005). This is troubling for policymakers if individuals experience earnings volatility coinciding with market imperfections, such as the imperfect loanable funds market for human capital. Inequality may be worsened if such phenomena occur unevenly across groups. From essay 2, demographic heterogeneity in the trend and level of volatility provides new evidence that volatility occurs differentially by race, gender, education, and marital status. For example, families where the household head is female, less educated, or Black report higher levels of earnings and income volatility. Yet, these trends are incomplete for policymakers because they are unconditional and may be driven in part by differences in earnings levels, labor market skills, or local economic conditions. Labor market skills may not insulate individuals from volatility, as earnings volatility rises among male household heads both with and without college. This is also true for prime age individuals in their mid 40's, when workers have acquired formal and on-the-job training thought to combine for more income and earnings stability (essay 3). The varying levels and trends in earnings volatility call for a deeper understanding of its occurrence, but few studies up to this point attempt to identify economic or demographic relationships with volatility.

This essay investigates the demographic, labor market, and industry characteristics associated with exposure to volatile earnings by merging elements of human capital theory and lifecycle earnings models. The resulting empirical specification corrects for heterogeneous human capital and lifecycle earnings profiles by grouping individuals into education birth-year cohorts following the approach of Deaton (1985) and Blundell, Duncan, and Meghir (1998). The possibility of a lifecycle earnings profile driving volatility can be seen from the rise in earnings and income volatility throughout the 1980s and 1990s (essay 2), suggesting a specific group or cohort of workers may drive the trends; it is also documented in the literature on lifecycle earnings profiles (Polachek 2007). Outside of these lifecycle effects, it would be helpful to understand if rising earnings volatility has more or less to do with workers' education, gender, race, local economic growth, or industry of employment.

Since at least Mincer (1958) and human capital theory, earnings models account for such differences, describing how different human capital investments and resulting skill sets along with observable traits relate to earnings growth over the lifecycle. Along with the documented U-shape in earnings volatility, this literature finds that the returns to education vary by age, race, gender (Smith and Welch 1979), and location (Black, Kolesnikova, and Taylor 2009; Bollinger, Ziliak, and Troske 2009). This essay applies insights from human capital theory to understand earnings volatility over the lifecycle by raising similar questions. To do so, my approach tests the importance of demographic, industry, and local economic variables for explaining earnings volatility after accounting for education-birth-year cohort and non-random selection (Heckman 1979) into and out of the labor force.

Using the matched Current Population Survey (CPS), I find that earnings volatility among men and women begins at a relatively high level within the initial years of entering the labor force and falls over time. After this initial decline, earnings volatility of workers with education beyond high school rises and forms a U shape as men reach their mid-40s and women approach 50. After controlling for education and year-of-birth cohort, I then find earnings levels, race, industry, and local labor market conditions predict exposure to earnings volatility. These predictions differ in importance and are sensitive to gender and the econometric specification employed. Because the U.S. economy may have some credit market imperfections, an improved understanding of earnings volatility may have important policy implications. By extending human capital theory to explain the occurrence of volatility, society can more optimally provide temporary public assistance to smooth consumption. This, in turn, may aid in correcting capital market imperfections.

3.2 Background

The literature on volatility has placed an important emphasis on methodological differences in measuring volatility, including the construction of permanent, transitory, and total volatility trends over roughly 40 years (Gottschalk and Moffitt 1994, 2009; Dahl, DeLeire, and Schwabish 2008; Dynan, Elmendorf, and Sichel 2008; essay 2). Because of this focus on the permanent and transitory components of volatility, the discussion within the literature has emphasized structural causes of volatility and how these then influence the observed rise in the variability of wages since the 1970s. Essay 2 provides a background discussion of total, transitory and permanent volatility measurement and trends.

Several studies find volatility rising among men and falling among women (Shin and Solon 2010; Dynan, Elmendorf, and Sichel 2008; essay 2) since the 1970s. Some studies show, depending on the measure used, volatility negatively related to economic growth (Dahl et al. 2008), while others find that job changers actually have lower volatility due to their continuous employment, so that high volatility may occur during high growth periods when people are more willing to change jobs (Celik, Juhn, McCue, and Thompson 2009). The possible culprits of volatility extend beyond job loss and economic risk to include voluntary labor force exits such as childcare, along with permanent changes including earnings volatility induced by incentive-pay structures (Celik et al. 2009) and skill-biased technological change (Gottschalk and Moffitt 2009; Hacker and Jacobs 2008; Autor, Katz, and Kearney 2008). Technological change may render transitions into new industries and occupations costlier in terms of skill acquisition for a new job. A consequence of this may be higher transitory volatility from higher transition costs and skill gaps between occupations (Violante 2002). There is limited evidence from the PSID that parents may pass on volatile earnings to their children. Shore (2010) estimates an intergenerational model in which parents' income volatility is ultimately found to predict risk taking, for which volatility of incomes among their adult offspring serve as a proxy.

A few papers estimate economic models related to predicting volatility determinants. Cameron and Tracy (1998) use matched CPS data to document trends and possible volatility determinants. They focus on the role of education, industry heterogeneity, and job stability in explaining volatility, where volatility is measured as the residual earnings variance. They find Government and Manufacturing to be among the least volatile trades with respect to earnings, and that education is also associated with lower volatility of earnings. They restrict their data sample to individuals remaining within the same industry across both years of the two-year panel and estimate regressions of volatility on a set of industry and education indicators, controlling for lifecycle growth profiles. Gittleman and Joyce (1996) use matched-CPS data to examine earnings instability in America throughout the 1970s and 1980s. In line with essay 2, they find that lesser educated persons and minorities exhibit higher levels of earnings volatility.

3.3 Cohort Regression Model of Earnings Volatility

This essay extends the literature on human capital theory and earnings volatility by estimating earnings volatility functions. I identify demographic, economic, and industry correlates of earnings volatility exposure by extending Cameron and Tracey's (1998) empirical model using matched-CPS to account for education and birth-year cohort membership. I do so by using a pseudo panel approach for cross-section data that replaces individual observations with cohort means (Deaton 1985; Blundell, Duncan, and Meghir 1998). Blundell et al. (1998) relate how the individual's labor supply equation is similar to a labor supply equation where the individuals are organized by groups or cohorts. I apply this to the estimation of earnings volatility as the dependent variable. Beginning with (1), the individual-level regression model for earnings volatility is

$$V_{ict} = \alpha_{ic} + m_{ct} + UR_{ict}\gamma + IND_{ict}\delta + \beta' x_{ict} + u_{ict} \tag{1}$$

Here, V_{ict} represents individual i's earnings volatility in a defined cohort c at time t, α_{ic} denotes some individual fixed effect, m_t is a time fixed effect, x_{ict} are demographic controls for race, and IND_{ict} is the individual's industry in cohort c at time t, measured with error u_{ict}. Cohorts are determined by membership in one of three education groups and year of birth at five year intervals. Thus, every individual i belongs to one cohort. The next step requires grouping the individual data by cohort and constructing a data set of yearly, cohort means from the micro-level cross-sectional data. With this, the empirical strategy pools the set of individual observations within cohorts into a data set of cohort mean observations. Cohorts can then be followed throughout cross-sectional data over time in a manner analogous to individuals observed within a longitudinal panel. This similarity to individual panel data relies on the random sampling assumption appropriate for cross sectional data sets such as the CPS, so that cohorts followed across years are representative and the same groups are observed continuously (Baltagi 2008).

The procedure of grouping by education-birth year cohort enables me to estimate the measure of total volatility employed in essay 2 as the dependent variable, the standard deviation of the arc percent change in earnings. I construct a pseudo panel of individuals as described above by allocating each individual to one of 45 five-year birth-education cohorts, comprised of 15 birth cohorts and three education groups (less than high school, high school graduate, and more than high school). After collapsing the data into education birth-year cohort means, this method makes it is possible to look across and within cohorts to identify life cycle profiles of volatility, shown in figures 3.1 and 3.2. Assuming linearity in parameters, the resulting cohort regression on this collapsed data will estimate equation (2) at the cohort level using OLS with cohort and time fixed effects. The result is a panel data regression model where the cohorts are akin to individual observations within a panel for the earnings volatility equation:

$$(2) \qquad \overline{V_{ct}} = \overline{Z_{ct}} + \overline{u_{ct}} = \overline{\alpha_c} + \overline{m_t} + \overline{UR_{ct}}\gamma + \overline{IND_{ct}}\delta + \beta'\overline{x_{ct}} + \overline{S_{11}} + \overline{S_{10}} + \overline{S_{01}} + \overline{u_{ct}}.$$

Subscripts c and t refer to the education-age cohort and year, respectively. $\overline{V_{ct}}$ and $\overline{x_{ct}}$ represent cohort specific earnings volatility and demographic controls for race, respectively - means that vary over time and across cohorts. As a result, explanatory variables are measured as proportions or rates within specific cohorts. $\overline{\alpha_c}$ and $\overline{m_t}$

represent the cohort fixed effects and time effects. These fixed effect terms are meant to control for time-invariant, unobserved cohort effects that would otherwise remain in the error term u_{ct}. They are derived from the initial cohort and time fixed effects in equation 1, which are then collapsed into the cohort-mean data design. u_{ct} otherwise contains these cohort fixed effects in the absence of controls for $\overline{\alpha_c} + \overline{m_t}$.

In equation (2) I estimate mean cohort selection parameters $\overline{S_{11}}$, $\overline{S_{10}}$, and $\overline{S_{01}}$, to account for the non-random decision to engage in continuous work (1,1), exit the labor market (1,0), or enter the labor market (0,1) between periods (Wooldridge 2002). Mincer (1974), Ben-Porath (1967) and other adaptations of the seminal human capital model (Polachek 2007) acknowledge that continuous workers' earnings profiles differ from those of discontinuous workers, and the decision to enter or leave work is driven by childbearing and various other preferences that are difficult to observe. Transitions into and out of work can represent the largest volatility swings in the data, and the endogenous choice that workers face potentially imposes a bias on the results. By addressing this form of omitted variables bias, I mitigate an inherent sample selection issue introduced by Gronau (1974) and Heckman (1979) in the area of labor supply.

The selection equation is generated using a first stage probit of continuous work, labor force entry or exit on race, non-labor income, state unemployment rates, earned income tax credit (EITC) maximum benefits, cash welfare (Aid to Families with Dependent Children (AFDC)/Temporary Assistance for Needy Families (TANF)), food stamp maximum benefit levels, and state minimum wages on the individual-level data. Similar to the procedure that leads to equation (2), after estimating the individual-level inverse mills ratios S_{11}, S_{10}, and S_{01}, I then create a set of cohort-level mean selection correction terms for each year constructed from individual inverse mills ratios observed within each cohort. These are denoted $\overline{S_{11}}$, $\overline{S_{10}}$, and $\overline{S_{01}}$ in equation (2) to distinguish mean cohort-level selection parameters from individual-level selection parameters. It is permissible for the explanatory variables between the main empirical model and the first-stage selection probits to overlap, but many of the included policy regressors in the probit represent exclusion restrictions omitted from the main volatility regressions. These policy regressors are chosen because they are believed to impact the individual's decision to enter, exit, or maintain continuous work. Since the 1980s, there has been variation in benefit levels for the EITC, making it among the largest means-tested benefit program in terms of outlays. Over the same time period the direct-cash assistance AFDC/TANF programs also saw dramatic reform throughout the 1980's and especially in 1996 (Haskins 2001). States have discretion to set minimum wages above the nationally mandated level, so that there is also variation across states on this dimension as well. All of these factors and the resulting inverse mills ratio constructed from the first-stage probit attempt to account for the individual's work behavior between periods.

Three identifying assumptions are needed under this pseudo-panel framework. First, as just described

(3) $$E(\overline{u_{ct}} \mid w, c, t) = \overline{\alpha_c} + \overline{m_t} + \delta\overline{\lambda_{ct}},$$

where $\overline{\lambda_{ct}}$ represents the included selection controls described in (2). (3) assumes unobserved differences in volatility across cohorts are captured additively by a combination of time-invariant cohort effects and time fixed effects, along with controls for selection into the labor force. A second identifying assumption requires between-cohort variation in demographics, local economic controls, and industries after netting out fixed cohort effects, time effects, and selection. This then implies that

(4) $\quad E(\overline{V_{ct}} \mid w, c, t) = bE(\overline{x_{ct}} \mid w, c, t) + \overline{\alpha_c} + \overline{m_t} + \delta\overline{\lambda_{ct}},$

The explanatory variables $\overline{x_{ct}}$ are uncorrelated with deviations of $\overline{\alpha_c}$ from its own average $\overline{\overline{\alpha_c}}$ over the duration of the panel, with the analogous assumption required for time effects $\overline{m_t}$ (Wooldridge 2002). Thus, the fixed effects can and may be correlated with the explanatory variables, which is acceptable so long as deviations are uncorrelated with the explanatory variables. As is the case in survey data analysis, concerns arise regarding measurement error. The risk is that OLS estimates are, at the very least, consistent and biased, and at worse, inconsistent and biased (Davidson and MacKinnon 2004). For the main estimation as shown in (2), a third assumption for consistency via OLS is that cohort sample sizes in the CPS provide large sample sizes so that the mean fixed effects $\overline{\alpha_c}$ estimated for each cohort can sufficiently capture the cohort-specific unobserved effects $\overline{\alpha_{ct}}$, which are not fixed over time. Table 3.1 presents summary statistics that provide a snapshot of the cohort data, including mean cohort size, which is approximately 12,000. There is substantial deviation in sample sizes between cohorts, as shown in table 3.2.

3.3.1 Defining Volatility

Volatility is defined as a total measure. Mathematically, it is the standard deviation of the arc percent change, defined as

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

where y_{it} is earnings for person *i* in time *t*. $\overline{y_i} = \frac{y_{it}+y_{it-1}}{2}$. I adopt a variant of this method, used in essay 2, allowing for the analysis of negative earnings. This measure picks up both transitory and permanent volatility, and it also allows for negative earnings to enter into the definition – a feature that is not possible in definitions using log earnings. When combined with the matched-CPS data described below, the definition offers a novel approach to measuring earnings volatility. A longer discussion of the summary volatility measure occurs in essay 2.

3.4 Data

The data in essay 3 are generated using the 1981–2009 waves (1980–2008 calendar years) of the March Annual Social and Economic Study of the CPS. A detailed description of the match process is contained in essay 2. The large sample size in the CPS enables me to estimate associations within subgroups while maintaining statistical power, an important feature enabling me to identify associations to volatility within education cohorts. The unit of observation at the cohort level is an individual between the ages of 16 and 60. The rotating design of the CPS makes it possible to match approximately one-half of the sample from one March interview to the next, with the end goal of creating a series of 2-year longitudinal panels. The final file is an interrupted time series across 28 years with gaps in *calendar* years 1984-1985 and 1994-1995 due to data sample redesign. In total there are roughly 20,000 observations in an average year when a match is possible. As described above, I follow Deaton (1985) and Blundell, Duncan, and Meghir (1998), collapsing the matched data set, by cohort and birth year, into 1 of 45 cohorts differentiated across education groups for less than high school, high school, or post high school education, and the individual's membership in a 5 year year-of-birth cohort band. An example of a unique cohort observation is an individual born between 1980 and 1985 with education beyond high school. Importantly, following Cameron and Tracey (1998) I require that observations included in the collapsed data maintain the same education, race, gender, and industry across the two-year panel. This excludes individuals moving across education groups or industries between years. After accounting for non-random selection into work, the final data set contains only continuous workers.

Earnings are adjusted for inflation using the personal consumption expenditures deflator, in 2008 dollars. Data on EITC maximum benefits, welfare cash maximum benefits, and state minimum wage levels used in estimating the selection equations (table 3.3) were obtained from a master data set maintained by the University of Kentucky Center for Poverty Research (www.ukcpr.org).

3.5 Summary Statistics

Table 3.1 gives a detailed look at summary statistics across the cohort. It presents sample means over the cohort-level data. For example, mean earnings are around $38,000, average cohort unemployment is below 6 percent, and services industry work is dominant. There are approximately 12,000 observations per cohort on average, though this ranges from cohort 27 and a high of 38,438 to a low of 255 in cohort 45 (table 3.2). To assist in understanding who falls within these cohorts, table 3.2 shows, for example, that individuals in cohort 27 are born between 1947 and 1951 with education beyond high school. Those in cohort 45 are born in or prior to 1921 with education beyond high school. The cohort sample sizes show rising educational attainment throughout America over the twentieth century, especially among baby-boomers.

3.6 Lifecycle Profile of Volatility

Figures 3.1, 3.2, and 3.3 depict cohort level trends in volatility focused on the timing of volatility over the life cycle for all individuals, men, and women, respectively, which has potentially important welfare implications related to mobility. If volatility is largely concentrated early in the life cycle when job change and geographic is more frequent, then the welfare consequences are likely attenuated relative to a situation where it is increasing with age. Two key implications of human capital theory are that earnings levels increase at a decreasing rate and that variation in earnings levels falls with age before rising again (Polachek 2007). This finding is confirmed in figures 3.1-3.3, where each panel contains the time series for 15 birth cohorts, with each panel representing one of three education groups. Figure 3.1 shows that, across education groups, volatility declines rapidly until about age 40, but among those with education at or beyond high school volatility actually begins to increase at age 45 and thus is U-shaped across the life cycle. For individuals with a less than high school education volatility levels off from its decline after age 40. Figure 3.2 presents the parallel graph of individual earnings volatility across the life cycle for men only. As with earnings volatility across all individuals, volatility stabilizes by the late 30s among men and then follows a similar upward trajectory around age 45 for those with high school education or more than high school, though the trend is actually more pronounced. For women, figure 3.3 shows a consistent decline in earnings volatility over the lifecycle, though the rate of decline falls around age 40. Around their mid 40s, the volatility trends for women with high school education or beyond rise much like that observed for more educated men. A reason for this observed U-shape in earnings volatility might be labor force entry when young and labor-force exit when old. However, the observed rise in volatility among men and women occurs before the early 60s, when workers can begin collecting social security benefits to support their labor force exit. Instead, this rise in volatility occurs earlier in the lifecycle than is predicted in lifecycle models of earnings variation (Polachek 2007), where retirement is a primary culprit. This initial finding shown in figures 3.1-3.3 suggests earnings volatility could be driven by events and characteristics beyond lifecycle trends. Some of these characteristics will be identified in the main results, described below.

3.7 Cohort Regression Results

The results of first-stage probit models controlling for selection into work, out of work, and continuous work are shown in table 3.3. The unobserved characteristics of individuals who transition into and out of the labor force are important, as these decisions ultimately impact observed volatility. In my selection equations, I account for race, gender, state unemployment, non-labor income (transformed by dividing non-labor income by 10,000), and government transfers that may all be correlated with individual decisions to work and the reservation wage. Blacks and females are less likely to work continuously, and a weaker labor market as exhibited by unemployment lowers the likelihood of continuous work. Access to more generous government transfer programs and non-labor income are associated with lower continuous work. A higher minimum wage is positively correlated with continuous work, and it lowers the chance of labor force transitions. Racial and ethnic minorities along with females are more likely to transition into and out of the labor market. Government transfer programs are generally linked to a greater chance of exiting or entering the labor force. The selection equations are estimated on the full sample of individual observations, prior to collapsing the data into cohort-level means.

The regression results in tables 3.4-3.7 are shown separately for men and women with and without controls for selection. Education is accounted for via education birth-year cohort effects. Moving left to right, baseline models estimate the role of race and average state labor market characteristics in explaining observed volatility, without and with average earnings. Columns 3-6 then control for cohort fixed effects and year effects, adding in average earnings and industry shares.

I find cohorts with a larger share of racial and ethnic minorities are associated with higher earnings volatility in base model regressions without cohort or time effects (tables 3.4-3.5). After controlling for average earnings the coefficient on Black is negative among men and women and is statistically significant for women. Other racial and ethnic male minorities maintain a reduced but significant positive association to volatility and their female counterparts maintain a negative association upon controlling for cohort and time effects in columns 3-6. For men and women higher earnings are related to lower earnings volatility. I transform average earnings, dividing by 100. Unemployment has opposite relationships between men and women. As it rises, state unemployment is linked with lower earnings volatility among men and higher volatility among women. Government, Construction, and Manufacturing are the least volatile industries for men. Upon conditioning for mean cohort earnings, men in the Construction and Manufacturing display lower earnings volatility. Women in Government, Trade, Manufacturing, and Transportation/Utilities exhibit lower volatility. These results are sensitive to model specification, as Trade becomes a significantly low-volatility industry and government becomes higher-volatility for women upon controlling for average earnings.

3.7.1 Accounting for Selection Into and Out of the Labor Market

As discussed earlier, it is important to consider the impact of selection into and out of the labor market. Individuals transitioning into work or out of work by definition experience high volatility. Repeating the exercise shown in tables 3.4-3.5, I show results for men and women accounting for selection into these transition states (tables 3.6 and 3.7). Black women have consistently lower volatility than their white counterparts after controlling for selection. For both men and women, the relationship between Other racial and ethnic minorities, average earnings, and earnings volatility described in tables 3.4 and 3.5 is maintained after selection controls are included. The positive unemployment-volatility relationship is fades upon introducing selection controls for women but the negative link remains among men. The industry-volatility association is generally the same, with the exception that trade is relatively less volatile among men after controlling for selection

Overall, a link between race and higher volatility appears for women at the cohort level, though this does not hold up or is noticeably reduced once cohort and time effects are accounted for. Other race and ethnicity males also show a strong, positive link to volatility that is larger in absolute terms among the baseline specifications, between 37.735 and 77.357 with cohort and selection controls and between 41.084 and 204.178 in the baseline models (tables 3.4 and 3.6). Unemployment is procyclical among women and counter-cyclical for men, from 2.897 to 6.362 standard deviation points for women and -10.937 to -13.413 points for men. Across all models, average earnings are small in magnitude but have a statistically significant, negative association to volatility between -0.082 to -0.195 (multiplied by 100) so that higher earners are linked to lower earnings volatility. Across gender Government industry workers show the least volatility for men and very low volatility for women. For men, Manufacturing is another industry with relatively lower earnings volatility across the econometric specifications. Among women, Transportation/Utilities is the industry category with the lowest earnings volatility, all else equal.

3.8 Conclusion and Future Work

For men, the link between race and volatility exists among Other racial and ethnic minorities. The relationship between volatility and Black women is maintained in the fixed effects models with selection. In the baseline models, unemployment rate has a positive association with volatility among women and it appears weakly positive in one model accounting for cohort fixed effects. Meanwhile, men display a negative unemployment-volatility relationship. Per Celik et al. (2008), this may suggest a labor market strategy where, within a household, men maintain stable employment during relatively weaker economic times, whereas women may be responding to economic instability either voluntarily or involuntarily. One of the strongest, consistent findings is the negative link between earnings levels and volatility, so that higher earners could expect, on average, lower earnings volatility. Volatility elasticities evaluated at the sample means for volatility and earnings are approximately -0.5, so that a 1 percent increase in individual earnings leads to a -0.5 percent decline in earnings volatility. Industry covariates suggest that workers within the Government, Manufacturing, and Transportation/Utilities industries exhibit some of the lowest volatility levels across men and women. These results are sensitive to the inclusion of average earnings between columns 5 and 6 throughout tables 3.4-3.7.

Given the nature of this exercise, it is difficult to fully evaluate the causal mechanisms of exposure to earnings volatility. Still, the cohort design of the study allows me to uncover important implications. Compared with essay 2, where I find differences in family income and earnings volatility levels across education levels, and that the least educated bear the highest levels of earnings and income volatility, I look within cohorts separated by education level and 5-year birth intervals. In so doing, I find that significant differences in the predicted level of volatility emerge within these skill groups. Being non-White and having lower earnings are associated with higher earnings volatility, and local unemployment seems to matter differently for men and women once cohort fixed effects are considered. Also, the public sector industries are consistently linked to lower volatility for men and women.

A takeaway from this essay is the existence of differences in total volatility within education groups. Local economic conditions may matter, and minorities, persons working outside stable government industries, and lower earners may find themselves more likely to face earnings volatility. These differences in volatility exposure may then raise new questions about volatility's consequences, and suggest the possibility of inequality in its occurrence across the earnings distribution, race, industry, and local economic conditions. In Essay 4, I investigate what, if any, consequences result from exposure to income volatility during childhood.

Table 3.1 Summary Statistics by Education-Birth Year Cohort (2008 Dollars)

Variables	Mean	Standard Deviation
Individual Earnings ($)	37,801.59	11,870.20
% Change in Individual Earnings	2.55	7.10
SD(% Change in Individual Earnings)	71.67	29.33
Unemployment Rate	5.72	.47
Demographics Within Cohort		
% Female	48.60	4.15
% Less Than High School	13.40	34.06
% High School	35.33	47.80
% More Than High School	51.28	49.98
% White	87.78	2.45
% Black	7.97	2.23
% Other	4.24	1.28
Industry Shares Within Cohort		
Manufacturing	16.78	5.69
Construction	6.72	3.15
Services	40.74	12.67
Trade	14.15	4.22
Transportation/Utilities	6.89	2.22
Mining	0.78	0.39
Government	5.52	2.51
Agriculture (Omitted Category)	2.25	1.15
Miscellaneous Industry	8.34	7.73
Mean Observations Per Cohort	11,787.02	6,861.59

Table 3.2 Matched-CPS Sample Size by Education Birth-Year Cohort, 1980-2008

Cohort	Birth Year Interval	Education	Sample Size
1		Less High School	5,203
2	1987 – 1992	High School	1,188
3		Post High School	1,489
4		Less High School	6,355
5	1982 – 1986	High School	3,202
6		Post High School	5,259
7		Less High School	6,046
8	1977 – 1981	High School	5,577
9		Post High School	9,560
10		Less High School	7,999
11	1972 – 1976	High School	7,812
12		Post High School	14,375
13		Less High School	9,024
14	1967 – 1971	High School	13,949
15		Post High School	22,463
16		Less High School	12,068
17	1962 – 1966	High School	22,282
18		Post High School	28,971
19		Less High School	8,789
20	1957 – 1961	High School	29,250
21		Post High School	36,388
22		Less High School	8,488
23	1952 - 1956	High School	29,551
24		Post High School	40,287
25		Less High School	8,331
26	1947 - 1951	High School	25,172
27		Post High School	38,438
28		Less High School	7,839
29	1942 - 1956	High School	19,579
30		Post High School	23,993
31		Less High School	7,177
32	1937 - 1941	High School	13,826
33		Post High School	12,636
34		Less High School	6,575
35	1932 - 1936	High School	10,496
36		Post High School	7,679
37		Less High School	5,556
38	1927 - 1931	High School	6,779

Table 3.2 (Continued)

39		Post High School	4,489
40		Less High School	3,352
41	1922 - 1926	High School	3,492
42		Post High School	2,024
43		Less High School	443
44	Before 1921	High School	448
45		Post High School	255

Cohort sample size counts represent the total number of individual observations within 1 of 45 education birth-year cohorts over the period 1980-2008. Individuals must meet the criteria of education (less than high school, high school diploma, or post-high school) and 5 year year-of-birth interval to be assigned to 1 of 45 cohorts.

Table 3.3 Probit Labor Force Participation Selection Equation

LABOR FORCE DECISION	P(1,1) Continuous Workers	P(1,0) Labor Force Exit	P(0,1) Labor Force Entry
Black	-0.451***	0.213***	0.171***
	(0.008)	(0.012)	(0.012)
Other	-0.310***	0.115***	0.111***
	(0.011)	(0.017)	(0.016)
Female	-0.667***	0.364***	0.290***
	(0.005)	(0.008)	(0.008)
Unemployment Rate	-0.014***	0.013***	0.010***
	(0.001)	(0.002)	(0.002)
Non Labor Income	-0.041***	0.014***	0.026***
	(0.001)	(0.001)	(0.001)
AFDC-Food Stamp Benefit	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
EITC Max Benefit	-0.000***	-0.000*	0.000
	(0.000)	(0.000)	(0.000)
State Min Wage	0.020***	-0.021***	-0.053***
	(0.003)	(0.005)	(0.004)
Constant	1.373***	-2.057***	-1.949***
	(0.017)	(0.026)	(0.025)
Observations	301,276	301,276	301,276

Columns 1-3 represent first-stage probit regressions estimating the likelihood of continuous work (denoted P(1,1)), labor force exit (denoted P(1,0)), and labor force entry (denoted P(0,1)). As described in the essay, covariates are chosen that relate to the individual's reservation wage and theoretically predict their labor force entry, exit, or continuous work history.

Table 3.4 Determinants of Men's Cohort Earnings Volatility (w/o Selection), 1980-2008

SD(Arc Pct. Change)	(1) Base Model	(2) Base Model	(3) Cohort/Year Effects	(4) Cohort/Year Effects	(5) Cohort/Year Effects	(6) Cohort/Year Effects
Black	96.762***	-20.075	14.973	12.843	-12.535	-7.117
	(22.195)	(17.308)	(17.663)	(21.482)	(15.777)	(15.165)
Other	204.178***	107.660***	58.572**	77.357***	55.210**	47.644**
	(32.427)	(24.543)	(23.398)	(28.427)	(21.632)	(20.795)
Average Earnings		-0.104***	-0.150***			-0.075***
		(0.005)	(0.009)			(0.010)
Unemployment Rate	0.950	-0.609	-11.821***	-13.413***	-13.029***	-12.244***
	(0.914)	(0.685)	(3.485)	(4.237)	(3.027)	(2.908)
Manufacturing					-24.712*	-37.981***
					(12.823)	(12.449)
Construction					-21.315	-33.053**
					(16.268)	(15.703)
Service					-0.372	-15.806
					(17.220)	(16.671)
Trade					10.557	-14.852
					(17.823)	(17.474)
Transportation/Utilities					-4.217	-2.516
					(25.092)	(24.090)
Mining					-50.668	-55.350
					(52.538)	(50.443)
Government					-80.746**	7.094
					(34.748)	(35.539)
Miscellaneous Trade					130.992***	89.352***
					(14.349)	(14.950)

Table 3.4 (Continued)

Constant	49.815***	111.753***	193.859***	119.382***	106.454***	160.359***
	(5.641)	(4.988)	(20.402)	(23.889)	(21.890)	(22.320)
Observations	672	672	672	672	672	672
R-squared	0.0775	0.4877	0.6758	0.5197	0.7603	0.7795

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Selection equations estimate a first stage probit on a set of demographic and policy. Average earnings is transformed, multiplied by 100.

Table 3.5 Determinants of Women's Cohort Earnings Volatility (w/o Selection), 1980-2008

SD(Arc Pct. Change)	(1) Base Model	(2) Base Model	(3) Cohort/Year Effects	(4) Cohort/Year Effects	(5) Cohort/Year Effects	(6) Cohort/Year Effects
Black	58.552***	-18.664*	-7.531	-16.928	-15.276	-12.941
	(16.426)	(11.093)	(10.646)	(11.159)	(10.111)	(10.070)
Other	11.144	0.936	-57.705***	-66.448***	-62.738***	-59.673***
	(27.428)	(18.016)	(17.181)	(18.076)	(16.118)	(16.037)
Average Earnings		-0.195***	-0.110***			-0.047***
		(0.007)	(0.013)			(0.015)
Unemployment Rate	5.751***	0.365	5.938**	6.362**	3.230	3.502
	(0.847)	(0.585)	(2.398)	(2.527)	(2.260)	(2.246)
Manufacturing					-100.769***	-113.198***
					(37.955)	(37.909)
Construction					-2.654	-6.529
					(36.672)	(36.439)
Service					-91.249**	-103.873***
					(37.568)	(37.534)
Trade					-56.665	-75.222**
					(37.581)	(37.807)
Transportation/Utilities					-121.080***	-130.673***
					(45.298)	(45.092)
Mining					-213.532	-259.783
					(203.531)	(202.679)
Government					-91.877*	-70.933
					(48.149)	(48.299)

Table 3.5 (Continued)

Miscellaneous Trade					-17.597	-39.658
					(37.325)	(37.756)
Constant	53.218***	132.918***	98.900***	83.641***	136.019***	159.303***
	(5.323)	(4.398)	(24.553)	(24.912)	(45.188)	(45.512)
Observations	679	679	679	679	679	679
R-squared	0.0903	0.6083	0.7867	0.7626	0.8164	0.8192

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Selection equations estimate a first stage probit on a set of demographic and policy variables. Average earnings is transformed, multiplied by 100.

Table 3.6 Determinants of Men's Cohort Earnings Volatility, 1980-2008

SD(Arc Pct. Change)	(1) Base Model	(2) Base Model	(3) Cohort/Year Effects	(4) Cohort/Year Effects	(5) Cohort/Year Effects	(6) Cohort/Year Effects
Black	87.482***	-8.852	-12.541	-19.139	-19.244	-16.996
	(20.923)	(17.711)	(19.722)	(22.720)	(18.481)	(17.724)
Other	91.824***	41.084*	34.351	19.742	41.171*	37.735*
	(27.622)	(22.532)	(22.798)	(26.243)	(22.314)	(21.403)
Average Earnings		-0.082***	-0.126***			-0.077***
		(0.004)	(0.009)			(0.011)
Unemployment Rate	1.956	0.569	-11.973***	-10.937***	-11.956***	-11.848***
	(1.395)	(1.132)	(3.465)	(3.992)	(3.186)	(3.055)
Manufacturing					-28.288**	-45.636***
					(12.651)	(12.366)
Construction					-25.221	-38.759**
					(15.941)	(15.400)
Service					-0.763	-17.759
					(16.969)	(16.440)
Trade					-3.907	-29.905*
					(17.648)	(17.300)
Transportation/Utilities					-10.448	-13.002
					(24.569)	(23.562)
Mining					-52.125	-55.495
					(51.471)	(49.359)
Government					-83.025**	-8.731
					(34.878)	(34.986)
Miscellaneous Trade					111.364***	63.793***
					(14.999)	(15.813)

Table 3.6 (Continued)

Selection (1,1)	339.146***	307.164***	109.132*	389.467***	110.829**	45.713
	(48.345)	(39.185)	(59.735)	(64.854)	(55.089)	(53.586)
Selection (1,0)	273.558**	112.126	-31.735	65.109	-13.093	-28.956
	(121.097)	(98.439)	(126.883)	(145.995)	(117.477)	(112.672)
Selection (0,1)	-151.737***	-0.180	-40.524	41.304	28.236	-15.431
	(55.085)	(45.338)	(53.153)	(60.878)	(49.442)	(47.793)
Constant	-328.814*	-237.595	334.044	-138.256	60.797	228.600
	(192.796)	(156.194)	(221.578)	(249.050)	(202.290)	(194.629)
Observations	669	669	669	669	669	669
R-squared	0.3965	0.6049	0.7198	0.6273	0.7673	0.7864

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Selection equations estimate a first stage probit on a set of demographic and policy variables including non labor income and the maximum EITC benefit for adult workers with one dependent child. Average earnings is transformed, multiplied by 100. For men, the results are restricted to household heads.

Table 3.7 Determinants of Women's Cohort Earnings Volatility, 1980-2008

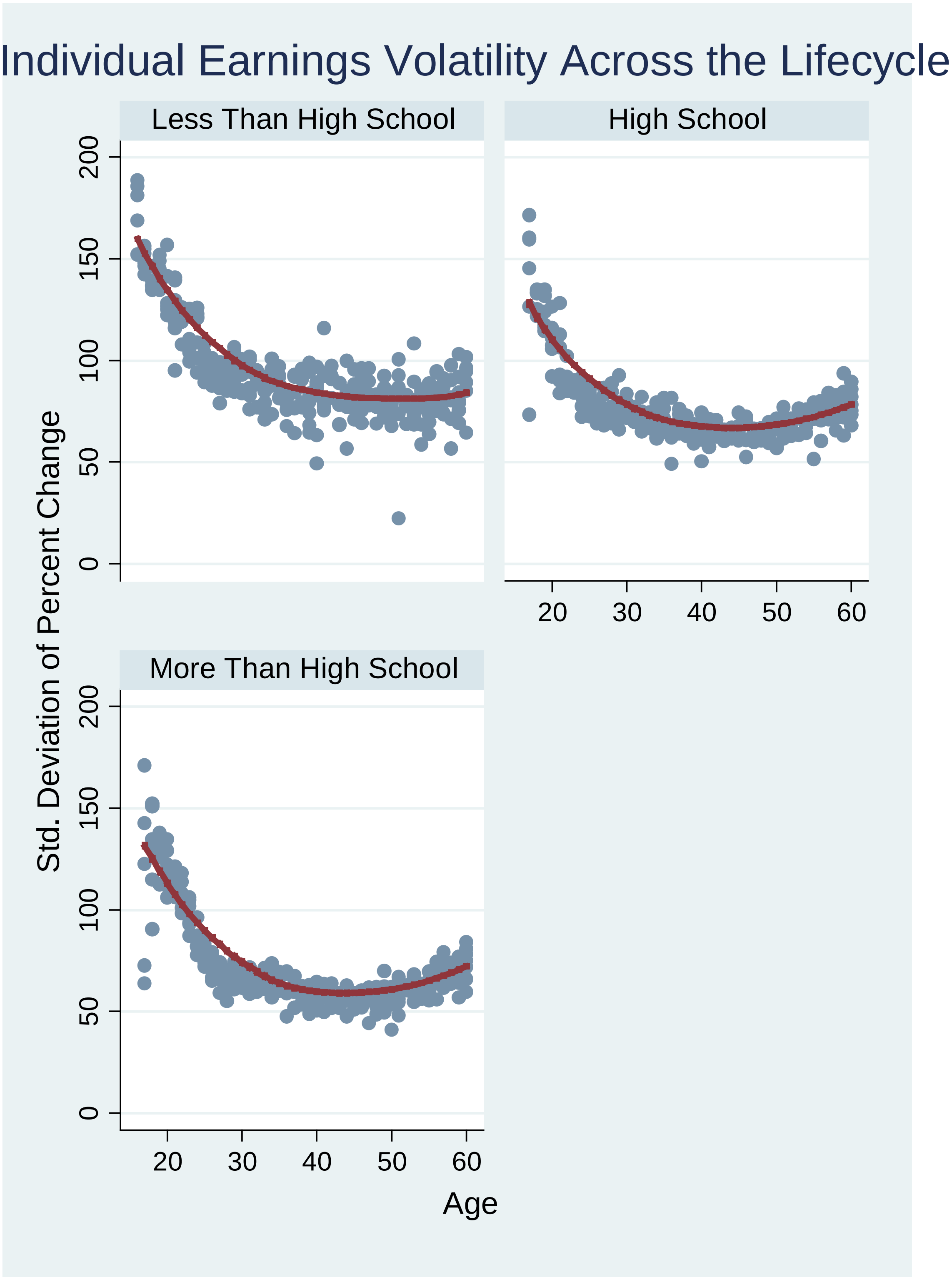
SD(Arc Pct. Change)	(1) Base Model	(2) Base Model	(3) Cohort/Year Effects	(4) Cohort/Year Effects	(5) Cohort/Year Effects	(6) Cohort/Year Effects
Black	75.625***	-11.029	-33.094***	-53.891***	-30.225**	-24.267**
	(19.999)	(13.450)	(12.713)	(13.242)	(12.252)	(12.061)
Other	-20.447	-31.675*	-66.944***	-86.331***	-61.656***	-54.903***
	(27.033)	(17.753)	(16.394)	(17.224)	(15.669)	(15.410)
Average Earnings		-0.194***	-0.117***			-0.074***
		(0.007)	(0.013)			(0.015)
Unemployment Rate	5.987***	2.897***	1.957	2.590	-0.462	-0.311
	(1.440)	(0.951)	(2.271)	(2.407)	(2.177)	(2.134)
Manufacturing					-91.416**	-110.807***
					(35.605)	(35.094)
Construction					-8.503	-12.594
					(34.443)	(33.756)
Service					-85.034**	-103.660***
					(35.379)	(34.858)
Trade					-50.176	-78.221**
					(35.398)	(35.120)
Transportation/Utilities					-116.134***	-134.327***
					(42.629)	(41.921)
Mining					-285.566	-362.194*
					(190.134)	(186.903)
Government					-100.678**	-71.022
					(45.062)	(44.537)
Miscellaneous Trade					-9.991	-41.543
					(35.335)	(35.175)

Table 3.7 (Continued)

Selection (1,1)	45.877	143.614***	35.008	139.190***	-54.492	-78.819*
	(43.550)	(28.782)	(42.714)	(43.488)	(42.663)	(42.075)
Selection (1,0)	230.044*	281.157***	-102.930	-65.954	-148.707	-156.205
	(134.309)	(88.200)	(103.515)	(109.678)	(100.175)	(98.162)
Selection (0,1)	-187.893***	-80.698**	85.970**	148.550***	47.008	28.880
	(57.378)	(37.845)	(37.070)	(38.566)	(35.898)	(35.354)
Constant	-59.564	-358.456***	165.035	-194.556	381.017**	529.200***
	(196.697)	(129.536)	(176.707)	(187.193)	(176.223)	(170.617)
Observations	677	677	677	677	677	677
R-squared	0.1990	0.6552	0.8205	0.7978	0.8403	0.8469

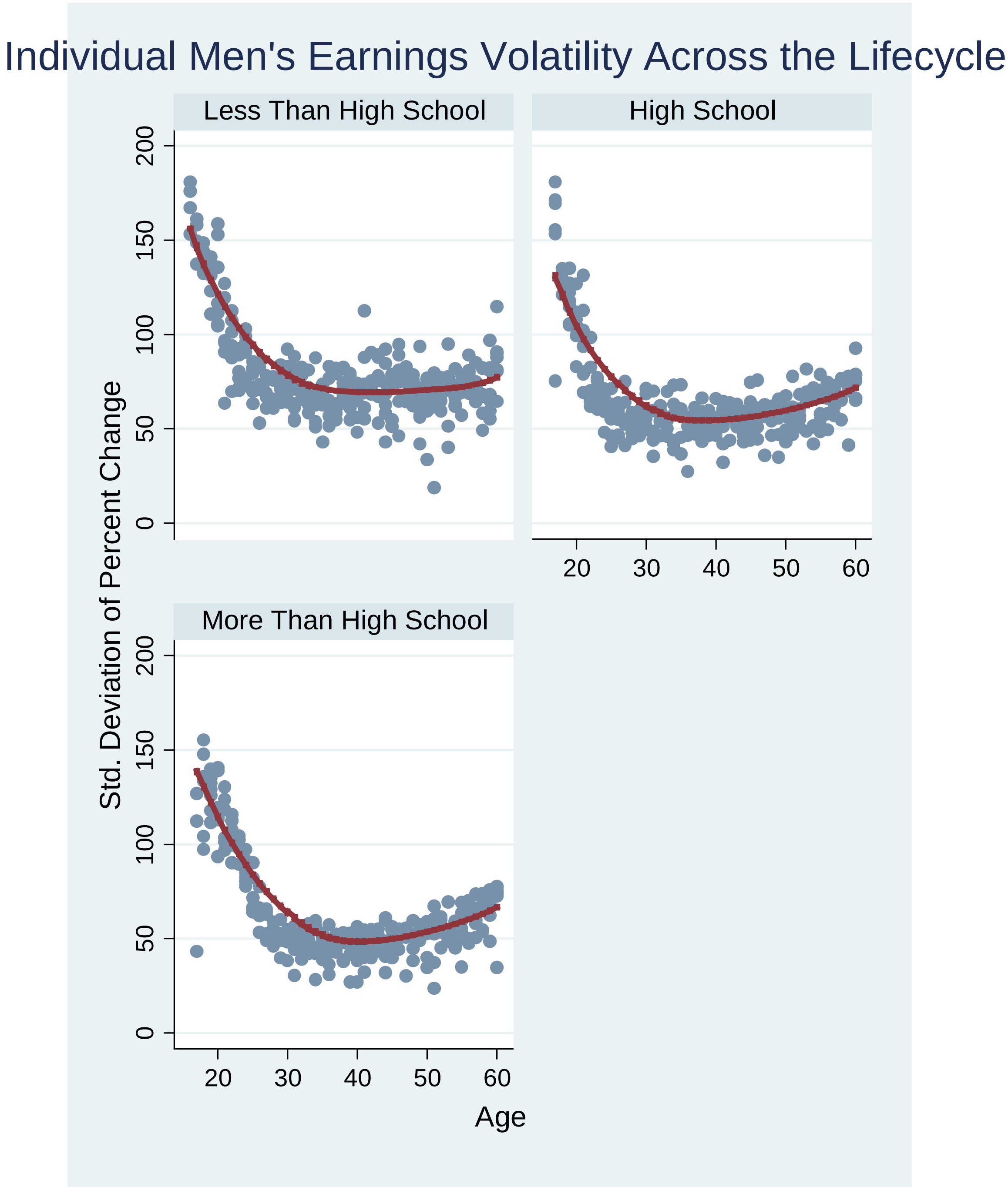
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Selection equations estimate a first stage probit on a set of demographic and policy variables including non labor income and the maximum EITC benefit for adult workers with one dependent child. Average earnings is transformed, multiplied by 100. For women, the regressions are not restricted to household heads.

FIGURE 3.1



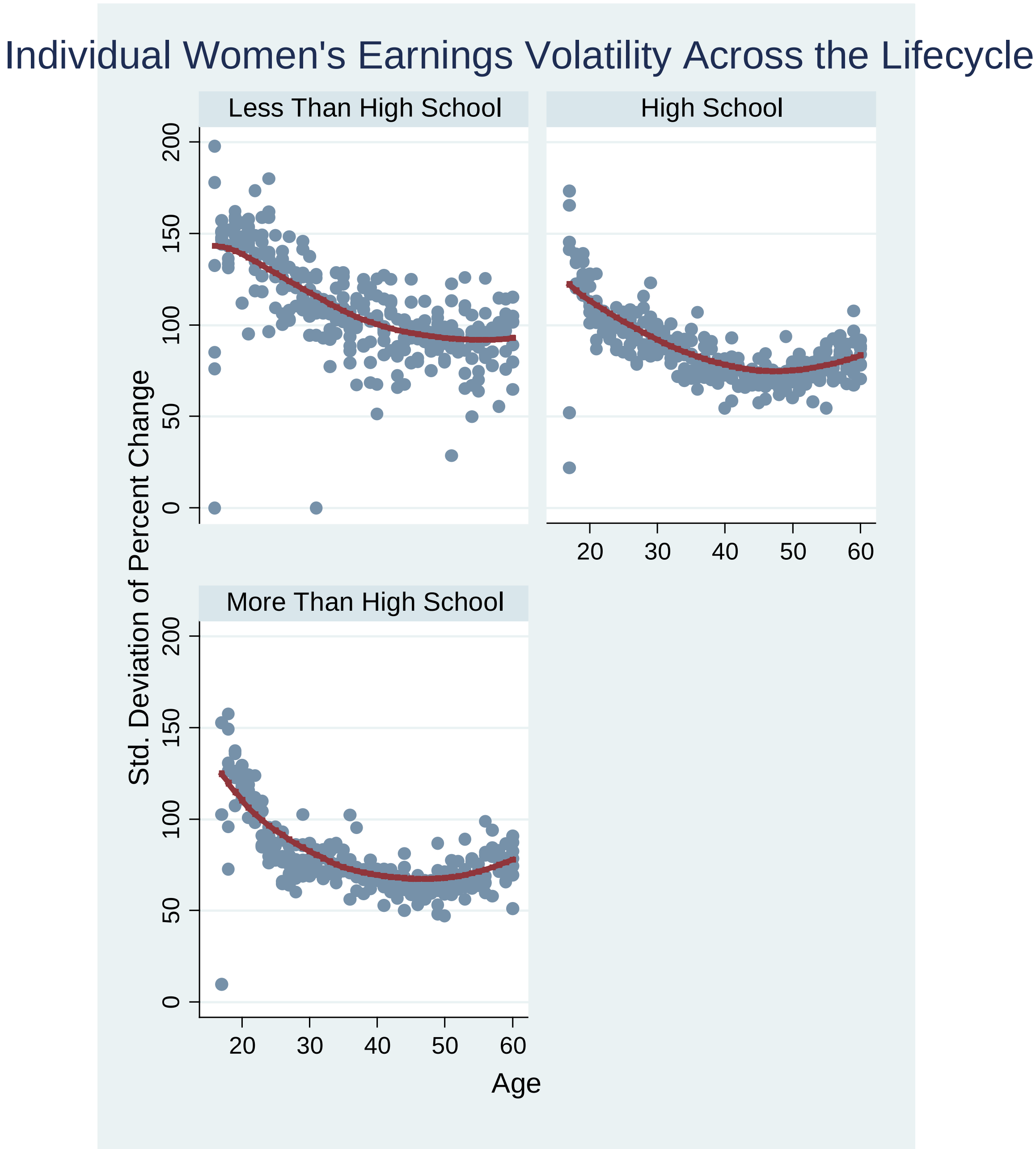
Individual Earnings Volatility Across the Lifecycle
Less Than High School
High School
More Than High School
Std. Deviation of Percent Change
0
50
100
150
200
20
30
40
50
60
Age

FIGURE 3.2



Individual Men's Earnings Volatility Across the Lifecycle
Less Than High School
High School
More Than High School
Std. Deviation of Percent Change
0
50
100
150
200
20
30
40
50
60
Age

FIGURE 3.3


Individual Women's Earnings Volatility Across the Lifecycle
Less Than High School
High School
More Than High School
Std. Deviation of Percent Change
0
50
100
150
200
20
30
40
50
60
Age

4 CHILDHOOD INCOME VOLATILITY AND ADULT OUTCOMES

4.1 Introduction

Income volatility in the United States has been on the rise since the 1970's, increasing by at least one-third (Gottschalk and Moffitt 1994; Keys 2008; Dynan et al. 2008; essay 2). Driven largely by earnings, it exhibits cyclical behavior (Dahl, Schwabish, and DeLeire 2008) and is attributed to both short-term economic shocks and permanent structural change throughout the economy (Gottschalk and Moffitt 2009). Several studies focus on specific examples of volatility, finding that health shocks, workplace injury, divorce, plant closings, and job loss can have long term effects on adults (Currie et al. 2010; Woock 2009; Eliason and Storrie 2007; Charles and Stephens 2002; Huff Stevens 1997). For children, it is unclear whether membership in families with volatile incomes has any long term effect. While the literature does confirm that growing up in poverty is associated with lower education, earnings, and cognitive ability (Duncan and Brooks-Gunn 2000; Duncan et al. 2008; Dahl and Lochner 2005), we do not know if growing up in households with unstable incomes per se warrants concern.

Research examining the long term effects of volatility is lacking. Most volatility research has, up to this point, focused on trends, statistical measurement, and the implications such measures have when interpreting changes in income inequality in the United States. Although the literature relating income to long term outcomes and mobility mainly focuses on measured levels, not volatility, these studies help explain income's socioeconomic correlates. Studies identify a connection between early childhood poverty, and both lowered earnings and receipt of public assistance as an adult (Duncan, Kalil, and Ziol-Guest 2008). One channel enabling such relationships across generations may be human capital (Becker and Tomes 1979; Lillard and Willis 1994; Blau 1999; Ludwig and Miller 2007). This essay draws motivation from a model of mobility where parental income determines human capital for children in the household, which then largely determines the children's adult earnings, income, and well-being (Becker and Tomes 1979). Work on early human capital formation describes how initial skills are necessary to acquire additional skills in the future (Cuhna, Heckman, Lochner, and Masterov 2005), and modest, positive associations exist between income and educational attainment (Duncan et al. 2008), and performance on math and reading assessments (Dahl and Lochner 2005). Such skill deficits may drive findings in studies estimating intergenerational relationships.

In this essay I examine the long-term consequences of income volatility during childhood on subsequent adult outcomes. There has been extensive evidence on intergenerational economic mobility in earnings, income, education, and wealth (Becker and Tomes 1979; Mazumder 2005; Solon 1992; Zimmerman 1992; Meghir and Palme 2005; Black et al. 2005; Charles and Hurst 2003). The mobility model adopted here augments the standard intergenerational income elasticity (IGE) model to include income volatility. One mechanism that gives rise to the intergenerational transmission of volatility in the standard Becker and Tomes (1979) framework is imperfect capital markets (Loury 1981; Mazumder 2005). In this context imperfect capital markets imply that income shocks can persist. By accounting for the long term effect of shocks to income during childhood, this paper addresses a missing component in the literature on the transmission of mobility.

To empirically implement the model I link families in the Panel Study of Income Dynamics (PSID) across generations. Income volatility during childhood is defined as the volatility of family income from labor market earnings, total taxable non-labor income, and government transfers between ages 0 and 16. For each person, volatility is calculated by decomposing total volatility into its permanent and transitory components (Gottschalk and Moffitt 1994; 2009). Volatility enters the model both separately and interacted with income level.

The adult outcomes I examine include income level, educational attainment, and health for children growing up in households with higher income volatility. Adult income is measured at age 25 and beyond, educational attainment is measured as whether the person completes post high school education, and health status is measured by whether adult participants consider themselves to be in poor health. To capture the experiences of adults near the age thresholds of 25, 30, and 40, linear dependent variable models examine outcomes at age groups 24-26, 29-31, and 39-41 respectively. The OLS classical errors-in-variables assumption is violated in the income IGE models, as families with higher lifetime mean income typically experience relatively higher rates of income growth over the lifecycle. This leads to intergenerational estimates that are too low if second generation income is recorded while primary earners are in early adulthood and too high as workers approach older age. To address this, the income IGE models account for lifecycle earnings growth and adopt specifications found to minimize left-side measurement error in second generation incomes (Haider and Solon 2006; Lee and Solon 2007).

I find that on average higher income volatility exposure during childhood is associated with lower adult income and lower educational attainment. For education, the magnitudes of these associations are generally small. The sample families predominantly experience positive income change between years, and I control for lifecycle growth in family incomes to address this concern. I then test the relationship of several volatility measures to adult outcomes. Finally, I instrument for potentially endogenous family income volatility exposure during childhood.

4.2 Literature

4.2.1 Intergenerational transmission and mobility

While relatively little work exists on the intergenerational aspects of volatility, the inheritability of economic status is well documented in the literature on intergenerational transmission (Solon 1992; Zimmermann 1992; Charles and Hurst 2003). In these models, IGE's are summary measures of the relationship between income, earnings, or wealth across generations and, by design, known causal factors are omitted in the regressions. An IGE of 1 denotes no mobility across generations and a value of 0 denotes perfect mobility. Becker and Tomes (1986) find an intergenerational elasticity of 0.2 for the United States using single year measures of fathers' income and earnings, providing initial evidence of a highly mobile society. Recent work estimating IGE's has generally overturned this finding by accounting for lifecycle effects and measurement error using longer measures of permanent earnings or incomes, with IGE estimates ranging between 0.4 and 0.6 (Solon 1992; Zimmerman 1992; Mazumder 2005; Gouskova et al. 2010).

Shore (2010) presents rare evidence that volatility is passed across generations. He models the intergenerational transmission of risk, using income volatility as a proxy for riskiness. Children of parents with higher income volatility will experience higher permanent income volatility as adults, and channels for transmitting volatility include education and self employment of parents. Income volatility is found to reduce inequality and promote mobility, weakening the relationship between parental and child income. I replicate this finding in baseline estimates of volatility, which pool instability from both positive and negative income changes.

Prior to Shore (2010) income shocks have typically been described as a measurement problem to overcome in explaining permanent income (Duncan 1988; Blau 1999) or assumed to be mean zero over time (Becker and Tomes 1979). Thus the introduction of volatility as an explanatory variable in mobility models is rare up to this point. The volatility literature has documented trends in instability, or volatility, over the past 40 years with a focus on the United States. Gottschalk and Moffitt's (1994) work in the area established the method of applying permanent income decompositions to volatility studies. In their seminal piece, they introduce permanent and transitory earnings volatility as underlying explanations for observed wage gaps of the 1970's and 1980's. They find that transitory volatility explains between one-third and one-half of the increase in overall earnings variability over this time period, underscoring the importance of accounting for economic risk in the discourse on rising income and earnings inequality. Many recent analyses documenting historical trends conclude that income and earnings volatility rose over the past 30 to 40 years (Dynan, Elmendorf, Sichel 2008; essay 2). This increasing trend occurs across race and education groups since the 1970's, though groups with fewer skills and lower earnings exhibit higher levels (Gottschalk and Moffitt 1994; Keys 2008; essay 3). If family income volatility during childhood has an intergenerational effect, the adult outcomes of children from the 1970's and 1980's, who faced relatively high volatility during childhood, would reflect this (Gottschalk and Moffitt 2009).

4.2.2 Instability

Like intergenerational elasticities, volatility is a summary measure. It captures events that add and take away income. Parents may maximize utility to the benefit of their children, but downward economic instability may threaten this effort. A variety of event studies have documented specific examples of volatility or instability. This work attempts to explain the role of job loss and income shocks in predicting earnings (Oreopolous, Page, and Huff Stevens 2005), health (Ruhm 2003; Eliason and Storrie 2007), marriage, and divorce (Mayer 1997; Eliason 2004; Charles and Stephens 2002; Conger et al. 1990; Hankins and Hoekstra 2010). The conclusions from these studies are mixed, due in part to methodological differences in modeling exogenous relationships (Mayer 1997).

When considering how volatility and labor market instability are related, the differences between permanent and transitory income volatility should be highlighted. Permanent income volatility is likely the result of differences in skills and the return for skills within the economy, and transitory income volatility is associated with risk and shocks (Gottschalk and Moffitt 2009). This risk may be voluntary or involuntary, and it can reflect a variety of decisions and events within the household, such as bonuses for performance or household employment risk within the labor market (Gottschalk and Moffitt 2009). Recent evidence estimates a link between transitory income volatility and divorce (Nunley and Seals 2010). Facing income volatility from a variety of underlying sources, investment in children's human capital may change and preferences between consumption and investment may also change (Attanasio and Meyer 2010). If volatility causes parents to reduce human capital investment, it can harm children. However, it is equally possible that volatility reflects income growth, so that the variation of income within a family represents a wider set of investment possibilities for children.

4.3 A Model of Mobility with Volatility

The basic framework of the intergenerational mobility model is a log-linear regression of adult offspring income on the income level of the working-age parent(s):

(1) $$y_{it}^{child} = \alpha + \beta y_{i,t-1}^{parent} + \varepsilon,$$

where y_{it}^{child} represents adult offspring income in period *t* and $y_{i,t-1}^{parent}$ is the income of the working-age parent(s) in period *t-1*. Thus, β denotes the intergenerational income elasticity and is a summary measure of the relationship between incomes across generations, measured with mean zero error ε (Solon 1992; Zimmerman 1992). Causal parameters are not directly recovered in this framework, but the theory of human capital investment and mobility, described below and in the appendix on intergenerational mobility, underscores the potential influence of parental income and investment in offspring human capital towards determining β (Becker and Tomes 1979; Solon 1999, 2004). The resulting empirical studies provide a straightforward description of the degree to which American families move up or down the continuum of economic status over time.

The theory of intergenerational mobility assumes that transitory income volatility has no role in predicting income mobility. This is supported largely by the permanent income hypothesis, which predicts households borrow against transitory negative income shocks by accessing perfectly functioning capital markets while saving positive income shocks. There are, however, reasons to expect that transitory volatility does transmit across generations. Constant relative risk aversion utility models of family consumption and saving accounting for prudence (i.e. precautionary savings) by decision makers underscore the role of income variances in determining optimal choices. In these models, rising variability of income affects consumption, human capital investment, and utility (Attanasio and Weber 2010). Thus, previous intergenerational models relying on the permanent income hypothesis to justify omitting higher income moments exclude an important component of the family's utility maximization process. Statistically, transitory shocks persist over several years (Hyslop 2001), and both permanent and transitory shocks contribute substantially to measured inequality (Gottschalk and Moffitt 1994). As mentioned previously, the timing of these shocks, possibly during early human capital formation, means that some children will be exposed to shocks at stages of child development where the acquisition of basic skills occurs (Cuhna et al. 2005). These skills allow for the acquisition of more complex skills later in childhood and into adulthood, which may largely determine labor market income and earnings.

Imperfections in capital markets (Loury 1981; Becker and Tomes 1986; Mazumder 2005) may constrain access to loanable funds and constitute a final reason motivating the inclusion of transitory income shocks in an intergenerational model. Such loans would insure against unanticipated shocks that threaten human capital investment in children. Imperfections of several kinds may arise in this market, as future ability or income of the child investment is noisy to predict, but necessary to justify investment. If collateralized through a child borrower, a loan for human capital investment amounts to indentured servitude and cannot legally or realistically occur (Becker and Tomes 1986; Kane and Ellwood 2000). In a study on permanent income and the Black-White test score gap, Rothstein and Wozny (2010) also describe human capital investment decisions of parents as a function of permanent income, explicitly assuming the absence of credit constraints or any uncertainty. They note, as do I, that violations of this assumption would impact these human capital investment decisions.

I adapt the theoretical model of mobility to include a decomposed definition of total income $y_{i,t-1}$, so that transitory and permanent shocks from volatility eventually enter and influence the family's utility maximization problem.

(2) $$y_{i,t-1} = \mu_{i,t-1} + v_{i,t-1},$$

$\mu_{i,t-1}$ represents permanent income and $v_{i,t-1}$ represents transitory income. The family maximizes utility over current consumption and investment in future generations. Permanent income $\mu_{i,t-1}$ and transitory income $\mathrm{v}_{\mathrm{i,t-1}}$ enter the family budget constraint, where income is spent on consumption $\mathrm{C}_{\mathrm{i,t-1}}$ and investment in child human capital $\mathrm{I}_{\mathrm{i,t-1}}$. This is shown by substituting the decomposition in (2) for income in the intergenerational model (Solon 2004):

(3) $$y_{i,t-1} = \mu_{i,t-1} + v_{i,t-1} = \mathrm{C}_{\mathrm{i,t-1}} + \mathrm{I}_{\mathrm{i,t-1}}.$$

Solving for permanent income, $\mu_{i,t-1}$:

(4) $$\mu_{i,t-1} = \mathrm{C}_{\mathrm{i,t-1}} + \mathrm{I}_{\mathrm{i,t-1}} - v_{i,t-1}.$$

The productivity of parental investment in human capital is determined as follows:

(5) $$\mathrm{h}_{\mathrm{i,t-1}} = \theta\log\left(\mathrm{I}_{\mathrm{i,t-1}} + \mathrm{G}_{\mathrm{i,t-1}}\right) + \alpha\mathrm{e}_{\mathrm{it}} + \alpha\mathrm{u}_{\mathrm{t}}.$$

This production function $\mathrm{h}_{\mathrm{i,t-1}}$ for human capital accumulation includes parental investments and government investment. θ denotes positive marginal productivity of human capital investment. As described in the Appendix, the determinants of lifetime income include a set of innate and environmental factors e_t beyond human capital investment that are fixed and endogenous in estimates of the IGE. Human capital production, determined largely by parental investments, has consequences for determining income of children in adulthood, y_{it}:

(6) $log y_{it} = \delta_i + \rho h_{i,t-1}$.

ρ reflects the income return on human capital. Introducing a basic Cobb-Douglass utility function with preferences α, family decision makers

(7) $\max_{C_{t-1}, y_t} U = (1-\alpha) log C_{t-1} + \alpha log y_t$,

and, substituting for current period consumption *t-1* and adult income of the next generation *t*, family utility takes the following form:

(8) $U_i = (1-\alpha)\log\left[\mu_{i,t-1} - I_{i,t-1} + v_{i,t-1}\right] + \alpha\delta_i + \alpha\theta\rho\log\left[I_{i,t-1} + G_{i,t-1}\right] + \alpha\rho e_{it}$.

This is, again, an adaptation of Solon (2004) with a decomposed definition of income. Economic shocks to family income may equally reflect a variety of events, including raises, bonuses, changes in family structure, or job loss. Accordingly, the implications for family utility are not straightforward. Maximizing utility, families invest in children during period *t-1*:

(9) $\frac{\partial U_i}{\partial I_{i,t-1}} = -(1-\alpha)/[y_{i,t-1} - I_{i,t-1} + v_{i,t-1}] + \alpha\theta\rho/[I_{i,t-1} + G_{i,t-1}] = 0$.

In some instances, families may choose to invest zero resources, finding instead that the level of public investment in children G is sufficient. (9) reflects an interior solution, where public resources do not satisfy parents. Solving for the optimal amount of investment I^*:

(10) $\mathrm{I}^* = (\frac{1}{(1-\alpha)+\alpha\theta\rho})[\mu_{i,t-1}\alpha\theta\rho - G_{i,t-1}(1-\alpha) + v_{i,t-1}\alpha\theta\rho].$

The variance of investments, I*, reflects how different degrees of transitory income volatility $\mathrm{var}(v_{i,t-1})$, permanent volatility $\mathrm{var}(\mu_{i,t-1})$, and total volatility $\mathrm{var}(y_{i,t-1})$ relate to variation of human capital investment in future generations. This model demonstrates that the investment choices of parents can vary according to the variation in both permanent and transitory income:

(11) $\mathrm{var}(\mathrm{I}^*) = \left(\frac{1}{(1-\alpha)+\alpha\theta\rho}\right)^2 \{[(\alpha\theta\rho)^2\mathrm{var}(\mu_{i,t-1}) + (1-\alpha)^2\mathrm{var}(G_{i,t-1}) +$

$(\alpha\theta\rho)^2\mathrm{var}(v_{i,t-1})] + 2(\alpha\theta\rho)(1-\alpha)\mathrm{cov}(\mu_{i,t-1}, G_{i,t-1}) -$

$2(\alpha\theta\rho)(1-\alpha)\mathrm{cov}(v_{i,t-1}, G_{i,t-1}) + 2(\alpha\theta\rho)^2\mathrm{cov}(\mu_{i,t-1}, v_{i,t-1})\}$

I approximate the magnitude of shocks to income using a measure of transitory income volatility, $var(v_{i,t-1})$, introduced by Gottschalk and Moffitt (1994). Like total income or earnings, I decompose income volatility into its permanent and transitory components (Gottschalk and Moffitt 1994):

(12) $\mathrm{var}(y_{i,t-1}) = \mathrm{var}(\mu_{i,t-1}) + \mathrm{var}(v_{i,t-1}).$

The permanent and transitory components are assumed to be additive and independent. Transitory income volatility is then measured as the sum of squared deviations around a family specific mean of log income, shown in equation (13) below:

(13) $\mathrm{var}(v_{i,t-1}) = \sigma_{v_i}^2 = (\frac{1}{T_i-1})\sum_{t=1}^{T_i}(y_{it} - \bar{y}_i)^2,$

where $\bar{y}_i$ is the person-specific mean income over a specified time period T_i during childhood. Permanent volatility is defined as between-person income variation

(14) $\mathrm{var}(\mu_{i,t-1}) = \sigma_{\mu}^2 = \left(\frac{1}{N-1}\right)\sum_{t=1}^{T_i}(y_i - \bar{y})^2 - (\frac{\sigma_{\bar{v}}^2}{\bar{T}}).$

Finally, from the left-hand side of equation (12), I re-introduce a measure of total income volatility, var($y_{i,t-1}$), from essays 2 and 3. This measure combines transitory and permanent volatility components in (13) and (14) and has the properties and advantages described in greater detail in the first two essays. To restate from essays 2 and 3, total volatility is defined as

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

where y_{it} is income for person or family i in time t.

The solution in equation (11) yields several predictions. From the independence assumption stated in (12), the last term on the right hand side of (11) is canceled out. Consistent with Attanasio and Weber (2010), a higher variance of permanent income or transitory income, all else equal, is associated with higher variances of investment in child human capital. A high variance of government spending on human capital raises the variance of family investment in human capital. Highly altruistic families' contributions to human capital are more volatile given levels of permanent volatility, $\mathrm{var}(\mu_{i,t-1})$, or transitory volatility, $\mathrm{var}(v_{i,t-1})$. Higher levels of θρ, the overall market return to human capital, are positively associated with the magnitude of permanent and transitory income shocks. Because $v_{i,t-1}$ shocks to income can be positive or negative, the implications for human capital and adult well-being are ambiguous, but the model confirms that transitory and permanent volatility could both have a non-zero intergenerational impact through human capital investment and formation. By definition, these implications carry over to total volatility, the sum of permanent and transitory volatility.

(16) $$\mathrm{cov}(\mu_{i,t-1}, G_{i,t-1}) \neq \mathrm{cov}(v_{i,t-1}, G_{i,t-1}) \neq \mathrm{cov}(\mu_{i,t-1}, v_{i,t-1}) \neq 0.$$

(16) acknowledges many of the public human capital investments $G_{i,t-1}$ received by children are means-tested benefits based on the permanent $\mu_{i,t-1}$ and transitory $v_{i,t-1}$ income levels of the family (examples include subsidized food programs, Head Start, and targeted interventions for children deemed to be at-risk for low achievement). Also, transitory income may be related to the level of permanent income. For now, it is established that such effects are theoretically non-zero. When evaluating the potential welfare consequences of volatility, it is important to note the existence of public safety net programs acting as an insurance mechanism. These programs potentially impact individual decision-making and consumption habits and therefore complicate identification of a true exogenous volatility effect.

The optimizing decisions of parents with respect to their own consumption and human capital investment into offspring represent structural parameters underlying the reduced-form empirical mobility model specification as described in (1). The preceding framework shows that these parameters include a decomposed definition of family income that recognizes the role of transitory income fluctuations in determining adult outcomes. The reduced-form intergenerational mobility model in equation (1) is therefore augmented to include income volatility from the structural representation, $V_{i,t-1}^{parent}$:

(17) $y_{it}^{child} = \alpha + \beta y_{i,t-1}^{parent} + \gamma V_{i,t-1}^{parent} + \varepsilon.$

Moving forward, equation (17) is the basic augmented intergenerational elasticity model estimated throughout the paper. The addition of income volatility to the intergenerational mobility model shows that volatility has an intergenerational relationship to income and well-being. Thus, γ is assumed to be non-zero. Through the mechanism of human capital investment, volatility is theoretically associated with higher overall volatility of human capital investment, which supports the inclusion of higher income moments empirically.

Estimating the intergenerational role of transitory income volatility amounts to testing, indirectly, how volatile or unstable incomes correlate with human capital investment, and the subsequent relationship to observable adult outcomes. As stated in Becker and Tomes (1979), substituting measures of offspring quality or welfare for adult income in the utility function yields similar theoretical results for income distributions and inequality. This lends support to the inclusion of education and health outcomes in the analysis – lifetime quality measures which, along with income, parents plausibly seek to maximize in their children.

4.4 Empirical Model: Testing the Association between Volatility and Adult Outcomes

In my empirical model, holding the level of family income during childhood constant, I estimate the relationship between family income volatility during childhood V_i and a set of adult outcomes O_{iy}. For each adult individual *i*, I estimate regressions to determine if shocks are transmitted across generations:

(18) $$O_{iy} = \alpha + \beta\overline{I_{0-16_i}} + \gamma V_{0-16_i} + \mathbf{X}\delta + \varepsilon_i.$$

When outcome O_{iy} is adult offspring income, equation (18) yields the income IGE for offspring aged 25 and older. It is the canonical intergenerational elasticity model (Solon 1992; Lee and Solon 2007; Grawe 2006; Mazumder 2005; Gouskova, Chiteji, and Stafford 2010) estimated via OLS with controls for income volatility during childhood years 0-16. Non-income outcomes O_{iy} for high school dropout, post high school educational attainment, health status, and non-marital child bearing are tested in (18) using an OLS binary linear probability model. I also present results tabulated in appendix regression tables using an alternative specification substituting parental education for permanent family income during childhood. During childhood years 0-16, mean family income $\overline{I_{0-16_i}}$ is an approximation for permanent income. Family income is defined as the income, earnings, and transfers received in person i's household. To account for potential non linearities in mean income and income volatility, I use a logarithmic transformation of family income. Non-income outcomes are estimated over three age groups *y*: 24-26, 29-31, and 39-41 year olds. These groups are selected to approximate smoothed results for 25, 30, and 40 year old adults.

The separability of income and volatility is tested via interactions of the two variables. A vector of demographic **X**'s includes age A_i and race of parent, gender of offspring, education of parents, and the number of offspring. Education is a 0/1 variable equal to one if either parent attends college for four or more years. Age of the household head, A_i, most often the father, is averaged over the observed childhood years of the offspring. Properly accounting for life-cycle earnings profiles is important, as both earnings and income are known to follow a concave growth profile over prime age working years (Weiss 1986). In the volatility literature, life-cycle effects are often accounted for by replacing income with residuals from a regression of income on an age quartic (Gundersen and Ziliak 2008). For intergenerational studies, such effects are modeled with an age quartic within the set of explanatory variables. For estimates of permanent and transitory volatility, I combine both approaches, using an age quartic of household head's average age A_i in the set of demographic variables while estimating volatility using residuals purging lifecycle effects. For total volatility, I elect to follow the intergenerational literature and rely on the age quartic controls to pick up lifecycle effects. In a series of robustness checks using the Current Population Survey, I find that the total volatility measure is not sensitive to lifecycle controls. Income IGE models also include an age quartic for offspring age interacted with mean family income during childhood. Intergenerational estimates are tabulated when all child volatility years V_i are available, requiring at least one observation across three defined child volatility developmental stages: ages 0-5, 6-10, and 11-16.

The estimation of intergenerational models, where the same individuals are followed over time, produces positive autocorrelation of the individual specific error terms over the panel. At the same time, the errors likely have unequal variances, violating the OLS assumption of identical, independently distributed errors. This implies the OLS standard errors are no longer consistent. To address this, the estimates are corrected for heteroscedasticity using Huber-White corrected standard errors, and they are clustered on a unique identifier for each child observation to account for autocorrelation.

4.5 Measurement and Data

The PSID is a longitudinal survey that began in 1968 and has continued to be administered at the University of Michigan. It consists of two independent samples, the Survey Research Center (SRC) sample and the Survey of Economic Opportunity (SEO) sample. Due to challenges in the SEO survey design, this essay uses the SRC sample of the PSID (Shin and Solon 2009). The PSID collects detailed economic, social, and demographic information on 1968 participant families and their descendants. Over time, offspring of the families are followed as they age and begin their own families. The PSID spans multiple generations between 1968 and 2007. It started with 4,800 families and is estimated to have reached over 7,000 families by 2001. As of 2003, the PSID collected information on over 65,000 individuals spanning as much as 36 years (Institute for Social Research 2006). Major changes in the collection of the PSID throughout the 1990's include a switch to biennial interviews in 1997 and a doubling in the length of interviews between 1995 and 1999 (Gouskova, Andreski, and Schoeni 2010).

To construct the intergenerational sample, I use the Family Identification and Mapping System from the PSID, which links parents and offspring. Unique individual identifiers and yearly family interview numbers, along with demographic variables for age and marital status, indicate when offspring leave their childhood family units. The main income measure, family money income, can be tracked for offspring over the lifecycle. Individuals are observed as dependent children within families, though most of the information collected applies to adults. As subjects enter adulthood they participate in the PSID survey. The resulting panel is unbalanced since, depending on the age of the subject, there are a range of data on adult income and earnings.

The data file I construct is a sample of 2,186 unique offspring. The final file size ranges between approximately 1,200 and 1,400 unique adult offspring observations for 24-26 year olds and under 1,000 adult offspring observations for 29-31 and 39-41 year olds. This depends on cell sizes for dependent and independent variables. Sample sizes for each intergenerational outcome are reported in the regression tables. For regressions on the likelihood of adult poor health status, there are insufficient degrees of freedom to estimate results for 40 year olds. Several factors contribute to this limitation. First, in this sample, the average adult child above 25 is 33 years old. Next, self-reported health status is collected in 1986 and 1988 onward, leaving fewer observations compared to data starting from the 1970's. In results for the likelihood of non marital child bearing, the tabulation of female-only regressions reduces the sample by one-half, resulting in insufficient power to estimate these results for 39-41 year olds as well.

Family money income, the main income measure used, is a summary measure of earnings and income for all members of the family. As described earlier, it is the summation of total taxable income, non-taxable transfer income, and social security income for the head (husband), wife, and other members of the family. Families, as defined by the PSID, include cohabitating adults and single individuals living alone in a distinct household. When the mother and father are both present, fathers are automatically assigned head status. The PSID assigns a family income value for all persons in a family based on the family interview number. As such, I have family income for mothers, fathers, heads of household, and offspring. Topcoding rules for family income change throughout the survey. Before 1979, the topcode value of income was $99,999, by 1980 it is $999,999, and in 1981 it increases to $9,999,999. During 1968-1993, family income was bottom coded at $1, but after 1994 the definition allows for negative family income of -$999,999 from business or farm losses. As with previous work on income volatility and dynamics, I address changes in the collection of PSID income and earnings data by imposing a consistent topcoding and bottomcoding strategy. The top 1 percent of family income (Shin and Solon 2009) is excluded, and I assign a value of $1 to family incomes of zero and below (Dynan et al. 2008).

For income elasticity models in (18) the offspring's age equals year minus birth year minus 40, *y-b-40*. It is then normalized so that offspring age equals zero at age 40. This has the useful feature of simplifying the interpretation of intergenerational elasticities at age 40, where several recent studies recommend evaluating the IGE to minimize bias in estimates of permanent income (Haider and Solon 2006; Lee and Solon 2007).

4.6 Summary Statistics and Volatility Trends

Table 4.1 provides summary statistics for the intergenerational data sample. Average parental family income (in 2006 dollars) is approximately $67,000. Summary statistics for volatility, education, gender, age, and race are also included in Table 4.1. Upon comparing my sample volatility statistics to those of from other studies, I observe a 24 to 30 percent rise in volatility between 1972 and 2007 (Figure 4.1), similar to the nearly 25 percent increase in Dynan et al. (2008) and 38 percent increase in essay 2 over a similar time frame. The trend increase for offspring volatility (Figure 4.1, panel 1) is lower than that for heads (Figure 4.1, panel 2), though the level of volatility is the highest. Mean sample volatility, 0.75, is higher than previous studies. Those studies, however, do not typically pool volatility over 40 years and tend to focus on prime-age white males (Keys 2008).

4.7 Results

The regression results are reported in tables 4.2-4.19, with alternative specifications in appendix tables 4.1-4.8 summarized separately. Baseline results for volatility are shown along with interaction models allowing for the estimation of the average treatment effect of volatility on outcomes O_i (Wooldridge 2002). The interactions test the separability of demeaned average log family income and log volatility during childhood, but primarily are meant to transform γ, shown in equation (2), into the average treatment effect at the mean level of permanent family income within the population. The 24-26, 29-31, and 39-41 age groups in non-income regression models are hereafter referred to as 25, 30, and 40, respectively. The results presented are divided into sections based on the outcome being tested – income, education, or health and behavior. These sections summarize results from empirical models testing the association of outcomes to transitory volatility and total volatility, respectively, as defined in section 4.3. Next, the results from instrumental variables models are shown. Finally, I describe appendix regressions that utilize an alternative specification. In many instances, small sample sizes either significantly constrain or prohibit confident interpretation of the results for 40 year olds. They are, however, noted where the results for 40 year olds are available and seem relevant for the discussion.

4.7.1 Income

Earnings and income mobility are studied extensively using the PSID, and I estimate the relationship between parents' income (income during childhood), volatility between ages 0 and 16, and offspring adult income. In log points, baseline childhood transitory volatility exposure during childhood predicts lower levels of income in adulthood between 0.019 and 0.021 (table 4.2); in models testing the separability of income and income volatility, transitory volatility has no statistically significant association to permanent income during childhood. These and all interaction models are evaluated at the mean level of income during childhood, \$67,000, and the mean level of volatility (see table 4.1). Family economic background, as proxied by income during childhood between birth and age 16, exhibits a statistically significant income IGE between 0.406 and 0.460 for 40 year olds.

The income IGE for total volatility ranges from 0.439 to 0.600 (table 4.2, lower panel). Being Black and having additional siblings also predicts lower income in adulthood. Total volatility is associated with a statistically significant higher adult income in the Base model (table 4.2, column 1) without covariates. In models where total volatility is interacted with demeaned family income during childhood, total volatility is negatively associated with adult income. This coefficient is insignificant by itself but significant when combined with the interaction of family income and total volatility. These mixed results suggest that volatility's impact may be sensitive to the level of income. The combination of elasticities generated from transitory and total intergenerational mobility models are comparable to an elasticity of around 0.4 from Solon (1992) and 0.4 to 0.6 from Mazumder (2005) and Gouskova et al. (2010). The intergenerational income elasticities generated in the process of estimating volatility's relationship provide a useful reference point to gauge the reliability of the estimates.

4.7.2 Education

To examine the impact of family income volatility on parental investments in child human capital, I test the role of volatility on the likelihood of high school dropout (tables 4.3-4.4) and post high school educational attainment (table 4.5-4.6). Baseline transitory volatility is associated with a higher likelihood of dropout, but the association is statistically insignificant. Among 25 year olds, permanent income during childhood is related to a lower chance of dropout, as are Black race and Female. Individuals with additional siblings are more likely to drop out of high school, all else equal.

In table 4.4, the association between drop out and total childhood income volatility exposure is tested. Total volatility is insignificant for 25 year olds but predicts a small, significant increase in the drop out chance for 30 year olds by 0.001. 25 and 30 year old Blacks and females are less likely, holding other variables constant, to drop out of high school and having more siblings is associated with a greater risk of drop out among 25 year olds.

Transitory volatility exposure is associated with a lower, statistically insignificant chance of post high school attainment (table 4.4) between -0.024 and -0.025 for 25 year olds. The association remains insignificant but changes signs moving to 30 and 40 year olds. The results are statistically zero, for all ages, when demeaned volatility is interacted with the demeaned level of income during childhood. Family income level, measured in log points, is the strongest positive correlate of post high school education. Females are generally predicted to have higher education attainment likelihood, and individuals with more siblings are less likely to pursue additional training beyond high school. Examination of the partial effect on post high school education of income during childhood, the relationship to family income is between 0.179 and 0.184 for 25 year olds, and 0.131 and 0.145 for 30 year olds.

The joint significance of total volatility and permanent income during childhood suggests post high school educational attainment may be less likely given exposure to total volatility (table 4.6, columns 2 and 4). As is the case in the previous estimates of adult education and volatility exposure, family permanent income, gender, and the number of siblings are the strongest predictors of educational attainment.

4.7.3 Health and Behavior

Another measure of quality that parents may seek to maximize in their children is health. Transitory volatility exposure during childhood has a small, positive, insignificant association to poor adult health for 25 year olds and a small, statistically significant negative association to poor health among 30 year olds between -0.008 and -0.009 (Table 4.7). Income level does not appear to play an important role, though it does have the expected (negative) sign with respect to the likelihood of poor health. These mixed results for transitory volatility and health fit with some parts of the literature on economic risk and health – rest while on layoff may improve the health of unemployed workers (Ruhm 2003). On the other hand, the stress associated with job loss may induce stress and threaten health (Eliason and Storrie 2007). Like models for transitory volatility exposure, Poor health status in total volatility specifications (table 4.8) is less likely among Other race individuals, 25 year olds, Black 30 year olds, as well as those from homes with higher permanent income. There are no significant impacts for health from exposure to total volatility during childhood.

Non marital child bearing is examined in table 4.9. I find no statistically important relationship between transitory volatility and non-marital child bearing, though the signs are consistently negative. Higher permanent income during childhood is linked to a lower likelihood of non-marital childbearing, whereas Black race is related to a higher likelihood of non-marital child bearing as an adult, at all ages. Similar to the transitory volatility model specifications, total volatility exposure has no important relationship to the occurrence of non-marital child bearing, but non marital child bearing is associated with permanent childhood family income among 30 year olds and Black race among 25 and 30 year olds (table 4.10).

4.7.4 Volatility and Negative Asymmetry

Thus far, it appears that volatility might be associated with lower educational attainment through a joint relationship with family income, but the economic significance is weak. To test the dependence of this conclusion on asymmetries within the volatility measure, the final set of specifications control for negative volatility. Overall summary measures of volatility contain a range of individual family income trends. In this sample, the volatility being recorded in the overall definition V_i is potentially driven by positive income growth. Negative volatility in childhood is defined as before, with the added condition that family income is in decline 50 or more percent of the time. I estimate regressions with negative volatility covariates alongside overall volatility, identical otherwise to equation (18).

(19) $$O_{iy} = \alpha + \beta\overline{I_{0-16_i}} + \gamma V_i + \theta V_{i,d} + \mathbf{X}\delta + \varepsilon_i.$$

For income, the specification adds volatility terms $V_{i,d}$ separately and interacted with income $\overline{I_{0-16_i}}$, where d denotes volatility in families experiencing income decline 50 or more percent of the time between the child's birth and age 16.

(19) is referred to as the asymmetric model, denoting the specification of overall volatility with negative volatility simultaneously.

To evaluate the importance of these asymmetries, I note changes in the sign, magnitude, and statistical significance of the volatility estimates relative to the overall baseline results. Regression tables 4.11-4.19 account for negative volatility. Negative transitory volatility has a statistically significant negative association with adult income (top panel Table 4.11) – raising the possibility that negative volatility may be associated with lower adult income. This negative volatility term is a dummy variable; the net effect is to potentially reduce the overall positive association between volatility and adult income. The coefficients on baseline negative volatility range from -0.4 to -0.51. It is plausible that volatility from downward income shifts has different impacts from overall volatility. The interaction of negative volatility and income has a negative association with adult income. The bottom panel of table 4.11 summarizes results for exposure to negative total volatility. Consistent with negative transitory volatility, the relationship to adult income is again negative, although the coefficients are smaller and range between -0.005 and -0.007.

A relationship consistent with the Becker and Tomes (1979) theory of investment emerges between post high school education and negative volatility (Tables 4.14-4.15) among 25 year olds. The baseline coefficient on negative transitory volatility (table 4.14) is -0.195; the overall net effect of volatility combines to lower the chance of post high school education attainment for 25 year olds by -0.218. Other signs in this empirical specification are consistent with the main results described in sections 4.7.1-4.7.3, including income, race, gender, and number of siblings. This is then confirmed in the empirical specification for negative total volatility (table 4.15). Here, individuals are -0.003 points less likely to attain post high school education. Thus, while a statistical association occurs with education, the estimated impacts across all models are usually small.

For 30 year olds, negative volatility predicts a lower chance of non marital child bearing by -0.047 (Table 4.18). Understanding the behavioral mechanisms that might yield a negative link between downward income mobility and childbearing will require more attention. Overall baseline volatility may mask different intergenerational implications based on the degree to which asymmetric effects from extended income growth or decline dominate. However, the results here suggest that the estimates on negative volatility's relationship are small, with the exception of those for adult income and for post high school attainment.

4.7.5 Discussion of Main Results

Across the main empirical models in tables 4.2-4.19, some consistent relationships appear between family income, race, gender, number of siblings, and adult outcomes. For volatility, the strongest relationship is with education and health. The strongest statistical volatility-education link occurs within the asymmetric model of transitory volatility and with models of volatility as a total definition. The results suggest collectively that volatility exposure and income level may be jointly related to lower educational attainment, but the magnitudes are small. The signs on some the coefficients for post high school attainment in the transitory volatility models (table 4.4) suggest that efficiency issues may potentially mask additional negative relationships. Transitory volatility is related to better health as a 30 year old. Given that some theories suggest economic risk could help or harm health, it is plausible that this association is somehow related to job loss (Ruhm 2003).

In some cases, the results are not consistent across age, implying the determinants of education differ by age. Another plausible explanation for age-specific results here and throughout the study is sample attrition bias (Wooldridge 2002), whereby different types of persons respond as ages increase over time. Some study participants do leave the sample, and PSID attritors are less educated, have lower earnings, and are less likely to be married (Fitzgerald et al. 1998). Consistent with documented trends, child bearing outside of marriage is less likely for mothers from higher income backgrounds and more likely if the adult is Black, all else equal (Moynihan 1965; Cancian and Reed 2001).

4.7.6 Instrumental Variables Strategy for Volatility and Intergenerational Outcomes

Instability within families from income growth or decline could result in more time at work and less time investing in children directly during developmental years. If time and money are not perfectly substitutable, this would lower child human capital investment and, by consequence, adult income. The results described up to this point may contain unobserved heterogeneity modeled in equation (10) as well as appendix equations (6), (7), and (8). Because of this, income volatility may be endogenous. As a solution, I attempt to separate the impact of exogenous economic shocks from individual decisions, preferences, and inherited behavior with county level data. I instrument for transitory income volatility using the mean county unemployment statistics from the Local Area Unemployment Statistics program of the U.S. Department of Labor, matched to individuals using restricted-access Geocoded data provided to me by the PSID. For persons within the PSID, I link data from their county of residence so that I can compute the mean unemployment rate during childhood, as an instrument for transitory volatility. Shocks from business cycle fluctuations within the local labor market are theoretically taken exogenously by families and their children, reducing omitted variables bias in the OLS estimates.

Referring back to notation defining volatility, $\sigma_{v_i}^2$, and unobserved traits e_{it} in section 4.2, the conditions for county economic indicators as valid instruments are that

(19) $cov(UR, \sigma^2_{v_i}) \neq 0$

and

(20) $cov(UR, \mathrm{e}_{\mathrm{it}}) = 0.$

The error term e_{it} is inclusive of unobserved preferences and inherited behavior. Exogenous income volatility resulting from events within the local economy can theoretically reduce endogeneity in reduced form estimates.

The overall instrumental variables (IV) strategy is ineffective. To summarize the results, weak instruments limit my ability to effectively estimate volatility's potential intergenerational relationship. The first stage results, regressing average county unemployment on the full set of included explanatory variables including the endogenous volatility parameter, uniformly fail tests of significance individually and jointly. Thus, there is no apparent link between local unemployment and volatility, and unemployment appears to be an invalid instrument. As a consequence, the theoretical relationship in (19) fails to materialize in the data. The results of the instrumental variables estimation are shown in tables 4.20-4.28. There are several potential extensions for identifying a valid instrument of income volatility. These include the variance of unemployment, as well as county-level data on crime and population change.

Throughout the IV models, many of the demographic associations established in tables 4.2-4.19 remain intact. For example, in IV models for transitory volatility family income during childhood is associated with a lower likelihood of having a child outside of marriage and higher income as an adult. The model predicts Blacks to be more likely to have a child outside of marriage. Within the total volatility IV models the chance of non marital child bearing is higher among Black women, an association which appears through all of the intergenerational models.

4.7.7 Appendix Results on Volatility and Intergenerational Outcomes

In appendix tables 1-9, I estimate intergenerational models for transitory volatility and total volatility by substituting parents' education for family income during childhood. Appendix table 1 shows the strong relationship between income and education, and the purpose in this section is to test whether volatility's intergenerational impacts are sensitive to the use of family income as a measure of family background characteristics.

The total volatility empirical models find, all else equal, that volatility exposure is related to a higher likelihood of high school dropout and a lower likelihood of education beyond high school (Appendix tables 3 and 5). In absolute terms, the effects are around 0.001 for 25 year olds. Parents' education in the appendix regressions performs similarly to family income during childhood in the main empirical results, suggesting it to be decent proxy variable for family income. Across main empirical and appendix models, females exhibit higher educational attainment relative to men, and the presence of additional siblings during childhood lowers the chance of additional education. Blacks are less likely to drop out of high school, minorities are less likely to report poor health as an adult, and Blacks are more likely to have a child outside of marriage.

4.8 Conclusion and Future Work

To estimate an intergenerational model with transitory family income volatility, I link parents and offspring in the PSID between 1970 and 2007. The purpose of this is to identify what, if any, consequences occur for adult outcomes from growing up with volatile family income as a child. For health and non-marital child bearing, more work is needed to consider the mechanisms that affect behavioral outcomes, looking beyond standard economic models to include insights from the vast psychology literature on child outcomes. This work could inform the interdisciplinary literature concerned with understanding the intersection of income and child outcomes. Research on income dynamics and volatility should push further on the importance of volatility at the tails of the childhood age distribution, focusing more on early childhood and teenage years. To do so, this study can ultimately extend beyond academic outcomes to consider behavioral outcomes that might have an even clearer link to volatile family income. A second recommended extension is to consider how volatility differs based on the voluntary versus involuntary nature of the definition, and the implications of these differences when interpreting the results. Anticipated volatility implies that individuals can blunt the potential downside effects by insuring against the event. While the instrumental variables strategy introduced here takes a first, though unsuccessful, step towards doing this, another approach involves codifying volatility associated with major events, including illnesses and job losses. Several studies cited in this essay focus on such events. Doing so might help to separate instability of incomes that is anticipated and related to traits such as risk taking, versus that which occurs suddenly and requires immediate, drastic shifts in the family's consumption bundle.

The economic theory of intergenerational mobility and empirical evidence shown in this essay imply that exposure to volatility during childhood may be linked to slightly lower educational attainment in young adulthood. In general, the strongest results are for 25 and 30 year olds in the main and asymmetric models. Unfortunately, intergenerational estimates for 40 year olds contain very small cell sizes, such that confident estimation at this age will likely require more time for PSID participants to proceed through the life course and continue survey participation. Along with small effects related to volatility exposure, the even stronger link between permanent income and education outcomes leave open the possibility of imperfections within credit markets for human capital (Loury 81; Kane and Ellwood 2000; Mazumder 2005). That the results emerge strongest for education attainment suggest that the application of the Becker and Tomes (1979) intergenerational model fits best with outcomes possessing a clearly definable human capital objective, such as post high school attainment. In the U.S., where education is fully subsidized through the tax system from kindergarten through grade twelve, additional parental investments in human and financial capital must occur in order for offspring to successfully matriculate into 2 and 4 year college programs.

If adult educational outcomes are compromised by downside volatility as the asymmetric model suggests, efforts to help families reach their optimal private human capital investment level could improve the well-being of adult children (Mazumder 2005). A modest policy prescription to address the findings regarding educational attainment would promote precautionary savings among families to facilitate smooth child human capital investment profiles. A benefit of such a policy is that, whether volatility derives from income growth or decline, additional savings raises utility for prudent families by providing insurance against unanticipated events (Attanasio and Weber 2010). This may be appropriate given the negligible size of the volatility-education link in most of the models presented.

A secondary set of findings also emerge from this essay that may concern policymakers. These indicate a strong consistent connection of higher permanent family income during childhood to educational attainment, higher income, and overall well-being as an adult. They also suggest a strong positive link between Black women and parenting outside of a marital relationship, which may be a channel through which Black poverty operates across generations, since one parent households have fewer resources on average compared with two parent households (Moynihan 1965). Consistent with Hauser et al. (2000) and Guryan (2004), Blacks are likelier to graduate high school conditional on family income. Finally, it appears that the need to divide resources across siblings may harm individuals. Those with more siblings are predicted to have lower adult income and are less likely to graduate high school or go on to pursue any post high school training. These findings do merit attention.

Beyond promoting precautionary savings, additional public investments in child human capital may help close the gap between the educational investments advantaged and disadvantaged families make, raising incomes and improving adult well-being for descendants of lower-income families. The current safety net uses food, housing, and cash assistance programs to intercede for low and moderate income families, yielding real-time benefits. By comparison, a policy directing additional resources to childhood and young adult education will not provide immediate relief from hardship for recipient children. Yet, recent policy debates over state and federal based education grants for low-income students make these results timely. If policymakers' objectives include immediate needs as well as longer-term economic mobility, grants for education and training beyond high school might be made more available, not less. Over time, such a strategy could lower the apparently large consequences of low permanent income during childhood and loosen the link between low family incomes as a child and reduced human capital and income in adulthood.

Table 4.1 Summary Statistics Adjusted for Inflation (2006 Dollars)

Variables	Mean	Standard Deviation
Earnings and Income		
Offspring Family Income in Adulthood ($)	$67,873.04	46,445.62
Head's Family Income in Childhood ($)	67,161.04	43,757.99
Average Childhood Transitory Volatility (Ln)	0.75	4.32
Average Childhood Total Volatility (Std. Dev)	28.32	21.87
Average County Unemployment Rate	6.61	2.22
Age of Offspring (if offspring over 25)	33.14	6.81
Age of Father (if offspring over 25)	61.87	8.51
Age of Mother (if offspring over 25)	59.16	10.03
Education		
% Less Than High School - Offspring	5.79%	23.34%
% High School - Offspring	31.74%	46.54%
% Some College - Offspring	27.57%	44.68%
% College - Offspring	34.91%	47.67%
% Less Than High School - Father	25.76%	43.73%
% High School - Offspring - Father	36.56%	48.16%
% Some College - Offspring - Father	15.22%	35.92%
% College – Offspring – Father	22.47%	41.74%
% Less Than High School - Mother	20.65%	40.48%
% High School - Offspring - Mother	48.87%	48.16%
% Some College - Offspring - Mother	17.03%	37.59%
% College - Offspring - Mother	13.46%	34.13%
Race & Gender		
% White - Head of Household	91.62%	27.71%
% Black - Head of Household	5.78%	23.33%
% Other - Head of Household	2.59%	15.90%
% Female	48.37%	49.97%
Sample – Observations with Child Income 0-16		
Number of offspring matched to parents	2,186	
Sample size (person-years)	57,395	

Note: Summary statistics are topcoded at 1% and bottomcoded at $1.

Table 4.2 Childhood Income Volatility Exposure and Adult Income

ADULT INCOME	Baseline	Full	Baseline	Full
$Income_{0-16}$	0.460***	0.408***	0.462***	0.406***
	(0.119)	(0.118)	(0.118)	(0.118)
Transitory $Volatility_{0-16}$	-0.019	-0.021	-0.019	-0.021
	(0.038)	(0.037)	(0.038)	(0.037)
$Income_{0-16}$ * Transitory Vol_{0-16}			0.008	-0.007
			(0.079)	(0.076)
Demographics	No	Yes	No	Yes
Observations	1,365	1,365	1,365	1,365
R-squared	0.0998	0.1167	0.0998	0.1167
Joint F Test			0.125	0.165
ADULT INCOME	Baseline	Full	Baseline	Full
$Income_{0-16}$	0.494***	0.439***	0.600***	0.558***
	(0.118)	(0.117)	(0.101)	(0.101)
Total $Volatility_{0-16}$	0.002*	0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$Income_{0-16}$ * Total Vol_{0-16}			-0.007***	-0.006***
			(0.001)	(0.001)
Demographics	No	Yes	No	Yes
Observations	1,366	1,366	1,366	1,366
R-squared	0.1010	0.1173	0.1238	0.1359
Joint F Test			18.00	14.94

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for parents' education, race, gender, number of siblings, and age in Full models not shown. F-statistics tests joint significance of $Volatility_{0-16}$ and $Income_{0-16}$ * Vol_{0-16}. Intergenerational income elasticities include order 4 polynomial of offspring age normalized to age 40, as well as normalized offspring age interacted with income during childhood (parents' income), also not shown.

Table 4.3 Childhood Income Volatility Exposure and High School Dropout (Transitory Definition)

DROPOUT	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$\text{Income}_{0\text{-}16}$	-0.054***	-0.054***	-0.031	-0.044**	-0.032	-0.032
	(0.020)	(0.019)	(0.021)	(0.022)	(0.025)	(0.024)
Transitory $\text{Volatility}_{0\text{-}16}$	0.007	0.007	0.013	0.011	0.002	0.002
	(0.012)	(0.012)	(0.014)	(0.014)	(0.007)	(0.006)
$\text{Income}_{0\text{-}16}$ * Transitory $\text{Vol}_{0\text{-}16}$		-0.006		-0.057		0.001
		(0.030)		(0.037)		(0.024)
Black	-0.052**	-0.052**	-0.053***	-0.052***	-0.036	-0.036
	(0.025)	(0.025)	(0.012)	(0.012)	(0.024)	(0.025)
Other	-0.029	-0.029	-0.008	-0.004	-0.012	-0.012
	(0.018)	(0.018)	(0.030)	(0.030)	(0.012)	(0.012)
Female	-0.044***	-0.044***	-0.035***	-0.035***	-0.031	-0.031
	(0.012)	(0.012)	(0.013)	(0.013)	(0.021)	(0.021)
No. of Siblings	0.010*	0.010*	0.003	0.002	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	-4.204	-4.163	-6.506*	-5.982	-4.265	-4.264
	(3.411)	(3.411)	(3.912)	(4.008)	(7.653)	(7.675)
Observations	1,329	1,329	873	873	158	158
R-squared	0.0475	0.0475	0.0291	0.0330	0.0367	0.0367
Joint F Test		0.156		1.460		0.0893

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory $\text{Volatility}_{0\text{-}16}$ and $\text{Income}_{0\text{-}16}$ * Transitory $\text{Vol}_{0\text{-}16}$.

Table 4.4 Childhood Income Volatility Exposure and High School Dropout (Total Volatility Definition)

DROPOUT	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$Income_{0-16}$	-0.049**	-0.059**	-0.022	-0.030	-0.039	-0.051
	(0.023)	(0.026)	(0.023)	(0.026)	(0.031)	(0.035)
Total $Volatility_{0-16}$	0.000	0.001	0.001	0.001*	-0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$Income_{0-16}$ * Total Vol_{0-16}		0.001		0.000		0.001
		(0.001)		(0.000)		(0.000)
Black	-0.052**	-0.054**	-0.055***	-0.056***	-0.038	-0.041
	(0.025)	(0.025)	(0.012)	(0.012)	(0.023)	(0.025)
Other	-0.028	-0.026	0.000	0.002	-0.013	-0.015
	(0.019)	(0.019)	(0.032)	(0.032)	(0.015)	(0.015)
Female	-0.044***	-0.044***	-0.032**	-0.032**	-0.032	-0.031
	(0.012)	(0.012)	(0.013)	(0.013)	(0.023)	(0.023)
No. of Siblings	0.010*	0.010*	0.002	0.002	-0.002	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Constant	-4.438	-4.444	-7.886**	-7.723**	-4.470	-4.956
	(3.417)	(3.419)	(3.973)	(3.913)	(8.014)	(8.102)
Observations	1,401	1,401	872	872	158	158
R-squared	0.0490	0.0508	0.0374	0.0389	0.0375	0.0430
Joint F Test		1.162		1.454		1.083

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Total $Volatility_{0-16}$ and $Income_{0-16}$ * Total Vol_{0-16}.

Table 4.5 Childhood Income Volatility Exposure and Post Secondary Education (Transitory Definition)

POST SECONDARY	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$Income_{0-16}$	0.179***	0.184***	0.131**	0.145***	0.126	0.141
	(0.039)	(0.038)	(0.051)	(0.051)	(0.109)	(0.102)
Transitory $Volatility_{0-16}$	-0.024	-0.025	0.011	0.013	0.005	0.007
	(0.024)	(0.024)	(0.031)	(0.032)	(0.067)	(0.067)
$Income_{0-16}$ * Transitory Vol_{0-16}		0.031		0.064		0.086
		(0.053)		(0.076)		(0.153)
Black	-0.001	-0.001	-0.043	-0.044	-0.258	-0.266
	(0.056)	(0.056)	(0.077)	(0.077)	(0.233)	(0.229)
Other	0.043	0.044	0.090	0.085	-0.130	-0.136
	(0.063)	(0.063)	(0.088)	(0.089)	(0.154)	(0.156)
Female	0.095***	0.095***	0.104***	0.104***	-0.005	-0.005
	(0.025)	(0.025)	(0.033)	(0.033)	(0.072)	(0.072)
No. of Siblings	-0.033***	-0.033***	-0.039***	-0.038***	-0.046	-0.045
	(0.010)	(0.010)	(0.013)	(0.013)	(0.028)	(0.029)
Constant	6.661	6.436	7.745	7.158	47.321	47.392
	(8.143)	(8.137)	(12.037)	(12.167)	(37.043)	(37.214)
Observations	1,329	1,329	873	873	158	158
R-squared	0.1674	0.1677	0.1329	0.1337	0.1629	0.1648
Joint F Test		0.599		0.443		0.175

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory $Volatility_{0-16}$ and $Income_{0-16}$ * Transitory Vol_{0-16}.

Table 4.6 Childhood Income Volatility Exposure and Post High School Education (Total Volatility Definition)

POST SECONDARY	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$\text{Income}_{0\text{-}16}$	0.199***	0.251***	0.152***	0.227***	0.148	0.214**
	(0.040)	(0.037)	(0.056)	(0.050)	(0.115)	(0.096)
Total $\text{Volatility}_{0\text{-}16}$	0.001	-0.001	0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
$\text{Income}_{0\text{-}16}$ * Total $\text{Vol}_{0\text{-}16}$		-0.003***		-0.004***		-0.004
		(0.001)		(0.001)		(0.002)
Black	0.001	0.008	-0.044	-0.033	-0.253	-0.235
	(0.056)	(0.056)	(0.077)	(0.075)	(0.232)	(0.235)
Other	0.042	0.034	0.090	0.073	-0.126	-0.118
	(0.063)	(0.064)	(0.088)	(0.089)	(0.155)	(0.153)
Female	0.095***	0.096***	0.101***	0.103***	-0.001	-0.009
	(0.025)	(0.025)	(0.033)	(0.033)	(0.073)	(0.072)
No. of Siblings	-0.033***	-0.032***	-0.038***	-0.038***	-0.047*	-0.051*
	(0.010)	(0.010)	(0.013)	(0.013)	(0.028)	(0.029)
Constant	6.062	6.091	8.398	7.002	48.023	50.574
	(8.140)	(8.064)	(12.052)	(11.690)	(36.617)	(36.256)
Observations	1,401	1,401	872	872	158	158
R-squared	0.1686	0.1793	0.1366	0.1547	0.1640	0.1778
Joint F Test		6.558		11.56		1.355

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. F-statistics tests joint significance of Total $\text{Volatility}_{0\text{-}16}$ and $\text{Income}_{0\text{-}16}$ * Total $\text{Vol}_{0\text{-}16}$.

Table 4.7 Childhood Income Volatility Exposure and Self Reported Poor Health (Transitory Definition)

POOR HEALTH	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$Income_{0\text{-}16}$	-0.006	-0.004	-0.008*	-0.009*
	(0.004)	(0.006)	(0.005)	(0.005)
Transitory $Volatility_{0\text{-}16}$	0.009	0.008	-0.006*	-0.006*
	(0.007)	(0.007)	(0.004)	(0.004)
$Income_{0\text{-}16}$ * Transitory $Vol_{0\text{-}16}$		0.011		-0.003
		(0.017)		(0.004)
Black	0.010	0.010	-0.005*	-0.005*
	(0.018)	(0.018)	(0.003)	(0.003)
Other	-0.008***	-0.007***	-0.002	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Female	0.001	0.001	0.004	0.004
	(0.005)	(0.005)	(0.004)	(0.004)
No. of Siblings	-0.008	0. 136	0. 437	0. 391
	(1.654)	(1.649)	(1.453)	(1.474)
Constant	0.615	0.523	-1.473	-1.440
	(1.324)	(1.338)	(1.721)	(1.697)
Observations	1,250	1,250	803	803
R-squared	0.0068	0.0079	0.0110	0.0111
Joint F Test		0.738		1.470

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory $Volatility_{0\text{-}16}$ and $Income_{0\text{-}16}$ * Transitory $Vol_{0\text{-}16}$. Coefficients and standard errors on No. of siblings are transformed, dividing by 1000.

Table 4.8 Childhood Income Volatility Exposure and Self Reported Poor Health (Total Volatility Definition)

POOR HEALTH	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$\text{Income}_{0\text{-}16}$	-0.007	-0.008	-0.009**	-0.011**
	(0.006)	(0.007)	(0.005)	(0.005)
$\text{Total Volatility}_{0\text{-}16}$	-0.006	-0.002	-0.006	-0.002
	(0.012)	(0.011)	(0.011)	(0.012)
$\text{Income}_{0\text{-}16}$ * $\text{Total Vol}_{0\text{-}16}$		0.009		0.008
		(0.007)		(0.006)
Black	0.010	0.010	-0.004*	-0.004*
	(0.018)	(0.019)	(0.003)	(0.003)
Other	-0.007***	-0.007***	-0.003	-0.003
	(0.003)	(0.003)	(0.002)	(0.002)
Female	0.001	0.001	0.004	0.004
	(0.005)	(0.005)	(0.004)	(0.004)
No. of Siblings	0.012	0.007	0.032	0.030
	(0.162)	(0.160)	(0.147)	(0.147)
Constant	0.719	0.707	-1.384	-1.353
	(1.330)	(1.329)	(1.692)	(1.697)
Observations	1,323	1,323	802	802
R-squared	0.0044	0.0046	0.0091	0.0095
Joint F Test		0.755		1.420

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of $\text{Total Volatility}_{0\text{-}16}$ and $\text{Income}_{0\text{-}16}$ * $\text{Total Vol}_{0\text{-}16}$. Coefficients and standard errors on $\text{Total Volatility}_{0\text{-}16}$, $\text{Income}_{0\text{-}16}$ * $\text{Total Vol}_{0\text{-}16}$, and No. of Siblings are transformed, dividing by 100.

Table 4.9 Childhood Income Volatility Exposure and Non Marital Child Bearing (Transitory Definition)

OWB	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$Income_{0-16}$	-0.052**	-0.052**	-0.026	-0.031
	(0.022)	(0.022)	(0.017)	(0.020)
Transitory $Volatility_{0-16}$	-0.004	-0.005	-0.016	-0.016
	(0.015)	(0.016)	(0.015)	(0.016)
$Income_{0-16}$ * Transitory Vol_{0-16}		0.001		-0.034
		(0.032)		(0.039)
Black	0.386***	0.386***	0.337***	0.334***
	(0.096)	(0.096)	(0.117)	(0.116)
Other	0.030	0.030	-0.022	-0.020
	(0.064)	(0.064)	(0.015)	(0.016)
No. of Siblings	0.004	0.004	0.003	0.002
	(0.008)	(0.008)	(0.007)	(0.007)
Constant	0.800	0.789	-1.847	-1.380
	(4.227)	(4.273)	(3.157)	(3.282)
Observations	638	638	417	417
R-squared	0.1500	0.1500	0.1389	0.1401
Joint F Test		0.0554		2.235

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory $Volatility_{0-16}$ and $Income_{0-16}$ * Transitory Vol_{0-16}.

Table 4.10 Childhood Income Volatility Exposure and Non Marital Child Bearing (Total Volatility Definition)

OWB	24-26	24-26	29-31	29-31
	(1)	(2)	(3)	(4)
Income$_{0-16}$	-0.049**	-0.047**	-0.016	-0.019
	(0.021)	(0.020)	(0.018)	(0.018)
Total Volatility$_{0-16}$	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Income$_{0-16}$ * Total Vol$_{0-16}$		-0.000		0.000
		(0.001)		(0.000)
Black	0.386***	0.386***	0.339***	0.339***
	(0.096)	(0.096)	(0.116)	(0.116)
Other	0.030	0.030	-0.022	-0.020
	(0.064)	(0.064)	(0.015)	(0.015)
No. of Siblings	0.004	0.004	0.002	0.002
	(0.008)	(0.008)	(0.007)	(0.007)
Constant	0.784	0.922	-1.489	-1.616
	(4.235)	(4.294)	(3.160)	(3.198)
Observations	671	671	417	417
R-squared	0.1500	0.1501	0.1387	0.1392
Joint F Test		0.0674		0.887

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Total Volatility$_{0-16}$ and Income$_{0-16}$ * Total Vol$_{0-16}$.

Table 4.11 Childhood Income Volatility Exposure and Adult Income

ADULT INCOME	Baseline	Full	Baseline	Full
$Income_{0\text{-}16}$	0.452***	0.403***	0.452***	0.399***
	(0.119)	(0.118)	(0.118)	(0.118)
Transitory $Volatility_{0\text{-}16}$	-0.016	-0.019	-0.017	-0.019
	(0.038)	(0.037)	(0.038)	(0.037)
Negative Transitory $Volatility_{0\text{-}16}$	-0.510**	-0.421*	-0.494**	-0.400*
	(0.245)	(0.231)	(0.243)	(0.230)
$Income_{0\text{-}16}$ * Transitory $Vol_{0\text{-}16}$			0.012	-0.000
			(0.080)	(0.076)
$Income_{0\text{-}16}$ * Negative Transitory $Vol_{0\text{-}16}$			-0.325	-0.417
			(0.407)	(0.391)
Demographics	No	Yes	No	Yes
Observations	1,365	1,365	1,365	1,365
R-squared	0.1060	0.1208	0.1062	0.1212
Joint F Test			2.306	2.159
ADULT INCOME	Baseline	Full	Baseline	Full
$Income_{0\text{-}16}$	0.498***	0.443***	0.599***	0.557***
	(0.118)	(0.117)	(0.102)	(0.102)
Total $Volatility_{0\text{-}16}$	0.002*	0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Negative Total $Volatility_{0\text{-}16}$	-0.007**	-0.006**	-0.005*	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
$Income_{0\text{-}16}$ * Total $Vol_{0\text{-}16}$			-0.006***	-0.006***
			(0.001)	(0.001)
$Income_{0\text{-}16}$ * Negative Total $Vol_{0\text{-}16}$			0.001	0.002
			(0.004)	(0.004)
Demographics	No	Yes	No	Yes
Observations	1,366	1,366	1,366	1,366
R-squared	0.1057	0.1205	0.1265	0.1377
Joint F Test			2.129	1.760

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for parents' education, race, gender, number of siblings, and age in Full models not shown. F-statistics tests joint significance of Negative $Volatility_{0\text{-}16}$ and $Income_{0\text{-}16}$ * Negative $Vol_{0\text{-}16}$. Intergenerational income elasticities include order 4 polynomial of offspring age normalized to age 40, as well as normalized offspring age interacted with income during childhood (parents' income), also not shown.

Table 4.12 Childhood Income Volatility Exposure and High School Dropout (Negative Transitory Definition)

DROPOUT	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$\text{Income}_{0\text{-}16}$	-0.053***	-0.051***	-0.031	-0.038*	-0.033	-0.032
	(0.020)	(0.019)	(0.021)	(0.022)	(0.026)	(0.025)
Transitory $\text{Volatility}_{0\text{-}16}$	0.006	0.006	0.012	0.008	0.002	0.002
	(0.012)	(0.012)	(0.014)	(0.014)	(0.007)	(0.007)
Negative Transitory $\text{Volatility}_{0\text{-}16}$	0.043	0.031	0.127	0.111	-0.063	-0.064
	(0.081)	(0.076)	(0.104)	(0.099)	(0.056)	(0.058)
$\text{Income}_{0\text{-}16}$ * Transitory $\text{Vol}_{0\text{-}16}$		-0.009		-0.065*		0.001
		(0.030)		(0.036)		(0.025)
$\text{Income}_{0\text{-}16}$ * Negative Transitory $\text{Vol}_{0\text{-}16}$		0.207		0.681*		0.042
		(0.313)		(0.366)		(0.082)
Black	-0.053**	-0.053**	-0.049***	-0.048***	-0.036	-0.036
	(0.026)	(0.026)	(0.011)	(0.011)	(0.024)	(0.025)
Other	-0.028	-0.028	-0.006	-0.002	-0.009	-0.010
	(0.018)	(0.018)	(0.030)	(0.030)	(0.012)	(0.012)
Female	-0.045***	-0.044***	-0.037***	-0.038***	-0.031	-0.031
	(0.012)	(0.012)	(0.013)	(0.013)	(0.021)	(0.021)
No. of Siblings	0.010*	0.010*	0.001	0.002	-0.001	-0.001
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	-4.005	-4.119	-5.887	-7.142*	-4.471	-5.130
	(3.383)	(3.413)	(3.809)	(3.995)	(7.691)	(8.394)
Observations	1,329	1,329	873	873	158	158
R-squared	0.0480	0.0496	0.0349	0.0521	0.0376	0.0377

Table 4.12 Continued

Joint F Test	0.276	2.003	0.618

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Transitory Volatility$_{0\text{-}16}$ and Income$_{0\text{-}16}$ * Negative Transitory Vol$_{0\text{-}16}$.

Table 4.13 Childhood Income Volatility Exposure and High School Dropout (Negative Total Definition)

DROPOUT	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$\text{Income}_{0\text{-}16}$	-0.049**	-0.060**	-0.023	-0.031	-0.039	-0.053
	(0.023)	(0.026)	(0.024)	(0.026)	(0.031)	(0.036)
$\text{Total Volatility}_{0\text{-}16}$	0. 028	0.054	0. 077	0.010	-0. 028	0. 013
	(0. 054)	(0.052)	(0. 062)	(0.067)	(0. 103)	(0. 113)
$\text{Negative Total Volatility}_{0\text{-}16}$	0.016	0.019	0. 186	0. 163	-0. 142	-0.177
	(0.130)	(0.128)	(0. 185)	(0. 177)	(0. 117)	(0. 120)
$\text{Income}_{0\text{-}16}$ * $\text{Total Vol}_{0\text{-}16}$		0.057		0. 040		0.070
		(0.054)		(0.046)		(0.050)
$\text{Income}_{0\text{-}16}$ * $\text{Negative Total Vol}_{0\text{-}16}$		0.124		-0. 886		-0. 831
		(0.182)		(0. 192)		(0. 430)
Black	-0.052**	-0.054**	-0.052***	-0.054***	-0.039	-0.043*
	(0.025)	(0.026)	(0.012)	(0.012)	(0.024)	(0.026)
Other	-0.028	-0.026	0.001	0.003	-0.009	-0.008
	(0.019)	(0.019)	(0.032)	(0.032)	(0.015)	(0.013)
Female	-0.044***	-0.044***	-0.034**	-0.032**	-0.032	-0.030
	(0.012)	(0.012)	(0.013)	(0.013)	(0.023)	(0.023)
No. of Siblings	0.010*	0.010*	0.001	0.001	-0.001	-0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Constant	-4.405	-4.526	-7.497*	-7.036*	-4.853	-4.743
	(3.451)	(3.464)	(3.980)	(3.950)	(8.108)	(8.354)
Observations	1,401	1,401	872	872	158	158
R-squared	0.0491	0.0511	0.0408	0.0437	0.0389	0.0448

Table 4.13 Continued

Joint F Test	0.234	0.588	1.250

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Total Volatility$_{0\text{-}16}$ and Income$_{0\text{-}16}$ * Negative Total Vol$_{0\text{-}16.}$ Coefficients and standard errors on Total Volatility$_{0\text{-}16,}$ Negative Total Volatility$_{0\text{-}16,}$ Income$_{0\text{-}16}$ * Total Vol$_{0\text{-}16,}$ and Income$_{0\text{-}16}$ * Negative Total Vol$_{0\text{-}16}$ are transformed, dividing by 100.

Table 4.14 Childhood Income Volatility Exposure and Post Secondary Education (Negative Transitory Definition)

POST SECONDARY	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$Income_{0-16}$	0.178***	0.182***	0.131**	0.141***	0.131	0.123
	(0.038)	(0.039)	(0.051)	(0.051)	(0.111)	(0.103)
Transitory $Volatility_{0-16}$	-0.023	-0.023	0.012	0.015	0.006	0.009
	(0.024)	(0.024)	(0.031)	(0.032)	(0.067)	(0.067)
Negative Transitory $Volatility_{0-16}$	-0.195*	-0.193	-0.072	-0.062	0.353	0.348
	(0.117)	(0.118)	(0.164)	(0.164)	(0.459)	(0.399)
$Income_{0-16}$ * Transitory Vol_{0-16}		0.034		0.069		0.097
		(0.053)		(0.076)		(0.155)
$Income_{0-16}$ * Negative Transitory Vol_{0-16}		-0.058		-0.465		-1.447*
		(0.267)		(0.469)		(0.741)
Black	0.001	0.001	-0.045	-0.046	-0.253	-0.281
	(0.056)	(0.056)	(0.077)	(0.077)	(0.238)	(0.218)
Other	0.039	0.040	0.089	0.084	-0.147	-0.111
	(0.063)	(0.063)	(0.089)	(0.090)	(0.157)	(0.152)
Female	0.095***	0.095***	0.105***	0.106***	-0.010	0.003
	(0.025)	(0.025)	(0.033)	(0.033)	(0.072)	(0.073)
No. of Siblings	-0.031***	-0.030***	-0.038***	-0.038***	-0.051*	-0.049*
	(0.010)	(0.010)	(0.013)	(0.013)	(0.029)	(0.029)
Constant	5.762	5.562	7.394	8.017	48.467	70.985*
	(8.175)	(8.167)	(12.036)	(12.152)	(38.555)	(36.661)
Observations	1,329	1,329	873	873	158	158
R-squared	0.1700	0.1704	0.1332	0.1351	0.1653	0.1785

Table 4.14 Continued

Joint F Test	1.456	0.582	2.436

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Transitory Volatility$_{0\text{-}16}$ and Income$_{0\text{-}16}$ * Negative Transitory Vol$_{0\text{-}16}$.

Table 4.15 Childhood Income Volatility Exposure and Post Secondary Education (Negative Total Definition)

POST SECONDARY	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$\text{Income}_{0\text{-}16}$	0.199***	0.247***	0.153***	0.226***	0.151	0.181*
	(0.040)	(0.038)	(0.056)	(0.050)	(0.115)	(0.101)
$\text{Total Volatility}_{0\text{-}16}$	0.001	-0.000	0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
$\text{Negative Total Volatility}_{0\text{-}16}$	-0.003*	-0.002	-0.000	0.001	0.005	0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.008)	(0.007)
$\text{Income}_{0\text{-}16}$ * $\text{Total Vol}_{0\text{-}16}$		-0.003***		-0.004***		-0.003
		(0.001)		(0.001)		(0.002)
$\text{Income}_{0\text{-}16}$ * $\text{Negative Total Vol}_{0\text{-}16}$		0.002		0.036**		-0.284**
		(0.003)		(0.018)		(0.120)
Black	0.003	0.009	-0.044	-0.031	-0.249	-0.257
	(0.057)	(0.056)	(0.077)	(0.075)	(0.236)	(0.222)
Other	0.038	0.032	0.090	0.072	-0.140	-0.081
	(0.063)	(0.064)	(0.088)	(0.089)	(0.158)	(0.153)
Female	0.095***	0.096***	0.101***	0.096***	-0.003	-0.000
	(0.025)	(0.025)	(0.033)	(0.033)	(0.073)	(0.072)
No. of Siblings	-0.031***	-0.030***	-0.038***	-0.038***	-0.049*	-0.053*
	(0.010)	(0.010)	(0.013)	(0.013)	(0.028)	(0.028)
Constant	5.400	5.413	8.355	5.768	49.345	74.763**
	(8.160)	(8.101)	(12.050)	(11.725)	(38.065)	(36.570)
Observations	1,401	1,401	872	872	158	158
R-squared	0.1710	0.1810	0.1366	0.1597	0.1654	0.1904

Table 4.15 Continued

Joint F Test	2.051	2.165	2.907

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Total Volatility$_{0-16}$ and Income$_{0-16}$ * Negative Total Vol$_{0-16}$.

Table 4.16 Childhood Income Volatility Exposure and Self Reported Poor Health (Negative Transitory Definition)

POOR HEALTH	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
Income$_{0\text{-}16}$	-0.005	-0.004	-0.008*	-0.009*
	(0.004)	(0.006)	(0.005)	(0.005)
Transitory Volatility$_{0\text{-}16}$	0.009	0.008	-0.006*	-0.006*
	(0.007)	(0.007)	(0.004)	(0.004)
Negative Transitory Volatility$_{0\text{-}16}$	0.008	0.009	-0.006	-0.007
	(0.018)	(0.019)	(0.005)	(0.005)
Income$_{0\text{-}16}$ * Transitory Vol$_{0\text{-}16}$		0.012		-0.003
		(0.017)		(0.004)
Income$_{0\text{-}16}$ * Negative Transitory Vol$_{0\text{-}16}$		-0.033*		0.019
		(0.020)		(0.028)
Black	0.010	0.010	-0.005*	-0.005*
	(0.018)	(0.018)	(0.003)	(0.003)
Other	-0.007***	-0.007***	-0.002	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Female	0.001	0.001	0.004	0.004
	(0.005)	(0.005)	(0.004)	(0.004)
No. of Siblings	-0.010	-0.003	0.053	0.053
	(0.169)	(0.170)	(0.147)	(0.147)
Constant	0.650	0.587	-1.506	-1.525
	(1.318)	(1.335)	(1.728)	(1.758)
Observations	1,250	1,250	803	803
R-squared	0.0069	0.0083	0.0112	0.0113

Table 4.16 Continued

Joint F Test	2.009	0.872

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Transitory Volatility$_{0-16}$ and Income$_{0-16}$ * Negative Transitory Vol$_{0-16}$. Coefficients and standard errors on No. of Siblings are transformed, dividing by 100.

Table 4.17 Childhood Income Volatility Exposure and Self Reported Poor Health (Negative Total Definition)

POOR HEALTH	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$Income_{0-16}$	-0.007	-0.008	-0.009*	-0.011**
	(0.006)	(0.007)	(0.005)	(0.005)
Total $Volatility_{0-16}$	-0. 007	-0.003	-0. 005	-0. 001
	(0. 012)	(0.011)	(0. 011)	(0. 012)
Negative Total $Volatility_{0-16}$	0. 013	0.009	-0.013	-0. 014
	(0. 028)	(0.027)	(0.009)	(0. 009)
$Income_{0-16}$ * Total Vol_{0-16}		0.009		0.009
		(0.007)		(0.006)
$Income_{0-16}$ * Negative Total Vol_{0-16}		-0.013		0.061
		(0.024)		(0.062)
Black	0.010	0.010	-0.004*	-0.005*
	(0.018)	(0.019)	(0.003)	(0.003)
Other	-0.007***	-0.007***	-0.003	-0.003
	(0.003)	(0.003)	(0.002)	(0.002)
Female	0.001	0.001	0.004	0.004
	(0.005)	(0.005)	(0.004)	(0.004)
No. of Siblings	0.004	0.002	0.041	0.041
	(0.164)	(0.162)	(0.147)	(0.147)
Constant	0.743	0.739	-1.413	-1.413
	(1.325)	(1.324)	(1.698)	(1.728)
Observations	1,323	1,323	802	802
R-squared	0.0045	0.0047	0.0093	0.0097

Table 4.17 Continued

Joint F Test	0.152	1.474

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Total $Volatility_{0\text{-}16}$ and $Income_{0\text{-}16}$ * Negative Total $Vol_{0\text{-}16}$. Coefficients and standard errors on Total $Volatility_{0\text{-}16}$, Negative Total $Volatility_{0\text{-}16}$, $Income_{0\text{-}16}$ * Total $Vol_{0\text{-}16}$, $Income_{0\text{-}16}$ * Negative Total $Vol_{0\text{-}16}$, and No. of Siblings are transformed, dividing by 100.

Table 4.18 Childhood Income Volatility Exposure and Non Marital Child Bearing (Negative Transitory Definition)

OWB	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$\text{Income}_{0\text{-}16}$	-0.053**	-0.055**	-0.027	-0.033*
	(0.022)	(0.022)	(0.017)	(0.020)
Transitory $\text{Volatility}_{0\text{-}16}$	-0.004	-0.004	-0.015	-0.015
	(0.015)	(0.016)	(0.015)	(0.016)
Negative Transitory $\text{Volatility}_{0\text{-}16}$	-0.029	-0.017	-0.047*	-0.043
	(0.049)	(0.053)	(0.026)	(0.027)
$\text{Income}_{0\text{-}16}$ * Transitory $\text{Vol}_{0\text{-}16}$		0.003		-0.033
		(0.033)		(0.040)
$\text{Income}_{0\text{-}16}$ * Negative Transitory $\text{Vol}_{0\text{-}16}$		-0.263		-0.080
		(0.184)		(0.100)
Black	0.385***	0.385***	0.335***	0.331***
	(0.096)	(0.096)	(0.117)	(0.116)
Other	0.029	0.029	-0.023	-0.021
	(0.064)	(0.064)	(0.015)	(0.016)
No. of Siblings	0.004	0.003	0.004	0.003
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.888	1.320	-1.725	-1.053
	(4.251)	(4.298)	(3.172)	(3.226)
Observations	638	638	417	417
R-squared	0.1503	0.1514	0.1400	0.1413
Joint F Test		3.392		2.722

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Transitory $\text{Volatility}_{0\text{-}16}$ and $\text{Income}_{0\text{-}16}$ * Negative Transitory $\text{Vol}_{0\text{-}16}$.

Table 4.19 Childhood Income Volatility Exposure and Non Marital Child Bearing (Negative Total Definition)

OWB	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$Income_{0\text{-}16}$	-0.048**	-0.043**	-0.016	-0.019
	(0.021)	(0.020)	(0.018)	(0.019)
Total $Volatility_{0\text{-}16}$	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Negative Total $Volatility_{0\text{-}16}$	-0.001	-0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$Income_{0\text{-}16}$ * Total $Vol_{0\text{-}16}$		-0.000		0.000
		(0.001)		(0.000)
$Income_{0\text{-}16}$ * Negative Total $Vol_{0\text{-}16}$		-0.012		-0.001
		(0.008)		(0.003)
Black	0.386***	0.378***	0.339***	0.338***
	(0.096)	(0.096)	(0.116)	(0.116)
Other	0.030	0.029	-0.022	-0.020
	(0.064)	(0.064)	(0.015)	(0.015)
No. of Siblings	0.004	0.004	0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.875	0.589	-1.488	-1.616
	(4.252)	(4.313)	(3.145)	(3.176)
Observations	671	671	417	417
R-squared	0.1505	0.1545	0.1387	0.1392
Joint F Test		3.311		0.0378

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Negative Total $Volatility_{0\text{-}16}$ and $Income_{0\text{-}16}$ * Negative Total $Vol_{0\text{-}16}$.

Table 4.20 IV Estimation of Childhood Income Volatility Exposure and Adult Income

ADULT INCOME	Baseline	Full	Baseline	Full
$Income_{0\text{-}16}$	0.502**	0.489**	-19.361	-8.835
	(0.215)	(0.213)	(749.493)	(167.116)
Transitory $Volatility_{0\text{-}16}$	1.973	1.962	23.694	9.323
	(3.494)	(3.172)	(880.557)	(168.772)
$Income_{0\text{-}16}$ * Transitory $Vol_{0\text{-}16}$			-81.196	-37.248
			(3068.823)	(673.094)
Demographics	No	Yes	No	Yes
Observations	1,359	1,359	1,359	1,359
ADULT INCOME	Baseline	Full	Baseline	Full
$Income_{0\text{-}16}$	1.945	2.238	1.908	4.597
	(2.066)	(2.544)	(2.665)	(18.357)
Total $Volatility_{0\text{-}16}$	0.079	0.096	0.076	0.216
	(0.109)	(0.135)	(0.168)	(1.011)
$Income_{0\text{-}16}$ * Total $Vol_{0\text{-}16}$			-0.001	0.006
			(0.025)	(0.083)
Demographics	No	Yes	No	Yes
Observations	1,359	1,359	1,359	1,359

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for parents' education, race, gender, number of siblings, and age in Full models not shown. Intergenerational income elasticities include order 4 polynomial of offspring age normalized to age 40, as well as normalized offspring age interacted with income during childhood (parents’ income), also not shown. Instrument for Volatility is average county unemployment rate during childhood.

Table 4.21 IV Estimation of Childhood Income Volatility Exposure and High School Dropout (Transitory Definition)

DROPOUT	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$\text{Income}_{0\text{-}16}$	-0.020	-0.345	-0.039	-0.174	-0.029	-0.725
	(0.124)	(0.970)	(0.025)	(0.235)	(0.027)	(11.097)
$\text{Transitory Volatility}_{0\text{-}16}$	-1.050	0.438	-0.071	-0.279	0.131	2.521
	(2.841)	(3.008)	(0.548)	(0.684)	(0.386)	(43.888)
$\text{Income}_{0\text{-}16}$ * $\text{Transitory Vol}_{0\text{-}16}$		-1.719		-0.604		-5.554
		(5.897)		(0.983)		(92.444)
Black	-0.098	-0.024	-0.066	-0.088	0.010	1.295
	(0.142)	(0.164)	(0.092)	(0.104)	(0.118)	(22.754)
Other	0.030	-0.119	0.007	0.087	-0.020	0.370
	(0.190)	(0.300)	(0.111)	(0.196)	(0.025)	(6.324)
Female	-0.052	-0.023	-0.039	-0.044	-0.041	-0.207
	(0.036)	(0.080)	(0.024)	(0.030)	(0.030)	(3.002)
No. of Siblings	0.021	-0.017	0.005	0.000	-0.008	-0.214
	(0.030)	(0.087)	(0.013)	(0.016)	(0.024)	(3.608)
Constant	9.528	3.769	-8.166	-4.541	-4.256	5.194
	(41.368)	(58.305)	(9.015)	(11.193)	(9.541)	(267.312)
Observations	1,394	1,394	868	868	158	158

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. Instrument for Transitory Volatility is average county unemployment rate during childhood.

Table 4.22 IV Estimation of Childhood Income Volatility Exposure and High School Dropout (Total Volatility Definition)

DROPOUT	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
$Income_{0\text{-}16}$	-1.501	-2.600	-1.562	-4.366	-4.326	-3.422
	(2.900)	(8.505)	(3.472)	(32.344)	(43.644)	(29.970)
Total $Volatility_{0\text{-}16}$	-0.069	-0.110	-0.074	-0.282	-0.208	-0.182
	(0.141)	(0.377)	(0.169)	(2.129)	(2.117)	(1.619)
$Income_{0\text{-}16}$ * Total $Vol_{0\text{-}16}$		0.005		-0.056		-0.015
		(0.025)		(0.430)		(0.146)
Black	-0.112	-0.141	-0.083	0.053	-1.491	-1.077
	(0.175)	(0.357)	(0.142)	(0.925)	(14.813)	(9.213)
Other	-0.124	-0.159	-0.198	-0.927	-0.702	-0.629
	(0.265)	(0.547)	(0.482)	(7.035)	(7.000)	(5.466)
Female	-0.053	-0.071	-0.069	-0.135	-0.745	-0.694
	(0.068)	(0.138)	(0.122)	(0.824)	(7.302)	(5.917)
Constant	31.348	46.549	7.437	-8.100	-149.328	-127.276
	(77.100)	(175.035)	(40.502)	(86.624)	(1548.540)	(1150.175)
Observations	1,394	1,394	867	867	158	158

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. Instrument for Total Volatility is average county unemployment rate during childhood.

Table 4.23 IV Estimation of Childhood Income Volatility Exposure and Education Beyond High School (Transitory Definition)

POST SECONDARY	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
$\text{Income}_{0\text{-}16}$	0.053	0.853	0.158	0.148	0.297	-1.639
	(0.534)	(1.919)	(0.116)	(0.486)	(0.229)	(31.752)
$\text{Transitory Volatility}_{0\text{-}16}$	4.852	-0.420	-2.081	-0.792	1.508	7.957
	(12.255)	(7.387)	(3.180)	(1.588)	(2.078)	(125.733)
$\text{Income}_{0\text{-}16}$ * $\text{Transitory Vol}_{0\text{-}16}$		4.069		0.217		-14.976
		(11.573)		(2.063)		(264.437)
Black	0.204	-0.042	-0.402	-0.176	0.162	3.677
	(0.614)	(0.380)	(0.562)	(0.261)	(0.741)	(65.137)
Other	-0.234	0.221	0.450	0.218	-0.119	0.886
	(0.842)	(0.666)	(0.634)	(0.404)	(0.334)	(18.081)
Female	0.131	0.049	0.042	0.080	-0.076	-0.542
	(0.157)	(0.170)	(0.134)	(0.064)	(0.188)	(8.594)
No. of Siblings	-0.087	0.026	0.001	-0.014	-0.138	-0.684
	(0.128)	(0.187)	(0.082)	(0.040)	(0.117)	(10.329)
Constant	-54.341	-19.736	-13.096	-5.000	58.312	78.995
	(178.192)	(122.263)	(51.763)	(27.398)	(75.264)	(777.102)
Observations	1,394	1,394	868	868	158	158

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. Instrument for Transitory Volatility is average county unemployment rate during childhood.

Table 4.24 IV Estimation of Childhood Income Volatility Exposure and Education Beyond High School (Total Volatility Definition)

POST SECONDARY	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Income}_{0\text{-}16}$	2.228	2.219	2.387	4.816	-0.524	0.517
	(3.630)	(6.395)	(4.344)	(33.328)	(6.313)	(5.845)
$\text{Total Volatility}_{0\text{-}16}$	0.095	0.085	0.105	0.300	-0.036	0.020
	(0.176)	(0.282)	(0.212)	(2.193)	(0.307)	(0.313)
$\text{Income}_{0\text{-}16}$ * $\text{Total Vol}_{0\text{-}16}$		-0.006		0.057		0.001
		(0.020)		(0.443)		(0.027)
Black	0.055	0.060	-0.036	-0.166	-0.542	-0.103
	(0.234)	(0.280)	(0.207)	(0.966)	(2.133)	(1.818)
Other	0.176	0.150	0.378	1.079	-0.184	-0.062
	(0.350)	(0.416)	(0.628)	(7.248)	(1.027)	(1.064)
Female	0.116	0.120	0.156	0.213	-0.098	0.069
	(0.093)	(0.109)	(0.164)	(0.854)	(1.052)	(1.146)
Constant	-35.562	-30.294	-5.020	-7.674	33.385	63.859
	(97.514)	(129.551)	(54.181)	(146.177)	(244.701)	(207.456)
Observations	1,394	1,394	867	867	158	158

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. Instrument for Total Volatility is average county unemployment rate during childhood.

Table 4.25 IV Estimation of Childhood Income Volatility Exposure and Self Reported Poor Health (Transitory Definition)

POOR HEALTH	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$\text{Income}_{0\text{-}16}$	-0.046	0.134	-0.008	-0.106
	(0.118)	(0.235)	(0.011)	(0.773)
Transitory $\text{Volatility}_{0\text{-}16}$	0.939	0.363	-0.230	-0.241
	(2.520)	(1.931)	(0.312)	(1.035)
$\text{Income}_{0\text{-}16}$ * Transitory $\text{Vol}_{0\text{-}16}$		0.946		-0.384
		(1.601)		(3.188)
Black	0.034	0.017	-0.043	-0.034
	(0.084)	(0.054)	(0.055)	(0.094)
Other	-0.038	0.018	0.039	0.075
	(0.110)	(0.081)	(0.071)	(0.462)
Female	0.005	-0.007	-0.005	-0.006
	(0.030)	(0.026)	(0.016)	(0.051)
No. of Siblings	-0.011	0.006	0.005	0.000
	(0.030)	(0.026)	(0.008)	(0.023)
Constant	-7.981	-10.267	-2.936	0.729
	(25.922)	(24.303)	(4.291)	(26.875)
Observations	1,317	1,317	799	799

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. Instrument for Transitory Volatility is average county unemployment rate during childhood.

Table 4.26 IV Estimation of Childhood Income Volatility Exposure and Self Reported Poor Health (Total Volatility Definition)

POOR HEALTH	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$\text{Income}_{0\text{-}16}$	0.166	0.975	0.077	0.069
	(0.565)	(18.472)	(0.087)	(0.099)
$\text{Total Volatility}_{0\text{-}16}$	0.008	0.045	0.004	0.004
	(0.028)	(0.846)	(0.004)	(0.006)
$\text{Income}_{0\text{-}16}$ * $\text{Total Vol}_{0\text{-}16}$		-0.000		0.000
		(0.010)		(0.001)
Black	0.017	0.037	-0.003	-0.003
	(0.031)	(0.506)	(0.008)	(0.007)
Other	0.001	0.031	0.005	0.005
	(0.034)	(0.742)	(0.014)	(0.018)
Female	0.000	0.003	0.007	0.007
	(0.010)	(0.053)	(0.008)	(0.008)
Constant	-4.043	-21.080	-2.536	-2.547
	(16.604)	(410.913)	(2.768)	(2.682)
Observations	1,318	1,318	798	798

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. Instrument for Total Volatility is average county unemployment rate during childhood.

Table 4.27 IV Estimation of Childhood Income Volatility Exposure and Non Marital Child Bearing (Transitory Definition)

OWB	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$Income_{0\text{-}16}$	-0.046	-0.132	-0.035**	-0.067
	(0.033)	(0.458)	(0.016)	(0.067)
Transitory $Volatility_{0\text{-}16}$	-0.078	-0.152	0.032	0.009
	(0.281)	(0.527)	(0.125)	(0.126)
$Income_{0\text{-}16}$ * Transitory $Vol_{0\text{-}16}$		-0.930		-0.250
		(4.966)		(0.365)
Black	0.385***	0.290	0.345***	0.313***
	(0.099)	(0.518)	(0.113)	(0.117)
Other	0.030	0.016	-0.024	-0.010
	(0.065)	(0.112)	(0.015)	(0.027)
No. of Siblings	0.004	-0.008	0.003	0.001
	(0.008)	(0.066)	(0.008)	(0.008)
Constant	0.881	8.522	-1.807	1.896
	(3.947)	(42.204)	(3.570)	(7.323)
Observations	667	667	415	415

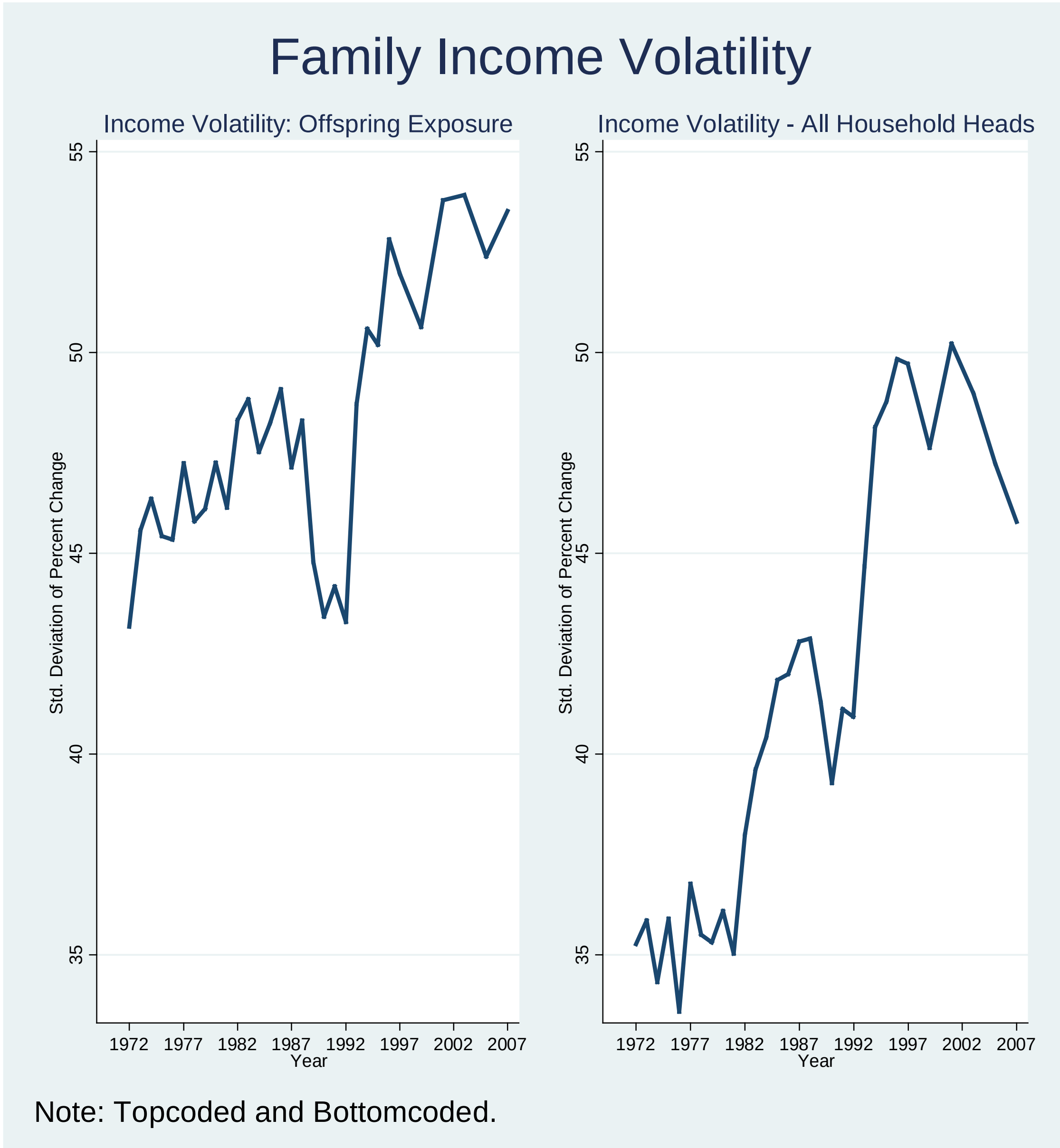
Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. Instrument for Transitory Volatility is average county unemployment rate during childhood.

Table 4.28 IV Estimation of Childhood Income Volatility Exposure and Non Marital Child Bearing (Total Volatility Definition)

OWB	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)
$\text{Income}_{0\text{-}16}$	3.159	-1.412	-0.297	-0.154
	(54.399)	(9.019)	(1.388)	(0.319)
Total $\text{Volatility}_{0\text{-}16}$	0.160	-0.072	-0.014	-0.016
	(2.715)	(0.477)	(0.076)	(0.054)
$\text{Income}_{0\text{-}16}$ * Total $\text{Vol}_{0\text{-}16}$		-0.007		-0.010
		(0.057)		(0.045)
Black	0.439	0.386*	0.328**	0.335***
	(0.905)	(0.198)	(0.149)	(0.123)
Other	0.391	-0.126	-0.063	-0.101
	(6.180)	(1.043)	(0.217)	(0.292)
Constant	-40.599	18.451	-6.294	-1.026
	(698.916)	(122.866)	(20.714)	(8.959)
Observations	668	668	415	415

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. Instrument for Total Volatility is average county unemployment rate during childhood.

FIGURE 4.1



Family Income Volatility
Income Volatility: Offspring Exposure
Income Volatility - All Household Heads
Std. Deviation of Percent Change
35
40
45
50
55
1972
1977
1982
1987
1992
1997
2002
2007
Year
Note: Topcoded and Bottomcoded.

5 CONCLUSION

The three essays of this dissertation yield a set of results that could inform policymakers concerned with the occurrence of economic volatility in America. First, the results from essay 2 suggest that income volatility is on the rise throughout many American households. This is a broad finding occurring across race, education, and family structure. While those who are continuously employed contribute substantially to this rising volatility, labor force transitions explain an increasing proportion of earnings volatility among males. From essay 3, individuals with low average earnings and members of racial and ethnic minority groups are more likely to report higher earnings volatility. Between essays 2 and 3, I find that volatility increases occur largely throughout the 1970s and 1980s and are disproportionately borne by those less skilled, with lower earnings, and both racial and ethnic minorities. Finally, volatility exposure during childhood may be related to lower educational attainment as an adult in essay 4. However, when compared to the mobility consequences of permanent family income, race, and family size, the intergenerational volatility impact appears to be small.

Earnings and income volatility may threaten family and child well-being in instances where consumption smoothing is not possible or even imperfect. This dissertation identifies differences in volatility levels, trends, and correlates across different races, education groups, and family structures. It then estimates how volatility exposure during childhood relates to adult outcomes. These results, which merit further inquiry, begin the process of understanding how volatility may impact well-being across the population. Taken together, the three essays that comprise the dissertation provide an updated, comprehensive inquiry into the occurrence and potential consequences of volatility. Future work on volatility can directly explore the responsiveness of public programs to volatile earnings. This includes trend analysis utilizing a full variance decomposition of income sources. In an intergenerational context, volatility along different points of the age distribution also warrants further examination. Finally, essay 4's study of volatility within a model of intergenerational mobility can be expanded by using data sets beyond the PSID, including the National Longitudinal Surveys as well as administrative earnings records. The results of this research will hopefully add to our collective understanding of labor market dynamics in the United States and the second moment of wages, particularly earnings and income volatility. This improved understanding could raise new questions regarding the stabilizing role of the U.S. tax and transfer system, the provision of social insurance benefits, and well-being in the face of economic volatility.

Appendix List of Tables

Appendix Table 1 Correlation between Parental Income and Parental Educational Attainment

	Mean Parental Income
Parents Education	0.395***
	(0.004)
Constant	10.718***
	(0.003)
Observations	2,093
R-squared	0.1446

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Parents Education is 0/1 variable indicating either parent attended 4 or more years of college or university.

Appendix Table 2 Childhood Income Volatility Exposure and High School Dropout (Transitory Definition)

DROPOUT	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Ed	-0.047***	-0.051***	-0.034***	-0.030**	-0.034***	-0.040**
	(0.008)	(0.011)	(0.009)	(0.013)	(0.013)	(0.017)
Transitory Volatility$_{0\text{-}16}$	0.006	0.006	0.010	0.009	-0.009	-0.009
	(0.008)	(0.008)	(0.010)	(0.010)	(0.006)	(0.007)
Parents Ed * Transitory Vol$_{0\text{-}16}$		0.007		-0.006		0.010
		(0.015)		(0.017)		(0.011)
Black	-0.041*	-0.041*	-0.059***	-0.059***	-0.037**	-0.037**
	(0.023)	(0.023)	(0.017)	(0.017)	(0.016)	(0.016)
Other	0.090*	0.090*	0.109*	0.110*	0.138	0.137
	(0.048)	(0.048)	(0.063)	(0.062)	(0.130)	(0.130)
Female	-0.050***	-0.050***	-0.043***	-0.043***	-0.029*	-0.029*
	(0.010)	(0.010)	(0.011)	(0.011)	(0.016)	(0.016)
No. of Siblings	0.023***	0.023***	0.024***	0.024***	0.020**	0.020**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)
Constant	3.507**	3.509**	4.902***	4.889***	6.381	6.529
	(1.726)	(1.722)	(1.324)	(1.335)	(5.206)	(5.273)
Observations	2,202	2,202	1,531	1,531	596	596
R-squared	0.0705	0.0705	0.0763	0.0764	0.0929	0.0933
Joint F Test		0.670		0.474		1.139

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory Volatility$_{0\text{-}16}$ and Parents Ed * Transitory Vol$_{0\text{-}16}$.

Appendix Table 3 Childhood Income Volatility Exposure and High School Dropout (Total Volatility Definition)

DROPOUT	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Ed	-0.045***	-0.013	-0.030***	-0.015	-0.016	0.011
	(0.008)	(0.013)	(0.009)	(0.014)	(0.010)	(0.019)
Total Volatility$_{0\text{-}16}$	0.001***	0.001***	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Parents Ed * Total Vol$_{0\text{-}16}$		-0.001***		-0.001		-0.001*
		(0.000)		(0.001)		(0.001)
Black	-0.031	-0.031	-0.042*	-0.043**	-0.033**	-0.033**
	(0.023)	(0.023)	(0.022)	(0.022)	(0.013)	(0.014)
Other	0.096**	0.092*	0.112*	0.112*	0.138	0.135
	(0.048)	(0.048)	(0.062)	(0.062)	(0.124)	(0.122)
Female	-0.041***	-0.041***	-0.033***	-0.033***	-0.027*	-0.025*
	(0.010)	(0.010)	(0.011)	(0.011)	(0.014)	(0.013)
No. of Siblings	0.019***	0.019***	0.021***	0.021***	0.017***	0.017***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Constant	1.442	1.402	2.698	2.659	-0.152	1.037
	(1.653)	(1.617)	(1.729)	(1.715)	(4.621)	(4.603)
Observations	2,300	2,300	1,606	1,606	640	640
R-squared	0.0694	0.0720	0.0747	0.0756	0.1180	0.1225
Joint F Test		5.910		3.244		2.331

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Total Volatility$_{0\text{-}16}$ and Parents Ed * Total Vol$_{0\text{-}16}$.

Appendix Table 4 Childhood Income Volatility Exposure and Post Secondary Education (Transitory Definition)

POST SECONDARY	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Ed	0.335***	0.353***	0.324***	0.348***	0.383***	0.436***
	(0.020)	(0.026)	(0.025)	(0.031)	(0.036)	(0.044)
Transitory Volatility$_{0-16}$	0.004	0.003	0.016	0.013	0.028	0.029
	(0.015)	(0.015)	(0.019)	(0.019)	(0.026)	(0.024)
Parents Ed * Transitory Vol$_{0-16}$		-0.031		-0.042		-0.093**
		(0.029)		(0.037)		(0.046)
Black	0.022	0.023	0.022	0.023	0.103	0.106
	(0.045)	(0.045)	(0.060)	(0.060)	(0.121)	(0.123)
Other	-0.052	-0.050	0.051	0.054	-0.147	-0.136
	(0.061)	(0.060)	(0.069)	(0.069)	(0.101)	(0.100)
Female	0.082***	0.082***	0.080***	0.079***	0.051	0.048
	(0.020)	(0.020)	(0.025)	(0.025)	(0.039)	(0.039)
No. of Siblings	-0.049***	-0.049***	-0.053***	-0.053***	-0.040***	-0.040***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)
Constant	-4.188***	-4.196***	-4.723**	-4.808**	12.021	10.612
	(1.468)	(1.469)	(2.042)	(2.049)	(14.081)	(14.199)
Observations	2,202	2,202	1,531	1,531	596	596
R-squared	0.1672	0.1675	0.1640	0.1647	0.1850	0.1897
Joint F Test		0.564		0.761		2.248

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory Volatility$_{0-16}$ and Parents Ed * Transitory Vol$_{0-16}$.

Appendix Table 5 Childhood Income Volatility Exposure and Post Secondary Education (Total Volatility Definition)

POST SECONDARY	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Ed	0.331***	0.303***	0.321***	0.299***	0.366***	0.359***
	(0.020)	(0.031)	(0.024)	(0.036)	(0.035)	(0.052)
Total Volatility$_{0\text{-}16}$	-0.001**	-0.001**	-0.001	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parents Ed * Total Vol$_{0\text{-}16}$		0.001		0.001		0.000
		(0.001)		(0.001)		(0.002)
Black	0.008	0.008	0.015	0.016	0.053	0.053
	(0.043)	(0.043)	(0.059)	(0.059)	(0.115)	(0.115)
Other	-0.055	-0.051	0.049	0.049	-0.131	-0.131
	(0.059)	(0.060)	(0.068)	(0.068)	(0.099)	(0.100)
Female	0.063***	0.063***	0.048**	0.048**	0.024	0.023
	(0.020)	(0.020)	(0.024)	(0.024)	(0.038)	(0.038)
No. of Siblings	-0.046***	-0.046***	-0.051***	-0.050***	-0.040***	-0.040***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)
Constant	-0.601	-0.565	-0.817	-0.761	22.697	22.377
	(1.686)	(1.665)	(2.471)	(2.459)	(14.455)	(14.611)
Observations	2,300	2,300	1,606	1,606	640	640
R-squared	0.1639	0.1643	0.1598	0.1601	0.1835	0.1836
Joint F Test		3.187		1.334		1.299

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Total Volatility$_{0\text{-}16}$ and Parents Ed * Total Vol$_{0\text{-}16}$.

Appendix Table 6 Childhood Income Volatility Exposure and Self Reported Poor Health (Transitory Definition)

POOR HEALTH	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Ed	0.003	0.001	0.003	0.005	-0.005	-0.007
	(0.004)	(0.007)	(0.004)	(0.006)	(0.004)	(0.005)
Transitory Volatility$_{0\text{-}16}$	0.005	0.005	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
Parents Ed * Transitory Vol$_{0\text{-}16}$		0.004		-0.004		0.003
		(0.012)		(0.003)		(0.002)
Black	0.006	0.006	-0.003*	-0.003*	-0.004	-0.005
	(0.012)	(0.012)	(0.002)	(0.002)	(0.003)	(0.004)
Other	0.008	0.009	-0.004**	-0.004**	-0.000	-0.000
	(0.014)	(0.014)	(0.002)	(0.002)	(0.001)	(0.001)
Female	0.002	0.002	0.002	0.002	-0.006	-0.006
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
No. of Siblings	0.001	0.001	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.286	0.282	-0.197	-0.204	-1.325	-1.285
	(0.301)	(0.299)	(0.222)	(0.229)	(1.190)	(1.169)
Observations	1,828	1,828	1,453	1,453	532	532
R-squared	0.0034	0.0036	0.0033	0.0037	0.0070	0.0074
Joint F Test		0.849		1.101		0.881

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory Volatility$_{0\text{-}16}$ and Parents Ed * Transitory Vol$_{0\text{-}16}$.

Appendix Table 7 Childhood Income Volatility Exposure and Self Reported Poor Health (Total Volatility Definition)

POOR HEALTH	24-26	24-26	29-31	29-31	39-41	39-41
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Ed	0.003	0.007	0.003	0.000	-0.005	-0.007
	(0.004)	(0.006)	(0.004)	(0.006)	(0.003)	(0.005)
Total Volatility$_{0-16}$	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parents Ed * Total Vol$_{0-16}$		-0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Black	0.006	0.006	-0.003*	-0.002*	-0.003	-0.003
	(0.012)	(0.012)	(0.001)	(0.001)	(0.003)	(0.003)
Other	0.008	0.008	-0.004**	-0.004**	0.000	0.000
	(0.014)	(0.014)	(0.002)	(0.002)	(0.001)	(0.001)
Female	0.002	0.002	0.002	0.002	-0.005	-0.005
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
No. of Siblings	0.001	0.001	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Constant	0.258	0.248	-0.226	-0.220	-1.194	-1.280
	(0.263)	(0.264)	(0.199)	(0.200)	(1.068)	(1.128)
Observations	1,839	1,839	1,528	1,528	571	571
R-squared	0.0022	0.0025	0.0032	0.0034	0.0061	0.0064
Joint F Test		0.659		0.814		0.855

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Total Volatility$_{0-16}$ and Parents Ed * Total Vol$_{0-16}$.

Appendix Table 8 Childhood Income Volatility Exposure and Non Marital Child Bearing (Transitory Definition)

OWB	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
Parents Ed	-0.008	0.004	-0.020**	-0.009	-0.003	0.009
	(0.011)	(0.015)	(0.009)	(0.012)	(0.004)	(0.011)
Transitory Volatility$_{0\text{-}16}$	0.012	0.011	0.012	0.009	0.024	0.022
	(0.011)	(0.010)	(0.014)	(0.012)	(0.024)	(0.022)
Parents Ed * Transitory Vol$_{0\text{-}16}$		-0.023		-0.023		-0.026
		(0.016)		(0.017)		(0.030)
Black	0.253***	0.253***	0.224***	0.224***	0.068	0.070
	(0.057)	(0.057)	(0.070)	(0.070)	(0.076)	(0.076)
Other	0.000	0.001	-0.025***	-0.026***	-0.014	-0.007
	(0.034)	(0.034)	(0.009)	(0.009)	(0.012)	(0.008)
No. of Siblings	-0.001	-0.001	0.001	0.001	0.002	0.002
	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)
Constant	0.487	0.487	-0.988	-1.039	4.000	3.464
	(1.570)	(1.564)	(0.866)	(0.856)	(3.660)	(3.106)
Observations	1,065	1,065	743	743	289	289
R-squared	0.0987	0.0997	0.0978	0.0990	0.0665	0.0739
Joint F Test		1.003		1.878		0.901

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Transitory Volatility$_{0\text{-}16}$ and Parents Ed * Transitory Vol$_{0\text{-}16}$.

Appendix Table 9 Childhood Income Volatility Exposure and Non Marital Child Bearing (Total Volatility Definition)

OWB	24-26 (1)	24-26 (2)	29-31 (3)	29-31 (4)	39-41 (5)	39-41 (6)
Parents Ed	-0.005	-0.010	-0.018**	0.009	-0.004	0.004
	(0.011)	(0.019)	(0.009)	(0.015)	(0.006)	(0.008)
Total Volatility$_{0\text{-}16}$	0.001*	0.001*	0.001	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parents Ed * Total Vol$_{0\text{-}16}$		0.000		-0.001*		-0.000
		(0.001)		(0.001)		(0.000)
Black	0.246***	0.247***	0.247***	0.246***	0.053	0.053
	(0.055)	(0.055)	(0.072)	(0.072)	(0.061)	(0.061)
Other	-0.002	-0.002	-0.031***	-0.027***	-0.009	-0.009
	(0.035)	(0.036)	(0.012)	(0.009)	(0.008)	(0.009)
No. of Siblings	-0.001	-0.001	0.000	-0.000	-0.000	-0.001
	(0.004)	(0.004)	(0.004)	(0.005)	(0.001)	(0.001)
Constant	0.349	0.354	-1.075	-1.114	2.809	2.754
	(1.630)	(1.625)	(0.855)	(0.858)	(2.865)	(2.861)
Observations	1,117	1,117	780	780	314	314
R-squared	0.1030	0.1030	0.1190	0.1218	0.0300	0.0316
Joint F Test		1.783		2.280		0.899

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Coefficients for education and age not shown. F-statistics tests joint significance of Total Volatility$_{0\text{-}16}$ and Parents Ed * Total Vol$_{0\text{-}16}$.

Appendix Current Population Survey Data

In this appendix describing Current Population Survey (CPS) data, years refer to calendar years. 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 I use before 1977.

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 the income category for "Means Tested Transfers and Credits" excludes these variables before 1979. When I 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 are combined 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. I account for federal taxes using taxsim throughout the panel. In years before 1977, state tax rates are unavailable and therefore not accounted for in the analysis. Federal and state taxes are accounted for after 1976.

Appendix A Basic Framework of Intergenerational Mobility

The empirical analysis of income volatility's intergenerational consequences is informed by the seminal Becker and Tomes (1979) model of intergenerational mobility, in an adaptation influenced heavily by Solon (1999, 2004). This adaptation adds an approximation for income shocks to the model, formalizing the role of persistent transitory shocks to income (Lillard and Willis 1978; Hyslop 2001; Mazumder 2005). I describe the basic features of the intergenerational model, below. Parental income in time t-1 determines the quality of the offspring in time t, where this is measured by the child's future or lifetime income, $y_{i,t}$:

(1) $y_{i,t} = \varphi\left(y_{i,t-1}\right).$

In a multi-period setting for a family i, the function φ is nondecreasing in income, y, and describes the intertemporal relationship between the incomes of parents in period t-1 and adult offspring in period t (Durlauf 2009). In more detail (Solon 1999), the Becker and Tomes (1979) model allows for parents to allocate income between C_{t-1}, consumption for themselves, and I_{t-1}, human capital investment in their children. From equation 1, parental income, y_{t-1}, is defined as

(2) $y_{t-1} = C_{t-1} + I_{t-1}$

Education investments are a salient example of variables included in human capital investment (I_{t-1}) but human capital investment also includes quality neighborhoods, stimulating learning environments outside of formal schooling, and childcare (Blau 1999). In addition to parental investment in human capital, lifetime adult income, y_t, is also influenced by endogenous factors E_t:

(3) $y_t = (1 + r)I_{t-1} + E_t.$

These $\mathrm{E_t}$ determinants of lifetime income are a combination of innate and environmental factors, including reputation, family connections, ability, race, culture, and goals. $\mathrm{E_t}$ represents the set of elements beyond parental investment determining the child's lifetime income or quality, and r is the rate of return to human capital. $\mathrm{E_t}$ is decomposed so that

(4) $\mathrm{E_t} = \mathrm{e_t} + \mathrm{u_t}$.

This decomposition accounts for the child's given endowment of income capacity, $\mathrm{e_t}$, and the presence of luck, $\mathrm{u_t}$. $\mathrm{E_t}$ can admit negative and positive terms that influence the child's lifetime income or quality, and this is likely both endogenous and potentially inheritable. The size of this omitted component is debatable. Altonji and Dunn (2000) find that typical intergenerational associations overstate the role of parental characteristics and neglect the role of similarities in labor supply preferences across generations. Yet, Mason (2007) concludes family preferences explain a small share of the racial gap in intergenerational mobility relative to social class. Parents consider their optimizing choices of C_{t-1} and I_{t-1} as part of a family that spans an unknown number of generations into the future, and the well-being of children and future generations enters the utility function positively. The parents are still self interested, but current consumption comes at the cost of future consumption, as well as investments in future generations. Parents' taste for consumption versus child investment varies by α, the preference parameter reflecting the tradeoff between parental current period interests and altruism in the Cobb-Douglass utility function:

(5) $\max_{C_{t-1},\, y_t} U = (1-\alpha) log C_{t-1} + \alpha log y_t$.

α is bounded between 0 and 1, and the model assumes that $\mathrm{E_t}$ are known to the parents.

With a knowledge of $E_t{}'s$ components, the resulting equation for the child's lifetime income, y_t, after substituting the optimal amount of investment, I_{t-1}, is

(6) $$y_t = \alpha(1 + r)y_{t-1} + \alpha E_t.$$

Setting β = α(1+r) yields a simplified expression where, assuming stationary of y such that the variance of y is equivalent across generations, child income is at least partially determined by parental income:

(7) $$y_t = \beta y_{t-1} + \alpha E_t.$$

Here, β reflects the correlation between lifetime income of parents and children, or between parents' income and lifetime child quality. Equations 3, 4, and 6 demonstrate how factors outside of parental income and investment potentially influence the transmission of intergenerational income and earnings relationships. Substituting the decomposition of E_t (4) into (7) shows children's lifetime income (quality) is influenced by parental investment and income, parental preferences, ability of the child, and luck:

(8) $$y_t = \beta y_{t-1} + \alpha e_t + \alpha u_t.$$

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