The Good, The Bad and The Ugly: Measurement Error, Nonresponse and Administrative Mismatch in the CPS*

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Abstract

Using the Current Population Survey Annual Social and Economic Supplement matched to Social Security Administration Detailed Earnings Records, we link observations across consecutive years to investigate a relationship between item nonresponse and measurement error in the earnings questions. Linking individuals across consecutive years allows us to observe switching from response to nonresponse and vice versa. We estimate OLS, IV, and finite mixture models that allow for various assumptions separately for men and women. We find that those who respond in both years of the survey exhibit less measurement error than those who respond in one year. Our findings suggest a trade-off between survey response and data quality that should be considered by survey designers, data collectors, and data users.

JEL: C18, J31, C21
Keywords: Earnings, survey response, Current Population Survey

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1 Introduction

Survey data have been at the forefront of social science research because these data are publicly available, often for long periods of time, and generally offer a broad collection of variables and population representativeness. For example, research into the determinants of earnings not only requires measures of earnings, but also measures of education, labor market experience, sex, race, among others. A leading example is the Current Population Survey Annual Social and Economic Supplement (CPS ASEC), which has been collected in some form since March of 1962. An increasingly popular alternative to surveys is administrative data from tax records. These data contain measures of earnings or income, and often very large sample sizes, but generally do not contain much demographic information and are not available publicly. However, most survey data suffer from data quality issues such as measurement error and nonresponse. Both sources of error have been investigated separately, as we discuss below, and in this paper we extend the literature by investigating whether measurement error and nonresponse are jointly related using survey data from the CPS ASEC linked to administrative data from Social Security.

A well-established literature has focused on measurement error in survey reports of earnings (Mellow and Sider, 1983; Duncan and Hill, 1985; Bound and Krueger, 1991; Bound et al., 1994; Pischke, 1995; Bollinger, 1998; Bound et al., 2001; Roemer, 2002; Kapteyn and Ypma, 2007; Meijer et al., 2012; Abowd and Stinson, 2013; Jenkins and Rios-Avila, 2023b; Bollinger and Tasseva, 2023). Although there are exceptions, most studies find support for a "common person" hypothesis: low-income individuals tend to over-report earnings, while high-income individuals tend to under-report earnings. Kapteyn and Ypma (2007), Meijer et al. (2012), Abowd and Stinson (2013) and Jenkins and Rios-Avila (2023b) call into question the typical assumption that the administrative record is correctly measured. These studies find support that administrative data may have match error or measurement error. We also find evidence that challenges the "administrative gold standard" assumption. This in turn suggests that the "common person" hypothesis is less in evidence, or even nonexistent.

A more recent, and growing, literature considers nonresponse in survey data (Hirsch and Shumacher, 2004; Bollinger and Hirsch, 2006; Nicoletti et al., 2011; Bee et al., 2015;

Hokayem et al., 2015; Bollinger et al., 2019; Meyer and Mittag, 2019; Neri and Porreca, 2023). We focus on item nonresponse, as opposed to unit nonresponse, which means that while a participant generally answers other questions on the survey, that individual does not respond to certain questions. One of the highest rates of item nonresponse in the CPS are the questions about labor market earnings. As noted initially in Hirsch and Shumacher (2004), the rate of item nonresponse to the earnings questions in the CPS ASEC and the CPS Monthly Outgoing Rotation Group rose dramatically through the 1990's and especially the early 2000's. In the 1980's, the earnings nonresponse rate hovered around 12 to 15%. During the 1990's the rate rose and through the mid 2000's and 2010's was as high as 25%. (See Bollinger and Hirsch (2006), Bollinger et al. (2019)). There are many possible reasons for the nonresponse to earnings questions. One possible reason is simply ignorance. The interview structure of the CPS means that nearly 50% of all responses are proxy responses. The CPS asks the household to designate a single individual as the respondent, rather than separately interviewing each member of the household. Earnings nonresponse for proxy responses is - on average - substantially higher than for respondents as a proxy respondent may just not know what other household members earn. Other reasons for nonresponse are stigma or threat. Stigma may occur if individuals feel embarrassment about their earnings: either because they are too high, or they are too low, relative to some perceived norm. Threat can occur for a variety of reasons such as tax evasion or simply fear of release of sensitive information.

Initial work on earnings nonresponse in the CPS (Hirsch and Shumacher, 2004; Bollinger and Hirsch, 2006) established that the Census imputation procedure led to bias in regression coefficients unless researchers limited their specification to only the variables used in the procedure, and measured in the same way. These findings led to the recommendation that researchers drop imputed earnings and possibly re-balance the sample with inverse probability weights (as in Wooldridge (2007), or use a selection model to address nonresponse (Bollinger and Hirsch, 2013), or possibly to even construct an imputation approach consistent with the underlying research model of interest (Little and Rubin, 2014; Bollinger et al., 2019). Bollinger and Hirsch (2006) find that in practice the IPW approach has little impact on the results at the mean. However, Bollinger and Hirsch (2013), Bollinger et al. (2019), and Valet et al. (2018) investigated the implications of the resulting sample selection and found that nonresponse was concentrated on those individuals with low earnings or high earnings. That is, like the "common person" finding, nonresponse to the earnings question is concentrated among those in the tails of the distribution. This concentration of measurement error and nonresponse among the same groups of earners suggests there may be a relationship between nonresponse and measurement error.

A number of authors have considered the possibility of a relationship between survey nonresponse and measurement error. Bollinger and David (2001) find a relationship between measurement error in Food Stamp Program participation in the first waves of the 1984 Survey of Income and Program Participation (SIPP) and subsequent attrition from the sample. They hypothesize a "good reporter - bad reporter" type phenomenon. Individuals who engage with the survey provide accurate responses and remain in the sample ("good reporter"). Those who do not engage have responses that contain errors and are likely to fail to respond to the survey at all ("bad reporter"). Similar hypotheses have been forwarded as far back as Cannell and Fowler (1963) and Cochran et al. (1954).

Manski and Dominitz (2017) examine the potential trade-off between improved response rates and measurement error. A number of authors (Groves (2006); Olsen (2007); Abraham et al. (2009)) examine how correlation between a variable of interest and response propensity would affect nonresponse bias. Another direction of this research classifies respondents as "reluctant" when it takes survey enumerators multiple calls and discussion to obtain an interview (Kreuter et al., 2010; Triplett et al., 1996; Stoop, 2005; Dahlhamer et al., 2006; Fricker, 2007). Nicoletti et al. (2011) establish bounds for poverty rates allowing for very general missing and nonresponse patterns while Hokayem et al. (2015) establish bounds for poverty rates allowing for item nonresponse in earnings. The work here differs from this previous work in that we have individuals who both respond and do not respond to the earnings question in two different time periods. In many ways this provides a cleaner definition of "reluctant responder" than previous work, and focuses on the specific earnings question.

We investigate the relationship between nonresponse and measurement error and the structure of the measurement error in the CPS ASEC earnings question. We find support for the conjecture that there is a relationship between nonresponse and measurement error. To do this, we make use of the restricted-access CPS ASEC matched to Social Security Detailed Earnings Records (DER) for the years 1996-2019. This allows us to observe earnings for individuals who do not report earnings in the CPS, as well as those who do. The CPS sample structure allows for a two-year panel of individuals, allowing us to observe two opportunities for participants to respond to the earnings question in the ASEC, along with two overlapping opportunities to observe administrative earnings records. The vast majority of respondents report their earnings in both years. However, a growing proportion - well over 20% by the end of the sample - of respondents switch from response to nonresponse or vice versa, and nearly symmetrically so. Those who otherwise participate in the survey but fail to report their earnings in both years are the smallest of the four possible groups. Thus for nearly 20% of the sample, we can observe response in one period, and nonresponse in the other. It is comparing this group to those who respond in both periods that allows us to address the question of whether nonresponse and reporting error may be linked.

Like Kapteyn and Ypma (2007) and more recently Jenkins and Rios-Avila (2023b) we find little evidence for the "common person" phenomenon. As with most prior work, when we treat the administrative record as a "gold standard" we do find support for the common person structure. However, when we allow for mismeasurement - either additive white noise or incorrect matches between the administrative record and the survey record (mismatch) - it appears that measurement error in the ASEC most closely resembles additive noise. Our evidence suggests that while there may be some mismatch between the administrative records and the survey, growing measurement errors in the administrative record, which on average are negative suggesting missing under the table earnings, account for the typical common person finding.

Perhaps most strikingly, we find that the quality of the data provided by the remaining respondents is improving over time. Through our 24 years of data, we note rising nonresponse implies that a larger portion of the sample are refusing to respond in both periods. We find that the measurement error variance of those who respond in both periods is falling slightly, as is the measurement error variance of those who respond in only one period. We argue that this implies, similar to the ideas in Manski and Dominitz (2017), Kreuter et al. (2010) and others, that there is a trade-off between response and quality, and that the worst respondents are moving over time toward nonresponse.

These findings are important in a number of respects. First, they suggest that attempts to cajole or otherwise improve response from non-respondents may be less valuable than previously thought. If these individuals are failing to provide quality data, it may be best to simply allow them the freedom to refuse. Second, the results suggest that using their responses for either imputations for other missing data may not be wise. Furthermore, assumptions of random measurement error and random nonresponse are problematic. The concentration of both nonresponse and measurement error in the tails of the distribution suggests that perhaps these individuals have higher costs (psychic or simply recall) in providing data.

In the next section we describe the restricted-access data used in our analysis. This is then followed in Section 3 with the specification of the empirical framework we deploy to study the relationship between non-response and measurement error. Section 4 presents the main results under alternative modeling assumptions for the error processes. Section 5 then offers a discussion on the implications of our findings for future research on earnings, while Section 6 concludes.

2 Data

The data derive from the 1996 through the 2019 CPS ASEC. The ASEC is important in that it is the source of official U.S. income and poverty statistics, and one of the most common data sources for examining income distributions and inequality, as well as for understanding the determinants of earnings and the impact of policies on earnings. The monthly Current Population Survey is administered to approximately 60,000 households, with an additional 30,000 households added to the ASEC supplement since 2001. The survey is structured so that the address is the sampling unit with a rotation group design whereby the respondent is interviewed for four consecutive months, then dropped for eight months, and then interviewed for another four months. Thus an address chosen and initially contacted in January, would appear in the January, February, March and April monthly survey. One year later the same address is recontacted, and included in the sample for those same months in that second year. In March, the ASEC is administered. Among a wide variety of additional questions, earnings from all employment, and details on the industry and occupation of the primary employer for the prior calendar year are elicited.

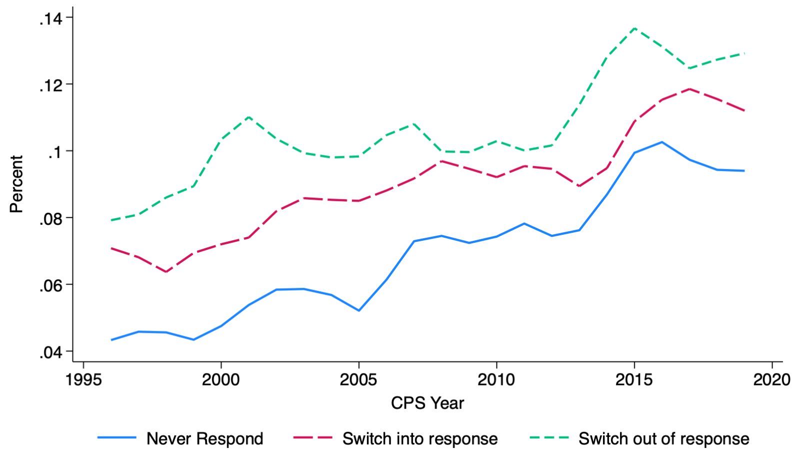
We focus on workers between the ages of 18 to 62 in the first year of the ASEC in which we observe them. Because of the rotation structure of the CPS, any individual first appearing in the ASEC, can potentially appear in the ASEC the following year. Using standard CPS household and individual identifiers, we construct the sample of individuals who are linked across response years to create a two-year panel of individuals. As mentioned before, the CPS is not an individual or family-based sample, but rather an address-based sample. Thus, individuals who move from their original address are not followed by the CPS the next year, and hence cannot be linked. The sample sizes in 1996 (the first year) of the sample and 2019 (the last year of the sample) are approximately half, as we do not include 1995 or 2020 data. Individuals in 1996 are only those who matched to the 1997 survey. This eliminates individuals who were in their second year of participation, or who moved between the first and second ASEC interviews. Symmetrically, those retained in 2019, were in their second year of the survey, and were matched to 2018 only. The linked ASEC sample is somewhat selective: it tends to be older, more highly educated, have a higher concentration of whites and married individuals than the full sample (Bollinger et al., 2019). It has also been found (Bollinger, 1998; Ziliak et al., 2023) that this group has lower measurement error (as measured by variance). Attempts to correct for this selection using IPW and other methods seem to have little impact on most results (Bollinger et al., 2019). We separate men and women throughout the analysis.

Using the Census Bureau internal files, the CPS ASEC data are matched to earnings data from the DER. The DER is an extract of Social Security's Master Earnings File and includes total earnings as reported on a worker's Form W-2, wages and salaries and income from (positive) self-employment subject to Federal Insurance Contributions Act and/or Self-Employment Contributions Act taxation reported on Form 1099, as well as deferred contributions to 401(k), 403(b), 408(k), 457(b), and 501(c) retirement and trust plans. We include all of these sources in our DER earnings measure. For workers with multiple W2's or 1099's in a given year, we aggregate across all jobs to produce one annual DER earnings observation per worker. In this way, DER earnings align with ASEC earnings from all wage and salary job plus nonnegative self-employment earnings. The DER and ASEC files have a "Protected Identification Key" (PIK) for each individual, which uniquely identifies that individual and is used for matching. Although not the individual's Social Security Number (SSN), it plays a similar role and is based upon the Numident file maintained by the Social Security Administration. The Census Bureau uses name, address, birth date, sex, and in some years SSN to identify individuals and assign their PIK. In early samples, match rates were lower because many respondents refused to provide their Social Security numbers and/or did not agree to have their information linked to tax records. In 2006, the Census Bureau stopped collecting Social Security numbers and switched from an "opt in" to an "opt out" policy and match rates rose. Our overall match rate is 81%, but rates for years after 2005 are between 85% and 90%. As discussed in Bollinger et al. (2019), non-matched individuals are more likely to be foreign born, and are more likely to have lower educational attainment. They also report lower earnings in the CPS.

The final analysis sample consists of workers between ages 18 and 62, who have been linked across two years of the CPS ASEC, and who have been matched to the DER records. We also drop individuals whose earnings are top-coded in the internal ASEC (less than 1% of the sample), and individuals whose entire ASEC supplement record was imputed ("whole impute"). We note that this sample is not representative of the U.S. population, or even the population of U.S. workers. Hence we do not use sampling weights in this analysis. The advantage of our sample though is that it allows us to investigate measurement error and nonresponse through comparison of the CPS ASEC to the DER earnings over multiple years.

Figure 1 shows nonresponse patterns for the earnings question across two years (see Appendix Table A2). We note three important trends. First, the rate of never responding in either year rises over time (never respond in blue). Second, the rates for those who switch also rises over time (switch into in red, switch out in green). Finally, the switch into response and switch out of response rates are similar, although generally switching out occurs at a higher rate. We define switchers as individuals who provided a response to the earnings question in the sample year, were linked to their respective adjoining year, but did

Figure 1: Non-Response Rates



Notes: Earnings non-response rates for adults in the labor market in linked years of CPS ASEC response rates.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

not provide a response in that year. We will use this group as a proxy for those who may be "bad reporters." Responders are those who responded to the earnings question in both years, and are a proxy for "good reporters."

Table 1 provides means for common demographic variables and earnings for all members of the analysis sample. In addition to the sample selection criteria we outline above, the analysis sample drops those who never respond to the earnings questions because we cannot observe the measurement error in earnings for those who never provide a response. We note that on average CPS earnings are slightly higher than DER earnings. The smaller samples for lnDER and lnASEC reported at the bottom of the table reflect zero (or missing) earnings in each case. DER earnings are missing if there were no earnings reported to Social Security. ASEC earnings can be zero if they report zero or had no earnings. Due to Census disclosure avoidance policy, sample sizes are rounded to the nearest 1000 observations.

Table 1: Means by Response Status

Variable	Respond Any		Respond Both		Switcher	
	Male	Female	Male	Female	Male	Female
Responder	0.89	0.90	1	1	0.50	0.50
Switcher	0.22	0.20	0	0	1	1
Real DER Earnings	52780	30610	52960	30830	52120	29770
Real ASEC Earnings	53270	31410	53490	31410	52500	31430
Ln(DER Earn)	10.42	9.88	10.44	9.88	10.35	9.89
Ln(ASEC Earn)	10.55	10.02	10.58	10.04	10.45	9.95
Age	41.67	41.3	41.6	41.18	41.89	41.78
White	0.86	0.84	0.87	0.84	0.83	0.80
Black	0.078	0.10	0.073	0.10	0.10	0.12
Asian	0.05	0.05	0.05	0.05	0.06	0.06
Amerind	0.01	0.01	0.01	0.01	0.01	0.01
Hispanic	0.10	0.10	0.10	0.10	0.11	0.11
Less Than HS	0.05	0.04	0.05	0.04	0.06	0.04
HS Graduate	0.30	0.26	0.29	0.26	0.31	0.28
Some College	0.20	0.21	0.20	0.21	0.20	0.22
Associate Deg.	0.10	0.12	0.10	0.12	0.09	0.12
BA	0.21	0.22	0.21	0.22	0.20	0.21
MA	0.08	0.09	0.08	0.09	0.07	0.08
Professional Deg.	0.02	0.01	0.02	0.01	0.02	0.01
Phd	0.02	0.01	0.02	0.01	0.02	0.01
Married	0.67	0.62	0.68	0.63	0.64	0.60
All N	419000	418000	327000	332000	92000	85000
lnDER N	393000	385000	308000	308000	85000	77000
lnASEC N	392000	373000	304000	294000	87000	79000

Notes: Sample of all adults age 18-62, matching across consecutive CPS years, no whole imputed, who were PIKed and had positive earnings for either DER or ASEC, and who responded in at least one year. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018. Respond any includes all individuals who provided earnings in at least one of the two years for which we observe them. Respond both are individuals who provided earnings in both years in which we observe them. Switchers provided earnings in only one year.

The first pair of columns in 1 is our main sample, which includes individuals who provide an earnings response in at least one of the two CPS years for which we observe them. The second pair of columns are those who provide earnings responses in both years we observe them. The third pair are those who only respond in one of the two years. We note there are few differences between the latter two groups (respond both and switchers). Earnings, on average, are quite similar, although men who respond in both periods report nearly \$1000 higher earnings than those who respond in only one year. Those who respond in both years are more likely to be White and less likely to be Black. Educational differences are remarkably small, while those who respond in both periods are slightly more likely to have a BA or MA, and less likely to have only a high school degree, the differences are 2 percentage points or less in all cases.

3 Empirical Models

We posit a model of the data generating process consistent with the models found in Kapteyn and Ypma (2007), Abowd and Stinson (2013), and Jenkins and Rios-Avila (2023b), which allows for a variety of possible special cases that we consider and discuss in the results section. We begin by assuming that log earnings are determined by a standard Mincerian-type wage equation:

$$Y_{it}^{*} = X_{it}\beta + u_{it}, \tag{1}$$

where Y_{it}^{*} is person i's log earnings in time period t. Here, t will refer to either the first or second year in the ASEC survey. The X_{it} are standard explanatory variables including potential experience (age-education-6), education, race, and city size. Models are estimated separately by sex. The term u_{it} is meant to capture unobserved factors that determine earnings. The ideal Y_{it}^{*} is not directly observed. Rather, we observe two different measures of earnings:

$$Y_{it}^{D} = \begin{cases} Y_{it}^{*} + \varepsilon_{1it}^{D} & \text{with prob. } p \\ \mu_Y + \varepsilon_{2it}^{D} & \text{with prob. } 1-p \end{cases} \tag{2}$$

$$Y_{it}^{C} = \begin{cases} \delta_1 + \rho_1 Y_{it}^{*} + \varepsilon_{1it}^{C} & \text{with prob. } q \\ \delta_2 + \rho_2 Y_{it}^{*} + \varepsilon_{2it}^{C} & \text{with prob. } 1-q \end{cases} \tag{3}$$

The first measure, Y_{it}^{D} in equation (2), is the earnings as measured in the administrative DER records. The second measure, Y_{it}^{C} in equation (3), is the survey report from the

CPS ASEC. The two models for Y_{it}^D represent both a mismeasured version (the first row in equation(2)) and a mismatched version (the second row in equation(2)). The data for X_{it} derive solely from the match to the CPS. If a mismatch occurs we expect no correlation between the observed X_{it} from the survey and the observed Y_{it}^D from the administrative records. Hence in the second model the data are a random draw from the entire distribution of earnings.

The CPS ASEC measure of earnings, Y_{it}^C, likewise posits two models, but in this case they capture two measurement error models allowing for different types of response. As noted above, the severity of the measurement error problem is often summarized in the two parameters $(\rho, \sigma_{\varepsilon}^2)$. Hence we posit that $|\rho_1 - 1| > |\rho_2 - 1|$ and $\sigma_{\epsilon 1}^2 > \sigma_{\epsilon 2}^2$: the individuals who respond like the second model in equation (3) are better reporters than those who respond like the first model in equation (3). We label this second group "good reporters." The empirical question we seek to answer is whether we find "good reporters" and "bad reporters." We hypothesize that nonresponse can help us discern who is in which group a priori. Typically, we will assume that individuals reporting in both periods are "good reporters" (group 2) while switchers are not (group 1).

The response models in equation (3) provide the necessary terms to summarize biases in linear regression models using CPS earnings as either a dependent or regressor variable. Bound et al. (2001) provide a nice discussion of these cases. Briefly, if the CPS earnings are a dependent variable the ρ coefficient summarizes the bias, while if it is used as a right hand side variable both ρ and the variance of ε^C, $\sigma_{\varepsilon 1}^2$, determine the bias.

The approach used by Kapteyn and Ypma (2007) and Jenkins and Rios-Avila (2023b) adds two additional equations, where $Y_{it}^D = Y_{it}^*$ and $Y_{it}^C = Y_{it}^*$. They also allow for the first model in equation(2) to be a more general linear relationship:

$$Y_{it}^D = \alpha_0 + \alpha_1 Y_{it}^* + \epsilon_{1it}^D. \tag{4}$$

They include two additional probabilities for the case of correct reports in both the CPS and DER data. We label the probability that the survey reports in the CPS are exact as R_C, and the probability the administrative report in the DER is exact as R_D. We also report the probability of mismatch between the DER and ASEC as $PR(miss)$ in our tables. We further allow R_C to differ by response type, good reporter or bad reporter, as above. Note that the models we specify have no correct (except by chance) reports in the CPS, but possibly correct reports in the DER (depending on the variance of ε^D_{1it}). We estimate these models below, and discuss implications as well.

Different assumptions on models of earnings measurement (equations 2 and 3) have led to different estimates of both the relationships between Y^D_{it} and Y^C_{it}. Much of the classical measurement error literature (Bound and Krueger, 1991; Bollinger, 1998; Bound et al., 2001) assumes that $p = 1, q = 1$, and $V\left(\varepsilon^D_{1it}\right) = 0$: that is the administrative records are equivalent to the true earnings (Y^*_{it}) and that there is one simple summary model of misreporting. Bollinger (1996) showed that a simple linear model may not be appropriate, however, Kapteyn and Ypma (2007), Abowd and Stinson (2013) and Jenkins and Rios-Avila (2023b) suggest that if bad matches are allowed ($p < 1$) the linear model fits well. Kapteyn and Ypma (2007) provide some evidence that the bad matches seem to explain much of the "common person" hypothesis implying $\rho_1 < 1$.

Bollinger and David (2001), while not considering earnings, suggest that there is a relationship between measurement error and nonresponse. They also suggest that there may be two types of respondents: (1) those who are engaged with the survey, attempt to give accurate responses, and continue to participate over time and across questions; and (2) those who are not engaged and are the primary source of both nonresponse and measurement error. Our model above attempts to capture all of these factors, but as such is complicated and difficult to estimate. We note that, in fact, the structure of the nonresponse equation - and the findings of Bollinger and David (2001) would indicate further that q may be a function of R_{it}: measurement quality is related to nonresponse.

Our approach discussed in the next section considers a variety of restrictions on the models for estimation. The comparison of the models provides some insight into the underlying measurement process. Rather than claim that we have found the right model (as is often done), we explore and examine a variety of models and use the differences in these estimates to gain deeper insights.

4 Results

We seek to investigate whether there is a relationship between reporting error among CPS ASEC earnings respondents and nonrespondents to the earnings question. Hence, we estimate the measurement error model above (and subsequently nonresponse models) under a variety of assumptions: (1) DER records assumed correct; (2) DER records with additive white noise error; and (3) allowing for both measurement error and mismatch in the DER earnings

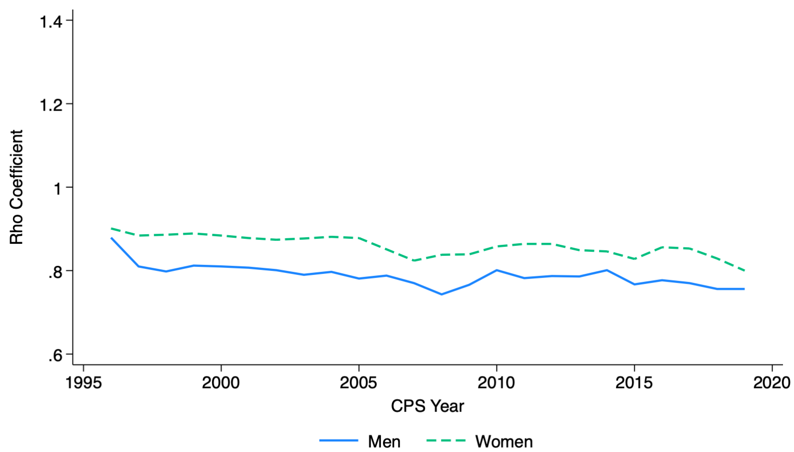
4.1 Model 1: DER Records assumed correct

This section uses OLS primarily to estimate the models above, but also reports a set of estimates using finite mixture models. We begin with estimates of the standard type of measurement error models often seen in the literature: the administrative record is taken as correct while the survey data are allowed to be mismeasured. These are not our preferred model, but we begin with them as they are comparable to a long literature in this field. Comparing them to subsequent models aids in interpretation of that literature and subsequent models.

Formally, we are assuming that $Y_{it}^{D} = Y_{it}^{*}$, and thus in equation 2, $p = 1$ and $V\left(\varepsilon_{1it}^{D}\right) = 0$. These assumptions imply that the regression of Y_{it}^{C} on Y_{it}^{D} identifies ρ as the slope coefficient and $V\left(\varepsilon_{it}^{C}\right)$ as the variance of the residuals. Appendix Tables A3 and A4 present the measurement error model estimates under the assumption that the DER measure is correct. We focus on figures that display the estimates for discussion.

To be comparable with prior literature (Bound et al., 1994; Bound and Krueger, 1991; Bollinger, 1998), Figures 2 and 3 combine all individuals in the sample year who respond to the survey in that year and ignores the response status in the matched year. Figure 2 demonstrates support for the typical finding of "common person" as the coefficient on the natural log of the DER earnings, ρ, is less than one. The values range from 0.88 (in 1996) to 0.77 (in 2017 and other years) for men and 0.9 (in 1996) to 0.8 (in 2019) for women. The measure of σ_{ϵ} (Figure 3) is the standard deviation of the residual from the simple regressions. We consider this the best measure of the amount or severity of measurement error. The estimated ρ coefficient represents systematic mismeasurement, while σ_ϵ represents the random component. For women, we see higher estimated ρ (ranging from .8 to .9) and typically lower σ_ϵ. These findings are often used to support claims that women are better reporters than men: both less systematic error and less random error. We note, however, that the trend decline in ρ suggests that systematic mismeasurement is getting worse for both men and women.

Figure 2: Rho Estimates, Simple Model, Pooled Sample

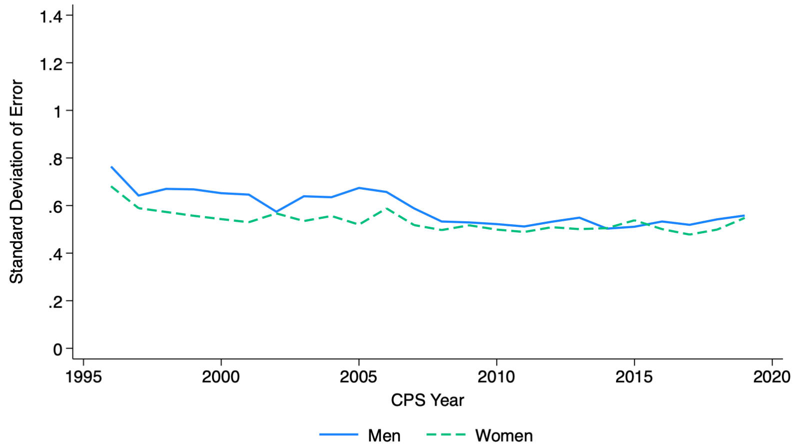


Notes: OLS regression of log ASEC Earnings on log DER Earnings, adults working in both years. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

We then estimate the models separately by response status. Figures 4 and 5 present the estimated ρ and σ_ϵ by response status and sex (see Appendix Tables A3 and A4 for all simple OLS estimates). Female responders have higher estimates of ρ, but all still significantly less than one. Generally the differences between the responders and switchers are statistically significant except for some years for men prior to 2005. The estimated ρ coefficients from the pooled model (Figure 2 above fall slightly below the estimates for the responders in nearly every year and for both men and women. This is unsurprising as switchers are a small portion of the sample and the pooled estimates are an average of the two ρ's.

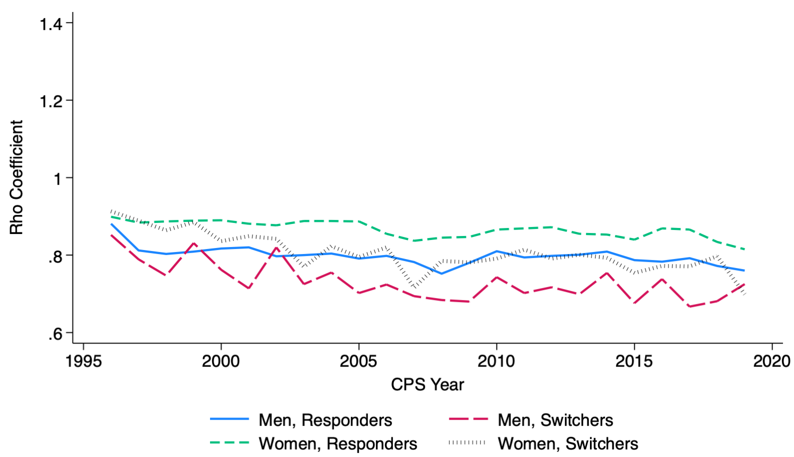
Turning to the estimates of the standard deviation in Figure 5, we find that $\sigma_{\epsilon 1}$ is much larger for switchers than for responders. Testing indicates statistical significance across all years for both men and women. Following the literature, we consider those with higher σ_ϵ to

Figure 3: Standard Deviation of Error, Pooled Sample



Notes: Mean Squared Error from OLS regression of Log ASEC Earnings on log DER Eanings, adults working both years. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Figure 4: OLS Rho Estimates from Simple Model by Response Status

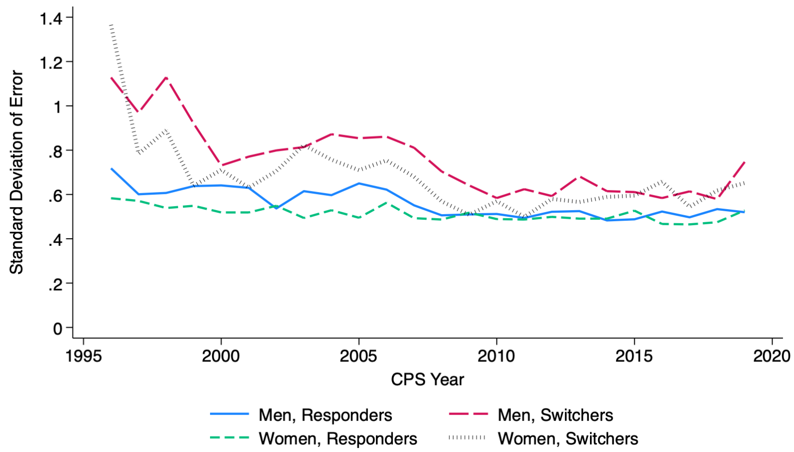


Notes: OLS regression of log ASEC Earnings on log DER Earnings, adults working in both years. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

have worse measurement error. The pattern is clear for both men and women: switchers are associated with higher measurement error. However, there is some evidence of convergence between switchers and responders over time toward lower levels of measurement error.

The above analysis forces the rate of "bad reporters", q, in the model for the CPS response

Figure 5: Standard Deviation of Error from Simple Model by Response Status



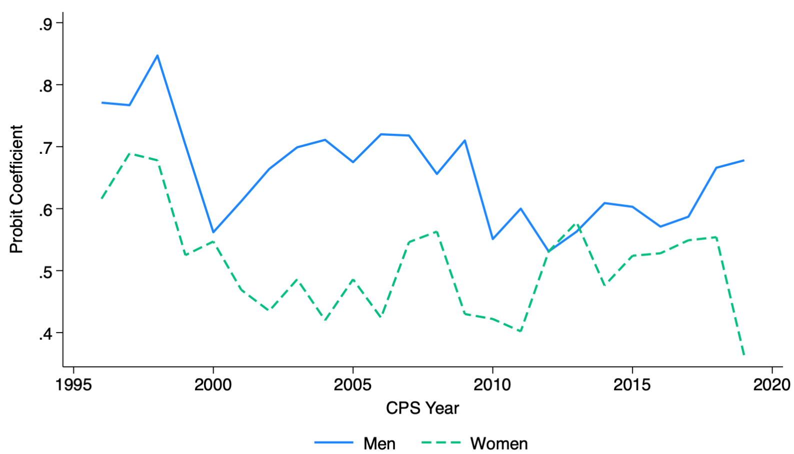
Notes: Mean Squared Error from OLS regression of Log ASEC Earnings on log DER Eanings, adults working both years. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

found in equation (3) to be identical to and determined solely by response status. Thus q is equal to the proportion of switchers in each year (see Appendix Table A2). Another approach to estimation is to allow the data to determine the "good reporters" and the "bad reporters." We use a finite mixture model approach where the probability of being in either group is a function of the response status measured as an indicator for responding in both periods.

Finite mixture models (FMM) posit a data generation process where the response is from two (in our case) possible distributions. The latent groups are not identified in the data, and the latent probabilities are estimated. The model is identified by assumptions about the functional form of the distribution, which we assume to be normal in our case. Each respondent's answer to the earnings question is drawn from one of the two normal distributions. Because normal distributions are fully characterized by the mean and variance, we specify that our two means follow equation (3) above, while the variances do not include co-variates but differ across the two latent classes. The researcher does not know which latent class the observation is drawn from and we use a probit model which includes the switching indicator as a factor (regressor). The system is estimated by maximum likelihood.

Because the latent group function is estimated, we can test if those who respond in both periods are more likely to be in the "good reporters" group, which we define as the latent class with the lowest variance of the error term σ_ϵ. Thus, class 1 are the bad reporters and are labeled with subscript 1 following equation (3), and class 2 are the good reporters. The full results are presented in Appendix Tables A5 and A6. Figure 6 presents the coefficient on being a respondent in both periods on the probability of being a "good reporter" in class 2. The coefficient on the indicator for responding in both years of the survey is large, positive, and highly statistically significant. This indicates that responding in both periods is highly related to the two classifications determined by the mixture model. Note that identification in these models is based largely on the error variance and homoskedasticity assumptions. The intercept terms are large and positive as well, demonstrating that most respondents are in the "good reporter" category. We note that the relationship is strongest for men and is lower - especially for women - later in the sample.

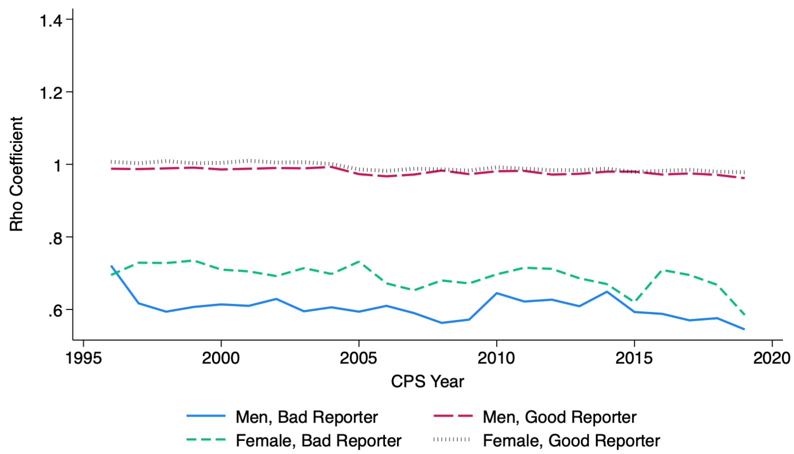
Figure 6: Class Coefficient from FMM model



Note: Coefficient from probit class model in FMM estimation.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

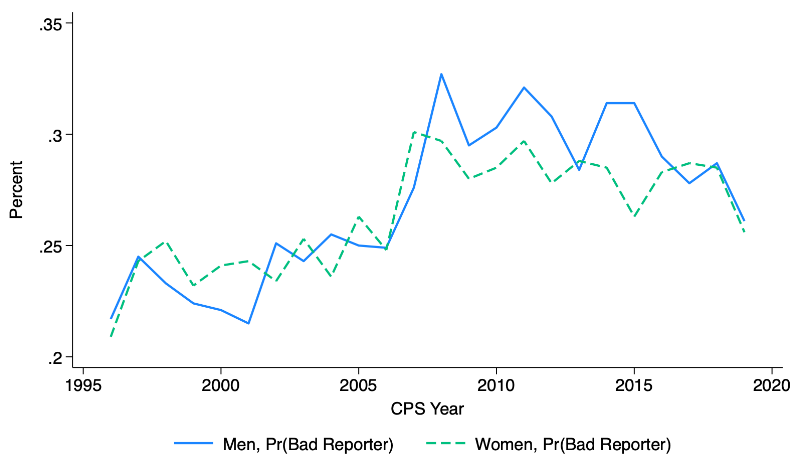
Figure 7 presents the estimates of the ρ coefficients. Similar to the simple regression model, the coefficient ρ_1 (bad reporters) ranges from 0.721 to 0.545, significantly less than one. Thus the bad reporters have high random error and high systematic error as well. In contrast the coefficient for the good reporters (class 2) (ρ_2) is close to one - although still statistically different from one in all cases. The FMM model also provides post estimation probabilities of being in each latent class, presented in Figure 8. We see that bad reporters are generally under 30% of the sample. This suggests that one important possibility is that the common person results are largely driven by a small (but growing) group of bad reporters.

Figure 7: Rho coefficients from FMM estimation



Note: Rho coefficient from FMM regression of log ASEC earnings on log DER earnings. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Figure 8: Probability of Class 1 (Bad Reporters) from FMM estimation



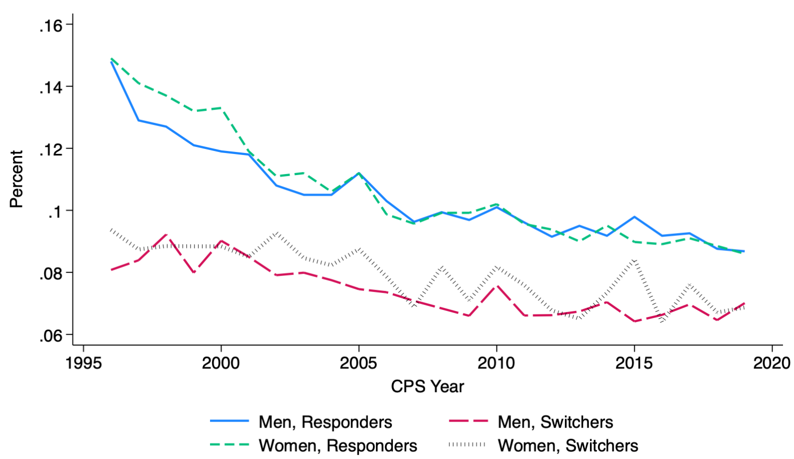
Note: Predicted probability of Class (good or bad reporter) from FMM estimation. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Our final set of estimates under the assumption that the DER earnings have no errors are based on the Kapteyn and Ypma (2007) model (hereafter KY) as implemented in the Stata

KY-fit command developed by Jenkins and Rios-Avila (2023a). Following the assumptions for this section, we assume that the DER is still a gold standard with no mismatch. Similarly, we estimate models of response for CPS ASEC data separated by switchers. The main difference between this model and the simple model using OLS is that the KY model allows some proportion of the CPS ASEC reports to be correct (labeled S=R in the appendix tables) and models those observations separately, so they are not included in the estimates of the two CPS ASEC measurement equations. We take a small bandwidth of 0.01 log points to classify these correct answers (similar to Kapteyn and Ypma (2007) and Jenkins and Rios-Avila (2023b)). Similar to FMM, the KY model assumes an underlying normal distribution for the true earnings and models the two reported earnings as jointly normally distributed. Identification derives directly from this normal distribution assumption.

We report the full results in Appendix Tables A7 and A8. In Figure 9 we present the proportion of the sample whose survey reported earnings agrees with (within .01) the DER report of their earnings, PR(S=R). These are considered correct reports. For those who respond in both periods, this ranges from as high as 15% to as low as 9%. For those who switch, it ranges from approximately 6.5% to as high as 9%. We note that the proportion is falling over time for those who respond in both periods. This is less clear for the switchers.

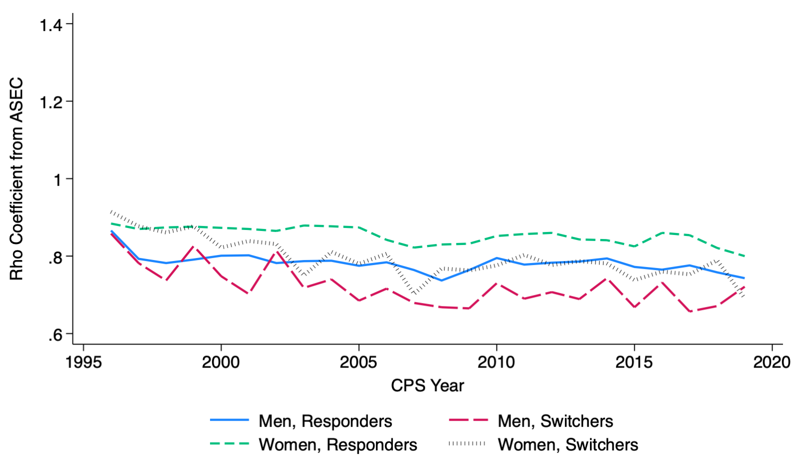
Figure 9: Probability of Survey = Admin, KY-fit Estimates



Note: Proportion of survey observations considered ”correct” reports in model.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

In Figure 10 we present the estimates of both ρ_1 (switchers) and ρ_2 (report both periods) from the KY-fit model. The estimates are similar to those from the simple OLS model– they are in the range of .665 to .866 and the estimates for the switchers are lower than for those who report in both periods. All are statistically significantly different from one. In Figure 11 we present the estimates of the standard deviation of the error. Like the linear models above, the estimates of σ_ϵ are higher for the switchers than those who respond in both periods. The overall estimates of σ_ϵ are larger than the comparable OLS model, but the reason is somewhat mechanical: the KY model removes the observations where the survey equals the administrative record (S=R, or they are very close), thus taking out the observations with lowest σ_ϵ.

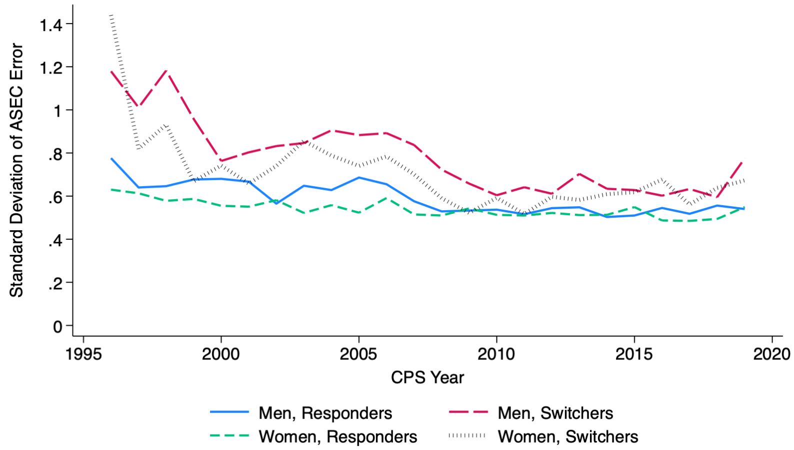
Figure 10: Rho coefficients from Simple KY-Fit Model



Note: Estimated from KY-fit (Jenkins and Rios-Avila, 2023a) routine. Log ASEC Earnings on log Der Earnings with no error in DER and no mismatch.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

An important trend is generally found in all the models: estimates of σ_ϵ are trending down over time. This is particularly evident for the "bad reporters" (either switcher or in the FMM model). In combination with overall rising nonresponse, and especially rising rates of nonresponse for both time periods (who are not used in the estimates), we interpret these results as some evidence that those providing the least accurate responses are moving from responding to not responding in at least one period, and perhaps especially moving to not responding at all.

Figure 11: Standard Deviation of Error from Simple KY-Fit Model



Note: Estimated from KY-fit routine. Log ASEC Earnings on log Der Earnings with no error in DER and no mismatch.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

4.2 Model 2: DER records with additive white noise error

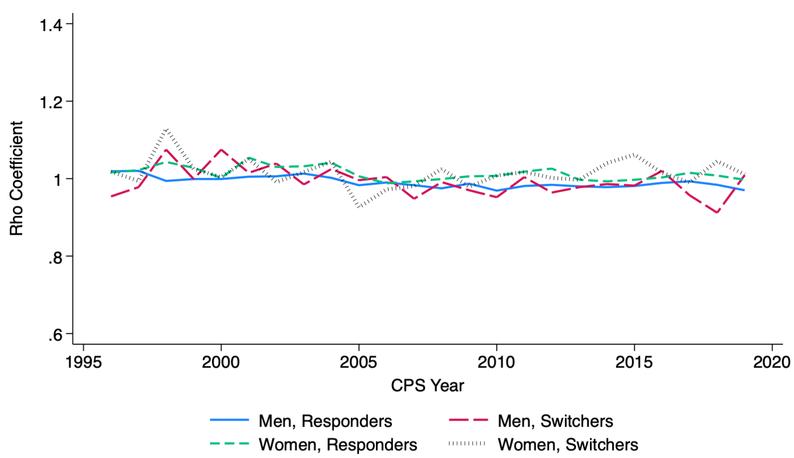
Several authors have provided evidence that administrative earnings may not be without error. A number of sources of error can occur, off the books earnings being the most common. This would imply that $p = 0$ still, but allows $V\left(\varepsilon_{it}^{D}\right) > 0$ in equation (2). In this case, the regression of Y_{it}^{C} on Y_{it}^{D} (as in the previous section) would result in estimates of ρ that are biased toward zero: the classical measurement error bias result. However, a simple instrumental variables (IV) estimator is easily motivated by the Mincer model in equation (1). The regression of Y_{it}^{D} on X_{it} will produce consistent estimates of the parameters β in the Mincerian model. The additive error term does not impact the consistency of those parameters. Hence, we can rewrite equation 3 (the model for Y_{it}^{C}) as

$$\begin{aligned} Y_{it}^{C} &= \delta + \rho Y_{it}^{*} + \varepsilon_{1it}^{C} = \delta + \rho\left(X_{it}\beta + u_{it}\right) + \varepsilon_{it}^{C} \\ &= \delta + \rho\left(X_{it}\beta\right) + \left(\rho u_{it} + \varepsilon_{it}^{C}\right) = \delta + \rho\widehat{Y}_{it}^{D} + \left(\rho u_{it} + \varepsilon_{it}^{C}\right). \end{aligned} \tag{5}$$

The error term $\left(\rho u_{it} + \varepsilon_{it}^{C}\right)$ is uncorrelated with $\widehat{Y}_{it}^{D}$, the predicted value from the regression of Y_{it}^{D} on X_{it}. Note, however, that this estimator - like all IV estimators - is consistent even if there is no measurement error in Y_{it}^D. Hence, if there is no measurement error in the DER data, the estimated coefficients from the regression of Y_{it}^C on Y_{it}^D should not differ from the estimated coefficients from the regression of Y_{it}^C on $\widehat{Y}_{it}^D$. This is our preferred estimator because it nests both models and allows testing of the common person hypothesis, but also because it does not require homoskedasticity or strong distributional assumptions for identification.

The results of the IV estimates are presented in Appendix Tables A9 and A10. First stage models were estimated separately by sex and year and include education, experience, race and city size. As with the OLS results, we present estimates combining all observations and then split by respond both years (good reporters) and switchers (bad reporters). The combined results are in the appendix tables, while the estimates of ρ by switcher and responders are presented in Figure 12. The most obvious and notable difference between the results here and the simple linear model is the coefficient on lnDER: ρ is now very close to one. Indeed, while it does decline slightly over time, in general it is not statistically or economically significantly different than one. This approach yields no evidence for the common person hypothesis.

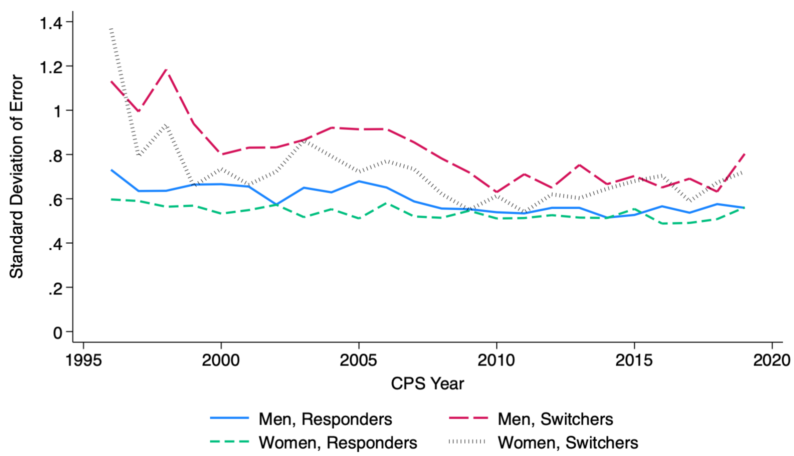
Figure 12: Rho Coefficients from IV Estimation



Note: IV estimation using education, experience, race, city size and year as instruments. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

We next turn to the relative size of σ_ϵ for the two groups. We estimate σ_ϵ adjusting for the first stage regression by simply subtracting off the error variance from the first stage as the model implies. The four estimates are presented in Figure 13. As with all prior results, the individuals who respond in both periods have significantly lower (both statistically and economically) σ_ϵ, indicating we continue to associate more measurement error with the switchers. We note too, the σ_ϵ is clearly declining over time for both groups, supporting the conclusion that the poorest respondents (in terms of accuracy) are moving to never responding.

Figure 13: Standard Deviation of Error from IV Estimation



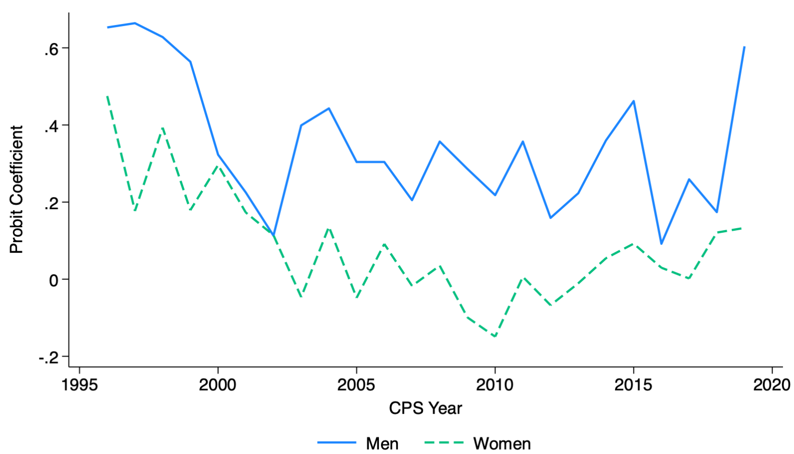
Note: IV estimation using education, experience, race, city size and year as instruments. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

We emphasize that these estimates are comparable to those produced by Kapteyn and Ypma (2007), Abowd and Stinson (2013), and Jenkins and Rios-Avila (2023b) who find that the common person result fades when mismatch between the administrative records and survey is allowed (in our case where the DER record not correctly matched to the CPS record). One form of measurement error in the DER would be this kind of mismatch. The KY model forces some mismatch on the data, with heavily parametric assumptions including homoskedasticity as well as normality. The IV model allows for it, but nests the classic gold standard model. We will examine a more general KY model allowing for mismatch in the next subsection below.

Before proceeding to the last model, we first present estimates using the finite mixture model approach combined with the IV approach. Like the simple FMM from the prior section, the separation into two classes is allowed to be related to the response status, but not required. This allows us to test whether a relationship between switcher status and measurement error (specifically unexplained variance) exists. The main regression models are IV estimators. Again, as before, identification stems from the underlying normal distributions of the two (latent) types of reporters.

The results are presented in Appendix Tables A11 and A12. Figure 14 presents the coefficient on switcher status from the class probability part of the model. As with the FMM results in the simple model, the response status is highly correlated with being in the good responder group (with lower σ_ϵ) for men. For women the correlation is much smaller and even of the wrong sign at times, suggesting perhaps a different mechanism for women. However, identification of the model is highly driven by a homoskedasticity assumption for the σ_ϵ's which may sever the link if there is a great deal of heteroskedasticity within reporter type.

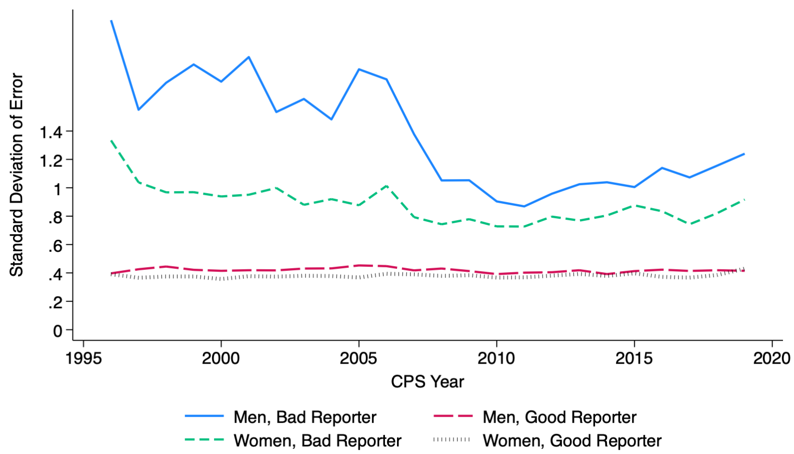
Figure 14: IV-FMM Estimates of Coefficient in Class Probability



Note: Coefficient from probit class model in IV-FMM estimation.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

The estimates of the σ_ϵ from the two classes are presented in Figure 15. As with all other previous estimates the good reporter $\sigma_{\epsilon 2}$ is substantially (and statistically significantly) lower than the bad reporter $\sigma_{\epsilon 1}$. In the case of men, where the classification is strongly associated with response, this supports the idea that response and measurement error are related. The weaker relationship for women may not. We note too that for both men and women, there is less evidence of a downward trend in σ_ϵ for either class of reporter. Finally, the estimated ρ_1, presented in Figure 16, is larger than one, while the estimated ρ_2 is smaller than one. Comparing this to the FMM results discussed above suggests that some more complicated mechanism than measurement error in the DER is present. However, again, concern arises over identification based on functional form of error variances.

Figure 15: IV-FMM Standard Deviation of Error



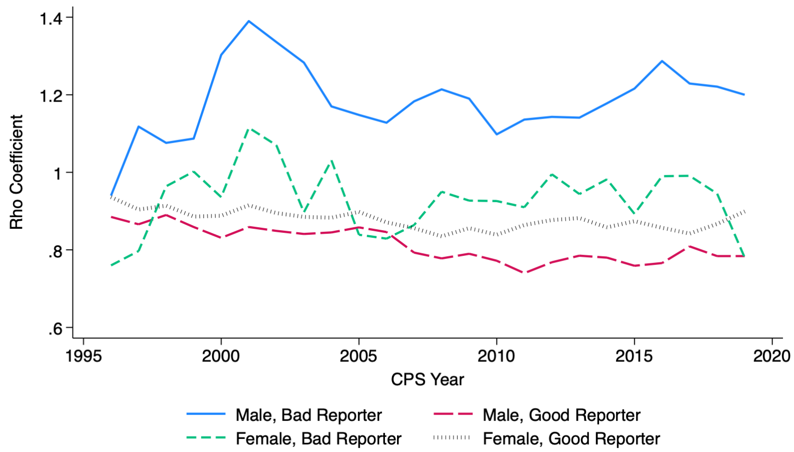
Note: Root mean squared error from IV-FMM regression of log ASEC earnings on log DER earnings.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Our preferred model in this section is the IV estimates in Appendix Tables A9 and A10, and Figures 12 and 13. The key conclusions from those estimates are that some type of measurement error in the DER is likely driving the typical common person result. We find decreasing error variances and a strong relationship between error variance and response status.

4.3 Model 3: Allowing for both measurement error and mismatch in the DER earnings

In the final specification, we allow for both mismatch and general measurement error in the DER. We rely on the Kapteyn and Ypma (2007) approach as operationalized by the KY-fit

Figure 16: IV-FMM Rho Coefficient



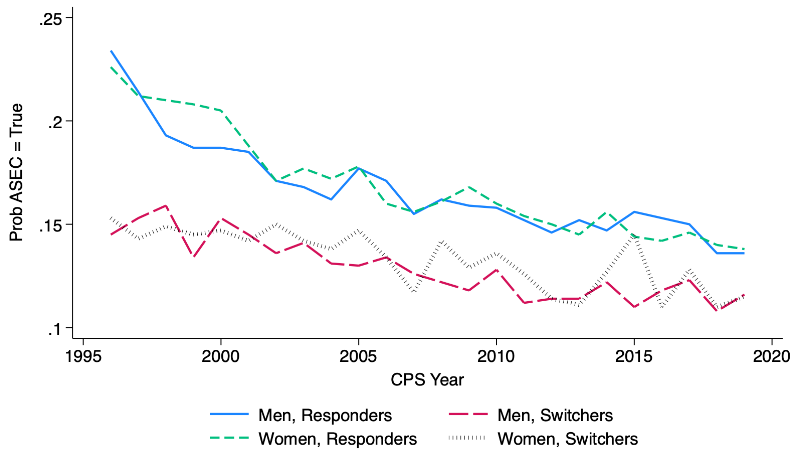
Note: Rho coefficient from IV-FMM regression.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

estimator in STATA written by Jenkins and Rios-Avila (2023a). We use their model 6 which allows for some proportion of the DER to be equal to the true latent earnings. As with the simple KY model estimated above, we fit two measurement error models to the CPS ASEC report, using the respondent status to separate them. The KY model also allows for some proportion of the CPS ASEC reports to be equal to the true latent measure (and thus not included in estimation of the measurement error model). As with the simpler KY-model, it is a normality assumption on true latent earnings along with normality on the error components which provide identification. Mismatch between DER and CPS is modeled as a draw from the true earnings distribution (for DER) that is independent of the CPS measure. The independence also provides identification power.

Appendix Tables A13 and A14 present the results from estimating this model. As with the simple version, we note in Figure 17 that the probability of having the survey equal the true response R_C is higher for those who respond in both periods (R_{C2}) than for those who switch response status (R_{C1}). In both cases, but most dramatically for the responders (the good reporters), this falls through the sample period from over 20% to only 14%. Figure 18 presents the estimated ρ coefficients for the CPS ASEC report. Estimates for both the switchers and the respondents are close to one, although slightly higher in initial periods.

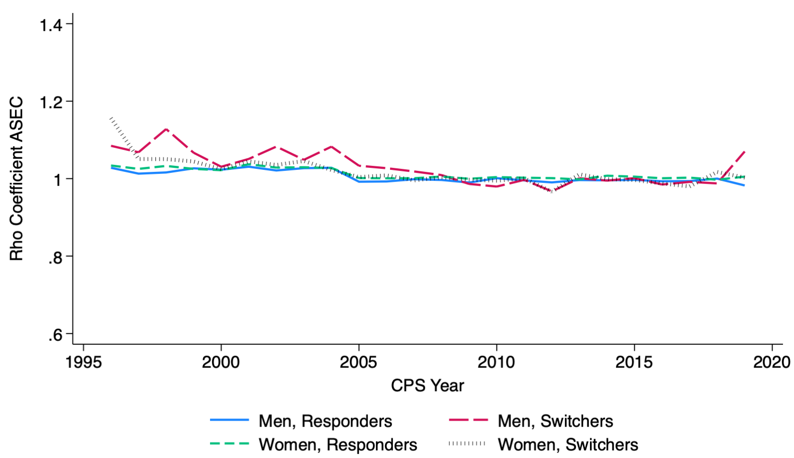
Again, suggesting that when measurement error is allowed in the DER, the common-person hypothesis is not supported. In Figure 19 we find that σ_ϵ is fairly constant throughout the period or slightly rising both for men and women and both response groups.

Figure 17: Full KY-fit estimates of ASEC - true earnings probability



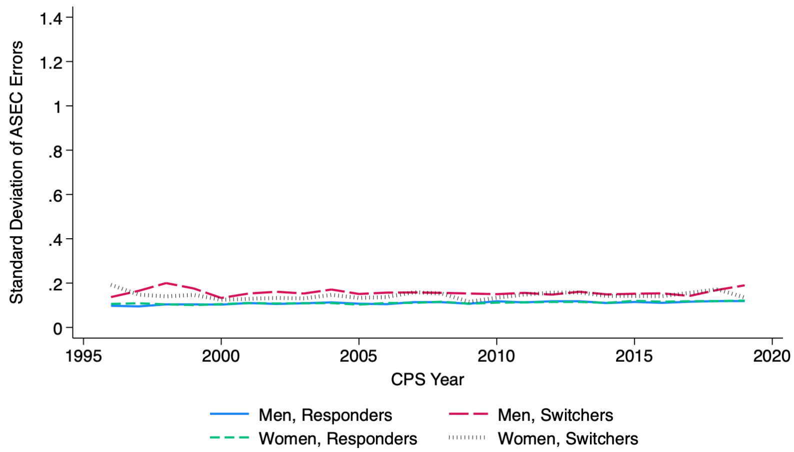
Note: Estimated probability of ASEC equal to true earnings. Using KY-fit model 6.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Figure 18: KY-fit estimated rho coefficients ASEC earnings



Note: Estimated rho coefficients for log ASEC earnings on true earnings. Using KY-fit model including mismatch, errors in DER, errors in ASEC.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Figure 19: KY-fit estimates of Standard Deviation of Error ASEC earnings

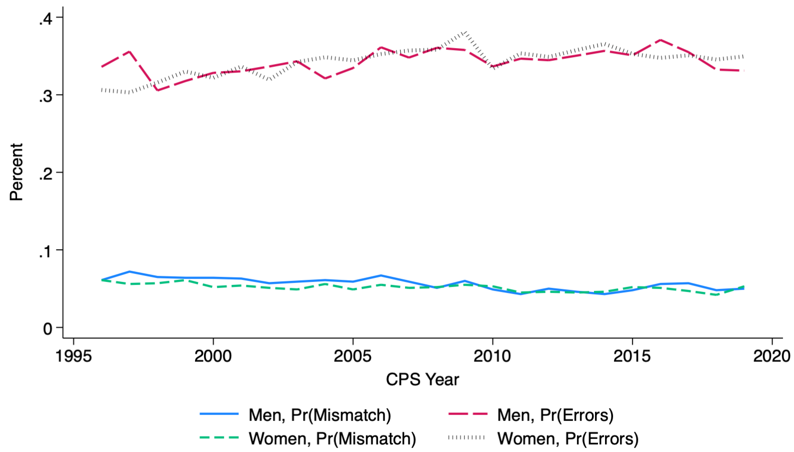


Note: Estimated Root Mean Squared error.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Here though, the results for the DER model are interesting. We highlight the two probabilities in Figure 20 where we present the probability that the DER record is a mismatch to the ASEC record (Mismatch lines) and the probability that there are errors in the DER record. The probability of mismatch is relatively low, at around 5% throughout the period. Perhaps more importantly, we do see that the probability of the DER having an error (e.g. DER not equal to the true earnings) is not zero, but also not particularly high. Roughly 35% of the observations have some error. In Figure 21 we examine the ρ estimates for the DER measurement error model. These estimates are quite close to one, and generally not statistically significantly different from one. Thus while about 40% of the observations for the DER are either mismatches or have some error, fully 60% are correct reports. Combined with the estimated ρ being close to one, a small classical measurement error model for the DER seems appropriate.

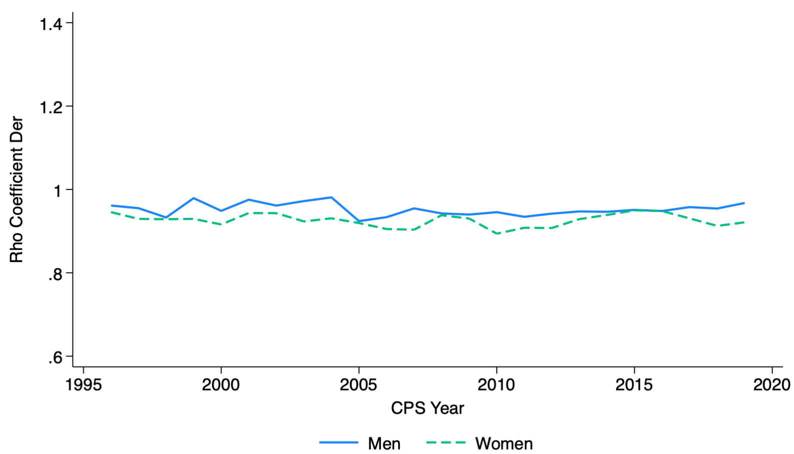
The KY model is highly parametric, and as such the results should be interpreted with some caution relative to the IV estimates presented above. However, taken with the IV and other results, they support the conclusion that there are some kind of errors in the DER which lead to biases if not addressed in estimating the structure of the measurement error.

Figure 20: Full KY-fit estimates of Probability of mismatch and Prob DER $\neq$ true



Note: Probability of error is probability DER not true earnings. Using KY-fit model 6.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Figure 21: KY-fit estimates of rho coefficients DER Earnings



Note: Estimated rho coefficients for log DER earnings on true earnings. Using KY-fit model including mismatch, errors in DER, errors in ASEC.
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

5 Implications for Estimation

In this section, we investigate the implications of nonresponse and measurement error by estimating models using the DER measure of earnings on four groups in the CPS ASEC (by sex): all workers, respondents, respondents in both years, and switchers. This helps us understand the potential biases from selection. We then estimate the same model for the same groups using the CPS ASEC measure of earnings. This allows a comparison to establish biases from various sources.

We focus here on results pooling the CPS ASEC years 2015 through 2019. Results pooling years 1996 through 2000 are similar and in the appendix. In Tables 2 and 3 we present estimates of selected coefficients from standard log-earnings Mincer wage regressions using the DER measure of earnings. In addition to the variables presented we also control for Census region and MSA size. We focus on education and race coefficients in our discussion.

Table 2: DER Mincer Wage Regressions, Men, 2015-2019

	All Men	Responders	Respond Both	Switchers
lths12	-0.373***	-0.379***	-0.387***	-0.360***
	(0.021)	(0.024)	(0.027)	(0.041)
ed12nodip	-0.398***	-0.419***	-0.396***	-0.442***
	(0.035)	(0.041)	(0.046)	(0.064)
edsomecoll	0.0647***	0.0737***	0.0746***	0.0525**
	(0.0116)	(0.0133)	(0.0145)	(0.0226)
edassoc	0.260***	0.269***	0.275***	0.227***
	(0.014)	(0.016)	(0.017)	(0.028)
edBA	0.642***	0.636***	0.633***	0.647***
	(0.011)	(0.013)	(0.014)	(0.022)
edMA	0.891***	0.874***	0.865***	0.900***
	(0.015)	(0.017)	(0.018)	(0.032)
edPro	1.345***	1.314***	1.300***	1.391***
	(0.030)	(0.034)	(0.037)	(0.063)
edPhd	1.195***	1.180***	1.162***	1.286***
	(0.026)	(0.029)	(0.031)	(0.056)
exp	0.313***	0.342***	0.354***	0.268***
	(0.006)	(0.007)	(0.007)	(0.012)
exp2	-0.018***	-0.020***	-0.021***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
exp3 (000's)	0.445***	0.507***	0.532***	0.351***
	(0.018)	(0.021)	(0.022)	(0.036)
exp4 (0000)	-0.041***	-0.048***	-0.050**	-0.032***
	(0.002)	(0.002)	(0.002)	(0.004)
black	-0.388***	-0.408***	-0.422***	-0.331***
	(0.014)	(0.017)	(0.018)	(0.027)
asian	-0.090***	-0.093***	-0.100***	-0.050
	(0.016)	(0.018)	(0.020)	(0.031)
amerind	-0.392***	-0.437***	-0.469***	-0.291***
	(0.036)	(0.042)	(0.046)	(0.066)
hispanic	-0.133***	-0.128***	-0.127***	-0.120***
	(0.012)	(0.014)	(0.015)	(0.024)
Constant	8.406***	8.312***	8.282***	8.515***
	(0.025)	(0.029)	(0.032)	(0.050)
Observations	69,500	53,500	45,000	17,000
R-squared	0.298	0.305	0.307	0.294

OLS regressions with log earnings as dependent variable. Models control for MSA size and Census division. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table 3: DER Mincer Wage Regressions, Women, 2015-2019

	All Women	Responders	Respond Both	Switchers
lths12	-0.443***	-0.441***	-0.425***	-0.482***
	(0.028)	(0.032)	(0.035)	(0.052)
ed12nodip	-0.282***	-0.285***	-0.280***	-0.324***
	(0.044)	(0.052)	(0.057)	(0.084)
edsomecoll	0.117***	0.125***	0.139***	0.077***
	(0.014)	(0.016)	(0.018)	(0.025)
edassoc	0.300***	0.317***	0.333***	0.227***
	(0.015)	(0.018)	(0.020)	(0.029)
edBA	0.677***	0.699***	0.724***	0.582***
	(0.013)	(0.015)	(0.017)	(0.025)
edMA	0.975***	0.998***	1.024***	0.889***
	(0.016)	(0.018)	(0.020)	(0.032)
edPro	1.512***	1.539***	1.568***	1.483***
	(0.036)	(0.042)	(0.045)	(0.076)
edPhd	1.435***	1.463***	1.504***	1.190***
	(0.032)	(0.037)	(0.039)	(0.070)
exp	0.234***	0.245***	0.250***	0.216***
	(0.006)	(0.007)	(0.008)	(0.012)
exp2	-0.015***	-0.016***	-0.016***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
exp3 (000)	0.401***	0.427***	0.433***	0.378***
	(0.020)	(0.023)	(0.023)	(0.038)
exp4 (0000)	-0.039***	-0.042***	-0.043***	-0.037***
	(0.002)	(0.003)	(0.003)	(0.004)
black	-0.066***	-0.081***	-0.091***	-0.021
	(0.014)	(0.017)	(0.019)	(0.027)
asian	0.030*	0.006	-0.022	0.150***
	(0.018)	(0.021)	(0.023)	(0.034)
amerind	-0.103***	-0.183***	-0.226***	0.101
	(0.040)	(0.047)	(0.053)	(0.071)
hispanic	-0.016	-0.025	-0.034**	0.038
	(0.014)	(0.016)	(0.017)	(0.026)
Constant	8.356***	8.285***	8.240***	8.491***
	(0.028)	(0.033)	(0.036)	(0.052)
Observations	67,500	53,000	45,500	16,000
R-squared	0.206	0.206	0.210	0.195

OLS regressions with log earnings as dependent variable. Models control for MSA size and Census division. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

We take the first column of results, labeled “All Men” and “All Women” columns as a baseline. We view these - with caution - as the true coefficients. The results in these two columns are qualitatively consistent with the general literature on Mincer wage regressions, finding strong returns to education, returns to experience which decline over time, and wage gaps for minorities.

Comparing those two columns with the the next three provides some insight into bias due to sample selection on response. For column 2 for men, including only those individuals who responded to the survey, we observe small economic differences (although often statistically significant) between the sets of coefficients. In a typical selection model, we would expect that coefficients would be attenuated and there seems to be little clear pattern of that. While the coefficient on edBA, for example, is 0.006 smaller, the coefficient on those with 12 years of education but no HS degree (edhs12nodip) is 0.021 larger in magnitude (-0.398 in column 1 and -0.419 in column 2). A similar pattern emerges for the women, although more often here the coefficients in the column of responders are slightly larger in magnitude, but not exclusively. This suggests something more complicated than a simple selection mechanism.

The third column presents results restricting the sample further to the good reporters, those who respond in both periods only. Because most respondents do respond in both years, the results are very similar to the second column, particularly for women.

The fourth column examines the switchers, or bad reporters. For both men and women we see larger differences between the column 1 - the full sample - and the switchers, where we see that both the magnitudes and directions differ. We conclude that while there may be some differences in measurement between the four samples, restrictions from response do not particularly impact coefficients in ways that overturn usual relationships or are otherwise economically meaningful.

Next we turn to Tables 4 and 5 which present estimates from the same samples but using the CPS ASEC earnings rather than DER earnings for survey years 2015-2019. These represent what data users who only have access to the public use samples would find. Small differences in the sample reflect missing administrative data for some individuals. Note that all columns except the ”Respond Both” will include imputations for those cases where no response was given. Differences between estimates here may in part reflect mismatch of characteristics in the imputation procedure as noted in Bollinger and Hirsch (2006). However, we note that the variables in this specification most closely match the imputation variables and thus little bias should occur. Column three of the CPS measure is closest in many ways to the baseline of column one in the DER measure, but in many cases differences (statistically significant) still exist.

No clear cut pattern emerges for the bias. This indicates that our finding that there is no strong evidence for the common person hypothesis is apparent. We also note that the R-squared for the "Respond Both" in the CPS ASEC measure for both men and women is larger than the R-squared in any other column, as we would expect if measurement error variance is lowest in the "good reporter" group. Similarly the R-squared in column four is decidedly lower than all other columns as we would expect if the additive white noise measurement error is highest among these non-cooperators. No such clear pattern exists in the DER table (Tables 2 and 3), reinforcing that the nonresponse is related to data quality when response does occur.

The key implication following from the results in this section is that removing earnings nonrespondents in the CPS ASEC appears to provide the most robust estimates in standard Mincer earnings regressions.

Table 4: CPS ASEC Mincer Wage Regressions, Men, 2015-2019

	All Men	Responders	Respond Both	Switchers
lths12	-0.377***	-0.333***	-0.314***	-0.464***
	(0.018)	(0.020)	(0.022)	(0.035)
ed12nodip	-0.297***	-0.293***	-0.288***	-0.311***
	(0.030)	(0.035)	(0.039)	(0.058)
edsomecoll	0.091***	0.088***	0.085***	0.084***
	(0.010)	(0.011)	(0.012)	(0.020)
edassoc	0.231***	0.236***	0.237***	0.224***
	(0.012)	(0.013)	(0.014)	(0.024)
edBA	0.605***	0.590***	0.581***	0.642***
	(0.009)	(0.010)	(0.011)	(0.020)
edMA	0.806***	0.783***	0.774***	0.865***
	(0.012)	(0.014)	(0.015)	(0.028)
edPro	1.232***	1.238***	1.231***	1.242***
	(0.024)	(0.028)	(0.030)	(0.056)
edPhd	1.094***	1.059***	1.049***	1.152***
	(0.022)	(0.023)	(0.025)	(0.050)
exp	0.283***	0.313***	0.326***	0.234***
	(0.005)	(0.006)	(0.006)	(0.011)
exp2	-0.016***	-0.019***	-0.020***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
exp3 (000)	0.409***	0.473***	0.501***	0.309***
	(.015)	(0.017)	(0.019)	(0.032)
exp4 (0000)	-0.038***	-0.044***	-0.047***	-0.028***
	(0.002)	(0.002)	(0.002)	(0.004)
black	-0.306***	-0.303***	-0.307***	-0.312***
	(0.012)	(0.014)	(0.015)	(0.024)
asian	-0.097***	-0.119***	-0.114***	-0.065**
	(0.013)	(0.015)	(0.016)	(0.027)
amerind	-0.275***	-0.337***	-0.352***	-0.186***
	(0.031)	(0.035)	(0.039)	(0.059)
hispanic	-0.157***	-0.181***	-0.176***	-0.132***
	(0.010)	(0.011)	(0.012)	(0.021)
Constant	8.716***	8.620***	8.590***	8.827***
	(0.022)	(0.025)	(0.027)	(0.046)
Observations	69,500	52,500	44,000	17,500
R-squared	0.305	0.324	0.328	0.277

OLS regressions with log earnings as dependent variable. Models control for MSA size and Census division. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table 5: CPS ASEC Mincer Wage Regressions, Women, 2015-2019

	All Women	Responders	Respond Both	Switchers
lths12	-0.452***	-0.426***	-0.431***	-0.497***
	(0.025)	(0.028)	(0.031)	(0.048)
ed12nodip	-0.195***	-0.191***	-0.215***	-0.143*
	(0.041)	(0.048)	(0.053)	(0.079)
edsomecoll	0.105***	0.116***	0.115***	0.095***
	(0.012)	(0.014)	(0.015)	(0.024)
edassoc	0.294***	0.300***	0.306***	0.273***
	(0.013)	(0.015)	(0.017)	(0.027)
edBA	0.636***	0.631***	0.637***	0.619***
	(0.011)	(0.013)	(0.014)	(0.023)
edMA	0.900***	0.895***	0.899***	0.896***
	(0.014)	(0.015)	(0.017)	(0.030)
edPro	1.404***	1.413***	1.424***	1.370***
	(0.031)	(0.035)	(0.035)	(0.071)
edPhd	1.313***	1.347***	1.371***	1.196***
	(0.028)	(0.030)	(0.033)	(0.065)
exp	0.229***	0.240***	0.241***	0.231***
	(0.006)	(0.007)	(0.007)	(0.011)
exp2	-0.015***	-0.016***	-0.016***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
exp3 (000)	0.409***	0.438***	0.439***	0.423***
	(0.017)	(0.020)	(0.022)	(0.036)
exp4 (0000)	-0.040***	-0.043***	-0.043***	-0.041***
	(0.002)	(0.002)	(0.002)	(0.004)
black	-0.062***	-0.066***	-0.073***	-0.018
	(0.013)	(0.015)	(0.017)	(0.025)
asian	0.020	0.003	-0.002	0.069**
	(0.016)	(0.018)	(0.019)	(0.032)
amerind	-0.067*	-0.106**	-0.128***	0.042
	(0.036)	(0.042)	(0.046)	(0.066)
hispanic	-0.060***	-0.076***	-0.076***	-0.035
	(0.012)	(0.014)	(0.015)	(0.024)
Constant	8.577***	8.552***	8.551***	8.557***
	(0.025)	(0.029)	(0.032)	(0.050)
Observations	65,500	50,000	42,500	16,000
R-squared	0.218	0.227	0.228	0.201

OLS regressions with log earnings as dependent variable. Models control for MSA size and Census division. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

6 Conclusions

There are three main findings from our analysis. The first result is that there is evidence that nonresponse and measurement error are related: individuals who fail to respond to the earnings questions in the survey in one year of the CPS ASEC, have higher measurement error than those who respond in both years of the CPS ASEC; those who appear to have higher measurement error are less likely to respond to the survey.

The second finding is that measurement errors occur in administrative records. This may be missing income, or it may be mismatch, though the former seems much more prevalent than the latter. Our preferred IV model should address either issue in estimating the measurement error structure in the survey data.

The third finding is that measurement error in the survey data appears to be closer to simple additive white noise. The “common person” hypothesis - where low earners over-report while high earners under-report - is not well supported.

These results have a number of implications both for researchers and for survey administration. For researchers, using the survey (CPS ASEC) earnings data (without imputed values) leads to little bias in estimates of earnings equations. The measurement error bias when earnings are the dependent variable is determined only by ρ and the best estimates suggest that it is close to 1 on average, indicating attenuation bias of 10% or less. While removing imputations is desirable , there appears to be little bias in doing so based on our results here . However, it should be noted that this applies primarily to estimates at the mean (and median); quantile regressions in the tails may be biased. These conclusions are supported in part by other literature (Bollinger and Hirsch, 2013; Bollinger et al., 2019)

When earnings are used as a regressor, measurement error will bias coefficients down. However, it appears to be classical. Instrumental variables approaches should work. The bias can be minimized by including only respondents who complete the earnings question for both years.

The implication for survey administration is more subtle. We note that the measurement error - as measured by the variance - has been likely improving over the sample period for those who respond to the earnings questions in both years. One interpretation is that the non-responders were giving poor data. However, given that the individuals remain in the sample, otherwise answering the survey, alternative approaches to reducing item non-response may be very valuable. Recent efforts by the Census Bureau to utilize unfolding brackets may be an excellent start, but researchers should be provided access to those data. That said, measurement error remains an issue, and approaches which increase the accuracy of respondents' reports remains an important focus.

Finally, administrative data are often viewed as the solution to many data quality problems. Our results here suggest that while administrative data may be important and serve a role, they may not be the gold standard solution suggested by their advocates. While we have some misgivings about the KY model, the evidence there suggests that matches fail approximately 5% of the time. Moreover, the model suggests that over 30% of the DER records have measurement error, likely missing earnings from under the table activities. As Kapteyn and Ypma (2007) point out, and we agree, it may be that these are reported in the ASEC, and give rise to the 'common person' hypothesis of early literature. Administrative records should be viewed as additional information. We believe that efforts at Census such as the NEWS program linking survey and administrative records are well guided and should be expanded.

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Supplemental Appendix Tables

For The Good, The Bad and The Ugly

Measurement Error, nonresponse and Administrative Mismatch in the CPS

Table A1: PIK Rates by Year

CPS Year	PIKed	N
1996	0.8381	130000
1997	0.8171	132000
1998	0.575	132000
1999	0.5265	132000
2000	0.532	134000
2001	0.7513	129000
2002	0.7934	217000
2003	0.7719	216000
2004	0.7149	213000
2005	0.6992	211000
2006	0.8835	209000
2007	0.8869	207000
2008	0.8776	206000
2009	0.8775	208000
2010	0.8812	210000
2011	0.8992	205000
2012	0.8932	201000
2013	0.8819	203000
2014	0.8723	200000
2015	0.871	199000
2016	0.8679	185000
2017	0.8575	186000
2018	0.8548	180000
2019	0.8544	180000
Total	0.8145	4425000

All March CPS respondents for interview years 1996 through 2019. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A2: Overall Response Rates

	Never 0-0	Switch into 0-1	Switch out 1-0	Always 1-1	Switchers	N
1996	0.0433	0.0708	0.0792	0.8067	0.15	17000
1997	0.0458	0.0681	0.0809	0.8052	0.149	33000
1998	0.0456	0.0637	0.086	0.8048	0.1497	31000
1999	0.0434	0.0694	0.0894	0.7978	0.1588	29000
2000	0.0475	0.072	0.1034	0.7772	0.1754	29000
2001	0.0538	0.074	0.1101	0.762	0.1841	29000
2002	0.0584	0.0819	0.1036	0.756	0.1855	36000
2003	0.0586	0.0858	0.0993	0.7563	0.1851	43000
2004	0.0568	0.0853	0.098	0.7599	0.1833	38000
2005	0.0521	0.085	0.0983	0.7645	0.1833	36000
2006	0.0614	0.0881	0.1047	0.7459	0.1928	44000
2007	0.0729	0.0917	0.108	0.7273	0.1997	52000
2008	0.0745	0.0969	0.0998	0.7288	0.1967	52000
2009	0.0724	0.0946	0.0996	0.7334	0.1942	53000
2010	0.0743	0.0921	0.1029	0.7307	0.195	51000
2011	0.0782	0.0954	0.1001	0.7262	0.1955	48000
2012	0.0745	0.0946	0.1016	0.7293	0.1962	47000
2013	0.0762	0.0894	0.1138	0.7206	0.2032	45000
2014	0.0869	0.0948	0.1281	0.6902	0.2229	38000
2015	0.0994	0.1088	0.1367	0.6552	0.2455	33000
2016	0.1026	0.1153	0.1312	0.6508	0.2465	34000
2017	0.0973	0.1185	0.1247	0.6594	0.2432	33000
2018	0.0943	0.1155	0.1273	0.6629	0.2428	31000
2019	0.094	0.112	0.1292	0.6648	0.2412	15000

Sample of all adults age 18-62, matching across consecutive CPS years, no whole imputes, who were PIKed and had positive earnings for either DER or ASEC. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A3: Men OLS Regression of Ln ASEC on Ln DER

	All Men				Male Respond Both				Male Switchers			
Year	ρ	SE	σ_ϵ	N	ρ_2	SE	$\sigma_{\epsilon 2}$	N	ρ_1	SE	$\sigma_{\epsilon 1}$	N
1996	0.879	(0.009)	0.764	7000	0.881	(0.009)	0.718	6000	0.852	(0.041)	1.128	1000
1997	0.81	(0.005)	0.642	13000	0.812	(0.005)	0.601	12000	0.789	(0.024)	0.969	1000
1998	0.798	(0.006)	0.67	13000	0.803	(0.006)	0.607	12000	0.747	(0.031)	1.129	1000
1999	0.812	(0.006)	0.668	12000	0.809	(0.006)	0.638	11000	0.831	(0.025)	0.92	1000
2000	0.81	(0.006)	0.652	12000	0.817	(0.006)	0.641	10000	0.762	(0.019)	0.731	2000
2001	0.807	(0.006)	0.646	11000	0.82	(0.006)	0.63	10000	0.714	(0.022)	0.771	1000
2002	0.801	(0.005)	0.574	14000	0.797	(0.005)	0.537	13000	0.82	(0.019)	0.799	1000
2003	0.79	(0.005)	0.639	16000	0.8	(0.005)	0.615	15000	0.725	(0.017)	0.814	1000
2004	0.797	(0.005)	0.635	15000	0.804	(0.005)	0.597	13000	0.755	(0.020)	0.872	2000
2005	0.781	(0.006)	0.674	14000	0.791	(0.006)	0.65	12000	0.702	(0.021)	0.854	2000
2006	0.788	(0.005)	0.657	17000	0.798	(0.005)	0.622	15000	0.724	(0.017)	0.861	2000
2007	0.77	(0.004)	0.588	19000	0.782	(0.004)	0.551	17000	0.694	(0.016)	0.811	2000
2008	0.743	(0.004)	0.533	19000	0.752	(0.004)	0.506	17000	0.684	(0.013)	0.704	2000
2009	0.766	(0.004)	0.529	20000	0.78	(0.004)	0.51	17000	0.68	(0.012)	0.641	3000
2010	0.801	(0.004)	0.522	18000	0.81	(0.004)	0.512	17000	0.743	(0.011)	0.584	1000
2011	0.782	(0.004)	0.512	17000	0.794	(0.004)	0.494	15000	0.702	(0.012)	0.624	2000
2012	0.787	(0.004)	0.532	17000	0.798	(0.004)	0.522	15000	0.717	(0.012)	0.593	2000
2013	0.786	(0.004)	0.549	16000	0.801	(0.004)	0.525	15000	0.699	(0.013)	0.682	1000
2014	0.801	(0.004)	0.503	13000	0.809	(0.004)	0.483	11000	0.754	(0.013)	0.615	2000
2015	0.767	(0.005)	0.511	11000	0.787	(0.005)	0.488	9000	0.676	(0.013)	0.611	2000
2016	0.777	(0.005)	0.533	12000	0.783	(0.005)	0.523	10000	0.738	(0.013)	0.584	2000
2017	0.77	(0.005)	0.519	11000	0.792	(0.005)	0.497	10000	0.667	(0.013)	0.614	1000
2018	0.756	(0.005)	0.542	11000	0.772	(0.005)	0.534	9000	0.681	(0.013)	0.579	2000
2019	0.756	(0.008)	0.558	5000	0.76	(0.008)	0.52	4000	0.725	(0.026)	0.747	1000

OLS regression of log ASEC on log DER, assumes DER is correct. Robust standard errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A4: Women OLS Regression of Ln ASEC on Ln DER

	All Women				Women Respond Both				Women Switchers			
Year	ρ	SE	σ_ϵ	N	ρ_2	SE	$\sigma_{\epsilon 2}$	N	ρ_1	SE	$\sigma_{\epsilon 1}$	N
1996	0.901	(0.008)	0.681	6000	0.899	(0.007)	0.583	5000	0.913	(0.051)	1.365	1000
1997	0.884	(0.005)	0.589	13000	0.884	(0.005)	0.571	12000	0.889	(0.023)	0.784	1000
1998	0.886	(0.005)	0.573	12000	0.887	(0.005)	0.539	11000	0.864	(0.027)	0.889	1000
1999	0.889	(0.005)	0.557	11000	0.889	(0.005)	0.549	10000	0.885	(0.020)	0.639	1000
2000	0.884	(0.005)	0.543	11000	0.89	(0.005)	0.519	10000	0.836	(0.019)	0.711	1000
2001	0.878	(0.005)	0.53	11000	0.881	(0.005)	0.519	10000	0.849	(0.020)	0.631	1000
2002	0.874	(0.005)	0.567	14000	0.877	(0.005)	0.549	12000	0.842	(0.018)	0.706	2000
2003	0.877	(0.004)	0.535	16000	0.888	(0.004)	0.494	14000	0.77	(0.020)	0.823	2000
2004	0.881	(0.004)	0.556	14000	0.888	(0.004)	0.529	13000	0.823	(0.019)	0.757	1000
2005	0.878	(0.004)	0.52	13000	0.887	(0.004)	0.495	12000	0.795	(0.019)	0.71	1000
2006	0.851	(0.004)	0.588	16000	0.855	(0.004)	0.563	14000	0.82	(0.017)	0.754	2000
2007	0.824	(0.004)	0.518	18000	0.837	(0.004)	0.493	16000	0.716	(0.015)	0.68	2000
2008	0.838	(0.003)	0.497	19000	0.845	(0.004)	0.487	17000	0.785	(0.012)	0.569	2000
2009	0.839	(0.003)	0.517	19000	0.847	(0.004)	0.518	17000	0.781	(0.010)	0.508	2000
2010	0.858	(0.004)	0.499	18000	0.866	(0.004)	0.489	16000	0.791	(0.012)	0.57	2000
2011	0.864	(0.004)	0.489	17000	0.869	(0.004)	0.487	15000	0.814	(0.012)	0.499	2000
2012	0.864	(0.004)	0.509	16000	0.872	(0.004)	0.499	14000	0.791	(0.013)	0.58	2000
2013	0.849	(0.004)	0.501	16000	0.855	(0.004)	0.491	14000	0.801	(0.012)	0.566	2000
2014	0.846	(0.004)	0.505	13000	0.853	(0.004)	0.491	11000	0.793	(0.014)	0.589	2000
2015	0.828	(0.005)	0.538	11000	0.84	(0.005)	0.527	9000	0.754	(0.014)	0.595	2000
2016	0.856	(0.004)	0.501	11000	0.869	(0.004)	0.467	10000	0.772	(0.016)	0.658	1000
2017	0.853	(0.004)	0.478	11000	0.866	(0.005)	0.465	9000	0.771	(0.013)	0.544	2000
2018	0.829	(0.005)	0.499	10000	0.834	(0.005)	0.475	9000	0.797	(0.015)	0.618	1000
2019	0.8	(0.008)	0.548	5000	0.815	(0.008)	0.528	4000	0.699	(0.025)	0.652	1000

OLS regression of log ASEC on log DER, assumes DER is correct. Robust standard errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A5: Men Simple Linear FMM

	Probit Class 2 (Good Reporters)				Class 1: Bad Reporters				Class 2: Good Reporters				
Year	respondboth	SE	Constant	SE	ρ_1	SE	$\sigma_{\epsilon 1}$	Prob Class1	ρ_2	SE	$\sigma_{\epsilon 2}$	Prob Class2	N
1996	0.771	(0.105)	0.594	(0.100)	0.721	(0.031)	1.599	0.217	0.988	(0.003)	0.124	0.783	7000
1997	0.767	(0.076)	0.44	(0.073)	0.617	(0.016)	1.228	0.245	0.987	(0.002)	0.120	0.755	13000
1998	0.847	(0.078)	0.436	(0.074)	0.594	(0.018)	1.313	0.233	0.989	(0.002)	0.121	0.767	13000
1999	0.703	(0.083)	0.612	(0.080)	0.607	(0.020)	1.337	0.224	0.991	(0.002)	0.128	0.776	12000
2000	0.562	(0.076)	0.768	(0.072)	0.614	(0.019)	1.312	0.221	0.986	(0.002)	0.128	0.779	12000
2001	0.612	(0.082)	0.755	(0.079)	0.61	(0.020)	1.311	0.215	0.988	(0.002)	0.138	0.785	11000
2002	0.664	(0.068)	0.517	(0.065)	0.629	(0.014)	1.067	0.251	0.99	(0.002)	0.125	0.749	14000
2003	0.699	(0.065)	0.524	(0.063)	0.595	(0.015)	1.215	0.243	0.989	(0.002)	0.132	0.757	16000
2004	0.711	(0.066)	0.452	(0.063)	0.606	(0.015)	1.176	0.255	0.993	(0.002)	0.130	0.745	15000
2005	0.675	(0.071)	0.501	(0.069)	0.594	(0.016)	1.272	0.25	0.973	(0.002)	0.126	0.75	14000
2006	0.72	(0.060)	0.487	(0.057)	0.61	(0.015)	1.245	0.249	0.967	(0.002)	0.135	0.751	17000
2007	0.718	(0.058)	0.342	(0.056)	0.59	(0.011)	1.036	0.276	0.972	(0.002)	0.131	0.724	19000
2008	0.656	(0.058)	0.147	(0.056)	0.563	(0.009)	0.834	0.327	0.983	(0.002)	0.118	0.673	19000
2009	0.71	(0.056)	0.257	(0.054)	0.572	(0.009)	0.875	0.295	0.973	(0.002)	0.122	0.705	20000
2010	0.551	(0.060)	0.35	(0.058)	0.645	(0.009)	0.872	0.303	0.981	(0.002)	0.121	0.697	19000
2011	0.6	(0.062)	0.223	(0.060)	0.622	(0.009)	0.820	0.321	0.982	(0.002)	0.116	0.679	17000
2012	0.531	(0.061)	0.35	(0.059)	0.627	(0.010)	0.882	0.308	0.972	(0.002)	0.124	0.692	17000
2013	0.563	(0.061)	0.44	(0.059)	0.609	(0.010)	0.941	0.284	0.974	(0.002)	0.132	0.716	16000
2014	0.609	(0.066)	0.262	(0.064)	0.649	(0.010)	0.826	0.314	0.98	(0.002)	0.117	0.686	13000
2015	0.603	(0.068)	0.282	(0.065)	0.593	(0.011)	0.820	0.314	0.98	(0.002)	0.121	0.686	11000
2016	0.571	(0.068)	0.421	(0.067)	0.588	(0.013)	0.897	0.29	0.972	(0.002)	0.132	0.71	12000
2017	0.587	(0.069)	0.467	(0.066)	0.57	(0.013)	0.879	0.278	0.975	(0.002)	0.132	0.722	11000
2018	0.666	(0.069)	0.36	(0.066)	0.576	(0.013)	0.919	0.287	0.971	(0.003)	0.130	0.713	11000
2019	0.678	(0.105)	0.469	(0.100)	0.545	(0.021)	0.992	0.261	0.962	(0.004)	0.136	0.739	5000

Finite mixture model of measurment error in ASEC. DER Earnings assumed correct. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A6: Women Simple FMM

	Probit Class 2 (Good Reporters)				Class 1: Bad Reporters				Class 2: Good Reporters				
Year	ceoff(respondboth)	SE	Constant	SE	ρ_1	SE	$\sigma_{\epsilon 1}$	Prob Class1	ρ_2	SE	$\sigma_{\epsilon 2}$	Prob Class2	N
1996	0.616	(0.119)	0.771	(0.116)	0.695	(0.028)	1.425	0.209	1.007	(0.002)	0.126	0.791	6000
1997	0.689	(0.084)	0.507	(0.081)	0.729	(0.016)	1.142	0.243	1.003	(0.002)	0.116	0.757	13000
1998	0.678	(0.086)	0.468	(0.083)	0.728	(0.015)	1.088	0.252	1.009	(0.002)	0.111	0.748	12000
1999	0.525	(0.095)	0.714	(0.093)	0.735	(0.017)	1.098	0.232	1.003	(0.002)	0.119	0.768	11000
2000	0.547	(0.081)	0.665	(0.078)	0.71	(0.016)	1.044	0.241	1.004	(0.002)	0.117	0.759	11000
2001	0.469	(0.089)	0.715	(0.087)	0.705	(0.016)	1.007	0.243	1.01	(0.002)	0.125	0.757	11000
2002	0.435	(0.076)	0.798	(0.073)	0.692	(0.015)	1.103	0.234	1.005	(0.002)	0.124	0.766	14000
2003	0.486	(0.072)	0.647	(0.069)	0.714	(0.013)	0.999	0.253	1.006	(0.002)	0.125	0.747	16000
2004	0.42	(0.077)	0.803	(0.075)	0.698	(0.015)	1.076	0.236	1.001	(0.002)	0.135	0.764	14000
2005	0.486	(0.076)	0.598	(0.074)	0.732	(0.013)	0.965	0.263	0.986	(0.002)	0.116	0.737	13000
2006	0.424	(0.066)	0.737	(0.063)	0.672	(0.014)	1.113	0.248	0.982	(0.002)	0.133	0.752	16000
2007	0.546	(0.063)	0.362	(0.061)	0.653	(0.010)	0.871	0.301	0.988	(0.002)	0.121	0.699	18000
2008	0.563	(0.062)	0.364	(0.060)	0.68	(0.010)	0.841	0.297	0.986	(0.002)	0.125	0.703	19000
2009	0.43	(0.061)	0.566	(0.059)	0.672	(0.010)	0.906	0.28	0.983	(0.002)	0.125	0.72	19000
2010	0.422	(0.063)	0.547	(0.061)	0.697	(0.010)	0.869	0.285	0.992	(0.001)	0.118	0.715	18000
2011	0.402	(0.067)	0.504	(0.066)	0.715	(0.010)	0.837	0.297	0.988	(0.002)	0.121	0.703	17000
2012	0.531	(0.066)	0.492	(0.065)	0.712	(0.011)	0.905	0.278	0.984	(0.002)	0.129	0.722	16000
2013	0.578	(0.065)	0.405	(0.063)	0.686	(0.011)	0.864	0.288	0.984	(0.002)	0.128	0.712	16000
2014	0.476	(0.071)	0.509	(0.070)	0.67	(0.012)	0.872	0.285	0.988	(0.002)	0.126	0.715	13000
2015	0.524	(0.072)	0.591	(0.069)	0.62	(0.015)	0.957	0.263	0.979	(0.002)	0.137	0.737	11000
2016	0.528	(0.071)	0.487	(0.068)	0.709	(0.013)	0.881	0.283	0.982	(0.002)	0.128	0.717	11000
2017	0.549	(0.073)	0.448	(0.071)	0.695	(0.012)	0.823	0.287	0.985	(0.002)	0.129	0.713	11000
2018	0.554	(0.074)	0.457	(0.073)	0.668	(0.013)	0.861	0.285	0.98	(0.002)	0.132	0.715	10000
2019	0.362	(0.112)	0.759	(0.107)	0.585	(0.023)	0.986	0.256	0.978	(0.004)	0.141	0.744	5000

Finite mixture model of measurment error in ASEC. DER Earnings assumed correct. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A7: Men Simple KY-fit Model

	Respond Both					Switchers					
Year	PR(S=R)	SE	ρ_2	SE	$\sigma_{\epsilon 2}$	PR(S=R)	SE	ρ_1	SE	$\sigma_{\epsilon 1}$	N
1996	0.148	(0.005)	0.866	(0.011)	0.776	0.0808	(0.011)	0.858	(0.044)	1.179	700
1997	0.129	(0.003)	0.793	(0.006)	0.64	0.0839	(0.008)	0.782	(0.025)	1.011	13000
1998	0.127	(0.003)	0.782	(0.006)	0.646	0.0922	(0.009)	0.737	(0.033)	1.182	13000
1999	0.121	(0.003)	0.791	(0.007)	0.677	0.0799	(0.008)	0.826	(0.027)	0.958	12000
2000	0.119	(0.003)	0.801	(0.007)	0.68	0.0902	(0.008)	0.748	(0.021)	0.763	12000
2001	0.118	(0.003)	0.802	(0.007)	0.667	0.085	(0.008)	0.702	(0.023)	0.803	11000
2002	0.108	(0.003)	0.782	(0.005)	0.565	0.0791	(0.007)	0.814	(0.020)	0.832	14000
2003	0.105	(0.003)	0.787	(0.006)	0.648	0.0799	(0.007)	0.718	(0.018)	0.846	16000
2004	0.105	(0.003)	0.788	(0.006)	0.628	0.0775	(0.007)	0.740	(0.021)	0.905	15000
2005	0.112	(0.003)	0.775	(0.006)	0.686	0.0746	(0.007)	0.685	(0.022)	0.883	14000
2006	0.103	(0.003)	0.784	(0.006)	0.655	0.0736	(0.006)	0.716	(0.018)	0.892	17000
2007	0.0963	(0.002)	0.764	(0.005)	0.576	0.0708	(0.005)	0.679	(0.017)	0.837	19000
2008	0.0994	(0.002)	0.737	(0.004)	0.529	0.0684	(0.005)	0.668	(0.014)	0.723	19000
2009	0.0969	(0.002)	0.764	(0.004)	0.533	0.066	(0.005)	0.665	(0.012)	0.658	12000
2010	0.101	(0.002)	0.795	(0.004)	0.537	0.0759	(0.006)	0.730	(0.012)	0.604	19000
2011	0.0961	(0.002)	0.778	(0.004)	0.516	0.0661	(0.006)	0.690	(0.013)	0.641	17000
2012	0.0915	(0.002)	0.783	(0.004)	0.544	0.0662	(0.005)	0.707	(0.013)	0.611	17000
2013	0.095	(0.002)	0.786	(0.004)	0.548	0.0674	(0.005)	0.689	(0.013)	0.703	16000
2014	0.0918	(0.003)	0.794	(0.005)	0.503	0.0704	(0.006)	0.743	(0.014)	0.634	13000
2015	0.0979	(0.003)	0.772	(0.005)	0.51	0.0642	(0.006)	0.668	(0.013)	0.628	11000
2016	0.0918	(0.003)	0.765	(0.006)	0.545	0.0663	(0.006)	0.732	(0.014)	0.602	12000
2017	0.0926	(0.003)	0.776	(0.005)	0.518	0.0697	(0.006)	0.657	(0.014)	0.633	11000
2018	0.0876	(0.003)	0.758	(0.006)	0.556	0.0646	(0.006)	0.671	(0.013)	0.595	11000
2019	0.0868	(0.004)	0.743	(0.008)	0.54	0.0701	(0.009)	0.721	(0.028)	0.775	5000

KY-fit model 1 (see Jenkins and Rios-Avila (2023a), allows for measurement error in ASEC only. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A8: Women Simple KY-fit Model

	Respond Both					Switchers					
Year	PR(S=R)	SE	ρ_2	SE	$\sigma_{\epsilon 2}$	PR(S=R)	SE	ρ_1	SE	$\sigma_{\epsilon 1}$	N
1996	0.149	(0.005)	0.884	(0.008)	0.63	0.0937	(0.013)	0.914	(0.056)	1.439	6000
1997	0.141	(0.003)	0.870	(0.005)	0.613	0.0874	(0.009)	0.877	(0.025)	0.819	13000
1998	0.137	(0.003)	0.874	(0.005)	0.578	0.0885	(0.009)	0.861	(0.029)	0.931	12000
1999	0.132	(0.003)	0.876	(0.006)	0.587	0.0884	(0.010)	0.877	(0.021)	0.668	11000
2000	0.133	(0.003)	0.873	(0.006)	0.555	0.0884	(0.008)	0.822	(0.020)	0.742	11000
2001	0.119	(0.003)	0.870	(0.006)	0.551	0.085	(0.009)	0.839	(0.021)	0.658	11000
2002	0.111	(0.003)	0.865	(0.005)	0.581	0.0927	(0.008)	0.831	(0.020)	0.74	14000
2003	0.112	(0.003)	0.879	(0.004)	0.522	0.0846	(0.007)	0.750	(0.022)	0.856	16000
2004	0.106	(0.003)	0.877	(0.005)	0.558	0.0823	(0.007)	0.811	(0.021)	0.788	14000
2005	0.112	(0.003)	0.874	(0.005)	0.523	0.0875	(0.008)	0.780	(0.020)	0.74	13000
2006	0.0987	(0.002)	0.842	(0.005)	0.591	0.0786	(0.006)	0.806	(0.019)	0.784	16000
2007	0.0957	(0.002)	0.822	(0.004)	0.515	0.0688	(0.006)	0.702	(0.015)	0.701	18000
2008	0.0992	(0.002)	0.830	(0.004)	0.51	0.0817	(0.006)	0.768	(0.013)	0.59	19000
2009	0.0992	(0.002)	0.832	(0.004)	0.543	0.071	(0.006)	0.763	(0.011)	0.522	19000
2010	0.102	(0.002)	0.852	(0.004)	0.513	0.0818	(0.006)	0.776	(0.013)	0.592	18000
2011	0.0956	(0.002)	0.857	(0.004)	0.51	0.0759	(0.006)	0.803	(0.012)	0.517	17000
2012	0.0938	(0.002)	0.860	(0.004)	0.522	0.0677	(0.006)	0.777	(0.014)	0.597	16000
2013	0.09	(0.002)	0.843	(0.004)	0.512	0.0651	(0.006)	0.787	(0.013)	0.582	16000
2014	0.0951	(0.003)	0.841	(0.005)	0.513	0.0734	(0.007)	0.781	(0.015)	0.609	13000
2015	0.0898	(0.003)	0.825	(0.005)	0.549	0.0842	(0.007)	0.738	(0.015)	0.618	11000
2016	0.0891	(0.003)	0.860	(0.005)	0.487	0.064	(0.006)	0.760	(0.017)	0.677	11000
2017	0.091	(0.003)	0.854	(0.005)	0.485	0.076	(0.007)	0.753	(0.014)	0.561	11000
2018	0.0885	(0.003)	0.821	(0.005)	0.494	0.0671	(0.006)	0.789	(0.015)	0.638	10000
2019	0.086	(0.004)	0.800	(0.008)	0.549	0.0687	(0.010)	0.691	(0.026)	0.673	5000

KY-fit model 1 (see Jenkins and Rios-Avila (2023a), allows for measurment error in ASEC only. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A9: Male IV Estimates

	All Men				Male Respond Both				Male Switchers			
	ρ	SE	σ_ϵ	N	ρ_2	SE	$\sigma_{\epsilon 2}$	N	ρ_1	SE	$\sigma_{\epsilon 1}$	N
1996	1.011	(0.016)	0.776	7000	1.019	(0.017)	0.731	6000	0.954	(0.062)	1.131	1000
1997	1.019	(0.011)	0.676	13000	1.02	(0.011)	0.635	12000	0.978	(0.043)	0.994	1000
1998	1.002	(0.012)	0.701	13000	0.994	(0.011)	0.636	12000	1.075	(0.066)	1.184	1000
1999	1.002	(0.012)	0.694	12000	0.999	(0.012)	0.664	11000	0.999	(0.045)	0.939	1000
2000	1.011	(0.012)	0.682	12000	0.999	(0.012)	0.666	10000	1.075	(0.038)	0.8	1000
2001	1.011	(0.012)	0.676	11000	1.005	(0.012)	0.655	10000	1.015	(0.044)	0.831	1000
2002	1.012	(0.010)	0.61	14000	1.006	(0.010)	0.574	12000	1.039	(0.037)	0.832	3000
2003	1.012	(0.010)	0.677	16000	1.013	(0.010)	0.65	15000	0.985	(0.033)	0.866	2000
2004	1.007	(0.010)	0.67	15000	1.002	(0.010)	0.629	13000	1.025	(0.038)	0.921	2000
2005	0.987	(0.011)	0.707	14000	0.983	(0.011)	0.679	12000	0.996	(0.043)	0.914	2000
2006	0.994	(0.009)	0.69	17000	0.99	(0.009)	0.651	15000	1.004	(0.034)	0.915	2000
2007	0.979	(0.008)	0.625	19000	0.983	(0.008)	0.588	17000	0.948	(0.031)	0.855	2000
2008	0.978	(0.007)	0.586	19000	0.975	(0.007)	0.556	17000	0.991	(0.028)	0.782	2000
2009	0.988	(0.007)	0.578	20000	0.987	(0.007)	0.553	17000	0.97	(0.024)	0.719	3000
2010	0.968	(0.007)	0.551	19000	0.969	(0.007)	0.539	16000	0.952	(0.023)	0.63	2000
2011	0.985	(0.007)	0.557	17000	0.981	(0.008)	0.534	15000	1.004	(0.027)	0.711	2000
2012	0.984	(0.008)	0.572	17000	0.984	(0.008)	0.559	15000	0.964	(0.025)	0.65	2000
2013	0.981	(0.008)	0.588	16000	0.98	(0.008)	0.559	14000	0.978	(0.027)	0.753	2000
2014	0.98	(0.008)	0.538	13000	0.978	(0.008)	0.515	11000	0.986	(0.025)	0.666	2000
2015	0.983	(0.009)	0.559	11000	0.981	(0.009)	0.527	9000	0.982	(0.029)	0.703	2000
2016	0.996	(0.010)	0.58	12000	0.989	(0.010)	0.566	10000	1.02	(0.028)	0.651	2000
2017	0.989	(0.009)	0.566	11000	0.993	(0.010)	0.537	10000	0.957	(0.028)	0.691	1000
2018	0.975	(0.010)	0.588	11000	0.984	(0.011)	0.576	9000	0.912	(0.026)	0.632	2000
2019	0.978	(0.016)	0.6	5000	0.97	(0.016)	0.559	4000	1.009	(0.052)	0.803	1000

Instrumental variables estimation of Log ASEC Earnings on Log DER earnings. Instruments for log DER Earnings include Mincer variables, and citysize. Robust standard errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A10: Female IV Estimates

	All Women				Women Respond Both				Women Switchers			
Year	ρ	SE	σ_ϵ	N	ρ_2	SE	$\sigma_{\epsilon 2}$	N	ρ_1	SE	$\sigma_{\epsilon 1}$	N
1996	1.019	(0.017)	0.694	6000	1.016	(0.015)	0.597	5000	1.018	(0.119)	1.368	1000
1997	1.023	(0.012)	0.609	13000	1.022	(0.012)	0.59	12000	0.994	(0.051)	0.792	1000
1998	1.051	(0.012)	0.6	12000	1.043	(0.012)	0.564	11000	1.129	(0.072)	0.934	1000
1999	1.032	(0.012)	0.577	11000	1.028	(0.012)	0.569	10000	1.025	(0.046)	0.657	1000
2000	1.008	(0.011)	0.558	11000	1.002	(0.011)	0.533	10000	1.004	(0.046)	0.735	1000
2001	1.058	(0.012)	0.562	11000	1.054	(0.012)	0.549	10000	1.051	(0.042)	0.664	1000
2002	1.03	(0.011)	0.592	14000	1.03	(0.011)	0.573	12000	0.991	(0.044)	0.723	2000
2003	1.034	(0.010)	0.56	16000	1.032	(0.010)	0.517	14000	1.017	(0.056)	0.863	2000
2004	1.043	(0.011)	0.582	14000	1.041	(0.011)	0.553	13000	1.044	(0.047)	0.792	1000
2005	1.005	(0.010)	0.537	13000	1.006	(0.010)	0.511	12000	0.926	(0.041)	0.722	1000
2006	0.988	(0.010)	0.606	16000	0.988	(0.010)	0.581	14000	0.972	(0.038)	0.77	2000
2007	0.994	(0.009)	0.548	18000	0.993	(0.009)	0.52	16000	0.981	(0.037)	0.734	2000
2008	1.003	(0.008)	0.527	19000	0.999	(0.008)	0.514	17000	1.025	(0.029)	0.622	2000
2009	1.004	(0.008)	0.547	19000	1.006	(0.008)	0.546	17000	0.979	(0.024)	0.55	2000
2010	1.009	(0.008)	0.524	18000	1.007	(0.008)	0.511	16000	1.008	(0.029)	0.613	2000
2011	1.019	(0.008)	0.516	17000	1.018	(0.008)	0.513	15000	1.017	(0.027)	0.54	2000
2012	1.026	(0.008)	0.539	16000	1.026	(0.008)	0.526	14000	1.002	(0.029)	0.62	2000
2013	0.999	(0.008)	0.527	16000	0.997	(0.008)	0.515	14000	0.997	(0.025)	0.603	2000
2014	1.001	(0.009)	0.531	13000	0.993	(0.009)	0.513	11000	1.04	(0.032)	0.645	2000
2015	1.011	(0.011)	0.574	11000	0.997	(0.011)	0.554	10000	1.062	(0.036)	0.68	1000
2016	1.009	(0.010)	0.527	11000	1.003	(0.010)	0.488	10000	1.015	(0.037)	0.704	1000
2017	1.015	(0.010)	0.509	11000	1.015	(0.010)	0.491	9000	0.99	(0.030)	0.589	2000
2018	1.016	(0.011)	0.537	10000	1.008	(0.011)	0.508	9000	1.045	(0.032)	0.673	1000
2019	1.007	(0.017)	0.588	5000	0.997	(0.017)	0.561	4000	1.011	(0.063)	0.723	1000

Instrumental variables estimation of Log ASEC Earnings on Log DER earnings. Instruments for log DER Earnings include Mincer variables, and citysize. Robust standard errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A11: Men IV and FMM Model Estimates

	Probability Class 2 (Good Reporters)				Class 1: Bad Reporters				Class 2: Good Reporters				
Year	respondboth	SE	Constant	SE	ρ_1	SE	$\sigma_{\epsilon 1}$	Prob Class 1	ρ_2	SE	$\sigma_{\epsilon 2}$	Prob Class 2	N
1996	0.653	(0.154)	1.726	(0.150)	0.94	(0.155)	2.181	0.0909	0.885	(0.013)	0.397	0.909	7000
1997	0.664	(0.106)	1.498	(0.104)	1.118	(0.089)	1.55	0.111	0.866	(0.010)	0.426	0.889	14000
1998	0.628	(0.119)	1.671	(0.116)	1.076	(0.105)	1.74	0.0973	0.89	(0.010)	0.445	0.903	13000
1999	0.564	(0.126)	1.884	(0.121)	1.087	(0.121)	1.869	0.0844	0.859	(0.010)	0.422	0.916	12000
2000	0.323	(0.121)	1.92	(0.121)	1.303	(0.101)	1.748	0.0996	0.831	(0.011)	0.415	0.9	12000
2001	0.225	(0.143)	2.159	(0.143)	1.39	(0.125)	1.921	0.0863	0.859	(0.011)	0.419	0.914	12000
2002	0.113	(0.123)	2.167	(0.124)	1.336	(0.089)	1.534	0.094	0.849	(0.010)	0.418	0.906	15000
2003	0.399	(0.105)	1.766	(0.107)	1.283	(0.073)	1.626	0.108	0.841	(0.009)	0.431	0.892	17000
2004	0.443	(0.101)	1.614	(0.102)	1.17	(0.067)	1.482	0.119	0.845	(0.009)	0.432	0.881	15000
2005	0.304	(0.122)	2.067	(0.121)	1.148	(0.095)	1.835	0.0882	0.858	(0.009)	0.453	0.912	14000
2006	0.304	(0.104)	2.112	(0.103)	1.128	(0.087)	1.764	0.0853	0.846	(0.008)	0.448	0.915	18000
2007	0.205	(0.098)	1.863	(0.100)	1.183	(0.055)	1.377	0.115	0.793	(0.008)	0.418	0.885	20000
2008	0.357	(0.089)	1.418	(0.093)	1.214	(0.041)	1.052	0.151	0.778	(0.008)	0.431	0.849	20000
2009	0.286	(0.084)	1.371	(0.088)	1.19	(0.038)	1.053	0.165	0.79	(0.008)	0.413	0.835	20000
2010	0.218	(0.083)	1.233	(0.087)	1.098	(0.036)	0.904	0.194	0.772	(0.008)	0.392	0.806	19000
2011	0.357	(0.085)	1.033	(0.092)	1.136	(0.034)	0.869	0.207	0.74	(0.009)	0.402	0.793	18000
2012	0.159	(0.089)	1.303	(0.095)	1.143	(0.038)	0.958	0.191	0.768	(0.009)	0.405	0.809	18000
2013	0.223	(0.087)	1.403	(0.088)	1.141	(0.040)	1.025	0.169	0.785	(0.009)	0.419	0.831	17000
2014	0.36	(0.105)	1.528	(0.111)	1.178	(0.053)	1.039	0.138	0.78	(0.010)	0.392	0.862	14000
2015	0.462	(0.105)	1.336	(0.113)	1.216	(0.052)	1.005	0.153	0.759	(0.011)	0.413	0.847	12000
2016	0.0919	(0.119)	1.802	(0.131)	1.287	(0.057)	1.14	0.132	0.766	(0.011)	0.423	0.868	12000
2017	0.259	(0.109)	1.528	(0.120)	1.229	(0.054)	1.073	0.149	0.809	(0.011)	0.414	0.851	12000
2018	0.174	(0.112)	1.669	(0.118)	1.221	(0.062)	1.156	0.14	0.784	(0.011)	0.419	0.86	11000
2019	0.604	(0.160)	1.511	(0.163)	1.2	(0.109)	1.24	0.118	0.784	(0.016)	0.415	0.882	5000

Finite Mixture model with Instrumental variables. Instruments for log DER Earnings include Mincer variables, and citysize. Robust standard errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A12: Women IV and FMM Model Estimates

	Probability Class 2 (Good Reporters)				Class 1: Bad Reporters				Class 2: Good Reporters				
Year	respondboth	SE	Constant	SE	ρ_1	SE	$\sigma_{\epsilon 1}$	Prob Class 1	ρ_2	SE	$\sigma_{\epsilon 2}$	Prob Class 2	N
1996	0.475	(0.131)	1.007	(0.131)	0.76	(0.117)	1.334	0.192	0.936	(0.018)	0.391	0.808	7000
1997	0.177	(0.102)	1.057	(0.104)	0.797	(0.068)	1.038	0.228	0.904	(0.013)	0.366	0.772	13000
1998	0.393	(0.099)	0.792	(0.099)	0.964	(0.067)	0.968	0.24	0.914	(0.013)	0.375	0.76	12000
1999	0.179	(0.113)	1.162	(0.114)	1.002	(0.077)	0.969	0.21	0.886	(0.013)	0.375	0.79	11000
2000	0.296	(0.095)	1.029	(0.097)	0.936	(0.072)	0.939	0.216	0.888	(0.013)	0.357	0.784	11000
2001	0.173	(0.107)	1.183	(0.109)	1.115	(0.078)	0.951	0.208	0.915	(0.014)	0.377	0.792	11000
2002	0.114	(0.090)	1.124	(0.092)	1.07	(0.063)	0.999	0.227	0.895	(0.012)	0.374	0.773	14000
2003	-0.0464	(0.091)	1.335	(0.092)	0.897	(0.061)	0.88	0.215	0.885	(0.012)	0.38	0.785	16000
2004	0.136	(0.090)	1.051	(0.093)	1.031	(0.056)	0.92	0.236	0.883	(0.013)	0.378	0.764	15000
2005	-0.0483	(0.100)	1.37	(0.103)	0.839	(0.063)	0.877	0.21	0.898	(0.012)	0.368	0.79	14000
2006	0.0915	(0.081)	1.238	(0.083)	0.829	(0.058)	1.014	0.211	0.871	(0.011)	0.394	0.789	17000
2007	-0.0173	(0.080)	1.208	(0.083)	0.864	(0.044)	0.793	0.233	0.856	(0.010)	0.39	0.767	19000
2008	0.035	(0.078)	1.151	(0.082)	0.95	(0.041)	0.743	0.235	0.835	(0.010)	0.379	0.765	19000
2009	-0.0992	(0.076)	1.19	(0.080)	0.927	(0.037)	0.779	0.249	0.856	(0.009)	0.384	0.751	19000
2010	-0.149	(0.080)	1.161	(0.084)	0.926	(0.036)	0.728	0.263	0.839	(0.010)	0.367	0.737	18000
2011	0.00621	(0.083)	1.153	(0.088)	0.91	(0.041)	0.727	0.239	0.864	(0.010)	0.369	0.761	17000
2012	-0.0675	(0.084)	1.277	(0.087)	0.995	(0.042)	0.797	0.228	0.877	(0.010)	0.381	0.772	17000
2013	-0.0106	(0.085)	1.278	(0.090)	0.944	(0.043)	0.769	0.22	0.882	(0.010)	0.393	0.78	16000
2014	0.0545	(0.091)	1.241	(0.096)	0.982	(0.049)	0.805	0.216	0.858	(0.011)	0.379	0.784	13000
2015	0.0922	(0.092)	1.22	(0.095)	0.893	(0.053)	0.876	0.214	0.874	(0.012)	0.397	0.786	11000
2016	0.0297	(0.097)	1.382	(0.103)	0.99	(0.059)	0.835	0.197	0.857	(0.012)	0.372	0.803	12000
2017	0.00186	(0.093)	1.271	(0.096)	0.991	(0.056)	0.743	0.219	0.842	(0.012)	0.367	0.781	11000
2018	0.121	(0.099)	1.339	(0.105)	0.945	(0.062)	0.821	0.191	0.867	(0.012)	0.385	0.809	11000
2019	0.133	(0.146)	1.358	(0.151)	0.78	(0.098)	0.917	0.187	0.899	(0.018)	0.43	0.813	5000

Finite Mixture model with Instrumental variables. Instruments for log DER Earnings include Mincer variables, and citysize. Robust standard errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A13: KY Fit Model for Men

	Respond Both					Switchers					DER Model							
Year	R_{C2}	SE	ρ_2	SE	$\sigma_{\epsilon 2}$	R_{C1}	SE	ρ_1	SE	$\sigma_{\epsilon 1}$	PR(miss)	SE	α_1	SE	R_D	σ_D	N
1996	0.234	(0.008)	1.028	(0.004)	0.0977	0.145	(0.020)	1.085	(0.016)	0.137	0.061	(0.005)	0.961	(0.013)	0.336	0.460	7000
1997	0.214	(0.006)	1.0129	(0.003)	0.0949	0.153	(0.015)	1.068	(0.013)	0.165	0.072	(0.004)	0.955	(0.010)	0.356	0.416	13000
1998	0.193	(0.005)	1.016	(0.003)	0.104	0.159	(0.015)	1.128	(0.015)	0.2	0.065	(0.004)	0.933	(0.012)	0.306	0.471	13000
1999	0.187	(0.006)	1.0266	(0.003)	0.104	0.134	(0.014)	1.067	(0.013)	0.176	0.064	(0.005)	0.979	(0.012)	0.318	0.464	12000
2000	0.187	(0.006)	1.0231	(0.003)	0.103	0.153	(0.013)	1.031	(0.009)	0.133	0.064	(0.004)	0.949	(0.012)	0.328	0.444	12000
2001	0.185	(0.006)	1.0308	(0.003)	0.11	0.145	(0.014)	1.051	(0.011)	0.153	0.063	(0.004)	0.975	(0.013)	0.330	0.455	11000
2002	0.171	(0.005)	1.0211	(0.003)	0.106	0.136	(0.012)	1.083	(0.011)	0.161	0.057	(0.003)	0.961	(0.010)	0.336	0.470	14000
2003	0.168	(0.004)	1.0271	(0.003)	0.109	0.141	(0.012)	1.049	(0.009)	0.153	0.059	(0.003)	0.972	(0.010)	0.343	0.478	16000
2004	0.162	(0.004)	1.0281	(0.003)	0.113	0.131	(0.011)	1.083	(0.010)	0.171	0.061	(0.004)	0.981	(0.012)	0.321	0.518	15000
2005	0.177	(0.005)	0.99203	(0.003)	0.107	0.13	(0.012)	1.033	(0.010)	0.151	0.059	(0.004)	0.924	(0.011)	0.334	0.495	14000
2006	0.171	(0.005)	0.99274	(0.003)	0.105	0.134	(0.011)	1.027	(0.009)	0.157	0.067	(0.003)	0.934	(0.010)	0.361	0.469	17000
2007	0.155	(0.004)	0.99847	(0.003)	0.114	0.126	(0.010)	1.019	(0.008)	0.158	0.059	(0.003)	0.955	(0.010)	0.348	0.516	19000
2008	0.162	(0.004)	0.99659	(0.002)	0.114	0.122	(0.010)	1.009	(0.007)	0.156	0.051	(0.003)	0.943	(0.010)	0.361	0.537	19000
2009	0.159	(0.004)	0.9899	(0.002)	0.107	0.118	(0.009)	0.986	(0.007)	0.153	0.060	(0.003)	0.940	(0.009)	0.358	0.493	20000
2010	0.158	(0.004)	1.00118	(0.002)	0.118	0.128	(0.010)	0.980	(0.007)	0.15	0.049	(0.003)	0.946	(0.010)	0.336	0.546	19000
2011	0.152	(0.004)	0.99537	(0.002)	0.113	0.112	(0.009)	0.997	(0.007)	0.156	0.043	(0.003)	0.934	(0.009)	0.347	0.559	17000
2012	0.146	(0.004)	0.99027	(0.002)	0.118	0.114	(0.009)	0.967	(0.008)	0.148	0.050	(0.004)	0.942	(0.011)	0.345	0.564	17000
2013	0.152	(0.004)	0.99639	(0.002)	0.118	0.114	(0.009)	1.001	(0.008)	0.161	0.046	(0.003)	0.947	(0.010)	0.350	0.544	16000
2014	0.147	(0.005)	0.99562	(0.003)	0.11	0.122	(0.011)	0.995	(0.008)	0.149	0.043	(0.003)	0.946	(0.011)	0.357	0.529	13000
2015	0.156	(0.005)	0.99674	(0.003)	0.115	0.11	(0.010)	1.001	(0.008)	0.152	0.048	(0.004)	0.951	(0.012)	0.351	0.537	11000
2016	0.153	(0.005)	0.99316	(0.003)	0.111	0.118	(0.011)	0.985	(0.009)	0.154	0.056	(0.004)	0.948	(0.011)	0.371	0.491	12000
2017	0.15	(0.006)	0.99362	(0.003)	0.116	0.123	(0.011)	0.992	(0.008)	0.142	0.057	(0.004)	0.958	(0.011)	0.355	0.480	11000
2018	0.136	(0.005)	1.0000908	(0.003)	0.119	0.108	(0.010)	0.988	(0.009)	0.169	0.048	(0.004)	0.954	(0.013)	0.332	0.550	11000
2019	0.136	(0.007)	0.9824	(0.005)	0.119	0.116	(0.016)	1.070	(0.018)	0.19	0.050	(0.006)	0.968	(0.019)	0.331	0.523	5000

KY-fit model 6 (see Jenkins and Rios-Avila (2023a)), including measurement error in both ASEC and DER measures and mismatch. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A14: KY Fit Model for Women

	Respond Both					Switchers					DER Model						
Year	R_C2	SE	ρ_2	SE	$\sigma_{\epsilon 2}$	R_C1	SE	rho_1	SE	$\sigma_{\epsilon 1}$	PR(miss)	SE	α_1	SE	R_D	σ_D	N
1996	0.226	(0.008)	1.034	(0.004)	0.106	0.153	(0.021)	1.156	(0.018)	0.192	0.061	(0.005)	0.9456	(0.013)	0.306	0.435	6000
1997	0.212	(0.005)	1.025	(0.003)	0.109	0.143	(0.015)	1.0506	(0.009)	0.148	0.056	(0.003)	0.9294	(0.012)	0.303	0.466	13000
1998	0.21	(0.005)	1.033	(0.003)	0.104	0.149	(0.016)	1.0504	(0.010)	0.14	0.057	(0.003)	0.9286	(0.010)	0.316	0.442	12000
1999	0.208	(0.006)	1.025	(0.003)	0.101	0.145	(0.016)	1.0442	(0.011)	0.147	0.061	(0.004)	0.9294	(0.010)	0.330	0.403	11000
2000	0.205	(0.006)	1.022	(0.003)	0.105	0.147	(0.014)	1.0245	(0.008)	0.125	0.052	(0.003)	0.916	(0.011)	0.322	0.433	11000
2001	0.188	(0.006)	1.037	(0.003)	0.11	0.142	(0.015)	1.0447	(0.009)	0.129	0.054	(0.004)	0.9434	(0.011)	0.336	0.422	11000
2002	0.171	(0.005)	1.029	(0.002)	0.108	0.15	(0.013)	1.0353	(0.008)	0.133	0.051	(0.003)	0.9432	(0.010)	0.319	0.458	14000
2003	0.177	(0.005)	1.029	(0.002)	0.109	0.142	(0.012)	1.0455	(0.007)	0.131	0.049	(0.003)	0.9233	(0.009)	0.342	0.455	16000
2004	0.172	(0.005)	1.027	(0.003)	0.11	0.138	(0.012)	1.0223	(0.009)	0.147	0.056	(0.003)	0.9308	(0.010)	0.348	0.435	14000
2005	0.178	(0.005)	1.002	(0.002)	0.103	0.147	(0.013)	1.00402	(0.009)	0.133	0.049	(0.004)	0.9194	(0.010)	0.344	0.451	13000
2006	0.16	(0.004)	1.001	(0.002)	0.11	0.134	(0.011)	1.0084	(0.007)	0.137	0.055	(0.003)	0.9051	(0.010)	0.353	0.468	16000
2007	0.156	(0.004)	1.001	(0.002)	0.111	0.117	(0.010)	0.99562	(0.008)	0.159	0.051	(0.003)	0.9034	(0.009)	0.357	0.480	18000
2008	0.161	(0.004)	1.005	(0.002)	0.116	0.142	(0.011)	1.00315	(0.008)	0.153	0.052	(0.003)	0.9382	(0.009)	0.358	0.476	19000
2009	0.168	(0.004)	1.000	(0.002)	0.107	0.129	(0.010)	0.99714	(0.006)	0.116	0.055	(0.003)	0.9303	(0.008)	0.381	0.447	19000
2010	0.16	(0.004)	1.004	(0.002)	0.112	0.136	(0.010)	0.99484	(0.006)	0.134	0.053	(0.003)	0.894	(0.009)	0.334	0.473	18000
2011	0.154	(0.004)	1.002	(0.002)	0.113	0.126	(0.011)	1.000674	(0.007)	0.148	0.045	(0.003)	0.9081	(0.009)	0.353	0.489	17000
2012	0.15	(0.004)	1.001	(0.002)	0.115	0.114	(0.010)	0.9664	(0.008)	0.157	0.046	(0.003)	0.9075	(0.009)	0.349	0.492	16000
2013	0.145	(0.004)	0.998	(0.002)	0.115	0.111	(0.010)	1.011	(0.007)	0.158	0.045	(0.003)	0.9289	(0.009)	0.358	0.489	16000
2014	0.156	(0.005)	1.008	(0.002)	0.111	0.127	(0.011)	0.99864	(0.008)	0.142	0.046	(0.003)	0.9388	(0.010)	0.366	0.476	13000
2015	0.144	(0.005)	1.005	(0.003)	0.12	0.145	(0.012)	0.99655	(0.008)	0.142	0.052	(0.004)	0.9499	(0.011)	0.353	0.484	11000
2016	0.142	(0.005)	1.001	(0.003)	0.116	0.11	(0.010)	0.9877	(0.008)	0.141	0.051	(0.004)	0.9482	(0.012)	0.348	0.486	11000
2017	0.146	(0.005)	1.003	(0.003)	0.118	0.128	(0.011)	0.9799	(0.009)	0.156	0.047	(0.004)	0.9306	(0.012)	0.351	0.475	11000
2018	0.14	(0.005)	0.997	(0.003)	0.119	0.11	(0.011)	1.0171	(0.009)	0.172	0.042	(0.004)	0.9126	(0.013)	0.345	0.503	11000
2019	0.138	(0.007)	1.005	(0.005)	0.121	0.115	(0.016)	1.00272	(0.012)	0.135	0.053	(0.006)	0.9212	(0.019)	0.350	0.486	5000

KY-fit model 6 (see Jenkins and Rios-Avila (2023a), including measurement error in both ASEC and DER measures and mismatch. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A15: Non-Response Probit Coefficients, Men

	Raw Errors		OLS Errors		FMM Probs		IV Errors		IV FMM Probs		KY-Fit Errors	
Year	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
1996	-0.000951	(0.001)	-0.00226	(0.001)	-0.0615	(0.010)	-0.00495	(0.002)	-0.0385	(0.018)	0.0324	(0.824)
1997	-0.0025	(0.001)	-0.0034	(0.001)	-0.0528	(0.007)	-0.00146	(0.002)	-0.0297	(0.013)	-0.724	(0.254)
1998	-0.00168	(0.001)	-0.00277	(0.001)	-0.0555	(0.007)	-0.00374	(0.002)	-0.0364	(0.013)	-0.524	(0.403)
1999	-0.00145	(0.001)	-0.00304	(0.001)	-0.0708	(0.008)	0.000327	(0.002)	-0.0307	(0.015)	-0.341	(0.442)
2000	-0.000938	(0.001)	-0.00239	(0.001)	-0.0602	(0.008)	-0.00262	(0.002)	-0.0163	(0.015)	-0.436	(0.280)
2001	0.000421	(0.001)	-0.000848	(0.001)	-0.0571	(0.009)	-0.00158	(0.002)	0.0115	(0.016)	-0.286	(0.445)
2002	0.000329	(0.001)	-0.00103	(0.001)	-0.0484	(0.008)	-0.00481	(0.002)	0.00151	(0.014)	-0.394	(0.321)
2003	-0.00144	(0.001)	-0.0045	(0.001)	-0.0743	(0.007)	-0.00252	(0.002)	-0.0182	(0.013)	-0.68	(0.319)
2004	-0.00109	(0.001)	-0.00296	(0.001)	-0.0694	(0.007)	-0.00138	(0.002)	-0.0315	(0.014)	-0.229	(0.348)
2005	-0.00132	(0.001)	-0.00349	(0.001)	-0.0592	(0.008)	0.000664	(0.002)	-0.0177	(0.015)	-0.9	(0.350)
2006	-0.00213	(0.001)	-0.00399	(0.001)	-0.0592	(0.007)	-0.000609	(0.001)	0.0152	(0.013)	0.83	(0.486)
2007	-0.000802	(0.001)	-0.0028	(0.001)	-0.0675	(0.007)	-0.00585	(0.002)	-0.00376	(0.013)	0.98	(0.504)
2008	-0.00243	(0.001)	-0.00607	(0.001)	-0.0764	(0.007)	-0.00176	(0.002)	-0.0106	(0.012)	-0.0771	(0.483)
2009	0.000182	(0.001)	-0.00364	(0.001)	-0.0471	(0.006)	-0.00179	(0.002)	-0.00555	(0.011)	0.269	(0.417)
2010	-0.00148	(0.001)	-0.00846	(0.002)	-0.0638	(0.007)	-0.00378	(0.002)	-0.0036	(0.012)	-0.451	(0.466)
2011	0.000266	(0.001)	-0.00226	(0.002)	-0.0565	(0.007)	-0.00185	(0.002)	-0.0135	(0.012)	-0.012	(0.430)
2012	-0.00125	(0.001)	-0.00523	(0.001)	-0.047	(0.007)	-0.00117	(0.002)	-0.0162	(0.012)	-0.695	(0.433)
2013	-0.00158	(0.001)	-0.00862	(0.002)	-0.0592	(0.007)	-0.000872	(0.002)	-0.0413	(0.013)	-0.147	(0.466)
2014	7.70E-05	(0.001)	-0.00289	(0.002)	-0.0724	(0.009)	-0.00454	(0.002)	-0.0321	(0.016)	-0.879	(0.540)
2015	0.00227	(0.001)	-0.00084	(0.002)	-0.0796	(0.010)	-0.00127	(0.002)	0.0137	(0.019)	0.259	(0.731)
2016	0.00111	(0.002)	-0.00636	(0.003)	-0.0639	(0.010)	-0.00236	(0.003)	-0.0321	(0.019)	0.976	(0.663)
2017	0.00109	(0.001)	-0.00251	(0.002)	-0.065	(0.010)	-0.00497	(0.002)	-0.013	(0.019)	0.18	(0.617)
2018	-0.00383	(0.001)	-0.00675	(0.002)	-0.0804	(0.010)	-0.00843	(0.003)	-0.0266	(0.019)	0.527	(0.634)
2019	0.00191	(0.002)	-0.000935	(0.003)	-0.0629	(0.015)	-0.000108	(0.004)	0.0332	(0.027)	-0.533	(0.806)

Probit models where dependent variable is switched response status. Additional controls include level of error, all Mincer controls, level and square of DER earnings. Standard Errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.

Table A16: Non-Response Probit Coefficients, Women

	Raw Errors		OLS Errors		FMM Probs		IV Errors		IV FMM Probs		KY-Fit Errors	
Year	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
1996	-0.0023	(0.00102)	-0.00478	(0.00134)	-0.0442	(0.00951)	0.000219	(0.00189)	0.0312	(0.0141)	-0.779	(0.471)
1997	-0.00303	(0.000648)	-0.00445	(0.000782)	-0.0346	(0.00702)	0.0029	(0.00151)	-0.0133	(0.0100)	-0.869	(0.262)
1998	-0.00094	(0.000893)	-0.00197	(0.00107)	-0.0515	(0.00728)	0.00136	(0.00147)	-0.00719	(0.0103)	-0.748	(0.367)
1999	-0.000769	(0.000931)	-0.00242	(0.00121)	-0.0617	(0.00789)	0.000145	(0.00172)	-0.0394	(0.0114)	0.121	(0.397)
2000	0.000563	(0.000925)	-0.000599	(0.00118)	-0.0369	(0.00806)	-0.000279	(0.00165)	-0.013	(0.0115)	-0.15	(0.376)
2001	-0.00156	(0.00131)	-0.00413	(0.00162)	-0.022	(0.00902)	0.00366	(0.00204)	-0.0118	(0.0127)	-1.143	(0.482)
2002	-0.00131	(0.000928)	-0.00447	(0.00128)	-0.0455	(0.00782)	-0.00341	(0.00188)	-0.0157	(0.0114)	-0.337	(0.324)
2003	-0.00126	(0.000701)	-0.00293	(0.000919)	-0.0493	(0.00740)	0.000586	(0.00154)	-0.0164	(0.0102)	-0.458	(0.322)
2004	-0.00234	(0.000969)	-0.00552	(0.00129)	-0.0433	(0.00754)	-0.00566	(0.00176)	0.0131	(0.0110)	-0.902	(0.392)
2005	-0.00106	(0.000855)	-0.00292	(0.00108)	-0.037	(0.00809)	-0.00252	(0.00187)	-0.0135	(0.0114)	-0.687	(0.436)
2006	-0.00201	(0.000925)	-0.00452	(0.00116)	-0.0374	(0.00697)	0.00174	(0.00179)	-0.0000957	(0.0103)	-1.177	(0.524)
2007	-0.000427	(0.000775)	-0.00282	(0.00108)	-0.0376	(0.00706)	-0.00163	(0.00182)	-0.00281	(0.0104)	-0.166	(0.481)
2008	-0.0026	(0.00124)	-0.00894	(0.00185)	-0.0464	(0.00677)	-0.0019	(0.00168)	-0.0013	(0.00996)	0.355	(0.525)
2009	-0.000177	(0.0012)	-0.00431	(0.00155)	-0.0456	(0.00670)	0.00388	(0.00171)	0.00312	(0.00969)	0.763	(0.444)
2010	0.00174	(0.00107)	-0.00048	(0.00146)	-0.0462	(0.00702)	0.00124	(0.00171)	0.00836	(0.0102)	-0.163	(0.525)
2011	-0.00122	(0.00128)	-0.0051	(0.00167)	-0.046	(0.00735)	-0.000802	(0.00179)	-0.0024	(0.0105)	-0.449	(0.466)
2012	-5.02E-05	(0.00111)	-0.00298	(0.00171)	-0.05	(0.00732)	0.000183	(0.00174)	-0.0194	(0.0109)	-0.41	(0.485)
2013	-0.000495	(0.00129)	-0.00533	(0.00184)	-0.0525	(0.00758)	0.000178	(0.00174)	0.00602	(0.0111)	-1.007	(0.492)
2014	0.00138	(0.00163)	-0.00249	(0.00228)	-0.0559	(0.00923)	-0.000717	(0.00211)	-0.026	(0.0135)	0.213	(0.563)
2015	0.000602	(0.00174)	-0.00717	(0.00253)	-0.0655	(0.0104)	0.00309	(0.00271)	-0.0162	(0.0158)	1.939	(0.684)
2016	0.0028	(0.00129)	-0.00129	(0.00237)	-0.0693	(0.0103)	0.000147	(0.00234)	-0.00418	(0.0154)	0.327	(0.631)
2017	-0.00294	(0.00157)	-0.0083	(0.00214)	-0.0648	(0.0103)	-0.00431	(0.00213)	-0.0155	(0.0161)	-0.281	(0.632)
2018	-0.00149	(0.00169)	-0.00639	(0.00244)	-0.0469	(0.0104)	-0.000345	(0.00231)	-0.0131	(0.0156)	0.14	(0.613)
2019	-0.00216	(0.00293)	-0.0125	(0.00415)	-0.0574	(0.0153)	-0.00241	(0.00339)	-0.0481	(0.0230)	-0.363	(0.934)

Probit models where dependent variable is switched response status. Additional controls include level of error, all Mincer controls, level and square of DER earnings. Standard Errors in parenthesis. Source: U.S. Census Bureau, Current Population Survey 1996-2019 Annual Social and Economic Supplement Social Administration Detailed Earnings Record, 1995-2018.