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RESEARCH ARTICLE

Income Dynamics and the Affordable Care Act

Lara D. Shore-Sheppard

Objective. To examine the sources of family income dynamics leading to movement into and out of Medicaid expansion and subsidy eligibility under the Affordable Care Act.

Data Source. Survey of Income and Program Participation (SIPP): 1996, 2001, 2004, 2008 panels.

Study Design. Considering four broad subsidy eligibility categories for monthly Modified Adjusted Gross Income (MAGI) (<138 percent of the Federal Poverty Level [FPL], 138–250 percent FPL, 250–400 percent FPL, and >400 percent FPL), I use duration analysis to examine determinants of movements between categories over the course of a year.

Data Collection/Extraction. Using detailed monthly data, I determine the members of tax-filing units and calculate an approximation of MAGI at the monthly level. The analysis sample is adults ages 22–64 years.

Principal Findings. Incomes are highly variable within a year, particularly at the lower end of the income distribution. Employment transitions, including transitions not involving a period of nonemployment, and family structure changes strongly predict sufficient income volatility to trigger a change in subsidy category.

Conclusions. Income volatility arising from employment and family structure changes is likely to trigger changes in subsidy eligibility within the year, but the sources and effects of the volatility differ substantially depending on the individual's position in the income distribution.

Key Words. Affordable Care Act, Medicaid, income volatility, health insurance

Provisions intended to help low- and moderate-income families obtain health insurance coverage are central components of the Affordable Care Act (ACA). These provisions include eligibility for Medicaid for individuals with family incomes up to 138 percent of the federal poverty level (FPL hereafter), premium tax credits and subsidized reduced cost sharing on a sliding scale for individuals with family incomes 138–250 percent of the FPL, and sliding-scale premium tax credits alone for individuals with family incomes 250–400

percent of the FPL.[1] While this tiered structure is straightforward in conception, the fact that family incomes are dynamic poses challenges for achieving the goal of universal health insurance using such a structure. To the extent that an individual spends periods within a year in different income categories, the goal of seamless universal coverage may become more difficult to attain. This has important implications both for individuals' health—as research has shown that transitions in coverage are associated with reductions in use of care—and for their economic well-being. Although the reform law requires that enrollment in Medicaid (and CHIP for children) and in the plans offered through the insurance exchanges be coordinated, frequent or significant changes in subsidy status make such coordination substantially more challenging. In addition, the Supreme Court decision making the Medicaid expansion optional for states means that in some states, income changes may lead not only to changes in coverage types but also to changes in insured status.

If movement between eligibility groups occurs frequently, states must be prepared for frequent redeterminations of eligibility and movement across subsidy categories. Moreover, as the premium subsidy is being implemented via a refundable, advanceable federal income tax credit, families that qualify for one level of subsidy at the time of application and receive an advance based on that level may actually qualify for a different level when their income is averaged over the entire tax year. Despite the importance of within-year income movements for subsidy and other public program eligibility, there has been little research on the determinants of such movements. Research on family income dynamics in labor economics has focused on movements across, rather than within, years, and while there is substantial research on employment and welfare participation dynamics, income volatility may arise from a variety of sources, including changes in family composition (potentially changing both the earnings contributions of family members and the income-to-needs ratio), movements into and out of employment, movements from one job to another, and earnings volatility within jobs, as well as changes in unearned income.

In this paper, I use data from the Survey of Income and Program Participation to investigate the sources of income dynamics sufficient to move individuals into, out of, and across four broad income groups corresponding to the various types of insurance subsidies under the ACA outlined earlier (<138

Address correspondence to Lara D. Shore-Sheppard, Ph.D., Department of Economics, Williams College and National Bureau of Economic Research, 24 Hopkins Hall Drive, Williamstown, MA 01267; e-mail: lshore@williams.edu.

percent of the FPL, 138–250 percent of the FPL, 250–400 percent of the FPL, and above 400 percent of the FPL). Knowledge about what factors lead to such movements and the circumstances of the families to which they occur will help policy makers implement the reform in such a way as to minimize the burden on families and reduce administrative costs for states.

Literature Review

There is a substantial and growing literature in labor economics examining income mobility over time, with early papers focused on decomposing earnings variance into permanent and transitory components (see, e.g., Gottschalk and Moffitt 1994 and Haider 2001) and with more recent work asking whether and to what extent year-to-year income volatility has increased since the 1970s (see, e.g., Dahl, DeLeire, and Schwabish 2011; Dynan, Elmendorf, and Sichel 2012; Hardy and Ziliak 2014). The emerging consensus is that year-to-year volatility has increased by between 10 and 100 percent, with greater volatility at the bottom of the income distribution (Hardy and Ziliak 2014). This finding suggests that volatility *within* the year may be substantial as well, but to date there has been no work focusing on short-run income volatility and its correlates. However, to the extent that month-to-month volatility is substantial, there are important implications for policies such as the ACA that rely on various levels of income-to-needs ratios (i.e., income accounting for family size) to determine eligibility.

The relationship between income dynamics and the structure of subsidized insurance under the ACA has been little studied thus far. An important exception is the paper by Sommers and Rosenbaum (2011). Sommers and Rosenbaum use data from the 2004 (and some of the 2008) SIPP to examine movements of individuals across the Medicaid threshold. They focus only on nonelderly adults with family incomes below 200 percent of the FPL at the start of the sample and examine semiannual snapshots of income for this group. They find evidence of substantial shifting between income levels conferring Medicaid eligibility and income levels conferring eligibility for subsidized coverage through the health insurance exchanges, with roughly half of their sample making a transition in at least one of the two 6-month periods in the year. They also examine some of the correlates of income fluctuations, including demographics, family composition, and initial income and health insurance status, finding that various demographic characteristics including marital status, gender, race, and education are highly correlated with the

probability of experiencing a transition between income categories. However, they do not attempt to examine the underlying changes in employment or family structure that lead to the income transitions they observe, nor do they distinguish income increases from decreases, looking only at whether income changed.

My work in this paper is similar in spirit to that of Sommers and Rosenbaum, but with several key differences. Most important, I examine possible events that may trigger sufficiently large changes in income to move an individual between subsidy categories, rather than fixed correlates alone. My methodology allows me to examine factors that may change over time, rather than only those that are fixed at the beginning of a spell. This is useful for policy, as understanding what events may lead to a particular type of income change (rather than just what characteristics are common among individuals experiencing income changes) will help policy makers design strategies to accommodate the observed income dynamics. While Sommers and Rosenbaum restrict their focus only to adults with incomes initially below 200 percent of the FPL, I examine dynamics across a more widely varying range of income categories. It is important to study high-income as well as low-income individuals to determine what events are likely to precipitate a move into subsidy eligibility among the formerly ineligible. I also examine dynamics that may occur at a higher frequency, using the monthly data rather than observing only 6-month snapshots. Higher frequency dynamics are certainly observed in the data, with roughly 25 percent of individuals observed to experience six or more transitions across income boundaries within a 2–4-year period. Finally, unlike Sommers and Rosenbaum, I distinguish the direction in which an income transition occurs, estimating models that allow the correlates of income increases and decreases to differ.

Methodologically, this paper is informed by the literature on poverty dynamics, in particular the work on poverty spells of Bane and Ellwood (1986) and Stevens (1999). Bane and Ellwood focus on single spells of poverty and show the important distinction between the stock of the poor at any one time and flows into and out of poverty. Stevens examines multiple spells, which allows her to look at reentry into poverty as well as exit from poverty. She finds that because the reentry probability is high, there is greater long-term persistence in poverty than had been previously recognized. Following Stevens, I examine movements into and out of each of the income groups studied, including both movements to higher incomes and movements to lower ones. The spells I identify are denominated in months, however, rather than being denominated in years as in the poverty dynamics literature.

DATA

To examine income dynamics at the subannual level, I use data from the Survey of Income and Program Participation (SIPP), a series of longitudinal datasets lasting between 2 and 4 years each, collected for a national sample of the U.S. population by the Census Bureau. I use data from the panels beginning in 1996, 2001, 2004, and 2008, which span the years 1996 to 2010. SIPP respondents are interviewed once every 4 months about income, employment, family composition, and program participation during the previous 4 months (termed a wave). While some researchers (see, e.g., Grogger 2004; Ham and Shore-Sheppard 2005) have suggested that the data should only be used at the 4-month level due to possible "seam bias" arising from a tendency to report the same answer for every month in the wave, recent research has shown that this approach is not preferable to the approach I use of including a dummy variable for the fourth month (see Ham, Li, and Shore-Sheppard 2009). While such a reporting pattern is a limitation of the data (likely to lead to fewer income changes than may actually have occurred), unfortunately there is no data source other than the SIPP that provides information about earned income and unearned income at the subannual level along with demographic and family structure information that could be used to compare with the SIPP results.[2]

Although I use information on all individuals in a family to determine relevant family income, as family composition may change over the year, the individual is the unit of analysis. The focus of my analysis is thus "original sample" adults, ages 22 to 64 (the ages most likely to be impacted by the provisions of the ACA discussed above), who live in states identified in the SIPP. The term "original sample" refers to the sample the Census Bureau identifies at the beginning of each panel's data collection and is the group of individuals the Census Bureau attempts to follow over time. Individuals who join the household at a later point are not followed if they move out. For the duration analyses, I use all months until the person drops out or the sample ends. I do not use any observations following a break in an individual's data. In panels prior to the 2004 panel, smaller states (Maine, Vermont, North Dakota, South Dakota, and Wyoming) are not identified in the data. As I link other state-level information such as unemployment rates to the SIPP, prior to 2004, I drop individuals in states that are not identified.

Using the detailed family relationship information reported in the data, I determine the members of a family corresponding as closely as possible to a

tax-filing unit (taxpayer, spouse if any, and all dependents). As some information that would allow me to determine a tax-filing unit more exactly is lacking from the survey (who is able to claim the child in the case of divorced parents with joint custody, for example), there are likely to be some cases where I have misidentified the family members; however, there is sufficient detail that the majority of families should be correctly identified. Once I have determined the family members in each month, I sum up relevant income over the members of the family to come as close as possible in the SIPP data to a monthly equivalent of modified adjusted gross income (MAGI).[3]

Within-Year Family Income Volatility

To the extent that incomes are fluid, individuals may move into and out of Medicaid and subsidy eligibility. Looking at the distribution of the lowest and highest income categories for individuals in a year (Table 1), it appears that among individuals who spend at least 1 month with income below 138 percent of the FPL, there is a nonnegligible percentage spending at least 1 month in one of the higher categories. Similarly, among individuals who spend at least 1 month in the above 400 percent of the FPL income category, at least some spend time in one of the other categories. Incomes appear to be more fluid at the bottom of the income distribution than at the top, with only 10 percent of individuals spending all year in the lowest category, but 25 percent of individuals spending all year in the highest category. The two ACA tax credit categories (the groups spanning the 138 percent to 400 percent of the FPL

Table 1: Distribution of Lowest and Highest Income Categories of Individuals in a Year

	Highest Income Category in Year				
	< 138% FPL	*138–250% FPL*	*250–400% FPL*	*> 400% FPL*	*Total*
Lowest income category in year					
<138% FPL	10	9	6	7	32
138–250% FPL	0	4	9	8	21
250–400% FPL	0	0	6	16	22
>400% FPL	0	0	0	25	25
Total	10	13	21	56	100

Note. Table entries presented as percentages. Data from 1996, 2001, 2004, and 2008 SIPP panels; original-sample adults between ages 22 and 64 years who are observed for an entire calendar year. Observations are person-years, and there are between 1 and 4 years per person. Weights used are constructed from the monthly weights at the beginning of the year.

income range) show high levels of fluidity, with a large fraction of the sample spending at least some time in one of them. In addition, those two categories have the smallest fraction of individuals who spend all year in that one category—of the roughly 45 percent of the sample who spend all year in one category, only 10 percent are in the 138–250 percent of the FPL category all year and only 13 percent are in the 250–400 percent of the FPL category all year.

METHODOLOGICAL APPROACH

To determine what factors and events are associated with movements by individuals across income categories, I estimate duration models of time in a particular income group, where the outcome of interest is the probability of switching from one income group to another. These models need to account for both *fresh spells*—spells beginning after the start date of the sample—and *left censored* or *interrupted spells*—spells in progress at the start date of the sample. The interrupted spells pose a particular challenge, as I cannot observe the length of the spells prior to the start of the sample. Consequently, the parameters for the two types of spells cannot be estimated in a single model. In this situation, there are two common approaches to dealing with these spells—discard them entirely, or follow the pragmatic suggestion of Heckman and Singer (1984) and give the transition rates for interrupted spells different parameters from the fresh spell transition rates. As many individuals begin in a particular category and never leave it, ignoring the left censored spells would give an incomplete picture of the relevant income dynamics in the adult population. Thus, I follow the second approach and estimate separate models for fresh and interrupted spells. In addition, for simplicity, I assume there is no unobserved heterogeneity and I do not estimate the overall likelihood of exit from a particular subsidy category, but instead estimate the parameters of the different transition rates separately.

There are four income groups (less than 138 percent of the FPL, 138–250 percent of the FPL, 250–400 percent of the FPL, and greater than 400 percent of the FPL), with exits from the middle two potentially being in either direction (to a higher income or a lower one) and exits from the bottom and top income groups only in one direction each. Thus, I define six types of transitions—less than 138 percent of the FPL to a higher income, 138–250 percent of the FPL or 250–400 percent of the FPL to a higher or lower income, and greater than 400 percent of the FPL to a lower income—each of which may be out of a fresh or interrupted spell, resulting in 12 transition rates to be estimated. Every spell that

an individual has over the course of the sample period is used in the analysis. Thus, for example, an individual who begins the sample period with income below 138 percent of the FPL, experiences an income increase bringing her income above 138 percent of the FPL but below 250 percent of the FPL, and then later experiences an income decline bringing her below 138 percent of the FPL again, contributes three spells to the various models: one interrupted spell below 138 percent of the FPL, a fresh spell 138–250 percent of the FPL, and a fresh spell less than 138 percent of the FPL. In each case, the duration is counted as time from the onset of the spell in question.[4]

In this highly simplified framework, I define the transition rate (Lancaster 1990) for moving from a fresh spell in income category j (that started at calendar time τ) to income category k (e.g., moving from between 138 and 250 percent of the FPL to a higher income) conditional on being in category j for t months as:

$$\lambda_{jk}(t\,|\,\cdot) = [1 + \exp\{-(h_{jk}(t) + \gamma_{jk}X_i(t+\tau))\}]^{-1} \tag{1}$$

where h_{jk} (t) denotes duration dependence and $X_i(t + \tau)$ is a vector of possibly time-changing explanatory variables at calendar time $t + \tau$ that capture demographic factors, economic conditions at $t + \tau$ and whether a particular event occurred in the last month. The other transition rates out of fresh spells are defined similarly. The transition rates out of interrupted spells are also defined this way, but the duration in those spells is calculated only from the start of the sample. To deal with "seam bias" in the SIPP—the problem that transitions are more likely to be reported between waves rather than within the wave—I follow the suggestion of Ham, Li, and Shore-Sheppard (2009) and include a dummy variable for the fourth month in each transition rate. For ease of interpretation, I report odds ratios (exponentiated coefficients), which represent the ratio of the odds if the corresponding variable is incremented by one to the odds if the corresponding variable is not incremented, or

$$\frac{\mathrm{P}(\text{transition}|x+1)/(1-\mathrm{P}(\text{transition}|x+1))}{\mathrm{P}(\text{transition}|x)/(1-\mathrm{P}(\text{transition}|x)} \tag{2}$$

for each variable x.

Note that although the unconditional probabilities of transition (shown in the last row of each table) are relatively small, these odds ratios should not be interpreted as relative risks, or $\mathrm{P}(\text{transition}|x+1)/\mathrm{P}(\text{transition}|x)$, as for some values of the variable x, the probability of transition could be considerably higher (and, thus, the odds ratio would overstate the risk ratio at that value of x).

RESULTS

The odds ratios resulting from estimating these models are reported in Tables 2–5, where I have grouped the results for all spells of a particular type together in a single table. In each table, the top panel shows the odds ratios for demographic factors and events, and the bottom panel shows the odds ratios for employment-related factors and events.

Demographic Factors and Events

The demographic and family structure factors show a fairly consistent pattern across income groups. Having more education or being in an adult-only or two-parent family are positively associated with income increases and negatively associated with income decreases, while being black or Hispanic, being in a larger family, or being in a single mother family show the reverse associations, and marital status appears only weakly related to income changes conditional on family structure. The magnitudes of the odds ratios for the demographics are similar across income groups as well. These results are broadly consistent with the results from Sommers and Rosenbaum, although they are not directly comparable, as Sommers and Rosenbaum looked only at whether a fluctuation occurred, not whether income increased or decreased, and they examined only individuals with income less than 200 percent of the FPL.

The events of a child entering the family or leaving the family are strongly related to the probability of an income group change, and in very interesting ways. Adding a child to the family is positively associated with a move to a lower income category (substantially so for spells in the higher categories) and negatively associated with moving up. This result does not hold for spells in the lowest income category, where adding a child to a family is associated with an increase in the probability of exiting the lowest income category. Moreover, the departure of a child from the family is associated with an increase in volatility—exits of all types from all spells are predicted to increase.[5] The differences may be due to the fact that some family size changes are planned and may reflect a family's increasing economic well-being, while others are unexpected and may pose challenges for the family's income-to-needs ratio. The departure of a child may involve the loss of an earner in some cases.

Table 2: Odds Ratios for Probability of Moving from Income <138% FPL to Higher Income

	P(Income Rises above 138% FPL) Spell in Progress at Start (1)	*P(Income Rises above 138% FPL) Fresh Spell (2)*
Demographic factors and events		
Education	1.026 (0.004)**	1.011 (0.003)**
Male	0.901 (0.016)**	0.874 (0.004)**
Age	0.977 (0.005)**	0.992 (0.003)*
Age^2/10,000	35.441 (22.358)**	2.912 (1.154)**
Black	0.926 (0.025)**	0.954 (0.009)**
Hispanic	0.876 (0.017)**	0.933 (0.010)**
Married	0.944 (0.025)*	0.979 (0.012)
Widowed	1.134 (0.032)**	1.071 (0.025)**
Divorced	1.027 (0.036)	1.052 (0.028)
Adults only	1.294 (0.025)**	1.071 (0.015)**
Two parents	1.336 (0.040)**	1.150 (0.022)**
Single mother	0.944 (0.020)**	0.919 (0.015)**
Single father	1.175 (0.074)*	1.043 (0.022)*
Family size	0.866 (0.006)**	0.891 (0.007)**
Child added to family	2.971 (0.243)**	1.619 (0.179)**
Child left family	3.310 (0.418)**	1.929 (0.183)**
Employment-related factors and events		
Employed	3.111 (0.071)**	2.335 (0.053)**
Family member employed	1.842 (0.041)**	1.553 (0.018)**
Works part time	0.622 (0.009)**	0.686 (0.014)**
Firm <25 employees	0.922 (0.016)**	0.938 (0.008)**
Firm 25–99 employees	1.024 (0.020)	0.979 (0.012)
Self-employed	1.448 (0.152)**	1.043 (0.036)
Union or covered by union contract	1.058 (0.026)*	1.136 (0.019)**
Lost job	1.477 (0.101)**	0.933 (0.026)*
Family member lost job	1.253 (0.098)**	0.895 (0.028)**
Switched to part time	3.980 (0.341)**	2.818 (0.291)**
Family member switched to P-T	3.111 (0.245)**	2.540 (0.298)**
Changed employers	3.883 (0.503)**	2.031 (0.140)**
Family member changed employer	3.169 (0.329)**	2.078 (0.181)**
Gained job	4.871 (0.893)**	4.736 (0.631)**
Family member gained job	3.863 (0.662)**	4.216 (0.546)**
Spell duration	0.750 (0.026)**	0.748 (0.006)**
Number of person-months	664,297	568,387
Number of spells	49,030	113,509
P(transition)	0.04	0.16

Note. Data from 1996, 2001, 2004, and 2008 SIPP panels; original-sample adults between ages 22 and 64 years. Observations are person-months. Weights used are the monthly weights. Estimates displayed as odds ratios. Robust standard errors clustered on sampling unit id (and thus corrected for repeated observations on the same individual) in parentheses. Omitted categories in the family status group are never married and individual living alone; omitted category in firm size is >99 employees or unknown. In addition to the variables shown, all models include a constant, a set of year dummies, the unemployment rate, industry dummies, and a dummy for the fourth month of the wave.

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

Table 3: Odds Ratios for Probability of Leaving 138–250% FPL Income Range

	P(Income Falls below 138%) Spell in Progress at Start (1)	*P(Income Falls below 138%) Fresh Spell (2)*	*P(Income Rises above 250%) Spell in Progress at Start (3)*	*P(Income Rises above 250%) Fresh Spell (4)*
Demographic factors and events				
Education	0.945 (0.004)**	0.926 (0.006)**	1.061 (0.005)**	1.058 (0.004)**
Male	1.001 (0.023)	0.987 (0.009)	0.955 (0.009)**	0.950 (0.005)**
Age	0.999 (0.006)	0.985 (0.006)**	1.001 (0.006)	1.021 (0.006)**
$Age^2/10{,}000$	0.738 (0.501)	2.600 (1.782)	1.316 (1.083)	0.121 (0.081)**
Black	1.142 (0.041)**	1.237 (0.022)**	0.825 (0.029)**	0.824 (0.011)**
Hispanic	1.186 (0.042)**	1.282 (0.027)**	0.747 (0.022)**	0.804 (0.018)**
Married	1.073 (0.044)	1.068 (0.026)**	1.023 (0.020)	0.999 (0.017)
Widowed	0.992 (0.051)	0.921 (0.027)**	1.067 (0.042)	1.008 (0.026)
Divorced	1.056 (0.038)	0.996 (0.020)	1.036 (0.024)	1.037 (0.016)*
Adults only	0.684 (0.053)**	0.688 (0.036)**	1.404 (0.075)**	1.275 (0.050)**
Two parents	0.761 (0.080)**	0.802 (0.050)**	1.470 (0.074)**	1.294 (0.057)**
Single mother	1.038 (0.065)	1.285 (0.052)**	1.013 (0.040)	0.798 (0.016)**
Single father	0.837 (0.058)**	0.971 (0.052)	1.190 (0.057)**	1.045 (0.021)*
Family size	1.153 (0.020)**	1.190 (0.011)**	0.829 (0.013)**	0.829 (0.005)**
Child added to family	13.393 (2.201)**	4.971 (0.641)**	0.926 (0.193)	0.670 (0.090)**
Child left family	2.151 (0.334)**	1.696 (0.085)**	2.847 (0.454)**	1.650 (0.172)**
Employment-related factors and events				
Employed	0.601 (0.015)**	0.567 (0.018)**	1.973 (0.083)**	1.837 (0.071)**
Family member employed	0.520 (0.012)**	0.448 (0.012)**	1.548 (0.054)**	1.614 (0.016)**
Works part time	1.136 (0.048)**	1.027 (0.006)**	1.059 (0.055)	0.995 (0.006)
Firm <25 employees	1.346 (0.039)**	1.455 (0.013)**	0.705 (0.013)**	0.742 (0.008)**
Firm 25–99 employees	1.095 (0.033)**	1.181 (0.030)**	0.930 (0.015)**	0.883 (0.008)**
Self-employed	1.011 (0.040)	1.010 (0.013)	1.020 (0.025)	0.991 (0.011)

Continued

Table 3: *Continued*

	P(Income Falls below 138%) Spell in Progress at Start (1)	*P(Income Falls below 138%) Fresh Spell (2)*	*P(Income Rises above 250%) Spell in Progress at Start (3)*	*P(Income Rises above 250%) Fresh Spell (4)*
Union or covered by union contract	1.387 (0.402)	1.418 (0.070)**	1.187 (0.151)	1.032 (0.043)
Lost job	24.027 (6.923)**	8.203 (1.636)**	0.683 (0.141)	0.502 (0.020)**
Family member lost job	8.889 (1.609)**	4.022 (0.703)**	0.676 (0.112)*	0.617 (0.038)**
Switched to part time	4.091 (0.362)**	1.869 (0.120)**	3.333 (0.206)**	1.937 (0.116)**
Family member switched to P-T	2.799 (0.255)**	1.871 (0.089)**	2.717 (0.347)**	1.611 (0.091)**
Changed employers	3.337 (0.272)**	1.842 (0.036)**	3.843 (0.286)**	1.772 (0.165)**
Family member changed employer	1.787 (0.216)**	1.238 (0.034)**	3.110 (0.338)**	1.810 (0.135)**
Gained job	0.947 (0.166)	0.742 (0.073)**	7.294 (1.411)**	4.254 (0.877)**
Family member gained job	0.706 (0.089)**	0.791 (0.095)	5.114 (1.024)**	3.129 (0.566)**
Spell duration	0.708 (0.015)**	0.734 (0.009)**	0.737 (0.008)**	0.743 (0.009)**
Number of person-months	326,556	830,284	326,556	830,284
Number of spells	41,038	211,413	41,038	211,413
P(transition)	0.04	0.08	0.06	0.14

Note. Data from 1996, 2001, 2004, and 2008 SIPP panels; original-sample adults between ages 22 and 64 years. Observations are person-months. Weights used are the monthly weights. Estimates displayed as odds ratios. Robust standard errors clustered on sampling unit id (and thus corrected for repeated observations on the same individual) in parentheses. Omitted categories in the family status group are never married and individual living alone; omitted category in firm size is >99 employees or unknown. In addition to the variables shown, all models include a constant, a set of year dummies, the unemployment rate, industry dummies, and a dummy for the fourth month of the wave.
*$p < .05$; **$p < .01$.

Table 4: Odds Ratios for Probability of Leaving 250–400% FPL Income Range

	P(Income Falls below 250%) Spell in Progress at Start (1)	*P(Income Falls below 250%) Fresh Spell (2)*	*P(Income Rises above 400%) Spell in Progress at Start (3)*	*P(Income Rises above 400%) Fresh Spell (4)*
Demographic factors and events				
Education	0.922 (0.003)**	0.895 (0.003)**	1.082 (0.007)**	1.092 (0.003)**
Male	0.994 (0.011)	0.980 (0.012)	0.955 (0.007)**	0.967 (0.004)**
Age	0.986 (0.004)**	0.979 (0.005)**	1.013 (0.007)	1.023 (0.005)**
Age^2/10,000	4.281 (2.249)**	5.469 (3.101)**	0.310 (0.283)	0.113 (0.065)**
Black	1.168 (0.056)**	1.234 (0.020)**	0.838 (0.018)**	0.799 (0.013)**
Hispanic	1.174 (0.075)*	1.251 (0.030)**	0.753 (0.033)**	0.769 (0.010)**
Married	1.109 (0.029)**	1.076 (0.018)**	0.995 (0.024)	1.009 (0.011)
Widowed	1.243 (0.090)**	1.134 (0.051)**	0.941 (0.043)	0.910 (0.040)*
Divorced	1.029 (0.025)	1.028 (0.014)*	1.018 (0.044)	0.996 (0.010)
Adults only	0.861 (0.028)**	0.671 (0.009)**	1.281 (0.043)**	1.386 (0.022)**
Two parents	0.890 (0.044)*	0.797 (0.020)**	1.321 (0.082)**	1.386 (0.036)**
Single mother	1.120 (0.045)**	1.231 (0.052)**	0.909 (0.036)*	0.774 (0.017)**
Single father	1.013 (0.059)	0.968 (0.028)	1.085 (0.073)	1.006 (0.041)
Family size	1.128 (0.015)**	1.203 (0.021)**	0.844 (0.018)**	0.799 (0.006)**
Child added to family	19.321 (1.944)**	6.771 (0.897)**	0.666 (0.134)*	0.473 (0.051)**
Child left family	1.814 (0.374)**	1.276 (0.059)**	2.298 (0.375)**	1.353 (0.102)**
Employment-related factors and events				
Employed	0.759 (0.017)**	0.687 (0.016)**	1.680 (0.067)**	1.636 (0.042)**
Family member employed	0.611 (0.015)**	0.548 (0.015)**	1.395 (0.028)**	1.489 (0.021)**
Works part time	1.100 (0.050)*	1.010 (0.007)	1.055 (0.045)	1.001 (0.004)
Firm <25 employees	1.120 (0.021)**	1.131 (0.018)**	0.818 (0.017)**	0.844 (0.010)**
Firm 25–99 employees	1.126 (0.041)**	1.196 (0.017)**	0.875 (0.016)**	0.874 (0.005)**
Self-employed	1.004 (0.042)	1.085 (0.014)**	0.951 (0.015)**	0.944 (0.008)**

Continued

Table 4: *Continued*

	P(Income Falls below 250%) Spell in Progress at Start (1)	*P(Income Falls below 250%) Fresh Spell (2)*	*P(Income Rises above 400%) Spell in Progress at Start (3)*	*P(Income Rises above 400%) Fresh Spell (4)*
Union or covered by union contract	1.278 (0.166)	1.284 (0.041)**	1.735 (0.214)**	0.978 (0.032)
Lost job	23.727 (5.851)**	8.331 (1.955)**	0.683 (0.083)**	0.501 (0.032)**
Family member lost job	8.902 (1.493)**	3.760 (0.741)**	0.691 (0.091)**	0.636 (0.031)**
Switched to part time	3.607 (0.287)**	1.879 (0.087)**	3.100 (0.167)**	1.703 (0.123)**
Family member switched to P-T	3.068 (0.251)**	1.714 (0.088)**	1.823 (0.215)**	1.451 (0.091)**
Changed employers	3.784 (0.251)**	2.099 (0.053)**	3.267 (0.389)**	1.607 (0.177)**
Family member changed employer	2.009 (0.186)**	1.475 (0.040)**	2.365 (0.201)**	1.583 (0.123)**
Gained job	0.703 (0.077)**	0.723 (0.054)**	7.395 (1.311)**	3.728 (0.734)**
Family member gained job	0.766 (0.110)	0.811 (0.060)**	4.407 (0.752)**	2.524 (0.443)**
Spell duration	0.703 (0.009)**	0.688 (0.018)**	0.743 (0.010)**	0.777 (0.007)**
Number of person-months	402,543	1,026,926	402,543	1,026,926
Number of spells	49,009	269,771	49,009	269,771
P(transition)	0.05	0.11	0.06	0.12

Note. Data from 1996, 2001, 2004, and 2008 SIPP panels; original-sample adults between ages 22 and 64 years. Observations are person-months. Weights used are the monthly weights (with the exception of column (2), which is estimated unweighted due to convergence difficulties in the weighted model). Estimates displayed as odds ratios. Robust standard errors clustered on sampling unit id (and thus corrected for repeated observations on the same individual) in parentheses. Omitted categories in the family status group are never married and individual living alone; omitted category in firm size is >99 employees or unknown. In addition to the variables shown, all models include a constant, a set of year dummies, the unemployment rate, industry dummies, and a dummy for the fourth month of the wave.
*$p < .05$; **$p < .01$.

Table 5: Odds Ratios for Probability of Moving from Income >400% FPL to Lower Income

	P(Income Falls below 400% FPL) Spell in Progress at Start (1)	*P(Income Falls below 400% FPL) Fresh Spell (2)*
Demographic factors and events		
Education	0.930 (0.004)**	0.962 (0.002)**
Male	1.004 (0.007)	0.967 (0.005)**
Age	0.973 (0.004)**	1.001 (0.002)
Age^2/10,000	22.296 (10.593)**	0.641 (0.160)
Black	0.969 (0.022)	0.930 (0.014)**
Hispanic	0.961 (0.030)	0.947 (0.022)*
Married	1.187 (0.029)**	1.066 (0.015)**
Widowed	1.128 (0.048)**	0.990 (0.031)
Divorced	0.984 (0.021)	1.015 (0.010)
Adults only	0.781 (0.029)**	0.881 (0.010)**
Two parents	0.875 (0.046)*	0.949 (0.021)*
Single mother	1.246 (0.074)**	1.063 (0.022)**
Single father	1.082 (0.082)	0.895 (0.024)**
Family size	1.081 (0.015)**	1.060 (0.007)**
Child added to family	10.533 (1.673)**	11.972 (1.385)**
Child left family	3.521 (0.277)**	1.334 (0.081)**
Employment-related factors and events		
Employed	0.768 (0.010)**	0.835 (0.007)**
Family member employed	0.649 (0.010)**	0.761 (0.010)**
Works part time	1.071 (0.059)	0.979 (0.004)**
Firm <25 employees	1.008 (0.016)	0.956 (0.017)*
Firm 25–99 employees	1.112 (0.016)**	0.992 (0.014)
Self-employed	1.051 (0.017)**	0.980 (0.015)
Union or covered by union contract	1.458 (0.107)**	0.916 (0.029)**
Lost job	15.503 (2.733)**	11.023 (2.091)**
Family member lost job	6.897 (0.956)**	4.620 (0.831)**
Switched to part time	3.312 (0.136)**	2.845 (0.233)**
Family member switched to P-T	2.522 (0.140)**	2.142 (0.146)**
Changed employers	3.846 (0.245)**	2.812 (0.122)**
Family member changed employer	2.519 (0.141)**	2.172 (0.084)**
Gained job	2.278 (0.152)**	1.138 (0.085)
Family member gained job	1.897 (0.089)**	1.128 (0.042)**
Spell duration	0.730 (0.034)**	0.690 (0.013)**
Number of person-months	1,494,783	926,248
Number of spells	84,468	176,286
P(transition)	0.03	0.15

Note. Data from 1996, 2001, 2004, and 2008 SIPP panels; original-sample adults between ages 22 and 64 years. Observations are person-months. Weights used are the monthly weights. Estimates displayed as odds ratios. Robust standard errors clustered on sampling unit id (and thus corrected for repeated observations on the same individual) in parentheses. Omitted categories in the family status group are never married and individual living alone; omitted category in firm size is >99 employees or unknown. In addition to the variables shown, all models include a constant, a set of year dummies, the unemployment rate, industry dummies, and a dummy for the fourth month of the wave.

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

Employment-Related Factors

As with the demographic factors, some employment-related factors show similar correlations at all levels of income, in particular being employed or having an employed family member, which unsurprisingly are positively correlated with income increases and negatively correlated with income declines. However, other factors differ in their effects. For individuals below 138 percent of the FPL, being self-employed or covered by a union contract is associated with a move over the 138 percent of the FPL boundary, while working part time implies a lower probability of an improvement in circumstances. Similarly, for individuals in the 138–250 percent of the FPL range, working part time is associated with a higher probability of an income decline, as is working in a small firm. However, being in a union or covered by a union contract is associated with an increased probability of an income *decrease*, while being self-employed is not statistically related to income moves either up or down. Among individuals with incomes between 250 and 400 percent of the FPL, self-employment has a similarly equivocal relationship with the probability of exits through either income increases or decreases, as does union status, while working in a small firm continues to be associated with higher probability of an income decline and a lower probability of an income increase.[6]

Although the results for employment-related factors described thus far have had different effects for individuals in different parts of the income distribution, the effects have generally not differed for fresh and in-progress spells. Interestingly, this is not the case when looking at entries into subsidy eligibility from above the 400 percent of the FPL cutoff. Factors including working for a small firm, being self-employed, and being covered by a union contract, all have odds ratios greater than one for the probability of a fall in income among in-progress spells, but less than one for the probability of a fall in income among fresh spells. Thus, although the overall probability of leaving the above 400 percent of the FPL category is higher for individuals in fresh spells (0.15 compared to 0.03 for in-progress spells), individuals in fresh spells working part time, in a small firm, or in a union-covered job are less likely to experience a fall in income.

Employment-Related Events

Losing or gaining a job has separate, strong effects on transitions typically in the direction one would expect.[7] For example, an individual who begins the sample with income between 138 and 250 percent of the FPL and loses a job

has over 20 times higher odds of experiencing a loss of income sufficient to push him or her below the 138 percent of the FPL cutoff than someone who does not lose a job. The impacts of job loss of a family member are estimated to be smaller, but are still strikingly high, as are the impacts of gaining a job either for the individual or a family member.

The results for job transitions that do not involve nonemployment are an important exception to the general pattern of opposite effects for exits to higher and lower income groups. Switching to part-time work, having a family member switch to part-time work, changing employers, or having a family member change employers are all associated with greater transitions, in *both* directions and for both in-progress and fresh spells in *all* income categories. These changes clearly signal instability in income and may arise either from positive circumstances or negative ones—an individual may change employers because he or she has obtained a better job or because he or she has quit or been fired and has found a less well compensated job.

CONCLUSIONS

The provisions of the Affordable Care Act intended to increase access to insurance coverage among the uninsured effectively divide the population into categories by income, with lower categories being eligible for Medicaid (if living in a state choosing to expand) and higher categories being eligible for tax-based subsidies. However, a large fraction of the population spends time in multiple income categories during a single year. The extent of within-year income fluctuations observed in the data are sufficient to trigger within-year subsidy eligibility changes in up to a third of all adults income-eligible for subsidized coverage or Medicaid. Overall, the results from the models of the probability of making a transition between income categories point to three general conclusions. First, employment transitions are crucial sources of income volatility. Even transitions not involving a period of non-employment are associated with significant volatility in income, though that volatility may be in multiple directions. Other transitions, particularly losing a job, lead to changes in directions that would be expected, but the magnitude of these changes is strikingly large. For everyone except those already in the bottom group, losing a job is associated with an increase in the odds of falling to a lower income category of between 8 and 24 times. As job loss is also associated with the loss of employer-sponsored insurance, it is essential that state eligibility determination procedures for Medicaid

and exchange-based subsidies recognize the implications of job loss for income dynamics. An individual losing a job midyear whose subsidy calculation uses information from both before and after job loss is likely to have a more accurate annual average subsidy calculation (and consequently, a lower chance of needing to reconcile advanced and actual subsidy at tax-filing time) but may have more difficulty affording insurance at the time of the loss. If the subsidy calculation relies on current income following job loss, the calculated subsidy will be higher, making insurance currently more affordable, but raising the chance that the individual will owe at the end of the year.

Second, some groups in the population have inherently more positive income trajectories. Education is robustly associated with lower probabilities of declining income and higher probabilities of increasing income, for example. Individuals in multiple-adult families typically have similar patterns. On the other hand, single mothers generally face higher probabilities of declining income and lower probabilities of increasing income. Members of minority groups (black and Hispanic) typically face greater likelihoods of declining income and lower probabilities of increasing income, with the notable exception of spells in the highest income category, where being black or Hispanic is weakly associated with a lower chance of a decline in income, all else equal.

Finally, job characteristics are related to the probability of an income transition, but not necessarily in the same way for individuals across the income distribution. Characteristics such as firm size, part-time status, and self-employment cannot be used reliably to predict which individuals are likely to experience an income transition in the absence of information about where in the income distribution the individual already falls.

These results indicate that within-year income volatility arising from employment and family structure changes may be substantial and is likely to trigger changes in subsidy eligibility within the year. However, the sources and effects of the volatility differ substantially depending on the individual's beginning level of income.

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NOTES

1. The Medicaid income cutoff is technically 133 percent with an additional income disregard of 5 percent, or 138 percent. For useful summaries of the provisions of the Affordable Care Act, see the Kaiser Family Foundation health reform web pages, which may be accessed at http://kff.org/health-reform/fact-sheet/summary-of-new-health-reform-law/.
2. The SIPP is subject to similar problems of income nonresponse encountered in every survey in which respondents are asked their incomes. Imputation is used when a respondent refuses to answer or is unavailable for the survey, as with other Census Bureau datasets. However, the research on data quality in the SIPP indicates that the 4-month recall period leads to improved data reporting relative to longer recall periods such as used in the Current Population Survey (see, e.g., Wheaton 2007).
3. While the income measures observed in the data should match the income components of MAGI fairly closely, I am unable to observe the expenses that are deducted from income and the taxable/nontaxable status of some income sources.
4. In the data, 35.6 percent of the individuals have only one spell, 10 percent have two, 11.7 percent have three, 7.1 percent have four, 7 percent have five, and nearly 24 percent have 6 or more spells. To check whether having multiple spells per individual used in the models (which occurs for fresh spells only; by definition there is only one type of spell in progress at the start of the data collection) leads to bias, I reran all of the fresh spell models using only the first observed fresh spell for each individual. The results did not differ substantively from the presented results, although unsurprisingly the standard errors tended to be larger.
5. The results for the child transition variables are not an artifact of simultaneously controlling for family size. When family size is omitted, the results for adding or subtracting a child are essentially the same.
6. The results for the industry dummies are not included in the interest of space. A table with the results is available as a Table S1. In general, they are difficult to char-

acterize briefly, with industry having a range of relationships with income transitions up and down the income distribution.

7. The two exceptions are job loss among individuals in spells of income below 138 percent of the FPL at the start of the sample (with a positive association with an income increase) and job gain among individuals in spells of income above 400 percent of the FPL (with a positive association with an income decline). It remains unclear why this is the case.

REFERENCES

Bane, M. J., and D. Ellwood. 1986. "Slipping into and out of Poverty: The Dynamics of Spells." *Journal of Human Resources* 15 (2): 338–75.

Dahl, M., T. DeLeire, and J. A. Schwabish. 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): 750–74.

Dynan, K. E., D. W. Elmendorf, and D. E. Sichel. 2012. "The Evolution of Household Income Volatility." *B.E. Journal of Economic Analysis & Policy: Advances*, 12(2), 2012, Article 3.

Gottschalk, P., and R. Moffitt. 1994. "The Growth of Earnings Instability in the U.S. Labor Market." *Brookings Papers on Economic Activity* 1994 (2): 217–54.

Grogger, J. 2004. "Welfare Transitions in the 1990s: The Economy, Welfare Policy, and the EITC." *Journal of Policy Analysis and Management* 23 (4): 671–95.

Haider, S. J. 2001. "Earnings Instability and Earnings Inequality in the United States, 1967–1991." *Journal of Labor Economics* 19 (4): 799–836.

Ham, J., and L. Shore-Sheppard. 2005. "The Effect of Medicaid Expansions for Low-Income Children on Medicaid Participation and Private Insurance Coverage: Evidence from the SIPP." *Journal of Public Economics* 89 (1): 57–83.

Ham, J., X. Li, and L. Shore-Sheppard. 2009. "Seam Bias, Multiple-State, Multiple-Spell Duration Models and the Employment Dynamics of Disadvantaged Women." NBER working paper # 15151.

Hardy, B., and J. P. Ziliak. 2014. "Decomposing Trends in Income Volatility: The "Wild Ride" at the Top and Bottom." *Economic Inquiry* 52 (1): 459–76.

Heckman, J. J., and B. Singer. 1984. "Econometric Duration Analysis." *Journal of Econometrics* 24 (1–2): 63–132.

Lancaster, T. 1990. *The Econometric Analysis of Transition Data*. Econometric Society Monograph No. 17. Cambridge, England: Cambridge University Press.

Sommers, B. D., and S. Rosenbaum. 2011. "Issues in Health Reform: How Changes in Eligibility May Move Millions Back and Forth between Medicaid and Insurance Exchanges." *Health Affairs* 30 (2): 228–36.

Stevens, A. H. 1999. "Climbing out of Poverty, Falling Back in: Measuring the Persistence of Poverty over Multiple Spells." *Journal of Human Resources* 34(3): 557–88.

Wheaton, L. 2007. "*Underreporting of Means-Tested Transfer Programs in the CPS and SIPP*," 2007 Proceedings of the American Statistical Association, Social Statistics Section. Alexandria, VA: American Statistical Association: 3622–9.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Table S1: Odds Ratios for Industry Dummy Variables for Models of Tables 2–5.