Trouble in the Tails? Earnings Non-Response and Response Bias across the Distribution

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Abstract: Earnings non-response in household surveys is widespread, yet there is limited evidence on whether and how non-response bias affects measured earnings. This paper examines the patterns and consequences of non-response using internal Current Population Survey (CPS ASEC) individual records matched to administrative SSA data on earnings for calendar years 2005-2010. Our findings include the following. Non-response across the earnings distribution, conditional on covariates, is U-shaped, with left-tail "strugglers" and right-tail "stars" being least likely to report earnings. Household surveys report too few low earners and too few extremely high earners. Particularly high non-response is seen among women with low earnings and among men with very high earnings. Throughout much of the earnings distribution non-response is ignorable, but there exists trouble in the tails.

Key words: CPS ASEC, non-response bias, earnings, measurement error hot deck imputation,

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1. Introduction

Household surveys typically have high rates of earnings (and income) non-response. For example, the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) and the American Community Survey (ACS) have non-response rates on annual earnings of close to 20%. The CPS monthly outgoing rotation group earnings files (CPS ORG) have earnings non-response rates of about 30%. Among households that do report earnings in these surveys, half the earnings reports are from a "proxy" respondent (often a spouse). Individuals for whom earnings are not reported have their earnings "allocated" using hot deck imputation procedures that assign to them the earnings of a "similar" donor who has reported earnings. Because the matching of donor earnings to non-respondents is imperfect, inclusion of imputed earners in wage analyses can introduce severe "match bias" in wage gap estimates. Simple remedies exist, but each of these rely on the assumption that non-response is missing at random.[1]

Despite the high rates of non-response to earnings questions in household surveys, we have limited knowledge regarding three important and closely related questions. First, is non-response bias ignorable; that is, do respondents and non-respondents have equivalent earnings, conditional on covariates? This is difficult to know absent external information on non-respondents' earnings. Second, how do non-response and patterns of response bias vary across the earnings distribution and are these patterns similar for women and men (or other groups)? And third, can the earnings of survey respondents accurately describe the unobservable distribution of a combined respondent and non-respondent sample?

In this paper, we address each of the questions above using CPS ASEC household files matched to administrative earnings records for March 2006-2011 (corresponding to calendar years 2005-2010). Although we cannot provide fully conclusive answers, we provide informative evidence and make substantial progress in addressing these fundamental questions. In what follows, we first provide background on each of these issues, followed by discussion of the methods used to address them, description of the matched CPS-DER data, and presentation and interpretation of the evidence.

2. Background: Earnings Non-response, Imputation Match Bias, and Response Bias

Official government statistics, as well as most research analyzing earnings (and income) differences, include both respondents and imputed earners in their analyses. In the CPS-ASEC, earnings non-response and imputation rates (we use these terms interchangeably) have increased over time, currently being about 20%. In addition to item non-response for the earnings questions, there also exists supplement non-response and "whole imputations" where households participating in the monthly CPS refuse participation in the ASEC supplement. As discussed subsequently, in this case non-participating households have their entire supplement records replaced by the records from a participating donor household. Supplement non-response and whole imputations are about 10%. Figure 1 shows the weighted non-response/imputation rates for earnings and the whole supplement for the March 1988 through 2012 CPS-ASEC (CY 1987-2011).

[1] Following Rubin (1976) and Little and Rubin (2002), we use the term "missing at random" (MAR) to mean earnings data missing at random *conditional* on measured covariates. "Missing completely at random" (CMAR) refers to missingness (non-response) not dependent on earnings values, observable or not. Data are "not missing at random" (NMAR) if non-response depends on the value of missing earnings, conditional on covariates. We use the term "response bias" (or "non-ignorable response bias") to mean that the earnings data are NMAR.

Researchers typically assume (usually implicitly) that non-response does not produce systematic biases in the measurement of earnings. Such an assumption is often unwarranted. For analyses of earnings or wage differentials common in the social sciences, inclusion of workers with imputed earnings frequently causes a large systematic, first-order bias in estimates of wage gaps with respect to wage determinants that are not imputation match criteria or are matched imperfectly in the hot deck procedure.

This so-called "match bias" (Hirsch and Schumacher 2004; Bollinger and Hirsch 2006) occurs even when non-response is missing completely at random. Wage differentials with respect to such attributes as union status, industry, location of residence, foreign-born, etc. are severely attenuated in typical analyses. Estimates using full samples roughly equal the weighted average of largely unbiased estimates from the respondent sample and of severely biased estimates close to zero among the non-respondent (imputed) sample. For example, the full sample union-nonunion log wage gap estimate for men of 0.142 shown by Bollinger and Hirsch is roughly the weighted average of the 0.191 estimate among earnings respondents and the 0.024 estimate among those with imputed earnings (Bollinger and Hirsch 2006, Table 2). The intuition is simple. Among those for whom earnings are imputed, most union workers are assigned the earnings of a nonunion worker; among nonunion workers, some are assigned the earnings of union workers. Absent a strong correlation between union status and attributes included in the hot deck match, the union-nonunion wage differential in the imputed sample will be close to zero. A more complex bias pattern occurs with respect to the earnings determinants that are included in the hot deck match but grouped into broad categories (e.g., schooling, age, occupation, etc., with gender providing the only exact match), leading to imperfect matches between earnings donors and non-respondents.

Although match bias can be substantial and of first order importance, it is easy to (largely) eliminate. Among the remedies are: simply exclude imputed earners from the analysis; exclude the imputations and reweight the sample by the inverse probability of response; retain the full sample but adjust estimates using a complex correction formula; or retain the full sample but conduct one's own earnings imputation procedure using all earnings covariates in one's model. In practice, each of these approaches eliminates first-order match bias and produces highly comparable results (Bollinger and Hirsch 2006). Each of these methods, however, assumes earnings are missing at random (MAR); that is, conditional on measured covariates, those who do and do not respond to the earnings questions would exhibit no systematic difference in earnings.[2]

Unfortunately, the validity of the MAR assumption is difficult to test. One approach is estimation of a selection model, as in Bollinger and Hirsch (2013), but such an approach relies on existence of an exclusion variable(s) that predicts non-response but is not correlated with earnings (conditional on controls), as well as reliance on distributional assumptions that cannot be directly verified. Using CPS survey methods or time period as exclusion variables (these measures affected response rates but not earnings), Bollinger and Hirsch concluded that there exists response bias, with negative selection into response (i.e., lower response for those with higher earnings, conditional on covariates). The bias appeared to be larger for men than for women. They found that bias was largely a fixed effect that showed up in wage equation intercepts, but had little discernible effect on estimated slope coefficients.[3] More

[2] Note that inclusion of non-respondents (imputed earners) in the estimation sample, while potentially introducing severe match bias, does *not* correct for response bias since the donor earnings assigned to non-respondents are drawn from the sample of respondents. Earnings of non-respondents are not observed.

[3] This latter conclusion was based on a comparison of wage equation coefficients from their full-sample selection models and those from OLS models in which imputed earners were excluded.

fundamentally, their study (and previous ones) estimates the central tendency for non-response bias. As shown in this paper, selection into non-response differs across the distribution.

A more direct approach for determining whether or not non-response is ignorable, the approach taken in this study, is to conduct a validation survey in which one compares CPS household earnings data with administrative data on earnings provided for both CPS earnings respondents and non-respondents. There are several well-known validation studies comparing earnings information reported in household surveys with earnings recorded in administrative data. But typically these studies include only workers reporting earnings in the household survey and do not examine the issue of response bias (e.g., Mellow and Sider 1983; Bound and Krueger 1991; for a survey see Bound, Brown, and Mathiowetz 2001).

We are not the first study to examine response bias using a validation study, but prior studies examining CPS non-response are quite old, use small samples, and examine restricted populations (e.g., married white males). Most similar to our analysis is a paper by Greenlees, Reece, and Zieschang (1982), who examine the March 1973 CPS and compare wage and salary earnings the previous year with 1972 matched income tax records. They restrict their analysis to full-time, full-year male heads of households in the private nonagricultural sector whose spouse did not work. Their sample included 5,515 workers, among whom 561 were non-respondents. Earnings were censored at $50,000. They conclude that non-response is not ignorable, with response negatively related to earnings (negative selection into response). Their conclusion is based on a regression of response on administrative earnings, which yields a negative sign, conditioning on a selected number of wage determinants. The authors estimate a wage equation using administrative earnings as the dependent variable for the sample of CPS respondents. Based on these estimates they impute earnings for the CPS non-respondents. Their imputations understate administrative wage and salary earnings of the non-respondents by 0.08 log points.[4]

David et al. (1986) conduct a related validation study using the March 1981 CPS matched to 1980 IRS reports. They conclude that the Census hot deck does a reasonably good job predicting earnings as compared to alternative imputation methods. Their results are based on a broader sample and use of a more detailed Census imputation method than was present in Greenlees et al. (1982). David et al. note bias, possibly reflecting negative selection into response.

Although informative and suggestive, it is not known whether results from these early studies examining response bias can be generalized outside their time period and narrow demographic samples. In short, there exists little validation evidence regarding CPS response bias with recent data. Nor have prior studies examined differences in response bias across the distribution; the nature of such bias could well differ between the tails and middle of the earnings distribution, as well as between the upper and

[4] Herriot and Spiers (1975) earlier reported similar results using these data, the ratio of CPS respondent to IRS earnings being 0.98 and of CPS imputed to IRS earnings being 0.91.

lower tails. Given the increasing rates of non-response over time, it is important to know whether non-response is ignorable and, if not, the size and patterns of bias.[5]

3. The CPS ASEC Imputation Procedure for Earnings

The Census Bureau has used a hot deck procedure for imputing missing income since 1962. The current system has been in place with few changes since 1989 (Welniak 1990).[6] The CPS ASEC uses a sequential hot deck procedure to address item non-response for missing earnings data. The sequential hot deck procedure assigns individuals with missing earnings values that come from individuals ("donors") with similar characteristics. The hot deck procedure for the CPS ASEC earnings variables relies on a sequential match procedure. First, individuals with missing data are divided into one of 12 allocation groups defined by the pattern of non-response. Examples include a group that is only missing earnings from longest job or a group that is missing both longest job information and earnings from longest job. Second, an observation in each allocation group is matched to a donor observation with complete data based on a large set of socioeconomic variables, the match variables. If no match is found based on the large set of match variables, then a match variable is dropped and variable definitions are collapsed (i.e., categories are broadened) to be less restrictive. This process of sequentially dropping a variable and collapsing variable definitions is repeated until a match is found. When a match is found, the missing earnings amount is substituted with the reported earnings amount from the first available donor or matched record. The missing earnings amount does not come from an average of the available donors.

For example, suppose the set of match variables consists of gender, race, education, age, and region where education is defined by less than high school, high school, some college, and college or more. If no match is found using this set of match variables, then the race variable could be dropped and education could be redefined by collapsing education categories to high school or less, some college, and college or more. If no match exists, then region could be dropped to obtain a match. This process of dropping and redefining match variables continues until the only match variable remaining is gender. This sequential match procedure always ensures a match.

The sequential hot deck used in the CPS ASEC is a variant of a cell hot deck procedure, but quite different from the cell hot deck used in the CPS monthly outgoing rotation group earnings files (CPS ORG).[7] Unlike the CPS ASEC procedure, the CPS ORG cell hot deck always requires an exact match on a given set of characteristics with fixed category ranges (i.e., match variables are never eliminated or collapsed). It replaces missing earnings with earnings from the most recent donor having the same set of characteristics. All cells (combinations of attributes) are stocked with a donor, sometimes with donors from previous months. Because all non-respondents are matched based on the same set of attributes, this makes it relatively straightforward to derive an exact match bias formula (Bollinger and Hirsch 2006)

[5] There is a separate literature that considers various methods to deal with missing data. These (very useful) methods, which often require strong distributional assumptions, shed little light on whether CPS earnings non-response is ignorable and, if so, how it varies over the distribution.
[6] The sequential hot deck procedures used in the March survey prior to 1989 were fairly primitive, with schooling not a match variable until 1975. Lillard, Smith, and Welch (1986) provided an influential critique of Census methods. Welniak (1990) documents changes over time in Census hot deck methods for the March CPS.
[7] For a description of cell hot deck categories used in the CPS ORG files over time, see Bollinger and Hirsch (2006).

and, more generally, for researchers to know a priori how the inclusion of imputed earners in their analysis is likely to bias statistical results.

The sequential hot deck used in the CPS ASEC has the advantage that it always finds a match within the current month. It has the disadvantage that one cannot readily know which characteristics are matched and the extent to which variable categories have been collapsed. The quality of an earnings match depends on how common are an individual's attributes (Lillard, Smith, and Welch, 1986). Use of a cell hot deck in the CPS ASEC like that used in the CPS ORG would not be feasible. Reasonably detailed matching would require reaching back many years in time to find donors. To insure exact matches within the same month would require that only a few broadly defined match variables could be used, thus lowering the quality of donor matches and imputed earnings.

The CPS ASEC also uses a hot deck procedure for what they refer to as whole imputes. Whole imputation refers to a household who has participated in the monthly CPS, but refused participation in the ASEC supplement. In this case the entire supplement is replaced (imputed) by a "similar" household that participated in the supplement. The whole imputation procedure uses 8 allocation groups. The set of match variables is smaller than the set used for item non-response, consisting of variables available from the monthly CPS for both the supplement nonrespondent and donor household. Nonrespondent households headed by a married couple are assigned a married donor household. To be considered a donor for whole imputations, an ASEC respondent household must meet a minimum requirement. The requirement is at least 1 person in the household has answered one of the following questions: worked at a job or business in the last year; received federal or state unemployment compensation in the last year; received supplemental unemployment benefit in the last year; received union unemployment or strike benefit in the last year; or lived in the same house one year ago. Like the sequential hot deck procedure for item non-response, the match process sequentially drops variables and makes them less restrictive until a donor is found. This requirement implies that donors do not have to answer all the ASEC questions and can have item imputations.[8]

Whole imputes account for about 10% of all ASEC supplement records. Looking ahead, households who did not participate in the CPS ASEC supplement have their earnings included in the matched administrative earnings data described below. However, we do not directly observe their household characteristics since it is the donor household that is included in the CPS. We only know the limited characteristics used in the household replacement match (sex is the one attribute for which a perfect match is guaranteed). For this reason, whole imputes are excluded from our principal analysis. In a later section, we compare the overall distributions of DER earnings for men and women who did and did not participate in ASEC. Both men and women in households not participating in ASEC have lower and more dispersed administrative earnings than workers from participant households. Absent covariates, however, we cannot draw strong inferences about the representativeness of these households.[9]

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[8] Whole imputations do not produce the "match bias" described previously because reported earnings are linked to worker attributes taken from the replacement household and not from the household refusing participation in ASEC. Earnings imputations for non-respondents among the replacement households will produce match bias.

[9] Supplement non-response may be more similar to unit non-response than to item non-response of earnings. Korinek, Mistiaen, and Ravallion (2007) examine potential bias from unit non-response. Papers in a special issue of *The Journal of Human Resources* examine the issue of attrition in panel data sets, which may have much in common with ASEC supplement non-participation since both involve a switch from participation to non-participation in an on-going household survey. Although the evidence is quite varied, a common theme in the papers on panel attrition

4. Data Description: The CPS-DER Earnings Match Files

The data used in our analysis are Current Population Survey (CPS) person records matched to Social Security Administration earnings records. The CPS files used are the Census internal CPS Annual Social and Economic Supplement (CPS ASEC) data for survey years 2006-2011 (reporting earnings for calendar years 2005-2010). In addition to the data included in CPS public use files, the internal file has top-coded values for income sources that are substantially higher than the public use top codes.[10]

The Census internal CPS ASEC is matched to the Social Security Administration's (SSA) Detailed Earnings Record (DER) file. The DER file is an extract of SSA's Master Earning File (MEF) and includes data on total earnings, including wages and salaries and income from self-employment subject to Federal Insurance Contributions Act (FICA) and/or Self-Employment Contributions Act (SECA) taxation. Only positive self-employment earnings are reported in DER (Nicholas and Wiseman 2009) because individuals do not make SECA contributions if they have self-employment losses. The DER file contains all earnings reported on a worker's W-2 forms. These earnings are not capped at the FICA contribution amounts and include earnings not covered by Old Age Survivor's Disability Insurance (OASDI) but subject to the Medicare tax. Unlike ASEC earnings records, the DER earnings are not capped. This is important given that there are substantial concerns regarding non-response and response bias in the right tail of the distribution, but knowledge on these issues is quite limited. That said, in the analysis that follows, we cap DER annual earnings at $2 million to avoid influence from extreme earnings on estimated wage equation coefficients. Our imposed $2 million cap on DER earnings "roughly matches" the cap on annual earnings in the internal CPS ASEC files.[11]

The DER file also contains deferred wages such as contributions to 401(k), 403(b), 408(k), 457(b), 501(c), and HSA plans. The DER file does not provide a fully comprehensive measure of gross compensation. Abowd and Stinson (2013) describe parts of gross compensation that may not appear in the DER file such as pre-tax health insurance premiums and education benefits. More relevant for our analysis, particularly for workers in the left tail of the earnings distribution, is that the DER file cannot measure earnings that are off the books and not reported to IRS and SSA. Moreover, the delineation between wage and salary versus self-employment earnings reported in the CPS can differ from that reported to IRS and SSA[12]. In our analysis, we can compare how discrepancies between CPS earnings reports (which are likely to include undocumented earnings) and the administrative data change in samples with and without demographic or industry-occupation groups of workers most likely to have undocumented earnings.

Workers in the DER file are uniquely identified by a Protected Identification Key (PIK) assigned by Census. The PIK is a confidentiality-protected version of the Social Security Number (SSN). The Census Bureau's Center for Administrative Records Research and Applications (CARRA) matches the

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is that households with lower earnings (observed in the early years of the surveys) are more likely to drop out of the sample. See, for example, Fitzgerald et al. (1998) on the PSID and McCurdy et al. (1998) on the NLSY. These results are consistent with our finding of lower earnings among households who opt out of participating in the ASEC supplement.

[10] Larrimore et al. (2008) document the differences in top code values between the internal and public use CPS files.

[11] The two components of our CPS total earnings variable, earnings on the primary job and all other earnings, are each capped at $1.1 million.

[12] Our current analysis is restricted to wage and salary earnings. In a future version, we will examine whether use of total earnings (wage and salary plus self-employment) reduces discrepancies between CPS and DER earnings.

DER file to the CPS ASEC. Since the CPS does not currently ask respondents for a SSN, CARRA uses its own record linkage software system, the Person Validation System, to assign a SSN.[13] This assignment relies on a probabilistic matching model based on name, address, date of birth, and gender. The SSN is then converted to a PIK. The SSN from the DER file received from SSA is also converted to a PIK. The CPS ASEC and DER files are matched based on the PIK and do not contain SSN. Our examination of CPS workers not matched to DER indicated that they were disproportionately low wage workers and in occupations where off-the-books earnings are most common. Bond et al. (2013) provide similar evidence using administrative data matched to the American Community Survey (ACS).

Since a worker can appear multiple times per year in the DER file if they have several jobs, we collapse the DER file into one earnings observation per worker per year by aggregating total earnings (Box 1 of W-2, labeled "Wages, tips, other compensation") across all employers. In this way, DER earnings is most compatible with CPS earnings from all wage and salary jobs (WSAL-VAL). Like the match to the DER, imputations of earnings occur at the individual level as well. We classify a worker as having imputed earnings if either wages and salary from the longest job (I-ERNVAL) or from other jobs (I-WSVAL) is imputed. We construct the CPS and DER average hourly wages by dividing annual CPS or DER earnings by annual hours worked. Annual hours worked comes from multiplying weeks worked (WKSWORK) by usual hours worked per week (HRSWK).

Match rates between the CPS and DER administrative data among earners beginning with the 2006 ASEC are about 85 percent. Figure 2 shows the match rates across the CPS-ASEC wage distribution for both PIK match and the joint PIK and DER match. Both rates are lower for those in the left tail of the CPS wage distribution, but these rates vary little throughout the rest of the distribution.

The principal regression sample used in our analysis includes full-time, full-year, non-student wage and salary workers ages 18 to 65 who have positive CPS and DER earnings reported for the prior calendar year. As explained previously, we exclude whole imputations. This 2006-2011 CPS-DER matched regression sample includes 287,704 earners, 157,041 men and 130,663 women. Earnings non-response rates among this sample is 19.5% among men and 19.3% among women (Table 1).

Table 1 provides summary statistics for our sample by gender. We focus on measures of earnings and earnings response. For men, overall weighted mean earnings in the CPS and in DER are roughly equivalent. Among women, CPS earnings are higher by somewhat less than $1. Evident in Table 1 is that log wages are higher in the CPS than the DER.[14] However, using the mean of log wages, CPS earnings exceed DER earnings, by 0.067 or 6.9 percent for men and by 0.071 or 7.4 percent for women. The seeming inconsistency between the exponentiated log differentials and percentage differences in mean dollars arises from the higher dispersion in DER than in CPS earnings, particularly so for men.

[13] The Census Bureau changed its consent protocol to match respondents to administrative data beginning in with the 2006 ASEC. Prior to this CPS collected respondent Social Security Numbers and an affirmative agreement allowing a match to administrative data; i.e., an "opt-in" consent option. Beginning with survey year 2006 (calendar year 2005), respondents not wanting to be matched to administrative data had to notify the Census Bureau through the website or use a special mail-in response; an "opt-out" consent option. If the Census Bureau doesn't receive this notification, the respondent is assigned a SSN using the Person Validation System. Under the prior "opt-in" consent option in the 2005 ASEC, the match rate among earners was 61 percent.

[14] All comparative statements in this section and the remainder of the paper have undergone statistical testing, and unless otherwise noted, all comparisons are statistically significant at the 10 percent significance level.

Percentage differences based on exponentiation of log differences can substantially overstate the arithmetic percentage difference if the focal earnings (in this case, CPS) has lower dispersion than the comparison earnings (the DER sample) (see Blackburn 2007). Very high earnings are far more common among men than women.

For responding men, DER wages ($27.05 in 2010$) are not statistically different from CPS wages for these same men ($27.11), but for responding women DER wages ($20.01) are lower than their CPS wages ($20.94). For non-responding men, their imputed CPS wages ($26.11) are substantially lower than their DER wages ($29.06). The opposite pattern is seen among non-responding women, whose imputed CPS hourly earnings is an average $20.22, as compared to their $19.31 DER wage. Focusing just on DER wages, CPS non-respondents exhibit higher DER wages than do respondents ($29.06 versus $27.05), whereas among women non-respondents exhibit lower DER wages than do respondents ($19.31 versus $20.01). The use of proxies is more prevalent for men than women (53.2% vs. 41.2% for proxies).

5. Is Response a Function of Earnings? Non-Response across the Distribution

Although evidence is limited, previous studies have concluded that there is negative selection into response. That is, as true earnings rise, non-response increases. Testing this is difficult with public use data since we do not observe earnings for those who fail to respond. We initially follow the approach by Greenlees et al. (1982), who measure the likelihood of CPS response as a function of matched 1973 administrative (i.e., DER) earnings matched to the CPS, conditional on a rich set of covariates. The Greenlees et al. analysis was conducted for white males working full-time/full-year married to non-working spouses.

To explore the relationship between non-response and earnings, the following model of non-response using our matched CPS-DER sample is estimate the following model:

$$NR_i = \theta \, lnWage_i + \ X_i\beta + u_i \qquad (1)$$

where NR_i represents an individual *i*'s earnings non-response status (0 or 1) and X_i includes the ln*Wage*- from DER and a rich set of covariates (potential experience, race, marital status, citizenship, education, metropolitan area size, occupation, industry, and year). Subsequent analysis move from use of a single linear log wage term to categorical measures for wage percentiles that allow for different responses throughout the earnings distribution. Our preferred specification estimates non-response rates at each percentile of the earnings distribution, separately for men and women.

$$NR_i = \theta_k Wage\ Percentile_{ik} + \ X_i\beta + u_i \qquad (2)$$

Table 2 provides estimates of the non-response to earnings relationship using linear probability models, with and without a detailed set of controls, along with the corresponding marginal effects estimates using probit estimation. Because OLS results are highly similar to those from probit, in subsequent tables we show only OLS results.

We first examine θ, the coefficient on ln*Wage*, as in Greenlees et al., which measures the central tendency of non-response with respect to the wage. We later turn to results allowing non-response to vary across the distribution by inclusion of wage percentile dummies. The top panel of Table 2 provides results for men and the middle panel for women. Shown are results with and without controls. Full estimation results on the control variables are available from the authors.

In contrast to Greenlees et al. (and other prior literature), our coefficients on earnings in Table 2 are negative rather than positive for both men and women. This suggests a central tendency of positive rather than negative selection into response. That said, the OLS coefficient for men (with controls) is very close to zero (-0.012 with s.e. 0.002), although highly significant given our sample size. Among women, we obtain a larger negative coefficient (-0.040 with s.e. 0.002), again indicating that on average non-response declines with earnings, conditional on covariates. Absent controls, the R^2 for each regression is effectively zero for men and women, the wage alone accounting for a small fraction of 1 percent of the total individual variation in non-response (column 1). Regressions with detailed controls plus the wage account for only 2 percent of the variation (column 3).

Although these results provide what we believe are accurate measures of central tendency for these broad samples of men and women, such results are not particularly informative. Our concerns are two-fold. First, our results for men appear to be just the opposite of that found by Greenlees et al. However, the Greenlees et al. result, which indicated negative selection into response, was for a small sample of married white men with non-working spouses in 1972, a sample not representative of today's workforce. Second, and most important, the relationship between non-response and earnings may vary over the distribution, potentially making measures of central tendency misleading. Non-response may decline, remain constant, or increase with respect to earnings over different ranges of the distribution, a possibility not thoroughly examined in prior studies.

In order to compare our results with those of Greenlees et al., we restrict our sample to married white men who are citizens, with spouse present. Unlike Greenlees et al., we include those with working spouses since married women's labor force participation is now closer to the norm rather than exceptional. For convenience we refer to this as our "Mad Men" sample, shown in the bottom panel of Table 2. This sample is likely to have a relatively small proportion of workers in the far left tail of the DER earnings distribution. In contrast to the negative coefficients on log earnings of -0.018 and -0.012 for all full-time/full-year men (columns 1 and 3), using the Mad Men sample flips the signs and produces coefficients of 0.018 and 0.013 (each with a s.e. of 0.002). These latter results are consistent with Greenlees et al., as well as previous studies finding negative selection into response.

Rather than focus on central tendency, it is far more informative to examine how non-response varies across the distribution. The well-known paper by Lillard et al. (1986, p. 492) speculated that CPS non-response is likely to be highest in the tails of the distribution (U-shaped), but to the best of our knowledge, no study has directly provided such evidence. Since we cannot observe reported CPS earnings for non-respondents, it is difficult to examine this relationship absent matched administrative data on earnings, as is possible with the matched CPS-DER.

To examine whether non-response changes across the distribution, we initially modify the non-response equation specification by grouping the bottom 90% of earners into deciles, while breaking up the top decile into finer percentile increments. As seen in Table 3, CPS non-response regressions are estimated for men, women, and the 'Mad Men' sample, with DER wage decile and percentile dummies included, with and without controls (the intercept is suppressed). Each decile/percentile coefficient represents the non-response rate at the given DER wage level, conditional on a rich set of covariates. Readily evident from the coefficients is that non-response rates are not constant across the distribution.

Rather, there exist U-shaped distributions of non-response, as hypothesized by Lillard et al. (1986). Focusing first on the male equation with controls (column 2), non-response is particularly high in the 1st decile of the DER wage distribution (0.165), roughly double the level seen throughout most of the distribution, with the exception of the highest percentiles. Non-response rises sharply at the top 1 percent.

Women exhibit a similar but weaker U-shaped pattern of non-response than do men. Their non-response rates in the bottom decile is similar to men, but declines to a slightly lower level throughout most of the distribution, and remains low until one reaches the top 1%. Note that the percentiles for women and men differ, the wage at, say, the 95th percentile for women being substantially lower than that for men. Below we examine non-response rates across percentiles of a common joint wage distribution for men and women. Also evident from Table 3 is that the 'Mad Men' sample of married white male citizens does not display as clear-cut a U-shaped non-response pattern as seen for the larger population of women or men, having instead relatively flat non-response throughout much of the earnings distribution before exhibiting rising non-response in the right tail.

Patterns of non-response across the entire distribution are most easily discerned visually. In Figure 3, we show non-response rates for both men and women for each percentile of the DER wage distribution. The top curve for each shows the unadjusted mean rate of non-response at each percentile of the DER wage distribution. The lower curve for each is based on equation (2), which includes a large set of covariates and a full set of percentile dummies (with one omitted percentile). We follow Suits (1984) and adjust the values of all the percentile dummy coefficients (along with the "zero" omitted percentile) to provide a measure of the conditional non-response rate at each percentile, relative to the mean rate.[15] By construction, the 100 values shown in the lower curve sum to zero.

In the top half of Figure 3 we show male non-response rates for each percentile of the DER wage. The pattern here shows a U-shape, with considerably higher non-response in the lower and upper tails of the distribution, but with rather constant non-response rates from about the 20th to 95th percentiles. There is very little difference between the unadjusted (top) and adjusted (bottom) curves, apart from the downward adjustment of the latter curve to reflect measurement relative to the conditional mean rate. Whereas we see non-response decline in the left tail throughout much of the first quintile, rising non-response is restricted to the top ventile. Non-response is largely uncorrelated with the wage throughout most of the distribution, the obvious exceptions being in the tails of the distribution.

The evidence for women (lower half of Figure 3) is qualitatively no different from that seen for men, indicating a U-shaped non-response pattern. That said, there are differences in the magnitudes of the tails. In the lower-end of the wage distribution, women exhibit higher rates of adjusted and unadjusted non-response than do men. High rates of non-response for earnings (and other income sources) among low-wage women may result in part from the (invalid) concern that reporting such information to Census might place income support program eligibility at risk. In the right tail of the distribution, women exhibit minimal increases in non-response, increases not easily discerned until one moves to the highest percentile. Although referring to the non-response pattern as "U-shaped" is convenient shorthand,

[15] The Suits (1984, p. 178) adjustment factor is the value k that makes the average of the percentile coefficients equal to zero. That is, $k = -(b_2 + b_3 + \ldots b_{100} + 0)/100$, where b represents the 99 included percentile dummies. The value k is added to each b and to "zero" for the omitted percentile. These Suits-adjusted coefficients are shown in the lower curves in Figure 3.

emphasis should be given to the high rates of female non-response in the left tail of the distribution coupled with rather similar rates throughout the rest of the distribution outside of the very top percentile.[16]

The male and female non-response curves shown across the wage distribution in Figure 3 are based on the gender-specific wage percentiles. At a given percentile, say the 90th percentile, the wage for men will be considerably higher than that for women. In Figure 4, we form percentiles based on the joint male-female DER wage distribution and then show the unadjusted non-response rates for men and women at each percentile of this common distribution. The male and female curves shown in Figure 4 are remarkably similar, indicating that women and men have similar likelihood of non-response at similar wage levels. We saw previously that high non-response in the left tail is most evident among women and high non-response in the right tail is most evident among men. These patterns appear because women are disproportionately concentrated in the left tail and men in the right tail. With a joint earnings distribution, male and female non-response behaviors are highly similar when compared at the same wage levels.

Our final evidence in this section is to show non-response rates for men and women with respect to percentiles across the *predicted* wage distribution, seen in Figure 5. Although this does not test for response bias, the results are informative, showing how non-response is related to an index of earnings attributes (education, demographics, location, and job type). The predicted wage for each worker is calculated based on coefficient estimates and worker attributes from the earnings equation

$$lnWage\text{-}DER_i = X_i\beta + \epsilon_i \qquad (3)$$

We use the same samples of CPS respondents and nonrespondents and same set of covariates used in the previous non-response equations, but with the log wage shifted to the left-side of the regressions. In addition to showing how non-response varies with each percentile of the predicted wage, we also show an OLS line fitted to the non-response points.

For women, Figure 5 provides little evidence of high non-response in either tail of the attribute distribution, let alone a U-shape. Men exhibit somewhat higher non-response in the left tail of the index and a slight rise in the right tail. For the most part, non-response is fairly constant throughout the attribute distribution, with a gradual decline in non-response as earnings attributes increase. What accounts for the U-shaped patterns of non-response (i.e., trouble in the tails) is not earnings attributes per se; rather, it is the *realization* of either very low or very high earnings.

Our interpretation of the non-response evidence up to this point is straightforward. The good news is that earnings non-response in the CPS appears to be largely ignorable throughout much of the earnings distribution, varying little with the realized level of earnings, conditional on covariates. To the extent that there is a pattern over the 20th to 95th percentiles, it is one consistent with weak positive selection into response, with non-response declining slightly over much of the distribution before turning up at very high levels of earnings. Where there most clearly exist problems is in the tails. Stated simply, non-response is highest among “strugglers” and “stars”. Characterizing selection into response based

[16] Coefficients on control variables in the non-response equations (available on request) provide information on which types of workers are least and most likely to not respond to the ASEC earnings questions, conditional on the wage (using the full set of percentile dummies). For the most part, demographic, location, and job-related measures account for little of the variation in response. Coefficients are generally similar for men and women. Most notable are high non-response probabilities found among workers who are black, Asian, never married, and residents in large (5 million plus) metro areas. Public sector workers are more likely to report earnings.

solely on estimates of central tendency over entire distributions, as seen in Table 2 and in prior literature, is largely uninformative and potentially misleading.

Rates of non-response are particularly high in the lower decile of male and female wage distributions. There are substantial disparities between reported CPS and DER earnings in the left tail; some of this difference is likely to result of off-the-books earnings. This is an issue we examine later in the paper. In the right tail, high non-response is seen primarily in the highest two percentiles for men and the top percentile for women. These percentiles correspond roughly to where individual earnings are top coded in the public use CPS. Analysis of workers with top-coded earnings is already difficult for researchers using public use files; high non-response among such earners makes such research all the more difficult.[17]

6. Complementary Evidence on Response Bias: DER Wage Residuals across the Distribution:

In the previous section, we provided evidence of response bias based on rates of non-response across the DER wage distribution, conditional on earnings covariates. An alternative way to demonstrate the same pattern of non-response bias is to examine differences in wage residuals across the distribution for CPS respondents and non-respondents, with residuals drawn from the DER wage equations with administrative earnings data observable for both groups.

The pattern of response bias is readily seen in Figure 6, which shows differences in DER wage residuals between CPS non-respondents and respondents (NR-R) across the distribution. Evident for men and women is that NR-R differences shift from negative to positive. In lower portions of the distribution we see positive selection into response, with CPS non-respondents having lower DER earnings residuals than respondents. In the middle of the distribution, differences between non-respondents and respondents are effectively zero, indicating little response bias. At the top of the distribution, CPS non-respondents have higher DER wage residuals than do respondents, indicating negative selection into response.[18]

Although our emphasis is on how response bias varies across the distribution, a measure of net bias over the entire distribution is also of interest. Examination of residuals provides a way of doing so. Structuring the data as done in this section provides a basis for doing so. Based on our full-sample log wage regression for men, the mean DER wage residual for CPS non-respondents is -0.011 and that for CPS respondents is 0.019, a -0.031 difference (by construction, the mean residual for the full sample is zero). This indicates that on average there is weak positive selection into response, with male CPS non-respondents having modestly lower DER earnings than respondents, conditional on covariates. Among women, the pattern of positive selection is somewhat stronger. The mean residual for female CPS non-respondents is -0.063 and that for CPS respondents is 0.022, a -0.085 difference as compared to -0.031 among men.

[17] Researchers using the CPS often assign mean earnings above the top-code based on information provided by Census or by researchers using protected internal CPS files (Larrimore et al. 2008). Because very high earners are less likely to report earnings in the CPS, there will be some understatement of high-end earnings due to non-ignorable response bias. An implication from our research is that top-code multiples should be somewhat higher than those recommended based on the estimated mean earnings of CPS respondents above the top-code.

[18] For both respondents and non-respondents, wage residuals are mechanically negative (positive) in the left (right) tails of the distribution. Our conclusions are based on *differences* in residuals for respondents and non-respondents.

These net differences in observed DER earnings for CPS respondents and observationally equivalent non-respondents are small, but non-trivial. Based on the 19.5% weighted non-response rate in our male sample, the overall upward bias in mean male CPS earnings due to positive selection would be about 0.6 percent (.195 times -0.031 equals -0.006). For women, upward bias is a substantive 1.6 percent (.193 times -0.085 equals -0.016). Taken together, this would imply that overall average earnings (for full year/full time workers) are overstated by roughly 1 percent due to response bias. Estimates of gender wage gaps are likely to be understated by about 1 percentage point.[19]

Finally, we note that the largest residual differences (thus suggesting strong response bias) are concentrated in the lowest percentiles of the earnings distribution. This is the portion of the wage distribution where we expect to see underreporting of DER earnings due to work off-the-books or discrepancies between the CPS and DER in whether earnings are reported as wage and salary or self-employment. We plan to examine the latter issue in the next version of the paper. We cannot directly determine whether workers who have higher off-the-books earnings are also less likely to respond to CPS earnings questions. If that is the case, however, then some portion of the apparent positive selection into response in the far left tail may result from alternative factors that lead to both CPS non-response and off-the-books earnings. This is an issue we examine below.

7. Additional Evidence and Robustness Checks

In this section, we provide evidence and robustness checks complementary to our prior analysis. We examine (a) DER earnings among households who did not participate in the ASEC supplement (so-called whole imputations); (b) how the sample exclusion of students and those who do not work full-time/full-year affected results; (c) identification of occupations and worker groups with relatively large shares of earnings off-the books (i.e., not recorded in DER) earnings; and (d) a robustness check in which our estimation sample is rebalanced to reflect underrepresentation of certain types of workers and jobs due to failure to create CPS-DER matches, either because an individual PIK is absent or the PIK cannot be matched in DER records [this work not yet available].

Whole imputations. As discussed earlier, roughly 10 percent of households who participate in the CPS refuse to participate in the ASEC supplement. A non-participating household is then assigned ASEC values based on a "whole impute" from a participating donor household. Households with whole imputes are excluded from our analysis because we not observe DER earnings for the donor household. We do observe DER earnings for the original non-respondent household, but do not have additional information about the household, the principal exception being gender (since matched donors are always the same sex). This allows us to compare the distributions of unadjusted DER earnings, by gender, for individuals in households with and without whole imputes.

Table 4 provides descriptive evidence on the DER earnings distribution for households who do and do not participate in the ASEC supplement. Examining the mean of log earnings, we clearly see that there exists negative selection into ASEC supplement response. Men in households that had whole supplement imputes had mean wages 21 log points lower than men in participating households. Women in these households had wages 23 log points lower. DER wage dispersion among the whole imputes is substantially larger than among workers in participating households, the standard deviation of the log

[19] The downward bias in average earnings is .546 (.006) + .454 (.016) = 0.011, where .546 and .454 are our sample proportions for men and women. Bias in the gender gap is calculated as the difference between 0.006 and 0.016.

wage being 1.00 versus 0.76 for men, and 0.94 versus 0.68 for women. As one moves across the distribution, wage differences between whole imputes and ASEC participants are largest in the lowest percentiles of the distribution, with the differences narrowing as one moves up the distribution, By the 95th percentile of the distribution, mean wages are roughly similar. At the top percentile, whole imputes have higher DER earnings than workers in participating households, 10 log points higher among men and 4 log points higher among women. In short, as compared to participating households, whole impute households include a disproportionate share of workers with low earnings and a moderately higher share of workers with exceptionally high earnings. [Note: Analysis shown for whole imputes calculates hourly earnings based on the initial household's annual DER earnings divided by hours worked, the latter reported by the replacement household (hours worked are not available for the non-responding household members). The analysis will be redone using annual rather than mismeasured hourly earnings.]

A complementary way to compare earnings for our primary sample and earnings among workers in non-participating households is to show overlapping kernel densities of the wage distributions for both groups of workers. We show this in Figure 7. The distribution of workers whose household had CPS whole imputes has a distribution of DER wages that is to the left and flatter (i.e., more dispersed) than the wage distribution for workers in participating households. Supplement non-participation is lower than is unit non-response for earnings and income (roughly 10 rather than 20 percent). Although the rate is low, it is likely that negative selection into supplement participation leads to some small understatement of both earnings inequality and poverty.

Sample exclusions. Excluded from our sample were students and those who did not work full time/full year. The purpose of the exclusion was to help us focus on a population that has relatively strong attachment to the labor market. School attendance questions are asked only of those below age 25. Although a considerable number of young persons are excluded, the total number is not large. The sample of workers who did not work full year or full time per week is a more substantive share of the sample. As a robustness check, we examine whether the non-response pattern for these excluded workers is similar to that seen for our primary sample. Figure 8 shows non-response rates for these excluded workers, by gender, at each percentile of their respective DER wage distribution. The pattern of non-response is noisy, as expected given their relatively small sample sizes. But both men and women display remarkably similar patterns of non-response as do our main samples, with non-response relatively flat over much of the distribution but with evidence of higher non-response in the lower and upper tails. In contrast to results from our primary samples, one does not see extremely high rates of non-response in the lower tail or at the highest percentiles among students and workers who are not FT/FY.

Occupations with off-the-books earnings. In order to gather information on workers who either have earnings off-the-books or cannot be matched to tax records, we identify occupations in which many CPS workers cannot be matched to DER wages (Table 5) and occupations where there exist the largest gaps between earnings reported in the CPS and earnings reported in DER administrative records (Table 6).

Recall that overall match rates of the CPS sample to DER are about 85% (Figures 1 and 2 show PIK and DER match rates over the entire ASEC wage distribution). The top half of Table 5 lists occupations with the lowest rates of a match of CPS earners to a PIK number; the bottom half provides the match rate to DER earnings. Note that the DER and PIK match rates are based on the same denominator of CPS earners. For example, among the sample of 2758 construction laborers, 1884 are matched to a PIK (68.3%), as reported in the top half of Table 5. Of those 1884 workers, 1710 (90.8%) are matched to DER earnings, producing an overall DER match rate (seen in the bottom half of Table 5) of 62.0% (1710 out of 2758).

Among the occupations with low PIK and DER matches are the construction trades (e.g., painters, drywall installers, roofers, brick masons, laborers, and helpers); dishwashers, cooks, dining attendants and bartender helpers, and food preparation workers; grounds maintenance workers; and agricultural and fishing related workers.

Using our matched CPS/DER sample, we also examine which occupations show the largest percentage (log) gap between CPS earnings and reported DER earnings. These occupations are shown in Table 6. Not surprisingly, there is considerable overlap between the occupations listed in Tables 5 and 6. Occupations including jobs with workers and/or earnings off-the-books also have workers for whom some portion of earnings is reported and some is not. In addition to the types of occupations summarized above, we see large CPS minus DER earnings gaps for occupations such as real estate brokers and agents, door-to-door sales workers, personal appearance workers, massage therapists, musicians, bartenders, and clergy.[20] A simple way to characterize "high-gap" occupations is that they include jobs or types of work where there is often an opportunity to avoid reporting earnings (Roemer 2002). In addition, many of these occupations are ones in which earnings (or some share of earnings) are reported to IRS and SSA as self-employment earnings, but that household members may report to Census as wage and salary earnings. [A revised version the paper will examine this using both W&S and SE earnings data from ASEC and DER.]

How serious is off-the-book earnings for our analysis? The short answer is that it appears to be less of a problem than we expected. Our concern was that some nontrivial portion of the high non-response seen in the left tail of the DER wage distribution, conditional on earnings attributes (e.g., Figures 2-3), was the result of workers with earnings off the books being reluctant to report earnings. Similarly, the negative values of DER wage residuals for non-respondents minus respondents (NR-R) seen in the left tail of the distribution (Figure 6), which we interpret as implying positive selection into response for low wage earners, could reflects in part underreported earnings in the left tail, again assuming that underreporting makes CPS response less likely. Although we cannot rule out these problems, our robustness checks suggest that these are not serious problems. In Figure 9, we remove from our male and female samples all workers in the "high gap" occupations included in Table 6, and then additionally remove all foreign-born noncitizens who may have high rates of earnings off the books. What we see in Figure 9 is that for both men and women, there is almost total overlap in non-response rates in the left tail (and elsewhere) for the full sample and the samples minus those in high gap occupations and foreign-born noncitizens.[21]

Rebalancing. [not completed] As previously documented, our estimation sample does not include CPS participants who could not be matched to DER earnings records. As a robustness check, we will

[20] Clergy are typically taxed as self-employed workers, but may report earnings in the CPS as wage and salary earnings, thus creating a gap between CPS and DER earnings. Clergy also receive payments for weddings and funerals that may go unreported, and may be exempt from paying taxes on allowances to fund housing, transportation, and conduct of services. Clergy generally pay Social Security payroll taxes at the self-employment rate, but may opt out of the system if they are opposed to public insurance for religious or conscientious reasons.

[21] Foreign born noncitizens are disproportionately employed in occupations with high levels of off-the-books earnings. As compared to native men and women, however, rates of earnings non-response are lower among foreign born noncitizens.

reweight our sample using inverse probability weighting (IPW), attaching higher weight to individuals with characteristics associated with low probabilities of a match, and lower weight to those with characteristics associated with high match probabilities. Probabilities will be estimated using probit estimation and modeling DER matches as a function of demographic and location attributes, plus detailed occupation and industry dummies. Following IPW, we will examine whether outcomes using the rebalanced sample differ substantially from those presented in our paper.

Proxy versus self reports. Roughly half of all earnings reports in the CPS are provided by proxy respondents, as seen in Table 1. And earnings non-response is substantially higher among individuals with a proxy respondent (Bollinger and Hirsch 2013). If one includes proxy dummies in a standard CPS wage equation, one finds substantive negative coefficients associated with the use of non-spouse proxies and coefficients close to zero for spousal proxies. In analysis not reported in this paper, we have used the matched CPS/DER data to examine the quality of proxy earnings reports. The analysis indicates that both spouse and non-spouse proxy reports are accurate, the exception being modest underreporting of married men's earnings by wife proxies (for related evidence, see Reynolds and Wenger 2012). The substantive proxy wage effects found in a standard Mincerian wage equation do not reflect misreporting, but instead worker heterogeneity not captured by standard covariates.

8. Dealing with Non-response: Guidance for CPS Users

The analysis in this paper has straightforward implications for researchers using the CPS, as well as similar household data sets such as the American Community Survey (ACS). As emphasized in previous work (Hirsch and Bollinger 2006) and discussed earlier in the paper, even if non-response were completely missing at random, severe “match bias” can arise in the estimation of earnings equation coefficients if researchers include nonrespondents with earnings values imputed by Census. The bias (i.e., attenuation) is severe for coefficients on variables not used as hot deck match criteria. Bias is more complex when earnings have been allocated using an imperfect match of donor characteristics (e.g., schooling, age, etc.). Among the several “remedies” for match bias (Bollinger and Hirsch 2006), the simplest and most widely used being to simply throw out imputed earnings and rely completely on analysis with respondents. The respondent sample can be reweighted by the inverse probability of response, but in practice this typically makes little difference.

The matched CPS-DER data allow us to examine directly whether relying solely on respondents’ earnings produces results similar to what would be produced using complete (but unobtainable) data. Because the DER sample includes administrative earnings for CPS nonrespondents as well as respondents, we can compare earnings function parameter estimates from respondent-only samples with those from complete samples, something not possible using the CPS.

Using the DER sample, we estimate log wage equations with a dense set of covariates, separately for the respondent, nonrespondent, and pooled samples. Using estimates from these regressions, in Table 7 we provide the predicted wage for men and women using means from the full CPS sample multiplied by coefficient estimates from regressions using, alternatively, the full, respondent-only, and nonrespondent samples. We use as our benchmark the predicted earnings based on coefficients from the full sample, not obtainable using CPS data because of the absence of nonrespondents’ earnings. We compare the full-sample predicted wage to those obtained using the coefficients from the respondent sample, which can be calculated using public CPS data.

Focusing first on men, use of full sample coefficients with the full sample worker attributes (X's) results in a predicted mean log wage of 2.984. This is very close to that obtained using respondent-only betas, which leads to a predicted mean log wage of 2.991, or 0.007 (roughly one percent) higher than obtained with the full sample. The equivalent values for women are 2.724 using full sample betas and 2.739 using respondent betas, a 0.015 difference using the respondent than full sample coefficients. These differences reflect a mean tendency toward positive selection into response in the CPS (more so for women than men). Such selection is more readily evident directly comparing predicted earnings using respondent (R) and nonrespondent (NR) betas. The R–NR predicted earnings difference is 2.991–2.962 = 0.029 for men and 2.739–2.658 = 0.081 for women. These differences are substantive. Because the nonrespondent shares of the total samples are relatively small (roughly 20 percent), the respondent only sample provides coefficient estimates reasonably close to what would be produced using the full sample, the latter not being an option with public use data. We also verified that differences between using respondent and non-respondent betas remain small when these are evaluated using respondent rather than full sample means (calculations are shown in the note to Table 7).

Although our assessment regarding the reliability of respondent-only samples is very much a positive one, this assessment is based on the accuracy of mean outcomes. As seen previously in the paper, the news is less rosy in the tails. Bias from non-response prevents researchers from observing many low earners over a fairly wide range and many high earners at the very top of the distribution. The former may be the more serious problem, at least for researchers using public use data. High non-response in the lower tail affects our ability to measure and understand low wage labor markets, low income households, and poverty. Problems in the right tail are concentrated among the very top percentiles, where individuals already have their earnings masked (top-coded) in public use files. Research on very high earners is severely constrained, even absent non-response. That said, public use files no doubt include too few top-coded earners due to response bias.

9. Conclusion

This paper addresses the fundamental question of how non-response varies across the earnings distribution, a difficult question to answer and one not adequately examined in prior literature. Using matched household and administrative earnings data, we find that non-response across the earnings distribution, conditional on covariates, is U-shaped, with left-tail "strugglers" and right-tail "stars" being least likely to report earnings. Women have particularly high non-response in the left tail; men have high non-response in the far right tail. Using a joint distribution of wages, we see little difference between women and men in non-response at the same wage level. Selection is not fixed across the distribution. In the left tail there is positive selection into response; in the far right tail there is negative selection. A reassuring conclusion from our analysis is that over most of the earnings distribution response bias is ignorable.[22] But there is trouble in the tails.

[22] As discussed earlier, even if non-response were completely missing at random, "match bias" would remain a first-order problem in estimating wage differentials with respect to attributes not matched (or imperfectly matched) in Census earnings imputations (Bollinger and Hirsch 2006). If non-response is largely ignorable, however, such bias is easily remedied using a variety of approaches, including simply excluding imputed earners from the analysis.

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Figure 1: Trends in Item and Total (Item + Supplement) Earnings Imputations in the ASEC

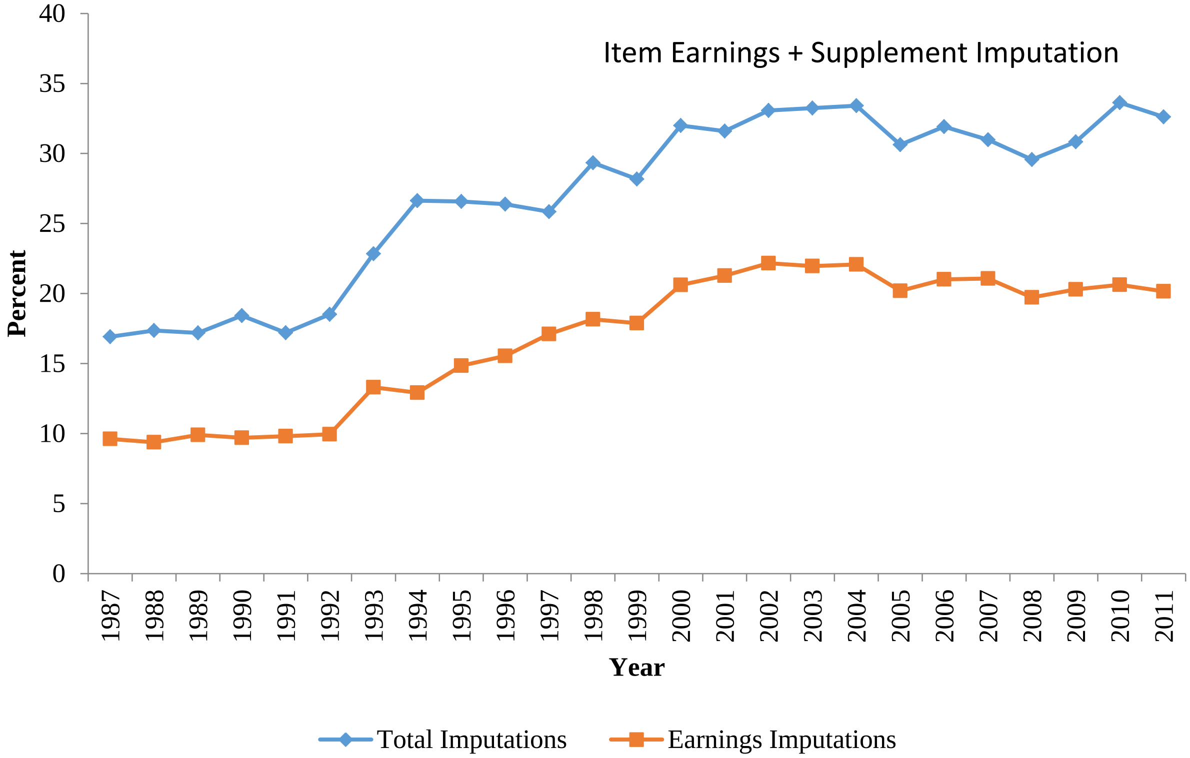
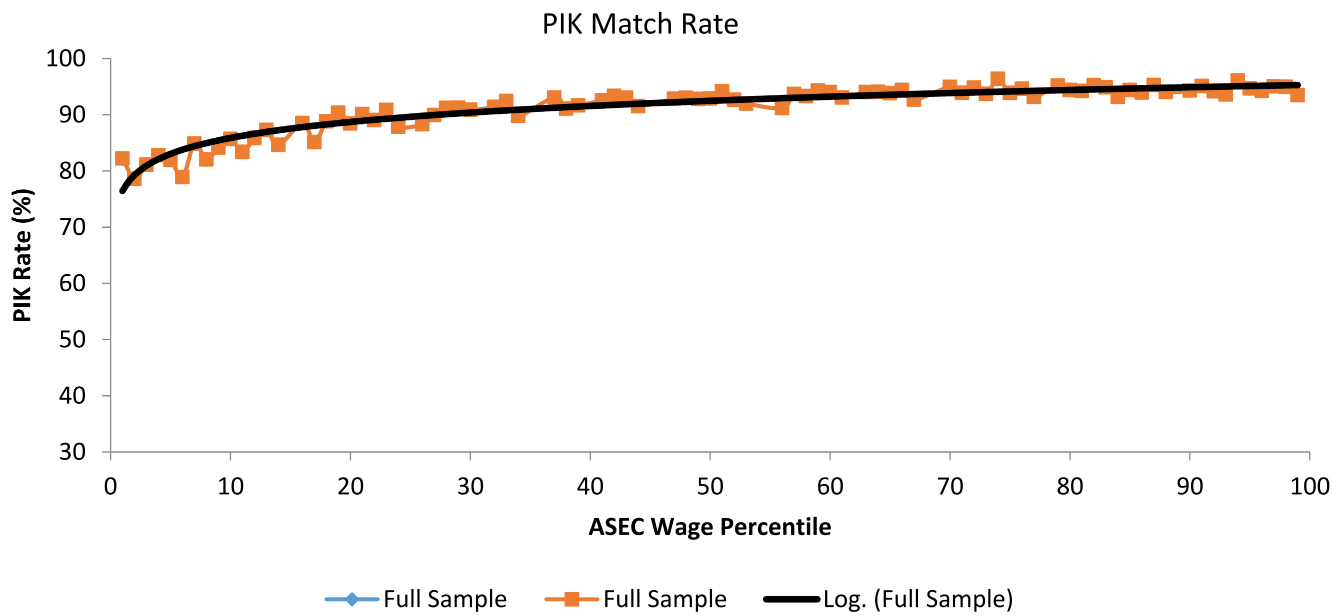
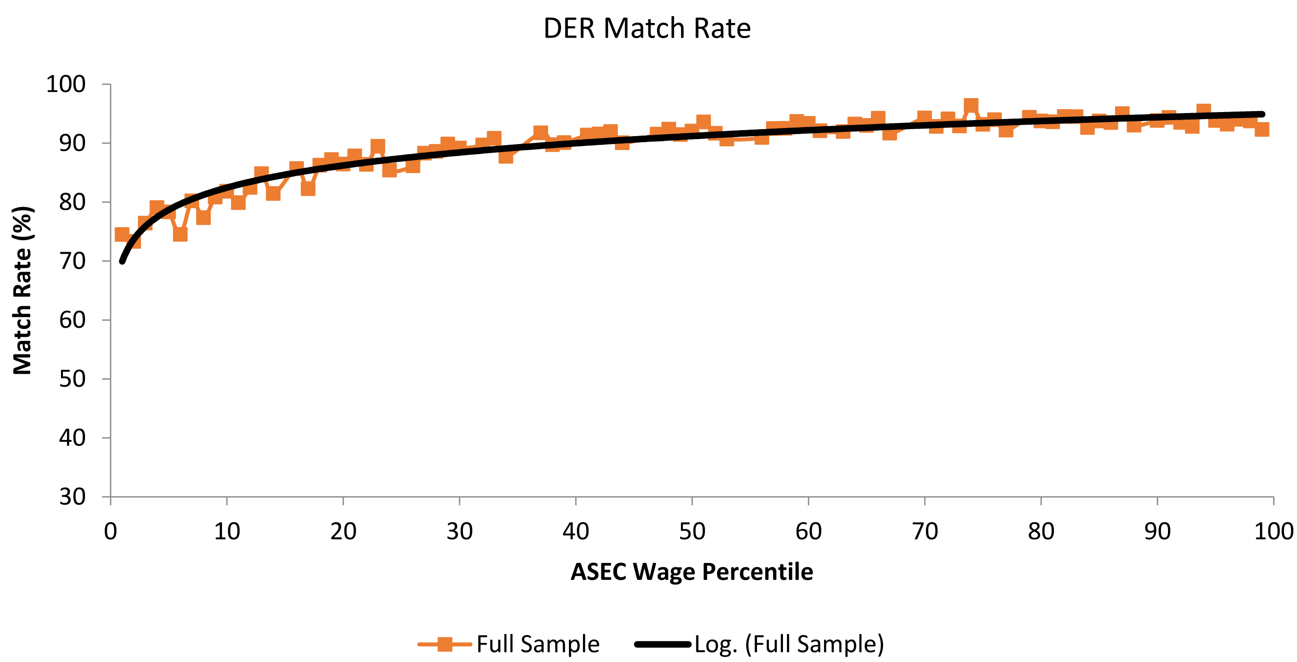


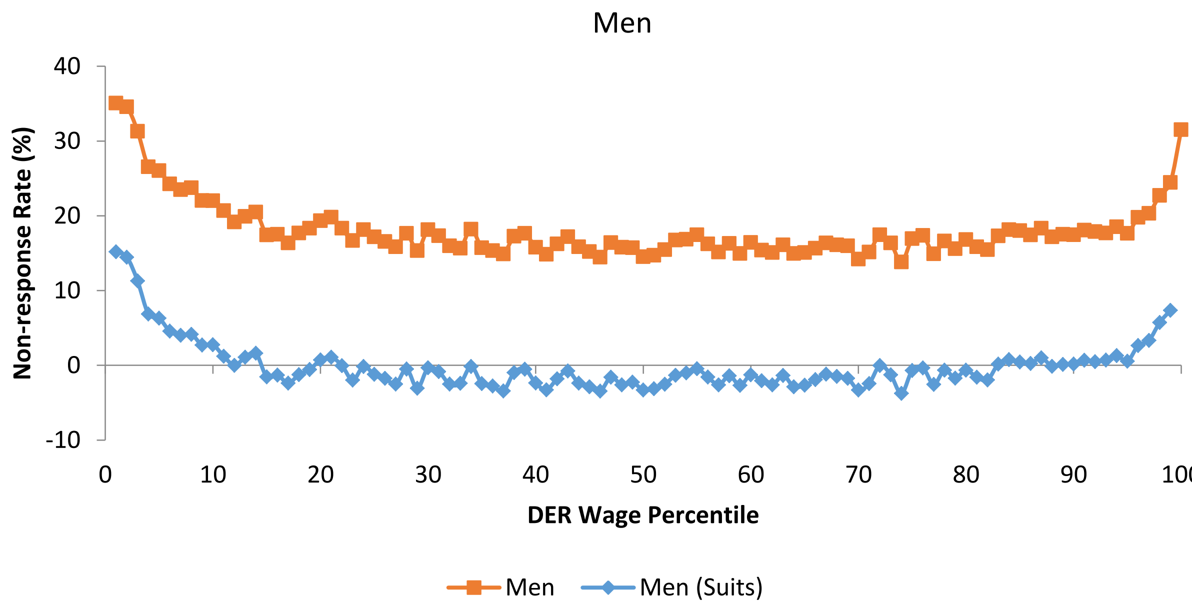
Figure 2: PIK and DER Match Rates across the ASEC Wage Distribution for Combined Male and Female Sample





Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Figures 3 Earnings Non-response Rates and Conditional Response Rates Relative to Mean by Percentiles over the Male and Female DER Wage Distributions

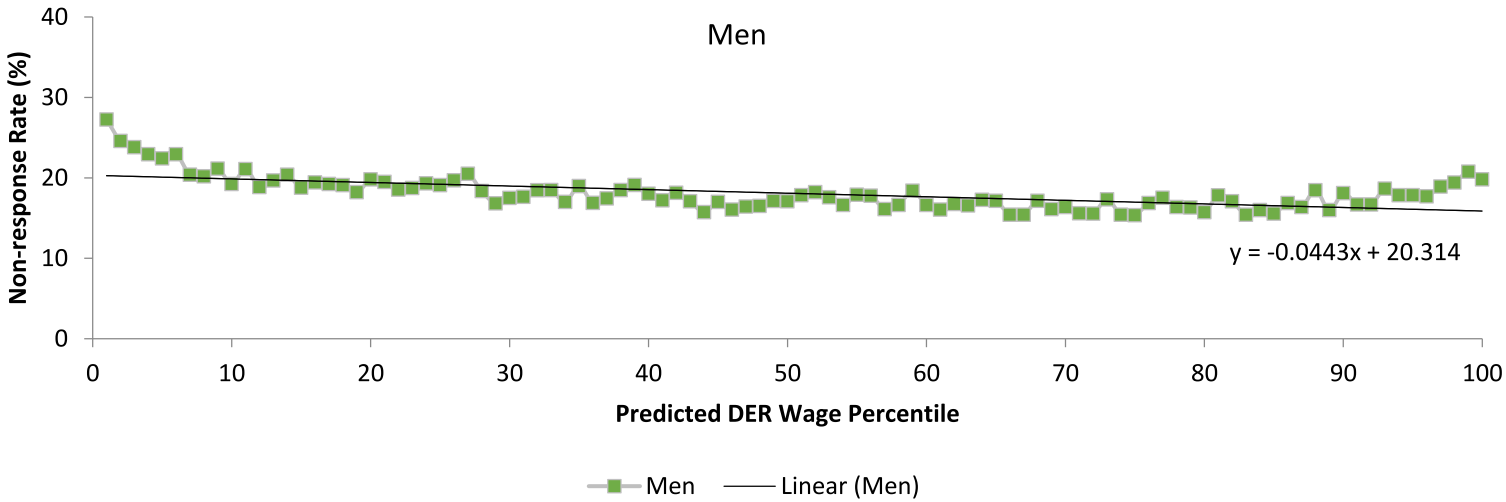


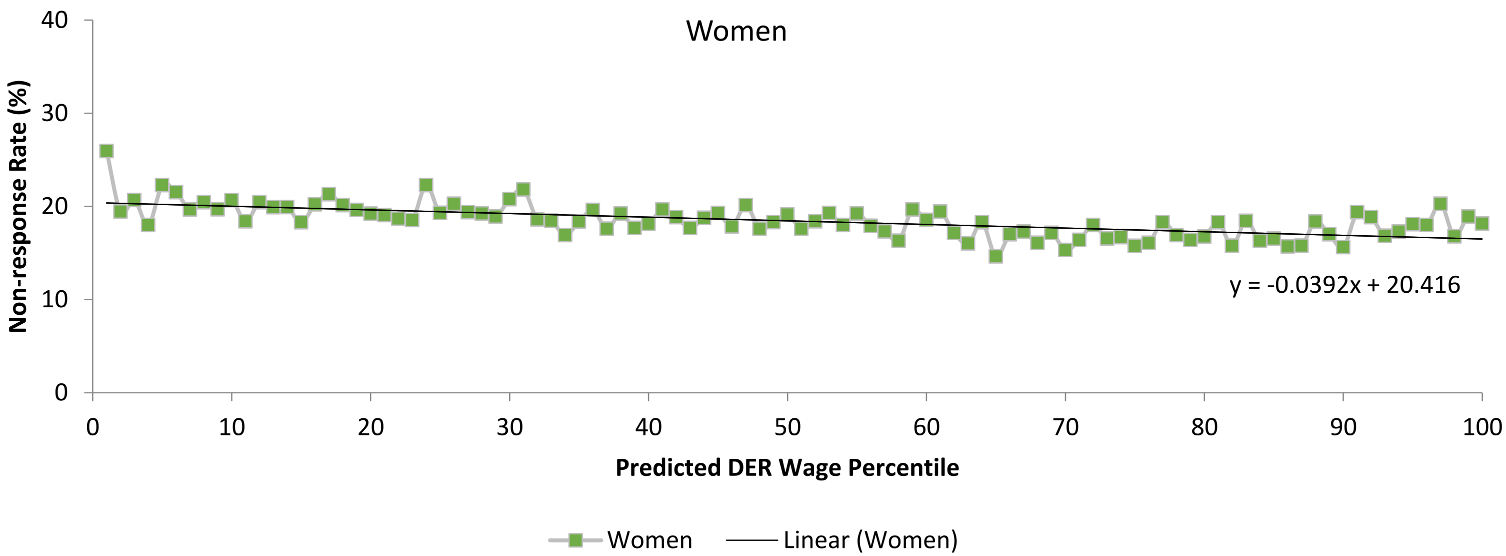
Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Figure 4: Earnings Non-response Rates by Percentile for Men and Women over the Joint Male-Female DER Wage Distribution

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

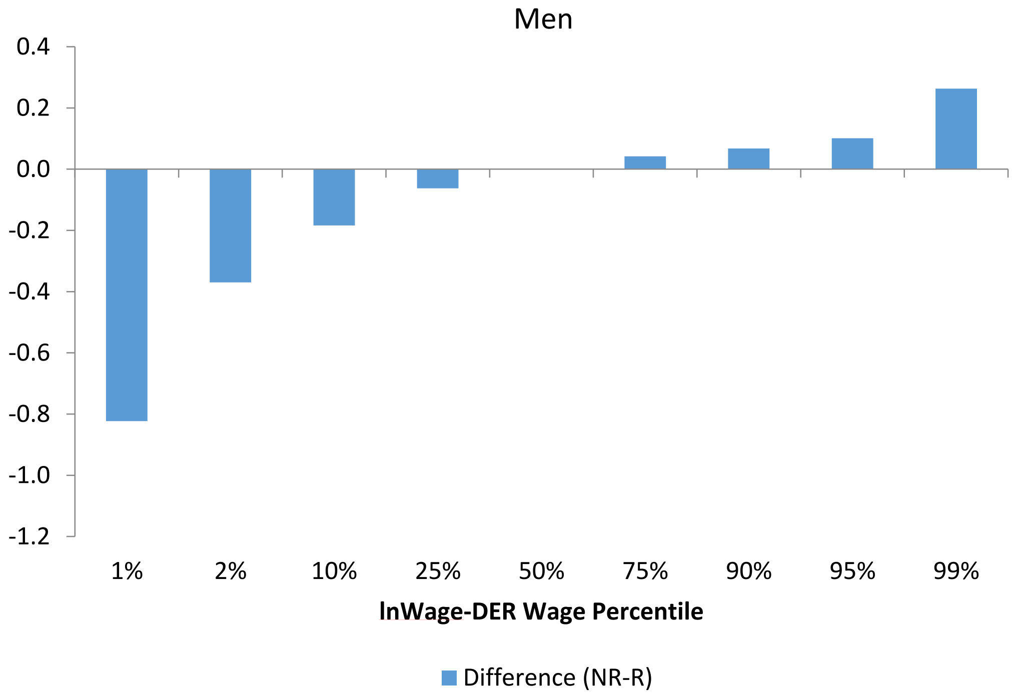
Figure 5: Non-response Rates by Predicted DER Wage for Men and Women

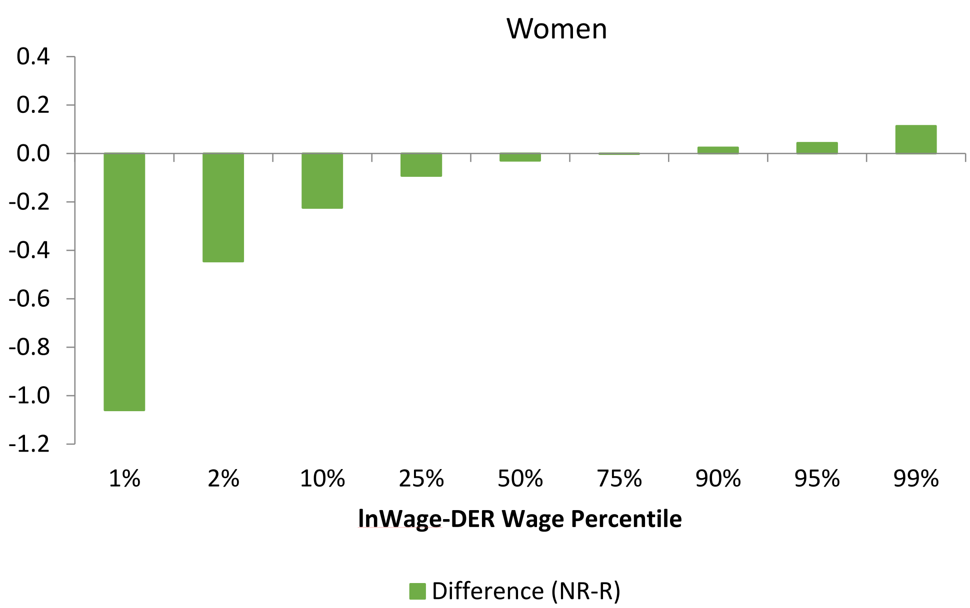




Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

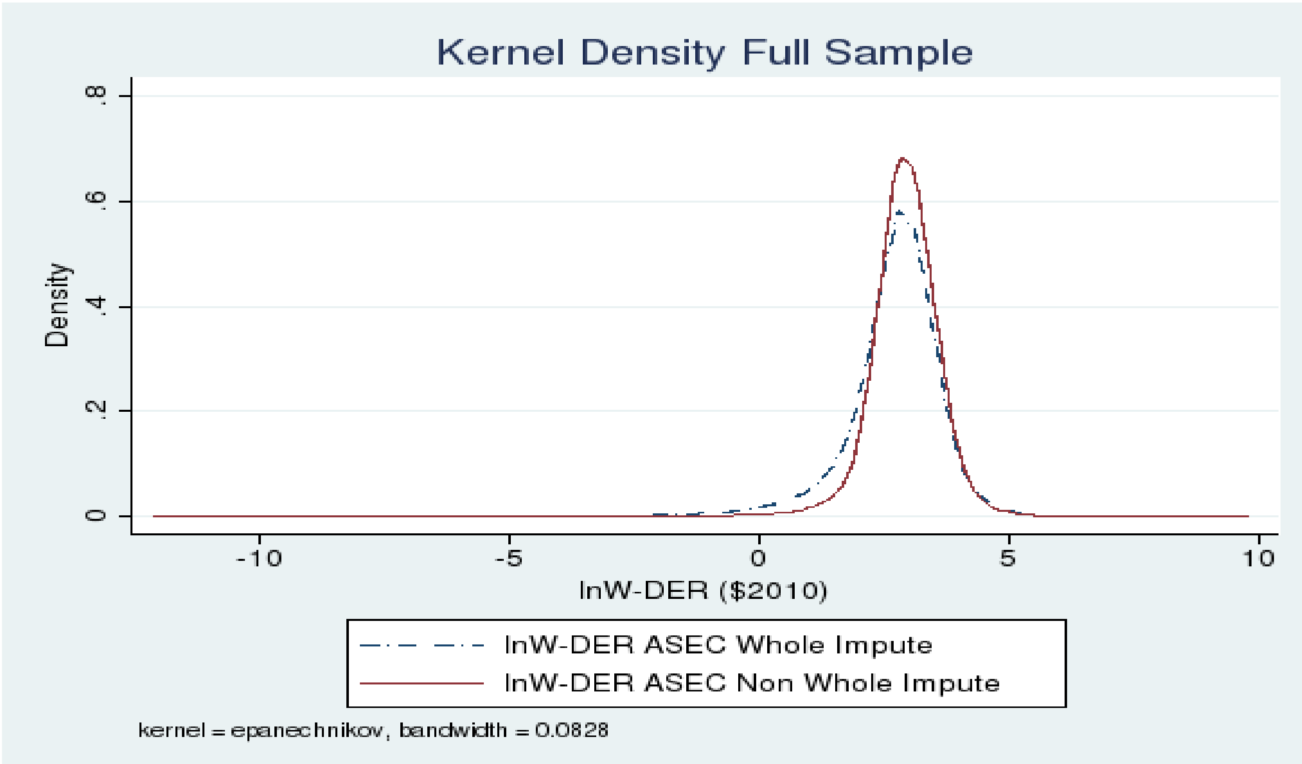
Fig 6: Differences in DER Wage Residuals between CPS Non-respondents and Respondents (NR – R) Across the Distribution, by Sex





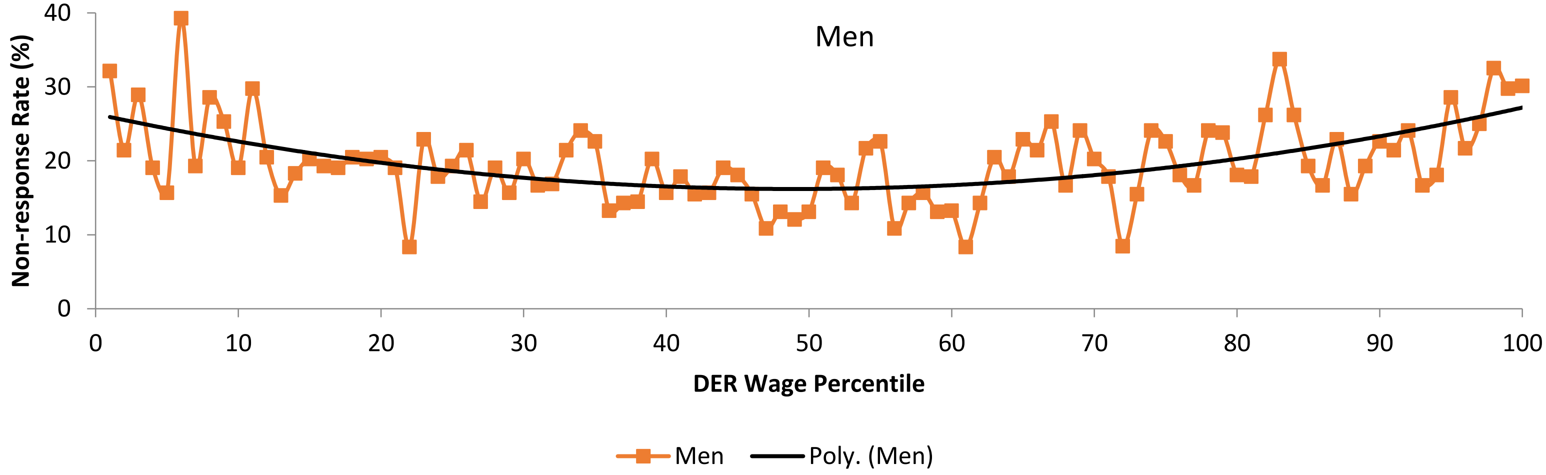
Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

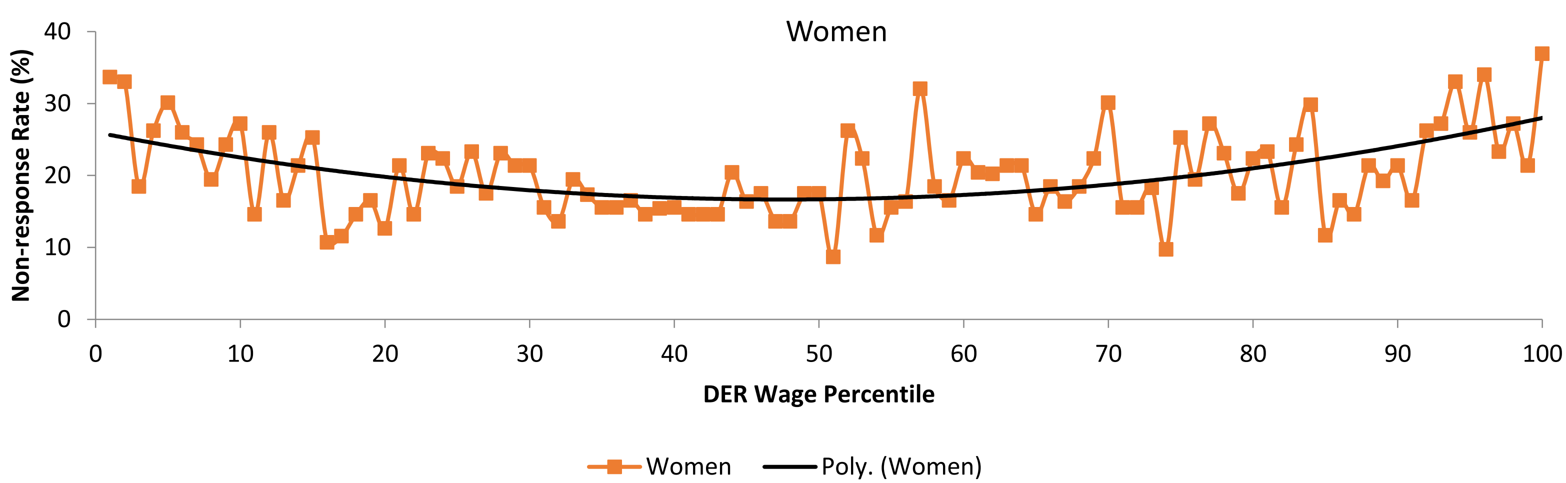
Figure 7: Kernel Densities of DER Log Wage among ASEC Supplement Participants and Whole Imputations (non-Participant Households), Combined Male-Female Sample



Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

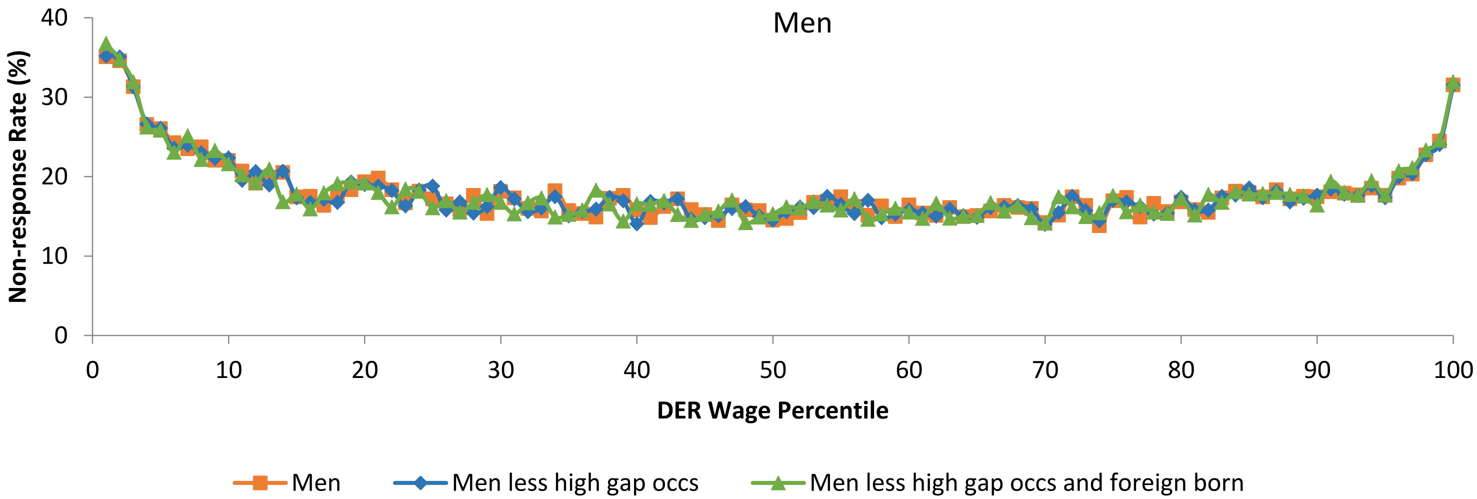
Figure 8: Non-response Rates by DER Wage for Workers Excluded from Sample, Students and Non FT/FY

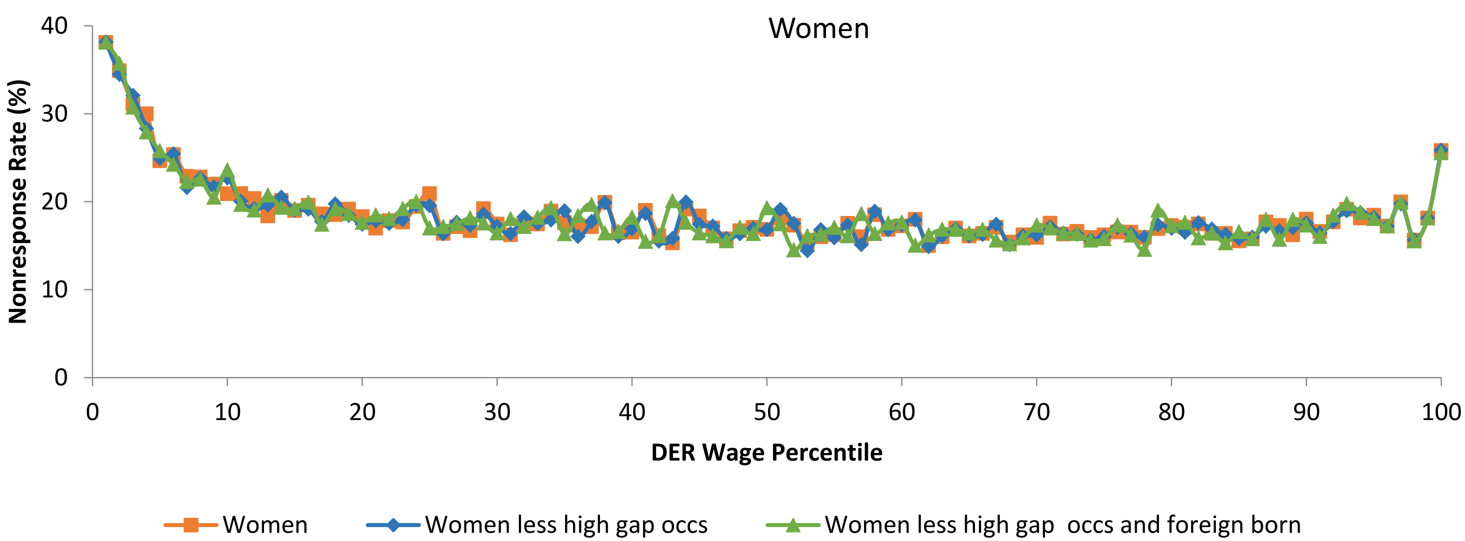




Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Figure 9: Non-response Rates by DER Wage Percentiles for Full Sample and Full Sample minus High Gap Occupations and Foreign Born Noncitizens





Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Table 1: Selected Summary Statistics for Estimation Sample

	Men		Women		
Characteristic	Mean	Std. Dev.	Mean	Std. Dev.	Difference
CPS ASEC Wage ($2010)					
Full Sample	$27.05	$27.14	$20.80	$18.57	$6.26
CPS Respondents	$27.11	$26.16	$20.94	$18.37	$6.18
CPS Non-respondents	$26.81	$30.83	$20.22	$19.38	$6.59
lnW (CPS)	3.075	0.652	2.849	0.604	0.23
DER Wage ($2010)					
Full Sample	$27.44	$63.63	$19.87	$17.33	$7.57
CPS Respondent	$27.05	$54.51	$20.01	$17.03	$7.04
CPS Non-respondent	$29.06	$92.11	$19.31	$18.53	$9.75
lnW (DER)	3.008	0.782	2.778	0.691	0.23
Non-response Rate (%)	19.5	39.6	19.3	39.5	0.23
Proxies (%)	53.2	49.9	41.2	49.2	12.03
Observations	157,041		130,663		

Note: All means are weighted using CPS ASEC Supplement weights.

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Table 2: CPS Mean Non-response with Respect to DER Wages for Men, Women, and 'Mad Men', 2006-2011

	(1) OLS	(2) Probit Marginal Effects	(3) OLS w/X's	(4) Probit w/X's Marginal Effects
		Men		
lnW–DER	-0.0178***	-0.0164***	-0.0124***	-0.0107***
	(0.00149)	(0.00140)	(0.00179)	(0.00163)
Constant	0.234***		0.291***	
	(0.00458)		(0.0128)	
Observations	157,041	157,041	157,041	157,041
R-squared	0.001		0.019	
		Women		
lnW–DER	-0.0357***	-0.0332***	-0.0397***	-0.0356***
	(0.00177)	(0.00161)	(0.00221)	(0.00192)
Constant	0.282***		0.307***	
	(0.00501)		(0.0147)	
Observations	130,663	130,663	130,663	130,663
R-squared	0.004		0.020	
		Mad Men †		
lnW–DER	0.0178***	0.0160***	0.0134***	0.0114***
	(0.00210)	(0.00184)	(0.00248)	(0.00210)
Constant	0.106***		0.139***	
	(0.00673)		(0.0299)	
Observations	78,179	78,179	78,179	78,179
R-squared	0.001		0.019	

*** p<0.01, ** p<0.05, * p<0.1

† 'Mad Men' sample includes married, white, male U.S. citizens with spouse present.

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Table 3: CPS Non-response across the DER Wage Distribution for Men, Women, and 'Mad Men', 2006-2011

	(1)	(2)	(3)	(4)	(5)	(6)
	Men		Women		Mad Men†	
DER Wage Deciles and Percentiles	Wage Decile Dummies OLS	Wage Decile Dummies and X's, OLS	Wage Decile Dummies OLS	Wage Decile Dummies and X's, OLS	Wage Decile Dummies OLS	Wage Decile Dummies and X's, OLS
Decile 10	0.269***	0.165***	0.273***	0.163***	0.185***	0.0275**
	(0.00354)	(0.00846)	(0.00390)	(0.00935)	(0.00439)	(0.0137)
Decile 20	0.186***	0.0869***	0.194***	0.0867***	0.148***	-0.00840
	(0.00328)	(0.00842)	(0.00365)	(0.00928)	(0.00423)	(0.0136)
Decile 30	0.174***	0.0784***	0.180***	0.0716***	0.140***	-0.0151
	(0.00302)	(0.00842)	(0.00336)	(0.00925)	(0.00392)	(0.0136)
Decile 40	0.164***	0.0697***	0.175***	0.0666***	0.144***	-0.0118
	(0.00295)	(0.00847)	(0.00332)	(0.00929)	(0.00397)	(0.0136)
Decile 50	0.156***	0.0632***	0.171***	0.0629***	0.150***	-0.00440
	(0.00290)	(0.00848)	(0.00330)	(0.00934)	(0.00404)	(0.0136)
Decile 60	0.160***	0.0692***	0.169***	0.0613***	0.150***	-0.00496
	(0.00293)	(0.00855)	(0.00328)	(0.00937)	(0.00403)	(0.0137)
Decile 70	0.155***	0.0657***	0.163***	0.0560***	0.142***	-0.0136
	(0.00289)	(0.00857)	(0.00323)	(0.00942)	(0.00395)	(0.0137)
Decile 80	0.161***	0.0725***	0.166***	0.0576***	0.162***	0.00563
	(0.00293)	(0.00864)	(0.00325)	(0.00948)	(0.00417)	(0.0138)
Decile 90	0.173***	0.0855***	0.168***	0.0585***	0.174***	0.0163
	(0.00302)	(0.00877)	(0.00327)	(0.00959)	(0.00429)	(0.0139)
Percentiles 91-95	0.180***	0.0934***	0.180***	0.0684***	0.192***	0.0318**
	(0.00433)	(0.00940)	(0.00475)	(0.0103)	(0.00630)	(0.0148)
Percentile 96	0.198***	0.112***	0.172***	0.0586***	0.219***	0.0582***
	(0.0101)	(0.0131)	(0.0104)	(0.0139)	(0.0148)	(0.0200)
Percentile 97	0.203***	0.119***	0.200***	0.0831***	0.235***	0.0744***
	(0.0102)	(0.0132)	(0.0111)	(0.0144)	(0.0152)	(0.0202)
Percentile 98	0.227***	0.143***	0.156***	0.0398***	0.271***	0.110***
	(0.0106)	(0.0136)	(0.0100)	(0.0137)	(0.0159)	(0.0208)
Percentile 99	0.245***	0.160***	0.181***	0.0642***	0.271***	0.106***
	(0.0108)	(0.0138)	(0.0107)	(0.0141)	(0.0159)	(0.0209)
Percentile 100	0.315***	0.228***	0.258***	0.141***	0.333***	0.166***
	(0.0117)	(0.0145)	(0.0121)	(0.0154)	(0.0169)	(0.0216)
Observations	157,041	157,041	130,663	130,663	78,179	78,179
R-squared	0.186	0.200	0.188	0.202	0.166	0.182

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

†"Mad Men" sample includes married, white, male U.S. citizens with spouse present.

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Table 4: DER Mean Log Wages ($2010) Across Wage Distribution among Men and Women in Households Participating in ASEC Supplement and Households not Participating (Whole Imputes)

	Full Sample			Men			Women		
Wage Percentiles/ Statistics	Whole Supplement Imputes	Supplement Participants	Log Difference	Whole Supplement Imputes	Supplement Participants	Log Difference	Whole Supplement Imputes	Supplement Participants	Log Difference
1%	-0.84	0.64	-1.48	-0.85	0.66	-1.51	-0.82	0.63	-1.45
5%	0.98	1.84	-0.86	1.10	1.93	-0.83	0.87	1.76	-0.89
10%	1.62	2.15	-0.53	1.75	2.26	-0.51	1.50	2.06	-0.56
25%	2.31	2.54	-0.23	2.44	2.66	-0.22	2.19	2.42	-0.24
50%	2.81	2.93	-0.12	2.94	3.05	-0.11	2.68	2.79	-0.12
75%	3.25	3.33	-0.08	3.38	3.45	-0.07	3.09	3.17	-0.09
90%	3.66	3.71	-0.05	3.80	3.83	-0.03	3.48	3.52	-0.04
95%	3.94	3.96	-0.02	4.12	4.10	0.02	3.73	3.74	-0.01
99%	4.67	4.61	0.07	4.93	4.82	0.10	4.28	4.24	0.04
Mean	2.69	2.91	-0.22	2.82	3.03	-0.21	2.54	2.77	-0.23
Std Dev	0.99	0.74	0.25	1.00	0.76	0.24	0.94	0.68	0.26
Variance	0.98	0.54	0.44	1.00	0.58	0.43	0.88	0.46	0.41
Obs	26,043	287,704		13,768	157,041		12,275	130,663	

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Table 5: Occupations with Lowest PIK and DER Match Rates

COC code	Occupation Description	Match Rates	Number	Count
PIK Match Rates:				
4140	Dishwashers	61.8%	239	387
2700	Actors	63.6%	7	11
6420	Painters	64.2%	566	881
6330	Drywall installers	64.3%	305	474
6600	Helpers, construction trades	64.8%	116	179
6510	Roofers	65.6%	223	340
6220	Brick masons	66.4%	235	354
6260	Construction laborers	68.3%	1884	2758
6300	Paving and surfacing	70.0%	28	40
6240	Carpet, floor, tile installers	70.1%	256	365
6050	Misc. agriculture workers	71.0%	1152	1622
7610	Helpers-installation, maintenance, and repair	71.2%	37	52
4130	Dining room and cafeteria attendants, bartender helpers	71.3%	290	407
8310	Pressers, textile, garment, and related	71.4%	110	154
4250	Grounds maintenance workers	72.0%	1325	1841
4020	Cooks	73.0%	2823	3866
8320	Sewing machine operators	73.2%	423	578
8450	Upholsterers	74.3%	75	101
4030	Food preparation workers	74.4%	690	927
DER Match Rates among those with and without PIK Matches:				
6460	Plasterers and stucco masons	47.1%	16	34
4140	Dishwashers	54.5%	211	387
6330	Drywall installers	57.2%	271	474
6420	Painters, construction and maintenance	57.8%	509	881
6600	Helpers, construction trades	59.8%	107	179
6510	Roofers	60.3%	205	340
6240	Carpet, floor, and tile installers	61.4%	224	365
6220	Brickmasons, blockwashers, and stone masons	61.6%	218	354
6050	Misc. agriculture workers	61.8%	1003	1622
6260	Construction laborers	62.0%	1710	2758
6100	Fishers and related fishing workers	63.0%	17	27
2700	Actors	63.6%	7	11
4500	Barbers	64.2%	61	95
8310	Pressers, textile, garment, and related materials	64.3%	99	154
6300	Paving, surfacing, and tamping equipment operators	65.0%	26	40
7610	Helpers--installation, maintenance, repair workers	65.4%	34	52
4130	Dining room and cafeteria attendants and bartender helpers	65.8%	268	407
6250	Cement masons, concrete finishers, and terrazzo workers	65.9%	137	208

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Table 6: Occupations with Largest Gaps between CPS and DER Earnings

COC code	Occupation Description	Mean $\ln W_{CPS} - \ln W_{DER}$	Count
6100	Fishers and related fishing workers	1.11	11
4500	Barbers	0.90	31
4920	Real estate brokers and sales agents	0.87	543
3260	Health diagnosing and testing practitioners	0.76	5
6460	Plasterers and stucco masons	0.75	16
4950	Door-to-door sales workers	0.67	99
4520	Misc. personal appearance workers	0.54	130
4160	Food prep and serving related workers	0.52	7
4340	Animal trainers	0.49	24
4420	Ushers, lobby attendants, ticket takers	0.47	27
2040	Clergy	0.47	917
500	Agents and managers of artists, performers, and athletes	0.44	52
6710	Fence erectors	0.43	35
3630	Massage therapists	0.42	67
2750	Musicians, singers, and related workers	0.39	74
2700	Actors	0.37	7
4040	Bartenders	0.36	536
6330	Drywall installers, ceiling tile installers, and tapers	0.33	244

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.

Table 7: lnW-DER Wage Equation Predicted Log Earnings with Full Sample, CPS Respondents, and CPS Non-respondents, 2006-2011

VARIABLES	(1) Using betas from lnW-DER All Men	(2) Using betas from lnW-DER Respondents	(3) Using betas from lnW-DER Non-respondents
Men			
Prediction with full sample X's	2.984	2.991	2.962
Prediction with respondent sample X's	2.991	2.998	2.971
Observations	157,041	128,651	28,390
R-squared of earnings equation	0.320	0.328	0.311
Women			
Prediction with full sample X's	2.724	2.739	2.658
Prediction with respondent sample X's	2.729	2.744	2.663
Observations	130,663	106,571	24,092
R-squared of earnings equation	0.337	0.357	0.285

See text for full discussion. Calculations discussed in text are shown below:

Men:
Bias using respondent sample betas rather than full sample betas with full sample X's:
diff of col 2 and col 1 betas, using DER full sample X's: 2.991 – 2.984 = 0.007
Difference between use of respondent versus non-respondent betas using full sample X's:
diff of col 2 minus col 3 DER full sample X's: 2.991 – 2.962 = 0.029
Difference in predicted wage using full vs. respondent X's, evaluated with respondent betas:
diff of col. 2 full sample X's minus col. 2 respondent sample X's: 2.991 – 2.998 = –0.007

Women:
Bias using respondent sample betas rather than full sample betas with full sample X's:
diff of col 2 and col 1 betas, using DER full sample X's: 2.739 – 2.724 = 0.015
Difference between use of respondent versus non-respondent betas using full sample X's:
diff of col 2 minus col 3 DER full sample X's: 2.739 – 2.658 = 0.081
Difference in predicted wage using full vs. respondent X's, evaluated with respondent betas:
diff of col. 2 full sample X's minus col. 2 respondent sample X's: 2.739 – 2.774 = –0.035

Sources: U.S. Census Bureau, Current Population Survey, 2006-2011 Annual Social and Economic Supplement. For information on sampling and nonsampling error, see www.census.gov/apsd/techdoc/cps/cpsmar13.pdf. Social Security Administration, Detailed Earnings Record, 2005-2010.