The Intergenerational Transmission of Income Volatility: Is Riskiness Inherited?

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Abstract

This paper examines the intergenerational transmission of income risk. Do risky parents have risky kids? Income volatility, a proxy for risk, is not observed directly; instead, it must be estimated – with substantial error – from the time-series variability of income. I characterize a process for income and use it to obtain individual-specific estimates of permanent and transitory income volatility for parents and their adult children in the Panel Study of Income Dynamics (PSID).

I find that parents with higher income volatility have children with higher permanent income volatility. Not only is one's place on the economic ladder inherited, this paper shows that economic mobility – the rate at which individuals move up or down the economic ladder – is also inherited. This effect is similar in magnitude to the intergenerational transmission of education, and is apparent only after correcting explicitly for the attenuation bias induced by estimation error in parents' volatility parameters.

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1 Introduction

Parents transmit elements of their human capital to their children. High-earning parents tend to have high-earning children (Solon, 1999). Well-educated parents tend to have well-educated children (Black, Devereux, and Salvances, 2005). Tall parents tend to have tall children (Persico, Postlewaite, and Silverman, 2005). Healthy parents tend to have healthy children. Personality is inherited as well (Plomin and Caspi, 1998; Plomin, Caspi, and John, 1999). There is generally reversion to the mean, so that tall parents tend to have children who are taller than average, but not as tall as they are. While these relationships may or may not be causal, finding them is typically a precursor to exploring the mechanisms that underlie them. To my knowledge, this is the first paper to look for evidence of intergenerational transmission of higher moments of human capital. Do parents with risky income streams have children with risky income streams?

This question has important implications for economic mobility. Intergenerational mobility can be achieved by affecting the initial income of adult children or the subsequent evolution of income. When income is volatility, individuals move through the earnings distribution faster (Haider, 2001; Solon, 2001). If children inherit income volatility from their parents, then they also inherit the ability to move up or down the economic ladder. As such, average estimates of intergenerational mobility may mask substantial heterogeneity; dynasties with high income volatility will have higher degrees of intergenerational mobility while dynasties with lower income volatility may be less mobile. These low-volatility dynasties will get "stuck" at a high or low level of income.

Intergenerational transmission of income volatility also has implications for social insurance. Since many social insurance schemes are often designed to reduce the unwanted effects of income volatility, the need for social insurance programs may be inherited. More importantly, it would show that the informational asymmetries that complicate voluntary private markets – and motivate mandatory social insurance programs – arise before birth. In theory, the adverse selection problem can be solved if insurance is purchased before informational asymmetries arise (Milgrom and Stokey, 1998). To the degree that riskiness is inherited, this early purchase will be impossible.

Estimating the inheritance of income risk is complicated by the fact that income risk cannot be measured directly; in fact, it is not a precisely defined idea. This paper uses income volatility as the best available proxy for income risk, with the understanding that volatility and risk will not coincide perfectly. Therefore, the paper aims to answer the more precise question: do parents with volatile incomes have children with volatile incomes? While it is trivial to estimate volatility moments – the variance in changes to income – from panel data, it is not clear how to interpret these moments without understanding the income process that generates them. For example, do large changes in income indicate predicted changes in income, transitory shocks to income, or permanent shocks to income? These distinctions are important when considering the impact of income volatility on economic mobility. Unlike a large positive transitory shock, a large positive permanent shock will carry over from year-to-year and so will move an individual up the economic ladder.

I characterize a labor income process that decomposes income into predictable and unpredictable components, and then decomposes innovations to the unpredictable component into permanent and transitory components. I use an optimally-weighted function of income moments from household heads in the Panel Study of Income Dynamics (PSID) to obtain individual-specific estimates of permanent and transitory income volatility. While these estimates include substantial estimation error, the estimation error in permanent and transitory income volatility is negatively correlated. This implies that permanent and transitory volatility *are not* estimated precisely while total income volatility – a positive linear combination of these two – *is* estimated precisely.

Using these estimates, I look for evidence that parents with higher income volatility have children with higher income volatility. From the sample of $4,807$ individuals in the PSID for whom I obtain individual-specific estimates of income volatility, there are $1,087$ adult children whose parents are also in the sample. Parents with high total income volatility tend to have children with high total income volatility, regardless of whether education, income, and demographic controls are included. While this result shows that some type of income volatility is inherited, it does not identify which feature of the income process, permanent or transitory volatility, is inherited.

I exploit information about the process for income and the procedure used to estimate income volatility given this process to correct explicitly for the bias induced by estimation error. When examined properly, the income volatility of parents, both permanent and transitory, has a substantial effect on the permanent income volatility of their adult children. The errors in these coefficient estimates are negatively correlated, so that jointly they are highly significant. As a result, the relationship between the *total* income volatility of parents and the *permanent* income volatility of their adult children is large and estimated with substantial precision. The effect is of roughly the same magnitude as the relationship between the education of parents and their children. However, there is no evidence that the transitory volatility of adult children is related to the volatility of their parents. Since transitory volatility captures measurement error in income, it is not surprising that the magnitude of transitory shocks is not inherited. This implies that the children of parents with high total volatility will have substantially higher degrees of economic mobility during their lives.

While identifying inheritance of educational mobility is important even in the absence of a wellunderstood mechanism, it is natural to look for channels through which parents might transmit income volatility to their children? Education and self-employment are both correlated with income volatility, and both exhibit strong intergenerational transmission. As such, they are obvious candidate mechanisms for the intergenerational transmission of income volatility. This paper documents that parents with more education have children with higher permanent income volatility. This is true only because their children have more education. Similarly, parents who have ever been self-employed or who are self-employed for more of their lives have children with higher levels of income volatility, though this is true only because their children are more likely to be self-employed. Since these better-educated and self-employed parents also have higher permanent income volatility, the intergenerational transmission of education and self-employment are two channels through which the intergenerational transmission of income volatility operates.

The rest of the paper is laid out as follows: Section 2 presents an income process and uses it to obtain individual-level estimates of income volatility for a panel of household heads; Section 3 examines the relationship between the income volatility of parents and their adult children; Section 4 presents some evidence on the channels through which the intergenerational transmission of income volatility may operate; Section 5 concludes.

2 Income Volatility

It is impossible to study the determinants of income volatility without a measure of that volatility. Unlike many other aspects of human capital such as health and education, income volatility cannot be observed directly; instead, it must be estimated from time-series data on income.[1] Subsection 2.1 sets up a model of the income process; Subsection 2.2 describes data from the Panel Study of Income Dynamics (PSID) used to estimate this process; Subsection 2.3 presents the procedure used to extract individual-specific estimates of income volatility from these data and describes the resulting estimates.

2.1 Income Process

Log income is assumed to take the following form:

$$\ln\left(Y_{i.t}\right) = c_0 + c_1 Z_{i,t} + \phi_t + \gamma_i + \eta_{i,t}. \tag{1}$$

[1] Permanent income also cannot be observed directly, and must be inferred from income at various points in time (Solon, 1999).

Log income is a function of time, ϕ_t, covariates such as age, education, race, and their interactions, Z, and a stochastic component. While equation (1) contains a time-invariant, individual-specific component, γ_i, it does not include heterogeneous rates of income growth, $(\gamma \times t)_i$. This model seeks to capture the evolution of the stochastic term, $\eta_{i,t}$, which I will refer to as excess log income or excess income. Excess log income, $\eta_{i,t}$, evolves in response to two types of shocks, permanent shocks, $\omega_{i,t}$, and transitory ones, $\varepsilon_{i,t}$:

$$\eta_{i,t} = \sum_{\tau=0}^{t} \omega_{i,\tau} + \varepsilon_{i,t}. \tag{2}$$

Permanent shocks persist forever, while transitory shocks last for only one period. Shocks are i.i.d., uncorrelated with one another, and distributed with mean zero and variances $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$, respectively.[2] The income volatility of an individual can therefore be characterized by a permanent volatility parameter, $\delta^2_{i,\omega}$, and a transitory volatility parameter, $\delta^2_{i,\varepsilon}$. This implies that one-period changes in excess income, $\nu_{i,t}$, are merely the sum of the permanent and transitory shocks in the current period, minus the transitory shock in the last period:

$$\nu_{i,t} \equiv \eta_{i,t} - \eta_{i,t-1} = \omega_{i,t} + \varepsilon_{i,t} - \varepsilon_{i,t-1}. \tag{3}$$

This paper is far from novel in proposing this income process. This process, or its variations, has been used in many papers including Carroll and Samwick (1997) and Meghir and Pistaferri (2004). The assumptions underlying it have been studied at length (e.g., Abowd and Card (1989)). The chief concern is that shocks may be somewhat persistent, neither completely permanent nor completely transitory after one year. The model implies zero auto-correlation at lags greater than one year:

$$E_t\left[\nu_{i,t}\nu_{i,t-j}\right] = 0, j > 1.$$

While Abowd and Card find evidence for positive autocorrelation at lags of one and two years, they find no evidence of autocorrelation at longer lags. In other words, after two years shocks will have disappeared completely or will persist forever. Ideally, an attempt to estimate this process should

[2] The assumption that $E\left[\varepsilon_{i,t}\right] = 0$ is innocuous, as γ_i can be renormalized for each i to make it so. If $E\left[\omega_{i,t}\right] = \kappa$, where κ is the same for all individuals, then the assumption that $E\left[\omega_{i,t}\right] = 0$ would also be innocuous, since including age as a covariate allows for an arbitrary growth in income over time. However, if $E\left[\omega_{i,t}\right] = \kappa_i$, where κ_i varies across individuals, then the assumption that $E\left[\omega_{i,t}\right] = 0$ is not innocuous. Equation (1) implicitly assumes that the expected growth-rate of income is the same for all individuals. This assumption could be loosed by including individual specific growth rates $(\gamma \times t)_i$ in equation (1). Doing so has almost no impact on the findings of the paper. Higher-order individual-specific trend terms, $(\gamma \times f(t))_i$, could also be included parametrically without difficulty, though at the cost of reduced statistical power.

be robust to the possibility that "transitory" shocks may persist for more than one period or that "permanent" shocks may take more than one period to come fully into effect.

2.2 Data

To estimate the moments of the income process described in Subsection 2.1, the first step is to obtain sample estimates of excess income $\hat{\eta}_{i,t}$ from equation (1). To do this, I use data from the Panel Study of Income Dynamics (PSID). The PSID is a nationally representative panel of U.S. households which has tracked families since 1968. It includes annual data on education, income, employment status, and a host of other variables. Importantly for the purposes of this paper, it includes not only families that were in the original sample but also families formed from those families. As a result, this panel includes income histories not only for parents, but also for their adult children, up to 2001. The PSID includes data on the households of $23,312$ unique household heads.[3]

As the measure of income, I use the household head's annual labor income. I drop observations on household heads who are younger than 25 or older than 65 years of age. I also drop any observations in which the head's labor income is missing or top-coded. One empirical challenge is how to handle observations where labor income is zero or close to zero. Algebraically, observations with zero labor income are problematic because the log of zero is undefined. Conceptually, these observations are problematic because observed labor income may not capture the underlying variable of interest, potential income. If the wage falls slightly from just above the reservation wage to just below it, the wage will fall dramatically. Actual income will not be a good proxy for potential income in this case. While the problem is serious in obtaining a correct estimate of income risk, the results about intergenerational transmission in this paper are robust to various *ad hoc* attempts to address this problem. For the results presented here, regressions will replace actual annual income with (federal minimum hourly wage) $\times$ 1000 hours, the income that would be earned if the head worked half-time for minimum wage. The results in the paper are not substantially affected by the way in which very low income observations are handled.

Since actual income is clearly a bad measure of potential income for those not in the labor force (e.g., retired people, students), I drop observations in which the head is out of the labor force. These adjustments lead to substantial gaps in data for some individuals. Therefore, I drop from the sample anyone for whom data is missing or dropped in more than four intervals, or with gaps

[3] In the PSID, the household head was originally set as the husband in any husband-wife pair. Otherwise, the head is the person in the family with the most financial responsibility for the household.

Table 1: Summary Statistics for Adult Children and their Parents

Household Heads	Adult Children		Their Parents		Corr.
	Mean	St. Dev.	Mean	St. Dev.	
Initial Age (Years)	25.8	2.0	38.3	6.7	14.5%
# of Observations	16.9	5.0	19.7	6.3	-30.4%
Education (Years)	13.6	2.1	11.7	3.2	47.2%
Labor Income ('000s of 2001 dollars)	35.9	23.5	38.4	27.1	39.7%
Ever Self-Employed? (1 or 0)	0.303	0.460	0.393	0.489	14.7%
Fraction of Time Self-Employed	0.077	0.183	0.142	0.278	21.0%
# of Parent-Child Pairs	1,087				

This table presents summary statistics on the 1,087 pairs of adult children and their parents for which there are volatility estimates available for both the parent and the child. These are the set of household heads with parent who is also a household head in the sample. For each adult child and parent household head, I show the initial age of the individual in the sample. Since observations with ages below 25 and over 65 are dropped, and there must be at least 10 observations, this initial age must be at least 25 and at most 56. I also present the number of observations for which there is income data for the adult child or the parent, the median (for that individual) real labor income (in thousands of 2001 dollars), the maximum number of years of education reported for that individual, whether the individual ever reported being self-employed, and the fraction of the sample that the individual reported being self-employed. For each of these variables, I report the mean and standard deviation for the adult child and their parent, and the correlation between the value for the adult child and their parent.

in the data of longer than four years.

I estimate equation (1) using OLS for the sample of household heads that has non-missing data on age, education, year, and income. I include the following right-hand side variables: a quartic in age; the interaction of age and the square of age with education dummies, occupation dummies, and race dummies; and year dummies.[4] I also include individual-specific fixed effects. This regression includes 117,453 observations on 12,194 individuals over a 33-year period. Covariates explain 35 percent of the variation in income within observations for an individual and 16 percent of variation across individuals. I use the residuals from this regression to capture a sample estimate of excess log income, $\hat{\eta}_{i,t}$. Of course, to the degree that the functional form used to estimate equation (1) is misspecified or omits important covariates known to the individual, predictable changes in income will be misidentified as risk.

Of the 12,194 household heads in this regression, only 4,807 have enough observations to obtain estimates of income volatility (discussed in Subsection 2.3 and presented in Tables 3 and 4). Of

[4] Education categories are elementary school, junior high school, some high school, high school graduate, some college, college graduate, and graduate school. Race categories are white, black, and other (e.g., non-white Hispanic, Asian). Occupations are grouped into the 9 categories consistently identified by the PSID as: professional, technical and kindred workers; managers, officials and proprietors; self-employed businessmen (a category dropped in later years); clerical and sales workers; craftsmen, foremen, and kindred workers; operatives and kindred workers; laborers and service workers, farm laborers; farmers and farm managers; and miscellaneous (armed services, protective workers, unemployed last year but looking for work, N.A.)

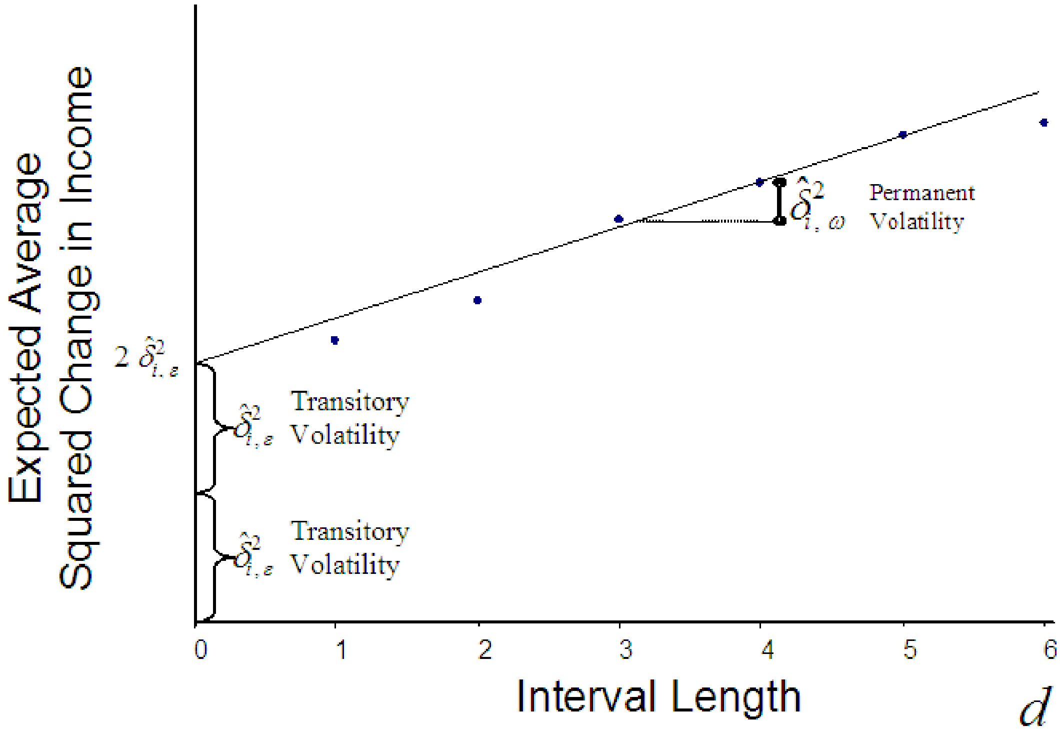
these, $1,087$ are the adult children of a parent with enough data in the sample. To get a sense of the sample, Table 1 presents summary statistics for these parent-child pairs. Each row presents a different variable for the household head: initial age, number of observations, maximum years of education reported, real (2001 dollars) median labor income for that individual in sample, whether ever self-employed and fraction of sample spent self-employed. For each of these variables, I present the mean and standard deviation for adult children, the mean and standard deviation for their parents (who will appear multiple times when a parent has more than one adult child in the sample), and the correlation between values for the adult child and their parent.

A self-evident though noteworthy feature of these summary statistics is the substantially different age ranges used to estimate the income volatility of adult children and their parents. Data on adult children begins on average at age 26. This reflects the fact that these adult children are observed as minors in their parents' homes and are included in the sample only at age 25. Since these children have on average 17 observations in the data, income volatility for adult children is calculated based on data from roughly ages 26 to 42 on average. Their parents begin the sample at roughly 38 and have on average 20 years of data, so that their volatility estimates come from the age range of roughly 38 to 57 on average. To the degree that income volatility may evolve stochastically over time (Topel and Ward, 1992; Meghir and Pistaferri, 2004), estimating income volatility for adult children and their parents at different points in time could bias downward the relationship between lifetime average income volatility for parents and their adult children (Haider and Solon, forthcoming). As a result, the estimates from this paper that children inherit income volatility from their parents are likely a lower bound.

2.3 Estimating Income Volatility

Given changes in the stochastic component of income, $\nu_{i,t}$, a variety of moments can be used to estimate income volatility. Several moments used in other papers, and their mappings to model parameters, are presented in Appendix A. This paper will follow the approach of Carroll and Samwick (1997), who use squared changes in excess log income over long periods of time. In particular, the change in excess log income between years t and $t-d$ is nothing more than transitory income in year t minus transitory income in year $t-d$ plus the sum of all permanent income shocks

Figure 1: Decomposing Total Income Volatility into Permanent and Transitory Components



in the d years between $t-d$ and d:

$$
\begin{aligned}
v_{i,t,d} &\equiv \eta_{i,t} - \eta_{i,t-d} = \sum_{\tau=t-d+1}^{t} \omega_{i,\tau} + \varepsilon_{i,t} - \varepsilon_{i,t-d},^{5} \\
E_t\left[(v_{i,t,d})^2\right] &= d\delta^2_{i,\omega} + 2\delta^2_{i,\varepsilon}.
\end{aligned}
\tag{4}
$$

This provides a natural decomposition of total volatility – squared changes in excess log income, $E_t\left[(v_{i,t,d})^2\right]$ – into permanent volatility, $\delta^2_{i,\omega}$, and a transitory volatility, $\delta^2_{i,\varepsilon}$. As the length of the interval$d$, over which squared changes are taken increases, the number of permanent shocks on this interval increases proportionally. However, the number of transitory shocks stays constant at two, one at the beginning of the interval and one at the end. The rate at which squared changes increase with the interval length, d, provides an estimate of the permanent volatility. The component of the total volatility which is insensitive to the interval length can be attributed to the transitory volatility.

[5]Note that $\nu_{i,t,1} \equiv \nu_{i,t}$.

The expected square of changes in excess log income, $E_t\left[(v_{i,t,d})^2\right]$, can be estimated from sample data as the individual-specific average of squared changes in income,

$$\hat{\nu}_{i,d}^2 \equiv \frac{1}{N_{i,d}}\Sigma_t \left(\hat{v}_{i,t,d}\right)^2. \tag{5}$$

$\hat{\nu}_{i,d}^2$ is just an average of squared changes over all possible intervals of length d from data for individual i. $N_{i,d}$ is the number of such intervals. This sample estimate can be computed for an individual for several values of d. These estimates can then be regressed on d and a constant. The coefficient on d estimates permanent volatility for individual i,$\delta_{i,\omega}^2$; the constant estimates twice the transitory volatility for individual i, $\delta_{i,\varepsilon}^2$. This idea is illustrated graphically in Figure 1. Here, the x-axis represents the length of time over which squared changes in excess income are calculated, d. The y-axis shows the average squared change in excess income, $\hat{\nu}_{i,d}^2$. Estimating permanent and transitory volatility, $\hat{\delta}_{i,\omega}^2$ and $\hat{\delta}_{i,\varepsilon}^2$, is equivalent to choosing the slope, $\hat{\delta}_{i,\omega}^2$, and intercept, $2\hat{\delta}_{i,\varepsilon}^2$, that best fits the trend. Regardless of the length of time over which $\hat{\nu}_{i,d}^2$ is calculated, the individual is hit by exactly two transitory shocks relevant for this interval, one at time t and the other at time $t-d$. The impact of transitory volatility on squared changes, $\hat{\nu}_{i,d}^2$, should be the same for all interval lengths, d. For this reason, it can be identified as the intercept in a regression of $\hat{\nu}_{i,d}^2$ on d. By contrast, for the d-year interval over which squared changes are taken, the individual is hit by d permanent shocks. Each year brings an additional permanent shock, and therefore increases $\hat{\nu}_{i,d}^2$ by $\delta_{i,\omega}^2$ on average. For this reason, the slope of the regression identifies the transitory volatility.

While the trend line – in a graph of the interval length, d, and squared changes in income over this interval, $\hat{\nu}_{i,d}^2$ – decomposes volatility into permanent and transitory components, the best way to draw such a line is not obvious. To address the problem that transitory shocks may be somewhat persistent or permanent shocks may not enter in full immediately, Carroll and Samwick do not use small interval lengths. Appendix A shows that excluding small values of d can still lead to an unbiased estimate of $\delta_{i,\omega}^2$ even when the process is misspecified. In this paper, I will follow Carroll and Samwick and use only moments with interval lengths of strictly more than two years, $d > 2$. I obtain individual-specific estimates of permanent and transitory income volatility, $\hat{\delta}_{i,\omega}^2$ and $\hat{\delta}_{i,\varepsilon}^2$, using the time-series variability of $\hat{\eta}_{i,t}$. I restrict the sample to household heads with 10 or more observations. I obtain estimates of $\hat{\nu}_{i,d}^2$, for $d = 3, 4, 5, 6$ using all observations on changes in excess log labor income, $\hat{v}_{i,t,d}$, for which there are data. Estimates of these moments, for the sub-sample of observations on which all moments are available, are presented in Table 2.[6] As expected, average

[6]For example, an individual with data in 1971, 1972, 1975, 1976, 1979, 1980, 1983, and 1984 will have 10 obser-

Table 2: Distribution of Total Volatility Estimates Over Various Interval Lengths

Distribution of Average Squared Changes in Excess Log Income, $\hat{\nu}^2_{i,d}$

Interval Length, d (years)	1	2	3	4	5	6
Median	0.069	0.106	0.130	0.158	0.178	0.209
Mean	0.225	0.283	0.320	0.348	0.369	0.395
St. Dev.	0.428	0.449	0.498	0.493	0.515	0.521
# of Individuals	5,060					

The table presents the distribution of individual-specific average values of $\hat{\nu}^2_{i,t,d}$. These are average squared changes in excess log labor income for individual i averaged over all values of t. Squared changes are over one- through six-year intervals ($d = 1$, 2, 3, 4, 5, and 6), as in Equation 5. Data is from the sample of household heads in the PSID who have at least 10 observations between the ages of 25 and 65 in which they are in the labor force. Annual income is replaced by 1,000 x (minimum wage) for heads with income below this level. Excludes heads with more than four skips in data, or skips longer than four years. Squared changes are of residuals from an income regression that includes year dummy variables, a quartic in age, the interaction of dummy variables for each level of education with age and age squared, and individual fixed-effects. Tables present the mean, standard deviation, number of individuals.

sample moments are increasing in the interval length, d.

The estimates, $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$, are obtained as a function of $\hat{\nu}^2_i \equiv \left[\hat{\nu}^2_{i,3}, \hat{\nu}^2_{i,4}, \hat{\nu}^2_{i,5}, \hat{\nu}^2_{i,6}\right]'$. Carroll and Samwick use an OLS regression, which assumes that deviations of realized values, $\hat{\nu}^2_{i,d}$, from true parameters, $d\delta^2_{i,\omega} + 2\delta^2_{i,\varepsilon}$, are i.i.d. across different values of d. In fact, moments with higher values of d are estimated less precisely since there are fewer non-overlapping observations when each observation spans more years of data. Furthermore, since all moments are calculated from the same data, deviations of realized moments from true moments will be correlated. The procedure used in this paper refines the equal-weighting of Carroll and Samwick by computing optimal weights that take into account that moments with higher values of d are estimated with less precision. The literature on Generalized Method of Moments (Hansen (1982), Chamberlain (1987), and others) shows that the most efficient estimator weights moments by the inverse of their variance-covariance matrix. Using this optimal weighting matrix to estimate income volatility is an innovation of this paper.

For vectors $d\iota \equiv [3, 4, 5, 6]'$, $\iota \equiv [1, 1, 1, 1]'$,

$$\begin{aligned} \left\{\hat{\delta}^2_{i,\omega}, \hat{\delta}^2_{i,\varepsilon}\right\} &= \arg \min_{\left\{\delta^2_{i,\omega}, \delta^2_{i,\varepsilon}\right\}} \hat{m}\left(\delta^2_{i,\omega}, \delta^2_{i,\varepsilon}\right)' W^{-1} \hat{m}\left(\delta^2_{i,\omega}, \delta^2_{i,\varepsilon}\right); \\ \hat{m}\left(\delta^2_{i,\omega}, \delta^2_{i,\varepsilon}\right) &\equiv \hat{\nu}^2_i - d\iota\delta^2_{i\omega} - 2\iota\delta^2_{i\varepsilon}. \end{aligned} \tag{6}$$

vations but not have any observations on changes in income, $\hat{v}_{i,t,d}$, with $d = 6$. All such observations are excluded from this and subsequent samples.

W is the optimal weighting matrix, the variance-covariance matrix of the moments, $\hat{m}$. This matrix takes into account that $\hat{v}_{i,t,d}$ will drawn from overlapping observations, both across values of d and for a given value of d, and that there are fewer non-overlapping observations when d is large. If shocks are normally distributed, the elements of this matrix are:

$$\begin{aligned} W_{dd} &= var\left(\bar{m}_d\left(\delta^2_{i\omega}, \delta^2_{i\varepsilon}\right)\right) = \frac{1}{N^2}\begin{bmatrix} 2N\left(d^2 + 2\Sigma_{s=1}^{d-1}\left(d-s\right)^2\right)\delta^4_\omega \\ +8Nd\delta^2_\omega\delta^2_\varepsilon + 12N\delta^4_\varepsilon \end{bmatrix} \\ W_{cd} &= W_{dc} = cov\left(\bar{m}_c\left(\delta^2_{i\omega}, \delta^2_{i\varepsilon}\right), \bar{m}_d\left(\delta^2_{i\omega}, \delta^2_{i\varepsilon}\right)\right) \text{ for } c < d \\ &= \frac{1}{N^2}\begin{bmatrix} N\delta^4_\omega\Sigma_{s=1}^{c-1}2\left(c-s\right)^2 + 2c^2\delta^4_\omega\Sigma_{s=-d+c+1}^{-1}N \\ +\left(2N-d+c\right)\left[2c^2\delta^4_\omega + 2\delta^4_\varepsilon + 2c\delta^2_\omega\delta^2_\varepsilon\right] \\ +2N\delta^4_\omega\Sigma_{s=-d+1}^{-d+c-1}\left(d+s\right)^2 + 4N\delta^4_\varepsilon \end{bmatrix} \end{aligned} \tag{7}$$

W is a function of $\left\{\delta^2_{i,\omega}, \delta^2_{i,\varepsilon}\right\}$. Since this matrix is needed to get the most efficient estimate of $\left\{\delta^2_{i,\omega}, \delta^2_{i,\varepsilon}\right\}$, a solution must be found iteratively. I begin by estimating $\left\{\delta^2_{i,\omega}, \delta^2_{i,\varepsilon}\right\}$ using the identify matrix, W_0. Then, I use the estimates I obtain, $\left\{\hat{\delta}^{(0)2}_{i,\omega}, \hat{\delta}^{(0)2}_{i,\varepsilon}\right\}$, to form $\hat{W}_1\left(\hat{\delta}^{(0)2}_{i,\omega}, \hat{\delta}^{(0)2}_{i,\varepsilon}\right)$; I use $\hat{W}_1$ to estimate $\left\{\hat{\delta}^{(1)2}_{i,\omega}, \hat{\delta}^{(1)2}_{i,\varepsilon}\right\}$; and so on. Iteratively, I use $\left\{\hat{\delta}^{(j-1)2}_{i,\omega}, \hat{\delta}^{(j-1)2}_{i,\varepsilon}\right\}$ to form $\hat{W}_j\left(\hat{\delta}^{(j-1)2}_{i,\omega}, \hat{\delta}^{(j-1)2}_{i,\varepsilon}\right)$, which is used to estimate $\left\{\hat{\delta}^{(j)2}_{i,\omega}, \hat{\delta}^{(j)2}_{i,\varepsilon}\right\}$.[7]

Note that this procedure – like procedures used to estimate income volatility in other papers – will sometimes generate negative values of $\hat{\delta}^2_{i,\omega}$ or $\hat{\delta}^2_{i,\varepsilon}$. While the true values of $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$ are clearly positive, so that

$$\begin{aligned} \hat{\delta}^2_{i,x} &< E\left[\delta^2_{i,x}|\hat{\delta}^2_{i,x} < 0\right], \ x \in \{\omega, \varepsilon\} \text{ while} \\ \delta^2_{i,x} &= E\left[\hat{\delta}^2_{i,x}|\delta^2_{i,x}\right]. \end{aligned} \tag{8}$$

This is confirmed by estimating the parameters on simulated data. In other words, while estimation error is not mean-zero given some values for estimated permanent and transitory volatility, $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$, it is mean-zero given true permanent and transitory volatilities, $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$. Given the substantial error involved in estimating these volatility parameters, it is not surprising that some estimates are outside the plausible range. Since these estimates will be used as inputs into regressions, and not as predicted values, mean-zero estimation error given $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$ is not problematic,

[7] For the estimates presented here, I iterated 10 times, which was more than sufficient to ensure convergence. When $\hat{\delta}^{(j-1)2}_{i,x} < 0$, $x = \{\omega, \varepsilon\}$, I use $\hat{\delta}^{(j-1)2}_{i,x} = 0$ for the purposes of calculating $\hat{W}_j$. Results are substantively unchanged when alternative assumptions are made. For example, $\hat{W}$ can be set to the identify matrix when $\hat{\delta}^{(j-1)2}_{i,x} < 0$, or $\hat{\delta}^{(j-1)2}_{i,x}$ can be set to the population average, either for $\hat{\delta}^{(j-1)2}_{i,x} < 0$ or in all cases, without changing the substance of the results.

even when some estimates of $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$ are implausible. The estimation procedure in Section 3 takes this into account explicitly.

Results are presented in the first column of Table 3, which shows various summary statistics about the joint distribution of permanent and transitory parameter estimates, $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$. So that the sample is not dominated by outliers – individuals whose incomes may not evolve according to the process described in this paper – I exclude from this and subsequent tables all observations with values of $\hat{\nu}^2_{i,3}$ above the 95th percentile. Note that this procedure censors observations with extreme shocks, either permanent or transitory; however, it does not censor observations with extreme allocations of total variance to permanent or transitory components. After excluding these outliers, $4,807$ observations remain. The mean permanent volatility parameter is 0.032, which corresponds to an annual standard deviation of 18%; the mean transitory volatility parameter is 0.070, which corresponds to an annual standard deviation of 26%. The standard deviations of these variance estimates are large; the standard deviation of permanent variance estimates is 0.090, while the standard deviation of transitory variance estimates is 0.188. These large standard deviations reflect the substantial estimation error in $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$. While the standard deviations of both permanent and transitory variance estimates are large, the correlation between them, at -0.68, is strongly negative. As a result, total volatility, $\hat{\nu}^2_{i,d}$, will have a relatively lower standard deviation, since its permanent and transitory components have negatively correlated estimation error.

The second column presents the same moments for the sub-sample (236 observations) with exactly 20 years of data. The left panel of Figure 2 presents a scatter plot of the distribution of the parameter estimates shown in column 2 of Table 3. The x-axis shows the value of the transitory volatility parameter; the y-axis shows the permanent volatility parameter. The strong negative correlation between the parameter estimates is visible in the negative slope of the trend in these points.

What distribution of true parameter values would generate this distribution of point estimates? Certainly, we would expect the variance of point estimates to be greater than the variance of true parameters; the variance of point estimates will depend not only on the variance of true parameters (across individuals), but also on the measurement error, the variance of point estimates given the true parameter (for a given individual). To get a sense of the impact of measurement error, I simulate the income process for a hypothetical individual with 20 years of data whose true volatility parameters are equal to the mean population parameters from the second column of Table 3. For each set of simulated data, I use the methods above to calculate estimated volatility parameters. The distribution of these parameters is presented in the third column of Table 3. The resulting estimates

Table 3: Joint Distribution of Permanent and Transitory Volatility Estimates

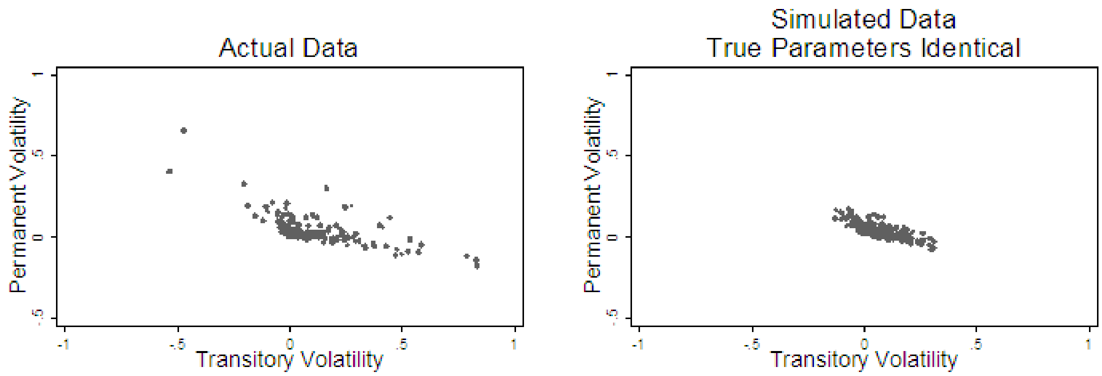
	Full Sample	Individuals with 20 Observations	Simulated Data
mean(Permanent Volatility)	0.032	0.029	⟵ calibrated
s.d.(Permanent Volatility)	0.090	0.077	0.044
mean(Transitory Volatility)	0.070	0.078	⟵ calibrated
s.d.(Transitory Volatility)	0.188	0.164	0.083
corr(Permanent, Transitory)	-0.68	-0.57	-0.79
Average # of Observations	17.8	20 by construction	⟵ calibrated
Individuals	4,807	236	N/A

Permanent and Transitory Volatility refer to $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$, constructed as described in the text. The first column presents features of the joint distribution of permanent and transitory volatility estimates for the full sample. The second column presents this joint distribution of parameter estimates for the sub-sample of individuals with exactly 20 years of data. The third column presents the joint distribution of sample estimates for a hypothetical sample of individuals with exactly 20 years of simulated data. The income paths of these individuals is simulated given the income process assuming that each hypothetical individual has permanent and transitory volatility parameters equal to the mean estimates from the second column. For a given individual, parameter are estimated from the vector of sample moments, $\hat{\nu}^2_{i,d}$, for $d = 3$, 4, 5, and 6. The weighting procedure used to obtain these estimates is detailed in the text of the paper. The first and second rows present the mean and standard deviation of the permanent volatility parameter estimates. The third and fourth rows present the mean and standard deviation of the transitory volatility parameter estimates. The fifth row presents the correlation between these parameter estimates. The sixth row presents the mean number of years of data per individual. The large but lower standard deviation of parameter estimates when there is no variation in the underlying parameters suggests that estimation error, while substantial, cannot explain the dispersion of estimates alone. The left and right panel of Figure 2, respectively present scatter plots of the joint distribution of parameter estimates from the second and third columns.

are unbiased, so that the mean parameter estimate is equal to the parameters used to simulate the data. Even when the true volatility parameters are the same for all observations so that there is no dispersion in *true* parameters, the dispersion of *estimated* parameters is considerable. For the simulated data, the standard deviations for estimates of the permanent and transitory volatility parameters are 0.044 and 0.083, respectively. While measurement error cannot account for all of the variation in parameter estimates, it accounts for a large fraction of it. Furthermore, the correlation between the volatility parameters estimated from simulated data is highly negative, -0.79. The right panel of Figure 2 presents an analogous scatter plot to the left panel, presenting the distribution of parameter estimates for the simulated data. These points are less diffuse than those calculated from actual data, indicating substantial variation in true parameters in the actual data. Estimation error alone cannot explain the diffuse parameter estimates we observe.

The negative correlation between the permanent and transitory parameter estimates is present in both panels of Figures 2; this correlation can be explained by the estimation procedure. The

Figure 2: Joint Distribution of Permanent and Transitory Volatility Estimates



Scatter plots of distribution of parameters summarized in Table 3. The left panel refers to column 2, the joint distribution of permanent and transitory volatility estimates for the set of individuals with exactly 20 years of data. The right panel refers to column 3, the joint distribution of volatility estimates from simulated data on hypothetical individuals with exactly 20 years of data and with true volatility parameters equal to the sample means from the actual data in the left panel. See Table 2 for details.

estimation procedure also explains why the total amount of risk, $E_t\left[(v_{i,t,d})^2\right] = d\delta^2_{i,\omega} + 2\delta^2_{i,\varepsilon}$, is estimated precisely while its decomposition into $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$ is not. If a positive permanent shock follows a negative permanent shock, this pair of permanent shocks is observationally equivalent to a transitory shock. Similarly, if several transitory shocks of the same sign happen to follow one another, these are observationally equivalent to a permanent shock followed several periods later by a permanent shock of the opposite sign. This misidentification of permanent shocks as transitory or transitory shocks as permanent drives the estimation error in both and the strong negative correlation between *estimated* parameters, even when there is none between *actual* parameters. This feature of the estimation procedure will be important when using volatility parameter estimates to look for evidence of intergenerational transmission of income volatility.

What observable attributes are correlated with income volatility? Table 4 presents the results of OLS regressions of the permanent and transitory volatility parameter estimates, $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$, on a variety of covariates. The first three columns present results for regressions with permanent volatility estimates, $\hat{\delta}^2_{i,\omega}$, as the dependent variable; the second three columns present results for regressions with transitory volatility estimates, $\hat{\delta}^2_{i,\varepsilon}$, as the dependent variable. The first row presents the coefficient on the number of years of schooling. For $\hat{\delta}^2_{i,\omega}$, coefficients are consistently and significantly positive, with a coefficient of roughly 0.00175. In other words, an extra four years of education increases the variance of permanent shocks by 0.007 (equivalent to increasing the annual standard deviation from 18% to 20%). Since education may increase the level of earnings, income controls may or may not be appropriate depending on the question of interest. The relationship between years of schooling and permanent income volatility is basically unaffected by the inclusion of income controls, as shown by column 2. The third column replaces years of schooling with dummy variables for various levels of educational attainment, with high school graduation as the omitted category. Results from this regression indicate that the relationship between education and permanent income volatility exists throughout the range of education levels. The coefficient on high-school dropouts is negative (relative to high school graduates), while it is positive (also relative to high school graduates) for levels of education greater than high school and greatest for those with graduate-level education. These regressions suggest a clear positive relationship between education and permanent income volatility. This is consistent with the findings of Meghir and Pistaferri (2004), who estimate permanent income volatility using the income moment in equation (22).

The relationship between education and transitory volatility estimates is much weaker and less clear than the relationship between education and permanent volatility. Without income controls, there is a negative relationship between education and transitory income volatility. Including a host of income controls leads to a positive but insignificant coefficient. This suggests that increased income reduces transitory volatility; increased education increases transitory income volatility but also increases the level of income, which blunts this effect. Since the relationship between the level of income and income volatility could result from mismeasurement, it is not clear how to interpret these results.

Not surprisingly, self-employment is positively correlated with both permanent and transitory income volatility. It is not clear if this correlation results from people with large realized income shocks becoming self-employed, from people who would have high income volatility in any job choosing self-employment, or because self-employment has a causal impact on income volatility. Surprisingly, seat-belt use – which may be a proxy for risk-tolerance in general – is not correlated with income volatility. Dummy variables for the individual's occupation at the time they enter the sample are included in columns 2, 3, 5, and 6, though their coefficients are not reported. At this level of aggregation, occupation dummies except for "self-employed businessmen" are insignificant, separately and jointly, after controlling for income and education.

Table 4: Determinants of Income Volatility

Dependent Variable:	Permanent Volatility, $\hat{\delta}^2_{i,\omega}$			Transitory Volatility, $\hat{\delta}^2_{i,\varepsilon}$		
Years of education	0.00189 (3.48)**	0.00187 (2.88)**		-0.00303 (2.68)**	0.00184 (1.36)	
Less than HS education			-0.00271 (0.74)			0.00177 (0.23)
Some College			0.00621 (1.69)			0.00413 (0.54)
College Education			0.00255 (0.53)			0.01583 (1.57)
Grad School Education			0.01144 (2.06)*			0.01323 (1.15)
Initial Labor Income (in '000s)		-0.00077 (3.62)**	-0.00076 (3.56)**		0.00109 (2.46)*	0.00111 (2.50)*
Median Labor Income (in '000s)		0.00032 (2.99)**	0.00033 (3.03)**		-0.00237 (10.51)**	-0.00240 (10.46)**
Race Black	-0.00384 (1.31)	0.00174 (0.56)	0.00126 (0.40)	0.01507 (2.47)*	0.01124 (1.74)	0.01094 (1.69)
Race Other	0.00572 (0.78)	0.00731 (1.01)	0.00667 (0.92)	-0.00707 (0.46)	-0.00410 (0.27)	-0.00497 (0.33)
Ever Self-Employed		0.02533 (7.12)**	0.02526 (7.09)**		0.01838 (2.49)*	0.01817 (2.45)*
Fraction Self-Employed		0.04261 (5.73)**	0.04251 (5.71)**		0.08257 (5.34)**	0.08290 (5.36)**
Have Seat Belts		-0.00170 (0.33)	-0.00156 (0.30)		-0.00031 (0.03)	0.00000 0.00
Wear Seat Belts		-0.00280 (0.58)	-0.00266 (0.55)		0.00050 (0.05)	0.00089 (0.09)
Occ. Dummies	No	Yes	Yes	No	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,807	4,807	4,807	4,807	4,807	4,807
R^2	0.02	0.017	0.062	0.062	0.015	0.064

Sample and the construction of the independent variable are identical to that described in Table 3. Race dummies for "black" and "other" are included. White is the omitted category. "Other" refers to all races other than "white" or "black". Income controls are for the initial labor income (in thousands) and the median labor income (in thousands) for the individual. Columns 1, 2, 4, and 5 include years of education as an independent variable. When the PSID reports only an education attainment (e.g., high school) instead of a number of years of education, I use an estimate of the number of years needed to attain this level of education. Columns 3 and 6 include dummy variables for types of educational attainment (e.g. less than high school, some college). High school graduation is the omitted category. Includes dummy variable for the final year in the sample and an indicator variable for the number of observations in the sample. Where noted, regressions include occupation dummy variables for the occupation of the individual in their first year in the sample. Occupation categories are the 9 categories consistently used in the PSID, detailed in the text. t-statistics are in parentheses. "*" indicates significance at the 5% level; "**" indicates significance at the 1% level.

3 Estimating Intergenerational Transmission

Do parents' attributes influence the income volatility of their children? The PSID is uniquely well-suited to answer this question. The PSID includes data on a group of original households, plus the spin-off households formed when individuals move out of households already in the sample. Therefore, it contains data not only for parents but also for their adult children. Of the $4,807$ household head's with income volatility estimates presented in Tables 3 and 4, $1,087$ are the adult children of a parent who is also in this sample.[8] Econometrically, we are interested in estimating an equation with a measure of the child's income volatility as the dependent variable and any parental attributes as independent variables. Since the set of possible parental attributes is nearly limitless, economists often focus on the direct intergenerational transmission of an attribute. In this case, do parents with higher income volatility have children with higher income volatility?

Before exploiting the decomposition of total volatility into its permanent and transitory components, $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$, I use a reduced-form regression to document that the total volatility of parents and their children are related. Table 5 presents the relationship between the total observed volatility for parents – the average squared change in excess log income for parents, $\hat{\nu}^{(p)2}_{i,d}$ – and the total observed volatility for their children, $\hat{\nu}^{(k)2}_{i,d}$, for $d = 3$, 4, 5, and 6. There is a strong relationship between the total volatility of parents and their adult children. OLS coefficients without covariates (odd numbered columns) range from 0.11 to 0.21, and are highly significant with t-statistics between 3.1 and 5.1. Including covariates for both the adult child and their parent for education, initial and median income, number of years in sample, a dummy for the final year in the sample (even numbered columns) has little impact on these results; also, the covariates for parents are insignificant. For this reason, covariates will be omitted from subsequent regressions, though including them will also no substantive impact on the results. These results clearly reject the hypothesis that there is no intergenerational transmission of income volatility.[9] However, this table contains little information about which type of volatility, permanent or transitory, is being transmitted. As a result, this regression cannot determine the degree to which economic mobility is inherited. Furthermore, the regressions reported do not correct for the attenuation bias induced by the fact that $\hat{\nu}^{(p)2}_{i,d}$ is a noisily measured estimate of $E_t\left[(v_{i,t,d})^2\right]$. However, they show that any subsequent results are not simply

[8] I define parent as the household head of the family in which the individual lived at age 14.

[9] As with all such tests, this is more precisely a joint rejection of the null and the model. In other words, it is a rejection of the joint hypothesis that neither volatility nor any misspecification in the model used to estimate $\hat{\nu}^{(p)2}_{i,d}$ is inherited. Put more colloquially, the statements "Parents with volatile incomes have children with volatility incomes," and "Parents with non-standard labor income profiles have children with non-standard labor income profiles," are observationally equivalent. Both statements indicate intergenerational transmission of the higher-order moments of human capital, but may have different policy implication.

Table 5: Intergenerational Transmission of Total Volatility: Reduced-Form Regression of Adult Children's Total Volatility on their Parents' Total Volatility

Dependent Variable: Total Volatility Estimate of Adult Child, $\hat{\nu}_{i,d}^{(k)2}$								
Independent Variable: Total Volatility Estimate of Parent, $\hat{\nu}_{i,d}^{(p)2}$								
Total Volatility Interval Length d (Years):	3		4		5		6	
$\hat{b}^{OLS}$	0.113 (3.05)	0.139 (3.47)	0.210 (5.11)	0.255 (5.81)	0.177 (4.42)	0.225 (5.17)	0.163 (4.08)	0.190 (4.44)
Time Controls	No	Yes	No	Yes	No	Yes	No	Yes
Educ. Controls	No	Yes	No	Yes	No	Yes	No	Yes
Income Controls	No	Yes	No	Yes	No	Yes	No	Yes
Individuals	1,087	1,087	1,087	1,087	1,087	1,087	1,087	1,087
R^2	0.008	0.107	0.024	0.117	0.018	0.097	0.015	0.094

Regressions use as both dependent and independent variables the average total excess income volatility measures, $\hat{\nu}_{i,d}^2 \equiv \frac{1}{N_{i,d}} \Sigma_t \left(\hat{v}_{i,t,d}\right)^2$ from equation 5 and summarized in Table 2. These are the average of all squared changes in excess log income taken over intervals of length d for individual i. Outliers are excluded by removing observations with values d of $\hat{\nu}_{i,3}^2$ in the largest 5%, as in Tables 3 and 4. The sample consists of the 1,087 children in the sample who also have a parent in the sample, and their parents. Note that parents with more than one adult child in the sample may appear more than once. When noted, regressions include as covariates the number of years the parent (and adult child) is in the sample, dummy variables for the last year the parent (and adult child) was in the sample, the number of years of education for the parent (and adult child), the median and initial income (in thousands) for the parent (and adult child). t-statistics are in parentheses.

an artifact of the way in which volatility is decomposed into permanent and transitory components.

Given this reduced-form relationship between the total volatility of parents and the total volatility of their children, it is natural to decompose this relationship into the impact of the permanent and transitory income volatility of parents on the permanent and transitory income volatility of their adult children. This is particularly important given that intergenerational transmission of permanent volatility implies that economic mobility is inherited, so that average estimates of intergenerational mobility mask groups with much lower rates of mobility. By contrast, intergenerational transmission of transitory volatility could merely reflect intergenerational transmission of measurement error when filling out surveys. Consider the following demeaned relationship between the volatility parameters of parents and their children:

$$\delta_i^{(k)2} = \delta_i^{(p)2}\beta + \theta_i.^{10} \tag{9}$$

This is nothing more than a mathematical expression of the idea that both the permanent and

[10] Note that excluding a constant term does not imply any loss of generality since we replace the permanent and transitory volatility parameters of parents and their children, $\delta_i^{(p)2}$ and $\delta_i^{(k)2}$, with their deviations from sample means.

transitory volatility parameters of parents may impact both the permanent and transitory volatility parameters of their adult children. Here, $\delta_i^{(p)2} \equiv \left[\delta_{i,\omega}^{(p)2}, \delta_{i,\varepsilon}^{(p)2}\right]$ and $\delta_i^{(k)2} \equiv \left[\delta_{i,\omega}^{(k)2}, \delta_{i,\varepsilon}^{(k)2}\right]$ refer to the $1x2$ vectors of true volatility parameters of the parent and child, respectively. β denotes the $2x2$ matrix representing the impact of parental volatility parameters on the child's volatility parameters, $\beta \equiv [\beta_{\omega\omega}, \beta_{\omega\varepsilon}; \beta_{\varepsilon\omega}\beta_{\varepsilon\varepsilon}]$. The β_{xy} coefficients, for $x, y \in \{\omega, \varepsilon\}$, refer to various channels through which this impact can happen. For example, $\beta_{\omega\varepsilon}$ represents the impact of the parent's permanent volatility on the transitory volatility of their adult child.[11] The $1x2$ vector $\theta_i \equiv [\theta_{i,\omega}, \theta_{i,\varepsilon}]$ refers to the error terms. If there are N pairs of children and their parents in the data, and if we let $\delta^{(p)2}$, $\delta^{(k)2}$, and θ refer to the $Nx2$ matrices whose ith rows are $\delta_i^{(k)2}$, $\delta_i^{(k)2}$, and θ_i, respectively, then a system of $2N$ equations can be characterized as $\delta^{(k)2} = \delta^{(p)2}\beta + \theta$. Similarly, we can use $\delta^{(p)2} \equiv \left[\delta_\omega^{(p)2}, \delta_\varepsilon^{(p)2}\right]$ and $\delta^{(k)2} \equiv \left[\delta_\omega^{(k)2}, \delta_\varepsilon^{(k)2}\right]$ to refer to the pairs of $Nx1$ vectors of volatility parameters.

Subsection 3.1 shows how to implement this regression when the right-hand side variable is estimated with error and Subsection 3.2 presents the results.

3.1 Estimation Error

The challenge in estimating the system of equations (9) is that the $1x2$ volatility vectors for a parent and adult child, $\delta_i^{(p)2}$ and $\delta_i^{(k)2}$, are measured with substantial error; we only observe estimates of these vectors, $\hat{\delta}_i^{(p)2}$ and $\hat{\delta}_i^{(k)2}$. By definition, these estimates are the sum of the true values, $\delta_i^{(p)2}$ and $\delta_i^{(k)2}$, and estimation error, $u_i^{(p)}$ and $u_i^{(k)}$, where $u_i^{(p)} \equiv \left[u_{i,\omega}^{(p)}, u_{i,\varepsilon}^{(p)}\right]$ and $u_i^{(k)} \equiv \left[u_{i,\omega}^{(k)}, u_{i,\varepsilon}^{(k)}\right]$.[12] In principle, measurement error in a left-hand side variable, estimation error in $\delta^{(k)2}$, will not bias estimates of β; it merely adds noise to θ and therefore reduces precision.[13]

More problematically, measurement error in the right-hand side variable, estimation error in

The algebra below will refer to these demeaned values, though the empirical work that follows will specify whether the relevant values are demeaned. Covariates can be added without difficulty, but are excluded here for expositional simplicity.

[11] For compactness, $\beta_{.,y}$ will refer to the y column of β, which indicates the impact of parental volatilities on the child's volatility parameter y; $\beta_{x,.}$ refers to the x row of β, which shows the impact of parental volatility parameter x on the volatility parameters of the child.

[12] In matrix notation, $\hat{\delta}_i^{(p)2} \equiv \delta_i^{(p)2} + u_i^{(p)}$ and $\hat{\delta}_i^{(k)2} \equiv \delta_i^{(k)2} + u_i^{(k)}$. Again, we can stack these equations to form $Nx2$ matrices so that $u_i^{(p)}$ and $u_i^{(k)}$ are the ith rows or $u^{(p)}$ and $u^{(k)}$, respectively, so that $\hat{\delta}^{(p)2} = \delta^{(p)2} + u^{(p)}$ and $\hat{\delta}^{(k)2} = \delta^{(k)2} + u^{(k)}$.

[13] This assumes that the realized shocks faced by parents and their children are uncorrelated, so that $E\left[u_i^{(p)\prime} u_i^{(k)}\right] = 0$. The results reported here include years of data in which both the child and their parent in present in the data set, so that this assumption is far from innocuous. However, such overlapping data can be eliminated by estimating income volatility for parents from only those years of data in which their children are not in the sample. This eliminates the possibility that both parents and their children may be hit by contemporaneous and correlated shocks. This restriction reduces the number of parent/child pairs with sufficient data by roughly half, and therefore substantially reduces the precision of coefficient estimates. However, it has almost no impact on the point estimates of coefficients. This indicates that the relationship between the volatility of parents and their children cannot be explained by any common shocks they might receive.

$\delta^{(p)2}$, will bias estimates of β towards zero.[14] This bias can be characterized for the OLS estimator,

$$b^{OLS} \equiv \left(\hat{\delta}^{(p)2\prime}\hat{\delta}^{(p)2}\right)^{-1}\hat{\delta}^{(p)2\prime}\hat{\delta}^{(k)2}. \tag{10}$$

Let $Q^{(p)*}$ refer to the probability limit of the $2x2$ variance-covariance matrix of the parents' true volatility parameters; let $\Sigma_{uu}^{(p)2}$ refer to the variance-covariance matrix of the measurement error for these volatility parameters:

$$\begin{aligned} Q^{(p)*} &\equiv \text{plim}\ \frac{1}{N}\delta^{(p)2\prime}\delta^{(p)2}, \text{ where} && (11)\\ \frac{1}{N}\delta^{(p)2\prime}\delta^{(p)2} &\equiv \begin{bmatrix} \frac{1}{N}\delta_{\omega}^{(p)2\prime}\delta_{\omega}^{(p)2} & \frac{1}{N}\delta_{\varepsilon}^{(p)2\prime}\delta_{\omega}^{(p)2} \\ \frac{1}{N}\delta_{\omega}^{(p)2\prime}\delta_{\varepsilon}^{(p)2} & \frac{1}{n}\delta_{e}^{(p)2\prime}\delta_{e}^{(p)2} \end{bmatrix}; \\ \Sigma_{uu}^{(p)2} &\equiv E\left[u_i^{(p)\prime}u_i^{(p)}\right] \equiv \begin{bmatrix} \sigma_{u_\omega}^{(p)2} & \rho^{(p)}\sigma_{u_\varepsilon}^{(p)}\sigma_{u_\omega}^{(p)} \\ \rho^{(p)}\sigma_{u_\varepsilon}^{(p)}\sigma_{u_\omega}^{(p)} & \sigma_{u_\varepsilon}^{(p)2} \end{bmatrix} \forall i. && (12) \end{aligned}$$

In this case, plim $\frac{1}{N}\hat{\delta}^{(p)2\prime}\hat{\delta}^{(p)2} = Q^{(p)*} + \Sigma_{uu}^{(p)2}$ and plim $\frac{1}{N}\hat{\delta}^{(p)2\prime}\hat{\delta}^{(k)2} = Q^{(p)*}\beta$, so that the OLS estimator will biased towards zero:

$$\text{plim}\ b^{OLS} = \left(Q^{(p)*} + \Sigma_{uu}^{(p)2}\right)^{-1} Q^{(p)*}\beta. \tag{13}$$

However, the OLS estimator can be transformed into an unbiased multivariate error-in-variables (MEIV) estimator, b^{MEIV}:

$$\begin{aligned} b^{MEIV} &\equiv Q^{(p)*-1}\left(Q^{(p)*} + \Sigma_{uu}^{(p)2}\right) b^{OLS} && (14)\\ \text{plim}\ b^{MEIV} &= \beta. \end{aligned}$$

To implement this correction, I need to estimate $Q^{(p)*-1}\left(Q^{(p)*} + \Sigma_{uu}^{(p)2}\right)$. This matrix is analogous to the reliability ratio in a standard univariate error-in-variables correction. While the total variation in parameter estimates, $\left(Q^{(p)*} + \Sigma_{uu}^{(p)2}\right)$, can be estimated readily from the total variation in parameter estimates as $\widehat{Q^{(p)*} + \Sigma_{uu}^{(p)2}} \equiv \frac{1}{N}\hat{\delta}^{(p)2\prime}\hat{\delta}^{(p)2}$, it is not possible to separate signal (true variation, $Q^{(p)*}$) from noise (measurement error, $\Sigma_{uu}^{(p)2}$) without additional information. This additional

[14] Note that language around the phrases "estimation error" and "measurement error" is tricky here. The literature on attenuation bias is concerned with "measurement error" in a right-hand side variable. Here, that "measurement error" is "estimation error" in the volatility parameters of parents but generally not error in the measurement of income from the survey. Provided it is not persistent, this error in the measurement of income is observationally equivalent to transitory volatility.

information comes from assuming the process for income described in equation (2) and then recalling the estimation procedure used in Subsection 2.3 to obtain permanent and transitory volatility estimates, $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$, given this process. Given that the process for income assumed already to develop estimators for $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$, assuming that same process when correcting measurement error in regressions with $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$ is relatively innocuous.

The joint distribution of true variation in model parameters, $\hat{Q}^{(p)*}$, is calibrated as follows. First, a guess for $\hat{Q}^{(p)*}$ is chosen. $\hat{Q}^{(p)*}$ is the variance-covariance matrix of the joint distribution from which permanent and transitory volatility parameters, $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$, are believed to be drawn. $\delta^2_{i,\omega}$ and $\delta^2_{i,\varepsilon}$ are assumed to be drawn from χ^2-distributions with means equal to the sample means. The variances of these distributions and the correlation between them are set according to $\hat{Q}^{(p)*}$.[15] Second, "true" volatility parameters are drawn from this distribution for hypothetical individuals. Third, income data are simulated for these hypothetical individuals, assuming that excess income evolves as in equation (2) and that shocks to log income are drawn from normal distributions with variances equal to the "true" volatility parameters drawn for these hypothetical individuals.[16] Fourth, the estimation procedure described in Subsection 2.3 is used to obtain an estimate of the volatility parameters for each hypothetical individual from their simulated data. The calibrated true parameter distribution, with variance-covariance matrix $\hat{Q}^{(p)*}$, is chosen so that the variance-covariance matrix of estimated volatility parameters from this simulated data matches the observed distribution of parameter estimates in the sample, $\widehat{Q^{(p)*} + \Sigma^{(p)2}_{uu}}$. The estimated distribution of estimation error, $\hat{\Sigma}^{(p)2}_{uu}$, is merely the residual from this procedure, $\hat{\Sigma}^{(p)2}_{uu} \equiv \widehat{Q^{(p)*} + \Sigma^{(p)2}_{uu}} - \hat{Q}^{(p)*}$.

The joint distribution of $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$ for the sub-sample of parents is presented in column 1 of Table 6; parents with more than one child in the sample appear more than once in this sub-sample. The total variation in parameter estimates (column 1, $\widehat{Q^{(p)*} + \Sigma^{(p)2}_{uu}}$) is decomposed into signal variation (true variation of parameters, $\hat{Q}^{(p)*}$, column 2) and noise variation (estimation error of parameters, $\hat{\Sigma}^{(p)2}_{uu}$, column 3) using the procedure described in the previous paragraph; presenting

[15] The standard χ^2-distribution has only one parameter, equal to the number of independent standard normal distributions that are summed to create it. However, it can be scaled by assuming that these normal distributions are not standard. In this case, I adjust the scale by assuming that the variance of these normal distributions can vary. The resulting two-parameter distribution is a Gamma distribution; it has the shape of a χ^2-distribution but can take on arbitrary mean and variance.

[16] Each hypothetical individual has 20 years of income data, since the average parent in the sample has 20 observations of data. When this exercise is performed for adult children, I use 16 years of data to match the sample of adult children.

Table 6: Decomposing Variation in Volatility Parameter Estimates into Parameter Variation and Estimation Error

Sample	Adult Children	Parents of Adult Children		
Distribution	Total Variation	Total Variation	Parameter Variation	Noise Variation
Mean(Permanent Volatility)	0.043	0.024	0.024	0
Mean(Transitory Volatility)	0.060	0.065	0.065	0
Var(Permanent Volatility)	0.011	0.0038	0.001	0.0028
Var(Transitory Volatility)	0.042	0.0194	0.0089	0.0105
Cov(Permanent, Transitory)	-0.015	-0.0047	-0.0005	-0.0042
Mean # of Obs.	16.0	20.0	NA	NA
Individuals	1,087	1,087	NA	NA

Permanent and Transitory Volatility refer to $\hat{\delta}^2_{i,\omega}$ and $\hat{\delta}^2_{i,\varepsilon}$, constructed as described in the text. The first and second columns repeat the first column from Table 3 for the subsamples of adult children and their parents, respectively, whose parents or adult children, respecitvely) are also in the sample. Parents with more than one child in the sample will have repeated observations. These columns present the moments of the joint distribution of estimated volatility parameters, $\hat{\delta}^2_i$, so that the variances and covariance make up the elements of $\left(\widehat{Q^{(k)*} + \Sigma^{(k)2}_{uu}}\right)$. The estimation procedure used to obtain these estimates is detailed in the text of the paper. The final two columns present the decomposition of this distribution of total variation for parents into its signal and noise components. This decomposition relies on the assumptions that the process for income follows equation 2 and that the true volatility parameters in the sample are drawn from gamma distributions. The calibration is performed as follows. First, the true parameter distribution (columns 3) is chosen. Note that the variances and covariance of this distribution form the elements of $\widehat{\mathrm{Q}}^*$. Second, simulated "true" volatility parameters for hypothetical individuals are drawn from this distribution. Third, income processes are generated for each simulated individual assuming that the income process follows equation 2 and that volatility parameters are as drawn. The number of observations drawn is the population average, in this case 20. Fourth, the estimation procedure described in the text is used to estimate the volatility parameters for each simulated individual. The true parameter distribution is chosen so that the distribution of estimated volatility parameters from this simulated data matches the observed distribution of parameter estimates in the sample (column 1). The distribution of noise (column 3) is merely calculated as the difference between the total variation (column 2) and the signal variation (column 3). More details are provided in the text.

Table 6 in matrix notation,

$$\widehat{Q^{(p)*} + \Sigma_{uu}^{(p)2}} = \begin{bmatrix} 0.0038 & -0.0047 \\ -0.0047 & 0.0194 \end{bmatrix} \tag{15}$$

is decomposed into

$$\hat{Q}^{(p)*} = \begin{bmatrix} 0.0010 & -0.0005 \\ -0.0005 & 0.0089 \end{bmatrix} \text{ and } \hat{\Sigma}_{uu}^{(p)2} = \begin{bmatrix} 0.0028 & -0.0042 \\ -0.0042 & 0.0105 \end{bmatrix}. \tag{16}$$

The negative covariance between $\hat{\delta}_{i,\omega}^{(p)2}$ and $\hat{\delta}_{i,\varepsilon}^{(p)2}$, the off-diagonal element of $\widehat{Q^{(p)*} + \Sigma_{uu}^{(p)2}}$, is mostly attributable to estimation error. As mentioned in Subsection 2.3, the estimation procedure sometimes misidentifies permanent volatility as transitory and vice versa. This induces a negative correlation in the parameter estimates even if none existed in the true distribution of parameters; this is readily apparent in the large, negative off-diagonal element of $\hat{\Sigma}_{uu}^{(p)2}$. However, there is a modest negative correlation in the true parameter values, as shown by the negative off-diagonal element of $\hat{Q}^{(p)*}$. Parents with high permanent volatility tend to have slightly lower transitory volatility. While most of the total variation in parameter estimates is attributable to estimation error, there is still substantial variation in the underlying parameters.

3.2 Multivariate Estimates

Results on the intergenerational transmission of total volatility, $\hat{\nu}_{i,d}^2$, in Table 5 have shown that there is a strong connection between the income volatility of parents and their children. However, regressions based on these moments give no insight into whether it is permanent or transitory income volatility of parents that impacts the income volatility of children; similarly, it gives no insight into whether it is permanent or transitory income volatility of children that is affected by parental income volatility. Put another way, while we are interested in obtaining estimates of the matrix $\beta \equiv \{\beta_{\omega\omega}, \beta_{\omega\varepsilon}; \beta_{\varepsilon\omega}, \beta_{\varepsilon\varepsilon}\}$, Table 5 shows only that some combinations of these coefficients are positive. A large coefficient on $\beta_{\varepsilon\varepsilon}$ could merely indicate that the tendency to answer questions about your income inaccurately, which shows up econometrically as transitory income volatility, is passed from parents to children. Alternatively, parents who face more permanent income volatility have children who also do, in which case $\beta_{\omega\omega}$ would be positive. This would be economically important because it would indicate that the degree of economic mobility is inherited. This section aims to differentiate these possibilities. Estimates from univariate regressions (not shown) are too imprecise to make headway in this decomposition, as the underlying independent variables, $\delta_{i,\omega}^{(p)2}$ and $\delta_{i,\varepsilon}^{(p)2}$, are estimated with too much error. Also, the negative covariance between $\delta_{i,\varepsilon}^{(p)2}$ and $\delta_{i,\varepsilon}^{(p)2}$, the off-diagonal element of $\hat{Q}^{(p)*}$ suggests that such univariate estimates may be biased.

To address these problems, I use a multivariate error-in-variables correction that exploits the negative correlation between estimation error in the permanent and transitory volatility parameter, $u_{i,\omega}^{(p)}$ and $u_{i,\varepsilon}^{(p)}$. Put another way, a low value of $\hat{\delta}_{i,\varepsilon}^{(p)2}$ suggests that a high value of $\hat{\delta}_{i,\omega}^{(p)2}$ may be spurious. Including both $\hat{\delta}_{i,\varepsilon}^{(p)2}$ and $\hat{\delta}_{i,\varepsilon}^{(p)2}$ as regressors in a regression and accounting explicitly for the correlation structure of the estimation error allows estimates of the elements of β which are unbiased and contain more information than those obtained from a univariate error-in-variables regression. This multivariate approach also allows for hypothesis testing with groups of parameters. The previous subsection presented an underlying distribution of true parameters consistent with the observed distribution of estimated parameters. This distribution provides an estimate of $\hat{Q}^{(p)*}$ which can be used to implement a multivariate error-in-variables correction:

$$
\begin{aligned}
b^{MEIV} &\equiv Q^{*-1}\left(Q^{*}+\Sigma_{uu}^{2}\right)b^{OLS}, \text{ implemented as} && (17)\\
\hat{b}^{MEIV} &= \left(\hat{Q}^{(p)*}\right)^{-1}\widehat{Q^{(p)*}+\Sigma_{uu}^{(p)2}}b^{OLS}. && (18)
\end{aligned}
$$

Table 7 presents both OLS and multivariate error-in-variables (MEIV) coefficients. In this table, the dependent variable is *either* $\hat{\delta}_{i,\varepsilon}^{(k)2}$ *or* $\hat{\delta}_{i,\varepsilon}^{(k)2}$; the independent variables are *both* $\hat{\delta}_{i,\varepsilon}^{(p)2}$ *and* $\hat{\delta}_{i,\varepsilon}^{(p)2}$. Using a multivariate regression and correcting for attenuation bias, the relationship between the permanent volatility of parents and the permanent volatility of their children is positive and quantitatively large, $\hat{b}_{\omega\omega}^{MEIV}=0.290$, but only marginally statistically significant, $t_{\omega\omega}^{MEIV}=1.58$. Cross-terms are important. The relationship between a parent's transitory volatility and their child's permanent volatility is positive, $\hat{b}_{\omega\varepsilon}^{MEIV}=0.167$, and significant, $t_{\omega\varepsilon}^{MEIV}=3.73$. The correlation of standard errors for these coefficients is negative, -0.25. As a result, while $\hat{b}_{\omega\omega}^{MEIV}$ is not estimated very precisely, the sum of $\hat{b}_{\omega\omega}^{MEIV}$ and $\hat{b}_{\omega\varepsilon}^{MEIV}$ *is* estimated precisely. Therefore, if $\beta_{\omega\omega}$ is lower than $\hat{b}_{\omega\omega}^{MEIV}$, we can be reasonably confident that $\beta_{\omega\varepsilon}$ is above $\hat{b}_{\omega\varepsilon}^{MEIV}$. In other words, parents' volatility parameters strongly influence the permanent volatility parameter of their children. While the relative importance of permanent and transitory volatility of parents in shaping children's permanent volatility is not identified precisely, jointly it is clear that they are very important.

Table 7: Multivariate Regressions of Child's Volatility on Their Parent's Volatility

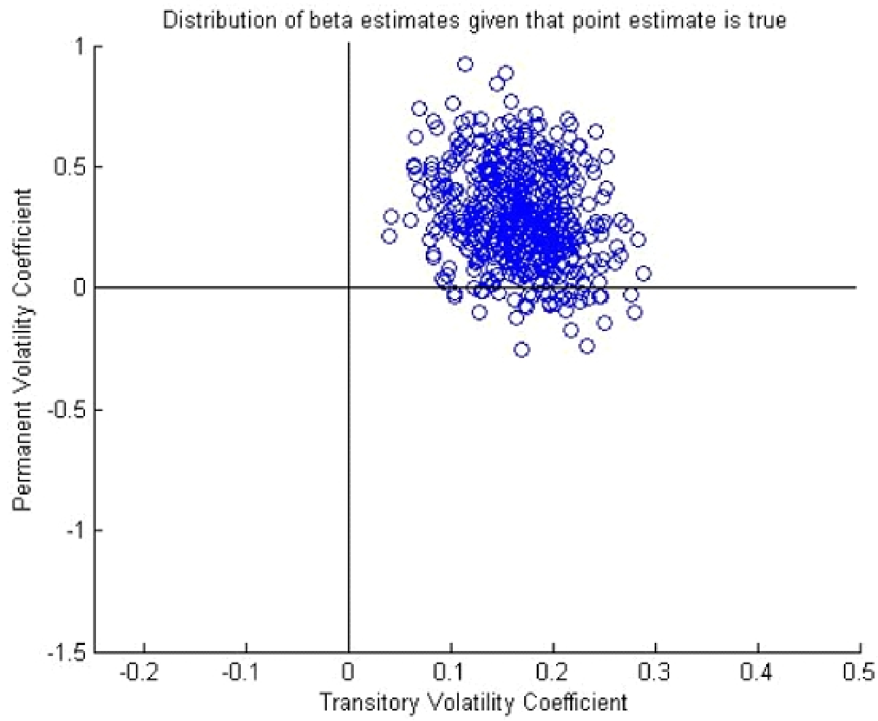
Dependent Variable	Permanent Volatility of Adult Child, $\hat{\delta}_{i,\omega}^{(k)2}$		Transitory Volatility of Adult Child, $\hat{\delta}_{i,\varepsilon}^{(k)2}$	
Regression	OLS	EIV	OLS	EIV
Parent's Permanent Volatility, $\hat{b}_{\cdot,\omega}^{2}$	0.199 (3.30)**	0.290 (1.58)	-0.088 (0.74)	-0.094 (0.25)
Parent's Transitory Volatility, $\hat{b}_{\cdot,\varepsilon}^{2}$	0.118 (4.38)**	0.167 (3.73)**	-0.062 (1.17)	-0.093 (1.03)
corr($\hat{b}_{\cdot,\omega}^{2}, \hat{b}_{\cdot,\varepsilon}^{2}$)	0.54	-0.25	0.54	-0.26
# of Parent-Child Pairs	1,087	1,087	1,087	1,087
R^2 (OLS)	0.018	N/A	0.0007	N/A

Table presents results of multivariate regressions. The sample is the universe of all $1,087$ parent/child pairs of household heads with income volatility parameter estimates. Regressions have the permanent and transitory volatility parameter estimate of the parent as their dependent variables and the permanent (columns 1 and 2) or transitory (columns 3 and 4) volatility parameter estimates of their adult children as the independent variables. There are no other covariates in these regressions. Variables are taken as the difference from their sample means so that the constant term can be ignored without loss of generality. The first and third columns present multivariate OLS regression results and OLS standard errors. The second and fourth columns adjust these OLS estimates using the MEIV correction described in the paper. Standard errors are simulated assuming that shocks are normal, the estimated coefficients are true, and the magnitude and structure of errors is as has been described in the paper. t-statistics are in parentheses. "*" indicates significance at the 5% level; "**" indicates significance at the 1% level. Joint confidence intervals are shown graphically in Figure 3 and Figure 4.

This is easy to see by looking at Figure 3, which presents a scatter plot of a simulated confidence intervals around the determinants of permanent volatility for adult children, $\left\{\hat{b}_{\omega\omega}^{MEIV}, \hat{b}_{\omega\varepsilon}^{MEIV}\right\}$. The hypothesis that the volatility parameters of parents are unrelated to the permanent volatility parameter of their adult children is strongly rejected, as is the hypothesis that they are jointly much smaller than their point estimates.

By contrast, there is no evidence that the transitory volatility of children is related to the income volatility of their parents. The relationship between the permanent and transitory income volatility of parents and the transitory income volatility of their children is negative, $\hat{b}_{\varepsilon\omega}^{MEIV} = -0.094$ and $\hat{b}_{\varepsilon\varepsilon}^{MEIV} = -0.093$, but insignificant, $t_{\varepsilon\omega}^{MEIV} = 0.25$ and $t_{\varepsilon\varepsilon}^{MEIV} = 1.03$. Figure 4 plots the confidence intervals around the joint determinants of transitory volatility for adult children, $\left\{\hat{b}_{\varepsilon\omega}^{MEIV}, \hat{b}_{\varepsilon\varepsilon}^{MEIV}\right\}$. The confidence range is extremely large and $\{0, 0\}$ is well within it. There is no evidence that the volatility parameters of parents have any impact of the transitory volatility parameter of their children. Since measurement error in income shows up econometrically as transitory volatility, it is not surprising that parents do not pass to their children the tendency to answer interviewers' questions inaccurately.

Figure 3: Confidence Interval for Determinants of Adult Child's Permanent Volatility



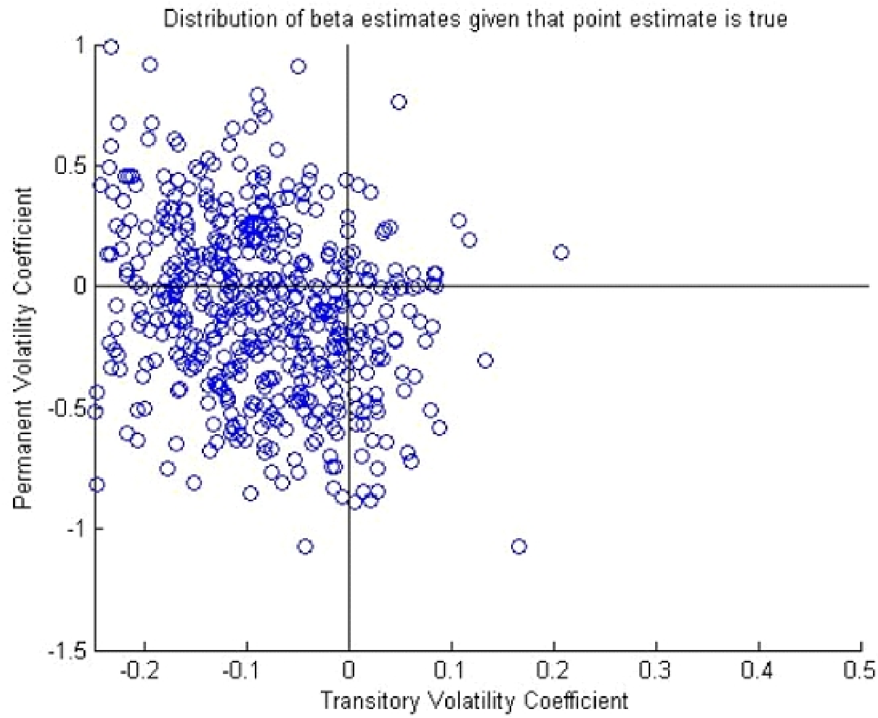
This figure plots the simulated confidence interval around $\left\{\hat{b}_{\omega\omega}^{MEIV}, \hat{b}_{\omega\varepsilon}^{MEIV}\right\}$. This assumes that the true degree of intergenerational transmission is equal to the multivariate error-in-variables corrected values and the distribution of true parameter estimates is as in Table 6. Data on 1,087 hypothetical parent-child pairs is simulated for hypothetical observations of lenth equal to the averages for parents and their children. MEIV estimates are calculated on these simulated data; this process is repeated to build up a reference distribution.

The regressions in Table 7 show that parents' income volatility impacts the permanent volatility of their children. However, it is not clear exactly how to decompose this effect into the parts attributable to the permanent and transitory volatility of parents. Put another way $\beta_{\omega\omega}$ and $\beta_{\omega\varepsilon}$ are both positive, but their relative magnitudes aren't estimated precisely. By contrast, the income volatility of parents does not seem to have a statistically significant effect on the transitory volatility of children. These effects can be seen in Table 8, which shows regressions of permanent or transitory volatility of children, $\hat{\delta}_{i,\omega}^{(k)2}$ or $\hat{\delta}_{i,\varepsilon}^{(k)2}$, on the total volatility of their parents, $\widehat{\hat{\nu}_{i,d}^{(p)2}}$. Instead of estimating the effects of $\hat{\delta}_{i,\omega}^{(p)2}$ and $\hat{\delta}_{i,\varepsilon}^{(p)2}$ separately, this regression recovers an estimate of a positive linear combination of these effects.[17] Since $\widehat{\hat{\nu}_{i,d}^{(p)2}}$ is a positive linear combination of $\hat{\delta}_{i,\omega}^{(p)2}$ and $\hat{\delta}_{i,\varepsilon}^{(p)2}$ and there is a negative correlation between $u_{i,\omega}^{(p)}$ and $u_{i,\varepsilon}^{(p)}$, $\widehat{\hat{\nu}_{i,d}^{(p)2}}$ has little measurement error and the coefficient on $\widehat{\hat{\nu}_{i,d}^{(p)2}}$ is estimated precisely. Table 8 shows that total income volatility of parents

[17] Here, the regression of interest is:

$$\delta^{(k)2} = \widehat{\hat{\nu}_{d}^{(p)2}}\beta_d + \theta_d.$$

Figure 4: Confidence Interval for Determinants of Adult Child's Transitory Volatility



This figure plots the simulated confidence interval around $\left\{\hat{b}^{MEIV}_{\varepsilon\omega}, \hat{b}^{MEIV}_{\varepsilon\varepsilon}\right\}$. This assumes that the true degree of intergenerational transmission is equal to the multivariate error-in-variables corrected values and the distribution of true parameter estimates is as in Table 6. Data on 1,087 hypothetical parent-child pairs is simulated for hypothetical observations of lenth equal to the averages for parents and their children. MEIV estimates are calculated on these simulated data; this process is repeated to build up a reference distribution.

has a substantial impact on the permanent income volatility of their children. This can be seen using actual moments ($\hat{\nu}^{(p)2}_{i,d}$, row 1) or predicted moments ($\widehat{\hat{\nu}^{(p)2}_{i,d}}$, rows 2 and 3), and is shown with and without a correction for measurement error (rows 2 and 3, respectively). By contrast, there is

The OLS regression coefficients will again be biased.

$$b^{UOLS}_d \equiv \frac{\widehat{\nu^{(p)2}_d}' \hat{\delta}^{(k)2}}{\widehat{\nu^{(p)2}_d}' \widehat{\nu^{(p)2}_d}} = \frac{\left(\hat{\delta}^{(p)2}\bar{d}\right)' \hat{\delta}^{(k)2}}{\left(\hat{\delta}^{(p)2}\bar{d}\right)' \left(\hat{\delta}^{(p)2}\bar{d}\right)} = \frac{\bar{d}'\hat{\delta}^{(p)2\prime}\hat{\delta}^{(k)2}}{\bar{d}'\hat{\delta}^{(p)2\prime}\hat{\delta}^{(p)2}\bar{d}} = \frac{\bar{d}'\hat{\delta}^{(p)2\prime}\left(\delta^{(p)2}\beta + \theta + u^{(k)}\right)}{\bar{d}'\hat{\delta}^{(p)2\prime}\hat{\delta}^{(p)2}\bar{d}}$$

$$\text{plim } b^{UOLS}_d = \frac{\bar{d}'Q^{(p)*}\beta}{\bar{d}'\left(Q^{(p)*} + \Sigma^{(p)2}_{uu}\right)\bar{d}}$$

The error-in-variables correction provides an estimate of a positive linear combination of the separate effects, β.

$$b^{UEIV}_d \equiv \frac{\bar{d}'\left(Q^{(p)*} + \Sigma^{(p)2}_{uu}\right)\bar{d}}{\bar{d}'Q^{(p)*}\bar{d}} b^{UOLS}_d = \left(1 + \frac{\bar{d}'\Sigma^{(p)2}_{uu}\bar{d}}{\bar{d}'Q^{(p)*}\bar{d}}\right) b^{UOLS}_d$$

$$\text{plim } b^{UEIV}_d = \frac{\bar{d}'Q^{(p)*}\beta}{\bar{d}'Q^{(p)*}\bar{d}}$$

Note that b_d is a 1x2 matrix, where the first (second) element refers to the impact of a linear combination of parental volatility parameters on the permanent (transitory) volatility of their children.

Table 8: Regression of Child's Permanent or Transitory Volatility on Parent's Total Volatility

Dependent Variable:	Adult Child's Permanent Volatility, $\hat{\delta}^{(k)2}_{i,\omega}$				Adult Child's Transitory Volatility, $\hat{\delta}^{(k)2}_{i,\varepsilon}$			
Independent Variable:	Parent's Total Volatility, $\hat{\nu}^{(p)2}_{i,d}$ Average Squared Change in Excess Log Income							
Interval Length d (Years):	3	4	5	6	3	4	5	6
Actual Moment, $\hat{\nu}^{(p)2}_{i,d}$, OLS	0.055	0.060	0.046	0.035	-0.025	-0.032	-0.022	-0.018
	(4.08)*	(5.02)*	(4.22)*	(3.50)*	(0.93)	(1.37)	(1.03)	(0.91)
Synthetic Moment, $\widehat{\hat{\nu}^{(p)2}_{i,d}}$, OLS	0.060	0.056	0.047	0.039	-0.031	-0.028	-0.023	-0.018
	(4.50)*	(4.47)*	(4.24)*	(3.93)*	(1.17)	(1.13)	(1.04)	(0.94)
Synthetic Moment, $\widehat{\hat{\nu}^{(p)2}_{i,d}}$, EIV	0.086	0.081	0.073	0.066	-0.044	-0.040	-0.035	-0.031
	(4.52)*	(4.49)*	(4.26)*	(3.95)*	(1.17)	(1.13)	(1.04)	(0.94)
Reliability Ratio	0.70	0.69	0.64	0.59	0.70	0.69	0.64	0.59
Observations	1,087	1,087	1,087	1,087	1,087	1,087	1,087	1,087
R^2 (Actual, OLS)	0.015	0.023	0.016	0.011	0.001	0.002	0.001	0.001

The dependent variable is the estimate of permanent (columns 1 through 4) or transitory (columns 5 through 8) income volatility for adult children. The independent variable is the total volatility of changes in income for their parents over 3-year (columns 1 and 5), 4-year (columns 2 and 6), 5-year (columns 3 and 7), and 6-year (columns 4 and 8) periods. Values are de-meaned so coefficients are ignored without loss of generality. The first row reports OLS regression coefficients (and t-statistics) when actual total volatility of parents, $\hat{\nu}^{(p)2}_{i,d}$, is the independent variable. The second row reports OLS regression coefficients (and t-statistics) when predicted total volatility of parents, $\widehat{\hat{\nu}^{2}_{i,d}}$, is the independent variable. The third row reports error-in-variable corrected coefficient estimates (and t-statistics) when predicted total volatility of parents, $\widehat{\hat{\nu}^{2}_{i,d}}$, is the independent variable. The fourth row reports the reliability ratios used to calculate the error-in-variables correction. The fifth row reports the number of observations used in these regressions. The sixth row reports the R^2 of the regression in the first row. Variables are taken as the difference from their sample means so that the constant term can be ignored without loss of generality. t-statistics are in parentheses. "*" indicates significance at the 1% level.

no significant impact of parents' total income volatility on the transitory income volatility of their children.

While these results exclude covariates, results change very little when covariates are included. In regressions not reported here, including education, income, race, number of observations, and year first in sample for the parents has very little impact on the results. This is not surprising since the low R^2 values in Table 4 indicate that most of the variation in the volatility parameters is orthogonal to these covariates. Including the attributes of children as covariates in these regressions is conceptually problematic as parents may influence the volatility of their children's income by influencing these covariates. However, this also makes very little difference for the results.

Table 5 showed that there was a relationship between the total volatility moments, $\hat{\nu}^2_{i,d}$ of parents and their children. What do we learn by decomposing these moments into their permanent and transitory components? The results from Table 7 (presented graphically in Figure 3) and Table 8 show that children inherit permanent risk from their parents. From Table 7 (presented graphically in Figure 4) and Table 8, there is no evidence that they inherit transitory volatility. Since transitory volatility might pick up measurement error, the inheritance of permanent volatility is more economically interesting than the inheritance of transitory risk. How substantial is the inheritance of permanent income volatility? It is interesting to compare these results to those for other types of intergenerational transmission. For example, it is well documented that parents with more years of schooling have children with more years of schooling. Using data from the PSID, which includes information about parent's education even when they are not in the sample, I regress the number of years of schooling of children on the number of years of schooling they report for their parents. These results are reported in columns 2 and 3 of Table 9. Parents with more years of schooling have children with more years of schooling. The coefficient on the father's education, when mother's education is omitted, is roughly 0.3 and is highly significant. Note that this coefficient is similar to that for permanent income volatility, $\hat{b}_{\omega\omega}^{MEIV}$.

4 Channels of Intergenerational Transmission

The last section documented the intergenerational transmission of income volatility. Estimating intergenerational relationships in the data is generally just a first step for researchers. Causality and the channel of action are arguably more important. For example, knowing that parents with more education have kids with more education is more useful for policy if the relationship is causal.[18] This section seeks evidence on the channels through which income volatility may pass from parents to their children.

Table 9 documents the intergenerational transmission of attributes that may be related to income volatility. Education may be one channel through which parents influence the income volatility of

[18] In the case of income volatility, identifying a correlation is important even when no causation or channel of action can be identified. If permanent income volatility is inherited, then so is intergenerational mobility. Regardless of the whether this relationship is causal, it is important to identify groups that may get "stuck" on a given rung of the socio-economic ladder.

Intergenerational transmission of income volatility could also motivate compulsory social insurance programs regardless of the mechanism of action. If insurance against future fluctuations in income can be purchased before informational asymmetries arise, a voluntary insurance market will provide sufficient protection from risk.

However, if parents' income volatility is private information and parents transmit this income volatility to their children, there is private information about future income volatility for individuals even before their birth. This means that the early purchase of insurance (before informational asymmetries arise) against large fluctuations in income (e.g., unemployment insurance) will not overcome adverse selection problems. Since adverse selection would lead to failure of a voluntary market, a mandatory scheme would be necessary to achieve the right level of insurance.

Table 9: Intergenerational Transmission of Education and Self-Employment

Dependent Variable	Child's Education (Years)			Child Ever Self-Employed		Child Fraction Self-Employed	
Father's Education		0.292 (23.92)*	0.204 (13.99)*				
Mother's Education			0.169 (10.62)*				
Father Ever Self-Employed?					0.129 (4.55)*		
Father Fraction Self-Employed							0.126 (6.36)*
Race Black	-1.382 (16.26)*	-0.801 (9.67)*	-0.714 (8.70)*	-0.141 (4.73)*	-0.123 (4.10)*	-0.069 (5.75)*	-0.056 (4.70)*
Race Other	-0.806 (3.76)*	-0.462 (2.31)	-0.26 (1.31)	0.031 (0.34)	0.022 (0.24)	0.002 (0.05)	-0.006 (0.18)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Cntrols	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,830	3,830	3,830	1,087	1,087	1,087	1,087
R^2	0.164	0.273	0.294	0.049	0.067	0.044	0.079

The first three columns use the sample of individuals who report the number of years of education received by both their mother and father, the independent variables from the first two rows. The dependent variable in the first three columns is the number of years of education of and reported by the adult child. The regressions in columns 5 through 8 are limited to individuals whose father is also in the sample. The dependent variable in columns 4 and 5 is a dummy variable for whether the individual reports ever being self-employed in the sample. This is a linear probability model. In column 5, one of the independent variables is a dummy variable for whether the child's father ever reports being self-employed in the sample. The dependent variable in columns 6 and 7 is a variable equal to the proportion of the sample the individual reports being self-employed. In column 7, one of the independent variables is the fraction of time the individual's father reports being self-employed in the sample. As before, dummy race variables "Black " and "Other" are included, with "White" as the omitted category. Dummy variables for the last year the individual was in the sample, and a control for the number of years the individual spent in the sample are also included. t-statistics are in parentheses. "*"indicates significance at the 1% level.

their children. It is well established that there is a relationship between the education of parents and their children. While this result is shown in the first three columns of Table 9, this paper is far from the first to make this point (Black, Devereux, and Salvances, 2005). Furthermore, this paper (as well as previous work by Meghir and Pistaferri (2004) and Carroll and Samwick (1997)) documents that own educational attainment influences income volatility; in particular, better-educated individuals face higher permanent volatility. Given these two facts, it seems plausible that parents may influence the income volatility of their children through the education they pass to them. Do better educated parents tend to have better educated children, who in turn have higher permanent income volatility?

Table 10 presents the relationship between parent's education and the income volatility of their children. The independent variable of interest is the number of years of schooling for the individual's

Table 10: Impact of Parents' Education on Their Children's Income Volatility

Dep. Variable	Child's Permanent Volatility, $\hat{\delta}^{(k)2}_{i,\omega}$				Child's Transitory Volatility, $\hat{\delta}^{(k)2}_{i,\varepsilon}$			
Father's Education	0.0006 (1.04)	0.0005 (0.83)	0.0002 (0.36)	0.0002 (0.28)	-0.0023 (1.86)	0.0001 (0.04)	-0.0016 (1.23)	-0.0001 (0.07)
Mother's Education	0.0010 (1.61)	0.0010 (1.60)	0.0007 (1.09)	0.0007 (1.12)	0.0007 (0.55)	0.0016 (1.20)	0.0014 (0.98)	0.0015 (1.09)
Joint F-Stat. (p-value)	4.12 (0.02)†	3.38 (0.03)†	1.16 (0.31)	1.11 (0.33)	1.92 (0.15)	1.07 (0.34)	0.85 (0.43)	0.75 (0.47)
Own Education			0.0019 (2.96)*	0.0019 (2.89)*			-0.0036 (2.62)*	0.0008 (0.58)
Initial Income (in '000s)		-0.0008 (3.64)*		-0.0008 (3.69)*		0.0009 (1.93)		0.0009 (1.92)
Median Income (in '000s)		0.0003 (2.57)*		0.0002 (1.82)		-0.0026 (11.3)*		-0.0026 (11.1)*
Race Black	-0.0036 (1.10)	-0.0050 (1.47)	-0.0022 (0.67)	-0.0042 (1.24)	0.0161 (2.30)*	0.0010 (0.13)	0.0135 (1.92)	0.0013 (0.18)
Race Other	0.0075 (0.95)	0.0084 (1.06)	0.0071 (0.89)	0.0089 (1.12)	-0.0042 (0.25)	-0.0052 (0.32)	-0.0051 (0.30)	-0.0051 (0.31)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,830	3,830	3,830	3,830	3,830	3,830	3,830	3,830
R^2	0.014	0.018	0.016	0.020	0.013	0.050	0.015	0.050

This table predicts the permanent and transitory volatility of adult children with various covariates. The sample is limited to adult children for which there is enough data to estimate volatility parameters, and information about the parents' years of education is provided by the child. The first two rows show the impact of the father's or mother's number of years of education. The third row shows the joint significance of both parents' coefficients is shown, with the F-statistic for the joint hypothesis that these coefficients are zero and the p-value associated with this event. †indicates joint significance at the 5% level. Elsewhere, t-statistics are in parentheses. "*" indicates significance at the 5% level. In indicated columns, the individual's initial (median) labor income in thousands is the independent variable in the fifth (sixth) row. As before, dummy race variables "black" and "other" are included, with "white" as the omitted category. Dummy variables for the last year the individual was in the sample, and a control for the number of years the individual spent in the sample are also included.

parents, as reported by that individual. The first column shows that parents with more education tend to have children with higher permanent income volatility. Jointly, the educational attainment of parents is highly significant. Both the mother's education and the father's education are significant if included separately, though these regressions are not included in the table. The mother's education and father's education are not significant individually when both are included together since they are highly colinear. These results are robust to the inclusion of controls for the individual's income (column 2) suggesting that parent's education does not impact income volatility through the level of income. Columns 3 and 4 repeat the regressions from the first two columns, but add the individual's education to the regression. Parents' education, separately or jointly, is now insignificant. Given the strong relationship between the education of parents and their children, this result shows that parents with more education have children with higher permanent income volatility only because they tend to have more educated children; Table 4 documented that better educated people had higher permanent income volatility. Columns 5 through 8 repeat the results from the first four columns, now using transitory volatility as the explanatory variable. While parental education does seem to influence the transitory volatility of their children, as in Table 4 this effect goes away once the individual's income is controlled for.

While education is one channel through which income volatility is transmitted from parents to their children, it cannot account for a large fraction of this intergenerational transmission. Put simply, including parent's education in the regressions in Tables 5 and 8 has very little impact on the coefficients on parent's income volatility. Including the individual's own educational attainment, or any other income or demographic characteristics, also has very little effect on the coefficients.

Table 4 explores self-employment is another channel through which volatility might plausibly be transmitted from parents to children. Columns 4 through 7 of Table 9 document that self-employment is transmitted intergenerationally; parents who have ever been self-employed or are frequently self-employed have children who are more likely to have ever been self-employed or be frequently self-employed. Table 4 shows that self-employment is highly correlated with income volatility, both permanent and transitory. Table 11 documents that the self-employment status of parents is related to the permanent income volatility of their children (columns 1 and 2). However, these results are found only because self-employed parents have children who become self-employed, and self-employed children have higher income volatility; after controlling for the self-employment status of children, the self-employment status of their parents has no impact on their income volatility (columns 3 and 4). The self-employment status of parents has no significant impact on the transitory income volatility of their children (columns 5 through 8), which is not surprising given that there is no evidence that transitory volatility of children is inherited.

Neither the results for education nor those for self-employment says anything about the direction of causality. It could be that self-employment and education of parents have a causal impact on the self-employment and education of children, and that self-employment and education have a causal impact on volatility. Alternatively, volatility of parents could have a causal impact on volatility of their children, with volatility having a causal impact on the decisions to receive education or become self-employed. While the former possibility seems more likely than the latter, neither hypothesis can be tested with the data.

Table 11: Impact of Parents' Self-Employment on Their Children's Income Volatility

Dep. Variable	Child's Permanent Volatility, $\hat{\delta}_{i,\omega}^{(k)2}$				Child's Transitory Volatility, $\hat{\delta}_{i,\varepsilon}^{(k)2}$			
Father Ever Self-Employed	0.0089 (1.06)	0.0100 (1.19)	0.0052 (0.64)	0.0063 (0.78)	-0.0210 (1.28)	-0.0216 (1.33)	-0.0205 (1.25)	-0.0221 (1.37)
Father Fraction Self-Employed	0.0206 (1.38)	0.0200 (1.35)	0.0004 (0.02)	0.0004 (0.03)	0.0059 (0.20)	0.0041 (0.14)	-0.0026 (0.09)	-0.0039 (0.13)
Joint F-Stat. (p-value)	3.99 (0.02)†	4.30 (0.01)†	0.34 (0.71)	0.50 (0.60)	1.10 (0.33)	1.28 (0.28)	1.36 (0.26)	1.68 (0.19)
Own Ever Self-Employed			0.0230 (2.63)*	0.0227 (2.60)*			0.0380 (2.15)*	0.0298 (1.70)
Own Fraction Self-Employed			0.1268 (5.80)*	0.1275 (5.88)*			-0.0297 (0.67)	-0.0267 (0.61)
Own Education			0.0016 (1.04)	0.0002 (0.08)			-0.0024 (0.76)	0.0042 (1.30)
Initial Income (in '000s)		-0.0019 (4.27)*		-0.0017 (4.04)*		0.0015 (1.69)		0.0016 (1.88)
Median Income (in '000s)		0.0006 (2.92)*		0.0007 (3.33)*		-0.0024 (5.91)*		-0.0025 (5.84)*
Race Black	-0.0004 (0.05)	-0.0031 (0.41)	0.0109 (1.57)	0.0086 (1.19)	0.0327 (2.41)*	0.0118 (0.83)	0.0324 (2.29)*	0.0179 (1.22)
Race Other	0.0471 (2.27)*	0.0416 (2.02)*	0.0485 (2.44)*	0.0430 (2.18)*	-0.0376 (0.93)	-0.0363 (0.91)	-0.0394 (0.98)	-0.0340 (0.85)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,087	1,087	1,087	1,087	1,087	1,087	1,087	1,087
R^2	0.033	0.051	0.114	0.13	0.039	0.07	0.044	0.074

The sample consists of all pairs of adult children and their parents where there is enough data on the household head to estimate income volatility for each. The dependent variable is the estimate of permanent (columns 1 through 4) or transitory (columns 5 through 8) income volatility for the individual. The first (second) row present coefficients on a dummy (continuous) variable for whether the father was ever (the fraction of time the father spent) self-employed. The third row shows the joint significance of both parents' coefficients is shown, with the F-statistic for the joint hypothesis that these coefficients are zero and the p-value associated with this event. Other covariates are described in Tables 9 and 10.

5 Conclusion

This paper provides evidence of intergenerational transmission of higher moments of human capital. Parents with higher income volatility have children with higher permanent income volatility. The relationship between the permanent income volatility of parents and their children is similar in magnitude to that for education.

Account explicitly for estimation error allows this paper to separate the inheritance of permanent volatility from transitory volatility. The fact that permanent volatility of adult children is inherited implies that economic mobility is inherited as well. As a back-of-the-envelope calculation, consider two otherwise identical adult children whose parents differed in their permanent volatility. One parent had the average level of permanent volatility (annual standard deviation of 15.5 percent) while the other had a permanent volatility parameter of only one-standard deviation above the mean (annual standard deviation of 23.6 percent). After a 25 year work history, this difference in permanent volatility would lead the standard deviation of log income for these otherwise identical parents to differ by 40 percent.[19] The second parent has substantially more diffuse set of possible outcomes and therefore a higher degree of economic mobility than the first. This difference in mobility for parents implies a large difference in the permanent volatility of their children (annual standard deviations of 21 and 23 percent, respectively). Over a 25 year work history, this difference in permanent volatility leads the standard deviation of log income for these otherwise identical children to differ by 10 percent.[20] Even this one-standard deviation difference in permanent volatility for parents implies a substantial difference in economic mobility which is passed from parent to child.

This simple illustration suggests that average estimates of intergenerational transmission mask substantial heterogeneity. Dynasties may differ not only in the level of income, but also in their degree of economic mobility. In this case, policies aimed at reducing persistent differences in income across groups may want to focus on groups where these differences are most persistent.

[19] The standard deviation for the first parent, $\sqrt{0.024} = 0.155$ is obtained from the first row of the third column of Table 6. The volatility of the second parent, $0.024 + \sqrt{0.0010} = 0.056$, is obtained from the first and third rows of this column. The standard deviation is then $\sqrt{0.056} = 0.236$. Then, compare the standard deviation for the first parent,$\sqrt{25 \bullet 0.024} = 0.77$, to that for the second parent, $\sqrt{25 \bullet 0.056} = 1.18$.

[20] The standard deviation for the first adult child, $\sqrt{0.043} = 0.207$ is obtained from the first row of the first column of Table 6. The volatility of the second adult child, $0.043 + 0.29\sqrt{0.0010} = 0.052$, is obtained from the first row of this column, the coefficient $b_{\omega\omega}^{MEIV} = 0.290$ from Table 7, and the variation in parents' parameters from the third row and column of Table 6. The standard deviation is then $\sqrt{0.052} = 0.228$. Then, compare the standard deviation for the first parent,$\sqrt{25 \bullet 0.043} = 1.04$, to that for the second parent, $\sqrt{25 \bullet 0.052} = 1.14$.

Note that this rough estimate incorrectly assumes the volatility parameters of adult children are time-invariant. To the degree that volatility parameters fall with age (and the relationship between the volatility of parents and their children remains stable over the life-cycle, an assumption that seems unlikely in light of (Haider and Solon, forthcoming) showing that the this assumption is untrue for the level of income), estimates here will understate the difference in mobility between the children of high- and low-volatility parents.

A Appendix: Mapping Income Moments to Volatility Parameters

If the income process is taken literally, the variance and first-order autocovariance can be used to estimate permanent and transitory volatility:

$$\begin{aligned} E_t\left[\nu_{i,t}^2\right] &= \delta_{i,\omega}^2 + 2\delta_{i,\varepsilon}^2 \\ E_t\left[\nu_{i,t}\nu_{i,t-1}\right] &= -\delta_{i,\varepsilon}^2. \end{aligned} \tag{19}$$

The variance of transitory shocks can be estimated from the degree to which changes in income are reversed immediately, the negative of the first-order autocovariance; the variance of permanent shocks is merely the total variance in the change in income, less the component attributable to transitory shocks. The major problem with this approach is that it misidentifies as permanent any shock which is not reversed immediately. For example, if transitory shocks last for two periods instead of one, then these moments have a different mapping to volatility parameters:

$$\begin{aligned} \eta_{i,t} &= \sum_{\tau=0}^{t} \omega_{i,\tau} + \theta_\varepsilon \varepsilon_{i,t-1} + \varepsilon_{i,t}, \text{ then} \\ \nu_{i,t} &= \omega_{i,t} + \varepsilon_{i,t} + \left(\theta_\varepsilon - 1\right)\varepsilon_{i,t-1} - \theta_\varepsilon \varepsilon_{i,t-2}, \text{ so that} \\ E_t\left[\nu_{i,t}^2\right] &= \delta_{i,\omega}^2 + 2\left(1 - \theta_\varepsilon + \theta_\varepsilon^2\right)\delta_{i,\varepsilon}^2 \\ E_t\left[\nu_{i,t}\nu_{i,t-1}\right] &= -\left(1 - \theta_\varepsilon\right)^2 \delta_{i,\varepsilon}^2. \end{aligned} \tag{20}$$

Similarly, if permanent shocks come into effect over two periods instead of immediately, as they would if a permanent raise was awarded mid-year, the relationship between moments and parameters will again be different:

$$\begin{aligned} \eta_{i,t} &= \sum_{\tau=0}^{t-1} \omega_{i,\tau} + \theta_\omega \omega_{i,t} + \varepsilon_{i,t}, \text{ then} \\ \nu_{i,t} &= \theta_\omega \omega_{i,t} + \left(1 - \theta_\omega\right)\omega_{i,t-1} + \varepsilon_{i,t} - \varepsilon_{i,t-1}, \text{ so that} \\ E_t\left[\nu_{i,t}^2\right] &= \left(1 - 2\theta_\omega + 2\theta_\omega^2\right)\delta_{i,\omega}^2 + 2\delta_{i,\varepsilon}^2 \\ E_t\left[\nu_{i,t}\nu_{i,t-1}\right] &= \theta_\omega\left(1 - \theta_\omega\right)\delta_{i,\omega}^2 - \delta_{i,\varepsilon}^2. \end{aligned} \tag{21}$$

Any model misspecification will bias estimates of volatility based on $E\left[\nu_{i,t}^2\right]$ or $E_t\left[\nu_{i,t}\nu_{i,t-1}\right]$. Other researchers have identified moments that can be used to measure income volatility even if transitory shocks are somewhat persistent or if permanent shocks do not reach their full impact immediately. One approach, taken by Meghir and Pistaferri (2004), is to estimate permanent risk as:

$$E_t\left[v_{i,t}\sum_{\tau=t-m}^{t+n} v_{i,\tau}\right] = \delta^2_{i,\omega}. \tag{22}$$

For n and m sufficiently large, this provides an unbiased estimate of permanent volatility even when permanent shocks come into force over time or when transitory shocks persist for more than one period (e.g. $\theta_\varepsilon, \theta_\omega > 0$).

As presented in equation (4), Carroll and Samwick (1997) identify permanent and transitory volatility using the squared changes in income over various lengths of time, d:

$$E_t\left[(v_{i,t,d})^2\right] = d\delta^2_{i,\omega} + 2\delta^2_{i,\varepsilon}.$$

If the true process is one in which transitory shocks last for two periods and permanent shocks take two periods to come fulling into effect,

$$\begin{aligned} \eta_{i,t} &= \sum_{\tau=0}^{t-1}\omega_{i,\tau} + \theta_\omega\omega_{i,t} + \theta_\varepsilon\varepsilon_{i,t-1} + \varepsilon_{i,t}, \text{ then} \quad (23)\\ v_{i,t,d} &= \left(\sum_{\tau=0}^{t-1}\omega_{i,\tau} + \theta_\omega\omega_{i,t} + \theta_\varepsilon\varepsilon_{i,t-1} + \varepsilon_{i,t}\right)\\ &\quad - \left(\sum_{\tau=0}^{t-d-1}\omega_{i,\tau} + \theta_\omega\omega_{i,t-d} + \theta_\varepsilon\varepsilon_{i,t-d-1} + \varepsilon_{i,t-d}\right), \text{ so that}\\ E_t\left[(v_{i,t,d})^2\right] &= \left(-2\theta_\omega + 2\theta^2_\omega + d\right)\delta^2_{i,\omega} + 2\left(1-\theta^2_\varepsilon\right)\delta^2_{i,\varepsilon} \text{ for } d>1;\\ &= \left(1-2\theta_\omega + 2\theta^2_\omega\right)\delta^2_{i,\omega} + 2\left(1-\theta_\varepsilon+\theta^2_\varepsilon\right)\delta^2_{i,\varepsilon} \text{ for } d=1. \end{aligned}$$

Here, in a regression with values of $d > 1$, the probability limit of the coefficient on d will be $\delta^2_{i,\omega}$; the coefficient will provide an unbiased estimate of permanent volatility. This motivates the use of only large value of d. Note that the intercept of a regression of these moments on d will still misidentify $\delta^2_{i,\varepsilon}$.

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