INSTITUTE for RESEARCH on POVERTY
UNIVERSITY OF WISCONSIN–MADISON

IRP Discussion Paper

No. 1429-15

Income Volatility in U.S. Households with Children:
Another Growing Disparity between the Rich and the Poor?

Pamela A. Morris*
Department of Applied Psychology
New York University
Email: Pamela.Morris@nyu.edu

Heather D. Hill
Evans School of Public Policy & Governance
University of Washington

Lisa A. Gennetian
Institute for Human Development and Social Change
New York University

Chris Rodrigues
Department of Applied Psychology
New York University

Sharon Wolf
Institute for Research on Poverty
University of Wisconsin–Madison

July 2015

This paper was supported in part by the William T. Grant Foundation with a grant to the first three authors (Grant #182212, "Income Instability, Family Processes, and Youth Development"). We thank Carly Tubbs for data analytic support in the early phase of this paper, James Ziliak for thoughtful comments on a presentation of this work, and Sean Reardon and the invitees to the 2012 Stanford University Conference on Income, Inequality, and Educational Success that launched and provided much initial guidance to this project.

*Please direct all correspondence to the first author.

IRP Publications (discussion papers, special reports, *Fast Focus*, and the newsletter *Focus*) are available on the Internet. The IRP Web site can be accessed at the following address: http://www.irp.wisc.edu.

Abstract

In this paper, we sought to document household income volatility as experienced by children over time, as one understudied aspect of household economic circumstances that might contribute to observed socioeconomic differences in children's achievement. Our analysis of six panels of the nationally representative Survey of Income and Program Participation (SIPP) across a 25-year period reveal that income volatility may be an additional factor contributing to the gap between the achievement of rich and poor children: We find that households with children at the 10th percentile of income have experienced *increasing* volatility across the last 25 years while their affluent peers at the 90th percentile have experienced *declining* income volatility. Our sensitivity analyses show that these findings are robust to a number of differing analytic approaches and are not due to the changing racial/ethnic composition of low-income households over this same time period.

Keywords: income inequality, income volatility, income trends

Income Volatility in U.S. Households with Children: Another Growing Disparity between the Rich and the Poor?

INTRODUCTION

A central goal of U.S. education and social policy is to reduce childhood economic disadvantage and its consequences and thus support children's future economic self-sufficiency. This focus is supported by consistent research evidence that both absolute and relative deprivation during childhood are detrimental to child health and development (e.g., Brooks-Gunn & Duncan, 1997; Gennetian, Castells, & Morris, 2010), and ultimately carry great social costs (Holzer, Whitmore Schanzenbach, Duncan, & Ludwig, 2008). In addressing childhood poverty, both research and policy have historically conceptualized income as a static state, measured at one point-in-time, or averaged across time. Yet, recent work highlights the potential risks that frequent fluctuations in income—what economists call "income volatility"[1]—pose to families and children's development (Hill, Morris, Gennetian, Wolf, & Tubbs, 2013; Sandstrom & Huerta, 2013).

Unlike the substantial research on child poverty and socio-economic gaps on children's achievement, there has been relatively little, if any, attempt to quantify income volatility during childhood and the extent to which the prevalence of this economic phenomenon has changed over time. There is reason to expect that income volatility for households with children has increased over time, because of well-documented trends of increasing volatility in earnings and income more generally (e.g., Bania & Leete, 2007; Dahl, DeLeire, & Schwabish, 2011; Dynan, Elmendorf, & Sichel, 2012; Moffitt & Gottschalk, 2012; Hacker, 2008; Haider, 2001; Hardy & Ziliak, 2014; Keys, 2008; Ziliak, Hardy, & Bollinger, 2011). There is debate in the literature about the timing of these increases, but general agreement that they began in the 1980s and were driven by increasingly precarious employment arrangements and family structures. Moreover, increasing volatility has been posited as one explanatory

[1]We use the terms "income volatility" and "income instability" interchangeably. This practice is consistent with prior work by Hacker & Jacobs (2008).

factor for the increase over time in income inequality. As explanations of socio-economic differences in children's educational achievement are explored and debated, income volatility may be one less-well understood mechanism—a key underexplored component of income dynamics. Indeed, fully understanding the range of household economic experiences that children face is essential to determining whether policies, such as the Earned Income Tax Credit, that directly supplement income or the Supplemental Nutrition Assistance Program, that indirectly increase family net income, should attempt to reduce income volatility and its consequences, in addition to the attention paid to meeting the primary objectives of providing a basic social safety net and enhancing overall family income.

Our analysis of six panels of the nationally representative Survey of Income and Program Participation (SIPP) across a 25-year period provides the first historical portrait of intrayear income volatility in households with children, both overall and by household income level. To inform the broader literature on income inequality and the achievement gap, we focus on households at the 10^{th} and the 90^{th} percentiles. We measure the volatility of overall, earned, and unearned income using the coefficient of variation (CV), and further test the sensitivity of the results with alternative measures. We also decompose the CV into monthly income mean and standard deviation to examine whether the changing trends in income volatility reflect changing income levels, income variability, or both.

This paper makes multiple contributions to the extant empirical literature on income volatility. First, prior research has not examined income volatility from the perspective of children, who are potentially most vulnerable to household economic circumstances. Second, we expand the time frame of analysis as much prior research on this topic documents time trends in income volatility only from the early 1990s to the early 2000s (for exceptions, see Hacker, Huber, Rehm, Schlesinger, & Valletta, 2010; Winship, 2009). To do so, we incorporate data from both the early 1980s and the late 2000s—approximately a 25-year period altogether—that captures two different recession periods and two economic boons. Finally, prior work on income volatility has typically focused on year-to-year volatility, without examining the volatility that may occur within a year, as frequently as monthly or quarterly. From a child development perspective, adapting to year-to-year volatility may be more manageable than adapting to volatility in income that occurs on shorter time scales (Hill et al., 2013).

We find relatively little change in income volatility across all households with children, but substantively meaningful differences in the volatility of income for low- as compared with high-income households. That is, households with children at the 10th percentile of income have experienced *increasing* volatility across the last 25 years while their affluent peers at the 90th percentile have experienced *declining* income volatility. The result is an increasing gap in income volatility between low- and high-income households: from the mid-1980s to the start of the most recent recession, the difference in monthly income volatility between low- and high-income households as measured by the coefficient of variation has grown more than *four times*. The increasing income volatility for the lowest income households is primarily from unearned, rather than earned, sources of income, indicating this is not just about the changing nature of the low-wage labor market but may also be indicative of the changing availability and continuity of social assistance benefits. Our sensitivity analyses further show that these findings are robust to a number of differing analytic approaches to this same question and are not due to the changing racial/ethnic composition of low-income households over this same time period.

TRENDS IN INCOME VOLATILITY

Early studies of earnings or income volatility were designed primarily to inform observed trends in income inequality. Researchers decomposed trends in income into a permanent and then a transitory component, defining the transitory component (or volatility) as the short-term variance of age-adjusted income (Gottschalk & Moffitt, 1994, 1999, 2009; Hacker, 2008; Haider, 2001; Moffitt & Gottschalk, 1995, 2002, 2011, 2012; Nichols, 2008). More recent studies use more straightforward descriptive analysis—for instance, measuring year-to-year percent changes in total levels—to examine changes in earnings or income volatility over time (e.g., Dahl et al., 2011; Dynan et al., 2012; Shin, 2012; Shin & Solon, 2011; Ziliak et al., 2011). The research literature in this area has also progressed from a focus on male earnings volatility (Celik et al., 2012; Haider, 2001; Gottschalk & Moffitt 1994, 1999, 2009; Moffitt

& Gottschalk, 1995, 2002, 2011, 2012; Neumark & Wascher, 1999; Stevens, 2001; Shin, 2012; Shin & Solon, 2011) to one on household income volatility (Carey & Shore, 2013; Dynan et al., 2012; Hacker, 2008; Jensen & Shore, 2011; Dahl et al., 2011; Gosselin & Zimmerman, 2008). However, only one study that we know of examines *intrayear* volatility in income (Bania & Leete, 2007), and none focuses on household income volatility during childhood.

Across prior studies, there is consistent evidence that earnings and income volatility have increased since the 1970s, but that most of the population-level increase occurred in the early 1980s (for a review, see Dahl et al., 2011). Some studies also find increases in earnings and income volatility in the late 1990s and early 2000s, but those results are sensitive to the data source and to the treatment of imputed data (Celik et al., 2012; Dynan et al., 2012; Gosselin & Zimmerman, 2008; Hacker, 2008; Shin & Solon, 2009). There is some agreement that earnings and income volatility remained high, but stable, after the 1980s among a subset of studies that use multiple administrative and survey data sources (and such studies allow for a broader range of sensitivity tests; Celik et al., 2012; Dahl et al., 2011; Moffitt & Gottschalk, 2008, 2012; Ziliak et al., 2011). For instance, Dahl et al. (2011) find an increasing trend in household income volatility through the late 1990s and early 2000s using the SIPP, but that trend becomes flat when they exclude imputed income values or use earnings data from administrative sources. Multiple studies find a much higher level of income volatility among low-income than high-income households (Bania & Leete, 2007; Hardy & Ziliak, 2014). Several of the most recent studies have sought to unpack the role of earned income from government transfers by examining the hypothesis that such income transfers can cushion against earned income drops. There is also growing evidence that the buffering effect on income volatility of family labor income and transfer income has decreased in the past four decades (Bania & Leete, 2007; Dahl et al., 2011; Gosselin & Zimmerman, 2008).

INCOME VOLATILITY AND CHILD WELL-BEING

While there is a substantial body of research and supporting theory to suggest that the level of resources may matter for children's development (Gennetian, et al., 2010), less empirical attention has been paid to the effects on children of volatility of household economic and nonfinancial resources. Yet, a body of research in developmental psychology and family sociology point to the implications of such income volatility for children, both in terms of engendering household chaos and promoting other forms of family instability (Ackerman, Kogos, Youngstrom, Schoff, & Izard, 1999; Wachs & Evans, 2010). Chaotic home environments may disrupt children's development by reducing the quantity and quality of time parents spend with their children and the regularity of household routines (Wachs & Evans, 2010). Moreover, the emerging field of behavioral economics—blending insights from economics and psychology—posits that income volatility, particularly among the poor, may further drain cognitive resources (Gennetian & Shafir, 2015), which otherwise could be devoted to family management, attentive, sensitive parenting, and monitoring of children's activities. And from neuroscience, we would expect that changing economic contexts, and the stress associated with it, could challenge physiological systems (Ganzel, Morris, & Wethington, 2010; McEwen, 1998), "readying" the body to respond to both stressful and nonstressful environments, with implications for allostatic load and a resulting plethora of physiological costs (McEwen & Stellar, 1993). Indeed the animal literature is replete with examples of the ways in which a variable nourishing environment can be have substantial behavioral consequences (Zeiler, 1968; Rosenblum & Paully, 1984).

In short, if parents are repeatedly challenged to manage family economic resources, interact with bureaucratic systems, or make difficult decisions about spending on their children, they may feel more stressed and have less energy to consistently provide a warm, responsive home environment and effectively supervise their children. Parents with stable but low income may experience some of these challenges, but they are more likely to adapt and develop coping strategies as long as their income level is predictable. And, low-income families are particularly susceptible to these effects because of the absence of secure financial cushions that could buffer the negative effects of income volatility. While income volatility and income level are related, the two concepts can be understood as distinct features of income dynamics and of the household economic circumstances that affect children's development.

INCOME VOLATILITY AND PUBLIC POLICY

Understanding the implications of income volatility on family life and children's well-being can lay the groundwork for more effective federal and state policymaking across numerous facets of policy design. Indeed, the decades of research on the challenges facing poor children has served as an important catalyst for a range of income- and work-support policies. By contrast, most social policies targeting low-income families are not designed to accommodate income volatility. Steady employment and earnings are an (implicit) eligibility requirement for several important safety net programs as proof of hours or wages are often required documentation to receive or continue to receive benefits. This is increasingly difficult as witnessed by the recent economic crisis when many low-income families lost not only employment, but also their benefits from employment-based safety net programs (Aber, Morris, & Raver, 2012).

Program features—including income eligibility limits, high marginal tax rates, and the timing and format of income-assistance delivery—could even unintentionally increase income volatility for those on the margin of eligibility (Romich, 2006). In addition, the monthly payment schemes used in most public assistance programs implicitly assume that individuals have the resources to budget through the month until the next payment is due to arrive (Gennetian, Seshadri, Hess, Winn, & George, 2011). Even at low income levels, the potential gap in income at the end of the month could be partially addressed by more frequent within-month disbursement. And presumptive eligibility for recertification of benefits (similar to what is applied in several localities for child care subsidies), is a policy strategy that may minimize the likelihood of unintended income loss. In short, income-support policies may exacerbate or mitigate income volatility depending on how they are designed, the criteria used to determine eligibility and recertification, and the immediacy, lag, and frequency of timing, in the actual disbursement of the benefit.

THE CURRENT STUDY

This study aims to address the following questions:

1. How volatile *is* income for households with children, and how has this changed over the past quarter century?

2. And, is this historical portrait similar for low- and high-income households (i.e., those at the 10th and 90th percentiles of the income distribution)?

3. To what extent are any trends in volatility that are observed due to changes in mean income or in the variation in income over this same period?

4. How volatile is earned as compared to unearned income for these same households with children?

5. How sensitive are these findings to differences in measurement, sample, and estimation strategy?

In addressing these questions, this paper expands our understanding of household economics to include income volatility as an unexplored mechanism in the study of socioeconomic disparities in child achievement.

Methods: Data, Sample, and Measures

Data

Data for this study come from six panels of the SIPP, including the 1984, 1991, 1996, 2001, 2004, and 2008 panels. The SIPP is a survey of households conducted by the U.S. Census Bureau, whose main objective is to provide accurate and comprehensive information about the income and program participation of individuals and households in the United States. The SIPP is uniquely positioned to answer our research questions because it not only collects detailed information about sources of income but does so by month and for several months over the course of a year. Each SIPP panel (as previously identified by calendar year) starts with a new sample of households, and each household is followed for a period of 2.5 to 4 years (depending on the panel), with income and program participation data collected for *every* month in the wave. The SIPP data collection occurs in three waves per year (i.e., triennially), with questions being asked at each wave about the prior four months. To create a comparable period of study from each panel, we restrict our analysis to the first nine waves (3 years) of each panel (and 8 waves for the 1991 panel since it was of shorter duration). When weights are applied, the data are representative of non-institutionalized individuals in the United States. No other nationally representative data set collects monthly income information over such an expansive time frame.

Sample

Our sample for the time trend analysis consists of children under the age of 18 throughout each respective panel period who were the child, grandchild, brother/sister, relative, or foster child of the reference person for the given household. Children who turn 18 at any point during the panel (i.e., who "age out" of being children) are excluded from the sample, but we include children who were born during the panel years. We further restrict the sample by including only those cases that have at least six waves of data over the panel period studied. The unit of analysis is the child. In cases where the child moves to a different household, we follow the child and attach income information from the new household to that child.

Data Collection Procedures

The SIPP gathers income information by surveying every member of the household above the age of 15 about their monthly income at each wave. Total household income is computed by adding up the reported income of everyone in the household, and is defined as all sources of money income before taxes. This measure includes earned income, cash transfer payments (i.e., means-tested income), lump-sum and one-time payments, regular salary or other income from self-owned business, property income, and any interest and dividend income (Westat, 2001). The SIPP uses hot deck imputation to address missing income values. The core analyses presented here use all reported and imputed values. We test the sensitivity of our results to using only those cases where less than 33 percent of total income was imputed.

The SIPP surveys households every four months, and asks individuals to report on their monthly income for each of the four months since the previous wave. Studies have shown that the income data collected in the SIPP is subject to reporter seam bias, such that income is reported with more error when recalled back to previous months, but much less error when reporting for the current month (Hill, 1987; Moore, 2007). In addition, survey respondents are more likely to assign transitions in income level to the month in which the survey is administered rather than to other months. It has been found that large drops in income of 50 percent or greater are five times more likely to occur in months that cross a wave boundary than in months within a wave (Acs, Loprest, & Nichols, 2009). Therefore, we use only the income observations *from the current month* for each of available waves per year. As we describe below, therefore, our measures of income volatility for each panel thus are constructed from up to nine observations of monthly income across three years.

Measures

Our primary measure of volatility is the coefficient of variation (CV), the ratio of the standard deviation to the mean. The CV is beneficial since it is invariant to scale and absolute level changes in income. We recognize, however, that the CV may miss qualitatively different volatility experiences for households, such as the distinction between one large income drop and a series of smaller dips in income, both of which produce similar CVs. That said, the extensive use of the CV in the literature, its statistical properties (most importantly, its invariance to level differences) and the ability to separately examine the numerator (standard deviation) from the denominator (the mean), as we leverage in analyses here, has a number of advantages.

We also present findings for one alternative measure—arc percent change—as a way to understand the sensitivity of our findings to the use of the CV measure. The arc percent change compares between-wave variation of total household income across the series of income reports from eight adjacent/consecutive waves over the three-year span. For each pair of consecutive monthly income reports provided, we calculate the ratio of the difference between reported monthly income and prior wave's monthly income to the average of these two income reports. Finally, we calculate the arc percent change as the standard deviation of the eight calculated ratios for each temporally adjacent income report pairings. One nice property of the arc percent change is that it is adaptable to negative values (for a recent application and description, see Ziliak et al., 2011).

We calculate the monthly CV for total household income, earned income, unearned income, and total household income plus the cash value of food stamp benefits. Each measure uses up to nine reports of monthly income provided across three years (i.e., income in the survey data collection month for each of three waves per each of three years). As indicated above, we also decompose total household income CV into its two subcomponents—the mean of individual child's total household monthly income and the respective standard deviation in the child's total household monthly income, reported over up to nine waves within each panel. We calculated average household monthly income over these same waves to categorize households into their income decile. All income values are adjusted for inflation to 2011 dollars, using the consumer price index.

EMPIRICAL APPROACH

Our primary analyses present the monthly household income CV for children in the United States for each of six panels from 1984 to 2010. Trends in intrayear income volatility are presented for our full sample of children from all U.S. households, as defined above, and for children in households with varying income levels, using our definition of income decile groups described above (see sensitivity analyses below for an alternative specification, as well). We focus on results for the lowest income decile—0–10th percentile—the highest income decile—90th–100th percentile—and, in some analyses, a middle income decile—40th–50th percentile, so that our analyses can inform existing research on income inequality.

We conduct a variety of additional analyses. First, we decompose the trends in monthly income volatility for the lowest and highest income deciles. We decompose the CV into monthly income mean and standard deviation to examine whether the changing trends in income volatility reflect changing income levels, income variability, or both. We next examine trends of specific components of income (e.g., earned and unearned income). Examining earned and unearned income separately allows us to understand whether any observed increases in the CV is due to increasing precariousness of work (in which case we would expect to see an increase in earnings CV, whether due to changes in wages or hours worked) or due to changed availability of safety net income for low-income families or due to changes in property values (in which case we would expect to see an increase in unearned income CV). Second, we examine whether patterns of income volatility vary when using an interyear measure of income volatility instead of an intrayear measure of income volatility. To calculate the year-to-year CV for total household income, we first estimate *annual* income for each of the three years by summing the three monthly income amounts reported in each year. Year-to-year CV is then calculated as the ratio of the standard deviation of the three annual estimates to the mean.

F-tests are used to test the statistical significance of differences in volatility level across the studies' six panels, and between groups within panels. T-tests examine specific contrasts. We use the longitudinal weights provided by the SIPP that correspond most closely to this ninth wave of data being considered. For the 1984, 1991, and 1996 panels, only a single "final" weight was available. For the 2001 to 2008 panels, we utilize the longitudinal weight for the 10^{th} wave.

We test the sensitivity of our results to a variety of changes in measurement, sample, and estimation, including estimating CV without survey weights; estimating volatility using arc percent change instead of CV; categorizing households into income deciles according to monthly income in wave 1 (rather than a mean monthly income); including income from the noncash Supplemental Nutrition Assistance Program (SNAP; formerly Food Stamps); and excluding cases where more than 33 percent of the total income amount reported was imputed. (Note that the last analysis omits the 1984 and 1991 panels because of differences in the panels in the ways in which imputed data are identified.)

Finally, we conducted analysis to examine how income volatility estimates change across key racial/ethnic and marital subgroups, to understand whether compositional changes in the racial/ethnic composition and single parent status of children of low-income households may be driving any differences we observe. To do so, we examine trends in intrayear volatility for two subgroups: (1) children of households in which the reference person's ethnic/racial origin was non-Hispanic white, and (2) children of households in which the reference person was married in the first wave of the studies' panel.

RESULTS

Trends in Income Volatility from 1984 to 2008 SIPP Panels

Table 1 and Figure 1 presents the coefficient of variation (CV) in children's monthly household income for all children across the six SIPP panels (1984, 1991, 1996, 2001, 2004, and 2008). The full sample of children shows very little fluctuation in level of volatility, from CV values of .33 in 1984, .32 in 1991, .37 in 1996, .40 in 2001, .36 in 2004, and .37 in 2008, suggesting that, when children from households of all income levels are considered together, the average level of volatility changes only slightly—with a slight rise from 1984 to 2001 and declining even less to 2008 (although given the very large sample of the SIPP, the F-test of even this small difference across all panels is significant at $F = 83.7$, $p < 0.001$).

Separating out children from the lowest and highest decile income households tells a considerably different story, however, as shown in Table 1 and Figure 2. For the lowest income decile, income volatility increases relatively steadily between 1984 and 2001, and again from 2004 to 2008 ($F = 47.4$, $p < 0.001$). The result is a 77 percent increase in income volatility for children in the lowest income households.

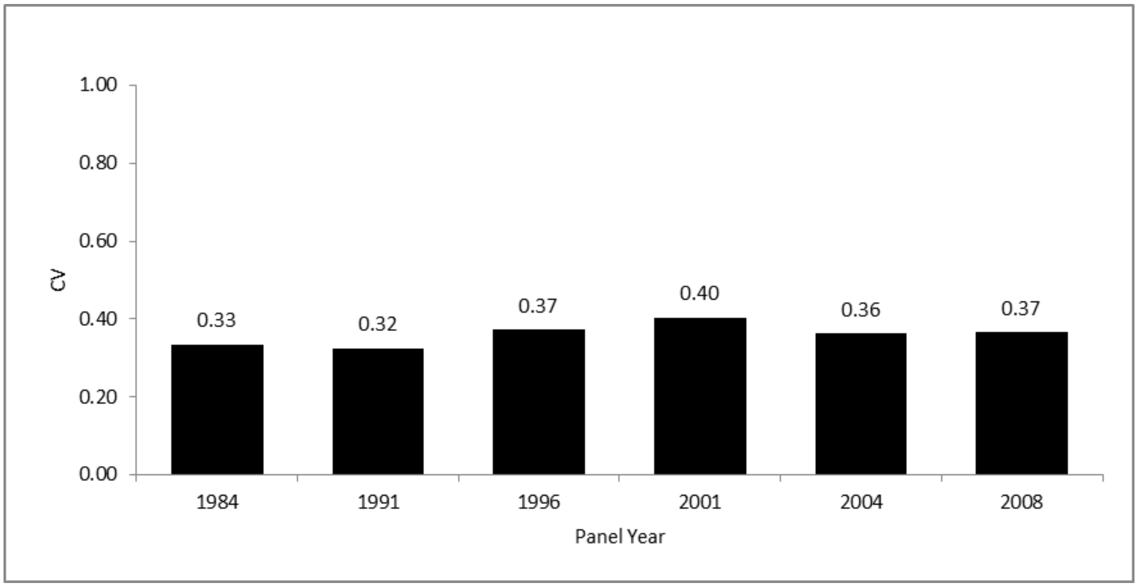
By contrast, children in the highest income households demonstrate a very different historical pattern, with income CV decreasing from .33 to .25 from 1984 to 1991 ($t = 6.2$, $p < 0.001$), then increasing to .40 from 1991 to 1996 ($t = 12.7$, $p < 0.001$), holding steady from 1996–2001 ($t = 0.8$, $p = 0.451$), falling to .27 from 1996 to 2008 ($t = 11.8$, $p < 0.001$). Overall, monthly income volatility fell modestly (by 18 percent) across the entire period.

The monthly income CV for children of middle income households (at the 40^{th}–50^{th} decile) appear to be relatively steady by comparison across these panels, in contrast to the changing patterns for children of low- and high-income households (although the F-test was significant: $F = 18.5$, $p < 0.001$ perhaps due to the rise in volatility in 2001); the CV barely changes from .31 in 1984 to .32 in 2008 ($t= 0.2$, $p = 0.807$).

Table 1. Monthly Income and Income Coefficient of Variation (CV) by SIPP Panels and Samples, for All Children, and for Children at Lowest, Middle, Highest Levels of Income

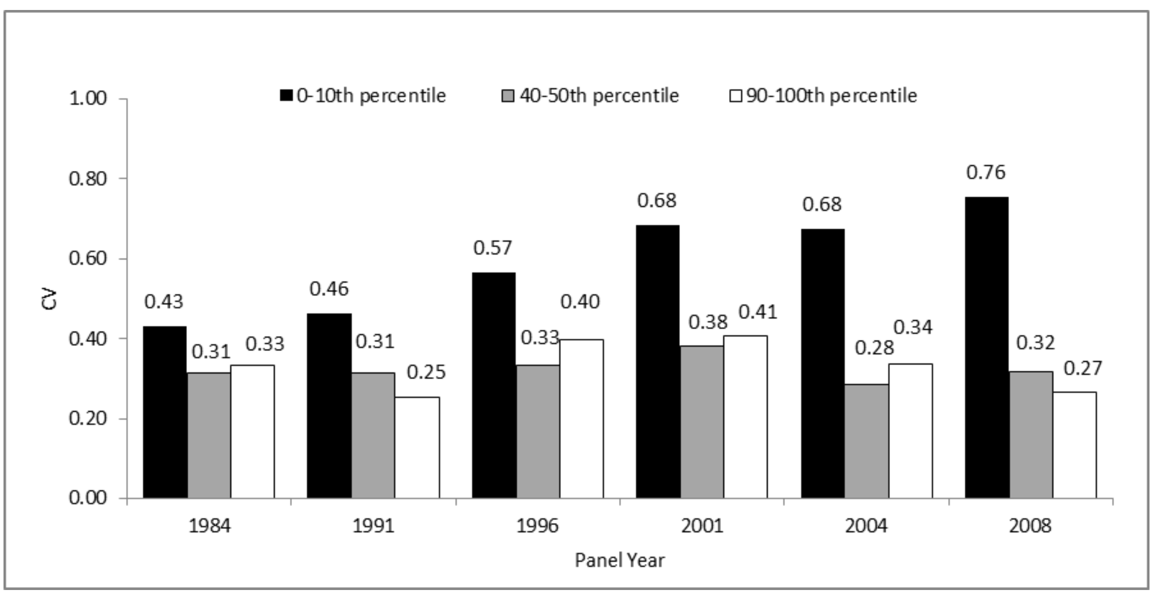
	1984		1991		1996		2001		2004		2008	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Monthly income SD												
Full sample	$1,690	$2,231	$1,528	$1,630	$2,137	$2,837	$2,340	$2,769	$2,021	$2,812	$1,791	$2,328
0-10th percentile	$391	$343	$415	$356	$577	$409	$647	$403	$580	$418	$565	$583
40-50th percentile	$1,300	$858	$1,306	$979	$1,431	$770	$1,723	$1,296	$1,277	$969	$1,328	$1,071
90-100th percentile	$4,457	$5,063	$3,389	$3,134	$6,599	$5,870	$7,001	$5,225	$6,010	$5,969	$4,753	$4,893
Monthly income												
Full sample	$5,323	$3,562	$5,371	$3,707	$6,032	$4,938	$6,270	$4,934	$6,389	$5,488	$6,139	$5,264
0-10th percentile	$913	$285	$941	$286	$1,073	$358	$1,046	$400	$960	$386	$861	$362
40-50th percentile	$4,138	$194	$4,185	$226	$4,291	$240	$4,529	$239	$4,488	$272	$4,217	$265
90-100th percentile	$12,823	$3,985	$13,320	$3,253	$16,104	$7,614	$17,069	$6,643	$17,759	$8,065	$17,550	$7,240
Income CV												
Full sample	0.33	0.26	0.32	0.26	0.37	0.27	0.40	0.29	0.36	0.32	0.37	0.38
0-10th percentile	0.43	0.37	0.46	0.42	0.57	0.40	0.68	0.43	0.68	0.50	0.76	0.80
40-50th percentile	0.31	0.21	0.31	0.23	0.33	0.18	0.38	0.29	0.28	0.21	0.32	0.25
90-100th percentile	0.33	0.29	0.25	0.21	0.40	0.31	0.41	0.27	0.34	0.31	0.27	0.24
Earnings CV												
Full sample	0.47	0.55	0.44	0.53	0.46	0.47	0.48	0.46	0.44	0.49	0.46	0.55
0-10th percentile	0.96	1.07	0.94	1.04	0.92	0.85	1.09	0.88	1.01	0.90	1.02	1.07
40-50th percentile	0.39	0.29	0.36	0.29	0.37	0.22	0.42	0.33	0.33	0.30	0.41	0.43
90-100th percentile	0.34	0.31	0.27	0.29	0.41	0.34	0.42	0.28	0.35	0.33	0.28	0.28
Unearned Income CV												
Full sample	1.28	5.24	1.14	1.65	1.21	1.84	1.23	1.50	1.18	1.42	1.27	4.28
0-10th percentile	0.50	0.65	0.68	2.27	0.79	0.80	0.89	0.82	0.81	0.79	0.98	0.96
40-50th percentile	1.46	2.10	1.25	1.10	1.31	0.96	1.28	1.16	1.09	0.97	1.19	2.13
90-100th percentile	1.88	14.34	1.08	1.85	1.17	1.48	1.27	0.93	1.12	0.84	2.10	11.24
Sample Sizes												
Full sample		7,944		7,499		12,266		11,287		5,970		10,275
0-10th percentile		617		662		1,008		964		555		927
40-50th percentile		812		756		1,217		1,159		635		1,043
90-100th percentile		874		802		1,335		1,190		624		1,082

Figure 1. Income Coefficient of Variation (CV), Full Sample



Note: Calculations using SIPP data panels.
F-test comparison results: (F=83.7, $p < 0.001$)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported over the first nine waves.
***The 1991 panel data only includes 8 waves of data.

Figure 2. Income Coefficient of Variation (CV), 1–10th, 40–50th, and 90–100th Percentile Groups



Note: Calculations using SIPP data panels.
F-test comparison results: (0–10th percentile: F=47.4, $p < 0.001$); (40–50th percentile: F=18.5, $p < 0.001$); (90–100th percentile: F=56.9, $p < 0.001$)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported over the first nine waves.
***The 1991 panel data only includes 8 waves of data.

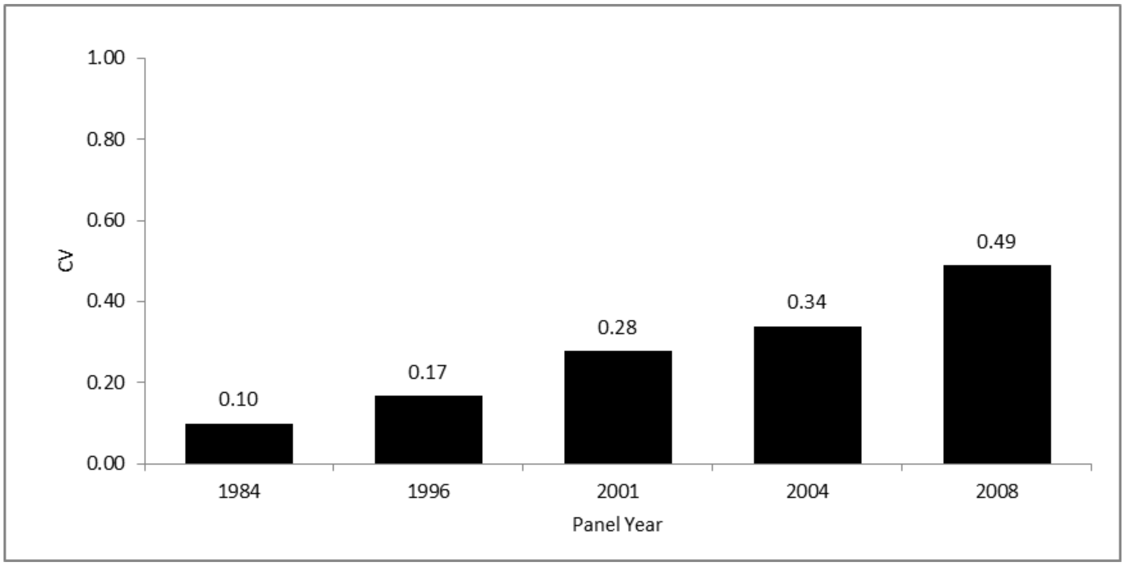
Another way to view these data is to calculate the gap between the highest and lowest income deciles, that is, the difference in monthly income CV for children in the lowest and highest income households (Figure 3). Examining these data shows that the gap grew steadily larger from .10 in 1984 to .49 in 2008, more than a four-fold increase. In 2008, children in low-income households experienced nearly three times the income volatility of children in high-income households ($t = 18.0$, $p < 0.001$). In comparison, in 1984 children in low-income households had substantively similar magnitude of income volatility as children in high-income households (although still statistically significantly different; $t = 5.6$, $p < 0.001$).

When examining year-to-year volatility as compared to intrayear volatility, we find a similar pattern of increasing gaps between children in rich and poor households. However, we also observe much lower levels of volatility for both groups as well as dampened trends across time. That is, children in households in the 0–10th percentile rise from .31 to .48 in year-to-year volatility, only a 54 percent rise from 1984 to 2008 ($t = 9.6$, $p < 0.001$), and those in the 90th–100th percentile showing almost no change over the full period (from .21 in 1984 to .19 in 2008; $t = 2.2$, $p <= 0.028$). Thus, for interyear volatility, the increasing gap between rich and poor children is still evident, but that gap is driven by the rise in income volatility among children in low-income households rather than the corresponding fall for children in high-income households, as is seen in intrayear volatility estimates. This highlights some of the detail to be gained in relying on intrayear as compared with interyear volatility estimates.

<u>Disaggregating the Trends in Monthly Income CV into the Mean and Standard Deviation</u>

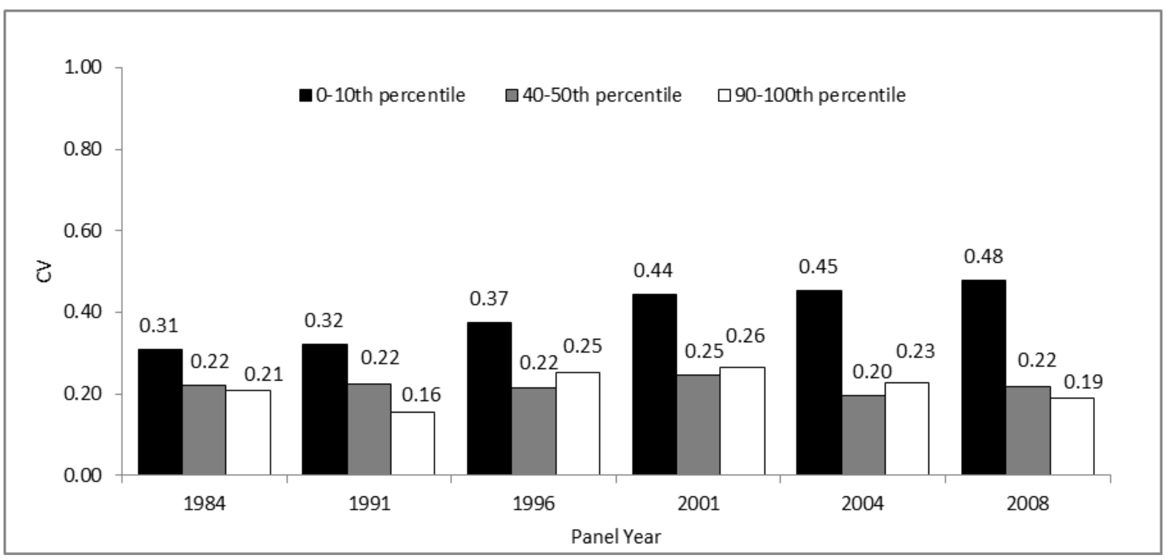
Given that the monthly income CV is made up of the ratio of two numbers— the mean and the standard deviation of monthly household income—the question arises: To what extent are these variations in volatility across time due to changes in the mean levels of income, variability in monthly income, or both? Figure 1 and the next two graphs show the CV disaggregated as an approach to address this question, first for the children in lowest income households and then for children in highest income households.

Figure 3. Income Coefficient of Variation (CV), Difference between Means of 0–10th and 90–100th Percentile Groups



Note: Calculations using SIPP data panels.
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported.

Figure 4. Inter-Year Income Coefficient of Variation (CV), 1–10th, 40–50th, and 90–100th Percentile Groups



Note: Calculations using SIPP data panels.
F-test comparison results: (0–10th percentile: F=33.2, $p< 0.001$); (40–50th percentile: F=6.6, $p< 0.001$); (90–100th percentile: F=38.6, $p< 0.001$)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first three years to the absolute value of the mean of total household income reported over the first three years.

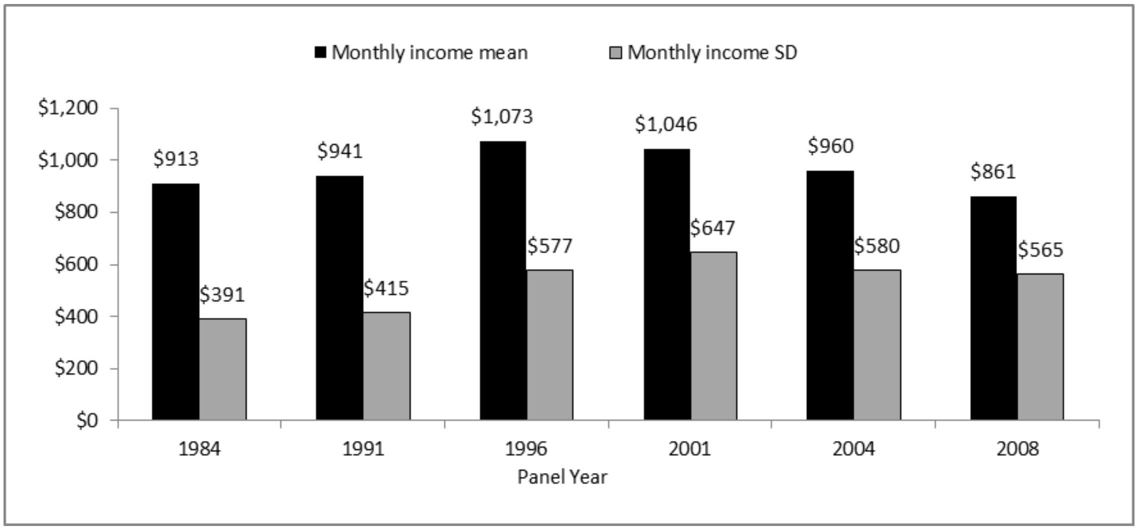
In Figure 5, disaggregated CV estimates for children in the lowest income households are presented. Taking the early and later periods separately, we find that the increase in volatility between 1984 and 2001 for children in low-income households is due to the increase in the variability (standard deviation) of monthly income, despite an increase in mean monthly income from 1984 to 1996. By contrast, the most recent increase from the 2004 to the 2008 panels appears to be due primarily to the reduction in mean monthly income; in fact, there is a small reduction in the standard deviation during this period but it is not large enough to offset the reduction in mean income, resulting in an increased CV.

Figure 6 presents these same disaggregated CV components for children in the highest income households. Here we observe the declines in standard deviation that drives CV declines from 1984 to 1991. We also find that the rise in volatility from 1991 to 1996 appears to be due to the increase in standard deviation that is not offset by the increase in the mean income also observed over this same period. From 2001 to 2008, the decline in volatility that we observe as measured by the CV is largely accounted for by a declining standard deviation in the context of relatively steady income over this period. Thus, for children in high-income households, changing income volatility is due to changing standard deviations. For children in low-income households, increases in income volatility are due to increasing standard deviations in the mid-80s to the early 2000s, but in this later period, increases are attributable to declining income in the context of relatively static standard deviation.

Disaggregating Changes in Income CV into Earned and Unearned Income

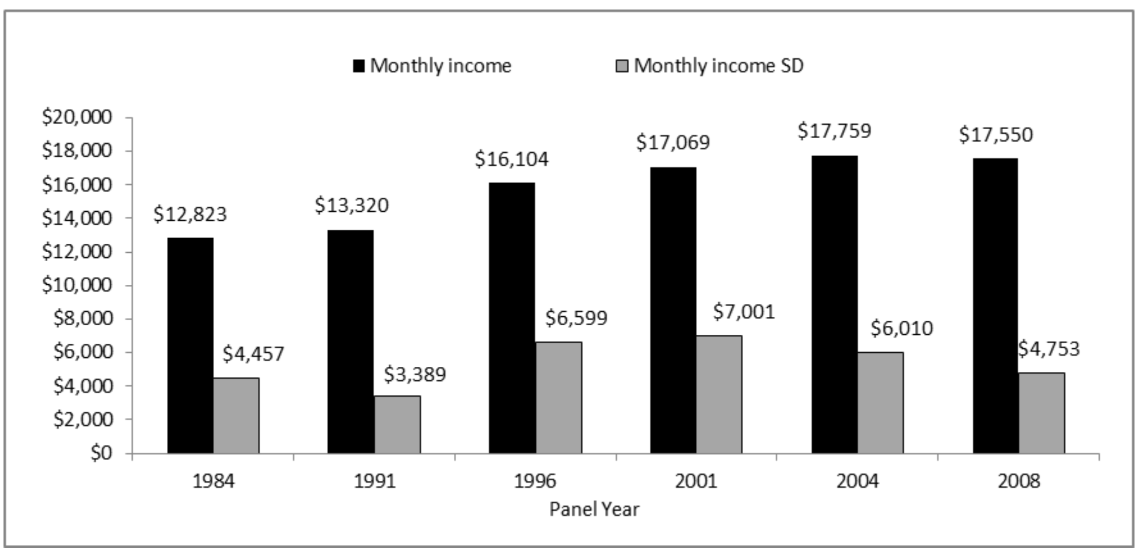
We next separate earned income from unearned income. Before turning to these results, descriptive data on earned income is instructive: earned income makes up a much smaller proportion of total income for the lowest decile income group than for the highest decile income group (perhaps unsurprisingly). For example, in 2008, 57 percent of total income for the lowest decile group is earned income, as compared to 97 percent of income for the highest decile group. And, reliance on earnings has been increasing dramatically for the low-income group over the 25-year period of the current study: with the low-income group's income made up of 32 percent earnings in the 1984 panel as compared to 57

Figure 5. Monthly Income Mean and Monthly Income Standard Deviation (SD), 0–10th Percentile Group



Note: Calculations using SIPP data panels.
F-test comparison results: (mean F=47.8, $p< 0.001$; SD F=40.1, $p< 0.001$)

Figure 6. Monthly Income Mean and Monthly Income Standard Deviation (SD), 90–100th Percentile Group



Note: Calculations using SIPP data panels.
F-test comparison results: (mean F=96.5, $p< 0.001$; SD F=72.1, $p< 0.001$)

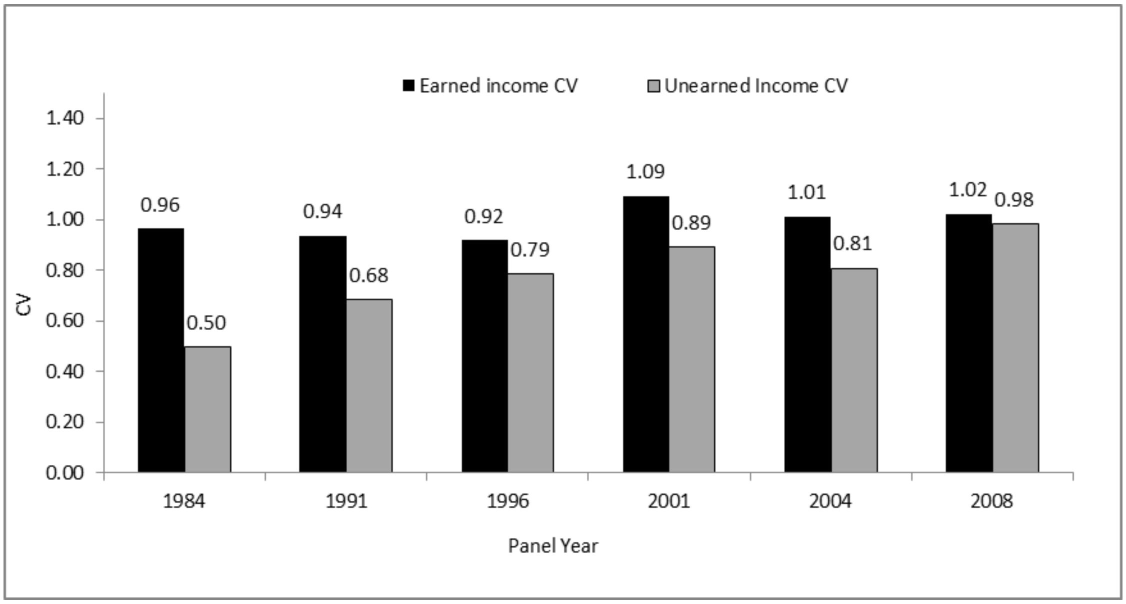
percent by the 2008 panel. By contrast, the higher income group has only slightly increased their reliance on earnings over this same period, from 91 percent in 1984 to 97 percent in 2008. Notably, as low-income families increase their work effort, we might expect increases in volatility as they are reliant on potentially less consistent sources of income (as compared to public assistance benefits that tend to vary less from month to month).

Data on the volatility of earned and unearned income is shown in the 2nd and 3rd panel of Table 1 and in Figures 7 and 8. As shown in Figure 7, for the 0–10th percentile income group, monthly *un*earned income CV shows a relatively steady rise from 1984 to 2008 (with the exception of a small dip in volatility from 2001 to 2004; $t = 2.0$, $p = 0.047$; $F = 16.1$, $p = 0.001$), that mirrors the pattern for the overall income CV. Monthly *earnings* CV shows a slight rise from 1996 to 2001 ($t= 4.5$, $p < 0.001$), but in all other periods is relatively steady or declines (but there is a statistically significant change as demonstrated by the F-test, $F = 4.1$, $p = 0.003$). Thus, for children in the lowest income households, the increase in income CV over the last 25 years appears to be due to the growing volatility of *unearned* sources of income, rather than from earnings.

For children of high-income households, in the 90th–100th percentile group, findings are shown in Figure 8. Most notably, the pattern of earnings CV matches that of total income CV. That is, earnings CV shows a slight decline from 1984 to 1991 ($t = 4.5$, $p < 0.001$) followed by a rise to 1996 ($t = 10.1$, $p < 0.001$) and then a decline from the 2001 to the 2008 panels ($t = 12.2$, $p < 0.001$) for a change overall ($F = 46.6$, $p < 0.001$). Given that earnings comprise a large proportion of income for this group, it is not surprising that income CV patterns would be driven largely by patterns of earned income CV.

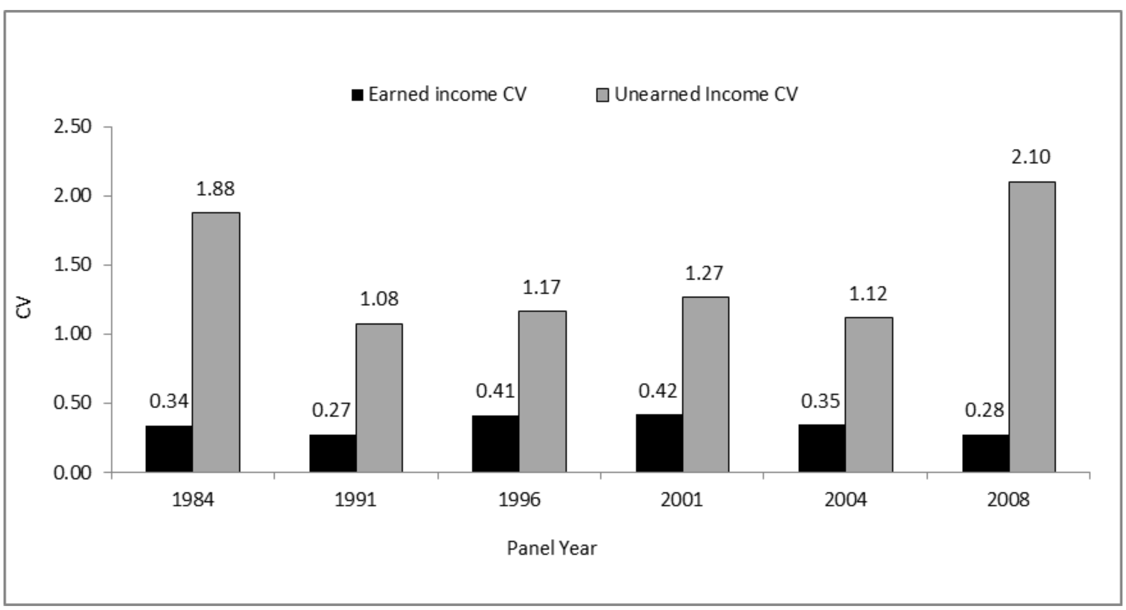
Unearned income CV for this same group shows substantial changes over this period ($F = 3.5$, $p < 0.001$), with a decline from 1984 to 1991 ($t = 1.6$, $p = 0.103$), increases slightly to 2001 ($t = 2.7$, $p = 0.007$) to decline again by 2004 ($t = 3.4$, $p = 0.001$) and then shows a substantial increase in 2008 ($t = 2.9$, $p = 0.004$). Notably, a substantial portion of unearned income for high-income households is composed of property income (which makes up 85 percent of highest income households' unearned income in 2008).

Figure 7. Earned and Unearned Income Coefficient of Variation (CV), 0–10th Percentile Group



Note: Calculations using SIPP data panels.
F-test comparison results: (Earned income CV: F=4.1, p=0.003; Unearned income CV: F=16.1 p= 0.001)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported.

Figure 8. Earned and Unearned Income Coefficient of Variation (CV), 90–100th Percentile Group



Note: Calculations using SIPP data panels.
F-test comparison results: (Earned income CV: F= 46.6, p< 0.001; Unearned income CV: F=3.5, p= 0.008)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported.

Sensitivity Analyses

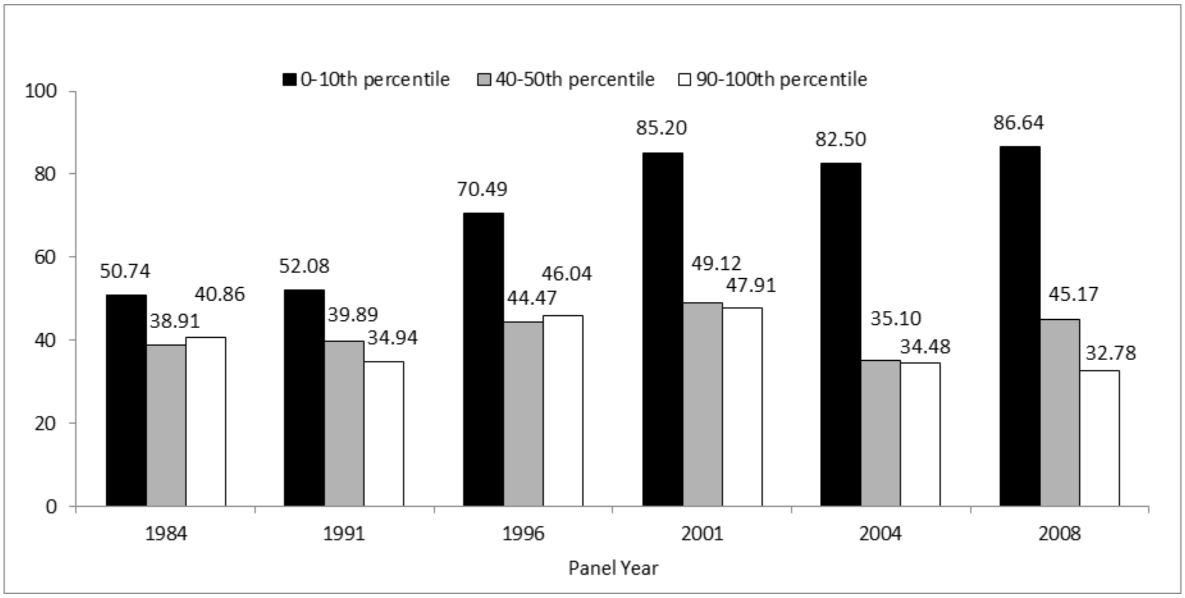
We conducted a number of tests of the sensitivity of the results to alternative modeling assumptions. First, we estimated our results without weights for the complex survey design of the SIPP and the attrition from the survey over time. This made no discernable qualitative or substantive difference in our results (results available upon request). We also examined whether patterns differed when using eight waves of data across all panels (given that only eight waves were available for the 1991 panel, but nine for all others); again, no qualitative or substantive discernable difference in the findings were detected (results available upon request).

Second, we examined whether the findings were sensitive to the use of an alternative measure of income volatility—arc percent change. Results are shown in Figure 9. They show little difference in the basic pattern of results.

Third, we tested whether our results were sensitive to the way income is measured to categorize children's households into decile groups. In short, in defining deciles using average monthly income, there was some concern that children in low-income households who experience large fluctuations in income would be categorized into a higher decile based on the use of the average measure, overestimating volatility in higher decile and underestimating volatility in the lowest decile groups. However, sensitivity analyses conducted defining deciles as household monthly income at wave 1 revealed similar findings with regard to volatility estimates.

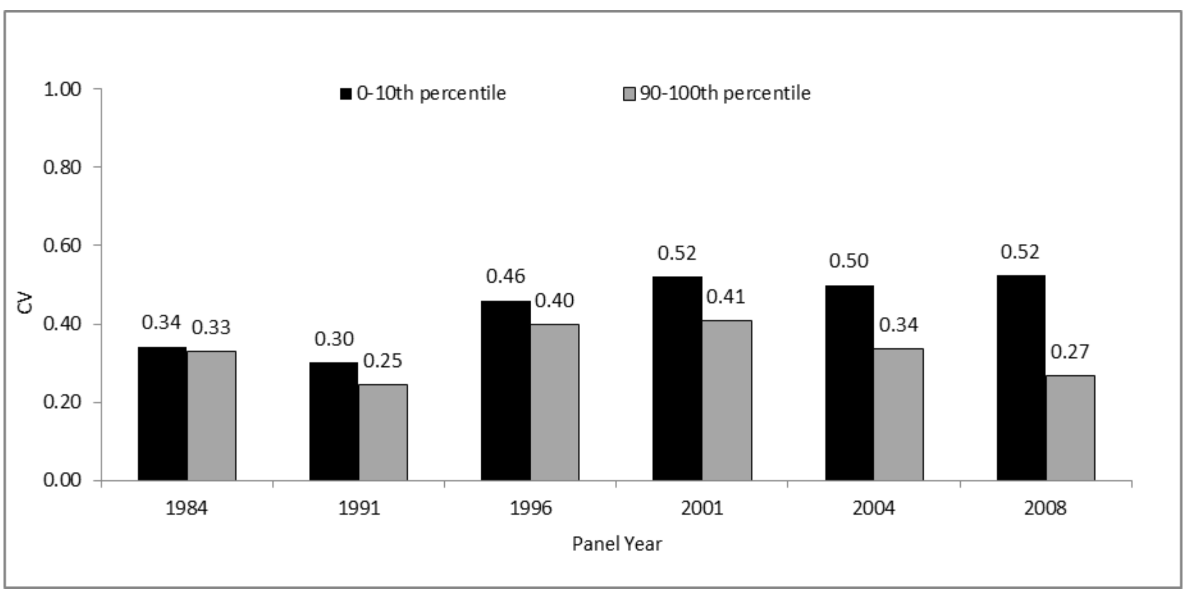
Fourth, we examined whether our results changed if we included income from the Supplemental Nutrition Assistance Program (SNAP; formerly Food Stamps), an important noncash source of income for the lowest income households (Figure 10). To test this question, SNAP income was added to the income value as cash income, and a new CV value was calculated. The results show that monthly income CV still rises from 1984 to 2008 for the lowest decile group ($F = 30.8$, $p < 0.001$), but not as dramatically as shown in Figure 2. That is, rather than rising from .43 in 1984 to .76 in 2008 (an increase of 77 percent; $t = 10.8$, $p < 0.001$), the inclusion of SNAP income results in an increase from .34 in 1984 to .52

Figure 9. Arc Percent Change, 1–10th, 40–50th, and 90–100th Percentile Groups



Note: Calculations using SIPP data panels.
F-test comparison results: (0–10th percentile: F=46.8, $p< 0.001$); (40–50th percentile: F=7.7, $p< 0.001$); (90–100th percentile: F=48.8, $p< 0.001$)

Figure 10. Income Including Food Stamps Coefficient of Variation (CV), 1–10th and 90–100th Percentile Groups



Note: Calculations using SIPP data panels.
F-test comparison results: (0–10th percentile: F=30.8, $p< 0.001$); (90–100th percentile: F=59.9, $p< 0.001$)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported.

in 2008 (or an increase of 53 percent; $t = 6.8$, $p < 0.001$). Not surprisingly, the inclusion of food stamp benefits leaves unchanged the income CV of the highest income households. The result is that there is still an increasing gap between rich and poor households in income volatility (from .01 in 1984 to .25 in 2008), but that gap is attenuated from the original findings. This is an indication of ways in which the U.S. safety net may mitigate income volatility for children in low-income households.

Fifth, analyses were conducted to determine the extent to which the process of imputation of income by the SIPP data team resulted in an underestimate of income volatility (if missing data are "smoothed over" by using information from prior waves). (Note that this analysis omitted the 1984 and 1991 panels because of differences in how imputed data are identified in the panels). Of note is the fact that while most households had some component of their income imputed (approximately 85 percent of children were in households that had some imputed income), that imputed income often made up a very small amount of their total income (with most households having only 16 percent in the 1996 panel; 20 percent in the 2001 panel; 12 percent in the 2004 panel; and19 percent in the 2008 panel of their income imputed). As such, our sensitivity analyses repeated the analysis for Figure 2, but for the subset of sample members for whom only a small portion of their total income (less than 33 percent) was imputed. Limiting the sample to household results in patterns that are very similar to those reported earlier, with increasing income CV from 1996 to 2008 for the lowest decile groups, and declining income CV from 2001 to 2008 for highest decile groups. Notably, excluding the sample with imputed data made a greater difference to the values for the lowest income decile than the highest income decile, perhaps because lowest income households are more difficult to track.

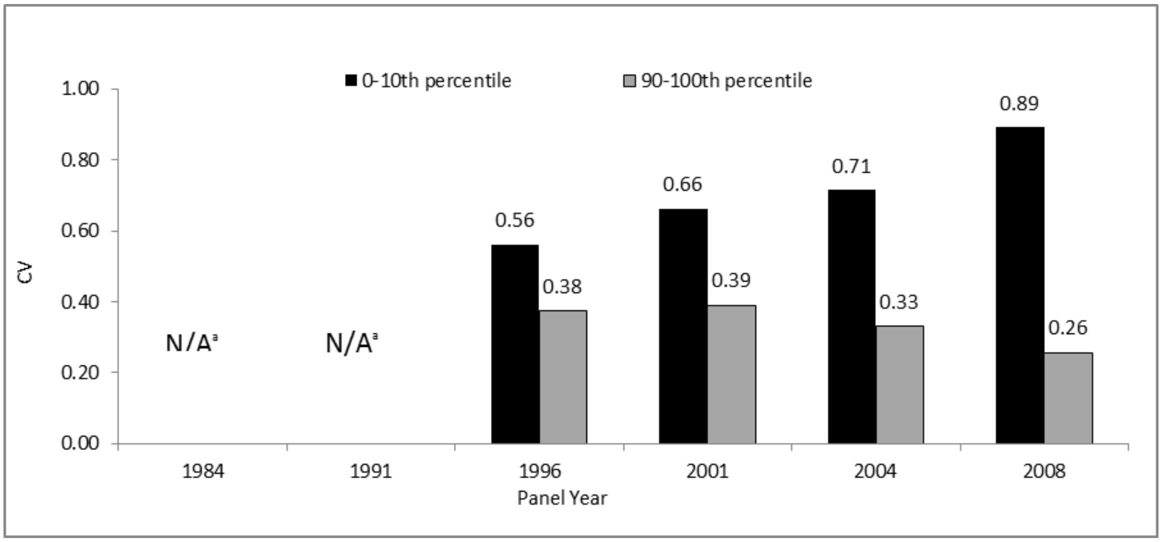
Finally, analyses were conducted to determine the extent to which the changing *demographics* of households at the low and top ends of the income distribution were driving the results observed as compared to the changing *experiences* of low- and high- income households, irrespective of such demographic shifts. To conduct this analysis, our focus was on two groups for whom there had been demographic shifts across the panel years: from the first to the last panel, the lowest decile was increasingly made up of households in which the reference person was (a) Hispanic and (b) unmarried. As such, we conducted analyses to determine if the same pattern of findings would be observed when limiting the sample to households with (a) non-Hispanic white household heads, and (b) married household heads—two of the potentially "more stable" subgroups (since sample sizes were very small for the other groups). Results are shown in Figures 12 and 13.

As shown in the figures, the same general pattern of an increase in income CV for the lowest income decile group from 1984 to the 2008 panel is demonstrated in the two subgroups examined. Results for children in non-Hispanic white-headed households look very similar to the full sample findings, with a steady increase in income CV over this period ($F = 15.3$, $p < 0.001$, suggesting that even among children in White-headed low-income households, there is an increase in income CV over this period. The same can be said about children in married households ($F = 7.0$, $p < 0.001$). However, the increase in income CV is slightly attenuated in this latter group as compared to that which was observed for the full low-income sample (from Figure 2). For this latter group, the increase in the income CV for the lowest income group is about 52 percent for the married low-income group ($t = 4.1$, $p < 0.001$), while it is 76 percent for non-Hispanic whites ($t = 6.6$, $p < 0.001$). Thus, the main conclusions appear to hold up even when considering shifts in single-parenthood as well as racial/ethnic shifts. A fuller examination of the variety of other compositional shifts over time would be important next-stage research, but is beyond the scope of this study.

DISCUSSION

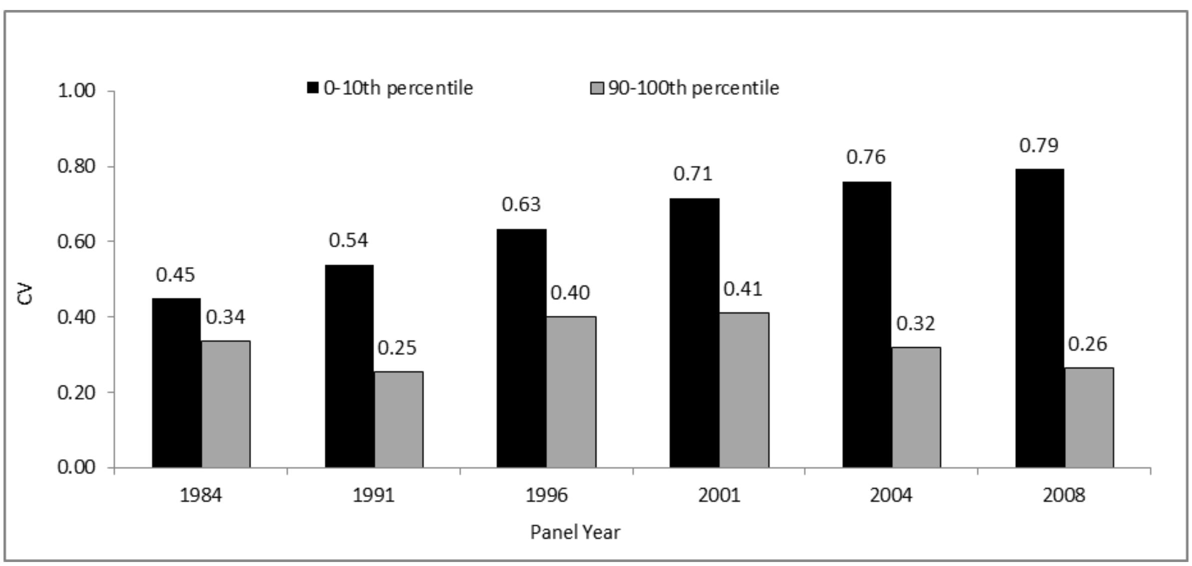
In an effort to contribute to the empirical literature on earnings and income volatility in the United States, we embarked on an ambitious set of analyses of SIPP data spanning a 25-year period that witnessed several periods of remarkable economic growth as well as recession. Unlike prior work, we specifically focus on households with children for two reasons: (a) because children are particularly vulnerable to large, unexpected, or frequent income fluctuations, and (b) because children, particularly those in low-income households, are the targets of public programs and income volatility may interfere with the success of such investments. A fuller examination of household economic circumstances that

Figure 11. Income Coefficient of Variation (CV), 1–10th and 90–100th Percentile Groups, Excluding Sample with >33% Imputed Income



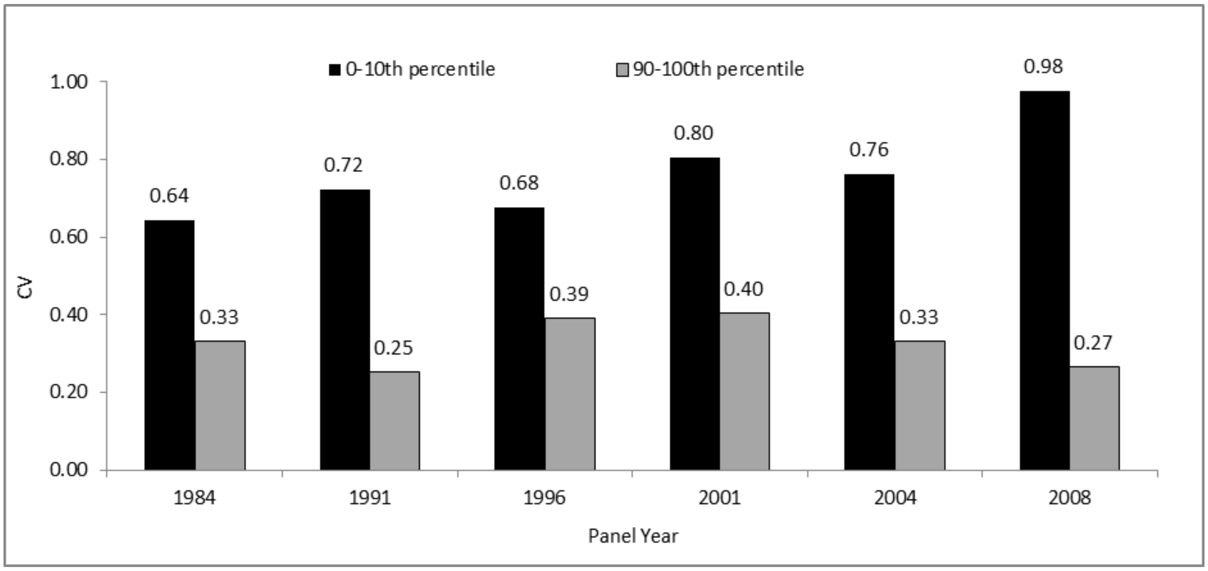
Note: Calculations using SIPP data panels.
This analysis omitted the 1984 and 1991 panels because of differences in the panels in the ways in which imputed data are identified. F-test comparison results: (0–10th percentile: F=28.2, $p< 0.001$); (90–100th percentile: F=35.8, $p< 0.001$)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported.

Figure 12. Income Coefficient of Variation (CV), Non-Hispanic White Household Head, 1–10th and 90–100th Percentile Groups



Note: Calculations using SIPP data panels.
F-test comparison results: (0–10th percentile: F=15.3, $p< 0.001$); (90–100th percentile: F=52.2, $p< 0.001$)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported.

Figure 13. Income Coefficient of Variation (CV), Household Head Married, 1–10th and 90–100th Percentile Groups



Note: Calculations using SIPP data panels.
F-test comparison results: (0–10th percentile: F=7.0, $p< 0.001$); (90–100th percentile: F=52.2, $p< 0.001$)
Within each panel, coefficient of variation (CV) is calculated as the ratio of the total household income standard deviation over the first nine waves to the absolute value of the mean of total household income reported.

considers changes in income dynamics in addition to income level provides a more complete context for understanding trends in child achievement gaps associated with family income level.

We generally document a rise in income volatility from 1984 to 2008 among children in poor households, and simultaneously, that children in households at the 10^{th} income percentile are experiencing higher income volatility over time relative to children in households at the 90^{th} income percentile. Said another way, children in poor households are financially less stable over time, while children in rich households are financially more stable. Thus, income volatility may be contributing to the differences observed in children's development and achievement by household income.

For children in both high- and low-income households, the trends in monthly income volatility are driven at various times by changes in monthly income level and monthly income variability. Our findings reveal that the increase in volatility between 1984 and 2001 for children in low-income households is due primarily to the increase in the variability of monthly income. The more recent increase, from the 2004 to the 2008 panels, appears to be due primarily to the reduction in mean monthly income, without a corresponding decline in variability.

Income volatility among the lowest income households appears to be driven by volatility in unearned, rather than earned income, which has implications for discussions regarding the social safety net. In fact, discussions of economic instability are often dominated by important evidence that low-wage jobs are fundamentally unstable. The findings reported here suggests that we need to also look at the stability of public assistance, and the interaction between unstable employment and public assistance, as well, if we want to better understand income volatility. Whereas recent policy discussions have rightly highlighted growing income inequality and the reduction in social mobility in the United States, financial stability may be a first-order concern to enable low-income households to take advantage of opportunities for economic mobility. And, of course, from a socioeconomic status (SES)-achievement gap perspective, income volatility may be part of the reason there has not been sufficient progress on this issue.

There are a number of limitations of this study; we highlight a few here. First, we rely primarily on a single measure of income volatility in this work (although notably we find similar results using both the CV and arc percent-change measures). While the CV has a number of statistical advantages, there are benefits of examining multiple measures to provide a more complete understanding of household patterns of income volatility. As indicated earlier, frequent small income shocks and a fewer large income shocks are not differentiated in these analyses, but may have different implications for children's achievement and development (Gennetian, Wolf, Morris, & Hill, in press). Second, our focus is on intra-year income volatility, with the objective of better identifying month-to-month income change. However, given the four-month interview cycles of the SIPP and the challenges with seam bias, we elected to rely on tri-annual income volatility instead. While this provides a more nuanced understanding of volatility from prior studies that have focused on year-to-year volatility (and for which there appears to be less volatility than our intrayear measures in this same data set), it is still a few steps removed from frequent income changes that we suspect families, especially those at the low end of the income distribution, experience (e.g., see work by the U.S. Financial Diaries project, 2014). Finally, and perhaps most importantly, the SIPP does not provide us with a complete time trend over the last 25 years. That is, we rely on six different panels of the SIPP rather than a single longitudinal panel. While the sampling weights should smooth any differences between the panels in sampling or data collection, we cannot completely rule out the possibility that differences in findings across panels are not influenced by such design differences.

In conclusion, we sought to better document income volatility as experienced by children over time, as one not well understood aspect of household economic circumstances that might contribute to observed socioeconomic differences in children's achievement. Our findings reveal that income volatility may be an additional factor contributing to the gap between the fortunes of rich and poor children in the United States. Indeed, the dynamic nature of family life is not captured in many studies of work, poverty, and the effectiveness of social assistance programs. Future research in a variety of disciplines and domains, including evaluations of specific social programs, can do more to capture the longitudinal and dynamic relationships between employment, program participation, income level, and income variability. One important place to start is to collect time-sensitive outcomes and frequent measurement of income by source. That said, evidence from this study raises questions about whether a continued focus on employment and income *level* are sufficient, or whether attention is needed to improve the stability of household income while also reducing poverty. As such, this work serves to introduce income volatility as a thus far neglected topic in the research and policy conversations about poverty, income, inequality, and, of course, SES disparities in child achievement.

References

Aber, L., Morris, P., & Raver, C. (2012). Children, families and poverty: Definitions, trends, emerging science and implications for policy. *Social Policy Report*, *26*(3), 1–19.

Ackerman, B.P., Kogos, J., Youngstrom, E., Schoff, K. & Izard, C. (1999). Family instability and the problem behaviors of children from economically disadvantaged families. *Developmental Psychology 35(1)*, 258–268. http://dx.doi.org/10.1037/0012-1649.35.1.258

Acs, G., Loprest, P., & Nichols, A. (2009). Risk and recovery: Understanding the changing risks to family incomes and their consequences. *Low-Income Working Families Brief.* Washington, DC: The Urban Institute.

Bania, N., & Leete, L. (2007). *Income Volatility and Food Insufficiency in U.S. Low-Income Households, 1992–2003*. Institute for Research on Poverty Discussion Paper #1325-07.

Brooks-Gunn, J., & Duncan, G. J. (1997). The effects of poverty on children. *The Future of Children*, 55–71. http://dx.doi.org/10.2307/1602387

Carey, C., & Shore, S. H. (2013). From the peaks to the valleys: Cross-state evidence on income volatility over the business cycle. *Review of Economics and Statistics*, *95*(2), 549–562. http://dx.doi.org/10.1162/REST_a_00299

Celik, S., Juhn, C., McCue, K., & Thompson, J. (2012). Recent trends in earnings volatility: evidence from survey and administrative data. *The BE Journal of Economic Analysis & Policy*, *12*(2). http://dx.doi.org/10.1515/1935-1682.3043

Dahl, M., DeLeire, T., & Schwabish, J. A. (2011). Estimates of year-to-year volatility in earnings and in household incomes from administrative, survey, and matched data. *Journal of Human Resources*, *46*(4), 750–774. http://dx.doi.org/10.1353/jhr.2011.0000

Dynan, K., Elmendorf, D., & Sichel, D. (2012). The evolution of household income volatility. *The BE Journal of Economic Analysis & Policy*, *12*(2). http://dx.doi.org/10.1515/1935-1682.3347

Ganzel, B. L., Morris, P. A., & Wethington, E. (2010). Allostasis and the human brain: Integrating models of stress from the social and life sciences. *Psychological review*, *117*(1), 134. http://dx.doi.org/10.1037/a0017773

Gennetian L. A., Castells N. & Morris P. A. (2010) Meeting the basic needs of children: Does income matter? *Children and Youth Services Review, 32*, 1138–1148. http://dx.doi.org/10.1016/j.childyouth.2010.03.004

Gennetian, L. A., Seshadri, R., Hess, N., Winn, A., & George, R. (2011). *Running out and acting out: food stamp benefit cycles and school disciplinary events among Chicago public school students*. Working paper.

Gennetian, L. A., & Shafir, E. (2015). The persistence of poverty in the context of financial instability: A behavioral perspective. *Journal of Policy Analysis and Management*. http://dx.doi.org/10.1002/pam.21854

Gennetian, L. A., Wolf, S., Morris, P. A. & Hill, H.H. (in press). Intra-year household income instability and adolescent school behavior. *Demography.*

Gosselin, P., & Zimmerman, S. (2008).*Trends in income volatility and risk, 1970–2004 (working paper May 2008)*. Washington, DC: The Urban Institute. Retrieved September 30, 2014, from http://www.urban.org/UploadedPDF/411672_income_trends.pdf

Gottschalk, P., & Moffitt, R. A. (1994). Welfare dependence: concepts, measures, and trends. *The American Economic Review*, 38–42.

Gottschalk, P., & Moffitt, R. (1999). Changes in job instability and insecurity using monthly survey data. *Journal of Labor Economics*, *17*(S4), S91-S126. http://dx.doi.org/10.1086/209944

Gottschalk, P., & Moffitt, R. (2009). The rising instability of US earnings. *The Journal of Economic Perspectives*, 3–24. http://dx.doi.org/10.1257/jep.23.4.3

Hacker, J. S. (2008). The great risk shift: The new economic insecurity and the decline of the American dream. *OUP Catalogue*.

Hacker, J. S., Huber, G. A., Rehm, P., Schlesinger, M., & Valletta, R. (2010). *The Economic Security Index: A new measure of the economic security of American workers and their families (July 2010).* New Haven, CT: Economic Security Index.

Hacker, J. S., & Jacobs, E. (2008). The rising instability of American family incomes, 1969–2004: Evidence from the panel study of income dynamics. *Economic Policy Institute.*

Haider, S. J. (2001). Earnings instability and earnings inequality of males in the United States: 1967–1991. *Journal of Labor Economics*, *19*(4), 799–836. http://dx.doi.org/10.1086/322821

Hardy, B & Ziliak, J.P. (2014). Decomposing trends in income volatility: The “wild ride” at the top and bottom. *Economic Inquiry, 52*(1), 459–476. http://dx.doi.org/10.1111/ecin.12044

Hill, D. (1987). Response errors around the seam: analysis of change in a panel with overlapping reference periods. In *Proceedings of the Section on Survey Research Methods, American Statistical Association* (pp. 210–215).

Hill, H. D., Morris, P., Gennetian, L. A., Wolf, S., & Tubbs, C. (2013). The consequences of income instability for children's well-being. *Child Development Perspectives*, *7*(2), 85–90. http://dx.doi.org/10.1111/cdep.12018

Holzer, H. J., Whitmore Schanzenbach, D., Duncan, G. J., & Ludwig, J. (2008). The economic costs of childhood poverty in the United States. *Journal of Children and Poverty*, *14*(1), 41–61. http://dx.doi.org/10.1080/10796120701871280

Jensen, S. T., & Shore, S. H. (2011). Semiparametric Bayesian modeling of income volatility heterogeneity. *Journal of the American Statistical Association*, *106*(496), 1280–1290. http://dx.doi.org/10.1198/jasa.2011.ap09283

Keys, B. (2008). Trends in income and consumption volatility, 1970–2000. *Income volatility and Food Assistance in the United States*, 11–34.

McEwen, B. S. (1998). Stress, adaptation, and disease: Allostasis and allostatic load. *Annals of the New York Academy of Sciences*, *840*(1), 33–44. http://dx.doi.org/10.1111/j.1749-6632.1998.tb09546.x

McEwen, B. S. & Stellar, E. (1993). Stress and the individual: Mechanisms leading to disease. *Archive of Internal Medicine, 153,* 2093–2101. http://dx.doi.org/10.1001/archinte.1993.00410180039004

Moffitt, R. A., & Gottschalk, P. (1995). *Trends in the autocovariance structure of earnings in the US, 1969–1987*. Johns Hopkins University, Department of Economics.

Moffitt, R. A., & Gottschalk, P. (2002). Trends in the transitory variance of earnings in the United States. *The Economic Journal*, *112*(478), C68–C73. http://dx.doi.org/10.1111/1468-0297.00025

Moffitt, R., & Gottschalk, P. (2008). Trends in the transitory variance of male earnings. Unpublished. Johns Hopkins University & Boston College.

Moffitt, R. A., & Gottschalk, P. (2011). *Trends in the Transitory Variance of Male Earnings in the US, 1970–2004* (No. w16833). National Bureau of Economic Research. http://dx.doi.org/10.3386/w16833

Moffitt, R. A., & Gottschalk, P. (2012). Trends in the transitory variance of male earnings methods and evidence. *Journal of Human Resources*, *47*(1), 204–236. http://dx.doi.org/10.1353/jhr.2012.0001

Moore, J. C. (2007). Changes to the SIPP 2004 Panel Wave 1 Recipiency History Topical Module and Their Impacts on Survey Estimates and Data Quality. *Survey Methodology*, 8.

Neumark, D., & Wascher, W. (1999, November). Using the EITC to increase family earnings: New evidence and a comparison with the minimum wage. In *Joint Center for Poverty Research Conference on The Earned Income Tax Credit: Early Findings, Evanston, IL*.

Nichols, A. (2008). Trends in income inequality, volatility, and mobility risk. *Washington, DC: Urban Institute*.

Romich, J. L. (2006). Difficult calculations: Low-income workers and marginal tax rates. *Social Service Review*, *80*(1), 27–66. http://dx.doi.org/10.1086/499086

Rosenblum, L.A. & Paully, G.S. (1984). The effects of varying environmental demands on maternal and infant behavior. *Child Development*. 55: 305–314. http://dx.doi.org/10.2307/1129854

Sandstrom, H. & Huerta, S. (2013). The negative effects of instability on child development: A research synthesis. Washington, DC: The Urban Institute. Accessed online 3/3/2015 at: http://www.urban.org/UploadedPDF/412899-The-Negative-Effects-of-Instability-on-Child-Development.pdf

Shin, D., & Solon, G. (2009). Trends in men's earnings volatility: What does the panel study of income dynamics show? Michigan State University. Unpublished.

Shin, D., & Solon, G. (2011). Trends in men's earnings volatility: What does the Panel Study of Income Dynamics show? *Journal of Public Economics*, *95*(7), 973–982. http://dx.doi.org/10.1016/j.jpubeco.2011.02.007

Shin, I. (2012). Income inequality and economic growth. *Economic Modelling*, *29*(5), 2049–2057. http://dx.doi.org/10.1016/j.econmod.2012.02.011

Stevens, A. H. (2001). Changes in earnings instability and job loss. *Industrial and Labor Relations Review*, 60–78. http://dx.doi.org/10.1177/001979390105500104

U.S. Financial Diaries. (2014). 83 charts to describe the hidden financial lives of working Americans [slide presentation]. Retrieved from http://www.usfinancialdiaries.org/83-charts

Wachs, T.D. & Evans, G.W. (2010). Chaos in context. In G. W. Evans and T. D. Wachs (Eds.), *Chaos and Its Influence on Children's Development: An Ecological Perspective* (pp. 3–13). Washington, DC: American Psychological Association. http://dx.doi.org/10.1037/12057-001

Westat (2001). Survey of Income and Program Participation user's guide, 3rd Ed. Washington, DC: US Census Bureau.

Winship, S. (2009). The Very Small Risk Shift: Trends in Family Income Changes. *Unpublished dissertation, Harvard University. http://www.scottwinship.com/dissertation.html*.

Zeiler, M. D. (1968). Fixed and variable schedules of response-independent reinforcement. *Journal of the Experimental Analysis of Behavior, 11(4)*, 405–414. http://dx.doi.org/10.1901/jeab.1968.11-405

Ziliak, J. P., Hardy, B., & Bollinger, C. (2011). Earnings volatility in America: Evidence from matched CPS. *Labour Economics*, *18*(6), 742–754. http://dx.doi.org/10.1016/j.labeco.2011.06.015