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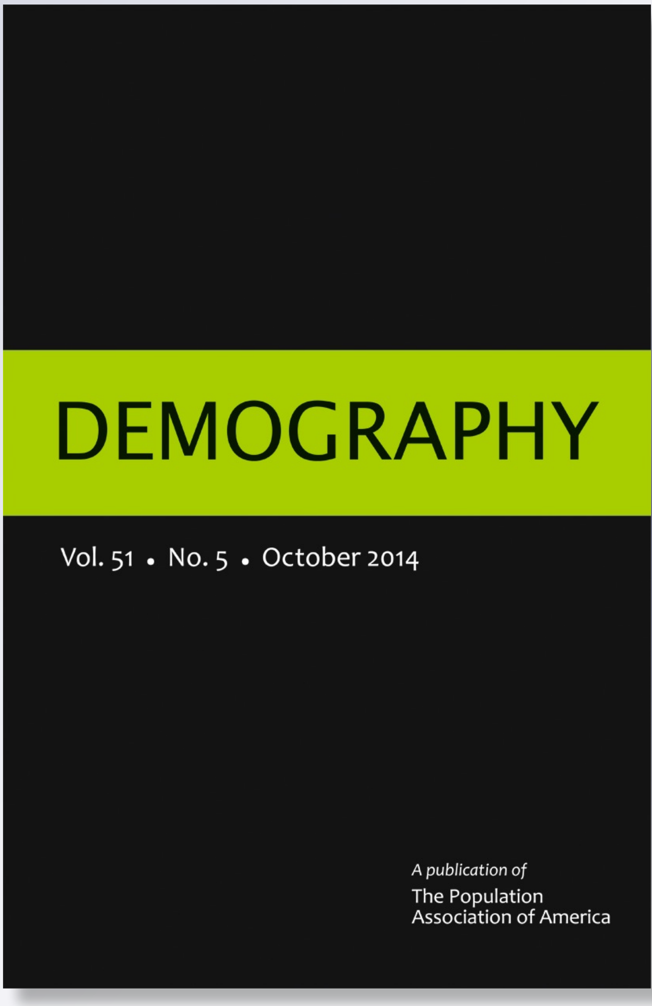
Demography

ISSN 0070-3370
Volume 51
Number 5

Demography (2014) 51:1641-1665
DOI 10.1007/s13524-014-0329-2



Springer

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Published online: 4 October 2014

Abstract Using data linked across generations in the Panel Study of Income Dynamics, I 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 measure income volatility at the family level in two ways: (1) instability as measured by squared deviations around a family-specific mean; and (2) instability as percentage changes of 25 % or more. Volatility enters the model both separately and interacted with income level. I find that family income volatility during childhood has a modest negative association with educational attainment. Volatility has a smaller descriptive role in explaining intergenerational outcomes relative to permanent income. Across the income distribution, the negative association between volatility exposure and educational attainment is largest for young adults from moderate-income families.

Keywords Intergenerational mobility · Volatility · Economic risk · Educational attainment · Early human capital investment

Introduction

Income volatility in the United States has been on the rise since the 1970s, increasing by at least one-third (Dynan et al. 2012; Gottschalk and Moffitt 1994; Haider 2001; Keys 2008; Ziliak et al. 2011). Driven largely by earnings, it exhibits cyclical behavior (Dahl et al. 2011) 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 (Charles and Stephens 2004; Currie et al. 2010; Eliason and Storrie 2007; Huff Stevens 1997; Woock 2009).

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Job losses may reduce achievement and educational attainment among children (Coelli 2009; Huff Stevens and Schaller 2011; Johnson et al. 2012), but it is unclear whether this effect is driven by volatile income or unobservable circumstances among the jobless. Although the literature does confirm that growing up in poverty is associated with lower education, earnings, and cognitive ability (Dahl and Lochner 2012; Duncan and Brooks-Gunn 2000; Duncan et al. 2008), we do not know whether growing up in households with unstable incomes *per se* warrants concern.

Research examining the long-term consequences of volatility is lacking. Most volatility research has, up to this point, focused on trends, statistical measurement, and the implications that such measures have when interpreting changes in income inequality in the United States (Burkhauser and Couch 2009). 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 lowered education, earnings, and receipt of public assistance as an adult (Duncan et al. 1994, 2008, 2011; Magnuson and Votruba-Drzal 2009; Mazumder and Davis 2012). One channel enabling such relationships across generations may be human capital (Becker and Tomes 1979; Blanden et al. 2011; Blau 1999; Lillard and Willis 1994; Ludwig and Miller 2007). This article therefore draws motivation from a model of mobility wherein parental income determines human capital for children in the household, which then largely determines the children's educational attainment, adult earnings, income, and well-being (Becker and Tomes 1979). Work on the early formation of human capital suggests that initial skills are necessary to acquire additional skills in the future (Cunha et al. 2006); furthermore, modest, positive associations exist between income and educational attainment (Duncan et al. 2008) on one hand and performance on math and reading assessments on the other (Dahl and Lochner 2012). Such skill deficits may drive findings in studies estimating intergenerational relationships.

In this article, I examine the long-term consequences of income volatility during childhood on subsequent adult outcomes. Extensive evidence exists on intergenerational economic mobility in earnings, income, education, and wealth (Becker and Tomes 1979; Black et al. 2005; Charles and Hurst 2003; Chetty et al. 2014; Mazumder 2005; Meghir and Palme 2005; Solon 1992; Zimmerman 1992). The mobility model adopted here augments the standard intergenerational income elasticity (IGE) model to include income volatility and then extends the model to include educational outcomes. Mechanisms giving rise to the intergenerational transmission of volatility in the standard Becker and Tomes (1979) framework are discussed, including human capital investment decisions of parents with volatile income amid imperfect capital markets (Loury 1981; Mazumder 2005). Becker and Tomes (1986) emphasized the role of functioning capital markets within intergenerational models, and in this context, imperfections within such markets imply that income shocks can persist. Part of this persistence may include a range of consequences from events related to income volatility impacting child learning and development (Hill et al. 2013), perhaps less likely to be addressed by households with costlier or otherwise constrained access to loanable funds. The emphasis on adult educational attainment along with adult income reinforces the importance of human capital as a determinant of socioeconomic outcomes, including income over the life cycle. By accounting for income shocks during childhood, this article 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 from 1970–2007. Income volatility during childhood is defined as the volatility of natural log family income from labor market earnings, total taxable nonlabor income, and government transfers between ages 0 and 16. For each person, volatility is calculated in two ways. First, I decompose residual total volatility into its permanent and transitory components and isolate the transitory measure as an explanatory variable (Gottschalk and Moffitt 1994, 2009). Prior to the log transformation, I residualize income by regressing family income on an age quartic for the household head. A second measure then estimates volatility as the number of between-year income shifts of 25 % or more (25 %+) (Dahl et al. 2011). With both approaches, volatility enters the model separately and is interacted with income level.

I examine income level and educational attainment for adults who, as children, grew up in households with varying incidence of income volatility. Adult income is measured at age 25 and beyond, and educational attainment is measured both by whether the child drops out of high school and whether s/he attains postsecondary education near the age threshold of 25, using a linear dependent variable model. The ordinary least squares (OLS) classical errors-in-variables assumption is violated in the income IGE models because families with higher lifetime mean income typically experience relatively higher rates of income growth over the life cycle. This leads to intergenerational income 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 life cycle earnings growth and adopt specifications found to minimize left-side measurement error in second-generation incomes (Haider and Solon 2006; Lee and Solon 2009).

Using two measures of volatility, I find that income volatility exposure during childhood is associated with lower educational attainment, although the magnitude of this association is modest relative to permanent income. The association is larger among adults from moderate income backgrounds where, for example, a 1 standard deviation increase in transitory volatility translates to a lower likelihood of postsecondary attainment by approximately 5 %, relative to a 2 % to 3 % lower likelihood of postsecondary education evaluated at the mean. To properly measure volatility over time, I exclude observations that do not contain at least 15 of 16 childhood years. At the same time, this reduces the size of the sample, which may have efficiency implications for intergenerational empirical models with small sample sizes, especially those examining volatility across the income distribution.

Background

Even though relatively little work exists on the intergenerational aspects of volatility, the inheritability of socioeconomic status (SES) is well documented in the literature on intergenerational transmission (Altonji and Dunn 2000; Charles and Hurst 2003; Solon 1992; Zimmerman 1992). The intergenerational mobility model posits that parental endowments and investments in child human capital largely determine adult offspring socioeconomic outcomes (Becker and Tomes 1979, 1986; Solon 1999) such as income, earnings, and education (Blanden et al. 2005; Blau 1999; Bloome and Western 2011; Ermisch and Pronzato 2011; Guldi et al. 2007; Oreopoulos et al. 2006). Parental income supports investment in child human capital, implying that transitory shocks to income potentially alter the level or timing of such investment. Because human capital formation drives educational attainment, which in turn influences lifetime income via labor market earnings (Polachek 2008), the empirical model explores the link between volatility and both adult income and adult educational attainment.

As described earlier, human capital is a primary mechanism underlying the linear relationship between the income level or SES $y_{i,g-1}^{parent}$ of working-age parents with children in generation $g-1$ and the adult income level y_{ig}^{child} of their adult offspring i in generation g:

$$y_{ig}^{child} = \alpha + \beta y_{i,g-1}^{parent} + \varepsilon_{ig}. \tag{1}$$

Total parental income in childhood generation $g-1$, $y_{i,g-1}^{parent}$ can be decomposed into a permanent income component $\mu_{i,g-1}^{parent}$ and a transitory income component $v_{i,g-1}^{parent}$ (Gottschalk and Moffitt 1994):

$$y_{i,g-1}^{parent} = \mu_{i,g-1}^{parent} + v_{i,g-1}^{parent} = C_{i,g-1}^{parent} + I_{i,g-1}^{child}. \tag{2}$$

Parental income in generation $g-1$ is spent on parental consumption $C_{i,g-1}^{parent}$ and investment in child human capital $I_{i,g-1}^{child}$. As shown in Eq. (2), shocks or variation in $v_{i,g-1}^{parent}$ could impact investment in children's human capital $I_{i,g-1}^{child}$ if families lack sufficient precautionary savings and also under imperfect credit markets, allowing volatility to enter the intergenerational model. Equations (1) and (2) are adapted from work by Solon (2004), which provides a more formal and extensive modeling of intergenerational mobility.

The empirical mobility model is a log-linear transformation of Eq. (1), regressing log adult offspring income on the log income of working-age parent(s) (Solon 1999):

$$\ln y_{ig}^{child} = \alpha + \beta \ln \bar{y}_{i,g-1}^{parent} + \varepsilon_{ig}, \tag{3}$$

where y_{ig}^{child} represents yearly adult offspring income in period or generation g, and $\bar{y}_{i,g-1}^{parent}$ is the mean income of the working-age parent(s) in period $g-1$, during childhood years of the offspring. β denotes the IGE, measured with a white noise error ε_{ig} (Zimmerman 1992). The IGE summarizes the relationship among income, earnings, or wealth across generations. An IGE of 1 denotes no mobility across generations, and a value of 0 denotes perfect mobility; and, by design, known causal factors are omitted in the regressions (Becker and Tomes 1986). Studies estimating IGEs account for life cycle effects and measurement error using longer measures of permanent earnings or incomes, with IGE estimates ranging between 0.4 and 0.6 (Gouskova et al. 2010b; Mazumder 2005; Solon 1992; Zimmerman 1992). 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 Eqs. (1) and (3). These parameters include a decomposed definition of family income that recognizes the role of income fluctuations in determining adult outcomes.

Like the IGE, volatility is a summary measure capturing events that add and take away income. Although measures of income and earnings volatility have seldom been used in an explanatory context, a variety of event studies have documented specific examples of economic volatility. This work attempts to explain the role of job loss and income shocks in predicting earnings (Oreopolous et al. 2008), health (Eliason and Storrie 2007; Ruhm 2005), marriage, and divorce (Charles and Stephens 2004; Conger et al. 1990; Eliason 2012; Hankins and Hoekstra 2011; Mayer 1997; Nunley and Seals 2010). For children, volatility by way of job loss may lead to lowered educational attainment and achievement as well as behavioral problems (Coelli 2009; Huff Stevens and Schaller 2011; Johnson et al. 2012), and this may be especially true for lower-income children whose families are unable to buffer such shocks (Page et al. 2009).

Volatility measures capture these types of income shocks experienced within families. The t subscript in Eq. (4) denotes individual years *within* time period or generation $g-1$ (e.g., youth). Similar to Eq. (2), though, now for family i in year t within generation $g-1$, I decompose the log of annual family income $\ln y_{it}$ into a permanent component μ_i and a transitory component v_{it}:

$$\ln y_{it} = \alpha_t \mu_i + \varphi_t v_{it}, \tag{4}$$

where μ_i is permanent income, v_{it} is transitory income, and α_t and φ_t are time-varying factor loadings on the permanent and transitory components. Assuming that permanent and transitory components are independent and that factor loadings equal 1 in all years, the variance of log income in Eq. (4) is

$$Var\left(\ln y_{it}\right) = \sigma^2_{\mu_i} + \sigma^2_{v_i}. \tag{5}$$

The decomposition in Eq. (5) differentiates between permanent volatility ($\sigma^2_{\mu_i}$) attributable to longer-term or structural income shifts and transitory volatility ($\sigma^2_{v_i}$) related to short-term events (Gottschalk and Moffitt 2009; Ziliak et al. 2011). Transitory volatility—a measure used in this study—is defined by yearly deviations $y_{it} - \bar{y}_i$ from mean (parental) income $\bar{y}_i$ specific to family i as measured over the first 16 years of the child's life T_i:

$$Transitory\ Volatility = \mathrm{var}\left(v_i\right) = \sigma^2_{v_i} = \left(\frac{1}{T_i - 1}\right) \Sigma_{t=1}^{T_i=16} \left(y_{it} - \bar{y}_i\right)^2. \tag{6}$$

Transitory volatility might approximate risk resulting from temporary increases in economic hardship consistent with adverse events (such as job loss, injury, divorce, or declining health) but could equally result from voluntary or positive events, including bonus or incentive pay (Dynan et al. 2012). A leading explanation for permanent volatility is skill-biased technological change (Autor et al. 2008), whereby structural changes in the economy put a higher premium on skilled labor reflected by greater income and earnings inequality throughout society (Gottschalk and Moffitt 2009). Total volatility measures combine transitory and permanent components with fewer assumptions. Hardy and Ziliak (2014), Ziliak et al. (2011), Dahl et al. (2011), and Dynan et al.

(2012) measured total volatility with the percentage change or close transformations, such as the standard deviation of income percentage changes. In this study, I follow Dahl et al. (2011) and define total volatility for each child-family observation *i* as the sum of the number of year-over-year percentage changes in family (parental) income greater than or equal to 25 % throughout the first 16 years of the child's life over *N* observations:

$$Total\ Volatility = \sum_{i=1}^{i=N} \sum_{t=1}^{T_i=16} \left(1 \middle| 100 \times \frac{y_{it} - y_{it-1}}{Y_{average}} \geq 25, 0 \text{ otherwise} \right), \tag{7}$$

where $Y_{average} = \left(Y_t + Y_{t-1}\right)/2$. Results using transitory and total measures of volatility comport with respect to statistical significance and direction, although the magnitude of the descriptive relationship is sensitive to the choice of measure.

Several studies have documented rising earnings and income volatility income over the past 30 to 40 years (Dynan et al. 2012; Gottschalk and Moffitt 1994, 2009; Ziliak et al. 2011), and socioeconomic subgroups with lower education levels and lower earnings have been shown to exhibit relatively higher levels of volatility (Gottschalk and Moffitt 1994; Keys 2008; Ziliak et al. 2011). If family income volatility during childhood is related to adult outcomes, intergenerational data sources such as the PSID provide useful socioeconomic outcomes for adults who were children during the 1970s and 1980s, periods of rising volatility. Shore (2012) and Dohmen et al. (2012) took such an approach, using panel data and concluding that parental income volatility leads to adult offspring income volatility, with volatility as a proxy for the transmission of risk from parents to children. I follow Shore (2012) in using the PSID to understand how higher-income moments of parental income transmit onto offspring, with a focus on income and education levels among adult offspring born before 1983. Prior to Shore (2012), income shocks had typically been described as a measurement problem to overcome in explaining permanent income (Blau 1999; Duncan 1988) or assumed to be mean zero over time (Becker and Tomes 1979). Thus, the introduction of volatility approximating for such shocks, as an explanatory variable in empirical mobility models, has been rare up to this point.

Volatility and Intergenerational Mobility

Empirical intergenerational mobility models assume that income volatility has no role in predicting income mobility. This is supported largely by the permanent income hypothesis, wherein households borrow against negative transitory income shocks by accessing perfectly functioning capital markets and/or savings while saving positive transitory income shocks. Yet, there are reasons to expect that income variance measures such as volatility 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, possibly reducing parental human capital investment in children (Attanasio and Weber 2010).

Statistically, transitory shocks persist over several years (Hyslop 2001), and both permanent and transitory shocks contribute substantially to measured inequality (Gottschalk and Moffitt 1994). The timing of these shocks, possibly during early human capital formation, may bring on harmful stressors at important stages of child development when basic skills and attitudes are being formed. These initial skills allow for the development of more complex skills, attitudes, coping mechanisms, and problem-solving techniques later in childhood and into adulthood, which may largely determine educational attainment and income (Cunha et al. 2006; Hill et al. 2013; Lochner and Monge-Naranjo 2012). Other forms of income volatility may instead reflect income growth and intragenerational upward mobility and may therefore support educational and developmental investments in children. For example, a pay raise or a profitable business venture within a family represents a wider set of investment possibilities benefiting children. Still, uncertainty from variable year-over-year income growth may nonetheless lower investments in children.

The aforementioned early child development consequences may occur because of the possibility of imperfect capital markets and constrained access to loanable funds. Early theory on mobility recognized that parents may be denied loans or credit cards that allow for consumption smoothing against negative income shocks. In the event of such denials or market imperfections, income shocks might reduce investments in children (Becker and Tomes 1986; Lochner and Monge-Naranjo 2012; Loury 1981; Mazumder 2005)—a final motivation for the inclusion of transitory income shocks in an intergenerational empirical model. Imperfections of several kinds arise in this market, given that 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). For example, Rothstein and Wozny (2013) at once described the human capital investment decisions of parents as a function of permanent income while acknowledging the negative impact of credit constraints amid economic uncertainty on parental human capital investment decisions.

Previous empirical intergenerational models relying on the permanent income hypothesis to justify omitting higher income moments seem to exclude an important component of the family's utility maximization process. I therefore adapt the mobility model in Eq. (3) to include shocks from income volatility. I then depart from the standard IGE model by substituting adult educational attainment for income as a dependent variable. In doing so, I follow empirical work by Oreopoulos et al. (2006), Hertz et al. (2007), and Pronzato (2010), and the theoretical insights of Becker and Tomes (1979, 1986) and Mincer (1974) emphasizing the importance of human capital for an array of intragenerational and intergenerational labor market and social outcomes. Thus, the reduced-form intergenerational mobility models in Eqs. (1) and (3) are augmented to include income volatility, $V_{i,g-1}^{parent}$:

$$O_{ig}^{child} = \alpha + \beta y_{i,g-1}^{parent} + \gamma V_{i,g-1}^{parent} + \varepsilon. \tag{8}$$

Moving forward, Eq. (8) is the basic augmented intergenerational mobility model, inclusive of adult income and educational attainment outcomes (O_{ig}^{child}) estimated throughout the article. The mobility model allows for the possibility that volatility has an intergenerational relationship to income and well-being, in which case γ is nonzero. Through the mechanism of human capital investment by parents, volatility is theoretically associated with higher overall volatility of human capital investment, which supports the inclusion of higher income moments empirically.

Empirical Model: The Association Between Volatility and Adult Outcomes

Holding the level of family income during childhood constant, I estimate the relationship between family income volatility during childhood $V_{i,g-1}^{parent}$ and a set of adult outcomes O_{ig}^{child}, which parents plausibly seek to maximize in their children (Becker and Tomes 1979; Blanden et al. 2011). For each adult individual *i*, I estimate the following model via OLS to determine whether shocks are transmitted across generations:

$$O_{ig} = \alpha + \beta \overline{I_{0-16_i}} + \gamma V_{0-16_i} + \mathbf{X}\delta + \varepsilon_i. \tag{9}$$

When outcome O_{ig} is adult offspring income, Eq. (9) yields the income IGE for offspring aged 25 and older. It is the canonical intergenerational elasticity model (Gouskova et al. 2010b; Grawe 2006; Lee and Solon 2009; Mazumder 2005; Solon 1992) estimated with controls for income volatility during childhood years 0–16 in generation $g-1$. Non-income outcomes (O_{ig}) for high school dropout and postsecondary educational attainment are tested in Eq. (9) by using an OLS binary linear probability model. During childhood years 0–16, mean family income, $\overline{I_{0-16_i}}$, is an approximation for permanent income.[1] Family income is defined as the income, earnings, and transfers received in person *i*'s household. To account for potential nonlinearities in mean income and income volatility, I use a natural logarithmic transformation of family income for parents as well as adult offspring. Educational outcomes are estimated based on the highest level of education attained by age 26 for respondents who are at least 24 years old, selected to approximate smoothed results for 25-year-olds. The separability of income and volatility is tested via interactions of the two variables. A vector of demographics **X** includes age (A_i) and race of parent, gender of offspring, education of parents, the number of siblings, and whether parents are continuously married. Education is a 0/1 variable equal to 1 if either parent attended 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 lifecycle earnings profiles is important because both earnings and income are known to follow a concave growth profile over prime-age working years (Weiss 1986). In the volatility literature, lifecycle 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 transitory volatility, V_{0-16_i}, I combine both approaches, using an age quartic of household head's

[1] In unpublished results, I use an alternative specification substituting parental education for family income during childhood. The results are robust to this alternative specification.

average age, A_i, in the set of demographic variables while estimating volatility using residuals purging life cycle effects. For percentage change volatility, V_{0-16_i}, I elect to follow the intergenerational literature and rely on the age quartic controls to pick up life-cycle effects.

Income IGE models include an age quartic for offspring age interacted with mean family income during childhood. For income elasticity models in Eq. (9), the offspring's age equals year t minus birth year b minus 40 ($t - b - 40$) thus normalizing so that offspring age equals 0 at age 40. This has the useful feature of simplifying the interpretation of intergenerational elasticities at age 40, the age at which recent studies (e.g., Haider and Solon 2006; Lee and Solon 2009) recommended evaluating the IGE to minimize bias in estimates of permanent income.

The estimation of intergenerational models, in which 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 that the OLS standard errors are no longer consistent. To address this, the estimates are corrected for heteroskedasticity using Huber-White corrected standard errors, and they are clustered on a unique identifier for each child observation to account for autocorrelation.

Data

The PSID is a longitudinal survey that began in 1968. It consists of two independent samples, the Survey Research Center (SRC) sample and the Survey of Economic Opportunity (SEO) sample. Because of challenges in the SEO survey design, this article uses the SRC sample of the PSID (Shin and Solon 2011). 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, resulting in a sample spanning multiple generations (McGonable and Schoeni 2006). Major changes in the collection of the PSID throughout the 1990s include a switch to biennial interviews in 1997 and a doubling in the length of interviews between 1995 and 1999 (Gouskova et al. 2010a).

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 income—can be tracked for offspring over the life cycle. Individuals are observed as dependent children within families, although most of the information collected applies to adults. As subjects enter adulthood, they participate in the PSID survey. The resulting panel is unbalanced because the range of data available on adult income and earnings varies depending on the age of the subject.

The data file that I construct consists of 1,070 adult observations in transitory and 25 % + total volatility models of educational attainment and adult income IGE empirical models, using PSID data from 1970–2007. In an effort to construct comparable samples between the income IGE models and adult education models, I restrict the estimating sample for educational outcome models to those with nonmissing values of adult offspring log income, and likewise restrict the income IGE models to allow only those observations with nonmissing adult offspring education. Accordingly, the summary statistics in Table 1 reflect the condition within the estimating models excluding sample respondents reporting missing values of log income, volatility, education, or demographics. Importantly, for both income IGE and educational attainment models, I impose the restriction of retaining

Table 1 Summary statistics adjusted for inflation (2006 dollars)

	Before Restrictions		After Restrictions, Main	
Variables	Mean	SD	Mean	SD
Adult Family Income (ln)	10.84	0.697	10.88	0.702
Childhood Family Income (ln)	10.88	0.500	10.88	0.505
Transitory Volatility (ln)	0.594	0.678	0.623	0.541
% Change Volatility	3.93	2.77	4.92	3.08
Offspring's Age	29.41	3.22	27.82	1.88
Father's Age	58.05	6.59	55.99	5.41
Mother's Age	55.59	6.04	53.79	4.81
Offspring's Education				
% Dropout	5.75	23.29	4.86	21.51
% High school	30.87	46.21	26.07	43.92
% Some college	30.73	46.15	33.55	47.24
% College	32.65	46.90	35.51	47.88
Father's Education				
% Dropout	15.94	36.61	9.16	28.86
% High school	35.02	47.72	32.80	46.97
% Some college	20.50	40.38	26.07	43.92
% College	28.54	45.17	31.96	46.65
Mother's Education				
% Dropout	13.56	34.25	6.54	24.74
% High school	45.48	47.72	44.30	46.97
% Some college	22.60	41.84	26.64	44.23
% College	18.36	38.72	22.52	41.79
Married (parents)	67.43	46.88	80.65	39.52
Race and Gender				
% White	87.72	32.83	89.07	31.22
% Black	6.21	24.14	4.86	21.51
% Other	6.07	23.89	6.07	23.90
% Female	48.68	49.99	46.63	49.91
Sample Size	1,366		1,070	

Notes: Restriction refers to the condition that observations contain data for 15 of 16 childhood years. Income is top-coded at 1 % and bottom-coded at $1. *Adult* refers to offspring aged 25 or older. *Childhood* refers to offspring age 16 or younger. *Age* for parents and offspring is the highest reported value. *Married* is continuous marital status.

observations for whom complete data exist for at least 15 observations over the first 16 years of the child's life. By dropping child-family pairs for whom several years of data are missing, I aim to avoid a potential attenuation bias in the results and generate accurate estimates of year-over-year income volatility. Missing income data potentially impart a downward bias on the association between volatility and adult outcomes. For example, parents with several years of missing income may erroneously be assigned a high volatility value when, in fact, the true income process between years is smoother than the missing data reflect. Indeed, unpublished results allowing for a minimum of three observations, with at least one observation across three defined child developmental stages (0–5, 6–10, and 11–16 years old), suggest that the importance of volatility is attenuated following this approach.[2] To construct the sample for educational outcomes (Tables 3, 4, 5, and 6), I collapse the data using unique identifiers for each offspring observation and retain relevant fixed data on income and demographic characteristics for child-family observations, exploiting variation between observations to identify the descriptive relationship between volatility and adult outcomes. All together, this reduces the sample to 1,070 unique offspring observations.

Family 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, nontaxable 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 both the mother and father are 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 data on family income for mothers, fathers, heads of household, and offspring. 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 top-coding and bottom-coding strategy. The top 1 % of family income (Shin and Solon 2011) is excluded, and I assign a value of $1 to family incomes of 0 and below (Dynan et al. 2012).[3]

Figure 1 depicts transitory income volatility trends using a three-year and nine-year moving average between 1975 and 1995, adjusted for family size. These are crucial years in which many sample respondent children are potentially exposed to instability incurred by working-age parents. From the late 1970s through 1995, family income volatility increased by 25 % for the nine-year moving average of transitory income volatility. This is consistent with a nearly 36 % increase in volatility described in Dynan et al. (2012), a 15 % increase in earnings volatility between the 1970s and 1980s reported in Ziliak et al. (2011), and rising income volatility over the past 20 to 30 years found in other studies (Dahl et al 2011; Gottschalk and Moffitt 2009; Hardy and Ziliak 2014). Table 1 provides summary statistics for income, income volatility, education,

[2] I also analyzed the association between income volatility during childhood and adult educational outcomes for persons between ages 29 and 31 (results not shown). When I retained observations containing 15 of 16 childhood years, the sample fell to 645 observations. The general results are consistent across models with respect to both statistical significance and direction of the relationships in question, although in some instances, the magnitudes differ. I therefore elect to focus the discussion on results for 25-year-olds.

[3] Before 1979, the top-code 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.

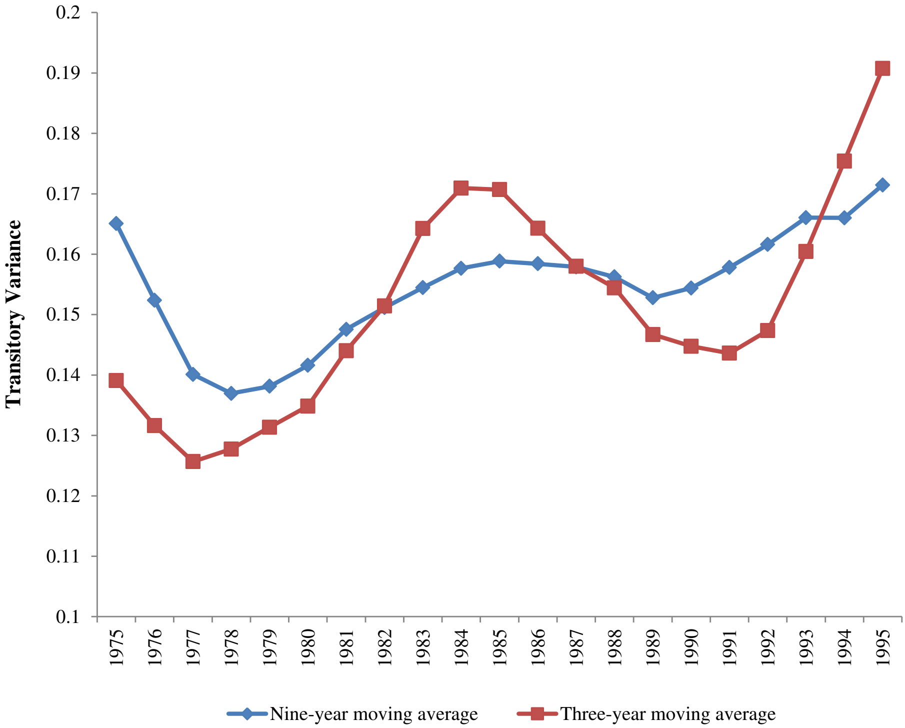

Fig. 1 Transitory family income volatility. Log transitory volatility figures are constructed using nine- and three-year moving averages (MA). For example, 1975 transitory volatility represents nine-year MA of volatility from 1972 to 1979. Transitory volatility estimates are adjusted for family size

gender, age, and race. Columns 3 and 4 (After Restrictions, Main) depict the characteristics of the main analysis sample, which retains family-offspring observations with at least 15 childhood observations between birth and age 16. Mean volatility is 0.623, and the families are relatively advantaged economically, with average family income of $69,011 in 2006 dollars. Almost 70 % of adult children acquired education beyond high school, 32 % of children in the sample have a father with a college degree, and 23 % have a mother with a college degree. Approximately 80 % of the children grew up in households with parents who were continuously married. In a comparison of the PSID sample before imposing sample restrictions (columns 1 and 2, (Before Restrictions)) and the main analysis sample, small differences emerge. After restrictions, the sample is slightly younger, is less racially diverse, and has higher educational attainment among parents and higher income volatility levels.

Results

The regression results are reported in Tables 2, 3, 4, 5, and 6. I demean average log family income and volatility during childhood, transforming γ in Eq. (8) into estimates evaluated at the mean level of permanent family income within the PSID sample. Interactions of volatility with family income test the separability of these measures.

Table 2 Childhood income volatility exposure and adult income (transitory definition)

Adult Income	(1)	(2)	(3)	(4)	(5)	(6)
$Income_{0–16}$	0.497†	0.441†	0.498*	0.441†	0.474†	0.419
	(0.256)	(0.248)	(0.254)	(0.245)	(0.276)	(0.265)
Transitory $Volatility_{0–16}$			–0.058	–0.054	–0.057	–0.054
			(0.042)	(0.041)	(0.042)	(0.041)
$Income_{0–16}$ × Transitory $Volatility_{0–16}$					0.042	0.039
					(0.119)	(0.109)
Black		–0.239†		–0.245†		–0.246†
		(0.136)		(0.135)		(0.134)
Other		–0.015		–0.012		–0.015
		(0.085)		(0.085)		(0.086)
1+ Parent With College		0.121**		0.121**		0.121**
		(0.046)		(0.046)		(0.046)
Female		0.036		0.035		0.034
		(0.042)		(0.042)		(0.042)
Number of Siblings		–0.034		–0.032		–0.032
		(0.024)		(0.024)		(0.024)
Parents Married		0.071		0.068		0.069
		(0.057)		(0.057)		(0.057)
Constant	19.019	10.803	18.564	10.403	18.225	10.131
	(19.420)	(19.634)	(19.381)	(19.598)	(19.307)	(19.569)
Observations	1,070	1,070	1,070	1,070	1,070	1,070
R^2	.0776	.0886	.0787	.0896	.0788	.0897
Joint *F* Test					0.961	0.870

Notes: Robust standard errors are shown in parentheses. Coefficients for age are not shown. *F* statistics test joint significance of Transitory $Volatility_{0–16}$ and $Income_{0–16}$ × Transitory $Volatility_{0–16}$. 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. Transitory $Volatility_{0–16}$ uses the residual from regressing income on an age quartic. Adult offspring income (dependent variable), $Income_{0–16}$, and Transitory $Volatility_{0–16}$ are constructed using log of mean family income from age 0–16.

† $p < .10$; * $p < .05$; ** $p < .01$

Income IGE models are summarized in Table 2 and include controls for transitory volatility. The results for educational attainment in Tables 3, 4, 5, and 6 are organized by the measure, transitory or total volatility, so as to check the sensitivity of the results to alternative measurement techniques.

Adult Income

I estimate income IGE models in columns 1–6 of Table 2, with controls for transitory volatility in columns 3–6. These estimates of the association between parents' income (income during childhood) and offspring adult income are

Table 3 Childhood income volatility exposure and educational outcomes (transitory definition)

	Dropout		Postsecondary	
	24–26	24–26	24–26	24–26
$Income_{0–16}$	–0.040*	–0.025	0.164**	0.137**
	(0.018)	(0.022)	(0.040)	(0.051)
Transitory $Volatility_{0–16}$	0.015	0.016	–0.044†	–0.047*
	(0.011)	(0.012)	(0.023)	(0.024)
$Income_{0–16}$ × Transitory $Volatility_{0–16}$		–0.023		0.043
		(0.028)		(0.047)
Black	–0.036	–0.036	–0.005	–0.006
	(0.030)	(0.030)	(0.062)	(0.062)
Other	–0.040	–0.039	–0.024	–0.025
	(0.024)	(0.024)	(0.057)	(0.057)
1+ Parent With College	–0.041**	–0.040**	0.247**	0.246**
	(0.012)	(0.012)	(0.029)	(0.029)
Female	–0.025†	–0.025†	0.068*	0.068*
	(0.013)	(0.013)	(0.027)	(0.027)
Number of Siblings	0.007	0.007	–0.023†	–0.022†
	(0.006)	(0.006)	(0.012)	(0.012)
Parents Married	0.000	0.000	0.078*	0.078*
	(0.018)	(0.018)	(0.035)	(0.035)
Constant	–8.794†	–8.768†	25.371*	25.322*
	(5.009)	(5.012)	(10.690)	(10.692)
Observations	1,070	1,070	1,070	1,070
R^2	.0397	.0405	.1635	.1641
Joint F Test		0.888		1.998

Notes: Robust standard errors are shown in parentheses. Coefficients for age are not shown. F statistics test joint significance of Transitory $Volatility_{0–16}$ and $Income_{0–16}$ × Transitory $Volatility_{0–16}$. Transitory $Volatility_{0–16}$ uses the residual from regressing income on an age quartic. Transitory $Volatility_{0–16}$ and $Income_{0–16}$ are constructed using log of mean family income from age 0–16.

$^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$

meant to test the association between childhood income volatility and income in adulthood while also confirming that the PSID intergenerational sample yields income elasticities consistent with those in the mobility literature. The results suggest that income volatility has no descriptive link to income mobility and that family economic background, as proxied by permanent income during childhood between birth and age 16 (Table 2, row 1), exhibits a statistically significant income IGE between 0.441 and 0.498. The intergenerational income elasticities and educational attainment models are not meant for causal interpretation, although the income IGEs in columns 2, 4, and 6 include a richer set of demographic controls. The children of one or more parents who attended college are predicted to have higher adult income than children from homes

Table 4 Childhood income volatility exposure and educational outcomes: 25 % income change definition

	Dropout		Postsecondary	
	24–26	24–26	24–26	24–26
Income$_{0–16}$	–0.027	–0.032	0.136**	0.249**
	(0.018)	(0.033)	(0.042)	(0.068)
25 % Change$_{0–16}$	0.005*	0.005*	–0.009*	–0.011*
	(0.002)	(0.002)	(0.005)	(0.005)
Income$_{0–16}$ × 25 % Change$_{0–16}$		0.001		–0.014†
		(0.004)		(0.009)
Black	–0.038	–0.037	–0.002	–0.004
	(0.030)	(0.030)	(0.062)	(0.062)
Other	–0.038	–0.038	–0.028	–0.029
	(0.024)	(0.024)	(0.057)	(0.058)
1+ Parent With College	–0.040**	–0.040**	0.246**	0.232**
	(0.012)	(0.012)	(0.029)	(0.030)
Female	–0.026*	–0.026*	0.070**	0.070**
	(0.013)	(0.013)	(0.027)	(0.027)
Number of Siblings	0.007	0.007	–0.023*	–0.022†
	(0.006)	(0.006)	(0.012)	(0.012)
Parents Married	0.001	0.001	0.076*	0.077*
	–0.027	–0.032	(0.035)	(0.035)
Constant	–9.074†	–9.031†	25.780*	24.790*
	(5.022)	(5.024)	(10.650)	(10.495)
Observations	1,070	1,070	1,070	1,070
R^2	.0418	.0419	.1642	.1672
Joint *F* Test		2.500		3.575

Notes: Robust standard errors are shown in parentheses. Coefficients for age are not shown. 25 % Change$_{0–16}$ represents count of instances in which family income during childhood changes by +/– 25 % between years. *F* statistics test joint significance of 25 % Change$_{0–16}$ and Income$_{0–16}$ × 25 % Change$_{0–16}$. Income$_{0–16}$ is constructed using log of mean family income from age 0–16.

$^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$

with lesser-educated parents, and black children are less likely to have higher income in adulthood than counterparts of other races/ethnicities (white race is the omitted category). Gender, number of siblings, parents' marital status, and other race/ethnicity have no independent, statistically significant association with adult income in the IGE models, although this changes as the adult outcomes of interest move to educational attainment.

The link between volatility and adult income could be diminished by the heterogeneity of occupational choices and greater historical variance of earnings observed among college-educated workers, in contrast to those with lower education and fewer employment opportunities (Polachek 2008). This is consistent with findings reported in Tables 3, 4, and 6, where a modest association between volatility and educational attainment occurs.

Table 5 Childhood income volatility exposure and high school dropout by position within income distribution

	Bottom 33 %	33–66 %	Top 33 %
Panel A. Transitory: Dropout			
$Income_{0–16}$	–0.024	0.036	0.018
	(0.035)	(0.126)	(0.042)
Transitory $Volatility_{0–16}$	0.029	0.008	0.007
	(0.031)	(0.011)	(0.014)
Black	–0.040	–0.034*	–0.030**
	(0.068)	(0.014)	(0.011)
Other	–0.045	–0.046*	–0.033*
	(0.078)	(0.018)	(0.013)
1+ parent with college	–0.116**	–0.024	–0.027
	(0.022)	(0.019)	(0.021)
Female	–0.057†	–0.016	–0.006
	(0.032)	(0.020)	(0.016)
Number of siblings	–0.004	0.017†	0.010
	(0.009)	(0.009)	(0.010)
Parents married	–0.042	0.025	0.017
	(0.044)	(0.026)	(0.020)
Observations	342	326	402
R^2	.0501	.0346	.0199
Panel B. 25 % Change: Dropout			
$Income_{0–16}$	–0.004	0.035	0.016
	(0.041)	(0.126)	(0.042)
25 % $change_{0–16}$	0.007	–0.000	0.003
	(0.006)	(0.003)	(0.002)
Black	–0.042	–0.034*	–0.025*
	(0.069)	(0.016)	(0.011)
Other	–0.043	–0.044*	–0.034*
	(0.077)	(0.018)	(0.013)
1+ parent with college	–0.118**	–0.024	–0.025
	(0.022)	(0.019)	(0.021)
Female	–0.060†	–0.016	–0.006
	(0.032)	(0.020)	(0.016)
Number of siblings	–0.003	0.018†	0.010
	(0.010)	(0.010)	(0.010)
Parents married	–0.039	0.025	0.018
	(0.044)	(0.026)	(0.020)
Observations	342	326	402
R^2	.0517	.0342	.0213

Notes: Robust standard errors are shown in parentheses. Coefficients for age are not shown. Income distribution location is determined by mean family income during childhood. Transitory $Volatility_{0–16}$ uses the residual from regressing income on an age quartic. Transitory $Volatility_{0–16}$ and $Income_{0–16}$ are constructed using log of mean family income from age 0–16.

$^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$

Table 6 Childhood income volatility exposure and postsecondary education by position within income distribution

	Bottom 33 %	33–66 %	Top 33 %
Panel A. Transitory: Postsecondary			
$\text{Income}_{0\text{–}16}$	0.038	0.089	0.007
	(0.070)	(0.274)	(0.099)
Transitory $\text{volatility}_{0\text{–}16}$	–0.049	$-0.098^{\dagger}$	–0.013
	(0.044)	(0.051)	(0.032)
Black	–0.130	0.133	0.030
	(0.091)	(0.100)	(0.102)
Other	–0.102	0.047	–0.010
	(0.109)	(0.155)	(0.076)
1+ parent with college	0.341**	0.230**	0.202**
	(0.073)	(0.049)	(0.044)
Female	$0.094^{\dagger}$	0.150**	–0.016
	(0.052)	(0.050)	(0.038)
Number of siblings	–0.009	–0.023	–0.029
	(0.019)	(0.022)	(0.019)
Parents married	0.194**	0.012	0.021
	(0.059)	(0.075)	(0.050)
Observations	342	326	402
R^2	.1292	.1042	.0871
Panel B. 25 % Change: Postsecondary			
$\text{Income}_{0\text{–}16}$	–0.015	0.100	0.017
	(0.075)	(0.277)	(0.100)
25% $\text{change}_{0\text{–}16}$	$-0.016^{\dagger}$	–0.001	–0.008
	(0.009)	(0.009)	(0.007)
Black	–0.125	0.145	0.016
	(0.093)	(0.104)	(0.103)
Other	–0.109	0.018	–0.009
	(0.108)	(0.157)	(0.077)
1+ parent with college	0.345**	0.229**	0.197**
	(0.072)	(0.049)	(0.044)
Female	$0.100^{\dagger}$	0.148**	–0.018
	(0.052)	(0.050)	(0.038)
Number of siblings	–0.012	–0.027	–0.027
	(0.018)	(0.022)	(0.019)
Parents married	0.187**	0.019	0.020
	(0.059)	(0.075)	(0.050)
Observations	342	326	402
R^2	.1355	.0934	.0897

Notes: Robust standard errors are shown in parentheses. Coefficients for age are not shown. Income distribution location is determined by mean family income during childhood. Transitory $\text{Volatility}_{0\text{–}16}$ uses the residual from regressing income on an age quartic. Transitory $\text{Volatility}_{0\text{–}16}$ and $\text{Income}_{0\text{–}16}$ are constructed using log of mean family income from age 0–16.

$^{\dagger}p < .10$; $^{**}p < .01$

Adult Educational Attainment

In Table 3, I test the association between exposure to transitory income volatility during childhood and both the likelihood of high school dropout and postsecondary educational attainment. Transitory volatility during childhood is associated with a statistically insignificant higher likelihood of dropout. A negative relationship to dropout emerges for females, persons with at least one college-educated parent, and persons from relatively higher-income families. There is stronger support for an association between volatility exposure during childhood and education beyond high school. The last two columns of Table 3 depict these results. Here, a one-unit increase in transitory volatility is associated with a 4 % to 5 % decrease in the likelihood of postsecondary educational attainment. Permanent family income (row 1), measured in log points, is the strongest positive correlate of postsecondary education, ranging from 0.137 to 0.164. Consistent with the estimates for dropout, females and children of at least one college-educated parent are predicted to have higher educational attainment. Parents' marital status is a positive correlate of postsecondary attainment, whereas it exhibits no predictive power for high school dropout.

Table 4 examines high school dropout and postsecondary educational attainment using the percentage change measure of total volatility. A one-year increase in the number of 25 % or higher income shifts is associated with a less than 1 % increase in the likelihood of dropout, statistically significant at the 95 % confidence level. A one-year increase in 25 % or higher income shifts experienced during childhood is associated with a 1 % lower likelihood of postsecondary educational attainment, also significant at the 95 % confidence level. The demographic correlates of both dropout and postsecondary educational attainment are generally robust to the measure of volatility specified, although permanent income appears to have a larger role and volatility a smaller one in explaining postsecondary attainment in the total volatility model (Table 4) relative to the transitory model (Table 3).

Income Volatility and Educational Attainment Across the Income Distribution

In Tables 5 and 6, intergenerational education outcomes are examined based on where mean parental family income lies in the distribution of incomes over ages 0–16 for their children. The families are divided into three groups: bottom 33 %; 34 % to 66 %; and top 33 %. For families with children, mean income is approximately $39,000 among the bottom 33 %, $59,000 between percentiles 34 and 66, and $93,000 among families in the top 33 % of income. Table 5 directly compares the association between volatility (transitory, 25 % or higher total) and high school dropout across the distribution. Table 6 conducts the same test for postsecondary educational attainment.

Across the income distribution, the association between volatility exposure and postsecondary educational attainment among young adults from households between percentiles 33 and 66 is statistically significant and larger than estimates for young adults from the bottom 33 %, the top 33 %, or at the mean. In panel A of Table 6, a one-unit increase in transitory volatility among young adults from families in the middle third of the income distribution is associated with a 10 % lowered likelihood of postsecondary educational attainment, significant at the 90 % confidence level. The results in Tables 5 and 6 are robust to the exclusion of controls for parental education, which appear to strongly predict dropout and postsecondary education across the income distribution. An insignificant association emerges between income volatility and dropout (Table 5). Similarly, no volatility/education association emerges among higher-income families, which is consistent with previous studies and the descriptive intergenerational model in Eq. (7). The fact that no statistically significant volatility/education link emerges between lower-income families may still be consistent with the model, particularly if children from moderate-income families fall outside the eligibility requirements of grants and subsidies for postsecondary education. With cell sizes of roughly 300, it could also be a consequence of efficiency limitations resulting from relatively small samples.

In summary, the results suggest a statistically significant association between volatility exposure and lower educational attainment. Consistent relationships also emerge with permanent income, race, gender, parents' education, and parents' marital status. Assessing the importance of these results is challenging, particularly with respect to the valuation of unit changes to demeaned, residualized transitory income volatility. In an effort to improve understanding of the results, I standardize coefficients and evaluate standard deviation changes to explanatory income volatility covariates:

$$\%\Delta \textit{Educational Outcome} = \left(\sigma_{volatility}\right) \times \left(\hat{\beta}_{volatility}\right), \tag{10}$$

where $\sigma_{volatility}$ denotes the standard deviation of income volatility, and $\hat{\beta}$ denotes the estimated volatility coefficient of interest. I automate this transformation of the regression coefficients using the Stata procedure constructed by Long and Freese (2005). Using the transformation, a 1 standard deviation increase in transitory volatility (0.541) is associated with a 2 % to 3 % lower likelihood of educational attainment beyond high school (Table 3). A 1 standard deviation increase in transitory volatility among children from the middle 33 % of the family income distribution translates to a 5 % lower likelihood of postsecondary attainment (Table 6). Interestingly, the transformed results are generally equivalent across both transitory and total definitions of volatility. The use of standard deviations allows for comparison across explanatory variables often considered in discussions of socioeconomic mobility, such as permanent income. For example, a 1 standard deviation increase in permanent income is associated with a 2 % decline in dropout chance in models using the transitory volatility measure, compared with a 1 % increase in dropout chance from a 1 standard deviation increase in 25 % or greater total volatility (Table 4). A 1 standard deviation increase in permanent income is associated with a 7 % to 8 % increase in the likelihood of postsecondary educational attainment in transitory models (Table 3), implying that the relationship to postsecondary attainment from a 1 standard deviation increase in volatility is 29 % to 36 % of the magnitude of the relationship from a 1 standard deviation increase in permanent income.

Lower income and volatile income carry an association with educational attainment overall—one that appears stronger for postsecondary attainment. This may be due to differences underlying the postsecondary attainment decision versus completing publicly provided K–12 education, along with sample high school dropout rates of 5 %, which are relatively low. If a true causal effect lies within these estimates, some consequences are worth briefly considering. Dropouts experience higher rates of unemployment, have lower family income and earnings, and are more likely to engage in criminal activity (Blank 2008; Haskins et al. 2009; Hauser et al. 2000; Lochner 2005) than their more-educated counterparts. Prospects for workers lacking postsecondary training are also deteriorating as they increasingly confront a "hollowed-out" labor market with fewer opportunities for middle-skill workers compared with the labor market of the 1960s, 1970s, or 1980s (Jaimovich and Siu 2012).

With the economic mobility consequences of education in mind, the estimates across the income distribution concur with related studies on parental job loss and children's education, which find larger negative estimates for adults from the bottom half of the socioeconomic spectrum (Johnson et al. 2012; Page et al. 2009). This negative association occurs alongside estimated college graduation rates of 11 % among young adults from the bottom income quintile to 25 % in the middle-income quintile of the PSID (Haskins et al. 2009). In other words, lower baseline graduation rates may raise the importance of income volatility and its negative association with adult education outcomes among low- and moderate-income households. The noticeably larger association among moderate to middle-income offspring merits attention because these families may face important tradeoffs that drive investment decisions in their children. In most instances, they do not qualify for federal grants or many of the school-based financial grant programs targeted to children from poor families (Haskins et al. 2009).

Such findings across the income distribution carry important implications, particularly in spite of sample sizes around 350. Efficiency issues may mask larger negative relationships between volatility exposure and educational attainment, particularly within the bottom 33 %, and future work would benefit from data that more completely accounts for lower SES households.[4] However, the SRC sample of the PSID seems an appropriate beginning point for this inquiry because it is among the preferred data sources in studies of both income mobility and income volatility. Still, the SRC is not without flaws, including attrition bias. PSID attritors are less educated, have lower earnings, and are less likely to be married (Fitzgerald et al. 1998). Such a population likely has higher income and earnings volatility (Ziliak et al. 2011), which could attenuate the results.

Conclusion

To estimate an intergenerational model with 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, patterns emerge for those adults who grow up with volatile family income as a child. Evaluated at the mean, where family income is roughly $70,000, volatility is associated with lower educational attainment in adulthood, but the link is moderate at best and smaller than the association between permanent income and educational attainment. For example, a 1 standard deviation increase in 25 % or greater total volatility is related to a 1 % increase in dropout likelihood, while a 1 standard deviation increase in transitory volatility is associated with a 2 % to 3 % lower likelihood of postsecondary education. Among moderate-income households, the association to adult

[4] The SEO sample of the PSID or the 1979 National Longitudinal Survey of Youth, for example, might provide a richer intergenerational file of low-income families, although these data come with their own tradeoffs.

education is larger, given that a 1 standard deviation increase in transitory volatility is associated with a roughly 5 % lower likelihood of education beyond high school. The empirical approach taken accounts for several often-mentioned culprits of economic hardship and instability, including family income, parental education, and parental marital status (Cancian and Reed 2001). This is nonetheless a descriptive estimate holding across model specifications and omitting a range of causal factors likely correlated with both intergenerational mobility and income volatility (Mason 2007). Future work could assess how recent volatility and public policies relate to measures of academic achievement, health, and socioemotional well-being during childhood using data on low-income families. Such indicators are precursors to adult socioeconomic outcomes (Cunha et al. 2006; Mazumder and Davis 2012).

The findings are consistent with a descriptive model in which risk aversion, credit constraints faced by parents, and the persistence of income shocks justify inclusion of both first- and second-income moments. If the baseline results and estimates from across the income distribution reflect a causal channel, shocks may be more harmful for adults from lower- and moderate-income families with higher volatility. Today, this would include prospective students from households affected by high unemployment and poverty during the Great Recession. Policy responses could include the continued provision of low interest loans, grants, and affordable options for educating college-bound children, including two-year colleges. Such a response is helpful if education is constrained by affordability. If, instead, income shocks during early childhood negatively impact the early human capital investments of parents, public policies subsidizing higher education may intervene too late. Underinvestment in human capital resulting from income shocks during childhood may leave some capable students without the skills to pursue education and training beyond high school.

Acknowledgments I thank Jim Ziliak, Chris Bollinger, Ken Troske, Scott Hankins, Bill Hoyt, Seth Sanders, Ngina Chiteji, Darrick Hamilton, Tim Smeeding, Tom DeLeire, Pamela Smock, Alison Jacknowitz, Laura Langbein, anonymous reviewers, and seminar participants at the University of Kentucky, University of Wisconsin–Madison Institute for Research on Poverty, Western Kentucky University, Mathematica Policy Research, and American University for helpful feedback and suggestions. I also thank conference participants of the Kentucky Economic Association, the AEA Pipeline Program at UC-Santa Barbara, and the Southern Economic Association.

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