In and Out of Poverty:

Episodic poverty and income volatility in the U.S. Financial Diaries[1]

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Abstract

We use data from the U.S. Financial Diaries study to relate episodic poverty to intra-year income volatility and to the availability of government transfers. The U.S. Financial Diaries data track a continuous year's worth of month-to-month income for 235 low- and moderate-income households, each with at least one employed member, in four regions in the United States. The data provide an unusually granular view of household financial transactions, allowing the documentation of episodic poverty, and the attribution of a large share of it to fluctuations in earnings within jobs. For households with annual income greater than 150 percent of the poverty line, smoothing within-job income variability reduces the incidence of episodic poverty by roughly half. We decompose how month-to-month income volatility responds to receipt of eight types of public or private transfers. The transfers assist households mainly by raising the mean of income rather than by dampening intra-year income variability.

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Depictions of persistent poverty stoke outrage at America's inequalities. Powerful evocations of it include Michael Harrington's *The Other America* (1962), Peter Edelman's *So Rich, So Poor* (2012), and, more recently, Kathryn Edin and Luke Shaefer's *$2 a Day: Living on Almost Nothing in America* (2015). Most experiences of poverty, however, are shorter and shallower. Three-quarters of poverty episodes between 2009 and 2011 lasted less than a year, for example, and half lasted six months or less; just 4 percent lasted for the full three year period (Edwards 2014). Understanding poverty requires a framework that recognizes both its persistence and the frequency of poverty exits and entrances (Cellini, McKernan, and Ratcliffe 2008).

We examine episodic poverty with data from the U.S. Financial Diaries project. The data set tracks 235 households and is not nationally representative, but the diaries provide an unusually granular view of monthly household earning, spending, and transfers, as well as formal and informal coping mechanisms. While previous studies separately document income volatility and episodic poverty, the data allow us to bring both together, document the prevalence of episodic poverty across income groups, connect episodic poverty to month-to-month income volatility, demonstrate the critical role of within-job paycheck variability, and show the limited role of transfers from public agencies and private networks in dampening this intra-year income volatility. Our aim is to describe patterns as a step toward creating an agenda for poverty analyses in which episodic poverty is a larger focus.

Episodic poverty has been relatively neglected in part because few surveys collect rich data on the month-to-month economic conditions of households. The Diaries study was designed to track all financial transactions for the households during an entire year. Each household started with at least one employed member, and the study covered four sites chosen to reflect a range of social and economic conditions: Northern California, Eastern Mississippi, greater Cincinnati, and the outer boroughs of New York City. The diaries are not actual journals completed by the study participants. Rather, twelve field researchers interviewed households at frequent intervals. Data from these sites include a monthly cash flow panel with detailed records of income, spending, borrowing, saving, and informal sharing. The aim was to create a "diary" in the sense of a complete record of day-to-day activities over time.

The Diaries, while not as large or representative as other data sets, included systematic protocols to assure data quality, with an eye to capturing cash transactions and the complex (and sometimes irregular) work schedules more typical of poorer households than others. The protocols reduce the worry common in other data that evidence of volatility and movement in and out of poverty is an artifact of measurement error.

Our results on intra-year volatility confirm and extend findings in the literature. The volatility of monthly household income, coupled with the large population share living close to the poverty line, means that episodes of poverty during a given year are relatively common. We find that 95 percent of households with annual income close to the poverty line (with income between 100 and 150 percent of the threshold) experienced at least one month of poverty, and that even one-third of households with annual income greater than twice the poverty line dipped into poverty for at least a month. We trace a large component of poverty-inducing volatility to earned income, especially to within-job pay fluctuations. Smoothing out those within-job pay fluctuations would reduce rates of episodic poverty by roughly half for households with annual income 150 percent or more above the poverty line. The results show that households protect their consumption to a limited degree through saving, borrowing, sharing with others, and relying on public transfers. Public transfers reduce measures of month-to-month income volatility for the sample's households, but their main impact is to increase average income. While transfers reach low-income households, the timing of assistance is such that it does little to directly buffer month-to-month income volatility in the sample.

The evidence suggests that developing a policy agenda to encompass those who are "sometimes poor" during the year, requires a stronger base for understanding the relationship between episodic poverty, transfer receipt, and households' own coping mechanisms. That framework should emphasize the challenges created by within-job income volatility and the need for improved public and private coping mechanisms.

Related Literature

Poverty and Income Volatility

The notion that most poverty spells are long-lasting was challenged by early studies using the Panel Study of Income Dynamics (PSID). The studies show that income volatility translates into relatively frequent movements in and out of poverty across years (Duncan 1984; Bane and Ellwood 1986; Stevens 1994). Mary Jo Bane and David Ellwood (1986), for example, use PSID data from the 1970s and 1980s to show that nearly 45 percent of poverty spells lasted no more than a year, 70 percent lasted no more than three years, and just 12 percent stretched beyond a decade. They reported that about half of all poverty spells were attributable to major life events including family partition and divorce, job loss, and health crises. Moreover, this temporary or episodic poverty accounted for most spells of poverty and characterized most households that ever experienced poverty, even if, at a particular point in time, the majority of spells were long-lasting (Bane and Ellwood 1986).

While the evidence of episodic poverty diverges from the focus of popular notions of persistent poverty (e.g., Harrington 1962), its incidence should not be surprising. Census data show that about 20 percent Americans live in households with income above the federal poverty line but below 200 percent of the line. These “near-poor” households are particularly vulnerable to income dips that can initiate spells of poverty, and their fraction of the population has remained relatively steady for four decades. During those decades, moreover, the labor market has shifted such that many jobs offer less security and less steady paychecks than before (Lambert 2008; Hollister 2011; Kalleberg 2013). The combination of proximity to the poverty line and growing income swings increases the likelihood of episodic poverty.

Income volatility has, by most measures, been on the rise, especially for the poorest. In seminal work, Peter Gottschalk and Robert Moffitt (1994) used the PSID between 1970 and 1987 to estimate the variability of labor earnings for white male household heads aged 20-59, finding an increase in variability between the 1970s and 1980s. Karen Dynan and colleagues (2012) review much of the subsequent literature and analyze a longer sample. They find a 30 percent increase in the volatility of household income in the PSID between 1971 and 2008, measured by the standard deviation of percent changes in annual income across two-year spans. A 2015 update finds that on average, in any given two-year period between 1979 and 2011, nearly half of households in the PSID had an income gain or loss of 25 percent of more (Pew Charitable Trusts 2015). Gottschalk and Moffitt (2009) tie the rise in income volatility to increases in income inequality.[2]

Bradley Hardy and James Ziliak (2014) use the U.S. Current Population Survey (CPS) to examine the year-to-year volatility experienced by families between 1980 and 2009. They find that the richest 1 percent of the population saw the sharpest increase during that time period. But in any given year (rather than over the entire 19 years), income volatility for the poorest 10 percent was higher than it was for the richest. And, because the poor had fewer tools to cope, income volatility likely also had much bigger ramifications for their lives. The authors show that in the same period, once-reliable strategies for coping were disappearing. For example, the earnings of spouses were negatively correlated before 1990, meaning that spouses experienced earnings spikes and dips at different times, cushioning the family from dramatic volatility. But Hardy and Ziliak show that that changed after 1990. After 1990, spouses' incomes more often moved up or down at the same time, amplifying rather than decreasing spikes and dips. Moreover, they found that while government support had previously helped to reduce volatility for lower-income households, its dampening role fell in the later period.

The PSID and CPS both provide data at the annual level. In contrast, the Survey of Income and Program Participation (SIPP) was designed to permit insight into income and

[2] Dynan et al. (2012) cite a range of studies of household income and individual earnings that show increases in volatility over time. Some results, however, are sensitive to the data set and specification. Dahl, DeLeire, and Schwabish (2011), for example, find that earnings volatility is flat between 1984 and 2004 in data that merges the Survey of Income and Program Participation (SIPP) and administrative data on labor earnings from the Social Security Administration. Winship (2011) finds that household income volatility rises in the PSID and Current Population Survey, but is stable in the SIPP (and favors the SIPP findings).

poverty from month-to-month, and it has been the main nationally-representative data source on intra-year income swings. Pamela Morris and colleagues (2015), for example, assembled data for families with children across a 25-year span of the SIPP, beginning in 1984 and ending with the 2008 panel. Overall, their analysis shows that month-to-month income volatility was relatively stable in that time. But two groups saw substantial changes. Volatility increased for the poorest 10 percent of households with children, while it fell for the richest 10 percent. Thus, over the past generation, Morris and colleagues (2015) estimate that the gap in income volatility between the poorest and richest grew by more than 400 percent, compounding the challenges of income inequality.

The SIPP also shows evidence of intra-year episodic poverty, with most spells lasting much less than a year. Ashley Edwards (2014) uses data from the SIPP to find that during the 36 months between 2009 and 2011, 29 percent of Americans experienced poverty for two months or more.[3] Only 4 percent, however, were poor for the entire three years. Nearly 3 in 4 spells of poverty lasted a year or less, half lasted less than 7 months, and 44 percent lasted just 2-4 months. Looking only at 2011, 8.3 percent of Americans were poor every month of the year, but about one quarter of Americans spent two or months below the poverty line (Edwards 2014).[4]

Edwards's subsequent (2015) analysis of monthly income shows a pattern that mirrors earlier findings on annual income from the PSID: that a larger number of people experience episodic poverty compared to those who experience persistent poverty. She analyses the SIPP for

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[3] Most studies of temporary poverty focus on spells of at least two months in a row. Given the relatively short time frame of the Diaries (most households were observed for a year only), our analysis here instead focuses on spells as short as one month.

[4] Even though the SIPP is a representative sample, it is an unrepresentative period in American economic life, coming so soon after the Great Recession of 2007-8. Still, Edwards shows that the basic shape of the evidence lines up with data from earlier periods.

the 48 months between January 2009 and December 2012, defining poverty spells as episodes of poverty lasting two months or more. She categorizes those who experience poverty for most of the reference period (a total time of 44 months or more) as a "chronic" population. This group comprised 14.7 percent of those ever poor and, relative to the whole group that experienced poverty at some point between 2009-2012, was more likely to be black, Hispanic, under the age of 18 or over 65, and to lack a college education. In contrast, two other groups experienced episodic poverty. One experienced poverty as a "crisis" population if between 2009 and 2012 they experienced just one or two poverty spells and were in poverty for five months or less. She estimates that this "crisis" group comprised 23.5 percent of individuals who were ever poor, and, demographically, they were more similar to the U.S. population as a whole (although more likely to be Hispanic, and to be female-headed or to be married-couple families). The third group was the "churner" population, which moved in and out of poverty and were often, but not always, poor.[5] The "churner" group experienced three or more spells on average and were poor between 23 and 69 percent of the reference period. They made up 8.5 percent of the population that was ever poor. They tended to be younger than the "chronic" poor. In sum, the populations were different, and the episodic group as a whole was considerably larger than the chronic group.[6]

Edwards (2015) estimates that the causes of entry to poverty are closely attached to employment status for the persistently poor. Individuals entering "chronic" poverty are more likely to have lost jobs and less likely to have seen a decline in their pay rate. But, for those experiencing episodic poverty, other factors play a larger role, including swings in income within

[5] See also estimates of the correlates of churning by Ann Huff Stevens, 1999.

[6] These three categories are not exhaustive, and Edwards (2015) accounts for just 47 percent of people entering poverty during the reference period. The others mainly experience episodes that are long but not "chronic."

a given job. People entering poverty in “crisis” disproportionately faced a drop in earned family income frequently associated with a drop in pay (as opposed to a drop in transfer income or a job loss). Those experiencing “churning” poverty were also relatively less likely than the “chronic” group to have experienced a job loss.

The results suggest that intuition taken from understanding persistent, long-term poverty fails when applied to short-term poverty. Most important, while studies of long-term poverty focus on poverty due to job loss and changes in household structure, neither is the leading cause of short-term poverty in Edwards’ (2015) SIPP analysis. Instead, the ups and downs of income with no change in employment status are critical.

Edwards’ finding aligns with other work emphasizing the role of within-job swings contributing to overall income volatility. Diana Farrell and Fiona Greig (2016) use a database of JP Morgan Chase bank account transactions to analyze volatility in household income and consumption. The data come from a random sample of 1 million primary account holders between October 2012 and September 2015. They find that month-to-month income swings were more pronounced than year-to-year swings, and that, on average, individuals saw a 40 percent change in total income between months. Across the sample, 55 percent of individuals saw changes in monthly income greater than 30 percent. For the poorest quintile, however, 70 percent saw swings at least that large. The authors attribute most of the income volatility observed in their sample to fluctuations in labor income, and 86 percent of it to within-paycheck variation.

Jonathan Morduch and Rachel Schneider (2017) report a similar result using the U.S. Financial Diaries data. They compare a measure of actual income volatility to versions of the same measure with different types income smoothed out, eliminating in turn any variation in total income coming from regular jobs, self-employment, and non-earnings. In their analysis, regular jobs contribute most to the sample's overall income volatility. They then extend the analysis to measure changes in income volatility after smoothing out within- versus between-job volatility, finding that over half of actual volatility can be attributed to changes in income from the same job. (Their findings draw on an earlier version of the present study; the present version provides a wider set of results.) The Diaries data allow us to go beyond the evidence in the papers above by explicitly connecting episodic poverty to income volatility and its sources.

Coping with Volatile Income

Households cope with volatile incomes by smoothing consumption through saving or borrowing, turning to public benefits, or seeking support from private networks. The SIPP data lends itself to understanding the impact of safety net programs on within-year income volatility. Using that data, Neil Bania and Laura Leete (2009) decompose income volatility due to earnings, public assistance (TANF), SNAP, WIC, and other income. They find that food stamp recipients had lower volatility than they would have had without the assistance, even as levels of income volatility increased for all groups between 1991 and 2001.

Hardy (2016) also finds a volatility-dampening effect of public transfers. He uses annual data from the Census' Current Population Survey to find that the programs TANF, SNAP, and EITC dampened the growth in household income volatility from year-to-year since 1980. The programs, especially TANF and SNAP, had a larger effect for poor households. However, he shows that black families, female-headed households, and those in the very lowest quintile saw smaller impacts from these programs.

Other studies question the public safety net's ability to improve financial stability, pointing to structures and processes that do not adequately account for volatile household incomes. Susan Lambert and Julia Henly (2016) outline how work requirements imposed since reforms in the 1990's have restricted the safety net's availability, particularly in periods of high unemployment or increasing volatility in work hours (see also Hill and Ybarra 2014; Ben-Ishai 2015). Jennifer Romich and Heather Hill (2017) trace problems to programs' often frequent recertification requirements that attach too much weight to intra-year income levels that do not reflect household averages (see also Moffit and Ribar 2008; Ribar and Edelhoch 2008). For example, households may lose benefits because of higher-than-average earnings in the period leading up to recertification, only to have their paychecks drop back down below average once benefits are cut off. If these households re-apply for their lost benefits, they contribute to a benefits churn that is costly for both households and administrators (Romich and Hill 2017; Ben-Ishai 2015). In support of these authors' recommendations to lengthen recertification periods, Mark Prell (2008) uses a statistical model to find that WIC programs, at least, should have an optimal recertification period at least one month longer than the six-month period in place at the time of his analysis. Others suggest reforming public transfer eligibility procedures with more sensitive, shorter recertification periods (Boadway et al 2008).

Heather Hill and Marci Ybarra (2014) note that no systematic evidence exists demonstrating the ability of the safety net to create greater income stability directly or to offer families greater protection in the face of employment instability. Dean Joliffe and Ziliak (2008) raise a key question about the interplay between transfers from different programs, and whether together they serve to dampen or exacerbate overall income volatility – an issue about which, they write, we are just starting to "scratch the surface" (p. 7).

In the absence of public support, households turn to private transfers from friends, relatives, or non-profit organizations. The Federal Reserve's 2014 Survey of Household Economics and Decision-Making, a nationally representative survey, indicates that nearly 30 percent of Americans experiencing a hardship in the previous year had received help from a family member or friend (Board of Governors of the Federal Reserve System 2015). Benjamin Keys (2008), however, finds that, despite the use of various mechanisms, consumption volatility has increased since the 1970's, suggesting that households have a limited ability "insulate consumption from income changes".

Households' own ability to self-protect is partly determined by the ability to generate short-term savings in the face of unstable income. In contrast, policy focus has been mainly on helping families build long-term assets like retirement accounts. Studies show that these accounts are vulnerable to leakage when users withdraw funds early (often with a penalty) in order to meet short-term consumption smoothing needs (Munnell and Webb 2015; Beshears et al 2015; Argento et al 2013).

Short-term debt is another (costly) means of smoothing consumption. Households juggle bills, use credit cards, and refinance home mortgages to make ends meet during negative income shocks, particularly employment-related ones (Seefeldt 2015; Sullivan 2008; Mann 2008; Traub and Ruetschlin 2012; Iversen et al 2011). Roberta Iversen and colleagues (2011) refer to strategies like this as the use of "debt as a safety net", and other studies describe how households turn to borrowing in the face of difficulty obtaining or maintaining public benefits (Seefeldt 2016). Laura Tach and Sara Sternberg Greene (2014) describe household strategies for paying down debt, including decisions around not paying certain obligations that are perceived to create unfair burdens.

Data from the U.S. Financial Diaries provide a new opportunity to explore patterns in episodic poverty, intra-year income volatility, and the effect of different coping tools available to households. The dataset provides monthly cash flow panels with reliable data that gives a detailed view of income from different sources alongside monthly spending. We use it to relate income volatility to monthly poverty spells, to compare between-job and within-job sources of volatility, and to better understand how households cope with fluctuating income.

Data Description

We use data from the U.S. Financial Diaries project to add to evidence on the sources of income volatility that can lead to intra-year poverty spells. The Diaries tracked the financial lives of 235 low- and moderate-income households for roughly twelve months between 2012 and 2013. Each household included at least one working member at the start of the study period. The Diaries are not actual journals filled out by respondents. Instead, data were collected by field researchers who met with households every two to six weeks. The term "diaries" reflects their relatively high-frequency of data on financial transactions and events. The focus of the Diaries is on within-year cash flows with an attempt to capture every dollar spent, earned, borrowed, saved and shared (Morduch and Schneider 2017). The aim was to collect comprehensive data that are more granular and reliable than prior surveys due to the frequent data collection, attention to informal and cash transactions, and the trust developed between field researchers and participants.

Anthony Hannagan and Morduch (2016) describe the steps that were taken to ensure data quality. Most important, attention was given to noisy cash flows that could spuriously show exit and entry from poverty. The key risks were recall bias and misremembered timing. For example, households may have forgotten when exactly income was received, so cash flows may have been clumped together in self-reported data, exaggerating volatility. The biases were more likely for households with greater dependence on cash and for those whose income was patched together from varying sources with irregular payments. These could include part-time work, self-employment, irregular hours, overtime, etc. Since households with these income types tended to be poorer, noise would exaggerate the appearance of income volatility for poorer households.

Given these risks to data quality, the Diaries methodology built in a series of steps to minimize noise. During data collection, field researchers revised questionnaires between each interview to capture new information as household circumstances changed. The team also tracked inconsistencies in the sums of inflows, outflows, and cash balances; evidence of inconsistencies triggered follow-on questions. In addition, after the main period of data collection field researchers followed up with the households to verify transactions that suggested unusually high or low values for income or spending. The team then determined if these spikes and dips were due to measurement error, probing which cash flows were missing or mis-recorded. They focused on outliers that could affect evidence on poverty, especially income values 50 percent above or below each household's median monthly income.[7]

[7] The follow-ups were extensive, as described by Hannagan and Morduch (2016): "In the follow-up period, the team also checked unusually big or small values of tax refund flows, sales of physical assets, and withdrawals from retirement accounts. A similar process was used to detect typos and mistaken duplicates of information. As a cross-check, the team then turned to data collected on the form of transaction and on financial mechanisms. The team checked income inflows against the mode and deposit data to determine the net amount of the income inflow. The team then checked summary statistics to detect outliers and patterns that appeared inconsistent with the field researchers' understandings of the households and the overall sample."

Twelve field researchers each collected data from ten different sub-sites. Sub-sites were part of four broader research sites: Northern California, Eastern Mississippi, the Cincinnati metropolitan area, and the outer boroughs of New York City. In California households were from either urban San Jose or nearby agricultural communities. The Cincinnati-area sample lived in either the urban center or in nearby suburbs or rural towns. In Mississippi, two field researchers collected data from different sets of households in the eastern part of the state. New York sub-sites included one of African-American families in Brooklyn, one of immigrants from Ecuador and Colombia in Queens, and another Queens-based group of immigrants from South Asia. Data collection began in June 2012 in all four regions. It got off to a rocky start in some sub-sites more than others, so it was drawn out past a full year to maximize the number of high-quality months of cash flows available for analysis. Data collection ended in June 2013 in California, July 2013 in Mississippi, and August 2013 in greater Cincinnati and New York.

Together the sites represent a variety of household characteristics and environments, but the households are not representative of the U.S. as a whole. Moreover, the data are not weighted to reflect national population shares. For example, the sample does not capture important parts of the American experience with poverty. The study design led to a sample with about a fifth of the households below the poverty threshold defined by the Census's Supplemental Poverty Measure (SPM), and even fewer in some sites. Because the study focused on working families, households that did not have at least one employed member were excluded from the sample. As a result, the data do not include people living in entrenched poverty.[8]

[8] The eligibility criteria for our sample required participating households to have a source of earned income, but 3 percent of our households spent the year without a job and surviving on public support. Household members lost the jobs they held between being recruited and the study beginning, and did not find jobs during the time we followed them.

Table 1 describes the sample as a whole and by regional site. It illustrates key differences as well as similarities across the four regions. The sample's average annual gross income is $34,348 with a median of $31,348. It is about two-thirds the size of the median reported by the Census Bureau: In 2012, real inflation-adjusted median household income in the U.S. was $52,666 (U.S. Bureau of the Census). To normalize the data across location and household structure, we compare household income to poverty thresholds defined by the Census Bureau's SPM. Income is thus expressed as a percentage of the SPM threshold, with poverty status defined as having income under 100 percent of the SPM threshold. An important advantage of deflating by the SPM is that it controls for differences in regional cost of living. It explains, for example, how households in the California sample have the highest average income in dollar terms, but, due to the relatively high cost of living, the lowest income as a percent of the SPM threshold. Overall, households in the Diaries lived relatively close to the poverty line during the study year at 160 percent of the poverty line on average.[9]

[Table 1 about here]

The four regions have a relatively consistent proportion of households headed by someone who is married (40 percent on average). They also look similar in terms of the age of their heads of households (42 years on average). The average household in every region includes more working-age women than working-age men. Other sample characteristics differ by study site, especially with respect to immigration status and race or ethnicity. A third of households are headed by an immigrant, all of which are based in California and New York City. Household heads who identify as black and non-Hispanic are drawn from three of the four sites, whereas the

[9] For more on the Census Bureau's calculation of SPM, see Short 2011.

sample’s South Asian heads of household are found only in New York City. The California sample is made up of only heads of household identifying as Hispanic or Latino, while white non-Hispanic heads of household are drawn only from the study’s Cincinnati and Mississippi regions. Given the heterogeneity in the sample, our main aim is to demonstrate the prevalence of income volatility and draw connections to poverty spells and coping mechanisms.

Episodic Poverty and Earnings Volatility

In the Diaries sample, households near the poverty line often move in and out of poverty during the year. Seventy percent of the sample spent at least one month in poverty; only two percent spent every month below the poverty line (which, as described above, partly results of the sample method selecting households with at least one working member at the start). Figure 1 displays these statistics by income level, breaking the sample into four groups based on their annual income as a percentage of the SPM threshold. The figure shows that 95 percent of those with income between 100 and 150 percent of SPM on average were “sometimes poor”, spending at least one month of the year in poverty. Of those between 150 and 200 percent of the SPM, 57 percent spent at least a month in poverty. Most surprisingly, nearly a third of those in the sample with income greater than twice the SPM threshold spent at least one month in poverty. Just 8 percent of households with annual income below the poverty line were always poor throughout the year.

We use the Diaries’ disaggregated income data to investigate the types of income fluctuations responsible for the observed episodic poverty. First, we re-calculate monthly incomes after removing volatility due to changes in employment (between-job volatility).

Second, we remove volatility due to monthly variation from within the same job (within-job volatility). We use these two new sets of monthly income totals to assess the roles of job changing versus within-job paycheck variability.[10]

[Figure 1 about here]

The second two sets of bars in Figure 1 show that at most income levels, smoothing either between-job volatility or within-job volatility reduces the percentage of households that are sometimes poor, and that the effect of smoothing within-job volatility has a larger impact. Smoothing away between-job volatility yields that the percentage of households that are sometimes poor in the highest income group would drop from 32 to 27. Its effect on episodic poverty is more muted for other income groups, though, and nowhere are the differences statistically significant at conventional levels.[11]

Comparisons in Figure 1 show that in the sample, most episodic poverty caused by earnings volatility can be traced to month-to-month within-job variations. The percentage of households experiencing episodic poverty with annual incomes above 200 percent of SPM would be cut by more than half, a drop from 32 to 13 percent, had they received steady monthly

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[10] Monthly income with between-job volatility smoothed is calculated in a 3-step process. First, average monthly income from each job is determined, excluding the $0-income months before each job began and after it ended. Then, average monthly income from all jobs combined is determined within each household, including months when no income was earned. Finally, monthly income totals are adjusted by subtracting from total income the sum of within-job means and adding back in the mean of income from all jobs combined. Smoothing within-job volatility follows a related 2-step process. We first subtract each job's actual monthly income from total monthly income. Then, we add back in to those months the sum of within-job means, described above, only during the months when each job was received.

[11] We note that between-job volatility helps households with annual incomes between 150 and 200 percent of SPM to avoid episodic poverty. This is possible due to the nature of correlations between the timing of jobs and fluctuations of other income sources.

incomes from each of their jobs. For households with annual incomes between 100 and 150 percent of SPM, the percentage of those who would be sometimes poor drops from 95 to 85 percent. These drops are statistically significant with 95 percent confidence.

Income and Spending Volatility

We turn to coefficients of variation to explore further. Following others in the field (Bania and Leete 2009; Morris et al 2015; Hannagan and Morduch 2016), our main measure of income volatility is the coefficient of variation (CV) of monthly income for each household during the study period. We thus calculate 235 CVs, one for each household, and analyze their distribution.

A household's income CV is defined as $CV = \sigma/\mu$, where σ is the standard deviation of the household's monthly income and μ is the mean monthly income for the household. The same calculation can be applied to any type of cash flow, and we do the same for monthly household spending. Unlike volatility measures like variance, CV allows the variability of richer and poorer households' data to be compared directly. The Diaries' average income CV is 0.36 after excluding income from tax refunds and credits (usually coming in the form of a "spike" in a single month of the year), and its average spending CV is 0.36 as well.[12]

[12] In measuring volatility, we have erred on the side of conservatism. In addition to excluding tax refunds and credits from monthly income, we took other steps to limit upward bias (accepting the cost of downward bias). Monthly income calculations, for example, also exclude funds categorized as "education assistance", also often received as large monthly "spikes", because of ambiguity as to whether they should be classified as grants or loans. Income totals also exclude gift cards received from the U.S. Financial Diaries team, roughly $650 total throughout the year, as thank-yous for participating in the study. The income calculation does include private transfers from family and friends. Monthly spending averages and standard deviations are calculated after excluding months when households received tax refunds or credits, also normally associated with spending "spikes". Finally, both income and spending means and standard deviations are calculated after excluding months in which income or spending totals fall

Figure 2 presents the CV by household income, again shown in four groups based on annual income as a percentage of SPM. The figure compares income CV with spending CV and, at first look, provides little evidence for consumption smoothing by households in the Diaries sample, as the average level of income and spending CVs track each other across income groups.[13] Analysis by Morduch and Schneider (2017), however, shows evidence of considerable consumption smoothing together with evidence of frequent spending spikes uncorrelated with income spikes. The result is that income and spending CVs turn out to be similar in magnitude, but not because households are living hand-to-mouth, simply consuming all their income in the month it is received.

[Figure 2 about here]

Figure 3 extends the between-job and within-job smoothing analysis from Figure 1. We compare the observed mean income CV for each income group with what it would have been without volatility due to job changes throughout the year, and then without volatility due to monthly within-job variation. It reflects the results from Figure 1 in that within-job volatility has a much larger effect on overall income CV levels. Smoothing between-job volatility causes average income CV to drop by 7 percent at most across income groups, from 0.41 to 0.38 in the lowest income group. With within-job volatility smoothed out, average income CV drops by at

below $100. This last exclusion aims to minimize the influence of months when incomplete data may have been collected, due to either human error or recall bias. These steps push the volatility measures toward being lower bounds of true volatility.

[13] The comparison between income CV and spending CV should be interpreted with care given that spending data in the U.S. Financial Diaries were underreported compared to income data. It is unclear whether the nature of missing data increases or decreases the spending CVs.

least 24 percent in each income group, from 0.41 to 0.31 in the lowest income group and from 0.37 to 0.28 for households with annual incomes greater than twice the SPM threshold.

[Figure 3 about here]

As a robustness check we measure changes in volatility based on the standard deviation of arc percent change (SDAPC) in income or spending from month-to-month. This volatility measure is also common in the literature (Dynan et al 2012; Ziliak et al 2011; Cappellari and Jenkins 2013). One advantage is that the SDAPC is bounded at 2.0, making its outliers less of a concern compared to outliers of the CV. The SDAPC is also useful for showing changes over time as opposed to showing volatility in a snapshot period. The measure is defined for each household as

$$\text{SDAPC} = \sqrt{var\{\frac{y_t - y_{t-1}}{\overline{y_t}}\}},$$

where y_t is household income or spending in time t and $\overline{y_t}$ is a household-specific mean monthly income or spending between time t and time t – 1. The sample's average income SDAPC is 0.50 when measured without tax refunds and credits. Note that this measure and CV are on two separate scales and not comparable with each other. We find roughly the same patterns of income and spending SDAPC across income groups as we do with CV.

Volatility and the Role of Transfers

In the face of imperfect consumption smoothing options, households may cope with volatile incomes by turning to public benefits or seeking support from private networks. This part of our analysis tests for the effect on CV of adding transfers to other income. We focus on five public transfers: SNAP, unemployment insurance, public assistance (TANF), Social Security for old age, and Social Security for disability (including SSD, SSI, and SSDI). We additionally analyze the roles of three types of private transfers: resources from family and friends, child support income, and help from non-profit or religious institutions. These eight transfers are those most prevalent in the Diaries data set.

Of the eight types of transfers analyzed, resources from family and friends were received by the highest portion of households, followed by SNAP, child support, Social Security for disability, and help from non-profits. Unemployment insurance, public assistance, and Social Security for old age were the least common types of transfers received by households in the Diaries sample. Half of the sample received a public transfer during the study period, excluding tax refunds and credits. (When counting tax refunds and credits, 86 percent of the sample received any public transfer.) Households received Social Security more consistently than other transfers: Among those receiving it for either old age or disability, it came nearly 10 out of 12 months per year on average. SNAP receipt was the next most consistent, followed by child support and public assistance receipt which receiving households brought in for about 7 months of the year on average. Least consistent were resources from family and friends, unemployment, and help from non-profits which all came into receiving households for fewer than five months per year on average.

We conduct a CV decomposition that relates transfers to income volatility for households. Specifically, we measure how the inclusion of transfers in household income affects income CV by comparing the CV of pre-transfer income with the CV of post-transfer income. At least three of the transfers analyzed – SNAP, public assistance, and unemployment insurance – are intended in part to act as temporary buffers for households experiencing lower-than-usual income. To that extent, we expect that their inclusion in income totals should reduce overall income CV on average. At the same time, if states allow for six to twelve months of transfer receipt before re-certification, then annual income (that is, pooled over multiple months) may naturally be a larger predictor of SNAP receipt than income in a particular month (see Romich and Hill 2017 on benefit re-certification). Social Security for old age and disability are supposed to come consistently throughout the year rather than as temporary buffers so their expected effect on income volatility is ambiguous.[14]

Each transfer's effect on CV can be driven by changes in the CV formula's numerator (σ, the standard deviation) or by changes in the denominator (μ, mean monthly income), or both. To understand the root of each transfer's effect we analyze the change from adding transfers on both components of income CV. Changes in the standard deviation would tell us that transfers affect volatility. Lower post-transfer standard deviations would imply that transfers perform an insurance function by filling in monthly income when other sources (mainly earnings) are lower than average. On the other hand, transfers that change CV only by raising average household income provide households with more resources but do not directly counter the ups and downs of other income. We use this decomposition to analyze the individual roles of each of eight transfers. We apply the same analysis to all types of government transfers combined in order to assess the collective effect of the public safety net.

[14] The expected effect of all three private transfers is ambiguous. On the one hand, households turn to their private networks in months when their income drops. But their ability to receive funds from these sources is limited by their private networks' ability to provide a buffer when needed. This problem may occur when people within the same community experience seasonal income fluctuations in tandem, or when non-profit organizations have assistance available on a rigid schedule.

Table 2 shows results for three different sample definitions in three different panels. Each row presents the effect of a different transfer on income CV. The first panel shows results for all households with income below 150% SPM, a sample of 124 households. The second panel does the same for all households that ever received any public transfer (not including tax refunds and credits), a sample of 117 households. The third panel shows the volatility effect of each transfer only for households that ever received it. The third panel thus shows the un-diluted effects on CV of each transfer, compared to the first two panels with expanded samples. The first two panels keep the sample consistent across the analysis of each income source.

The first two columns of Table 2 compare income CV before and after each transfer is included in total income. The third column uses values in the first two columns to calculate the percent change in average CV with the inclusion of each transfer. Finally, the fourth and fifth columns show how each component of income CV changes for the average household with the inclusion of each transfer.

The third column of Table 2 shows that the addition of most transfers to other income leads to either no change or a decrease in income CV on average. SNAP, for example, reduces average income CV by 7 percent for households with annual income below 150 percent of SPM, by 10 percent for households that ever received any public transfer, and by 12 percent among only households that ever received SNAP. Some transfers have a negligible effect on wider sample definitions while reducing CV more noticeably strictly among their recipients, Unemployment does not change average income CV among the full sample of households with annual income below 150 percent of SPM, while it brings its recipients' average income CV down by 21 percent. Resources received from family and friends are one exception to the CV-reducing effect of transfers, increasing the average income CV of its recipients by 3 percent. All public transfers combined serve to reduce income CV on average. For the samples shown in the first two panels of Table 2, this collective effect of the government safety net (not surprisingly) exceeds the effect of any form of public transfer on its own.

Table 2 illustrates that drops in income CV due to transfers are largely driven by the increases they cause in mean monthly income, not by reductions in income's variance. After the addition of nearly every transfer analyzed, the average percent change in the standard deviation of monthly income is lower than the average percent change in mean monthly income. This holds true for SNAP, for example, which causes the average household in the <150% SPM group's standard deviation to change by 2 percent compared to its effect of increasing the average mean by 12 percent. The exceptions to this pattern are resources received from family and friends and help from non-profits and religious institutions. Table 2 shows evidence that these two transfers' average effects on standard deviation are slightly larger than their average effects on the mean.

Moreover, the inclusion of most transfers ends up increasing, as opposed to decreasing, the standard deviation of monthly income, a sign that they exacerbate rather than buffer the income volatility experienced by Diaries households. Unemployment insurance is the only transfer that decreases the standard deviation of monthly income. It brings the standard deviation down by 4 percent on average among its recipients, suggesting that it tends to serve its aim of buffering months when other income is lower than usual. In contrast, other transfers increase income variance, helping households mainly by increasing recipients' average income levels.

[Table 2 about here]

An alternative measure of income volatility, the standard deviation of monthly income's SDAPC, provides a check on the validity of results in Table 2. Table 3 illustrates the sample's mean pre-transfer and post-transfer SDAPC in its first two columns. As in Table 2, the third column uses values in the first two columns to calculate the percent change in average SDAPC with the inclusion of each transfer. This second to last column shows that most transfers serve to reduce SDAPC on average in the Diaries sample, mirroring CV results.

[Table 3 about here]

The above analysis shows that most transfers reduce income volatility, as measured by CV, by increasing average monthly income more than reducing its variance. We further tested this finding with a preliminary regression analysis (not shown) of the relationship between transfer receipt and the level of other income by month, focusing on SNAP. SNAP is the most widely used government program by study participants, and it is also a key component of the public benefit structure at the national level: Judith Bartfeld and colleagues (2016) note that SNAP is "at the heart of the nation's safety net". Despite much thought that has been devoted to SNAP program management standards, it is still unclear how sensitive the eligibility-determination process is to intra-year income dips (see, for example, Joliffe and Ziliak 2008). Work requirements for certain households or recertification procedures that do not acknowledge intra-year income volatility may even make SNAP receipt positively correlated with non-SNAP income. While our analysis shows that food stamps appear well-targeted to populations in need, we found no association between receipt of SNAP benefits and the level of other, non-SNAP income in a given month (once controlling for a household's income through the year).[15] The

[15] The regression's dependent variable is a binary indicator for SNAP receipt in the month. Its main explanatory variable is all monthly income other than SNAP as a percent of its average within each household. The regression framework allows us to hold constant other variables as well. Our model includes annual income level, household demographic characteristics, and site fixed effects. A negative association between SNAP receipt and other, non-SNAP income in the month would be evidence that SNAP buffers when other income drops, dampening overall

result is in line with the CV decomposition in Table 2, supporting the idea that, while SNAP helps low income households, it does not directly act as a buffer against monthly income dips in this sample.

Conclusion

The results here draw on and extend previous work that finds substantial income volatility for American households. We connect intra-year income volatility to episodic poverty, showing that episodic poverty ties to within-job instability. While the results are in line with data from large, nationally representative data sets, the U.S. Financial Diaries sample is not nationally representative; it reflects the experience of just 235 households and under-weights both the poorest households and the best-off households. It thus serves as a way to connect patterns rather than as a guide to national trends.

In that context, the Diaries describe important connections. The data confirm patterns of high volatility concentrated at low-income levels and provides both support and more nuance to the idea that transfers reduce overall income volatility. We show that income volatility drives a substantial share of episodic poverty, and that much of income volatility is driven by within-job pay variability. We further find that most public and private transfers reduce income volatility for households in the sample. Our coefficient of variation (CV) decomposition shows that most transfers, including the combined effect of public benefits, affect CV by raising average

income volatility. No association or a positive association would suggest that SNAP is less responsive to dips in other monthly income, and may even exacerbate volatility. The sample includes 2,463 household-months across 223 households, excluding households that lack data for any of the demographic controls.

household income rather than by buffering fluctuations in month-to-month income. (Exceptions are unemployment insurance and resources received from family and friends.)

The evidence suggests that to develop a policy agenda for households experiencing episodic poverty, we need a firmer understanding of the relationship between episodic poverty, income volatility, and strategies used by households to cope with ups and downs. These strategies involve both transfer receipt and financial coping mechanisms like saving and borrowing to smooth consumption. Often, the agenda of those who seek to reduce poverty and the agenda of those who seek to help people better manage their financial lives are distinct. But the Diaries evidence shows that they should overlap. Caroline Ratcliffe and colleagues (2016), for example, show that the ability to smooth consumption with savings (aided by the lifting of asset-holding limits under SNAP rules) reduces the likelihood that program participants will need the program in the future. Similarly, Kristin Seefeldt (2015) and Tach and Greene (2014) highlight that smoothing consumption can entail taking on expensive debt, with a lasting legacy that can include high-cost obligations and the increased possibility of wage and tax refund garnishment. Financial choices and financial access, both helpful and unhelpful, are thus bound up with the poverty of vulnerable households.

The evidence also points to the need for innovations in safety nets. Lambert and Henly (2016) highlight how variability in work hours leads to income volatility. We draw two implications. First, schedule variability can pose challenges for workers who need to meet rigid work requirements to secure benefit eligibility (see also Seefeldt 2016). Certification procedures need to recognize that workers often have no control over their work hours in a given period (despite their desire to work). Second, together with our evidence, we anticipate that efforts to create more predictable and regular work schedules may have additional benefits by reducing the probability of episodic poverty for some workers.

Romich and Hill (2017) describe delays, lags, and other problems with benefit re-certification. Moreover, they argue that short-term income fluctuations “do not necessarily move families outside of the target population in a meaningful way” (p. 3). Implications include the benefits of lengthening re-certification periods and creating flexibility with regard to reporting requirements about income changes.

These findings help explain our finding of a lack of alignment between months in which incomes dip and months in which transfers are available. On one hand, the lack of alignment may be helpful, suggesting that vulnerable households are targeted in general, rather than in specific moments of need. On the other hand, the evidence suggests that some households in need may be unable to secure the support they require in particular moments of vulnerability (e. g. Edin and Shaefer 2015). This is an important area for further inquiry.

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Table 1. Descriptive statistics for the U.S. Financial Diaries sample

	Full Sample	Region			
		CA	MS	OH/KY	NY
Number of households	235	44	47	69	75
Household income and poverty					
Annual take-home household income ($)	34,348	38,737	30,853	37,321	31,226
Annual household income as percent of SPM	160	129	177	191	140
<100% SPM annually (%)	21	43	4	6	33
100-150% SPM annually (%)	31	23	32	32	36
150-200% SPM annually (%)	22	23	30	29	10
>200% SPM annually (%)	26	11	34	33	21
Months per year in SPM poverty	3.8	5.3	2.2	2.4	5.2
Demographic data					
Head of household is married (%)	40	41	40	38	40
Head of household is an immigrant (%)	35	64	0	0	73
Head of household is white non-Hispanic (%)	26	0	45	58	0
Head of household is black non-Hispanic (%)	30	0	55	41	23
Head of household is Hispanic or Latino (%)	32	100	0	1	40
Head of household is South Asian (%)	12	0	0	0	37
Head of household age*	42	35	47	39	45
Number of women age 18-65**	1.08	1.00	1.06	1.12	1.10
Number of men age 18-65**	0.75	0.75	0.74	0.85	0.95
Head of household is a woman (%)***	57	55	53	67	51
Income type receipt (%)					
SNAP	38	34	40	52	24
Unemployment	7	2	11	10	4
Public assistance/TANF	7	14	2	6	8
Social security: old age	6	2	13	6	3
Social security: disability	14	5	26	19	8
Any public transfer (excluding tax refunds)	50	43	60	65	33
Resources from family and friends	65	71	75	75	47
Child support income	15	11	21	26	4
Help from non-profits or religious institutions	9	11	6	17	1

Note: SPM = supplemental poverty line. Data were collected between 2012 and 2013.

* Missing data from one household in CA, one in NY

** Missing data from one household in OH/KY, one in NY

*** Heads of household were self-defined by respondents. Eighteen percent of woman-headed households are married, and they include 1.2 children on average. Compare with 67 percent of man-headed households that are married and include 1.4 children on average.

Table 2. The effect of income source on the CV of household income

	Mean CV without income type	Mean CV with income type	% change in mean CV	Mean % change in SD	Mean % change in mean	# house-holds
<150% SPM						
SNAP	0.41	0.38	-7	2	12	124
Unemployment	0.38	0.38	0	0	1	124
Public assistance/TANF	0.38	0.38	0	0	2	124
Social security: old age	0.40	0.38	-5	3	11	124
Social security: disability	0.39	0.38	-3	13	17	124
All public transfers together	0.49	0.38	-22	19	63	124
Resources from family and friends	0.38	0.38	0	9	8	124
Child support income	0.38	0.38	0	1	2	124
Help from non-profits or religious institutions	0.38	0.38	0	1	1	124
Conditional on any public transfer receipt						
SNAP	0.42	0.38	-10	2	14	117
Unemployment	0.40	0.38	-5	-1	2	117
Public assistance/TANF	0.39	0.38	-3	0	3	117
Social security: old age	0.41	0.38	-7	5	14	117
Social security: disability	0.41	0.38	-7	24	26	117
All public transfers together	0.54	0.38	-30	32	81	117
Resources from family and friends	0.38	0.38	0	13	9	117
Child support income	0.39	0.38	-3	0	2	117
Help from non-profits or religious institutions	0.38	0.38	0	1	1	117
Conditional on each income type receipt						
SNAP	0.42	0.37	-12	3	19	88
Unemployment	0.48	0.38	-21	-4	17	16
Public assistance/TANF	0.53	0.47	-11	2	17	17
Social security: old age	0.59	0.34	-42	41	123	13
Social security: disability	0.54	0.43	-20	83	91	33
All public transfers together	0.52	0.38	-27	32	81	117
Resources from family and friends	0.36	0.37	3	14	11	153
Child support income	0.38	0.36	-5	5	11	36
Help from non-profits or religious institutions	0.36	0.36	0	7	4	21

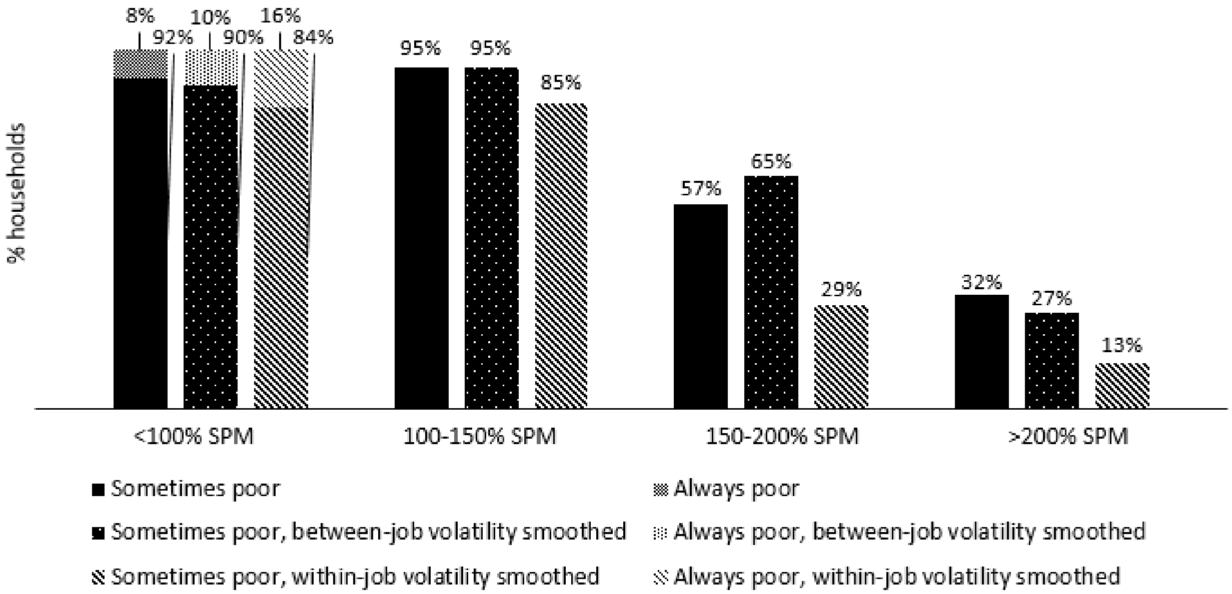
Note: CV = coefficient of variation. US Financial Diaries data.

Table 3. The effect of income source on the SDAPC

	Mean SDAPC without transfer	Mean SDAPC with transfer	% change in mean SDAPC	# house-holds
<150% SPM				
SNAP	0.58	0.52	-10	124
Unemployment	0.53	0.52	-2	124
Public assistance	0.53	0.52	-2	124
Social security: old age	0.54	0.52	-4	124
Social security: disability	0.52	0.52	0	124
All transfers together	0.64	0.52	-19	124
Resources from family and friends	0.55	0.52	-5	124
Child support income	0.53	0.52	-2	124
Help from non-profits or religious institutions	0.52	0.52	0	124
Conditional on any public transfer receipt				
SNAP	0.55	0.48	-13	117
Unemployment	0.49	0.48	-2	117
Public assistance	0.49	0.48	-2	117
Social security: old age	0.51	0.48	-6	117
Social security: disability	0.49	0.48	-2	117
All public transfers together	0.64	0.48	-25	117
Resources from family and friends	0.50	0.48	-4	117
Child support income	0.49	0.48	-2	117
Help from non-profits or religious institutions	0.48	0.48	0	117
Conditional on each income type receipt				
SNAP	0.56	0.47	-16	88
Unemployment	0.56	0.47	-16	16
Public assistance	0.65	0.58	-11	17
Social security: old age	0.68	0.46	-32	13
Social security: disability	0.58	0.54	-7	33
All public transfers together	0.64	0.48	-25	117
Resources from family and friends	0.49	0.47	-4	153
Child support income	0.46	0.43	-7	36
Help from non-profits or religious institutions	0.41	0.42	2	21

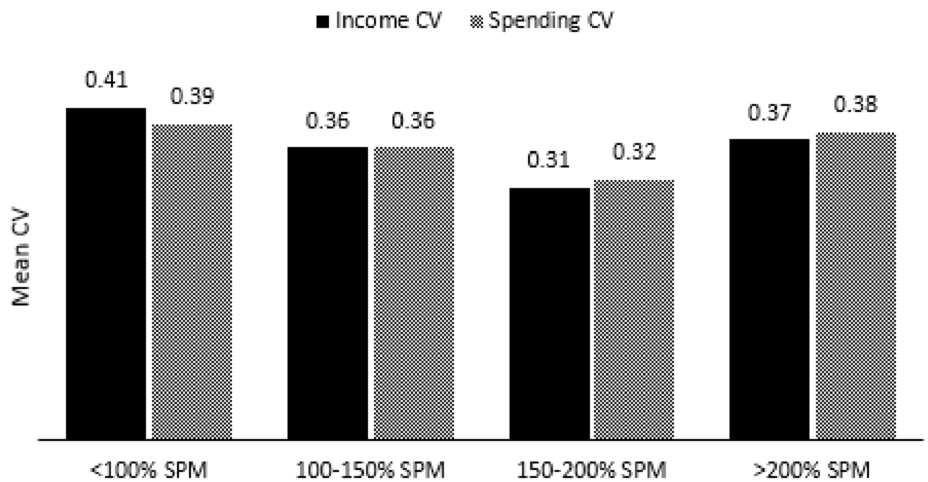
Note: SDAPC = standard deviation of the arc percent change of monthly household income. US Financial Diaries data.

Figure 1. The incidence of persistent and episodic poverty, by economic status



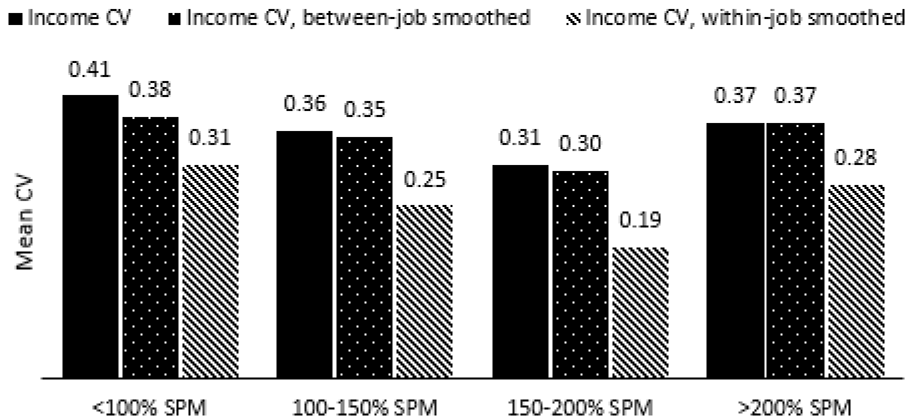
Note: 235 households in in US Financial Diaries data. Household income data are grouped by percentage of the supplemental poverty measure threshold (SPM). The difference between the unsmoothed data and data with smoothed between-job volatility is not statistically significant at the 10 percent level overall or for any individual income group. The difference between the unsmoothed data and data with smoothed within-job volatility is statistically significant with a p-value of 1 percent for the sample overall, and 5 percent for individual income groups.

Figure 2. Income and spending CV, by economic status



Note: 235 households in in US Financial Diaries data. The difference between the sample's income and spending CV is not statistically significant at any income level.

Figure 3. Income CV, controlling for between-job and within-job income variation.



Note: 235 households in US Financial Diaries data. The difference between observed income CV and income CV with between-job volatility smoothed is statistically significant at the 1 percent level for the sample as a whole, and for the lowest income group, though p-values jump to 0.179 and higher for the three higher income groups. The effect on CV of smoothing within-job volatility is statistically significant at the 1 percent level for the sample as a whole and within each income group. These analyses were replicated excluding seven outlier households with either income or spending CV greater than 1.0, and the results (not shown) roughly match those presented here.