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Food Insufficiency and Income Volatility in U.S. Households: The Effects of Imputed Earnings in the Survey of Income and Program Participation

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Abstract

This paper explores how the use of imputed earnings data to measure income in the Survey of Income and Program Participation affects the observed relationship between household income volatility and food insufficiency. The study finds that the inclusion of imputed earnings data when measuring income volatility substantially understates the association between large drops in household income and food insufficiency. After excluding observations with imputed earnings, large drops in income are associated with a 1.3 percentage point increase in the probability of food insufficiency, although the estimate is not statistically significant at conventional levels.

I. Introduction

Several studies (among others, Leete and Bania, 2010; Gundersen and Gruber, 2001) have used household surveys to document the prevalence of income volatility and the relationship between income volatility and food insufficiency. However, data imputation can produce misleading measures of income volatility, which, in turn, can produce misleading relationships between that volatility and food insufficiency.

The Survey of Income and Program Participation (SIPP), a widely used data source for analyzing income changes over time, frequently replaces missing values of income with randomly selected values from other records in the SIPP that are observationally similar and complete—a method known as hot-deck imputation. When income volatility is calculated using hot-deck imputed data, income changes are no longer based on changes within a household, but rather on differences in incomes between two households. Because income variability between households is substantially greater than income variability within households over time, using imputed data to estimate volatility leads to an overestimate of the amount of volatility.

In this paper, we consider the effect of using imputed earnings data when examining the relationship between income volatility and an outcome of interest—in this case, the probability that a household experiences food insufficiency.

II. Background

Labor economists have approached the use of imputed data in several ways. Most studies use imputed data when they are available. However, many studies, perhaps beginning with Lillard, Smith, and Welch (1986), question the use of hot-decked data in empirical analyses. For example, in studies of the wage distribution using the Current

Population Survey (CPS), DiNardo, Fortin, and Lemieux (1996) and Autor, Katz, and Kearney (2008) drop observations with imputed wage data. Other studies that drop observations with imputed earnings or income in their cross-sectional analyses include Hirsch and Schumacher (2004), Mellow and Sider (1983), Dooley and Gottschalk (1984), Welch (1979), and Bollinger and Hirsch (2006).

Studies that employ panel data to conduct longitudinal analyses also often exclude imputed observations. For example, Bound and Krueger (1991), in their influential study comparing measurement error in survey data with administrative data from the Social Security Administration, drop observations with imputed earnings data. Their finding that "longitudinal [survey] earnings data may be more reliable than previously believed"[1] is based only on non-imputed data. Additional panel studies that drop imputed earnings data include Kim and Solon (2005), Bound et al. (1994), and Bollinger (1998).

Several previous studies have examined the link between income volatility and food insufficiency.[2] Using the 1991 and 1992 panels of the SIPP, Gundersen and Gruber (2001) showed that food-insufficient households had higher income variability, were more likely to have experienced income shocks (such as loss of earnings or food stamps), and were less likely to have savings. Others have examined the effects of resources that mitigate the effects of income volatility. Using the Panel Study of Income Dynamics (PSID), Blundell and Pistaferri (2003) found that food assistance programs reduced but did not eliminate the effect of permanent income shocks on food expenditures at home between 1978 and 1992. Ribar and Hamrick (2003) found that the ownership of assets (which may be negatively related to income volatility) is negatively related to food

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[1] Bound and Krueger (1991), p. 1.
[2] Food insufficiency is generally defined as sometimes or often not having enough to eat.

insufficiency.

More recently, Leete and Bania (2010) found that households with relatively volatile incomes have an increased likelihood of experiencing food insufficiency. Their measure of income volatility is the level difference between monthly income and average income over the year. They point out that, if income volatility is due to measurement error, then coefficient estimates will be biased towards zero and thus will show no effect of income volatility on food insufficiency. In sensitivity tests, Leete and Bania show that excluding observations with imputed income results in larger estimates of the association between income drops and food insufficiency.

Our analysis extends previous work by more explicitly considering how income imputations in the SIPP affect the relationship between income volatility and food insufficiency. First, we document that large income changes are more likely to be observed among households that have imputed earnings even though these households are observationally similar to households without imputations. Second, our measures of household income and income volatility differ from those used in previous studies to focus attention on income volatility. We measure income volatility using the arc percentage change in household income over two years. Measurement of volatility in percentage terms allows households at different income levels to have different responses to the same difference in income amounts. In addition, our measure of household income does not include the value of food assistance—for instance, food stamps or Women, Infant, and Children (WIC) benefits—whereas their measure of income does include the value of food assistance. Researchers have found that households tend to receive food assistance when they are most food insecure,[3] and this self-selection results in higher rates of food insecurity among food assistance recipients (Nord and Golla, 2009). The inclusion of the value of food assistance in household income does not allow distinction between the association of income volatility with food insufficiency and the association of receipt of food assistance receipt with food insufficiency.

III. Data and Methods

In this section, we describe the SIPP data and the hot-deck imputation procedure. We present our analytic approach.

A. Data Source

The SIPP comprises a set of panel surveys that were conducted annually from 1984 to 1988, from 1990 to 1993, and then again in 1996, 2001, 2004, and 2008. In each panel, interviews are conducted at four-month intervals. Some information (including income, program participation, and household composition) is collected in each interview; other information (including measures of well-being) is collected less frequently. In this study, we use the 1991, 1996, and 2004 panels. The sample sizes for these panels range from 15,000 to 52,000 households, and the panels range in duration from 8 to 12 interviews (about 2.5 years to 4 years). At each interview, the survey collects information on the labor market earnings for each household member and all other sources of cash income for the household for each month over the previous four months, as well as a comprehensive set of demographic information. Non-labor income

[3] Food security measures access by all people at all times to enough food for an active, healthy life and is related to food insufficiency.

includes income from a wide array of possible sources, including unemployment insurance, welfare payments, retirement income (which includes Social Security, railroad retirement, and pension income), disability and Supplemental Security Income (SSI) payments, and interest and dividends. Our measure of household income is total (pre-tax) household income, which is the sum of earnings and non-labor income for each household member. We do not include the value of food assistance benefits such as food stamps and WIC. Income from each year is adjusted to 2006 dollars using the consumer price index research series for urban consumers.

To construct the measures of volatility used in this paper, we first construct the arc percent change in real total household income (Y) between two calendar years for each household:[4]

(1) $$\text{arc percent change} = 100\times(Y_t - Y_{t-1})/((Y_t + Y_{t-1})/2).$$

The arc percent change is symmetric with respect to the measures of income or earnings in the two years and is defined even when either Y_t or Y_{t-1} is zero. The arc percent change is not defined when both Y_t and Y_{t-1} are zero, and we drop observations with no income in both years.[5] For the remainder of the paper for expositional purposes, we will often refer to the arc percent change as the "percent change." To focus on the association between large income changes and food insufficiency, we calculate indicators

[4] See Allen and Lerner (1934), pp. 226–229, or Hensher, Rose, and Greene (2005), p. 392.

[5] Respondents in the SIPP often report the same earnings for all four months within a wave, resulting in more pronounced changes in income between waves than within waves. Because of this "seam bias," respondents whose information is collected in waves that fit completely within a calendar year are more likely to have greater variance in income across years than respondents whose waves span two calendar years (in which case, the same income is reported for some months in year 1 and year 2). Our analysis does not account for this.

for whether the household had income changes equal to or greater than 25 percent.[6]

We impose several sample restrictions. We exclude households headed by individuals younger than 25 or older than 55 at the time of the survey, because their incomes may be especially volatile as they enter or leave the labor market. We also exclude households with incomes in the top 1 percent or bottom 1 percent in any year to reduce the effect of outliers. In the analysis of the association between income volatility and food insufficiency, we restrict the sample to households with incomes below 200 percent of the federal poverty guidelines (FPL), measured in the second year, because it is unlikely that income changes are associated with food insufficiency in higher income households.

Our main outcome variable of interest is food insufficiency, which is measured consistently across SIPP panels.[7] Starting in 1991, the SIPP includes questions about food insufficiency once in each panel. We use only the 1991, 1996, and 2004 panels, for reasons we discuss below. We base our food insufficiency measure on respondents' answers to the following question: "Getting enough food can also be a problem for some people. Which of these statements best describes the food eaten in your household in the last four months?"[8] We code households as being food insufficient if they respond that there is "sometimes not enough to eat" or "often not enough to eat."[9] There is another

[6] Because this cutoff is arbitrary, we also examined an indicator for the household having a 50 percent or greater decline or increase in income.

[7] Measures of food security can be calculated from responses to the Food Security Supplement in the December CPS, but not in the SIPP. To reduce respondent burden, only lower-income households or those that report food insufficiency are asked questions in the food security module in the CPS.

[8] Though food insufficiency is self-reported, it is consistent with more objective measures of deprivation. It is negatively correlated with nutrient intake and food expenditures. See Rose, Gundersen, and Oliveira (1998) for a discussion of the related literature.

[9] In the 1996 and 2004 panels, 8 percent and 5 percent, respectively, of responses to the food insufficiency question were imputed. (The 1991 panel also contains imputed responses but the public data set does not include an indicator for whether an observation is imputed.) Observations with imputed food insufficiency

question regarding food insufficiency in the previous month. In this paper, we focus on the results using the four-month measure of insufficiency, though the main findings are unchanged when using the previous month's measure of insufficiency.

Because we are interested in the association between income change and an outcome, ideally food insufficiency would be measured at the end of the two-year income period. In some panels, the food insufficiency question was asked before a two-year income change could be measured and in others it was asked almost a year after an income change had occurred. The 1991, 1996, and 2004 panels measured food insufficiency near the end of the two-year period over which we calculate income change. Food insufficiency was measured in 1992, 1998, and 2005; we calculate income changes over the two-year periods: 1991–1992, 1997–1998, and 2004–2005.

B. Imputed Data

The Census uses a variety of methods to impute missing data (U.S. Census Bureau, 2001, chapters 4 and 6). The most common method is a hot-deck imputation method. The hot-deck imputation replaces missing values with randomly selected values from complete records that are observationally similar (based on a small number of variables) in the same data set.[10] Other widely used data sets including the CPS and the American Community Survey also use this method to impute missing values.

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are kept in the main analysis, and restricting the analysis to observations without food insufficiency and without imputed earnings results in imprecise estimates. Observations with imputed earnings are slightly more likely to have imputed food insufficiency too.

[10] According to the Census, "SIPP hot-deck imputation procedures are designed to preserve the univariate distribution of each variable subject to imputation. These procedures do not, in general, preserve the covariances among variables." (U.S. Census Bureau, 2001, chapter 4).

For this analysis, we focus on households with imputed earnings. This can arise when either wages or self-employment income data are missing for one or more household members in one or more months.[11] In the Census method of imputation, records are grouped by geographic area and then are stratified by age, race, sex, and other variables. Then missing values in a record are replaced with values contributed by a similar record (U.S. Census Bureau, 2001). The hot-deck imputation method is similar for other variables, though the exact variables used to stratify observations for matching may differ.

In most cases, imputation of missing data can result in improved estimates of the cross-sectional means and variances (see Rubin, 1987). However, the use of hot-deck imputed data can be problematic when constructing measures based on the change in the potentially imputed variable over multiple periods.[12] Observed changes are not "real" in that they are not calculated from differences in reported values over time for a given observation, but rather are calculated from differences in values across observations. For example, consider an observation in which the respondent provided income data, Y_1, in year 1, but not in year 2 (thus Y_2 was missing and was imputed using a hot-deck imputation). The measure of arc percent change for that observation, $100\times(Y_2 - Y_1)/((Y_2 + Y_1)/2)$, is based on the difference between the observation's actual income in year 1 and some other observation's income in year 2. This measure using imputed data is closely related to an observation's percent deviation from the sample average—a measure of cross-sectional variability. Because it is likely that cross-sectional income variability (the variability of income between households) is substantially greater than the variability in

[11] For this paper, we do not consider missing values that arise when no interviews are collected from a household. In general, these missing interviews are accounted for by using weights.
[12] For example, see the concerns raised over the use of imputed data in the SIPP in Williams (1992).

income within households over time, using imputed data to estimate the percent change in income likely leads to an overestimate of the amount of variability.

C. Methods

First, we document the increased likelihood of observing a large income change among all households, including those with imputed earnings. We estimate a linear probability model relating the probability that we observe a large change in income for a household, which we define as an increase or decrease in income of 25 percent or more (*V*) to demographic and employment characteristics. Specifically, we estimate:

$$V_{i,t+1} = \alpha Impute_i + \beta Z_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $Impute_i$ is an indicator for imputed earnings in either year and where Z_i is a set of household characteristics including age of household reference person, household income relative to FPL, number of children, education, race, household composition, receipt of food assistance, and hours of work, all measured at the end of the first year.[13]

Next, we see how imputed income affects the observed relationship between income volatility and food insufficiency in households with incomes below 200 percent of FPL. Controlling for income and other household characteristics, we estimate linear probability models relating the probability that a household experiences food insufficiency to the household experiencing high income volatility. We determine

[13] The results from separately estimating the association between imputed earnings and income drops or rises are similar—households with imputed earnings are more likely to have large changes in measured income. When the analysis is restricted to households with incomes below 200 percent of FPL, the association between large income changes (particularly large income drops) and the presence of imputed earnings data is larger than when observations from all income levels are included.

whether this relationship changes when we drop observations with imputed earnings.

In particular, we estimate the following relationship:

$$(3) \qquad I_{i,t+1} = BX_{i,t} + \gamma \cdot 1(A \le -25) + \zeta \cdot 1(A \ge 25) + e_{i,t+1}$$

where I_i is the indicator for household food insufficiency, X_i includes dummies for the education level of the household head (less than high school, high school, some college, and college or more [excluded]), marital status, the number of children in the household, and household income relative to FPL. 1(.) is the indicator function and A is the arc percent change defined in equation 1. Large increases and large decreases in income are included separately in the regression because large income drops (but not large income rises) are likely to be associated with food insufficiency. We also include dummy variables for each panel in equation 3.

The main coefficient of interest is γ, which indicates the difference in the probability (between households with large percentage drops in household income and households with relatively small changes in income) that a household has insufficient food.

IV. Results

In this section, we describe our sample, document the increased volatility in records with imputed data, and report the estimates of equation 3 from our linear probability model.

A. *Descriptive Statistics*

The rates of food insufficiency for each panel of the SIPP are shown in Figure 1. Over a four-month period in the 1991 panel, 2.6 percent of all households reported food insufficiency. This percentage dropped slightly in the 1996 panel (to 2.2 percent) and returned to 2.7 percent in the 2004 panel. Food insufficiency rates were substantially higher among lower-income households. Almost 8 percent of households with incomes below 200 percent of FPL reported food insufficiency in the 1991 panel. The share of lower-income households reporting food insufficiency fell in 1996 and rose slightly in 2004.

The share of households with imputed earnings has increased substantially over time (see Figure 2), which potentially complicates any analysis of the effect of income changes on an outcome of interest.[14] In the 1991 panel, 30 percent of household records had imputed earnings. This jumped to 51 percent in 1996 and then fell somewhat to 46 percent in the 2004 panel. Because earnings make up a substantial portion of household income for most households, changes in household earnings are closely correlated with household income volatility—more than 80 percent of households experiencing a drop in earnings exceeding 25 percent experience a drop in household income exceeding 25 percent.[15] For the remainder of the analysis, we will focus on households whose measured incomes include imputed earnings.

[14] Because of item non-response in recent years, other household surveys, including the Current Population Survey, have also experienced a rise in imputation rates among income variables. See Bollinger and Hirsch (forthcoming), Czajka (2009), and Meyer, Mok, and Sullivan (2009).
[15] The share of household records with any source of income imputed increased from roughly 40 percent in the 1991 panel to 58 percent in the 2004 panel. About 80 percent of records with any source of income imputed contained imputations of a household member's earnings (wages and self-employment income).

Households with imputed earnings appear similar to households with reported earnings (see Table 1). Both types of households have heads of households of similar ages, have similar educational attainments, work similar number of hours, and have comparable numbers of children. Households with imputed earnings have relatively higher household income (on average, 387 percent of FPL compared to 375 percent of FPL among households without imputed earnings). However, households with imputed data are significantly more likely than other households to have changes in income (increases or decreases) exceeding 25 percent.

The percentage of households experiencing large changes in total household income (income drops or increases greater than or equal to 25 percent) is displayed in Figure 3. Including all observations, we see that the percentage of households experiencing yearly changes in income that exceed 25 percent is large and growing, increasing from 28 percent in the 1991 panel to about 34 percent in the 2004 panel. Households that experience large changes in income are about equally divided into those experiencing large decreases in income and those experiencing large increases in income. When we exclude households with imputed earnings, the percentage of households experiencing large changes in income is roughly 25 percent in each panel, again about evenly divided between those with large decreases in income and those with large increases in income. The rise in the percentage of households with large income changes over time is consistent with the fact that the imputation rate has risen substantially over this time period. Income volatility calculated using imputed data picks up cross-sectional income variation which tends to be higher than income variation over time.

A similar pattern is observed when we restrict the sample to households below

200 percent of the poverty line (see Figure 4). The percentage of lower-income households with large changes in income grows at a slower rate when observations with imputed earnings are not included. Lower-income households that experience large changes in income are more likely to experience large decreases in income than to experience large increases in income.

These descriptive results suggest that imputation in the SIPP likely leads to a large number of households being incorrectly identified as having volatile incomes. This misclassification likely leads to an understatement of the association between rates of food insufficiency and income volatility. In the next section, we test those propositions.

B. *Association of Income Volatility and Food Insufficiency*

We confirm that, according to the SIPP, households with imputed earnings are more likely to experience large changes in income (see Table 2). After controlling for demographic and employment characteristics, households with imputed earnings have a 16 percentage point higher probability of experiencing a large percentage change in income. Incomes vary more for households with lower incomes relative to FPL and for households headed by younger workers and by those who are single, which is consistent with other findings (Congressional Budget Office, 2008).

Table 3 reports the main results from a linear probability model of equation 3 among households with incomes below 200 percent of FPL in year 2. The coefficients in Table 3 are the association between a household reporting food insufficiency in year 2 and experiencing an income drop or rise of 25 percent or more. The first column reports the association between large percent changes in income and food insufficiency among all households, including those with imputed earnings. The second column reports the association, when observations with imputed earnings are excluded.

Estimates using all observations, including those with imputed earnings, show that households that experienced a 25 percent or greater drop in income between year 1 and year 2 had a 0.06 percentage point lower chance of reporting food insufficiency, an effect which is statistically insignificant. Households experiencing a large rise in income had a 0.7 percentage point lower chance of reporting food insufficiency, an association that was also imprecisely estimated.

These estimates are biased downward, however, because of the inclusion of observations with imputed data. The exclusion of imputed observations yields a more plausible association between income drops and food insufficiency—households that experience large income drops have a 1.3 percentage point greater chance of food insufficiency (see column 2). Although this association is not statistically significant, the direction of the association is what we would expect—income drops are associated with a higher, not lower, probability of experiencing food insufficiency. Likewise, households that experience large increases in income are much less likely to report food insufficiency—exclusion of imputed observations results in a 0.4 percentage point lower chance of food insufficiency when incomes rise, although this effect is not statistically significant. In addition, the coefficient estimates of large income declines and large income increases are jointly statistically insignificant.

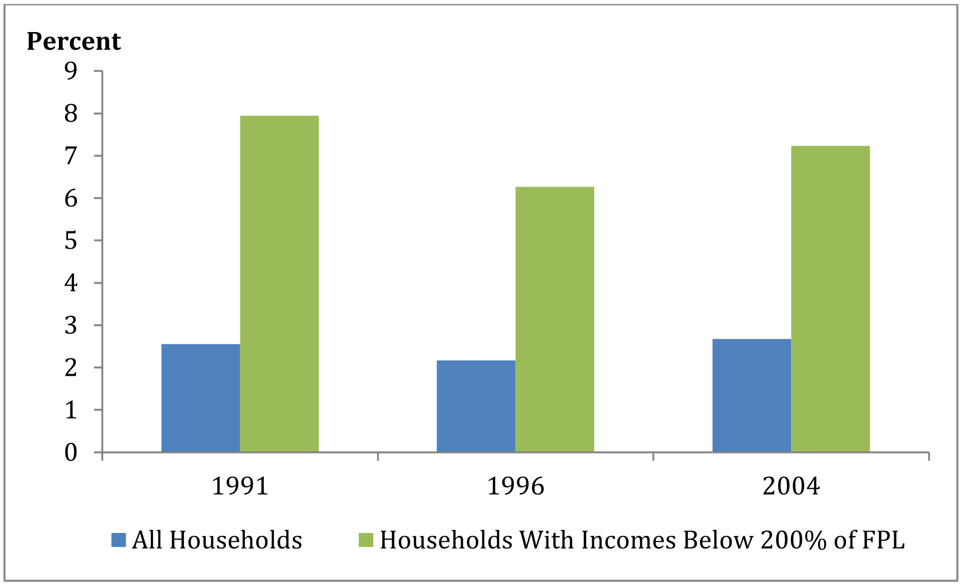
V. Discussion and Conclusions

This paper explores the impact of using imputed data in calculating income volatility and then measuring the association between income volatility and food insufficiency. Imputed data, particularly hot-deck imputed data, can contribute to misleading estimates when calculating changes in the potentially imputed variable over time, because the calculated changes in effect capture cross-sectional variation instead of variation over time.

We show that including imputed observations leads to a substantial understatement of the association between income drops and food insufficiency among lower-income households. In fact, including all imputed observations suggests that, when income falls, food insufficiency declines (although those results are imprecisely estimated). Excluding imputed observations yields substantially different results—large income drops are associated with a 1.3 percentage point greater chance of food insufficiency, although the estimate is still not precisely estimated.

The association between large income drops and food insufficiency estimated using non-imputed data goes in the opposite direction and is almost 21 times larger in magnitude than one would estimate when using all observations provided by the Census Bureau, which include those with imputed earnings. We strongly advise caution when examining changes in income in the SIPP that include imputed observations.

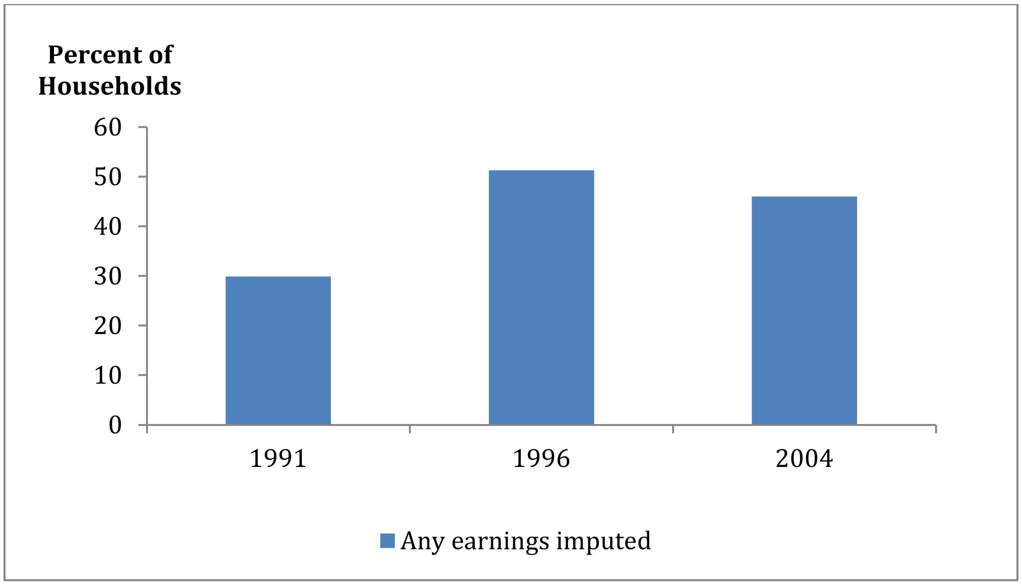
Figure 1: Households Reporting Food Insufficiency Over Previous Four Months



Source: Authors' calculations from the 1991, 1996, and 2004 panels of the Survey of Income and Program Participation.

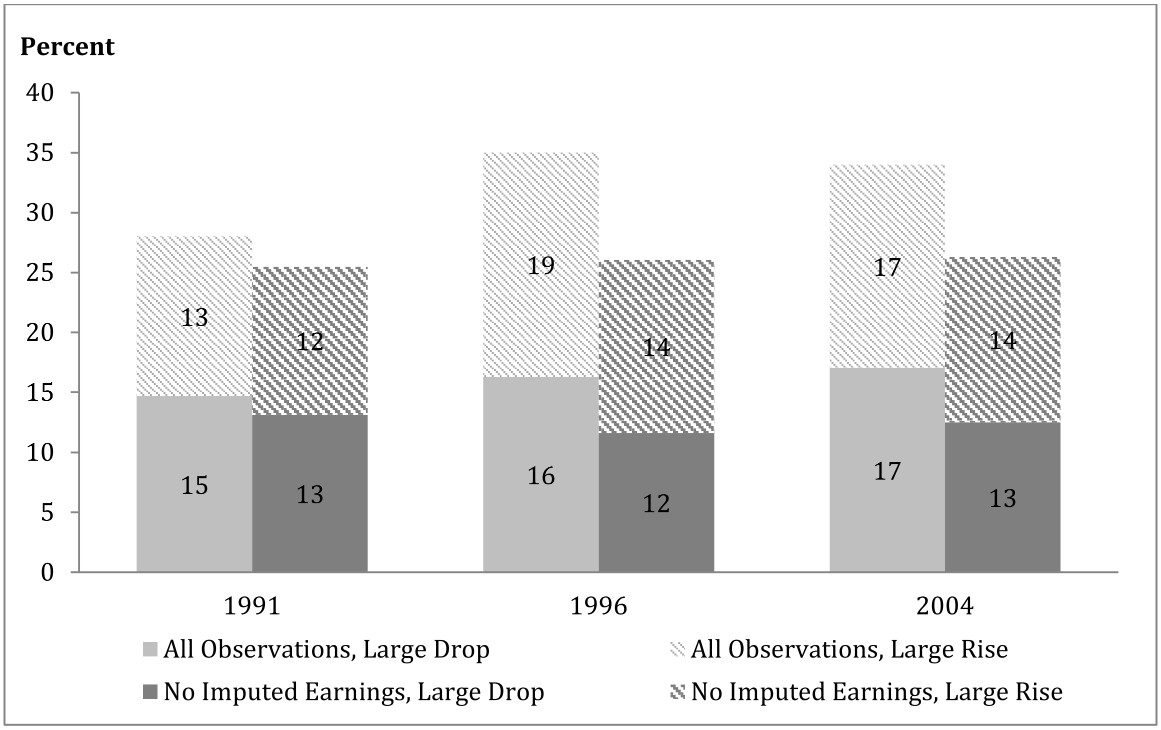
Note: FPL= federal poverty guideline.

Figure 2: Earnings Imputation Over a Two-Year Period



Source: Authors' calculations from the 1991, 1996, and 2004 panels of the Survey of Income and Program Participation.

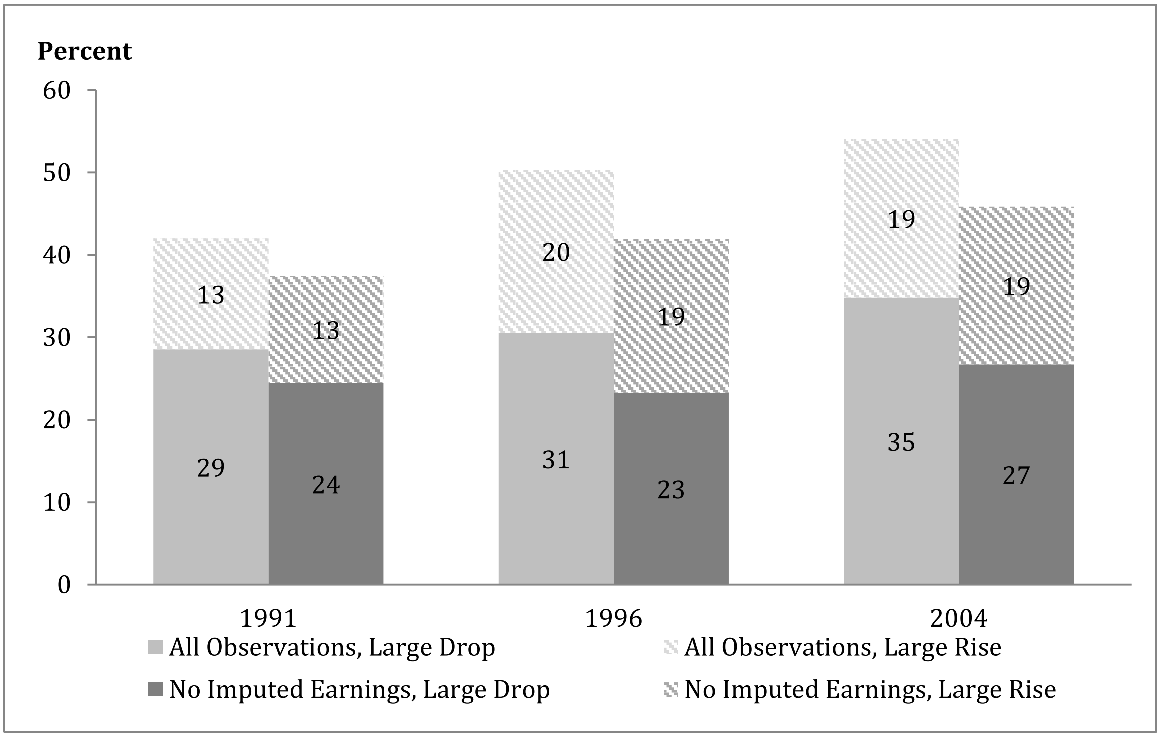
Figure 3: Households Experiencing a 25 Percent or Greater Change in Income



Source: Authors' calculations from the 1991, 1996, and 2004 panels of the Survey of Income and Program Participation.

Note: The category "All Observations" includes observations with reported earnings and observations with imputed earnings.

Figure 4: Households Below 200 Percent of the Poverty Level Experiencing a 25 Percent or Greater Change in Income



Source: Authors' calculations from the 1991, 1996, and 2004 panels of the Survey of Income and Program Participation.

Note: The category "All Observations" includes observations with reported earnings and observations with imputed earnings.

Table 1: Characteristics of Households in the Sample

	All Observations	Not Imputed	Imputed
Percent of households unless indicated otherwise			
Household income as percent of FPL	380	375	387
Number of children under age 17	1.1	1.1	1.1
High school graduate	29	29	28
More than high school	60	59	60
Black	11	10	13
Hispanic	10	10	11
Other race	4	4	5
Married with children	40	39	42
Married with no children	20	18	23
Single with no children	26	28	22
Male	59	60	57
Received food assistance	9	10	7
Number of hours worked (reference person)	1,684	1,700	1,661
Number of hours worked (spouse)	845	787	924
Age (years)	40	39	41
Income drop greater than or equal to 25 percent	16	13	21
Income rise greater than or equal to 25 percent	16	13	20
Number of households	41,295	22,465	18,830

Source: Authors' calculations from the 1991, 1996, and 2004 panels of the Survey of Income and Program Participation.

Note: Characteristic as measured in year 1. Weighted by household weights. FPL=federal poverty guideline.

Table 2
Association Between Imputed Earnings and 25 Percent of Greater Change in Income

Regressor	Coefficient	Standard Error
Imputed earnings	0.1577***	(0.0045)
Household income as percent of FPL	-0.0229***	(0.0011)
Age	-0.0035***	(0.0003)
Number of children under age 17	-0.0160***	(0.0030)
High school graduate	0.0000	(0.0001)
More than high school	0.0001	(0.0001)
Black	0.0000	(0.0001)
Hispanic	0.0001**	(0.0001)
Other race	0.0003**	(0.0001)
Married with children	-0.0149*	(0.0086)
Married without children	0.0190*	(0.0106)
Single without children	0.0317***	(0.0093)
Male	0.0024	(0.0050)
Food assistance in year 1	0.0500***	(0.0136)
Food assistance in year 2	0.0253*	(0.0139)
Hundreds of hours worked in year 1	-0.0041***	(0.0004)
Hundreds of hours worked in year 2	-0.0030***	(0.0004)
Spouse, hundreds of hours worked in year 1	-0.0027***	(0.0004)
Spouse, hundreds of hours worked in year 2	-0.0022***	(0.0004)
Constant	0.6110***	(0.0168)
Number of observations	41,295	
R-squared	0.1056	

Source: Authors' calculations from the 1991, 1996, and 2004 panels of the Survey of Income and Program Participation.

Notes: The dependent variable equals one if the household experiences a percentage change in income of 25 percent or more and zero otherwise. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3
Association Between Percent Change in Income of 25 Percent or More and Food Insufficiency

	(1) All Observations	(2) Excluding Imputed Observations
25% Drop in Income	-0.0006	0.0126
	(0.0060)	(0.0086)
25% Rise in Income	-0.0066	-0.0037
	(0.0071)	(0.0098)
Population	< 200% FPL	< 200% FPL
Mean of Dependent Variable	0.0721	0.0790
Observations	10,246	6,027
R-squared	0.0229	0.0249

Source: 1991, 1996, and 2004 panels of the Survey of Income and Program Participation.

Notes: Standard errors are in parentheses.
FPL=federal poverty guidelines.
*** p<0.01, ** p<0.05, * p<0.1

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