Money Talks:
The Effects of Monetary Incentives on Earnings Non-Response in the SIPP[*†]

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Abstract

The Survey of Income and Program Participation (SIPP) has a history of using conditional and discretionary monetary incentives to induce survey responses. While incentives have been effective in increasing unit response, little is known about their effect on item response. This paper exploits a multi-wave random monetary incentive experiment for the SIPP 2014 panel to examine the effect of incentives on earnings non-response. We show that individuals in incentive-receiving households have a 1.3-percentage-point lower earnings non-response rate than those in non-incentive households. This effect is robust to controls for observed and unobserved individual heterogeneity and non-random panel attrition in a correlated random effects specification. Further, we find the effect is driven by a $40 incentive assignment and not the $20 incentive. Consistent with theories linking unit and item non-response, we find that contemporaneous earnings non-response is associated with a higher probability of attrition in the following wave, but the $40 incentive mitigates this relationship.

Keywords: SIPP, earnings non-response, monetary incentives, unit response, attrition, experiment

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1. Introduction

Non-response is a persistent problem in household surveys (e.g., Groves 2006). Non-response behaviors can be broadly classified into two categories. *Unit* non-response occurs when individuals in sampled households are unable to be contacted or refuse participation in a survey. *Item* non-response takes place when unit participants do not provide answers to all questions (items) asked by the survey. In either form, non-response is a well-known missing data problem that reduces survey representativeness and may introduce selection bias.

Survey administrators have several strategies for mitigating non-response. First, advance letters inform sampled households of their selection for a survey. Such letters, legitimize the survey and emphasize the importance of their participation (Groves, Singer, and Corning 2000). Second, data collection and procedure designs include multiple contacts and follow-ups, allowing for numerous response opportunities should the household initially refuse or if the interviewer finds no one at home on the first attempt (Singer 2002). Third, different interview modes (e.g., Internet, mail, telephone, in-person) give sample members various opportunities to respond according to their preferences or availability (Ekholm et al. 2010). Fourth, monetary incentives (conditional or unconditional) offset the burden of the household's time commitment to the survey request (Bates, Dahlhamer, and Singer 2008). These strategies are typically aimed at enhancing unit response, but they might also affect item non-response.

Monetary incentives have been shown to increase unit response rates (Westra, Sunduchki, and Mattingly 2015; Singer and Ye 2013), but their influence on item non-response is less clear. One view maintains that unit and item non-response are fundamentally independent decisions (e.g., Groves, Singer, and Corning 2000). A competing view establishes a link between these two decisions. The response continuum model (Yan and Curtin 2010) places individual propensity to respond on a continuum from least cooperative (no unit response) to most cooperative (unit response and all item response). A survey attribute, such as a monetary incentive, can influence an individual's location on the response continuum. At an individual level, a conditional monetary incentive that shifts a respondent along the continuum toward full cooperation increases the propensity for item response; that is, there is a positive relationship between unit and item response. However, in the aggregate, the incentive could lead to more item non-response if most of the population is concentrated in the low-propensity-to-respond region of the continuum and their reluctance to cooperate manifests in the form of item non-response.[1] If the incentive nudges more people into unit response than it pushes unit responders into earnings response, then the net effect of the incentive would result in a higher earnings non-response rate.

In this paper, we examine the effect of conditional monetary incentives on earnings non-response. Household survey earnings data are the primary source of publicly available information on personal and household income in the United States. Estimates from these data are used to study inequality, poverty, and returns to human capital investments (e.g., Fan, Seshadri, and Taber 2017; Warren, Fox, and Edwards 2020). Although there are alternative sources of earnings measures to compensate for missing survey earnings, such

[1] A similar point was made by Serfling (2004), who hypothesized a negative relationship between unit and item response (or a "reverse" cooperation continuum) could occur at the individual level if a conditional monetary incentive was offered and individuals only participated to collect the incentive. Singer, Groves, and Corning (1999) explores whether perceptions about equity could create a negative relationship between incentives and survey response.

as administrative data, they do not provide a complete picture of household earnings profiles that surveys can. Administrative data have limitations in timeliness and disclosure and may suffer from under-reporting of self-employment earnings (Bee and Rothbaum 2019; Hurst, Li, and Pugsley 2014). Further, access to administrative data is highly restrictive, and there are questions about whether earnings concepts between administrative and survey data are comparable (Abowd and Stinson 2013). At the same time, earnings non-response rates in household surveys have been increasing over time (e.g., Hokayem, Bollinger, and Ziliak 2015).

The Survey of Income and Program Participation (SIPP) in its recent history incorporated monetary incentives as a way of increasing unit response. We examine whether the effects of this survey feature extend to earnings non-response.

The SIPP used monetary incentives in one or more waves of the 1996, 2001, 2004, 2008, and 2014 panels. Earnings non-response rates varied substantially between panels, which reflects a variety of differences in survey attributes. In addition to the use of monetary incentives, other differences include introduction of feedback in the instrument, increasing the length of the reference period from the preceding four months to the preceding calendar year, and the introduction of an event history calendar (EHC).[2] Earnings non-response rates trended upward over the course of each panel.

Monetary incentives are associated with lower rates of earnings non-response. Figure 1 presents earnings non-response rates over time by SIPP panel, as well as differences in earnings non-response by incentive receipt. Panel A shows the earnings non-

[2] The EHC is a heuristic device that allows respondents map events (e.g., job, education, and marital status spells) to specific calendar dates. Refer to National Academies of Sciences, Engineering, and Medicine (2018) for more information on the EHC and SIPP 2014 redesign.

response rate in the SIPP by wave for the 1996–2008 panels and the first two waves of the 2014 panel.[3] There is noticeable variation in the earnings non-response rates within panels and over time. The average non-response rate increased from about 10 percent in Wave 1 of the 1996 panel to 21 percent by Wave 8 of the 2001 panel. There was a marked downward shift in non-response rates in the 2004 and 2008 panels, when the survey instrument added earnings feedback[4] and provided respondents with more options for reporting earnings. While non-response rates reached higher levels in the 2008 panel compared to the 2004 panel, they peaked around 13 percent. The 2014 panel saw the introduction of a new survey instrument. Earnings non-response rates were 19 and 21 percent in Waves 1 and 2, respectively. In all panels, there is a general trend toward higher earnings non-response rates in later waves of the survey, though the increases are not always monotonic.

Panel B shows the difference in earnings non-response rates between individuals in incentive-receiving households and individuals in non-incentive households in the 1996–2008 panels. Over this period, monetary incentives differed by mode of distribution (i.e., random assignment, field representative discretion) and conditions for eligibility (e.g., survey participation).[5] Relative to individuals in non-incentive households, those in incentive households never had statistically significant higher earnings non-response rates,

[3] Incentives for SIPP 2014 Wave 3 were targeted (i.e., non-random) and there was no incentive offered for Wave 4. Therefore, we included only the first two waves of the 2014 panel.
[4] Feedback is a form of dependent interviewing in which a sample member's responses from the previous wave of a survey are carried forward to the current interview and incorporated in the survey instrument. Feedback assists with recall and may mitigate issues associated with seam bias (Moore 2007), but also reduces respondent burden—and therefore item non-response—by reminding respondents of their previous answers to specific questions. In the SIPP, typical items slated for feedback include jobs and their associated job characteristics. In the 2004 and 2008 panels, earnings amounts were added to the set of feedback items.
[5] Refer to Westra, Sunduchki and Mattingly (2015) for details about the use of incentives in each of these panels. The 1996 panel used incentives in various waves (Abreu and Winters 1999); however we only have access to incentive data for Wave 1.

and they had lower earnings non-response rates ($p \leq 0.05$) in all but 13 of the 38 waves for which incentive data are available. However, these differences may not have a causal interpretation because incentives were not generally offered randomly.

With the fielding of a new survey instrument for SIPP 2014, the Census Bureau conducted a randomized multi-wave experiment to evaluate the causal effect of conditional monetary incentives on unit response. Broadly speaking, incentive eligibility and amounts were varied across groups within a wave (cross-sectionally) as well as across waves (longitudinally). Incentives were paid out conditional on the completion of a "sufficient partial" interview by at least one household member.[6] At this stage of the interview, the respondent has not yet been asked questions about healthcare utilization and adult and child well-being. We use random incentive assignment and variation in earnings non-response in the 2014 SIPP to estimate the causal effect of monetary incentives on individual earnings non-response.

The incentive experimental design varied incentive amounts across households in the first two waves of the 2014 panel.[7] Households were randomly divided into four groups before the survey was implemented. In Wave 1, Groups 1 and 2 received \$0 and served as the cross-sectional control groups. Groups 3 and 4 were offered conditional incentives of \$20 and \$40, respectively. In Wave 2, Group 2 became eligible for \$40, and Group 3 became incentive ineligible. Group 4 was divided into two groups (4a and 4b) receiving no

[6] In the SIPP a sufficient partial interview occurs when an individual respondent makes it through household roster, EHC, and assets questions. In our sample, all individuals were at least unit responders and thus were in households that received the incentive if they were eligible.

[7] The monetary incentive program continued in Wave 3, but incentives were no longer assigned randomly; instead, they were offered to households with a greater likelihood of attrition based on a prediction model using the first two waves of data (Fields, Marlay and Campanello 2015).

incentive and $40, respectively. Group 1 remained incentive ineligible in Wave 2, meaning that Group 1 was the longitudinal control group.

We model the causal effect of incentives on earnings non-response using the potential outcome framework (Rubin 2005). In Wave 1, individuals cannot be observed in both incentive-receiving and non-incentive-receiving states. Random incentive assignment allows us to estimate the counterfactual non-response rate—the earnings non-response rate that would occur in the absence of a monetary incentive—from the sample of individuals in the control group (Groups 1 and 2). The difference in non-response rates for the treatment groups and the control provide a causal estimate of monetary incentives on non-response. We examine the effect of receiving any monetary incentive by comparing non-response rates in all incentive-receiving households (Groups 3 and 4) to the control, as well as the effect of different incentive amounts by comparing the non-response rates of Groups 3 and 4 to each other, and then separately to the control.

The varying incentive assignments between waves for the same households may complicate estimating the causal effect of monetary incentives on earnings non-response cross-sectionally in Wave 2. For example, Group 2 reflects households that were offered Wave 2 incentives after having already unit responded in Wave 1, Groups 3 and 4a were initially offered incentives in Wave 1 but had them "taken away" for Wave 2, and Group 4b maintained its $40 incentive offer in both waves. Comparing differences in non-response rates between incentive-receiving (Groups 2 and 4b) and non-incentive (Groups 1, 3, and 4a) individuals may not yield an unbiased estimate of the causal effect of incentives if the effects of incentive assignments in Wave 1 persist to Wave 2. For example, expectations about receiving future incentives might influence earnings non-response rates in Wave 2 for Groups 3 and 4a (Singer, van Hoewyk, and Maher 1998).

Further, non-random attrition that is correlated with incentive receipt in Wave 1 introduces another complication for estimating the causal effect of monetary incentives on earnings non-response in Wave 2 using cross-sectional data alone. To account for non-random attrition, we use a regression framework to estimate the causal effect of incentives while controlling for individual observable characteristics. However, if unobservable characteristics are correlated with attrition and the relationship between incentives and earnings response, then controlling for observable characteristics in the cross-section will not resolve issues associated with omitted-variable bias.

The longitudinal nature of SIPP allows us to use each respondent as their own control. We model individual unobserved heterogeneity as individual-specific constant terms. Estimation of the model requires eliminating the individual-specific effects, which can be accomplished using fixed effects ("within" and first-differences estimators) or random effects. We specify a correlated random effects (CRE) model using a Mundlak (1978) device to model unobserved heterogeneity; it defines the individual-specific intercepts as a function of individual time averages of time-varying regressors (e.g., incentive assignment). Wooldridge (2019) shows that this specification is robust in unbalanced panels and sample selection and develops conditions for when CRE generalizes to fixed effects or random effects.[8]

We find that individuals in incentive-receiving households who work for employers or other work arrangements have lower earnings non-response by 1.3 percentage points

[8] Wooldridge (2019) also shows that the CRE framework works well in non-linear models, which traditionally required the estimation of each individual-specific constant terms.

than individuals in non-incentive households. This effect is robust to controls for observable and unobservable characteristics. When including self-employed jobs, the effect of incentive on earnings non-response increases by 15 percent; that is, earnings from self-employment are less likely to be reported in the absence of an incentive.

Further, we show that earnings non-response in Wave 1 is positively correlated with attrition in Wave 2. This finding, coupled with the result that incentives lower earnings non-response, suggests that incentives indirectly lower attrition by lowering earnings non-response. We test whether incentives directly affect attrition by examining attrition rates by earnings non-response and incentive amount. We find that incentive receipt or amount has no qualitative effect on attrition for earnings responders. For earnings non-responders, the $40 incentive is associated with the lowest attrition rate.

The rest of the paper is organized as follows. Section 2 presents the potential outcomes framework with extensions to our regression and CRE specifications. Section 3 describes the SIPP data. We report our results in Section 4, and Section 5 discusses our finding and concludes.

2. Methods

The potential outcomes framework is useful for estimating causal effects from a binary treatment variable. Here, treatment refers to the conditional monetary incentive I, where $I = 1$ if a household receives a monetary incentive and $I = 0$ otherwise.[9] We assume that

[9] The experimental design included two distinct treatments: $20 and $40 incentives. Given that our primary research question is whether incentives affect earnings response, we characterize treatment as having any incentive. To the extent that $20 and $40 incentives have differential effects, the treatment effect would be a weighted average of the two; we test for differential effects of the incentive amounts Section 4.

individuals have two potential earnings response states (outcomes) r depending on whether they live in a household that received an incentive: r_1 if they do and r_0 if they do not.

A measure of the effect of incentives on earnings response for the randomly sampled *i*th individual is the difference in their earnings response in both states, $\Delta_i = r_{1i} - r_{0i}$. Taking the average of Δ_i over the entire population yields the average treatment effect (ATE)

$$\Delta = ATE = E(r_1 - r_0), \tag{1}$$

where $E(\cdot)$ is the expectation operator. Because r is a binary outcome variable, ATE estimates the average difference in earnings response *rates* between individuals in incentive households from those in non-incentive households. Of course, we are unable to calculate directly Δ_i since an individual cannot be observed simultaneously in both incentive and non-incentive states. Instead, we only observe earnings response outcomes and whether the individual was in an incentive household. It can be shown, then, that the observed outcome is

$$r = r_0 + I(r_1 - r_0). \tag{2}$$

If incentive assignment is random and thus independent of earnings non-response outcomes, then the components of ATE are

$$E(r|I = 1) = E(r_1|I = 1) = E(r_1) \tag{3}$$

$$E(r|I = 0) = E(r_0|I = 0) = E(r_0). \tag{4}$$

Plugging equations (3) and (4) into (1), the ATE is estimated by a simple difference in mean earnings non-response rates between those offered incentives and those who are not.

The ATE can also be specified as a regression-switching equation. Define the potential outcomes as

$$r_0 = \mu_0 + \upsilon_0, \quad E(\upsilon_0) = 0 \tag{5}$$

$$r_1 = \mu_1 + \upsilon_1, \quad E(\upsilon_1) = 0, \tag{6}$$

where $\mu_0 = E(r_0|I = 0)$, $\mu_1 = E(r_1|I = 1)$, and υ_0 and υ_1 are stochastic (random) elements with assumed zero mean. Substituting (5) and (6) into (2), we arrive at

$$r = \mu_0 + \upsilon_0 + I(\mu_1 - \mu_0 + \upsilon_1 - \upsilon_0). \tag{7}$$

Equation (7) is called a regression-switching equation because the incentive indicator I switches the regression from the counterfactual state to the treated state: $r = r_1$ when I = 1 and $r = r_0$ when I = 0.

The potential outcomes in Equation (7) can be estimated using data on individual response outcomes and incentive receipt by estimating the empirical equation

$$r_i = \alpha + \beta I_i + \epsilon_i, \tag{8}$$

where α is the counterfactual (r_0), β is the ATE, ϵ_i is an idiosyncratic error term assumed to be strictly exogenous (i.e., $E(\epsilon_i|I_i) = 0$), and i indexes individuals ($i = 1, 2, \dots, N$).

Violations of strict exogeneity may occur if the sample of unit responders used to estimate β in Equation (8) is non-random due to self-selection into unit response, non-random attrition (if estimating the ATE using Wave 2 data only), or the presence of an omitted variable (e.g., persistence of past incentive receipt). If these confounders are observable, we can account for them directly by adding them to Equation (8),

$$r_i = \alpha + \beta I_i + X_{it}'\gamma + \epsilon_i, \tag{9}$$

where X_i is a vector of observable individual characteristics that are correlated with incentive assignment and earnings non-response. In such situations, the ATE is still consistently estimated if strict exogeneity conditional on (X, I) is satisfied, $E(\epsilon_i|I_\mathrm{i}, X_i) = 0$. However, if other confounders are not observable then conditional exogeneity is violated and empirical estimation of Equation (9) will not produce an unbiased estimate of β without adding more structure to the model. Equations (8) and (9) can be estimated using cross-sectional (for each wave) or pooled data.[10]

If conditional exogeneity is violated because of individual-specific unobserved heterogeneity, then α in Equation (9) is no longer an unbiased counterfactual for r_1. Observing each respondent at least twice allows us to consider each respondent as their own control and move away from estimating a group counterfactual (e.g., α) toward individual-specific counterfactuals (e.g., α_i) in Equation (9).

$$r_{it} = \alpha_i + \beta I_{it} + X_{it}'\gamma + u_{it}, \tag{10}$$

In modeling individual-specific counterfactuals in Equation (10), we assume that individual unobserved heterogeneity (e.g., individual propensity to respond) is additive and time-invariant. Estimation of Equation (10) requires eliminating the individual-specific effects, which we do following Mundlak (1978). By averaging over t for each i, the individual-specific constant term can be written as $\alpha_i = \psi + \bar{Z}'{}_i\zeta + \eta_i$, where $\bar{Z}'{}_i$ is a vector of time averages of time-varying covariates.[11] Replacing α_i in Equation (10) yields our estimating equation

$$r_{it} = \psi + \bar{Z}'{}_i\zeta + \beta I_{it} + X_{it}'\gamma + e_{it}. \tag{11}$$

The coefficient β estimates the causal effect of incentives after controlling for observed and unobserved heterogeneity. Wooldridge (2019) shows that the parameters of Equation (11) can be estimated by pooled OLS, which is identical to fixed effects (within) estimator

[10] Pooled estimation requires the additional assumption of no serial correlation, which could be violated if incentive effects from one wave persist into the next.

[11] Unlike the within transformation for fixed effects, this specification allows for the inclusions of time-invariant regressors.

on the unbalanced panel. In addition, the coefficients of Equation (11) are estimable by non-linear methods (e.g., probit, logit).

3. Data

Measures of individual earnings response and household-level incentive receipt are taken from Waves 1 and 2 of the restricted-use SIPP 2014 panel. The redesigned SIPP instrument allows respondents age 15 and older to report up to eight jobs in the reference period.[12] Each job, which may include two distinct spells, is tied to a specific employer. Respondents are provided multiple ways to report their earnings, including different pay frequency options as well as different sources of earnings. This section describes our method for collapsing this complexity into a single indicator of earnings non-response for each respondent in a reference period. Incentives were assigned at the household level and indicators for incentive receipt and amounts are matched to respondents based on household indicators.

Each of the eight jobs is classified into work for an employer, own business, or other work arrangement ("contingent" work). Jobs one through seven can be classified into only one work arrangement. Job eight is a catch-all that records one or more types of employment arrangements, which may not be mutually exclusive.[13] We restrict our sample to the civilian population age 15 and over with at least one reported job. Self-employed workers might be less likely to have third-party reporting, which may influence their

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[12] Following the 1996 redesign, previous SIPP panels only outputted a maximum of two jobs and two businesses per respondent (Westat and Mathematica Policy Research, Inc. 2001).

[13] The variable EJB8_NUMJOBS indicates the number of work arrangements reported. For Waves 1 and 2 of SIPP 2014, 94 percent (unweighted) of respondents who reported employment on job line eight reported only one job. For those who reported multiple jobs, we cannot infer the type of work arrangements for individual jobs. Instead, we can only infer that a type of work arrangement occurred on at least one of those jobs. Job eight is not outputted to the public.

willingness to share earnings information with Census field representatives, particularly if they believe their information would be shared with other federal agencies (e.g., the Internal Revenue Service). At the same time, the self-employed may have volatile earnings that are more difficult to report. Because of these effects on potential earnings response propensities, we exclude self-employment jobs.[14] We also drop individuals with entirely imputed records.

We define earnings non-response as an indicator that any earnings amount for an individual was imputed in the reference year. Specifically, we use the status flags on wage and salary earnings and extra earnings (e.g., tips, commissions, bonuses, and overtime) across all job spells and earnings changes to identify missing earnings amounts.[15]

Individuals in incentive-receiving households are comparable to those in non-incentive households based on observable characteristics associated with earnings and unit response. Table 1 presents summary statistics for our sample of employees by incentive receipt pooled over both waves. The earnings non-response rate is about 19 percent among people in incentive households and 20 percent for those in non-incentive households. Proxy response has been shown to be highly correlated with earnings non-response (Bollinger and Hirsch 2013). About 31 percent of responses are given by a proxy in both incentive and non-incentive households. Seventy-one percent of interviews were conducted in-

[14] We later test the sensitivity of our results to these sample restrictions.

[15] Status flags simplify dealing with the complexity of earnings measures in SIPP. They indicate whether responses to a variable were reported or imputed and imputation method. To get a glimpse of this complexity, there are seven job lines with eight different pay frequencies and up to three earnings amounts (one original and two possible changes), plus earnings for job line eight, and four sources of extra earnings across each of the seven job lines, resulting in 197 variables. For wage and salary earnings (jobs one through seven), respondents can report up to two spells and changes in earnings from their original amount in each of those spells. Further, with each change respondents can also change the pay type (e.g., hourly wage to monthly salary). For each spell, the respondent may report regular wage and salary earnings at different frequencies depending on their preference (e.g., hourly, annually, monthly).

person for individuals in incentive households compared to 68 percent for non-incentive respondents.[16] Individuals show similar household, socioeconomic, and employment characteristics regardless of incentive assignment. Incentive-receiving households received an average of $34.40 for their participation in Waves 1 and 2 of the survey. However, pooling inevitably smooths over important design features of the incentive experiment. Individual characteristics for households in experimental groups who were offered incentives in one wave and not the other are represented in both columns of Table 1.

Sources of selection into Wave 1 and later Wave 2 may be correlated with incentive assignment.[17] To ensure that differences between treatment and control groups in earnings non-response is driven by the incentive and not respondent characteristics, we examine the composition of our sample by incentive assignment and wave. Table 2 presents the make-up of treatment and control groups by household, socioeconomic, and employment characteristics by wave. Table 2 accounts for the experimental design, in which incentives varied between groups and waves. In Wave 1, the treatment column comprises Groups 3 and 4, receiving $20 and $40, respectively. In Wave 2, the treatment column comprises Groups 2 and 4b, each receiving $40.

In general, the observational characteristics of the incentive and non-incentive individuals within and between waves are similar with few exceptions. Columns (1) and (2) show the composition of control and treatment groups, respectively, for Wave 1, and Column (3) presents the difference. Columns (4) – (6) present the same information for

[16] Typically, telephone interviews are reserved for Waves 2 and later.

[17] Recall that our sample is restricted to survey participants with reported jobs. Selection into reporting jobs (another form of item response), which sets the universe for earnings questions, could be correlated with incentive assignment across waves. In longitudinal data, item non-response in prior waves has been shown to be correlated with subsequent attrition (Loosveldt, Pickery, and Billiet 2002). If incentives affect item response in Wave 1 (e.g., job reporting) then those effects could persist into unit response in Wave 2.

Wave 2. For Wave 1, the proxy response rate is 1.4 percentage points higher for the treatment group than the control ($p \leq 0.05$). Households in the treated group are 5.4 percent larger than the control ($p \leq 0.1$). The treatment and control groups show some differences in educational attainment, with the former more likely to have some college (no degree) or a four-year college degree ($p \leq 0.01$) and the latter more likely to have an advanced degree ($p \leq 0.01$). In Wave 2, the only statistically significant differences between the treatment and control groups are a higher number of jobs ($p \leq 0.1$) and the share with only a high school degree ($p \leq 0.05$) among the treated. Columns (3) and (6) provide initial estimates of the unconditional treatment effect of incentive on earnings non-response by wave. We observe 1.0 and 1.4 percentage points lower earnings non-response among the treated than the control in Waves 1 and 2, respectively. In the next section, we examine the treatment effect in more detail.

4. Results

In this section, we report estimates from the potential outcome and regression frameworks outlined in Section 2. We begin by comparing individual earnings non-response rates by incentive receipt.[18] Next, we present results from the CRE model and examine the role of unobserved heterogeneity in earnings non-response. Finally, we conduct a simple test of one hypothesis of the response continuum model.

4.1. The Effect of Incentives on Earnings Non-Response

Figure 2 presents estimates of the ATE using Equation (1) (i.e., unconditional difference in means) for the pooled sample and by wave. Estimates are weighted by person weights

[18] Although the dependent variable presented in the theoretical framework of Section 2 was earnings response, for the empirical analysis we use earnings non-response as our dependent variable.

for the reference year. For the pooled sample, earnings non-response is 1.4 percentage points lower for individuals for incentive-receiving households (SE = 0.004). Earnings non-response is 1.0 (SE = 0.005) and 1.4 (SE = 0.006) percentage points lower for individuals in incentive-receiving households compared to those in non-incentive households in Waves 1 and 2, respectively.

Comparing differences in earnings non-response rates by incentive receipt masks important differences in the experimental design. The incentive experiment varied the incentive amount as well as incentive eligibility within and across waves. Figure 3 shows estimates of the ATE for four different experiment groups: \$20 – \$0, \$40 – \$0, \$40 – \$20 in Wave 1; and \$40 – \$0 in Wave 2. When compared to the incentive non-recipients, receiving the \$40 incentive lowers the non-response rate by 1.4 percentage points (SE = 0.006) in both waves. The ATE for the \$40 incentive group is negative compared to the \$20 group, but this difference is not statistically significant. Similarly, the difference in earnings non-response between the \$20 incentive and the non-incentive groups is not statistically significant (i.e., confidence intervals include zero).

Regression estimates of the ATE (Equation (8)) of monetary incentives on earnings non-response are presented in Table 3. Longitudinal weights through Wave 2 are used for all estimates. Columns (1) – (3) are pooled OLS estimates. Column (1) only includes the incentive indicator and a control for Wave 2. The monetary incentive lowers earnings non-response among individuals residing in incentive-receiving households by 1.0 percentage point.[19] Earnings non-response increases by 3.2 percentage points (SE = 0.004) in Wave 2,

[19] This difference between this estimate of the ATE and the 1.4 percentage points drop observed in Figure 2 is due to the use of longitudinal weights in Table 3 that assign a weight of zero to attritors between Waves 1 and 2. However, this difference is not statistically significant at the 10-percent level.

which is consistent with observations in previous panels (Figure 1), in which earnings non-response tended to increase with the duration of the panel. The R-squared of 0.2 percent shows that very little of the variation in earnings non-response is explained by incentive receipt and wave.

Column (2) adds variables that might be correlated with response propensity (Equation (9)). These include the number of household members aged 15 and older (in logs), the number of jobs held in the reference year (in logs), and indicators for whether earnings response for an individual was provided by a proxy, telephone interview mode (the omitted category is in-person interview), whether the respondent reported their earnings as an hourly pay rate, and whether the respondent reported having any extra earnings. In addition, the specification in Column (2) adds controls for individual demographic characteristics, such as race and ethnicity, sex, age, age squared, marital status, education, and foreign-born status. The estimated ATE increases in absolute value by 30 percent compared to Column (1), suggesting a negative correlation between these additional controls and incentive assignment. The additional controls also halved the estimated effect of the Wave 2 indicator, suggesting that these characteristics are also positively correlated with attrition. Further, this specification explained 5.5 percent of the variation in earnings non-response, which is a marked increase from 0.2 percent in the previous specification that excluded these controls.

If respondents vary in time-invariant unobserved ways that are associated with both earnings response and receipt of incentives, then the OLS estimates of the incentive effect will be biased even after controlling for observed heterogeneity. The specification used for Column (3) repeats the previous specification in Column (2) but adds controls for unobserved individual heterogeneity using the Mundlak device described in Equation (11).[20] The estimated coefficient in Column (3) shows that incentive recipients are 1.3 percentage points more likely to respond to earnings questions than non-incentive recipients. Although Wald tests reject the hypothesis that unobserved heterogeneity is equal to zero ($p \leq 0.01$), the unchanged estimated ATE from Column (2) to Column (3) indicates that unobserved heterogeneity is uncorrelated with the incentive effect on earnings non-response.

As a robustness check, we estimate logit models to account for the non-linearity of the binary dependent variable. Columns (4) and (5) repeat the specifications in Columns (2) and (3), respectively. Estimates are reported as average marginal effects.[21] In both logit specifications, the estimated marginal effect of incentives is unchanged from the OLS estimates. However, other indicators (e.g., interview mode, household size, total jobs, hourly pay) do show some sensitivity to the choice of estimation framework.

Until now, we restricted our sample to respondents age 15 and older who reported earnings from jobs for an employer or other work arrangements. Next, we examine whether our findings generalize to the self-employed and whether they are sensitive to the exclusion of school-age and retirement-age workers. The self-employed might have different ability or preferences for sharing income and earnings information with federal agencies. In addition, school-age and retirement-age workers might disproportionately select into part-time hourly work, which might affect the ease of reporting their earnings.

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[20] A fixed effects estimator using the within transformation would also control for unobserved heterogeneity but, given the experimental design and the binary incentive indicator, the time-demeaning process would restrict the identifying variation to individuals whose incentive assignment changed between Waves 1 and 2.
[21] We compute marginal effects for each individual and take the average of these effects.

Including the self-employed adds profits and other business income as earnings sources, with two implications for the resulting sample of all jobs. First, respondents who held self-employment jobs only are added to the sample. Second, if respondents held a mix of jobs for an employer and self-employment, and they reported earnings for the former but not the latter, then their earnings response status changes from an earnings responder to a non-responder.

Table 4 presents OLS and logit estimates of the ATE from our preferred CRE specifications for three separate samples. Panel A reports estimates for the employer-only sample from Columns (3) and (5) of Table 3. Panel B presents estimates for the age-restricted employer-only sample (age 18–65). The OLS estimate of -0.013 is unchanged from the sample that includes all ages. The logit estimate decreases in absolute value by 0.1 points (7.7 percent) to -0.012 (however, this difference is not statistically significant at the 10-percent level). The estimates for all jobs, including self-employment are shown in Panel C. For both OLS and logit specifications, the estimated incentive effect is 0.2 points (15.4 percent) higher in absolute value. Wald tests for each set of estimates reject the null hypothesis of no unobserved heterogeneity in earnings non-response ($p < 0.01$). These results show that excluding self-employment jobs underestimates the incentive effect on earnings non-response.

4.2. Direct and Indirect Effect of Incentives on Attrition

The response continuum model predicts a positive relationship between item and unit response at an individual level. If this hypothesis is correct, then the results presented in Section 4.1 suggest that incentives also indirectly lower attrition through their effect on earnings non-response. The SIPP panel data permit an explicit test of the relationship between item and unit non-response. In addition, the random incentive assignment could test whether incentives directly affect attrition.

To the extent that earnings non-response is indicative of a low propensity to respond, it may be associated with a higher probability of attrition. A direct test of the relationship between unit and item non-response is to compare the average rate of attrition in Wave 2 to earnings non-response in Wave 1 (e.g., Loosveldt, Pickery, and Billiet 2002; Yan and Curtin 2010). This test requires panel data since, in a cross-section, item non-response can only be identified from the set of unit responders. If we allow this test to vary by incentive amount and compare average attrition rates of earnings non-respondents by incentive assignment, we can infer whether incentives in Wave 1 directly affect attrition in Wave 2 and whether the effect varies by incentive amounts.

Figure 4 plots the probability of attrition in Wave 2 by earnings response and incentive amount in Wave 1. Regardless of incentive amounts, the probability of attrition is higher for earnings non-respondents than respondents. Specifically, the probability of attrition is 8.8, 10.1 and 5.3 percentage points higher for earnings non-respondents to respondents who received \$0, \$20, and \$40 incentives, respectively, in Wave 1 ($p < 0.05$ for all estimates). This is consistent with the hypothesis that unit and item response are positively correlated.

The incentive may directly affect attrition independent of its effect on earnings non-response. Among earnings non-responders, the \$40 incentive lowers the attrition rate by 5.0 percentage points more than the \$20 group ($p < 0.05$).[22] The incentive has no effect

[22] The attrition rate among \$40 incentive recipients who earnings non-respond is also 2.7 percentage points more than the control group non-responders. However, this difference is not statistically significant at the 10-percent level.

on attrition rates for earnings responders, which diminishes the combined effect of incentives on attrition.

5. Concluding Remarks

Monetary incentives have been used as leverage to elicit responses to household surveys. They have been shown to be effective in increasing unit response. However, it is less clear how incentives affect item response. In this paper, we presented data from a random conditional monetary incentive experiment in the SIPP 2014 panel to examine how incentives affect earnings non-response.

The SIPP monetary incentive experiment varied incentive amounts cross-sectionally within waves, as well as longitudinally between waves. We used a potential outcomes framework to estimate the ATE for receiving any incentive at any time relative to receiving no incentive, as well as differential effects of incentive amounts. We presented evidence that individuals in incentive-receiving households had an average earnings non-response rate decline of 1.4 percentage points in the pooled sample. We found that earnings non-response increased from Wave 1 to Wave 2, but the incentives had a stronger effect on earnings non-response in the Wave 2 subsample, where incentive-receipt lowers earnings non-response rates by 1.0 and 1.4 percentage points, respectively.

Previous studies of the SIPP 2014 incentive experiment found that $40 incentives were effective at increasing unit response whereas $20 incentives were not (Westra, Sunduchki, and Mattingly 2015). We found that this result extends to earnings non-response. We showed that individuals in households receiving $20 incentives were more likely to respond to earnings questions than those receiving no incentives, but this result was not statistically significant at conventional levels; we found a similar result comparing differences in earnings non-response for those receiving $40 to those receiving $20 incentives.

We extended the potential outcomes framework to a regression specification that controlled for observable and unobservable heterogeneity. We specified a correlated random effects (CRE) model that controlled for unobserved heterogeneity using a Mundlak (1978) device on the unbalanced panel following Wooldridge (2019). Regression estimates showed that incentives lowered earnings non-response of those who worked for employers or other work arrangeements by 1.3 percentage points on average. While Wald tests rejected the hypothesis of no unobserved heterogeneity, this estimate of the ATE was robust to including controls for observed and unobserved heterogeneity, as well as age restrictions. When adding self-employment to the sample, the estimated ATE was 1.5 percentage points lower for individuals in incentive-receiving households.

There are many different competing views about the relationship between unit and item non-response. One view maintains that determinants of unit and item non-response are fundamentally different (e.g., Groves, Singer, and Corning 2000). A second view places individual response propensity along a “cooperation” or “response” continuum (Serfling 2004; Yan and Curtin 2010) from least cooperative (no unit response) to most cooperative (unit response and all item response). The response continuum model hypothesizes a positive correlation between unit non-response and item non-response. We leveraged the SIPP panel to test this hypothesis by comparing attrition rates in Wave 2 by earnings non-response in Wave 1. We found that individuals who did not report their earnings in Wave 1 were more likely to attrit in Wave 2, which is consistent with a positive correlation between unit and item non-response. We also showed differences in attrition rates for incentive receipt and amounts conditional on Wave 1 earnings non-response. Individuals in households receiving for $40 incentives who also did not report their earnings in Wave 1 were less likely to attrit from the panel than those who received no incentive or $20. This result implies that the $40 incentive has a direct effect on attrition independent of its indirect effect through reducing earnings non-response.

References

Abreu, Denise A., and Franklin Winters. 1999. *Using Monetary Incentives to Reduce Attrition in the Survey of Income and Program Participation.* Washington, DC: U.S. Census Bureau, 1999.

Abowd , John M., and Martha H. Stinson. 2013. "Estimating Measurement Error in Annual Job Earnings: A Comparison of Survey and Administrative Data." *The Review of Economics and Statistics* 95 (5): 1451-1467.

Bates, Nancy, James Dahlhamer, and Eleanor Singer. 2008. "Privacy Concerns, Too Busy, or Just Not Interested: Using Doorstep Concerns to Predict Survey Nonresponse." *Journal of Official Statistics* 24 (4): 591-612.

Bee, Adam, and Jonathan Rothbaum. 2019. "The Administrative Income Statistics (AIS) Project: Research on the Use of Administrative Records to Improve Income and Resource Estimates." SEHSD Working Paper 2019-36, U.S. Census Bureau.

Bollinger, Christopher R., and Barry T. Hirsch. 2013. "Is Earnings Non-Response Ignorable?" *The Review of Economics and Statistics* 95 (2): 407-416.

Ekholm, Ola, Jens Gundgaard, Niels K. R. Rasmussen, and Ebba Holme Hansen. 2010. "The Effect of Health, Socio-Economic Position, and Mode of Data Collection on Non-Response in Health Interview Surveys." *Scandinavian Journal of Public Health* 38: 699-706.

Fan, Xiaodong, Ananth Seshadri, and Christopher Taber. 2017. "Understanding Earnings, Labor Supply, and Retirement Decisions." *Prepared for the 19th Annual Joint Meeting of the Retirement Research Consortium.* Washington, DC.

Fields, Jason, Matthew Marlay, and Patrick Campanello. 2015. "Survey of Income and Program Participation." *Proceedings of the 2015 Federal Committee on Statistical Methodology (FCSM) Research Conference.* Washington, DC.

Groves, Robert M. 2006. "Non-Response Rates and Non-Response Bias in Household Surveys." *Public Opinion Quarterly* 70 (5): 646-675.

Groves, Robert M., Eleanor Singer, and Amy Corning. 2000. "Leverage-Saliency Theory of Survey Participation: Description and an Illustration." *The Public Opinion Quarterly* 64 (3): 299-308.

Hokayem, Charles, Christopher Bollinger, and James P. Ziliak. 2015. "The Role of CPS Nonresponse in the Measurement of Poverty." *Journal of the American Statistical Association* 110 (511): 935-945.

Hurst, Erik, Geng Li, and Benjamin Pugsley. 2014. "Are Household Surveys Like Tax Forms? Evidence from Income Underreporting of the Self-Employed." *The Review of Economics and Statistics* 96 (1): 19-33.

Loosveldt, Geert, Jan Pickery, and Jaak Billiet. 2002. "Item Non-Response as a Predictor of Unit Non-Response in a Panel Survey." *Journal of Official Statistics* 18 (4): 545-557.

Moore, Jeffrey C. 2007. "Seam Bias in the 2004 SIPP Panel: Much Improved, but Much Bias Still Remains." *PSID Event History Calendar Research Conference.* Washington, DC: U.S. Census Bureau.

Mundlak, Yair. 1978. "On the Pooling of Time Series and Cross Section Data." *Econometrica* 46 (1): 69-85.

National Academies of Sciences, Engineering, and Medicine. 2018. *The 2014 Redesign of the Survey of Income and Program Participation.* Washington, DC: The National Academies Press.

Rubin, Donald B. 2005. "Causal Inference Using Potential Outcomes: Design, Modeling, Decisions." *Journal of the American Statistical Association* 100 (469): 322-331.

Serfling, Oliver. 2004. "The Interaction Between Unit and Item Non-Response in View of the Reverse Cooperation Continuum." *Unpublished paper; Department for Statistics and Econometrics, University of Basel.*

Singer, Eleanor. 2002. "The Use of Incentives to Reduce Nonresponse in Household Surveys." (Institute for Social Research Survey Research Center).

Singer, Eleanor, and Cong Ye. 2013. "The Use and Effects of Incentives in Surveys." *The ANNALS of the American Academy of Political and Social Science* 645 (1): 112-141.

Singer, Eleanor, John van Hoewyk, and Mary P. Maher. 1998. "Does the Payment of Incentives Create Expectation Effects?" *The Public Opinion Quarterly* 62 (2): 152-164.

Singer, Eleanor, Robert M. Groves, and Amy D. Corning. 1999. "Differential Incentives: Beliefs About Practices, Perceptions of Equity, and Effects on Survey Participation." *The Public Opinion Quarterly* 63 (2): 251-260.

Warren, Lewis, Liana Fox, and Ashley Edwards. 2020. *The Supplemental Poverty Measure in the Survey of Income and Program Participation.* SEHSD Working Paper 2020-20, Washington, DC: U.S. Census Bureau.

Westat and Mathematica Policy Research, Inc. 2001. *Survey of Income and Program Participation Users' Guide.* Supplement to the Technical Documentation, Washington, DC: U.S. Census Bureau.

Westra, Ashley, Mahdi Sunduchki, and Tracy Mattingly. 2015. "Designing a Multipurpose Longitudinal Incentives Experiment for the Survey of Income and Program Participation." *Proceedings of the 2015 Federal Committee on Statistical Methodology (FCSM) Research Conference.* Washington, DC.

Wooldridge, Jeffrey M. 2019. "Correlated Random Effects Models with Unbalanced Panels." *Journal of Econometrics* 137-150.

Yan, Ting, and Richard Curtin. 2010. "The Relation between Unit Non-Response and Item Non-Response: A Response Continuum Perspective." *International Journal of Public Opinion Research* 22 (4): 535-551.

Table 1.

Sample Summary Statistics by Incentive Receipt, SIPP 2014 Waves 1 and 2

Variable	Incentive	Non-Incentive	Difference
Earnings non-response	0.190	0.205	–0.014***
	(0.392)	(0.403)	(0.004)
Incentive amount $USD	34.4	0.000	34.4***
	(9.0)	(0.000)	(0.090)
Proxy response	0.312	0.311	0.001
	(0.463)	(0.463)	(0.004)
Household size	3.0	3.0	0.005
	(1.5)	(1.6)	(0.020)
In-person interview	0.707	0.684	0.024***
	(0.455)	(0.465)	(0.006)
Telephone interview	0.291	0.314	–0.023***
	(0.454)	(0.464)	(0.006)
Total job spells in wave	1.2	1.2	0.001
	(0.472)	(0.470)	(0.005)
Total jobs in wave	1.2	1.2	0.004
	(0.432)	(0.427)	(0.004)
Paid by the hour	0.408	0.409	–0.002
	(0.491)	(0.492)	(0.005)
Received extra earnings	0.148	0.142	0.006
	(0.355)	(0.349)	(0.004)
Wage and salary earner	0.977	0.978	–0.001
	(0.151)	(0.147)	(0.001)
Age (in years)	41.5	41.7	–0.176
	(14.4)	(14.4)	(0.142)
Men	0.509	0.511	–0.002
	(0.500)	(0.500)	(0.004)
White alone	0.796	0.791	0.005
	(0.403)	(0.407)	(0.005)
Black alone	0.122	0.122	–0.000
	(0.328)	(0.328)	(0.004)
Asian alone	0.052	0.056	–0.004
	(0.222)	(0.229)	(0.003)
Other race alone	0.030	0.031	–0.001
	(0.171)	(0.173)	(0.002)
Hispanic	0.157	0.158	–0.001
	(0.364)	(0.365)	(0.004)

Foreign born	0.173	0.174	–0.001
	(0.378)	(0.379)	(0.004)
High school degree	0.260	0.254	0.006
	(0.438)	(0.435)	(0.004)
Some college	0.212	0.207	0.005
	(0.409)	(0.405)	(0.004)
2-year college degree	0.098	0.100	–0.002
	(0.297)	(0.301)	(0.003)
4-year college degree	0.218	0.216	0.002
	(0.413)	(0.411)	(0.004)
Advanced degree	0.120	0.132	–0.013***
	(0.325)	(0.339)	(0.003)
Married	0.530	0.535	–0.005
	(0.499)	(0.499)	(0.005)
Divorced or separated	0.137	0.134	0.003
	(0.344)	(0.340)	(0.003)
Widowed	0.019	0.019	–0.001
	(0.135)	(0.138)	(0.001)
Observations	24,000	28,000	52,000

Source: Authors' calculations from the Survey of Income and Program Participation 2014, Waves 1 and 2.

Notes: Sample restricted to the set of individuals who reported jobs for an employer or other work arrangement. Incentive receipt indicated by a respondent's residence within a household selected to receive a conditional incentive. All estimates in relative frequencies unless otherwise noted. Numbers in parentheses are sample standard deviations for Incentive and Non-Incentive columns and standard errors for the Difference column. Figures weighted by annual weights (PFINWGT in month = 12). Sample sizes unweighted and are rounded according to Census disclosure avoidance policies. ***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$.

Table 2.
Sample Summary Statistics and Differences by Incentive Receipt and Wave, SIPP 2014 Waves 1 and 2

	Wave 1			Wave 2		
	Control	Treatment	Difference	Control	Treatment	Difference
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Earnings non-response	0.193	0.183	–0.010*	0.213	0.199	–0.014**
	(0.395)	(0.387)	(0.006)	(0.410)	(0.399)	(0.007)
Incentive amount $USD	0.000	30.1	30.1***	0.000	40.0	40.0
	(0.000)	(10.0)	(0.123)	(0.000)	(0.000)	(0.000)
Proxy response	0.286	0.300	0.014**	0.330	0.327	–0.003
	(0.452)	(0.458)	(0.006)	(0.470)	(0.469)	(0.007)
In-person interview	0.788	0.795	0.007	0.602	0.596	–0.006
	(0.409)	(0.404)	(0.007)	(0.489)	(0.491)	(0.010)
Telephone interview	0.210	0.204	–0.007	0.396	0.403	0.007
	(0.408)	(0.403)	(0.007)	(0.489)	(0.490)	(0.010)
Household size	3.0	3.0	0.054*	3.0	3.0	–0.047
	(1.5)	(1.6)	(0.028)	(1.6)	(1.5)	(0.036)
Total job spells in wave	1.2	1.2	0.003	1.2	1.2	0.011
	(0.432)	(0.447)	(0.006)	(0.497)	(0.499)	(0.008)
Total jobs in wave	1.1	1.1	0.003	1.2	1.2	0.014*
	(0.398)	(0.411)	(0.005)	(0.448)	(0.457)	(0.007)
Paid by the hour	0.391	0.394	0.003	0.424	0.425	0.001
	(0.488)	(0.489)	(0.007)	(0.494)	(0.494)	(0.009)
Received extra earnings	0.146	0.148	0.001	0.138	0.148	0.010
	(0.353)	(0.355)	(0.005)	(0.345)	(0.355)	(0.006)
Wage and salary earner	0.976	0.976	–0.000	0.979	0.977	–0.002
	(0.152)	(0.152)	(0.002)	(0.143)	(0.150)	(0.002)
Age (in years)	41.6	41.5	–0.053	41.9	41.6	–0.254
	(14.2)	(14.3)	(0.203)	(14.5)	(14.5)	(0.239)
Men	0.512	0.504	–0.008	0.510	0.515	0.005
	(0.500)	(0.500)	(0.005)	(0.500)	(0.500)	(0.006)
White alone	0.792	0.794	0.002	0.790	0.798	0.008
	(0.406)	(0.404)	(0.007)	(0.407)	(0.402)	(0.008)
Black alone	0.120	0.123	0.003	0.125	0.121	–0.004
	(0.325)	(0.329)	(0.005)	(0.330)	(0.326)	(0.007)
Asian alone	0.056	0.052	–0.004	0.055	0.051	–0.004
	(0.231)	(0.223)	(0.004)	(0.228)	(0.221)	(0.005)
Other race alone	0.032	0.030	–0.002	0.030	0.030	–0.000
	(0.176)	(0.171)	(0.003)	(0.171)	(0.170)	(0.003)
Hispanic	0.154	0.158	0.004	0.161	0.156	–0.005
	(0.361)	(0.364)	(0.006)	(0.367)	(0.363)	(0.008)
Foreign born	0.169	0.175	0.006	0.178	0.171	–0.008
	(0.375)	(0.380)	(0.006)	(0.383)	(0.376)	(0.008)
High school degree	0.265	0.257	–0.008	0.245	0.263	0.017**
	(0.441)	(0.437)	(0.006)	(0.430)	(0.440)	(0.007)
Some college	0.201	0.212	0.012**	0.212	0.211	–0.000
	(0.401)	(0.409)	(0.006)	(0.408)	(0.408)	(0.007)
2-year college degree	0.101	0.099	–0.002	0.100	0.097	–0.003

	(0.301)	(0.298)	(0.004)	(0.300)	(0.296)	(0.005)
4-year college degree	0.210	0.222	0.012**	0.220	0.213	–0.007
	(0.407)	(0.416)	(0.006)	(0.414)	(0.410)	(0.007)
Advanced degree	0.133	0.116	–0.017***	0.132	0.124	–0.007
	(0.339)	(0.320)	(0.005)	(0.338)	(0.330)	(0.006)
Married	0.535	0.534	–0.001	0.535	0.524	–0.011
	(0.499)	(0.499)	(0.008)	(0.499)	(0.499)	(0.009)
Divorced or separated	0.136	0.137	0.001	0.132	0.137	0.005
	(0.343)	(0.344)	(0.005)	(0.339)	(0.344)	(0.006)
Widowed	0.019	0.018	–0.001	0.019	0.019	–0.000
	(0.137)	(0.134)	(0.002)	(0.138)	(0.136)	(0.002)
Observations	14,500	15,000	29,500	13,500	8,900	22,500

Source: Authors' calculations from the Survey of Income and Program Participation 2014, Waves 1 and 2.
Notes: Sample restricted to the set of individuals who reported jobs for an employer or other work arrangement. Incentive receipt indicated by a respondent's residence within a household selected to receive a conditional incentive. All estimates in relative frequencies unless otherwise noted. Numbers in parentheses are sample standard deviations for Treatment and Control columns and standard errors for Difference columns. Figures weighted by annual weights (PFINWGT in monthcode = 12). Sample sizes unweighted and are rounded according to Census disclosure avoidance policies. ***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$.

Table 3.
Regression Estimates of the Average Treatment Effect of Monetary Incentives on Earnings Non-Response, SIPP 2014 Waves 1 and 2

	OLS			Logit	
Variable	(1)	(2)	(3)	(4)	(5)
Incentive receipt	–0.010**	–0.013***	–0.013***	–0.013***	–0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Wave 2	0.032***	0.016***	0.016***	0.019***	0.019***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Proxy response		0.153***	0.140***	0.144***	0.134***
		(0.005)	(0.005)	(0.010)	(0.009)
Telephone interview		0.054***	0.051***	0.040***	0.038***
		(0.006)	(0.005)	(0.008)	(0.008)
Log household size (age ≥ 15)		0.018***	0.018***	–0.049***	–0.051***
		(0.006)	(0.006)	(0.016)	(0.017)
Log total reported jobs		0.026***	0.026***	0.039***	0.041***
		(0.008)	(0.008)	(0.013)	(0.014)
Paid by the hour		–0.031***	–0.032***	–0.006	–0.007
		(0.005)	(0.005)	(0.008)	(0.008)
Received extra earnings		0.120***	0.107***	0.132***	0.117***
		(0.007)	(0.006)	(0.012)	(0.010)
Include (X_{it}, Z_i)	No	Yes	Yes	Yes	Yes
Observations	43,000	43,000	43,000	43,000	43,000
Clusters	15,500	15,500	15,500	15,500	15,500
R^2	0.002	0.055	0.057	0.056	0.058
Wald H_0: $\zeta = 0$			3.3***		55.7***

Source: Authors' calculations from the Survey of Income and Program Participation 2014, Waves 1 and 2.
Notes: Dependent variable = 1 if earnings non-respondent. Earnings non-response defined as having any earnings item imputed for all jobs in the reference period. Incentive indicates respondent resides in a household that was offered a monetary incentive for a completed interview. All estimates weighted by longitudinal person weights through Wave 2. Columns (1), (2), and (4) use pooled models. Columns (3) and (5) use a Mundlak (1978) device to control for unobserved heterogeneity. Standard errors (in parentheses) are clustered at the household level. R-squared for the logistic regressions is the pseudo R-squared. Wald test statistics (F for OLS, Chi-squared for logit; df = 17) pertain to tests of the hypothesis that all Mundlak-type variables are jointly equal to zero (i.e., a test for unobserved heterogeneity). Sample restricted to respondents age 15 and older who report working for an employer or other work arrangement in the reference period. Sample size and number of clusters rounded to four significant digits according to Census disclosure avoidance policies. ***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$.

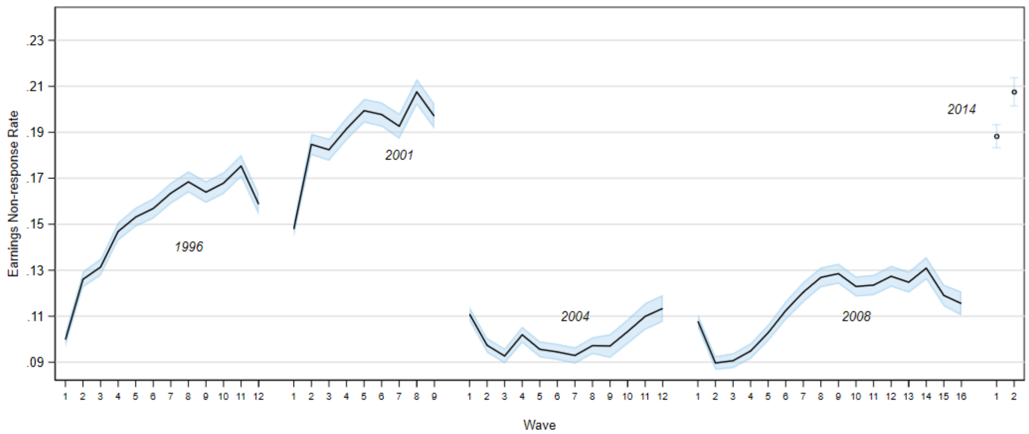
Table 4.
Robustness of Regression Estimates of the Average Treatment Effect of Monetary Incentives on Earnings Non-Response, SIPP 2014 Waves 1 and 2

	OLS	Logit
	(1)	(2)
Panel A. Employer-only		
Incentive receipt	–0.013***	–0.013***
	(0.005)	(0.005)
Observations	43,000	43,000
Clusters	15,500	15,500
R^2	0.057	0.058
Wald H_0: $\zeta = 0$	3.3***	55.7***
Panel B. Employer-only, Age 18–65		
Incentive receipt	–0.013***	–0.012***
	(0.005)	(0.005)
Observations	40,000	40,000
Clusters	14,500	14,500
R^2	0.057	0.058
Wald H_0: $\zeta = 0$	3.2***	56.5***
Panel C. All Jobs		
Incentive receipt	–0.015***	–0.015***
	(0.005)	(0.005)
Observations	47,500	47,500
Clusters	16,500	16,500
R^2	0.056	0.054
Wald H_0: $\zeta = 0$	4.8***	82.1***
Include (X_{it}, Z_i)	Yes	Yes

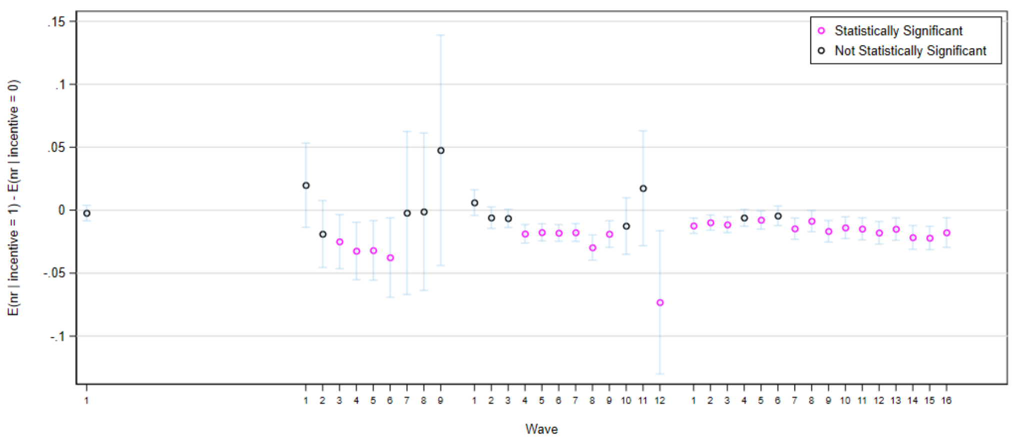
Source: Authors' calculations from the Survey of Income and Program Participation 2014, Waves 1 and 2.
Notes: Dependent variable = 1 if earnings non-respondent. Earnings non-response defined as having any earnings item imputed for all jobs in the reference period. Incentive indicates respondent resides in a household that was offered a monetary incentive for a completed interview. All estimates weighted by longitudinal person weights through Wave 2. Estimates use a Mundlak (1978) device to control for unobserved heterogeneity. Standard errors (in parentheses) are clustered at the household level. R-squared for the logistic regressions is the pseudo R-squared. Wald test statistics (F for OLS, Chi-squared for logit; df = 17) pertain to tests of the hypothesis that all Mundlak-type variables are jointly equal to zero (i.e., a test for unobserved heterogeneity). Panel A sample restricted to respondents age 15 and older who report working for an employer or other work arrangement in the reference period. Panel B sample refers to respondents aged 18–65 who report working for an employer or other work arrangement. Panel C includes estimates for all ages and jobs (including self-employed). Sample size and number of clusters rounded to four significant digits according to Census disclosure avoidance policies. ***$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.1$.

Figure 1.
Trends in SIPP Earnings Non-Response by Incentive Assignment, 1996–2014

Panel A.

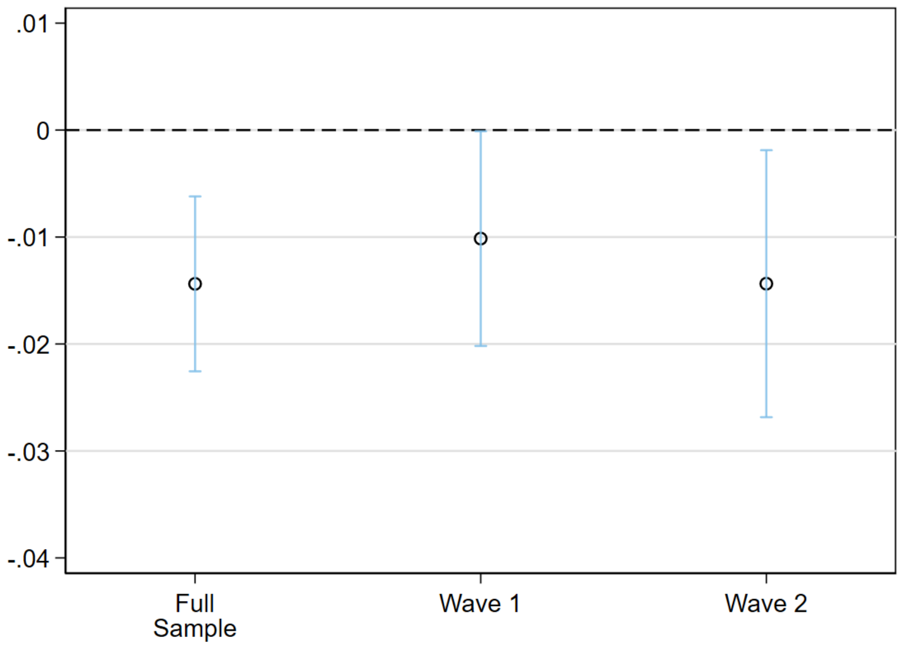


Panel B.



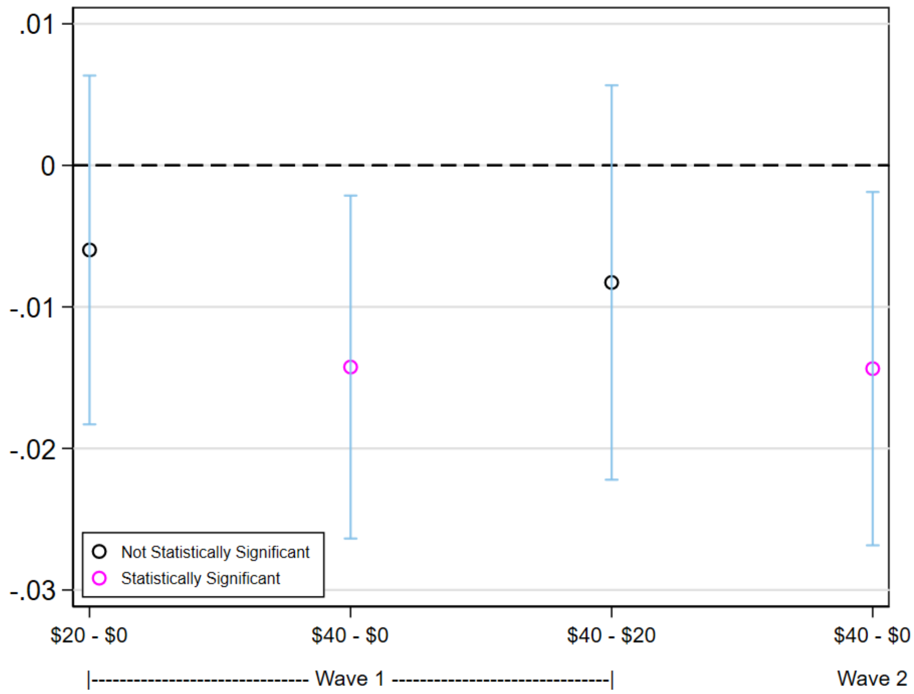
Source: Authors' calculations from the Survey of Income and Program Participation, 1996, 2001, 2004, 2008, and 2014 (Waves 1 and 2) panels. The 2014 data are not included in Panel B.
Notes: Panel A. shows the individual earnings non-response rate by wave for each SIPP panel. The shaded area represents the 95 percent confidence interval. Earnings non-response is measured as any earnings from an employer being imputed in a wave. Panel B. shows the difference in earnings non-response for incentive-receiving and non-incentive households. Negative numbers indicate that earnings non-response rates among individuals in incentive-receipt households are lower than those in non-incentive households. Whiskers on point estimates indicate 95 percent confidence intervals for the difference. Incentive receipt data for the SIPP 1996 panel are only available for Wave 1.

Figure 2.
Average Treatment of Effect of Incentive Receipt on Earnings Non-Response, SIPP 2014



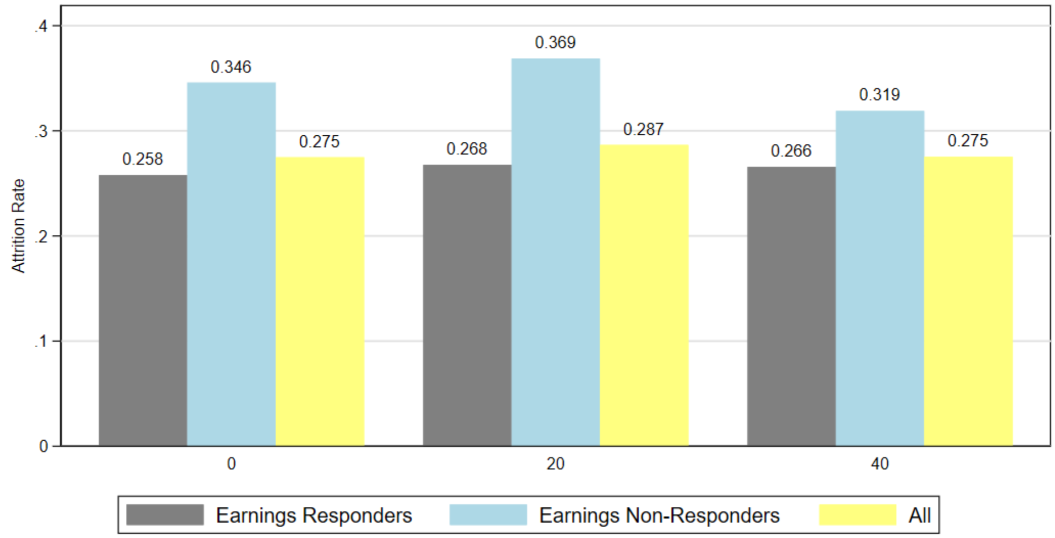
Source: Authors' calculations from the Survey of Income and Program Participation 2014, Waves 1 and 2.
Notes: The estimates are average individual earnings non-response rates for the pooled SIPP sample and by wave. Earnings non-response is defined as having any earnings question imputed for any job in the reference period. Estimates are weighted by annual person weights. Sample is restricted to the set of individuals who reported jobs for an employer or other work arrangement. Incentive receipt is defined by a respondent's address being randomly selected prior to Wave 1 to receive a conditional incentive. Whiskers on point estimates represent 95-percent confidence intervals.

Figure 3.
Average Treatment Effect of Incentive Amounts on Earnings Non-Response, SIPP 2014



Source: Authors' calculations from the Survey of Income and Program Participation 2014, Waves 1 and 2.
Notes: Estimates are differences in average individual earnings non-response rates for $20 – $0, $40 – $0, $40 – $20 in Wave 1, and $40 – $0 in Wave 2, respectively. Earnings non-response is defined as having any earnings item imputed for any job in the reference period. Estimates are weighted by annual person weights. Sample is restricted to the set of individuals who reported jobs for an employer or other work arrangement. Negative estimates indicate that 1) average earnings non-response rates among individuals in $20 and $40 incentive-receiving households are lower than those in non-incentive households, and 2) average earnings non-response rates among $40 incentive-receiving households are lower than those in $20 incentive households. Whiskers indicate 95-percent confidence intervals for the differences.

Figure 4.
Wave 2 Attrition Rates by Earnings Non-Response and Incentive Receipt, SIPP 2014



Source: Authors' calculations from the SIPP 2014, Wave 1.
Notes: Estimates are weighted average attrition rates in Wave 2 by incentive amounts ($0, $20, and $40) and earnings non-response status. Attrition is determined based on the presence of a longitudinal weight in Wave 2. Earnings non-response is defined as having any earnings item imputed for any job in the reference period. Attrition estimates are weighted by annual person weights in Wave 1. Sample is restricted to the set of individuals who reported jobs for an employer or other work arrangement.