# Errors in the Reporting of Unemployment Insurance and Unemployment: Estimates and Implications

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**Abstract**

We provide the first national, and only recent, estimates of the errors in reporting of survey unemployment insurance (UI) receipt using linked data. We also provide the first comparisons of administrative measures of unemployment to survey reports. Both sets of estimates indicate large errors with implications for many literatures. We link national data on UI receipt from the Internal Revenue Service to two of the most important Census Bureau surveys: the Current Population Survey Annual Social and Economic Supplement (CPS) and the Survey of Income and Program Participation (SIPP). As well as documenting other errors, we find that 39% and 35% of UI recipients have no recorded receipt in the CPS and SIPP, respectively. Errors are larger for Black and Hispanic individuals, those with lower incomes, and the elderly. Strikingly, 49% and 43% of UI recipients erroneously report never being unemployed in the CPS and the SIPP. These discrepancies are greater for those with lower UI amounts and during economic expansions, suggesting the presence of salience and perhaps stigma as explanatory factors. The results imply that UI is taken up at a higher rate, reduces poverty more considerably, and reaches racial and ethnic minorities to a larger degree than reported in the survey data. The results also suggest that unemployment is greatly understated, its cyclicality overstated, and weekly earnings understated.

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# 1. Introduction

Unemployment Insurance (UI) is a key component of the safety net intended to reduce the hardship of unemployment. In 2010, during the height of the Great Recession, more than $150 billion in UI benefits were paid out – more than the combined amounts of the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance to Needy Families (TANF), and the Earned Income Tax Credit (EITC). In 2020, a record $581 billion of UI benefits were paid out under pandemic-induced program expansions. Given the size and importance of UI, obtaining accurate estimates of who receives benefits and who is missed is crucial for assessing the degree to which the program is meeting its objectives. A decades-long literature has measured the magnitude of UI take-up and the determinants of receipt,[1] with more recent studies seeking to document disparities in UI receipt across subgroups.[2] A common finding in these papers, particularly those relying on survey data, is that a large share of eligible individuals do not receive benefits and that there are large disparities in UI take-up by race and ethnicity. There are also well-established literatures on unemployment that focus on its level, cyclical pattern, causes, costs, and other issues.[3]

However, many studies of UI and unemployment rely on survey data that are prone to error. Comparisons of survey and administrative totals have long pointed to transfer programs being severely underreported in survey data (Meyer, Mok, and Sullivan 2015). Figure 1 plots the evolution of UI benefit amounts against the share of actual dollars reported in the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) in recent years. The underreporting of UI is pronounced and appears to have worsened over time, with the reporting rate hitting 74% in 2008, drifting towards 60% in the 2010s, and collapsing below 40% in 2020. Yet, net underreporting rates embed a variety of different errors (e.g., false negatives, false positives, dollar misreporting, and coverage/weighting errors) that can cancel out. Distinguishing between these error components requires linking survey data to administrative records, and no

[1] See, e.g., Blank and Card (1991), McCall (1995), Anderson and Meyer (1997), Vroman (2009), and GAO (2022).
[2] See, e.g., Gould-Werth and Shaefer (2012), Nichols and Simms (2012), Bitler, Hoynes, and Schanzenbach (2021), Forsythe and Yang (2021), Kuka and Stuart (2021), and Skandalis, Marinescu and Massenkoff (2022).
[3] See, e.g., Bowen and Finegan (1969), Mortenson (1986), Blanchard and Katz (1997), Machin and Manning (1999), Mortenson and Pissarides (1999), Pissarides (2000), and Abraham and Kearney (2020).

study – to the best of our knowledge – has disentangled the extent and nature of UI misreporting at the individual level.[4]

While the accurate reporting of UI is of first-order importance, the measurement of unemployment itself is even more foundational. The unemployment rate is among the most important and frequently referenced economic statistics in the United States. Poorly reported measures of unemployment can also yield implications for many microeconomic and macroeconomic analyses, particularly if the errors add bias rather than statistical noise. A long literature has emphasized the misreporting of unemployment in surveys, but a fundamental limitation of our knowledge base is that we do not have complete administrative data on unemployment in the U.S. Prior studies have tended to examine within-survey inconsistencies or relied on assumptions about the true values of unemployment.[5]

In this paper, we leverage a novel linkage of administrative UI data to surveys to provide evidence on the reporting of UI receipt and unemployment. Specifically, we link the universe of UI payments on Form 1099-G from the Internal Revenue Service (IRS) to two major Census surveys: the CPS ASEC and the Survey of Income and Program Participation (SIPP). These linked data enable us to calculate the first national estimates of individual-level measurement error in UI receipt. More strikingly, our new data facilitate perhaps the most informative analysis to date of retrospectively reported unemployment in surveys. The 1099-G records provide an administrative measure of unemployment for a subset of the truly unemployed, allowing us to clearly identify errors in the survey reports of unemployment. The reference period of the tax records aligns exactly with that of the two survey datasets we analyze. Our focus is on reference year (tax year) 2010, which had the highest amount of UI benefits paid out prior to the pandemic and was thus a time when UI was particularly important.

We start by calculating aggregate biases in the CPS and SIPP, showing that total UI dollars in both surveys are understated by 36-38% compared to the linked values from Form 1099-G. The vast majority of the understatement comes from the presence of false negatives: 39% and 35% of

[4] The closest is Larrimore, Mortenson, and Splinter (2023), who examine the underreporting of UI dollars during the COVID-19 pandemic but do so by comparing unlinked estimates from the CPS ASEC and administrative records.
[5] Prior work has analyzed rotation group bias and differences in the reporting of unemployment by time in sample (Bailar 1975, Solon 1986, Krueger, Mas, and Niu 2017), misreporting of the length of unemployment (Poterba and Summers 1984), misreporting of unemployment status (Abowd and Zellner 1985, Poterba and Summers 1986), and the conflict between contemporaneous and retrospective measures of unemployment (Levine 1993). However, several studies using data from outside the U.S. (e.g., Sweden) have linked administrative unemployment register data to surveys to assess measurement error in retrospective work histories (Pina-Sanchez, Koskinen, and Lewis 2014, 2019).

UI recipients do not report any receipt in the CPS and SIPP, respectively. We then estimate misreporting rates by demographic subgroup, finding that survey-reported UI dollars are most understated for those who are less educated, lower-income, Black or Hispanic, and elderly. These patterns are again a direct result of the staggering false negative rates for these groups, ranging between 47-52% in the CPS and 37-53% in the SIPP. These differences remain after controlling for other predictors of survey error. We then show that the administrative UI data notably change our understanding of the determinants of UI take-up. While eligible Black and Hispanic individuals are no more likely to receive UI than white individuals according to survey data, they are significantly *more* likely to take up UI when using the linked administrative values. This result is robust to multiple ways of defining UI eligibility using survey and/or administrative data.

While our results on UI mainly focus on misreporting in surveys, we also examine errors in administrative measures of UI receipt – specifically on Form 1040, which many researchers have long regarded as containing "true" measures of taxable income for those filing tax returns. We find that 24% of true UI recipients according to Form 1099-G do not report UI receipt on Form 1040. Notably, 44% of this group (11% of true UI recipients) file a 1040 but report no UI benefits on their returns. Among the 56% of this group who do not file a 1040 at all, more than half appear to have taxable incomes above the filing threshold. These results provide a novel examination of the degree to which administrative income sources may be measured with error.

Lastly, and most strikingly, we observe large errors in the reporting of retrospective unemployment among UI recipients. Among all UI recipients according to 1099-Gs, 49% erroneously report never being unemployed in the CPS and 43% report not being unemployed in the SIPP. Nearly half of these discrepancies are associated with UI recipients who report working for the entire year on a full-time basis. We also find in both surveys that these discrepancies are decreasing in UI amounts, with those in the lowest ventiles of benefit receipt dollars much more likely to never report being unemployed than those with higher amounts of benefits received.. These patterns suggest a role for salience in explaining discrepancies, as those receiving UI for very short periods may be less likely to recall receipt. Finally, we show evidence that the evolution of these discrepancies follows a remarkably procyclical time series, with greater (lower) discrepancies during economic expansions (downturns). This pattern is again suggestive of not only salience but also stigma as a driving factor behind the unemployment discrepancies.

Our paper contributes to several important literatures. Several studies have used linked survey and administrative data to examine not only the magnitude of survey error for a given income source but also the correlation of such errors with demographic characteristics. The misreporting patterns for other benefits suggest that survey and administrative data sources can paint very different pictures of the rate of program take-up and the degree to which a program reaches different subgroups of the population.[6] In reviewing the results of existing studies, Meyer, Mittag, and Wu (2024) find a strong and robust, but previously largely unnoticed, pattern of greater measurement error for Black and Hispanic individuals relative to whites. This pattern persists across multiple income sources, surveys, and time periods. While our study is the first to study measurement error in UI using individually-linked microdata, a key contribution we make is to further clarify the degree to which survey errors vary across demographic subgroups. A critical implication of our results is that prior studies relying solely on survey data have overstated the Black-white and Hispanic-white gaps in UI take-up. This is a result of UI supporting Black and Hispanic individuals, among other subgroups, better than the survey data suggest.

Furthermore, our analysis of the underreporting of UI on tax returns relates to a small but growing literature on errors in administrative data. Like survey data, administrative records can be of heterogeneous quality. A number of studies have paid special attention to the quality of administrative data on earnings, with concerns about tax records not capturing informal wages (Abowd and Stinson 2013, Abraham et al. 2013, Bee et al. 2023, Meyer and Wu 2023) and understating self-employment/gig earnings (Collins et al. 2019, Abraham et al. 2021). Yet, outside of earnings, there is little work on the underreporting of other income sources in administrative records. This paper sheds light on such patterns for one income source (UI) by comparing reports on Form 1040 to true values on Form 1099-G, showing substantial evidence of underreported UI on 1040s. We therefore contribute to a growing base of evidence showing that administrative data sources are incomplete, suggesting that reliance on a single administrative source as "truth" may continue to yield underreported incomes. Our findings are also relevant to a literature on tax compliance (e.g., Slemrod 2019) and the determinants of non-filing (e.g., Langetieg, Payne, and Plumley 2018).

[6] See, e.g., Meyer, Mittag, and Goerge (2022) and Celhay, Meyer, and Mittag (2022) on SNAP/TANF, Bhaskar et al. (2019) on Medicare, Davern et al. (2009) on Medicaid, and Bee and Mitchell (2017) on Social Security and pensions.

Finally, our analysis of the reporting of unemployment contributes to a broad literature on the reporting of various employment characteristics. In addition to prior work on the misreporting of unemployment, a number of studies have examined measurement error in work time and hours (e.g., Borjas 1980, Rodgers et al. 1993, Bound et al. 1994, Borjas and Hamermesh 2024) as well as errors in earnings in both survey and administrative sources (e.g., Bound and Krueger 1991, Bollinger 1998, Abowd and Stinson 2013, Abraham et al. 2013, 2021). While we are focused on the measurement of unemployment, one could argue that the stark errors we document along this extensive margin are more concerning than the errors in intensive margin measures like work time and earnings amounts. Unemployment is the central ingredient in understanding labor market dynamics. Connecting our two sets of results, the extent to which it is misreported casts doubt on whether it can be used to determine the sample over which to calculate UI take-up and even provide a foundation upon which to impute UI receipt more accurately.

The rest of the paper proceeds as follows. Section 2 describes the survey and administrative data sources we use and how they are linked. Section 3 shows results on aggregate biases in survey UI values and decomposes these overall errors into their components. Section 4 then examines how the misreporting of survey UI varies across demographic subgroups, before using the linked administrative data to re-examine the determinants of UI take-up. Section 5 assesses errors in administrative measures of UI, and Section 6 analyzes the reporting of unemployment status among UI recipients. Section 7 concludes.

# 2. Data Sources and Linkage

In this section, we discuss the survey and administrative data sources used to measure UI receipt and the methods we use to link multiple data sources. As noted earlier, our focus is on reference year (tax year) 2010.

**Survey Data**

We use 2010 data from two Census surveys: the 2011 CPS ASEC (hereafter CPS) and the 2008 SIPP Panel. The CPS is the official source of income and poverty statistics in the U.S., and the SIPP is typically regarded as having the highest quality information on incomes and receipt of government programs. Both surveys ask respondents at the individual level whether or not they receive unemployment insurance (and, if so, the benefit amount received). Respondents are also

asked whether they are unemployed during the reference period, which is defined as spending more than zero weeks looking for work or on layoff from a job. While the reference period for the CPS is a calendar year, the default reference period in the SIPP is four consecutive months. We thus combine information across multiple interview waves in the SIPP to construct calendar year incomes that align with the reference periods in the CPS and administrative records.

We use two separate methodologies to combine information across SIPP interview waves. For our first method, we take as our analysis sample all individuals who appear in reference month 4 of Wave 6 (which spans April-July 2010), bring in information on survey incomes from other months in 2010 during which they appear, and proportionately scale up survey incomes for the individuals who are interviewed for only a portion of the year (see Meyer, Wu, and Curran 2021). This allows us to make use of the full survey sample, although we may over- or underestimate incomes for individuals who attrit from the survey. For the second method, we take as our analysis sample all individuals in reference month 4 of Wave 6 who are interviewed for every month of the 2010 calendar year, and we reweight our sample to account for attriting individuals. The advantage of this method is that we construct calendar year incomes using exclusively reported incomes (rather than imputing incomes for missing months), but the disadvantage is that doing so results in a smaller and potentially unrepresentative sample. To account for non-random attrition under this second method, we divide survey weights by the predicted probability that an individual is interviewed for every month of the 2010 calendar year conditional on observables in the survey (see Wooldridge 2007).

**Administrative Data**

To measure UI receipt in the administrative data, we rely on the universe of Form 1099-G records submitted to the IRS during the 2011 calendar year, primarily for the 2010 tax year.[7] These are information returns for individuals receiving certain government payments that include but are not limited to UI. Importantly, these records exist for all recipients of UI, regardless of whether or not they file tax returns. Using this source, we measure UI benefit dollars using the amount in Box 1 ("Unemployment Compensation") and define UI recipients as those having a positive amount in Box 1 of their 1099-G. Note that Box 1 also contains amounts for government paid family leave

[7] These data are provided to the U.S. Census Bureau under Section 6103(n) of Title 26, which gives access to the data for the purpose of tax administration.

(only for California and New Jersey) and temporary disability income (only for California) for a small share of individuals. While we cannot disentangle these programs from UI, we later show that dropping California and New Jersey from our analyses yield very similar results.

We also make use of the universe of IRS Form 1040 records as a secondary source on administrative UI amounts. We mainly rely on 1040s filed in processing year 2011 for tax year 2010, although as a robustness check we also examine late 1040s filed in 2012. Using this source, we measure UI benefit dollars using the amount in Line 19 ("Unemployment Compensation") and define UI recipients as those reporting a positive amount on Line 19 of their 1040. Note that 1099-Gs contain UI amounts at the individual level, while 1040s contain UI amounts at the tax unit level (which may reflect amounts for two individuals for married tax units). As we discuss later in this paper, we are able to empirically validate that all UI dollars in 1040s are effectively a subset of those in 1099-Gs. Our main analyses of survey misreporting make use of comparisons to 1099-Gs, but we can use 1040s to assess measurement error in an administrative data source. Finally, we use wages from IRS Form W-2 to help with simulating 1) UI eligibility and 2) incomes relative to the filing threshold (to assess the share of non-filing UI recipients who should have filed a 1040).

**Linking Data Sources**

We link administrative records to survey data using Protected Identification Keys (PIKs), which are created by the U.S. Census Bureau's Person Identification Validation System (Wagner and Layne 2014). Over 99% of all administrative tax records are linked to PIKs, while a smaller share (approximately 80-90%) of individuals in the CPS and SIPP are linked to PIKs. Our sample in the CPS consists of survey individuals who have PIKs and are not whole imputed, while our sample in the SIPP consists of survey individuals who have PIKs. We do not explicitly exclude whole imputed observations from our SIPP sample because they constitute a much smaller set of all individuals in the SIPP (relative to the CPS). Our linked samples of analyses therefore comprise 80% of the original sample in the CPS and 89% of the original sample in the SIPP.

To account for the bias arising from non-random missing PIKs (and whole imputations in the CPS), we divide individual survey weights by the predicted probability that an individual has a PIK (and is not whole imputed in the CPS) conditional on observable characteristics in the survey. We adjust for missing survey PIKs at the individual level because the administrative tax data contain incomes at the individual level. If we instead adjust missing survey PIKs at some

broader level like the family or household, then we would necessarily understate administrative income sources because we are including in our sample individuals who do not have a PIK (and therefore cannot be linked) but are part of a unit with at least one member who does. This contrasts with prior studies that adjust for missing PIKs at the family level (see, e.g., Meyer and Wu 2018, Meyer et al. 2021, Meyer and Wu 2023). These studies generally rely on administrative records containing incomes at the tax unit or assistance unit level, and so having at least one PIKed member in the survey family can enable income amounts to be brought in for the entire family.

# 3. Misreporting of UI in Survey Data

This section discusses the extent to which survey reports of unemployment insurance are misreported. As a starting point, we compare weighted totals for UI recipients and dollars in survey data (CPS and SIPP) to linked totals from the administrative records. We then use the linked microdata to calculate the magnitudes of errors at the extensive margin (false positives and false negatives) and intensive margin (incorrect dollars among true reporting recipients). Finally, we decompose the overall biases in dollars into these error components. For our analyses using the SIPP in this section, we report two sets of estimates corresponding to the two methods for combining information across interview waves.

**Comparisons of Aggregates**

Table 1 shows aggregate UI dollars and recipients in the CPS and SIPP using both survey and linked administrative (1099-G) values. Column 1 shows calendar year survey totals using the full survey samples and original survey weights. Columns 2 and 3 shows survey and administrative totals using the linked survey samples and adjusted survey weights. Column 4 shows the proportional bias in survey estimates (in Column 2) as a percentage of the linked administrative totals (in Column 3), and Column 5 shows the proportional bias in survey estimates (in Column 2) as a percentage of the universe 1099-G totals ($152 billion and 20.15 million recipients). While Columns 4 and 5 each use administrative values as their benchmarks, they can differ due to errors in survey coverage that affect Column 3 (arising from non-representative survey frames, differential unit non-response, and/or weighting issues).

Using the full samples, we start by observing similar levels of survey-reported UI dollars across both surveys ($97.4 billion in the CPS and $91.4-$93.8 billion in the SIPP) but higher levels

of survey-reported UI recipients in the SIPP (14.5-14.9 million individuals) than in the CPS (12.5 million individuals). The SIPP therefore does a better job than the CPS in capturing recipients, but the recipients in the SIPP have lower average amounts such that total dollars are lower in the SIPP. These totals remain virtually unchanged when transitioning to the linked survey sample for the CPS, while they increase slightly for the SIPP (Column 2). The similarities between Columns 1 and 2 partly serve to validate the IPW methodology for restoring the population representativeness of the linked subsample of analysis.

In each dataset, we find that survey reports sharply understate linked administrative values. In the CPS, total survey dollars and recipients are 31.2% and 34.2% lower, respectively, than their linked administrative counterparts (Column 4). In the SIPP, total survey dollars and recipients are 37.4% and 27.0% below the linked administrative totals for the sample of all individuals, while they are 38.9% and 24.4% below the linked administrative totals after restricting the sample to individuals interviewed for the entire calendar year. The understatement of survey totals for the CPS becomes even more pronounced when comparing to universe totals (Column 5), suggesting that UI recipients are under-covered by approximately 6-7% in the CPS.[8] In contrast, the survey estimates for the SIPP are similarly understated whether they are compared to linked or universe administrative totals, suggesting little to no generalized coverage error in the SIPP.

**Individual-Level Error Components**

The aggregate errors in Table 1 show pronounced underreporting of UI receipt in both the CPS and SIPP, but it remains to be seen how these overall errors break down across various components. Table 2 sheds light on individual-level misreporting by calculating the rate of false positives (true non-recipients who report receipt in the survey), the rate of false negatives (true recipients who do not report receipt in the survey), and measurement error in benefit amounts among true recipients who report receipt in the survey. The first two components can be thought of as misreporting on the extensive margin, while the third component can be thought of as misreporting on the intensive margin.

Focusing on false positives, we find that 0.33% of true non-recipients in the CPS falsely report receipt, compared to 0.80% of all individuals and 0.77% of non-attriting individuals in the

[8] Meyer and Wu (2021) find similar rates of under-coverage of SNAP recipients in the CPS. These errors can result from errors in the survey frame, unit non-response, and incomplete weighting adjustments.

SIPP.[9] Looking next at false negatives, we find that 39.2% of true UI recipients do not report receipt in the CPS, with this rate being only slightly lower in the SIPP for all individuals (38.0%) and for non-attriting individuals (35.1%). The higher false negative rate in the SIPP among all individuals (compared to the non-attriting sample) is likely a result of some attriting individuals receiving UI after leaving the survey but continuing to be assigned zero survey UI for the missing months. While these false negative rates are high, they are in the same general ballpark as the false negative rates calculated by prior studies for various programs.[10] Nevertheless, false negatives tend to be associated with below-average UI amounts from the 1099-Gs, suggesting that some of them are short-term UI recipients for whom receipt is less salient.

Among true reporting recipients, the mean net error in UI benefit amounts is $875 in the CPS and between $2,272-$2,485 in the SIPP. In the CPS, the relatively small net error for true reporting recipients appears to be a result of overreported amounts canceling out some underreported amounts. As evidence for this, the mean absolute error for this group is $3,030, more than three times as large as the mean net error and approximately a third of the average UI amount from 1099-Gs. The mean absolute error for true reporting recipients is even larger in the SIPP ($3,732 for all individuals and $3,590 for non-attriting individuals). However, the relative difference in the mean absolute error and mean net error is smaller in the SIPP than in the CPS, suggesting there is less overreporting of UI amounts in the SIPP among true reporting recipients.

To formally connect the aggregate dollar biases in Table 1 and the individual-level errors in Table 2, we use the methodology from Meyer and Mittag (2021) to decompose the overall bias in UI dollars into its sources. Specifically, we focus on the bias of survey dollars against universe totals from Column 5 of Table 1, which we break down into extensive margin reporting errors (false negatives and false positives), intensive margin errors in amounts among true reporting recipients, and a residual component that reflects generalized coverage error in the survey. The results are displayed in Figure 2, which shows that false negatives contribute the most to the overall negative bias. This is particularly true in the CPS, where false negatives themselves lead to a 26.2% downward bias in UI dollars (compared to an overall bias of 36.2%). In the SIPP, false negatives

[9] The higher rate of false positives for UI in the SIPP compared to the CPS is consistent with cross-survey patterns in false positives that have been previously found for SNAP (Meyer, Mittag, and George 2022).
[10] Using 2008-2011 CPS data for New York, Meyer and Mittag (2019) calculate false negative rates of 43% for SNAP, 63% for Public Assistance, and 36% for housing assistance.

contribute to a 25.2% and 22.8% downward bias in UI dollars for all individuals and non-attriting individuals (compared to overall biases of 36.8% and 38.2%, respectively).

False positive rates, on the other hand, result in an upward bias in UI dollars of 4.0% in the CPS, 6.4% in the SIPP among all individuals, and 5.0% in the SIPP among non-attriters. The larger bias in UI dollars among all false positives in the SIPP (compared to non-attriting false positives) is likely a result of our scaling up false UI dollars for individuals with missing interview months.[11] Measurement error among true reporting recipients translates to a 6.6% downward bias in UI dollars in the CPS and a 18.9% and 21.5% downward bias in UI dollars for all individuals and non-attriting individuals, respectively, in the SIPP. After dealing with false positives, false negatives, and misreporting of UI amounts among true reporting recipients, we find a remaining 7.3% downward bias in survey dollars in the CPS and a 1.0-1.2% upward bias in survey dollars in the SIPP. These residual biases can be interpreted as under-coverage of UI recipients in the CPS and slight over-coverage of UI recipients in the SIPP.

**Robustness Check: Accounting for Non-UI Incomes Reported on Form 1099-G**

As we mentioned in Section 2, a caveat of our analysis so far is that the Box 1 amounts on Form 1099-G may include some government programs beyond UI. These specifically include California's Family Temporary Disability Insurance program and governmental paid family leave programs (adopted only by California and New Jersey in 2010). Including these programs may lead us to overstate administrative UI dollars and thus overstate the degree of survey underreporting. While we cannot distinguish non-UI amounts from UI amounts on 1099-Gs, we can carry out robustness checks where we calculate estimates omitting California and New Jersey (and thus ensuring that 1099-G amounts reflect only UI benefits).

Appendix Table A1 shows similarly stark levels of underreporting even for this subsample. In terms of aggregate errors, we find that dollars are underreported by 29.1% in the CPS and 38.1-39.0% in the SIPP, while recipients are underreported by 32.6% in the CPS and 23.1-25.9% in the SIPP. Compared to the national estimates in Table 1, the biases here are only slightly smaller for the CPS (by about two percentage points) and remain effectively unchanged for the SIPP. Even

[11] In contrast, the false positive *rates* remain very similar across the two SIPP samples, since false positives in the SIPP are defined as true non-recipients who report receiving UI in the survey for at least one month of the reference period.

when examining individual-level error measures, Appendix Table A2 shows that the false negative rates for this subsample are 38.2% in the CPS and 34.4-37.5% in the SIPP – each within a percentage point of the comparable false negative rates calculated inclusive of California and New Jersey. Consequently, we conclude that these additional programs reported on 1099-Gs have trivial impacts on the overall misreporting rates that we calculate for the full population. Going forward, we therefore report all of our estimates for the full population.

# 4. UI Errors and Take-Up by Demographic Subgroups

Having so far discussed estimates of misreporting for the full population, we now describe how errors vary across key demographic subgroups. We start by calculating raw false positive and false negative rates, before decomposing the overall bias in dollars due to different error components. We then analyze the extent to which differences in false negative and positive rates remain statistically significant after controlling for other individual characteristics. We finally use the linked administrative data to re-examine the determinants of UI take-up. For simplicity, our main estimates in this section and in subsequent sections rely on the full-sample SIPP, rather than the subsample of non-attriting individuals.

### Raw Error Rates and Decomposing Biases in Overall Dollars

Table 3 starts by showing raw false positive and false negative rates across four categories of key demographic characteristics.[12] For our main estimates, we focus on differences by race and ethnicity, education level of the family head, family income (as a share of the poverty line), and the age of the family head. These reflect many of the characteristics that prior studies have focused on when examining disparities in program (and particularly UI) receipt, although we report error rates for additional characteristics in Appendix Table A3.[13] We interpret these error rates alongside their contribution to the overall biases in dollar amounts that we calculate by subgroup, which are shown in Figure 3a for the CPS and Figure 3b for the SIPP. These dollar biases are calculated relative to totals from the linked administrative values rather than the universe administrative

[12] While the false positive rates calculated in Section 3 are conditional on all true non-recipients (regardless of age), the false positive rates here are conditional on true non-recipients aged 18 and over.

[13] These additional characteristics include geography (specifically Census region and Census division), metropolitan status (urban versus rural), immigrant status, family type (elderly, single parent, multiple parents, single childless, and multiple childless individuals), and industry.

values, meaning we are unable to disentangle the variation in coverage error across subgroups. This is because these demographic characteristics do not appear in the administrative records. For the SIPP, Appendix Figure A1 show results for the non-attriting subsample that are largely comparable to the full-sample results.

Among racial and ethnic subgroups, Black (non-Hispanic) and Hispanic individuals consistently have the highest false negative rates in both surveys. In the CPS, a staggering 49.0% and 51.5% of true Black and Hispanic recipients do not report receipt in the survey, compared to only 33.2% of white recipients. In the SIPP, the false negative rates are 50.0% and 42.2% for Black and Hispanic recipients, compared to 33.3% for white recipients. Black individuals also have higher false positive rates (0.82% and 1.63% in the CPS and SIPP) compared to other racial and ethnic subgroups, suggesting that survey data are noisier in general for them. Overall, survey UI dollars for Black and Hispanic individuals are understated by 39.7-42.6% in the CPS and 44.0-50.0% in the SIPP, exceeding the understatement of dollars for all other racial subgroups. The false negatives are so pronounced that they explain 93-97% of the overall dollar bias in the CPS and 68-72% of the dollar bias in the SIPP for these subgroups. In the SIPP, Black and Hispanic individuals also tend to have greater misreporting of dollar amounts among true recipients.

Next, those with lower levels of educational attainment tend to have higher false negative rates and thus greater dollar underreporting. In the CPS, 46.8% of UI recipients without a high school diploma do not report receipt in the survey, with these rates monotonically decreasing in education attainment (to 32.73% for those with at least a bachelor's degree). False negative rates are more homogeneous in the SIPP, but they are still second-highest for those with less than a high school diploma (36.8%) and highest for those with only a high school diploma (42.4%). The larger false negative rates again translate to greater dollar underreporting for those with lower levels of education. Among those with a high school diploma or less, UI dollars are underreported by 30.4-40.0% in the CPS and 36.9-43.2% in the SIPP. False positive rates, on the other hand, have less of a noticeable gradient across educational levels; they are highest for high school graduates in the CPS and those with some college in the SIPP.

Moving to differences by survey-reported income (as a share of the poverty line), we observe somewhat varying patterns across surveys. In the CPS, false negative rates are highest at 52.2% among those with the lowest incomes – i.e., below 100% of the federal poverty line (FPL). In the SIPP, however, false negative rates are greatest (41.0-42.3%) for those with higher incomes

(above 300% FPL) and are still large at 39.7% for those with incomes below 100% FPL. False positive rates tend to be larger for those with incomes below 300% FPL in both surveys, but the patterns across more granular income bins are less clear. We see the greatest underreporting of overall UI dollars among those with incomes below 100% FPL (62.6% and 54.2% of dollars missed in the CPS and SIPP, respectively), but the underlying mechanisms differ across surveys. More than three-quarters of the net underreporting is due to false negatives in the CPS, while nearly half of the net underreporting is due to measurement error among true recipients in the SIPP. The differences across surveys could be due in part to contrasts in how incomes are reported, which would lead to differential misclassification of individuals into income buckets.

Finally, in looking at subgroups defined by the age of the family head, we observe a distinctly non-monotonic pattern for false negative rates. In the CPS, false negative rates are highest for those aged 25 or below (47.0%) and 65 or older (49.8%), while they range from 34.8% to 41.6% for ages in between. Similarly, in the CPS, false negatives are most pronounced among the youngest heads (57.9%) and elderly heads (53.1%), while they again range from 32.6% to 37.1% for ages in between. The overall underreporting of dollars is highest for the elderly in both the CPS (41.4% of dollars missed) and SIPP (57.0% of dollars missed). The overall bias in dollars is also high for heads below the age of 25 (35.8% in the CPS and 54.2% in the SIPP). Note that the differences in magnitudes between surveys are again due to false negatives contributing to nearly all of the underreporting in the CPS while the combination of false negatives and measurement error among true reporting recipients jointly contribute to the biases in the SIPP.

**Differences in Covariate-Adjusted Error Rates**

The previous subsection described unconditional patterns in misreporting across demographic subgroups. However, it remains to be seen whether or not these patterns hold after conditioning on other characteristics. Specifically, we run probit regressions of a binary indicator for misreporting on a variety of demographic and economic characteristics. When analyzing false negatives, our dependent variable is a dummy variable for not reporting receipt in the survey and our sample consists of all true recipients. When analyzing false positives, our dependent variable is a dummy variable for reporting receipt in the survey and our sample consists of all true non-recipients over the age of 18.

Table 4 shows the results of these regressions in both the CPS and SIPP. To aid the interpretation of magnitudes, we present average partial effects (APEs) on the probability of being a false negative or false positive reporter. We show selected coefficients that correspond to the key subgroups we have been focusing on, with the omitted variables for each category being white non-Hispanic (for race/ethnicity), having a BA or more (for education level), having income above 400% FPL (for income-to-poverty), and being 65 or older (for age). In addition to including all of these variables simultaneously as regressors, we control for a wide variety of other characteristics whose estimates can be found in the full regression output in Appendix Table A4.[14]

Even after controlling for other characteristics, we continue to observe statistically significant differences in error rates between a number of subgroups (particularly in terms of false negatives). When looking across race and ethnicity, we find that false negative rates are statistically significantly higher for all minority subgroups relative to white non-Hispanic individuals in both surveys. The magnitudes are meaningful. In the CPS, false negative rates are 11.9, 11.2, 9.5, and 6.6 percentage points higher for Hispanic, Asian (non-Hispanic), Black (non-Hispanic), and other race (non-Hispanic) recipients, with these differences translating to 17-30% of the dependent variable mean. In the SIPP, false negative rates are 11.0, 8.7, 6.4, and 5.8 percentage points higher for Black, Asian, other race, and Hispanic recipients relative to whites, with these differences amounting to 15-29% of the dependent variable mean. In terms of false positives, we continue to observe significantly higher covariate-adjusted error rates for Black individuals in both the CPS and SIPP, and for Asian and Hispanic individuals in the CPS only. When looking at differences by education, we no longer observe statistically significant differences between groups in terms of false negatives. We do find some evidence of greater false positives among those with lower education levels, but these patterns are statistically significant only in the CPS.

Turning next to differences by income, we find statistically significant gaps in false negative rates – particularly for the CPS – that mirror the unconditional patterns from the previous subsection. Specifically, those with incomes below 100% FPL in the CPS have false negative rates that are 23.4 percentage points higher than those with incomes above 400% FPL (with this difference amounting to nearly 60% of the dependent variable mean). The differences become

[14] These additional covariates include Census division (8 groups), an indicator for having UI item imputed, an indicator for being whole imputed (SIPP only), non-citizen, male, metro status, family type (4 groups), an indicator for being the reference person, number of adults in family, number of children in family, industry type (6 groups), the UI amount in administrative data (false negatives only), weeks worked in past year, and being a full-time worker in the past year.

smaller in magnitude but remain significant as we go up the income distribution in the CPS. In the SIPP, we again see that those with incomes below 100% FPL have higher false negative rates, although the difference is only 4.9 percentage points. In contrast to the CPS, there is not much of a gradient higher up in the SIPP income distribution, as those with incomes between 100-200% FPL actually have lower false negative rates relative to the omitted group, while those with incomes between 200-300% and 300-400% FPL have differences that are not statistically significant. We do not see consistent patterns in terms of false positives, which are lower for those with incomes below 100% FPL and higher for those with incomes between 100-200% FPL in the CPS, but higher for those with incomes between 100-200% and 200-300% FPL in the SIPP.

In terms of the age of the family head, we see striking patterns for both false positive and false negative rates that are largely consistent across both surveys. In the CPS, false negative rates are lower for all age bins relative to the omitted elderly (age 65+) group, although the gaps are largest and statistically significant only for those with ages between 45-54 and 55-64. In the SIPP, false negative rates are lower by 10.4-14.3 percentage points for all age groups between 25-64 relative to the elderly, while the difference for the youngest (age <25) group is negligible and not statistically significant. While false negatives tend to be more pronounced for the oldest and youngest groups, we observe the opposite pattern for false positives in both surveys. In particular, we find that false positive rates are significantly higher for the "middle" age bins (between 25 and 64) relative to those aged 65+, while the differences in false positives between the youngest and oldest groups are not statistically significant.

Outside of our key demographic characteristics, there are a number of other characteristics that are significantly predictive of false negative and false positive rates in both surveys (Appendix Table A4). Being a non-citizen is associated with higher false negative rates, even independent of Hispanic ethnicity. Having more adults in the family is also predictive of greater false negative rates, while having imputed UI receipt in the survey is associated with higher rates of both false negatives and false positives (which is indicative of survey imputations being less accurate than self-reports). We also find that false negative rates are higher for those with lower UI amounts per the administrative data, as well as for those reporting either not being in the labor force or working more weeks during the reference period (who also have fewer false positives). This is suggestive of salience playing a role in explaining false negatives, as those receiving UI for fewer weeks may

be less likely to recall receipt. However, the high error rates in the SIPP (whose recall period is a third the length of that in the CPS) suggest that salience cannot explain the whole story.

Overall, we find robust evidence of greater UI underreporting – driven by increased false negatives – among demographic subgroups traditionally regarded as being more disadvantaged or having less access to the UI system. These include Black and Hispanic individuals, those with less than a high school diploma, those with incomes below the poverty line, and the elderly (although the differences by education status appear to be explained by other covariates). These findings suggest that these groups are better served by the UI system than previously thought, precisely because they are less adequately served by the household surveys in which they are heavily misrecorded. Yet, it remains to be seen whether or not these errors are large enough to substantively change conclusions about gaps in UI take-up between groups. We explore these implications in the next subsection.

**Determinants of UI Take-Up**

In this subsection, we assess the consequences of UI misreporting in surveys on the determinants of UI take-up (i.e., receipt conditional on being eligible). These analyses are important for examining the targeting properties of the UI program and whether it is achieving its intended goals. Our findings are also directly relevant to recent studies examining disparities in UI receipt along a number of important margins, such as race and ethnicity.

Our empirical specification consists of a probit regression of a binary indicator for UI receipt (measured using either survey or administrative data) on a whole host of demographic and economic regressors. We focus on APEs associated with four of the subgroups that we previously focused on: Black individuals, Hispanic individuals, those with less than a high school degree, and those with incomes below the poverty line. We control for a variety of other variables that strongly overlap with covariates in the misreporting regressions and whose estimates can be found in Appendix Tables A5a-A5d (for the CPS, one table per analysis sample) and A6a-A6d (for the SIPP). We estimate these probit regressions using four samples: one consisting of all individuals aged 18 and over (whose results can be interpreted in terms of "receipt") and three other samples that reflect different interpretations of UI eligibility for individuals aged 18 and over (whose results pertain to "take-up"). For each sample, we also calculate the difference in APEs for a given

regressor between the two models (one using administrative UI receipt and the other using survey UI receipt as the outcome), with standard errors calculated using the delta method.

We measure UI eligibility in three ways because it is difficult to accurately classify eligibility using only a single method. Eligibility for UI typically requires that an individual be unemployed through no fault of one's own, looking for a job (i.e., in the labor force), and have sufficiently high base period wages whose thresholds vary by state and year. Neither survey or administrative data allow us to perfectly simulate these conditions. Our first sample consists of those simulated to be eligible for UI using survey data alone, consisting of all individuals who report being unemployed during the reference period year and have current-year wages above state-specific thresholds.[15] Our second sample relies on administrative records to simulate eligibility, designating individuals as eligible if they experience a 10% drop in W-2 wages from 2009 to 2010 and also have prior-year (2009) W-2 wages above state thresholds. Our third and final sample uses a combination of survey and administrative data, classifying individuals as eligible for UI if they report being unemployed in the survey and also have prior-year W-2 wages above state thresholds. Table 5, which shows average UI recipiency rates for each analysis sample, indicates that the administrative-only eligible sample is the least restrictive (with UI take-up rates ranging from 25.7-27.2% in both surveys using administrative values). The survey-only eligible sample is more restrictive (with UI take-up rates ranging from 39.7-44.2%) and the combined survey-administrative sample is most restrictive (with UI take-up rates ranging from 48.0-55.5%).

Figures 4a-4d show the APEs for each of our four key regressors (one set of figures per regressor), with separate estimates for survey versus administrative UI receipt as the outcome, sample of analysis, and survey (CPS versus SIPP). As Figures 4a and 4b demonstrate, the administrative data nearly always show higher rates of UI receipt for Black and Hispanic individuals (relative to white individuals) than the survey data. For Black individuals, these differences are statistically significant for three out of four samples using the CPS and two out of four samples using the SIPP. For Hispanics, the differences are also significant for three out of four samples using the CPS and for all four of the samples using the SIPP. The magnitudes of the differences are also meaningful, reaching up to 20-25% of the baseline administrative UI receipt

[15] We use current-year, rather than prior-year, wages from the survey because the CPS ASEC asks all income questions for the same reference period. This will lead to some degree of mismatch, but it reflects how users of the survey data will inevitably simulate eligibility.

rate in select samples. Perhaps most importantly, using the administrative data changes not only the statistical significance but (in some cases) also the sign of the APE on the minority indicators. Survey data generally show that Black individuals are *no more likely* and Hispanic individuals are sometimes *less likely* than white individuals to take up UI, while the administrative data tend to show that Black and Hispanic individuals are *more likely* to take up UI than whites.

For individuals with less than a high school degree, we observe somewhat varying patterns across surveys. In the CPS, the administrative data show higher rates of UI receipt (relative to those with a BA or more) than the survey data, but the differences are statistically significant for only two out of four samples. Conversely, in the SIPP, the survey data tend to overstate UI receipt rates for those with less than a high school diploma – although none of the differences between the survey and administrative APEs are statistically significant. These ambiguous patterns by education are not surprising, given the lack of significant differences in covariate-adjusted misreporting rates across education subgroups. Finally, for those with incomes below 100% FPL, the administrative data show much higher rates of UI receipt (relative to those with incomes above 40% FPL) than survey data. These differences are statistically significant at the 1% level in all four samples in both surveys, and the magnitudes of the differences are large – reaching up to 25% of the average UI receipt rate using administrative data. However, even after using administrative records to correct UI receipt, we still tend to find that low-income individuals are less likely to take up UI than their higher-income counterparts, although the magnitudes of these gaps differ based on the eligibility sample used.

# 5. Errors in Administrative Measures of UI

While we have so far documented large errors in the survey reporting of UI, it may be the case that administrative records contain errors as well. Here, we have an opportunity to examine such errors given the presence of two sources of administrative UI data: one that effectively reflects "self-reports" on 1040s and another that reflects a comprehensive measure of truth from 1099-Gs. We start by comparing total UI dollars between these sources, before decomposing the individual-level components of the discrepancy. We conclude by discussing implications for tax compliance.

**Discrepancies in UI Benefits Between 1040s and 1099-Gs**

We start by comparing aggregate UI dollars calculated from our two sources of administrative microdata. We estimate aggregate UI benefit dollars of $152 billion from Form 1099-G filings and $119 billion from Form 1040 filings that were filed in calendar year 2011 for tax year 2010 (Appendix Figure A2). While the aggregate UI dollars from our 1040 microdata are very similar to public aggregates from 1040 line item totals ($120.2 billion), they are approximately 22% lower than the totals from the 1099-G microdata.[16] To decompose the individual-level components of this discrepancy, we link the universe of Form 1040 records to Form 1099-G records. Note that this linkage is performed between universe records, so there is no need use survey weights or even reweight to account for non-PIKing (as more than 99% of tax records have a valid Social Security Number or Individual Taxpayer Identification Number and can thus be attached to a PIK).

Table 6 investigates the sources of the discrepancy in UI benefit dollars between the 1040 and 1099-G microdata. In Panel (a), we break down UI benefits in 1099-Gs based on whether or not they link to 1040s. We find that only 78.5% of UI dollars in the 1099-Gs (corresponding to 75.6% of individual recipients) link to 1040s that report positive UI income. In contrast, 6.2% of 1099-G UI dollars (corresponding to 10.6% of recipients) link to 1040s reporting zero UI income and 15.3% of 1099-G UI dollars (corresponding to 13.7% of recipients) do not link to any 1040.[17] Table 1 indicates that UI recipients who file a 1040 but do not report UI on their 1040s have lower benefit amounts ($4,423 per individual) than average, suggesting that they may have received UI for a shorter period of time and thus regard it as a less salient income source.[18] In contrast, UI recipients who do not file a 1040 have slightly higher benefit amounts ($8,385 per individual).

[16] Form 1040 estimates do not include any adjustments for IRS enforcement. Note that the IRS Automated Underreporter Program identifies and works a number of Form 1040 cases each year based on Form 1099-G unemployment underreporting. We also compare these totals to aggregates from a range of other public sources for 2010 (Appendix Figure A2). We obtain total UI dollars of $137 billion and $138.9 billion from the U.S. Department of Labor (DoL) and the National Income and Product Accounts (NIPA), respectively. The amounts from both of these sources fall approximately 9-10% short of the 1099-G totals. Using DoL totals supplemented with disaster unemployment allowance, trade readjustment allowance, and federal additional compensation, Meyer, Mok, and Sullivan (2015) calculate total UI dollars of $148.5 billion (within 2% of the 1099-G totals). Finally, we obtain total UI dollars of $160.1 billion from the Office of Management and Budget, which are 5% higher than the 1099-G totals.

[17] Some UI recipients may not have filed a 1040 because they had taxes withheld on their UI benefits and mistakenly believed that was sufficient.

[18] In 2009 (the year prior to our reference year), the first $2,400 of UI was tax-exempt under the American Recovery and Reinvestment Act (see https://www.irs.gov/pub/irs-news/ir_09-029.pdf). As a result, some UI recipients receiving less than $2,400 in benefits in 2010 may have mistakenly believed that this tax-exemption extended another year.

In Panel (b) of Table 6, we do the reverse analysis and break down UI benefits in 1040s based on whether or not they link to 1099-Gs. We find that 99.6% of 1040 UI dollars (corresponding to 99.2% of tax units) link to 1099-Gs. Moreover, the 1040 UI dollars for those linking to 1099-Gs ($118.5 billion) are very similar to the 1099-G UI dollars for those linking to 1040s ($119.3 billion). Thus, there is little net misreporting of UI dollars among those who report any UI receipt on a 1040. It is less informative to compare recipients across the data sources because of differences in the units of analysis (i.e., amounts from 1040s are reported at the tax unit level while amounts from 1099-Gs are reported at the individual level). In summary, the results in Table 1 suggest that the UI benefits found on 1040s constitute nearly a strict subset of the UI benefits on 1099-Gs, with the latter source also containing amounts for recipients who do not file tax returns or do not list their UI benefit amounts on their tax returns.

We conduct several robustness checks to ensure that these discrepancies cannot be materially explained by late 1040 filers or the presence of other non-UI income sources on Box 1 of Form 1099-G. After broadening our set of 1040s for tax year 2010 to include those filed in both processing years 2011 and 2012, we still find that only 80.6% of 1099-G UI dollars appear on a 1040 (Appendix Table A7). In other words, accounting for very late filers (processed in 2012) can only explain 10% of the gap in UI dollars between 1040s and 1099-Gs. Next, after excluding 1099-Gs filed for addresses located in California and New Jersey (the two states for which Box 1 on Form 1099-G may contain non-UI programs), we find that only 77.4% of 1099-G dollars appear on a 1040. This suggests that the presence of other income sources on 1099-Gs can explain at most a trivial fraction of the discrepancy in UI dollars between administrative sources.

**Incomes of Non-Filing UI Recipients**

In our final analysis of this section, we take a closer look at the incomes of UI recipients who do not file tax returns (1040s) and provide rough estimates of how many of these non-filers have incomes above the filing threshold (and therefore should have filed a 1040).[19] Because filing thresholds vary by filing status, we link these non-filers and their taxable incomes (defined for

Another hypothesis is that is that some UI recipients (based on 1099-Gs) may have listed their UI incomes on a line other than "Unemployment Compensation" on the 1040 (e.g., on the "Other Income" line).

[19] In general, non-filer UI recipients have higher UI benefit amounts than filer UI recipients across the income distribution. However, because UI benefits constitute a larger share of income for non-filers, we find that filers have higher amounts of taxable income than non-filers across the income distribution (Appendix Figure A3).

simplicity as UI amounts plus W-2 wages) to the CPS to predict filing status using survey-reported marital status and household structure. This simulation would not be possible using the administrative data alone, because filing thresholds vary by demographic characteristics that we can observe in the survey but no in the tax records. Appendix Figure A4 shows that the income distribution for non-filers in the linked CPS sample is nearly identical to the income distribution for non-filers in the 1099-G universe data (particularly below the 90$^{th}$ percentile), suggesting that estimates using the CPS are likely to be representative of population-level estimates.

Figure 5 shows the distributions of taxable incomes for three groups of non-filers linked to the CPS: those who would have filed a married (joint) return, those who would have filed as a head of household, and those who would have filed a single return. The filing thresholds in 2010 were $18,700 for married filers, $12,050 for head of household filers, and $9,350 for single filers, and we find that incomes are generally highest for married non-filers and lowest for head of household non-filers.[20] Overall, we estimate that 54.8% of non-filers have incomes above the filing threshold, with 63.4%, 46.7%, and 43.8% of married, head of household, and single non-filers having incomes above their respective filing thresholds. Because our definition of taxable income captures only a subset of all taxable income (missing sources such as retirement income, interest and dividends, etc.), these shares are lower bounds for the true shares of non-filers with incomes above the filing threshold. Applied to the numbers in Table 6, these estimates suggest that at least 7.5% of UI recipients do not file tax returns because they are non-compliant with the tax code.

# 6. Misreporting of Unemployment in Survey Data

Having so far discussed the measurement of UI in survey and administrative sources, we now present results that leverage our administrative UI records to shed light on the misreporting of unemployment status in survey data. We start by describing the degree to which survey-reported employment characteristics are inconsistent with either reported or true UI receipt. UI recipients must remain in the labor force and be looking for work in order to be eligible for benefits. While this requirement was relaxed during the COVID-19 pandemic, it remained in place during 2010 – even when UI benefits were extended to help individuals cope with a weak labor market during the Great Recession. We then explore how the errors in unemployment reporting vary by UI

[20] For simplicity, we use filing thresholds corresponding to those who are under age 65 and are not blind.

amount and also across the business cycle, shedding light on mechanisms that can potentially explain these discrepancies. Our estimates focus on the reporting of unemployment in CPS, although we perform a few calculations using the SIPP as robustness checks.

**Errors in Unemployment Among All UI Recipients**

Table 7 displays our main statistic of interest – the share of UI recipients who report never being unemployed (i.e., looking for work without work) during the reference period – along with various decompositions of this measure of error. We start by assessing discrepancies within survey data alone (Column 1), finding that 30.6% of all survey UI recipients never report being unemployed in the relevant calendar year. This striking degree of internal inconsistency is not driven by imputation; even after excluding individuals with imputed responses for UI receipt or weeks worked, we still find that 29.2% of survey UI recipients report never being unemployed during the reference period. It is worth noting that the employment and UI income questions are asked in different sections of the CPS interview, likely making it difficult for interviewers to reconcile or even notice such inconsistencies.

When using administrative data (1099-Gs) to classify UI receipt, we find that 49% of UI recipients now report never being unemployed in the survey (Column 2). Notably, more UI recipients fail to report that they are unemployed than fail to report UI receipt. Again, this share remains high at 47.7% even after excluding observations with imputed values of UI receipt or weeks worked. Breaking down this latter share based upon weeks worked and full-time status during the reference period yields some noteworthy patterns. More than half (53.1%) of all "never-unemployed" administrative UI recipients report working for nearly the full year (50-52 weeks), with 44.2% reporting not only working the full year but also on a full-time basis. In contrast, 30.5% of "never-unemployed" UI recipients report working zero weeks during the reference period (i.e., being out of the labor force). Of the remaining 16.4% of "never-unemployed" administrative UI recipients who report working for 1-49 weeks, the majority report working 25-49 weeks (11.6%) and also usually on a full-time basis (12.2%).

It is worth noting that we are testing errors in only one direction – i.e., the truly unemployed failing to report unemployment. Testing errors in the other direction would involve examining how many of the truly "never unemployed" incorrectly report being unemployed in the survey. Such an analysis, however, would not be possible using existing records. This is because one cannot

determine precise gaps in work histories in administrative employment records, which are typically at the annual level (e.g., for IRS tax records like Form W-2 or Form 1040) or quarterly level (e.g., for UI wage records), while unemployment spells can be a matter of weeks or days. Thus, the direction that we examine is the only one that is testable and we find it to be remarkably important.

Several hypotheses may help to explain the results we observe in terms of the misreporting of unemployment. It may be, for example, that many of the UI recipients who report working for all 52 weeks receive small amounts of UI for very temporary periods of unemployment (and therefore do not report UI nor the temporary unemployment spell). It may also be that some survey respondents confuse being out of the labor force with being unemployed (i.e., report being out of the labor force when they are in fact unemployed). Yet another factor could be that some individuals are non-compliant with UI rules or fraudulently receive UI even though they are genuinely never unemployed. This situation could occur if UI field offices can only imperfectly monitor recipients and thus cannot ensure that all recipients are actually looking for work (some UI recipients who are on temporary layoff may not be required to search). Our analyses in the remainder of this section will shed further light on some of these mechanisms.

**Distribution of Unemployment Errors by UI Amount**

Recall from the previous subsection that 47.7% of UI recipients, based on administrative records, erroneously report never being unemployed in the survey (after dropping imputed values). Figure 6 illustrates how this share (in the blue circles) breaks down along the distribution of UI amounts – specifically by ventile of UI dollars among recipients. Among UI recipients in the lowest ventile of benefits, we find that a staggering 80.6% never report being unemployed in the reference year. The average UI amount received by this group was $227 in 2010, suggesting that they are likely individuals who received benefits for very short periods of time (e.g., one week). The share of UI recipients with discrepant unemployment responses decreases steadily (albeit not monotonically) as benefit amounts increase. However, even for those in the highest ventiles of UI amounts, we still find that over 30% of recipients report never being unemployed in the survey. These are individuals who are likely receiving benefits for the entire year, with UI amounts in the highest ventile averaging more than $25,000 in 2010.

To further parse out the nature of these errors, we next examine the shares of successively narrower subsets of those who report never being unemployed: those who report working at all

(maroon squares in Figure 6), working for the full year (green triangles), and working for the full year on a full-time basis (orange diamonds). As expected, the majority of those with lower UI amounts report working during the reference year. In the lowest ventile, 75.5% (constituting nearly 94% of all discrepancies) of UI recipients report working at all, and 65.7% report working for the full year. These patterns are indicative of salience (or lack thereof) as an explanation for the errors, as those receiving UI for shorter periods may be less likely to recall receipt. In contrast, the majority of those with higher UI amounts report being out of the labor force (i.e., never working) during the reference period. This can be seen by taking the difference between the never-unemployed series (circles) and the working series (squares). In the highest ventile, 20.4% (comprising two-thirds of all discrepancies) of UI recipients report being out of the labor force. This is potentially consistent with survey respondents being confused between being unemployed and being out of the labor force.

Nevertheless, we also find evidence of errors that can be less readily accounted for by standard explanations. For example, even among those with high levels of UI benefits, a large share of UI recipients reports working for the full year – specifically, 20.5% among those in the $10^{th}$ ventile (averaging $5,140 in benefits), 16.3% among those in the $15^{th}$ ventile (averaging $10,250 in benefits), and 6.1% in the top ventile. These errors are particularly concerning, as these individuals likely received UI for most of 2010 but instead report working for the full year in the survey. They are also consistent with survey errors in work time that other authors have documented (see, e.g., Borjas and Hamermesh 2024). Even in the SIPP, we find that 42.7% of true UI recipients (and 66% in the lowest ventile of benefits) never report being unemployed during the reference period (Appendix Figure A5). These estimates indicate that salience and recall can only go so far in explaining these stark discrepancies, as the recall period in the SIPP is four months (three times shorter than that of the CPS).

**Cyclicality of Unemployment Discrepancies**

In our final analysis, we examine the time series of these discrepancies to assess the cyclicality of the patterns and whether or not there have been more structural changes over time. Specifically, we assess how the share of survey UI recipients who report never being unemployed fluctuates over a 36-year period ranging from 1987 to 2022. Because the administrative tax records are only accessible for a limited number of years, we perform this analysis using the public-use

CPS (for which we previously documented a large degree of internal inconsistency that was further magnified using the administrative UI records). Because we are comparing two sources of survey data to each other (both of which may contain errors), we will refer to inconsistencies as "discrepancies" rather than "errors". This analysis also enables us to assess how the results of our paper – which focus on calendar year 2010 – fit within a broader time period.

Figure 7 illustrates our results, plotting the trend in UI versus unemployment discrepancies (left-hand side y-axis) against the annual unemployment rate (right-hand side y-axis), with recession years shaded in gray. We observe a distinctive procyclical pattern in the time series of unemployment discrepancies among UI recipients. In particular, discrepancies tend to be lower during economic downturns (especially during recessions shaded in gray) and higher during economic expansions. Consequently, the year that we focus on in this paper (2010) is associated with the 7$^{th}$-lowest rate of discrepancy over a 36-year time span. In recent years, the magnitude of discrepancies has climbed steadily – with no decrease during the pandemic recession (unlike previous recessions). Since 2020, more than half of survey UI recipients inconsistently report never being unemployed. These rates would likely be even higher if we were to use administrative records to classify UI receipt.

These results again point to salience as a potential factor underlying the inconsistent reporting of unemployment, as the higher discrepancies during economic booms may be associated with UI benefits being smaller (or associated with shorter spells) and thus more difficult to recall. At the same time, stigma may also play a role in explaining the cyclicality of discrepancies. With UI receipt being less prevalent during economic expansions, recipients may feel more stigmatized about their unemployment status and thus report it less frequently. More generally, a key implication of the patterns in Figure 7 is that the cyclicality of unemployment is overstated in survey data – as relatively more UI recipients are improperly classified as not unemployed during economic expansions (meaning unemployment rates should increase by more during such periods). This has important consequences for a wide variety of literatures, including for macroeconomic models of economic fluctuations.

# 7. Conclusions

This paper provides the first individual-level estimates of the misreporting of UI and new estimates of the misreporting of unemployment, using administrative records from IRS Form

1099-G linked to the CPS and SIPP for reference year 2010. We find that total UI dollars in the CPS and SIPP are understated by 36-38%, with the majority of this understatement driven by false negatives. The under-reporting of UI is most pronounced for groups that have traditionally been thought to have the lowest receipt rates, including Black and Hispanic individuals, those with low incomes and education levels, and the elderly. We also show the extent to which certain administrative measures of UI (including from 1040s) are incomplete, suggesting that errors in reporting are not limited to survey data alone. Finally, our results suggest a sharp understatement of the incidence of unemployment from retrospective survey questions, with 49% of all UI recipients in CPS failing to report being unemployed during the reference year.

There are a number of implications associated with our results. The underreporting of UI in surveys provides yet another data point for the underreporting of income more generally, resulting in an overstatement of the share of individuals with incomes below the poverty line. On the flip side, the poverty reduction effects of UI and the share of income replaced by UI are understated using the survey data. The differential reporting of survey UI by education, race and ethnicity, and income implies that disparities along these dimensions are likely overstated and – in certain cases – reversed after using the administrative records to correct for measurement error. Consequently, a number of key subgroups are better served by the UI system than survey data would suggest – but only because they are less adequately served by household surveys, which provide less accurate information about their incomes. Furthermore, the misreporting of UI on 1040s and failure to file tax returns among certain UI recipients with sufficiently high incomes indicate that voluntary tax compliance may not be as robust as some have argued. The underreporting of UI in administrative data also suggests that a simple replacement of survey responses with 1040-based UI income will continue to understate income with some of the same (though less pronounced) problems as indicated above.

Our results on the misreporting of unemployment are perhaps the most striking. Many papers condition on an individual not having been unemployed when examining various questions, and authors often calculate hourly wages by dividing earnings by weeks worked and perform labor supply estimation using weeks worked in the prior year. The poor quality of retrospective unemployment or weeks worked raises concerns about the accuracy of such analyses that depend critically upon these measures. The similar rates of discrepancies in the CPS and SIPP (where the recall period of the latter survey is three times shorter than former) suggest that contemporaneous

measures of unemployment may also be sharply understated. These findings also highlight the likely large errors in using survey reports of unemployment to impute UI receipt.

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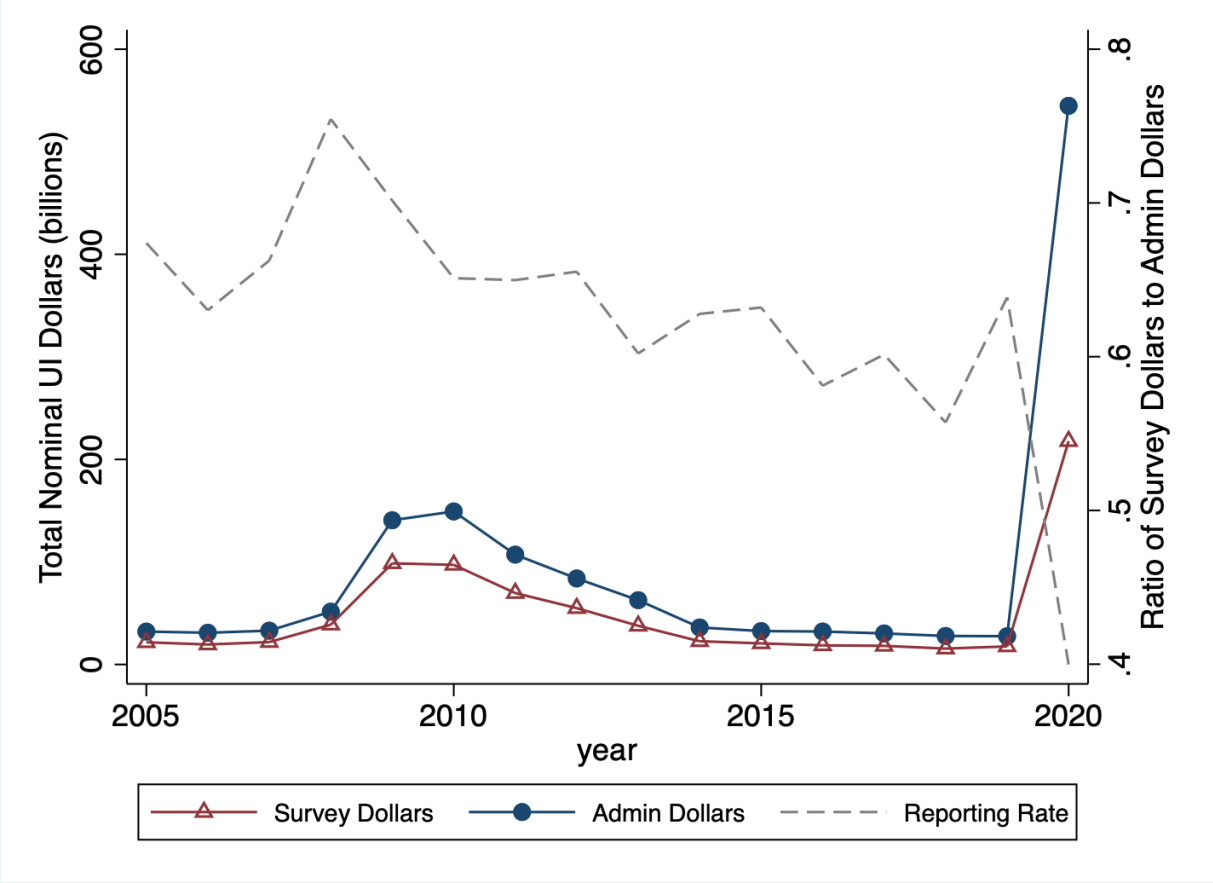
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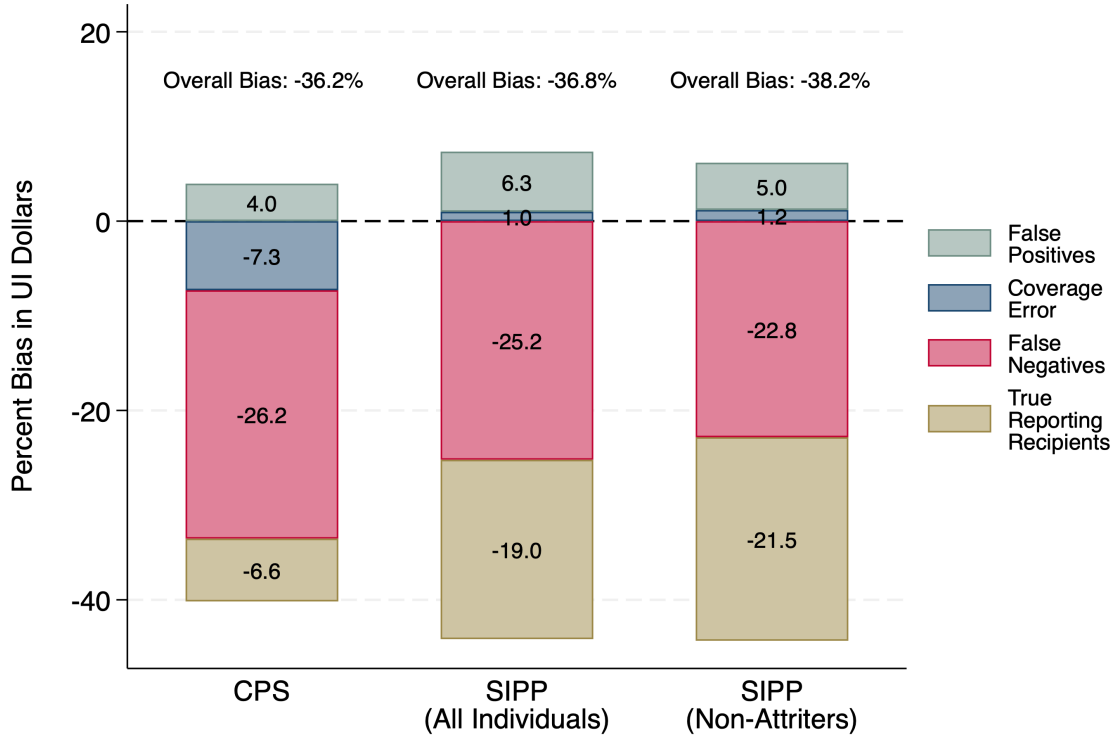
# Figures and Tables

**Figure 1. Trends in Total UI Dollars from Survey and Administrative Sources, 2005-2020**



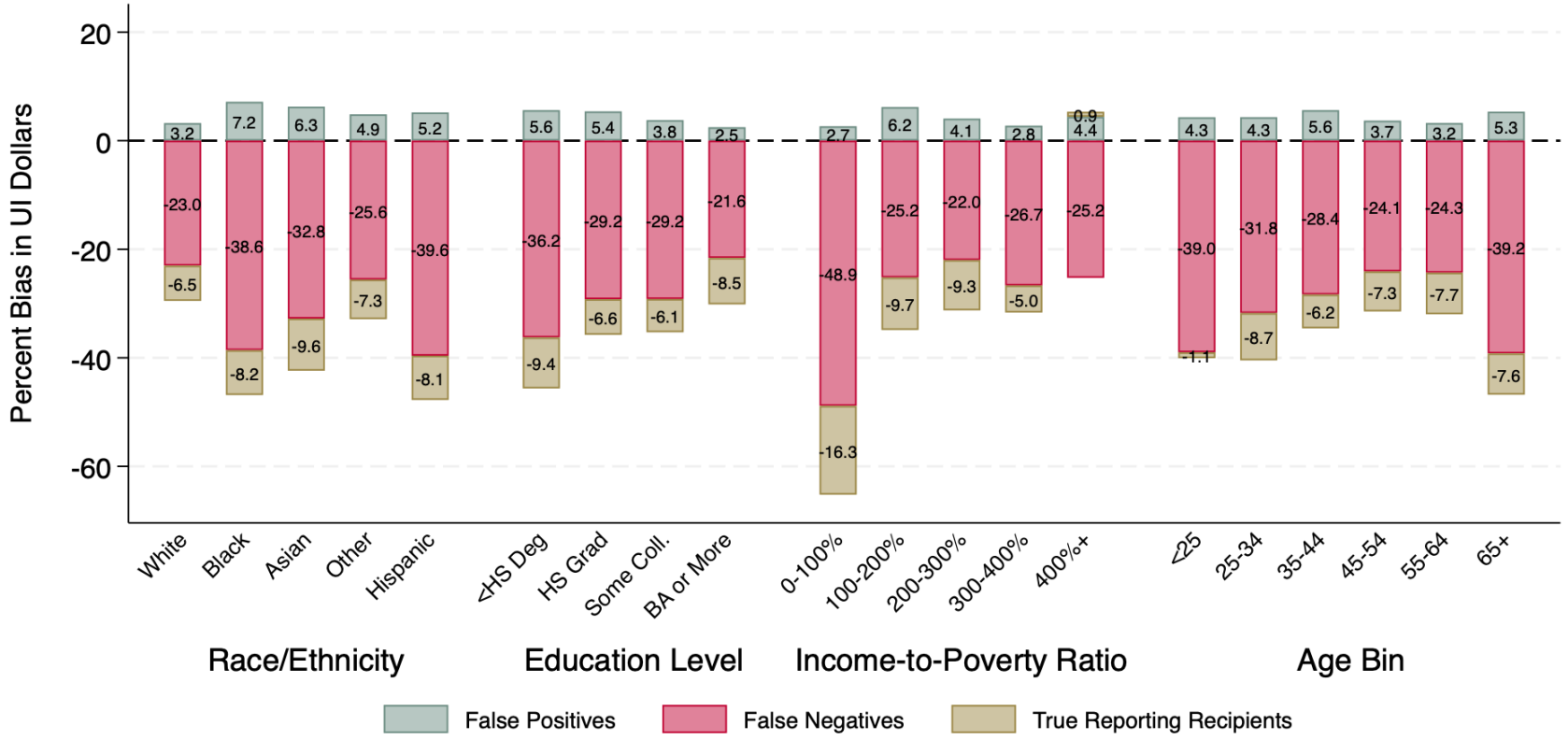

Source: 2006-2021 CPS ASEC (public-use), U.S. Department of Labor Unemployment Insurance Chartbook
Notes: This figure plots the time series of weighted total of UI dollars reported in the CPS ASEC (maroon triangles) against publicly available administrative totals from the U.S. Department of Labor (navy circles), with the corresponding axis being the left-hand side y-axis. All dollars are nominal (not adjusted for inflation). This figure also shows the ratio of total survey dollars to administrative totals (using the right-hand side y-axis) in the dashed line.

**Figure 2. Decomposition of Bias in Reported Survey UI Dollars**



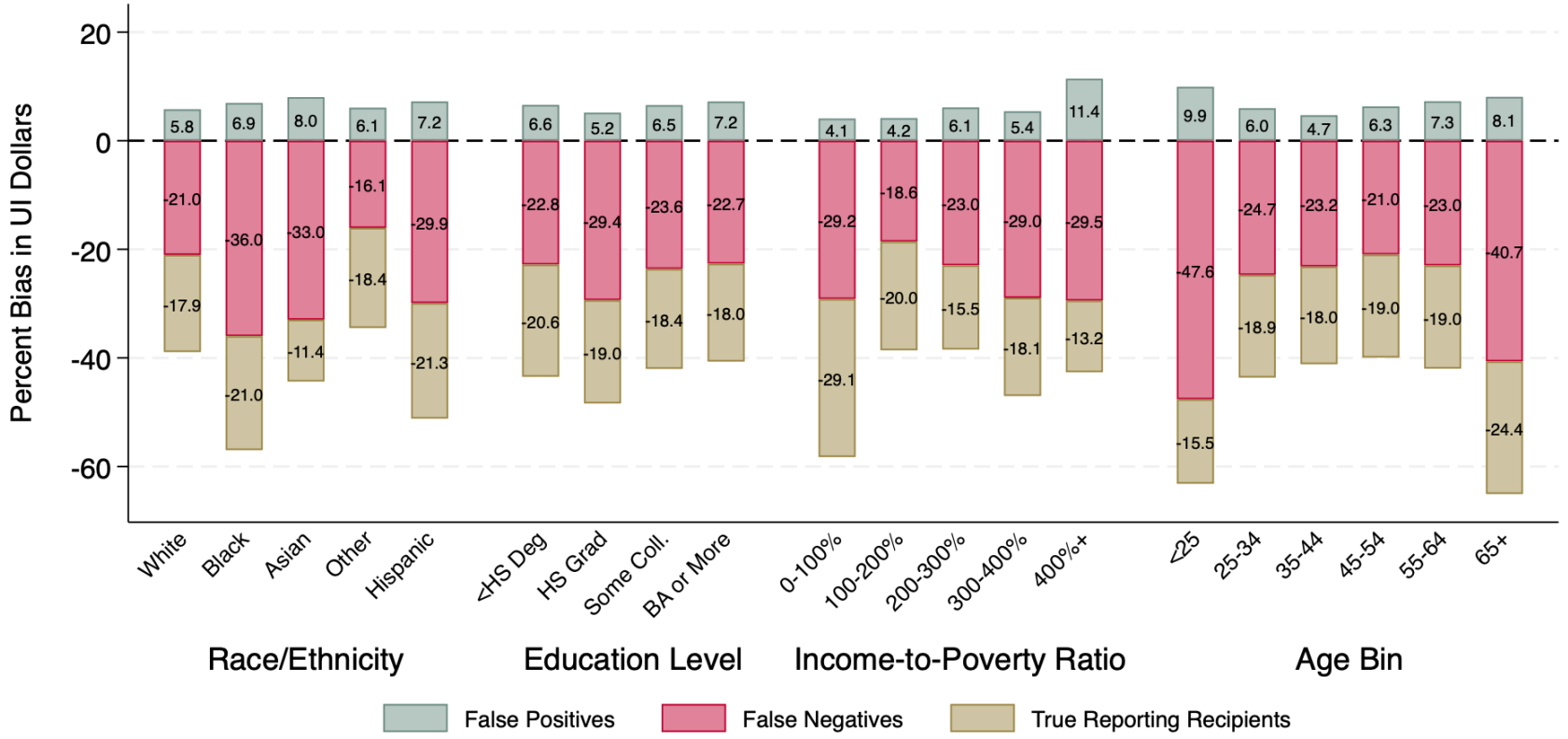

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This figure uses the methodology from Meyer and Mittag (2021) to decompose the total bias in survey-reported UI dollars (relative to universe administrative totals) into four components: false positives, false negatives, measurement error among true reporting recipients, and generalized coverage error. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting. The "SIPP (All Individuals)" sample refers to all individuals in reference month 4 of Wave 6 of the 2008 SIPP Panel, while the "SIPP (Non-Attriters)" sample refers to all individuals in reference month 4 of Wave 6 who were also interviewed for every month of the 2010 calendar year.

**Figure 3a. Decomposition of Bias in Reported Survey UI Dollars (by Key Subgroups in CPS)**



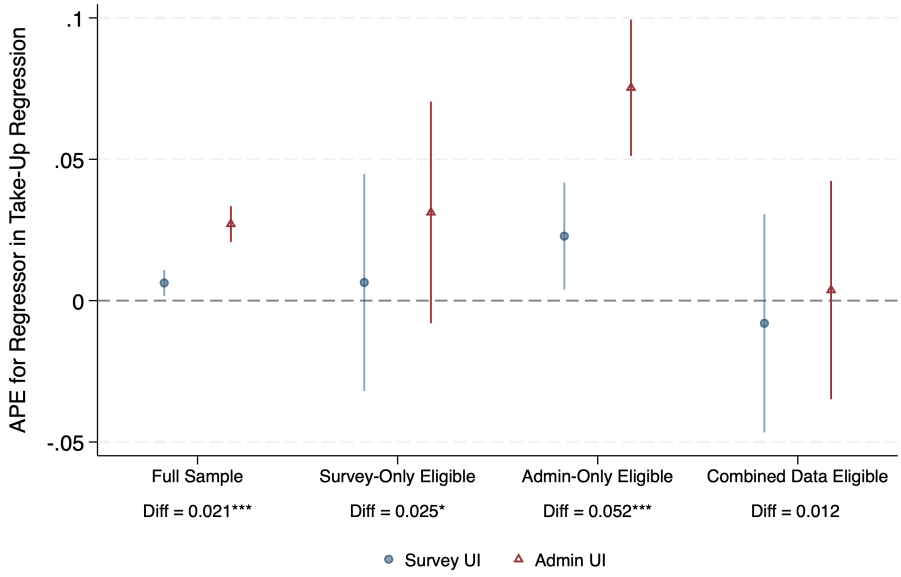

Source: 2011 CPS ASEC, IRS Form 1099-G (Tax Year 2010)
Notes: This figure uses the methodology from Meyer and Mittag (2021) to decompose the total bias in survey-reported UI dollars (relative to linked administrative totals) for key demographic subgroups into three components: false positives, false negatives, and measurement error among true reporting recipients. Note that we do not examine coverage error because the benchmarks are linked administrative totals rather than universe administrative totals. Survey weights are adjusted for non-PIKing and whole imputes using inverse probability weighting.

**Figure 3b. Decomposition of Bias in Reported Survey UI Dollars (by Key Subgroups in SIPP)**

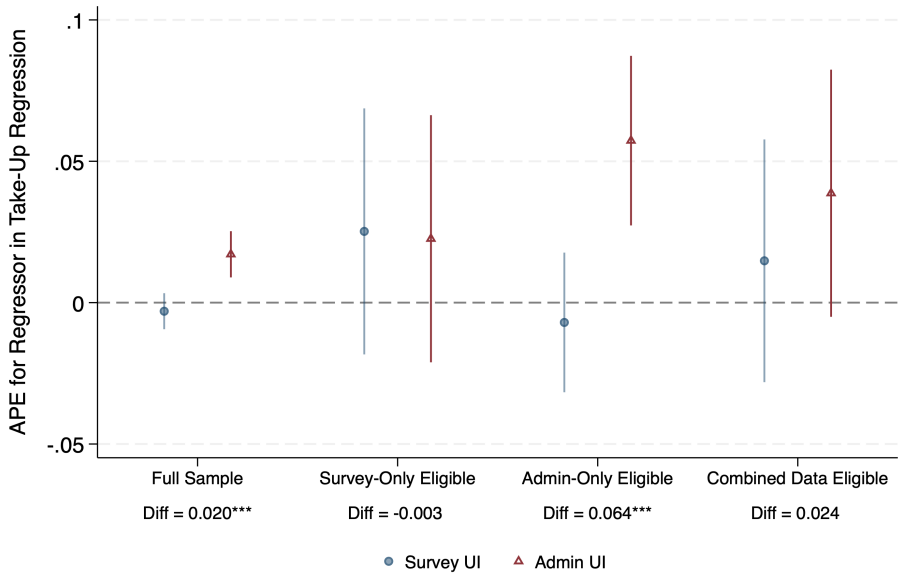



Source: 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This figure uses the methodology from Meyer and Mittag (2021) to decompose the total bias in survey-reported UI dollars (relative to linked administrative totals) for key demographic subgroups into three components: false positives, false negatives, and measurement error among true reporting recipients. Note that we do not examine coverage error because the benchmarks are linked administrative totals rather than universe administrative totals. Survey weights are adjusted for non-PIKing using inverse probability weighting.

**Figure 4a. Average Partial Effects of Black Non-Hispanic (vs White) on UI Take-Up**



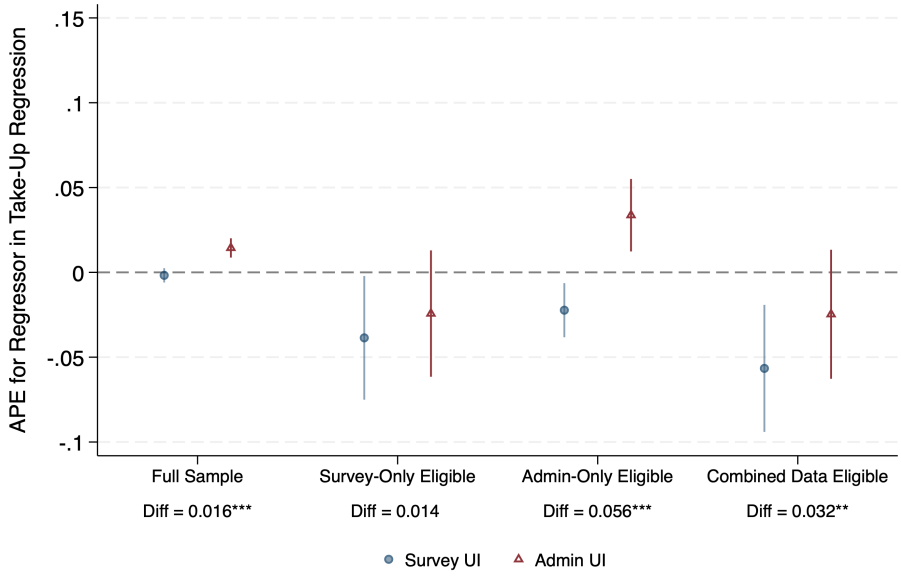

(a) CPS



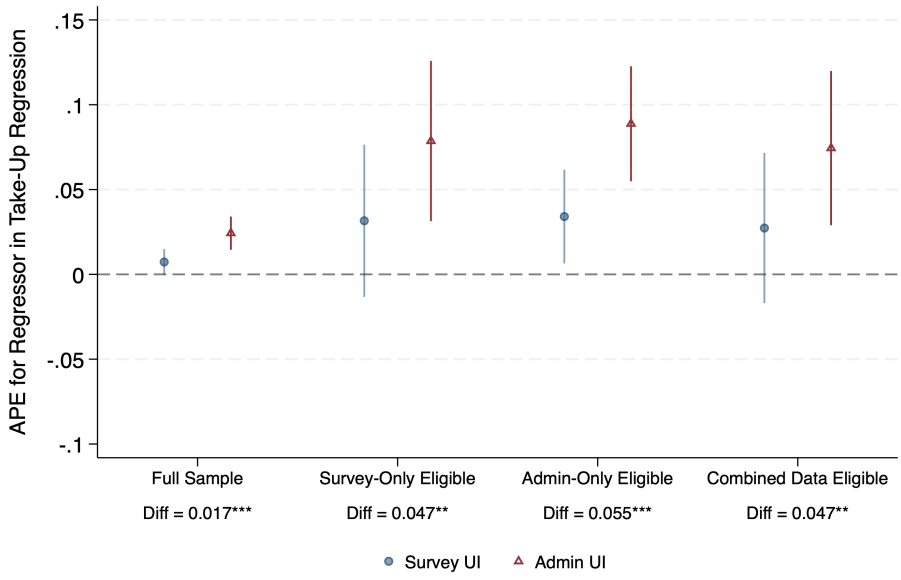

(b) SIPP

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: These figures show average partial effects of being Black non-Hispanic (relative to white non-Hispanic) on UI take-up, derived from probit regressions with survey or administrative UI receipt as the outcome and a variety of economic and demographic characteristics as the regressors. These regressions are run over four separate samples: all individuals aged 18+ (full sample), those simulated as eligible using survey data alone, those simulated as eligible using administrative data alone, and those simulated as eligible using a combination of survey and administrative data. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

**Figure 4b. Average Partial Effects of Hispanic (vs White) on UI Take-Up**



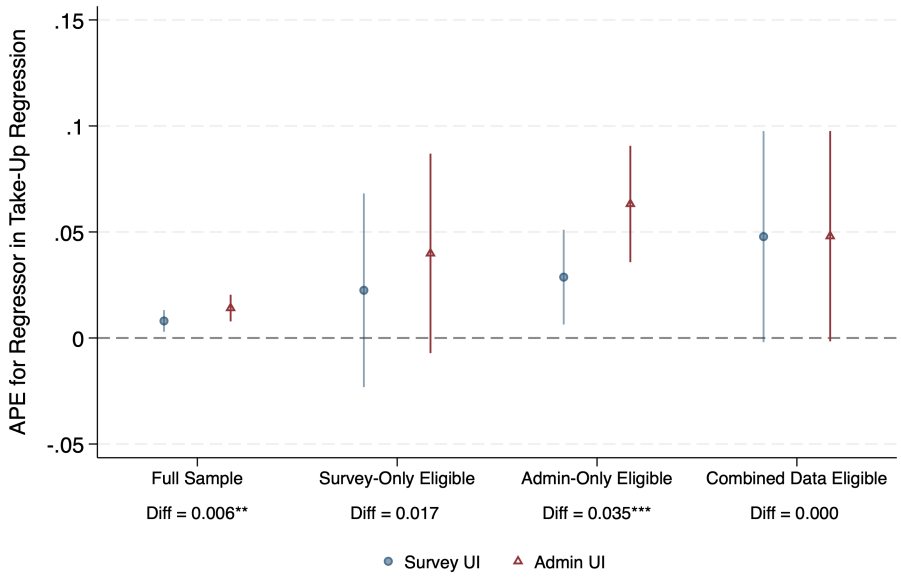

(a) CPS



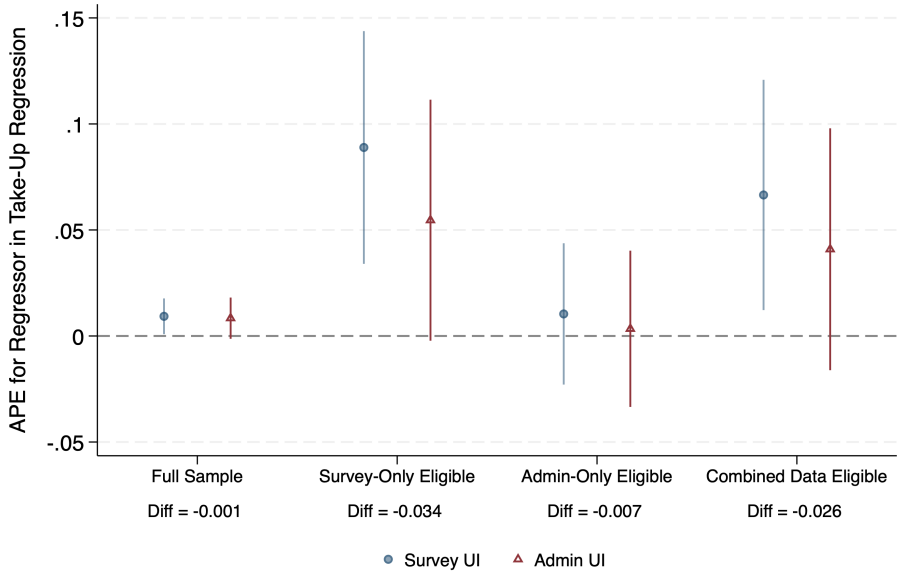

(b) SIPP

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: These figures show average partial effects of being Hispanic (relative to white non-Hispanic) on UI take-up, derived from probit regressions with survey or administrative UI receipt as the outcome and a variety of economic and demographic characteristics as the regressors. These regressions are run over four separate samples: all individuals aged 18+ (full sample), those simulated as eligible using survey data alone, those simulated as eligible using administrative data alone, and those simulated as eligible using a combination of survey and administrative data. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

**Figure 4c. Average Partial Effects of Less than HS Degree (vs BA or More) on UI Take-Up**



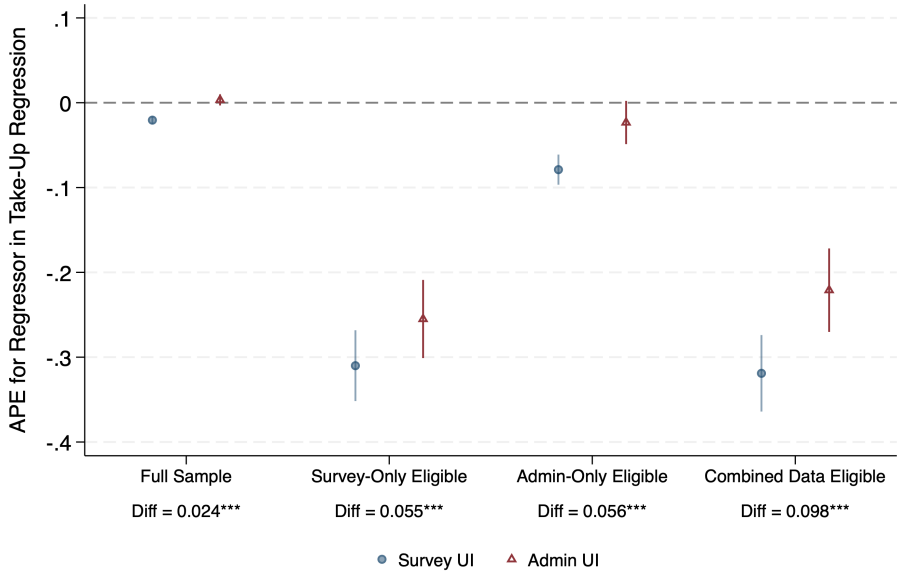

(a) CPS



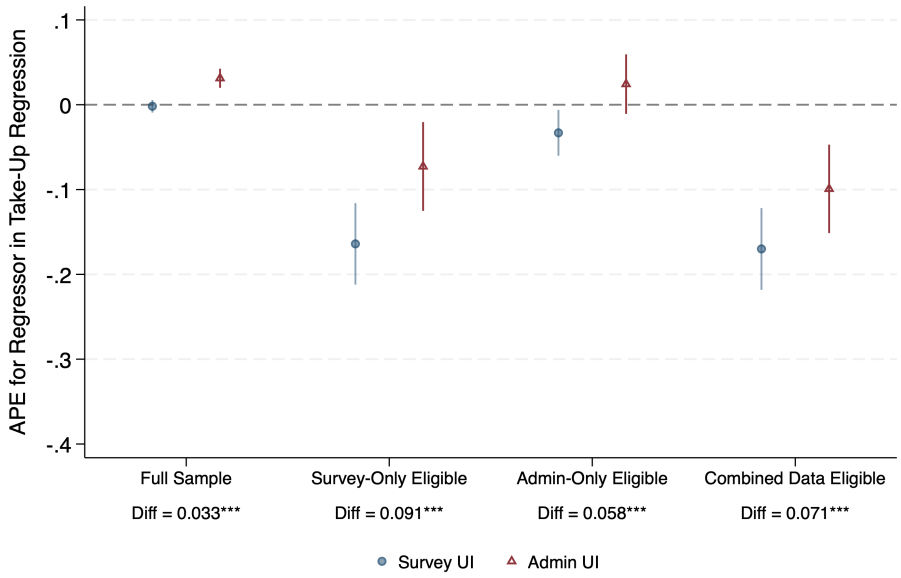

(b) SIPP

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: These figures show average partial effects of having less than a high school degree (relative to having a BA or more) on UI take-up, derived from probit regressions with survey or administrative UI receipt as the outcome and a variety of economic and demographic characteristics as the regressors. These regressions are run over four separate samples: all individuals aged 18+ (full sample), those simulated as eligible using survey data alone, those simulated as eligible using administrative data alone, and those simulated as eligible using a combination of survey and administrative data. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

**Figure 4d. Average Partial Effects of Income <100% FPL (vs >400% FPL) on UI Take-Up**



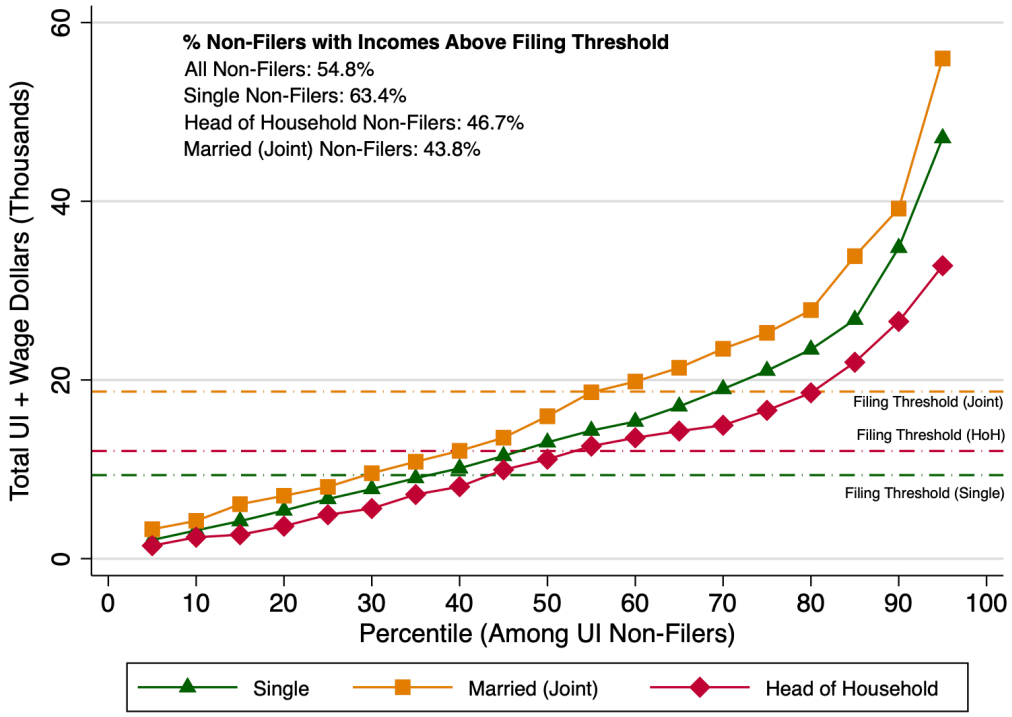

(a) CPS




(b) SIPP

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: These figures show average partial effects of having incomes <100% FPL (relative to having incomes >400% FPL) on UI take-up, derived from probit regressions with survey or admin UI receipt as the outcome and a variety of economic and demographic characteristics as the regressors. These regressions are run over four separate samples: all individuals aged 18+ (full sample), those simulated as eligible using survey data alone, those simulated as eligible using administrative data alone, and those simulated as eligible using a combination of survey and administrative data. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

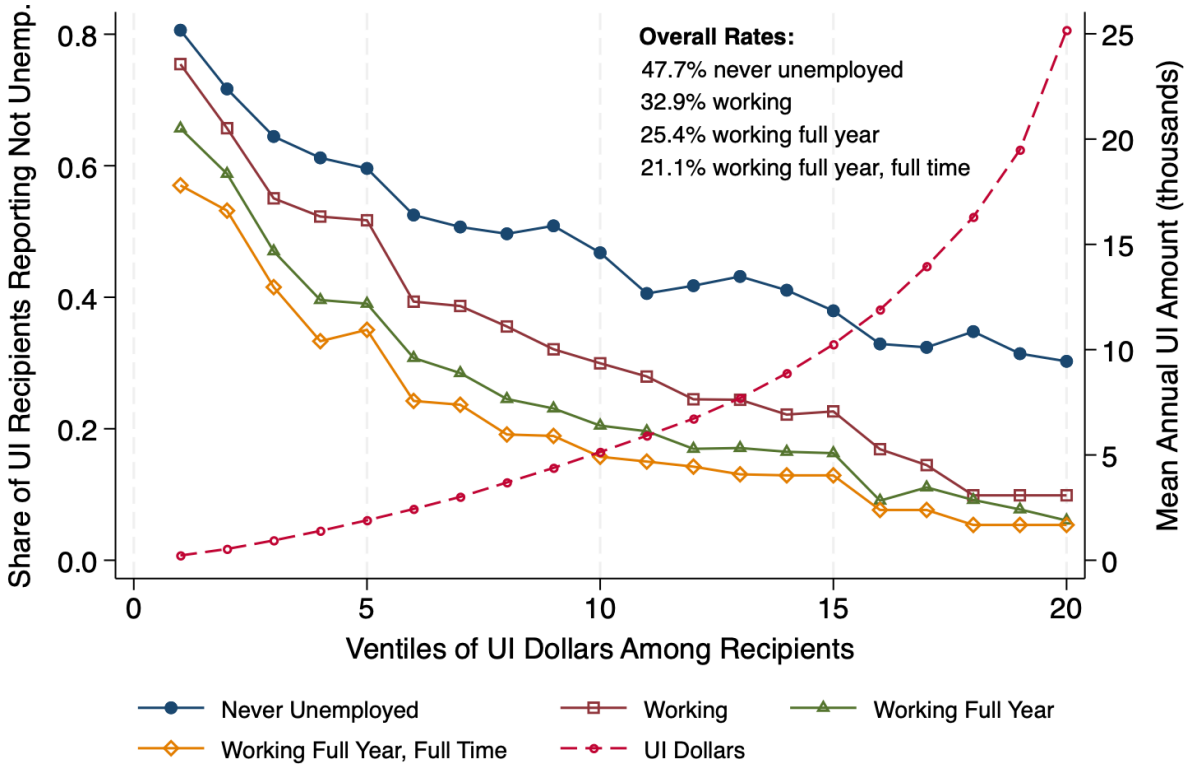
**Figure 5. Incomes of Non-Filer UI Recipients (by Predicted Filing Status in CPS)**




Source: 2011 CPS ASEC, IRS Forms 1040 (Tax Year 2010 and Calendar Year 2011 Filings), W-2 (Tax Year 2010), and 1099-G (Tax Year 2010)

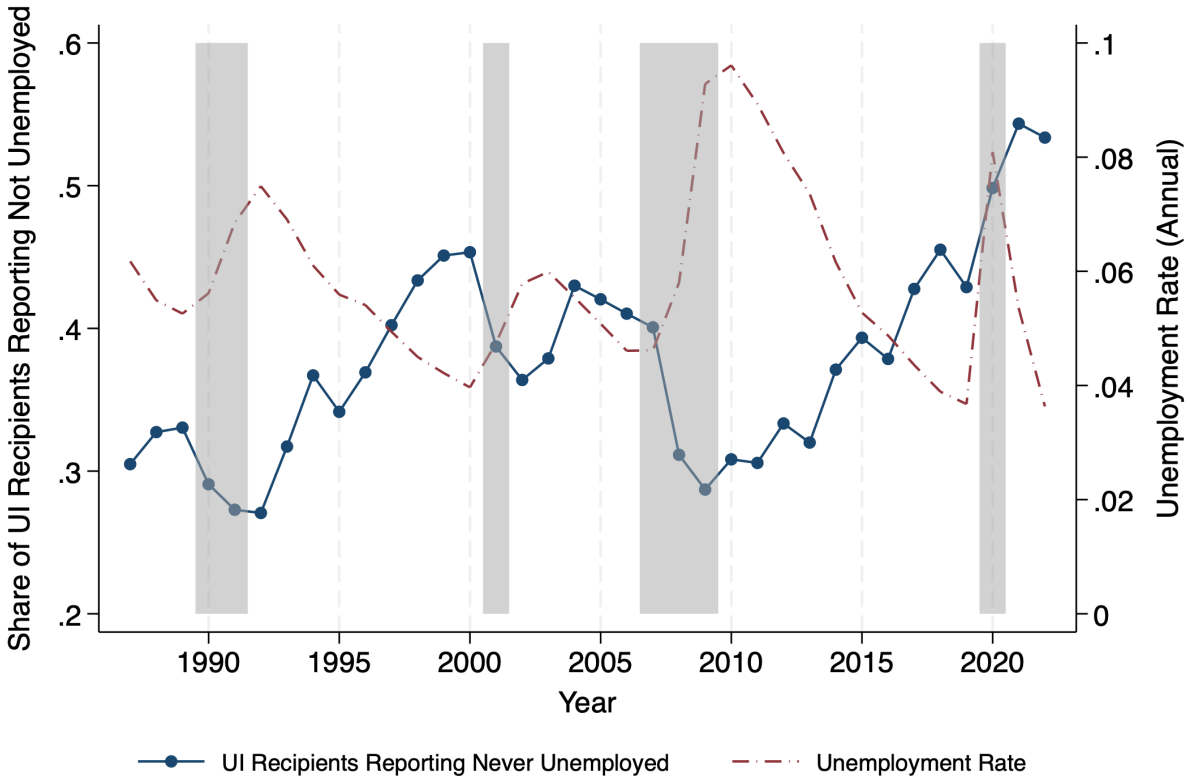
Notes: This figure shows the distribution of UI + wage dollars for non-filers linked to the CPS by potential filing status. Wages come from IRS Forms W-2 and comprise the sum of taxable wages and deferred compensation. Non-filers are individuals in the 1099-G microdata who do not link to a 1040. We define individuals as potential single filers if there are no children under 18 in their family, potential married (joint) filers if they report being married, and potential head of household filers if they are unmarried and there are children under 18 in the family. In 2010, the filing thresholds are $9,350 (single), $18,700 (married filing jointly), and $12,050 (head of household). Displayed percentiles are interpolated by averaging the actual percentile and the 7 observations on each side. Individuals are re-ranked across income categories. We limit our CPS sample to non-whole-imputed PIKed individuals and adjust for non-PIKing and whole imputes using inverse probability weighting.

**Figure 6. Share of UI Recipients Reporting Never Unemployed (by UI Amount)**




Source: 2011 CPS ASEC, IRS Form 1099-G (Tax Year 2010)
Notes: This figure shows the share of UI recipients, based on linked administrative records, who never report being unemployed (retrospectively) in the CPS by ventile of UI. Survey weights are adjusted for non-PIKing and whole imputes, and we drop observations with imputed values of UI or weeks worked. These shares are also calculated for successively narrower subsets of never unemployed, including working at all during the reference period, working for the full year, and working for the full year on usually a full-time basis. Finally, we plot (using the right-hand side y-axis) the average annual UI amount from the administrative records for each ventile.

**Figure 7. Discrepancies Between Survey-Reported UI and Unemployment, 1987-2022**




Source: 1988-2023 CPS ASEC (public-use)
Notes: This figure plots the share of survey-reported UI recipients who report never being unemployed in the survey (blue circles) against the annual average unemployment rate (maroon dashed line). Recessions are shaded in gray.

## Table 1. Aggregate UI Dollars and Recipients Recorded in CPS and SIPP, 2010

| | Full Survey Sample | Linked Survey Sample | | | |
|---|---|---|---|---|---|
| | Survey UI | Survey UI | Admin UI | Bias (vs. Linked Totals) | Bias (vs. Universe Totals) |
| | (1) | (2) | (3) | (4) | (5) |
| CPS | | | | | |
| Dollars (millions) | 97,360 | 96,970 | 140,900 | -31.19% | -36.20% |
| Recipients (millions) | 12.45 | 12.45 | 18.93 | -34.23% | -38.21% |
| Sample Size | 205,000 | 165,000 | 165,000 | | |
| Weighted Pop. (millions) | 306.1 | 306.0 | 306.0 | | |
| SIPP (All Individuals) | | | | | |
| Dollars (millions) | 93,780 | 96,010 | 153,500 | -37.44% | -36.84% |
| Recipients (millions) | 14.49 | 14.93 | 20.45 | -26.99% | -25.91% |
| Sample Size | 88,000 | 78,000 | 78,000 | | |
| Weighted Pop. (millions) | 303.9 | 303.6 | 303.6 | | |
| SIPP (Non-Attriters) | | | | | |
| Dollars (millions) | 91,440 | 94,000 | 153,800 | -38.88% | -38.16% |
| Recipients (millions) | 14.90 | 15.33 | 20.28 | -24.41% | -23.92% |
| Sample Size | 69,500 | 62,500 | 62,500 | | |
| Weighted Pop. (millions) | 303.9 | 303.5 | 303.5 | | |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table shows total UI dollars and recipients calculated from various survey and administrative sources. Column 1 shows estimates calculated using survey values in the full 2011 CPS ASEC and the 2008 SIPP Panel (Waves 5-8) samples, where the SIPP values are scaled up to reflect calendar year amounts. Columns 2 and 3 show estimates calculated using survey and administrative values for the linked CPS and SIPP samples, which consists of PIKed individuals (and additionally non-whole-imputes in the CPS). Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting. The "SIPP (All Individuals)" sample refers to all individuals in reference month 4 of Wave 6 of the 2008 SIPP Panel, while the "SIPP (Non-Attriters)" sample refers to all individuals in reference month 4 of Wave 6 who were also interviewed for every month of the 2010 calendar year.

## Table 2. Individual-Level Error Components in CPS and SIPP

| | CPS (1) | SIPP (All Individuals) (2) | SIPP (Non-Attriters) (3) |
|---|---|---|---|
| False Positives | | | |
| Percent (of True Non-Recipients) | 0.33% | 0.80% | 0.77% |
| False Negatives | | | |
| Percent (of True Recipients) | 39.19% | 38.03% | 35.13% |
| Average 1099-G Amount ($) | 5,374 | 4,928 | 4,870 |
| True Reporting Recipients | | | |
| Mean Absolute Error ($) | 3,030 | 3,732 | 3,590 |
| Mean Net Error ($) | -875 | -2,272 | -2,485 |
| Average 1099-G Amount ($) | 8,776 | 9,085 | 9,055 |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table calculates sources of errors in reported UI dollars in the linked survey data for both the CPS and SIPP. False positives are defined as the share of true non-recipients who report receipt in the survey and false negatives are defined as the share of true recipients who do not report receipt in the survey. Among true reporting recipients, the mean absolute error is calculated as the average of the absolute value of survey and administrative reports, while the mean net error is the average of the net difference in survey and administrative reports. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting. The "SIPP (All Individuals)" sample refers to all individuals in reference month 4 of Wave 6 of the 2008 SIPP Panel, while the "SIPP (Non-Attriters)" sample refers to all individuals in reference month 4 of Wave 6 who were also interviewed for every month of the 2010 calendar year.

## Table 3. False Positive and False Negative Rates (%) by Selected Demographic Subgroups

| Characteristics | CPS | | SIPP | |
|---|---|---|---|---|
| | False Positives | False Negatives | False Positives | False Negatives |
| | (1) | (2) | (3) | (4) |
| Race/Ethnicity | | | | |
| White, non-Hispanic | 0.32 | 33.16 | 0.93 | 33.28 |
| Black, non-Hispanic | 0.82 | 49.02 | 1.63 | 49.97 |
| Asian, non-Hispanic | 0.51 | 43.27 | 1.12 | 45.73 |
| Other, non-Hispanic | 0.71 | 37.28 | 1.39 | 35.79 |
| Hispanic | 0.65 | 51.53 | 1.34 | 42.24 |
| Education Level | | | | |
| Less than High School | 0.49 | 46.76 | 1.11 | 36.78 |
| High School Graduate | 0.68 | 40.28 | 0.97 | 42.39 |
| Some College | 0.37 | 38.50 | 1.20 | 36.29 |
| BA or More | 0.24 | 32.73 | 1.03 | 35.12 |
| Income-to-Poverty Ratio | | | | |
| 0-1x Poverty Line | 0.51 | 52.15 | 1.21 | 39.65 |
| 1-2x Poverty Line | 0.74 | 36.99 | 1.26 | 32.12 |
| 2-3x Poverty Line | 0.46 | 35.90 | 1.22 | 37.83 |
| 3-4x Poverty Line | 0.37 | 38.56 | 1.02 | 40.99 |
| > 4x Poverty Line | 0.30 | 36.45 | 0.92 | 42.32 |
| Age of Head | | | | |
| <25 | 0.30 | 47.04 | 0.56 | 57.90 |
| 25-34 | 0.56 | 41.64 | 1.61 | 37.01 |
| 35-44 | 0.68 | 39.29 | 1.35 | 37.09 |
| 45-54 | 0.60 | 34.87 | 1.64 | 32.61 |
| 55-64 | 0.34 | 34.78 | 1.01 | 34.15 |
| 65+ | 0.13 | 49.80 | 0.20 | 53.07 |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table calculates false positive and false negative rates for UI for various demographic subgroups. Note that false positive rates here are conditional on individuals age 18+ who are true non-recipients of UI. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

## Table 4. Partial Determinants of False Negatives and False Positives

| | CPS | | SIPP | |
|---|---|---|---|---|
| | **False Positives** | **False Negatives** | **False Positives** | **False Negatives** |
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Black, Non-Hispanic | 0.0036*** | 0.0945*** | 0.0023** | 0.1100*** |
| | (0.0009) | (0.0150) | (0.0009) | (0.0200) |
| Asian, Non-Hispanic | 0.0031** | 0.1120*** | 0.0012 | 0.0866** |
| | (0.0013) | (0.0282) | (0.0014) | (0.0368) |
| Other, Non-Hispanic | 0.0025 | 0.0661** | 0.0017 | 0.0639** |
| | (0.0016) | (0.0294) | (0.0020) | (0.0316) |
| Hispanic | 0.0037*** | 0.1190*** | 0.0015 | 0.0583*** |
| | (0.0009) | (0.0154) | (0.0011) | (0.0205) |
| <HS Grad | 0.0020** | 0.0022 | 0.0018 | -0.0010 |
| | (0.0008) | (0.0204) | (0.0012) | (0.0264) |
| HS Grad | 0.0033*** | 0.0113 | 0.0007 | 0.0240 |
| | (0.0006) | (0.0158) | (0.0008) | (0.0198) |
| Some College | 0.0009* | 0.0186 | 0.0004 | -0.0129 |
| | (0.0005) | (0.0157) | (0.0007) | (0.0181) |
| Income 0-1x FPL | -0.0016** | 0.2340*** | 0.0001 | 0.0492* |
| | (0.0008) | (0.0205) | (0.0010) | (0.0257) |
| Income 1-2x FPL | 0.0020** | 0.0725*** | 0.0024** | -0.0451** |
| | (0.0008) | (0.0162) | (0.0010) | (0.0207) |
| Income 2-3x FPL | 0.0003 | 0.0283* | 0.0025** | -0.0188 |
| | (0.0007) | (0.0149) | (0.0010) | (0.0190) |
| Income 3-4x FPL | -0.0002 | 0.0272* | 0.0012 | 0.0088 |
| | (0.0008) | (0.0159) | (0.0009) | (0.0201) |
| Age <25 | 0.0004 | -0.0496 | -0.0003 | -0.0052 |
| | (0.0008) | (0.0398) | (0.0008) | (0.0449) |
| Age 25-34 | 0.0040*** | -0.0300 | 0.0029*** | -0.106** |
| | (0.0010) | (0.0370) | (0.0011) | (0.0413) |
| Age 35-44 | 0.0066*** | -0.0448 | 0.0041*** | -0.104** |
| | (0.0012) | (0.0368) | (0.0011) | (0.0408) |
| Age 45-54 | 0.0054*** | -0.0843** | 0.0054*** | -0.143*** |
| | (0.0011) | (0.036) | (0.0012) | (0.0408) |
| Age 55-64 | 0.0027*** | -0.0738** | 0.0022** | -0.115*** |
| | (0.0009) | (0.0364) | (0.0009) | (0.0406) |
| DV Mean | --- | 0.3919 | 0.0108 | 0.3803 |
| Sample Size | 109,000 | 9,700 | 55,500 | 5,100 |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table shows average partial effects of race/ethnicity subgroups (relative to white non-Hispanic), education subgroups (relative to BA or more), income subgroups (relative to income >400% FPL), and age subgroups (relative to 65+) on UI misreporting, derived from probit regressions with an indicator for false positive or negative as the outcome (with controls). False negative (positive) regressions are run over all true recipients (non-recipients). Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

## Table 5. Average UI Recipiency Rates (%) for Each Analysis Sample

| | Full Sample | Survey-Only Eligible | Admin-Only Eligible | Survey + Admin Eligible |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| CPS | | | | |
| Survey UI | 5.36 | 39.82 | 17.88 | 50.27 |
| Admin UI | 8.12 | 44.24 | 25.72 | 55.47 |
| Observations | 116,500 | 7,500 | 19,000 | 7,300 |
| Pop. (millions) | 231.2 | 36.57 | 14.74 | 14.33 |
| SIPP | | | | |
| Survey UI | 6.52 | 36.68 | 19.89 | 44.03 |
| Admin UI | 8.92 | 39.65 | 27.16 | 48.02 |
| Observations | 60,500 | 5,300 | 9,600 | 5,600 |
| Pop. (millions) | 228.9 | 37.76 | 21.88 | 22.74 |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table shows average rates of UI recipiency conditional on being in four separate samples: all individuals aged 18+ (full sample), those simulated as eligible using survey data alone, those simulated as eligible using administrative data alone, and those simulated as eligible using a combination of survey and administrative data. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

## Table 6. Comparisons of Aggregate UI Benefits Between Form 1040 and Form 1099-G

| | Dollars (billions) | | Recipients (millions)* | | |
|---|---|---|---|---|---|
| | Amount ($) | As % of Total | Count | As % of Total | Dollars per Recipient |
| | (1) | (2) | (3) | (4) | (5) |
| | | A. Subgroups of 1099-G UI Recipients | | | |
| | *1099-G Dollars* | | *1099-G Recipients* | | |
| Link to 1040 with UI Income | 119.30 | 78.49% | 15.24 | 75.63% | 7,828 |
| Link to 1040 without UI Income | 9.45 | 6.22% | 2.14 | 10.60% | 4,423 |
| Does Not Link to 1040 | 23.21 | 15.27% | 2.77 | 13.74% | 8,385 |
| Total | 152.00 | 100.00% | 20.15 | 100.00% | 7,543 |
| | | B. Subgroups of 1040 UI Recipients | | | |
| | *1040 Dollars* | | *1040 Recipients* | | |
| Link to 1099-G | 118.50 | 99.58% | 14.64 | 99.19% | 8,094 |
| Does Not Link to 1099-G | 0.46 | 0.39% | 0.12 | 0.81% | 3,880 |
| Total | 119.00 | 100.00% | 14.76 | 100.00% | 8,062 |

* UI recipients are individuals in 1099-Gs and tax units in 1040s.

Source: IRS Forms 1040 (Tax Year 2010 and Calendar Year 2011 Filings) and 1099-G (Tax Year 2010)
Notes: Panel (a) shows total 1099-G dollars and recipient individuals, broken down by various subgroups (i.e., those that link to a 1040 with UI income, those that link to a 1040 without UI income, and those that do not link to a 1040). Table (b) shows total 1040 dollars and recipient tax units, broken down by various subgroups (i.e., those that link to a 1099-G and those that do not link to a 1099-G). Note that recipients in 1040s are tax units while recipients for 1099-Gs are individuals; as a result, the number of 1040 "recipients" by construction is lower than the number of individual recipients because a single tax unit may contain multiple individual recipients.

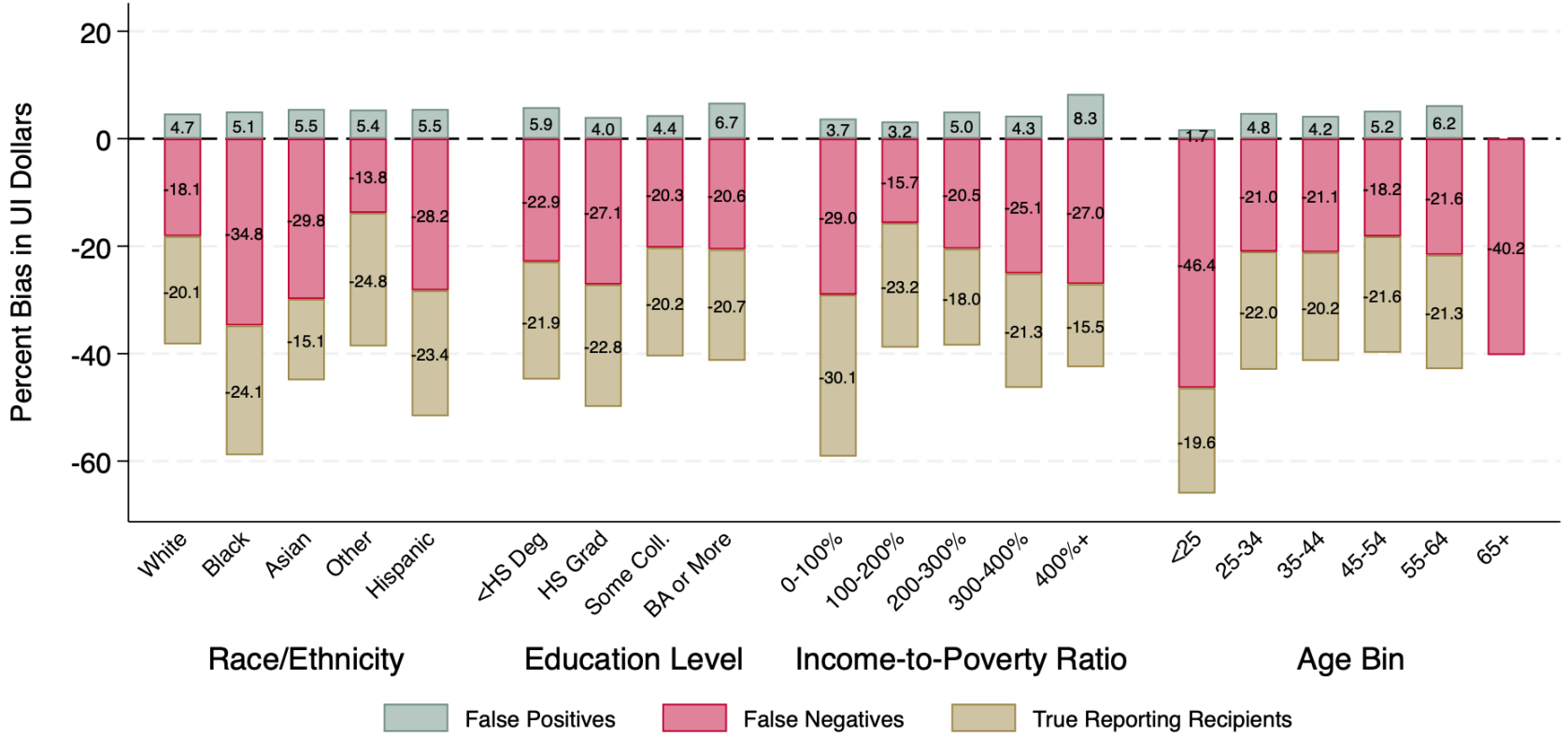
## Table 7. Employment Characteristics of UI Recipients in Linked CPS Data

| | Percent of Admin UI Recipients (1) | Percent of Survey UI Recipients (2) |
|---|---|---|
| Full Sample | | |
| % Reporting Never Being Unemployed in Survey | 49.01% | 30.63% |
| | | |
| Sample Size | 9,700 | 6,600 |
| Weighted Population (millions) | 18.93 | 12.45 |
| | | |
| Excluding those with Imputed UI or Weeks Worked | | |
| % Reporting Never Being Unemployed in Survey | 47.72% | 29.24% |
| Among Never Unemployed, Share Reporting Working for: | | |
| 0 Weeks | 30.50% | 30.99% |
| 1-24 Weeks | 4.75% | 7.14% |
| 25-49 Weeks | 11.72% | 19.47% |
| 50 Weeks | 3.37% | 5.83% |
| 51 Weeks | 0.78% | 1.66% |
| 52 Weeks | 49.98% | 34.91% |
| Among Never Unemployed, Share Reporting: | | |
| Never Working | 30.50% | 30.99% |
| Usually Working Full-Time Between 1-49 Weeks | 12.15% | 20.36% |
| Usually Working Full-Time Between 50-52 Weeks | 44.16% | 32.29% |
| Usually Working Part-Time Between 1-49 Weeks | 4.10% | 6.25% |
| Usually Working Part-Time Between 50-52 Weeks | 8.86% | 10.11% |
| | | |
| Sample Size | 9,200 | 6,300 |
| Weighted Population (millions) | 17.95 | 11.87 |

Data: 2011 CPS ASEC, IRS Form 1099-G (Tax Year 2010)
Notes: This table examines the employment characteristics (over the course of the 2010 reference year) of UI recipients in the CPS. Column 1 shows characteristics for individuals receiving UI based on linking to the administrative 1099-G microdata, and Column 2 shows characteristics for individuals reporting UI receipt in the survey. We limit our sample to non-whole-imputed PIKed individuals and adjust for non-PIKing and whole imputes using inverse probability weighting. We define an individual as never being unemployed in the survey if they never report spending any weeks looking for work without work during the reference year. Our checks on the survey data suggest that the number of weeks spent looking for work is equal to the number of weeks spent unemployed (because the sum of the number of weeks worked and the number of weeks looking for work is always capped at 52).

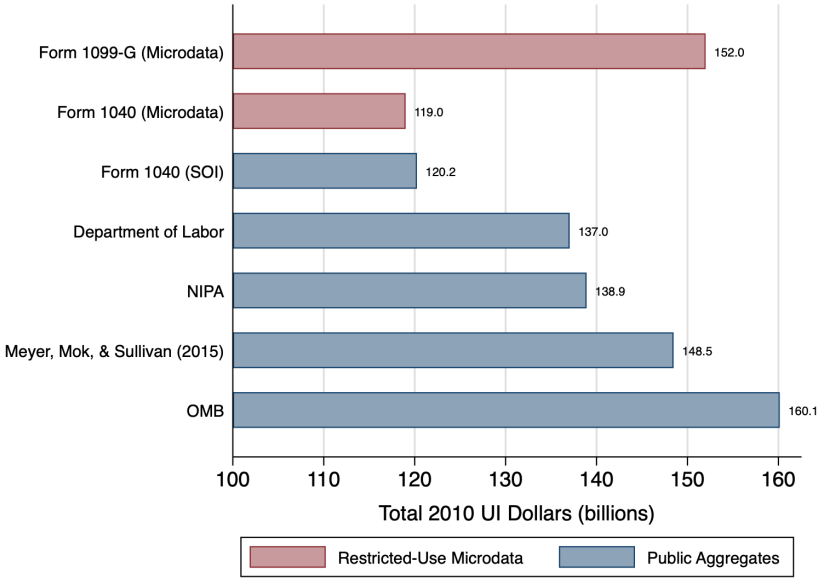
# Appendix Figures and Tables

**Figure A1. Decomposition of Bias in Reported Survey UI Dollars (by Key Subgroups in SIPP for Non-Attriting Subsample)**

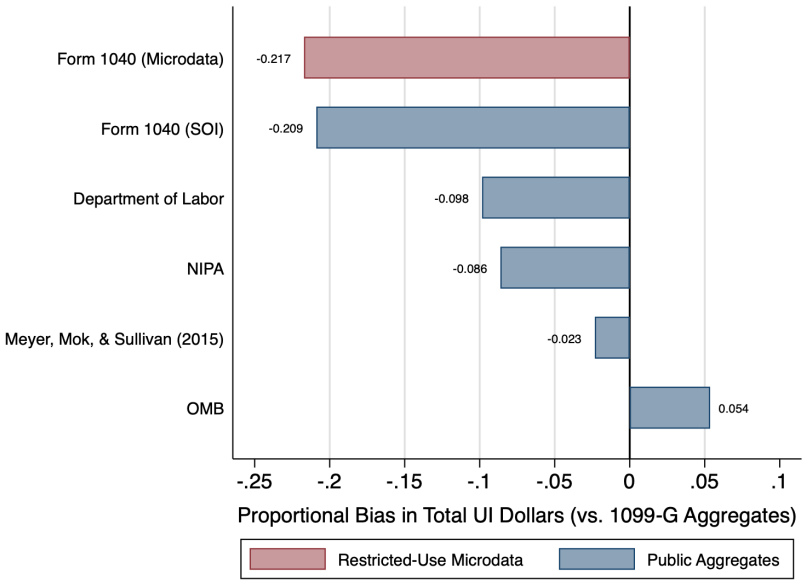



Source: 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This figure uses the methodology from Meyer and Mittag (2021) to decompose the total bias in survey-reported UI dollars (relative to linked administrative totals) for key demographic subgroups into three components: false positives, false negatives, and measurement error among true reporting recipients. Note that we do not examine coverage error because the benchmarks are linked administrative totals rather than universe administrative totals. Survey weights are adjusted for non-PIKing using inverse probability weighting, and the sample consists of all individuals in reference month 4 of Wave 6 who are surveyed in every month of 2010.

**Figure A2. Aggregate UI Benefits Paid ($) According to Various Sources**




(a) Aggregate UI Benefits Paid ($)

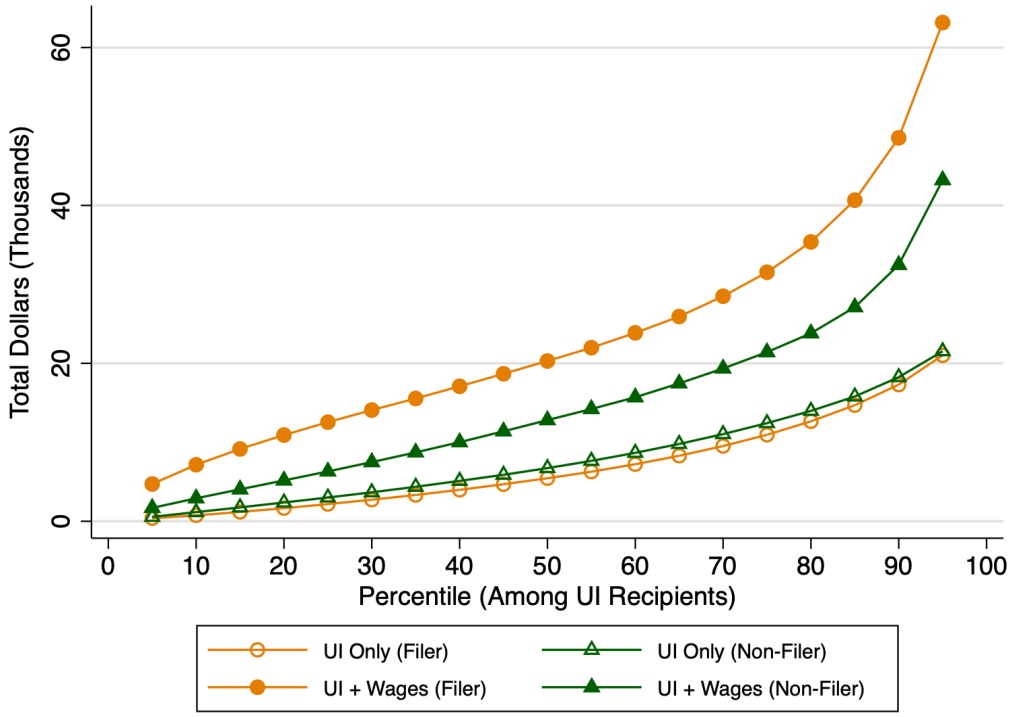



(b) Proportional Bias in Aggregate UI Benefits Paid

Source: IRS Forms 1040 (Tax Year 2010 and Calendar Year 2011 Filings) and 1099-G (Tax Year 2010), IRS SOI Line Item Totals (Box 19), U.S. Department of Labor Unemployment Insurance Chartbook, National Income and Product Accounts Table 3.12, Office of Management and Budget Historical Table 3.2, Meyer, Mok, and Sullivan (2015) Appendix Table 9

Notes: Panel (a) shows aggregate UI dollars from various administrative sources of data (both restricted and public-use), and Panel (b) shows the proportional bias in UI dollars when using totals from the 1099-G microdata as the benchmark.

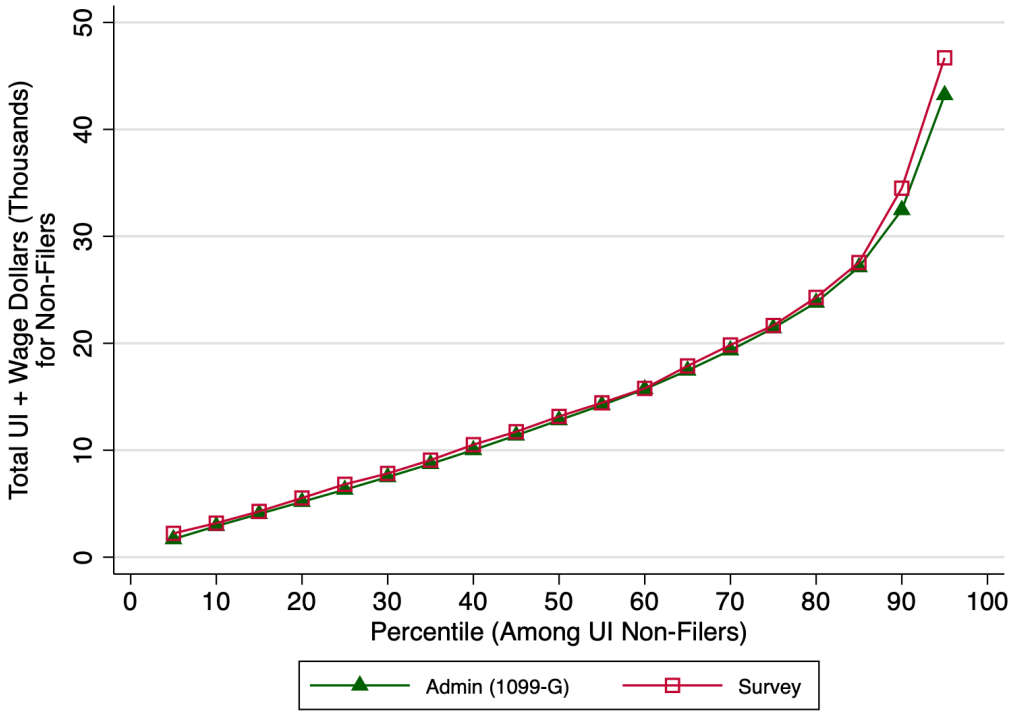
**Figure A3. Incomes of Filer and Non-Filer UI Recipients (Universe)**




Data: 2011 CPS ASEC, IRS Forms 1040 (Tax Year 2010 and Calendar Year 2011 Filings), W-2 (Tax Year 2010), and 1099-G (Tax Year 2010)

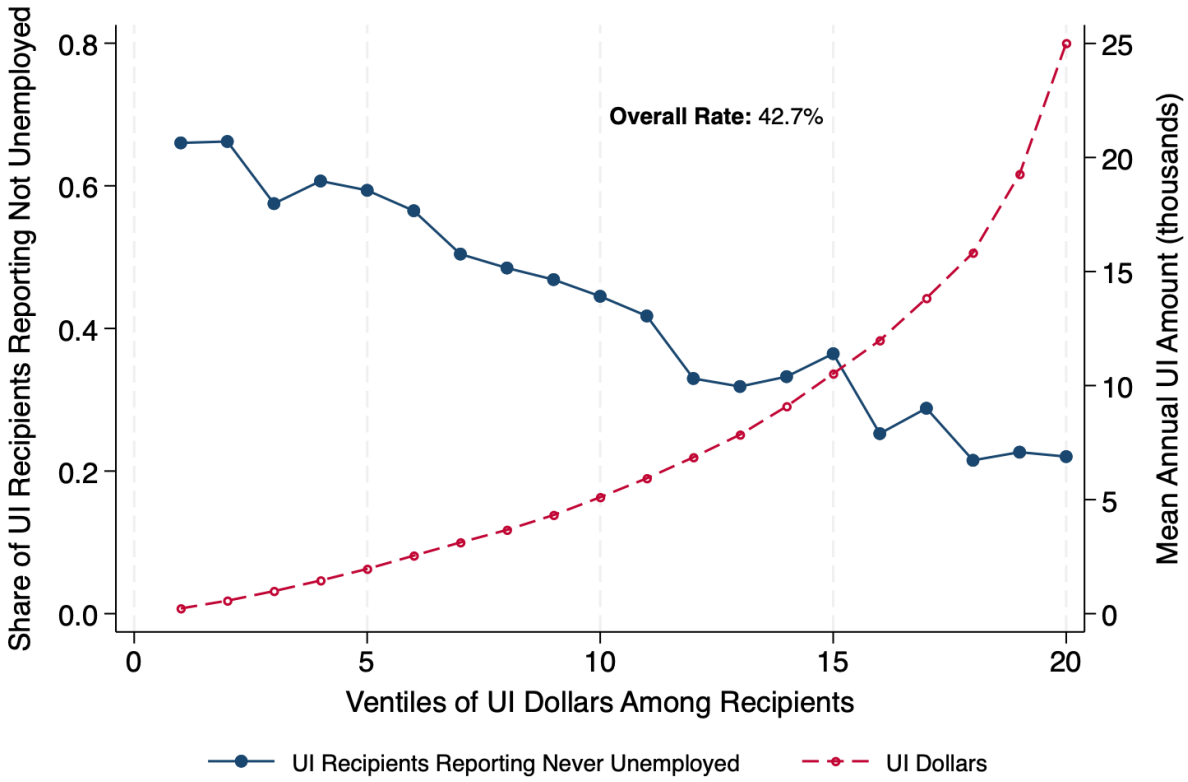
Notes: This figure shows the distribution of UI and UI + wage dollars for the universe of 1099-G recipients (divided into filers and non-filers). Wages come from IRS Forms W-2 and comprise the sum of taxable wages and deferred compensation. Filers are individuals in the 1099-G microdata who link to a 1040, while non-filers are individuals in the 1099-G microdata who do not link to a 1040. Displayed percentiles are interpolated by averaging the actual percentile and the 7 observations on each side. Individuals are re-ranked across income categories.

**Figure A4. Incomes of Non-Filer UI Recipients (Universe vs. Linked CPS)**




Data: 2011 CPS ASEC, IRS Forms 1040 (Tax Year 2010 and Calendar Year 2011 Filings), W-2 (Tax Year 2010), and 1099-G (Tax Year 2010)
Notes: This figure shows the distribution of UI + wage dollars for non-filers in the 1099-G universe and non-filers linked to the CPS. The linked CPS sample consists of non-whole-imputed PIKed individuals, and we adjust for non-PIKing and whole imputes using inverse probability weighting.

**Figure A5. Share of UI Recipients Reporting Never Unemployed (by UI Amount), SIPP**




Source: 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This figure shows the share of UI recipients, based on linked administrative records, who never report being unemployed (retrospectively) in the SIPP by ventile of UI. Survey weights are adjusted for non-PIKing, and we drop observations with imputed values of UI or weeks worked. We plot (using the right-hand side y-axis) the average annual UI amount from the administrative records for each ventile.

**Table A1. Aggregate UI Dollars and Recipients Recorded in CPS and SIPP (Excluding California and New Jersey), 2010**

| | Full Survey Sample | Linked Survey Sample | | |
|---|---|---|---|---|
| | Survey UI | Survey UI | Admin UI | Bias (vs. Linked Totals) |
| | (1) | (2) | (3) | (4) |
| CPS (excluding CA and NJ) | | | | |
| Dollars (millions) | 78,450 | 77,930 | 109,900 | -29.09% |
| Recipients (millions) | 10.30 | 10.30 | 15.28 | -32.58% |
| Sample Size | 181,000 | 147,000 | 147,000 | |
| Weighted Pop. (millions) | 260.20 | 261.00 | 261.00 | |
| SIPP (All Individuals excluding CA and NJ) | | | | |
| Dollars (millions) | 72,130 | 72170 | 116,600 | -38.09% |
| Recipients (millions) | 11.78 | 11.96 | 16.14 | -25.93% |
| Sample Size | 73,500 | 68,000 | 68,000 | |
| Weighted Pop. (millions) | 258.50 | 258.60 | 258.60 | |
| SIPP (Non-Attriters excluding CA and NJ) | | | | |
| Dollars (millions) | 70,290 | 70,860 | 116,100 | -38.97% |
| Recipients (millions) | 12.05 | 12.23 | 15.90 | -23.08% |
| Sample Size | 58,500 | 54,500 | 54,500 | |
| Weighted Pop. (millions) | 258.60 | 258.60 | 258.60 | |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table shows total UI dollars and recipients calculated from various survey and administrative sources, excluding California and New Jersey (which administered non-UI programs – including paid family leave in both states and Temporary Disability Income in CA – whose amounts are listed in Box 1 on Form 1099-G). Column 1 shows estimates calculated using survey values in the full 2011 CPS ASEC and the 2008 SIPP Panel (Waves 5-8) samples, where the SIPP values are scaled up to reflect calendar year amounts. Columns 2 and 3 show estimates calculated using survey and administrative values for the linked CPS and SIPP samples, which consists of PIKed individuals (and additionally non-whole-imputes in the CPS). Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting. The "SIPP (All Individuals)" sample refers to all individuals in reference month 4 of Wave 6 of the 2008 SIPP Panel, while the "SIPP (Non-Attriters)" sample refers to all individuals in reference month 4 of Wave 6 who were also interviewed for every month of the 2010 calendar year.

## Table A2. Individual-Level Error Components in CPS and SIPP (Excluding California and New Jersey)

| | CPS | SIPP (All Individuals) | SIPP (Non-Attriters) |
|---|---|---|---|
| | (1) | (2) | (3) |
| False Positives | | | |
| Percent (of True Non-Recipients) | 0.35% | 0.77% | 0.74% |
| False Negatives | | | |
| Percent (of True Recipients) | 38.16% | 37.50% | 34.39% |
| Average 1099-G Amount ($) | 5,274 | 4,797 | 4,749 |
| True Reporting Recipients | | | |
| Mean Absolute Error ($) | 2,907 | 3,512 | 3,426 |
| Mean Net Error ($) | -746 | -2,224 | -2,410 |
| Average 1099-G Amount ($) | 8,374 | 8,677 | 8,639 |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table calculates sources of errors in reported UI dollars in the linked survey data for both the CPS and SIPP, excluding California and New Jersey (which administered non-UI programs – including paid family leave in both states and Temporary Disability Income in CA – whose amounts are listed in Box 1 on Form 1099-G). False positives are defined as the share of true non-recipients who report receipt in the survey and false negatives are defined as the share of true recipients who do not report receipt in the survey. Among true reporting recipients, the mean absolute error is calculated as the average of the absolute value of survey and administrative reports, while the mean net error is the average of the net difference in survey and administrative reports. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting. The "SIPP (All Individuals)" sample refers to all individuals in reference month 4 of Wave 6 of the 2008 SIPP Panel, while the "SIPP (Non-Attriters)" sample refers to all individuals in reference month 4 of Wave 6 who were also interviewed for every month of the 2010 calendar year.

## Table A3. False Positive and False Negative Rates (%) for Other Demographic Subgroups

| Characteristics | CPS | | SIPP | |
|---|---|---|---|---|
| | False Positives | False Negatives | False Positives | False Negatives |
| | (1) | (2) | (3) | (4) |
| Census Regions | | | | |
| Northeast | 0.50 | 38.65 | 1.19 | 38.95 |
| Midwest | 0.49 | 35.33 | 0.96 | 33.11 |
| South | 0.35 | 44.27 | 0.91 | 43.39 |
| West | 0.49 | 36.91 | 1.40 | 35.54 |
| Census Divisions | | | | |
| New England | 0.53 | 36.22 | 1.26 | 34.49 |
| Middle Atlantic | 0.49 | 39.50 | 1.15 | 41.03 |
| East North Central | 0.52 | 36.12 | 1.08 | 34.26 |
| West North Central | 0.41 | 32.88 | 0.65 | 30.42 |
| South Atlantic | 0.34 | 47.12 | 1.08 | 44.48 |
| East South Central | 0.60 | 40.06 | 0.73 | 40.04 |
| West South Central | 0.25 | 41.08 | 0.80 | 41.46 |
| Mountain | 0.37 | 36.14 | 1.10 | 36.17 |
| Pacific | 0.54 | 37.17 | 1.52 | 35.26 |
| Metropolitan Status | | | | |
| Rural | 0.42 | 39.30 | 0.96 | 40.05 |
| Metropolitan | 0.46 | 39.12 | 1.11 | 37.51 |
| Immigration Status | | | | |
| Non-immigrant | 0.43 | 37.30 | 1.04 | 36.32 |
| Immigrant | 0.50 | 49.13 | 1.32 | 45.09 |
| Family Type | | | | |
| Single Parent | 0.47 | 33.50 | 0.82 | 33.17 |
| Multiple Parents | 0.47 | 37.66 | 1.22 | 40.85 |
| Single Childless | 0.63 | 36.40 | 1.47 | 32.11 |
| Multiple Childless | 0.43 | 40.84 | 1.20 | 37.96 |
| Elderly | 0.26 | 49.29 | 0.43 | 46.84 |
| Industry Code | | | | |
| Retail | 0.42 | 40.15 | 1.41 | 41.78 |
| Heavy Industry | 0.76 | 35.59 | 1.70 | 38.89 |
| Financial & Professional | 0.51 | 36.01 | 1.70 | 36.52 |
| Education & Health | 0.28 | 42.46 | 1.32 | 42.75 |
| Other | - | - | 1.23 | 36.77 |
| Not in Labor Force | - | - | 0.14 | 77.91 |
| Unemployed, in Labor | 3.01 | 18.15 | 3.97 | 15.17 |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table calculates false positive and false negative rates for UI for other demographic subgroups. Note that false positive rates here are conditional on individuals age 18+ who are true non-recipients of UI. Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

## Table A4. Partial Determinants of False Negatives and False Positives (Full Output)

| | CPS | | SIPP | |
|---|---|---|---|---|
| | False Positives | False Negatives | False Positives | False Negatives |
| | (1) | (2) | (3) | (4) |
| Race/Ethnicity | | | | |
| Black, | 0.0036*** | 0.0945*** | 0.0023** | 0.1100*** |
| Non-Hispanic | (0.0009) | (0.0150) | (0.0009) | (0.0200) |
| Asian, | 0.0031** | 0.1120*** | 0.0012 | 0.0866** |
| Non-Hispanic | (0.0013) | (0.0282) | (0.0014) | (0.0368) |
| Other, | 0.0025 | 0.0661** | 0.0017 | 0.0639** |
| Non-Hispanic | (0.0016) | (0.0294) | (0.0020) | (0.0316) |
| Hispanic | 0.0037*** | 0.1190*** | 0.0015 | 0.0583*** |
| | (0.0009) | (0.0154) | (0.0011) | (0.0205) |
| Census Divisions | | | | |
| Middle | -0.0014 | -0.0219 | 0.0003 | 0.0404 |
| Atlantic | (0.0013) | (0.0244) | (0.0020) | (0.0317) |
| East | -0.0012 | -0.0272 | -0.0016 | 0.0134 |
| North Central | (0.0013) | (0.0235) | (0.0017) | (0.0300) |
| West | -0.0019 | -0.0323 | -0.0023 | -0.0194 |
| North Central | (0.0013) | (0.0261) | (0.0018) | (0.0364) |
| South | -0.0034*** | 0.0347 | -0.0002 | 0.0573* |
| Atlantic | (0.0012) | (0.0236) | (0.0018) | (0.0307) |
| East | -0.0013 | -0.0074 | -0.0012 | 0.0200 |
| South Central | (0.0015) | (0.0284) | (0.0020) | (0.0372) |
| West | -0.0044*** | -0.0206 | -0.0023 | 0.0501 |
| South Central | (0.0012) | (0.0259) | (0.0018) | (0.0353) |
| Mountain | -0.0032** | -0.0208 | -0.0032* | 0.0132 |
| | (0.0013) | (0.0254) | (0.0018) | (0.0370) |
| Pacific | -0.0019 | -0.0365 | 0.0003 | -0.0054 |
| | (0.0012) | (0.0227) | (0.0018) | (0.0308) |
| Education Level | | | | |
| <HS Grad | 0.0020** | 0.0022 | 0.0018 | -0.0100 |

| | | | | |
|---|---|---|---|---|
| | (0.0008) | (0.0204) | (0.0012) | (0.0264) |
| HS Grad | 0.0033*** | 0.0113 | 0.0007 | 0.0240 |
| | (0.0006) | (0.0158) | (0.0008) | (0.0198) |
| Some College | 0.0009* | 0.0186 | 0.0004 | -0.0129 |
| | (0.0005) | (0.0157) | (0.0007) | (0.0181) |
| Family Income Relative to Poverty Line | | | | |
| Income 0-1x FPL | -0.0016** | 0.2340*** | 0.0001 | 0.0492* |
| | (0.0008) | (0.0205) | (0.0010) | (0.0257) |
| Income 1-2x FPL | 0.0020** | 0.0725*** | 0.0024** | -0.0451** |
| | (0.0008) | (0.0162) | (0.0010) | (0.0207) |
| Income 2-3x FPL | 0.0003 | 0.0283* | 0.0025** | -0.0188 |
| | (0.0007) | (0.0149) | (0.0010) | (0.0190) |
| Income 3-4x FPL | -0.0002 | 0.0272* | 0.0012 | 0.0088 |
| | (0.0008) | (0.0159) | (0.0009) | (0.0201) |
| Age | | | | |
| Age <25 | 0.0004 | -0.0496 | -0.0003 | -0.0052 |
| | (0.0008) | (0.0398) | (0.0008) | (0.0449) |
| Age 25-34 | 0.0040*** | -0.0300 | 0.0029*** | -0.1060** |
| | (0.0010) | (0.0370) | (0.0011) | (0.0413) |
| Age 35-44 | 0.0066*** | -0.0448 | 0.0041*** | -0.1040** |
| | (0.0012) | (0.0368) | (0.0011) | (0.0408) |
| Age 45-54 | 0.0054*** | -0.0843** | 0.0054*** | -0.1430*** |
| | (0.0011) | (0.0360) | (0.0012) | (0.0408) |
| Age 55-64 | 0.0027*** | -0.0738** | 0.0022** | -0.1160*** |
| | (0.0009) | (0.0364) | (0.0009) | (0.0406) |
| Family Type | | | | |
| Single Non-Elderly Parent | -0.0004 | -0.0768*** | -0.0004 | -0.0368 |
| | (0.0011) | (0.0222) | (0.0014) | (0.0302) |
| Single Non-Elderly Childless | 0.0006 | -0.0199 | 0.00002 | -0.0135 |
| | (0.0012) | (0.0222) | (0.00126) | (0.0288) |

| | | | | |
|---|---|---|---|---|
| Multiple Non-Elderly Childless | -0.0008<br>(0.0009) | 0.0203<br>(0.0184) | 0.0007<br>(0.0011) | -0.0043<br>(0.0231) |
| Elderly | 0.00003<br>(0.00144) | 0.0331<br>(0.0298) | -0.0004<br>(0.0012) | -0.0050<br>(0.0334) |
| <u>Industry Type</u> | | | | |
| Retail | 0.0010<br>(0.0011) | -0.2630***<br>(0.0288) | 0.0002<br>(0.0012) | -0.0180<br>(0.0291) |
| Heavy Industry | 0.0032***<br>(0.0011) | -0.3060***<br>(0.0291) | 0.0014<br>(0.0014) | -0.0372<br>(0.0291) |
| Financial & Professional Services | 0.0028**<br>(0.0012) | -0.2590***<br>(0.0308) | 0.0023*<br>(0.0014) | -0.0111<br>(0.0298) |
| Education & Health | 0.0007<br>(0.0011) | -0.2500***<br>(0.0310) | -0.0004<br>(0.0014) | -0.0014<br>(0.0308) |
| Other | -0.0013<br>(0.0014) | -0.2680***<br>(0.0345) | 0.0014<br>(0.0014) | -0.0422<br>(0.0366) |
| Not in Labor Force | -0.0087***<br>(0.0010) | 0.3770***<br>(0.0186) | -0.0089***<br>(0.0012) | 0.3640***<br>(0.0256) |
| <u>Other Variables</u> | | | | |
| Reference Person | -0.0001<br>(0.0006) | -0.0722***<br>(0.0127) | -0.0006<br>(0.0007) | -0.0072<br>(0.0152) |
| Non-Citizen | -0.0026***<br>(0.0005) | 0.0434**<br>(0.0221) | 0.0007<br>(0.0012) | 0.0652**<br>(0.0271) |
| Male | 0.0017***<br>(0.0005) | 0.0161<br>(0.0110) | 0.0020***<br>(0.0006) | -0.0135<br>(0.0135) |
| Metropolitan | -0.0001<br>(0.0005) | 0.0289***<br>(0.0105) | 0.0014**<br>(0.0006) | -0.0242<br>(0.0153) |
| Number of Adults | -0.00004<br>(0.00030) | 0.0130**<br>(0.0065) | -0.0010**<br>(0.0004) | 0.0186**<br>(0.0087) |
| Number of Children | -0.0003<br>(0.0004) | -0.0264***<br>(0.0072) | -0.0002<br>(0.0004) | -0.0019<br>(0.0094) |

| | | | | |
|---|---|---|---|---|
| UI Item | 0.0314*** | 0.3330*** | 0.8840*** | a |
| Imputed | (0.0048) | (0.0351) | (0.0236) | a |
| Whole Imputed | | | 0.0017* | 0.1750*** |
| Individual | | | (0.0010) | (0.0216) |
| Admin UI | | -11.0000*** | | -10.5000*** |
| Amount ($) | | (1.0200) | | (1.2100) |
| Weeks Worked | -0.00025*** | 0.0115*** | -0.0002*** | 0.0057*** |
| (in Past Year) | (0.00002) | (0.0004) | (0.0000) | (0.0005) |
| Full Time Job | 0.0004 | 0.0237 | -0.0005 | 0.0257 |
| (in Past Year) | (0.0007) | (0.0160) | (0.0009) | (0.0162) |
| DV Mean | --- | 0.3919 | 0.0108 | 0.3803 |
| Sample Size | 109,000 | 9,700 | 55,500 | 5,100 |

Source: 2011 CPS ASEC, 2008 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)
Notes: This table shows average partial effects for various determinants of UI misreporting, derived from probit regressions with an indicator for false positive or negative as the outcome. False negative (positive) regressions are run over all true recipients (non-recipients). Survey weights are adjusted for non-PIKing (and whole imputes in the CPS) using inverse probability weighting.

## Table A5a. Determinants of UI Take-Up, CPS (Sample: All Individuals 18+)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | -0.0008 | 0.0252*** | 0.0260*** |
| | (0.0051) | (0.0077) | (0.0064) |
| Asian, Non-Hispanic | -0.0097*** | -0.0097** | -0.0000 |
| | (0.0032) | (0.0038) | (0.0031) |
| Other, Non-Hispanic | -0.0014 | 0.0018 | 0.0032 |
| | (0.0040) | (0.0051) | (0.0041) |
| Hispanic | -0.0067 | 0.0230*** | 0.0297*** |
| | (0.0047) | (0.0071) | (0.0067) |
| (Black, non-Hispanic x Midwest) | -0.0022 | -0.0070 | -0.0048 |
| | (0.0071) | (0.0089) | (0.0078) |
| (Black, non-Hispanic x South) | 0.0135** | 0.0075 | -0.0060 |
| | (0.0059) | (0.0076) | (0.0065) |
| (Black, non-Hispanic x West) | 0.0007 | -0.0115 | -0.0122 |
| | (0.0082) | (0.0103) | (0.0085) |
| (Hispanic x Midwest) | 0.0084 | -0.0016 | -0.0100 |
| | (0.0073) | (0.0092) | (0.0085) |
| (Hispanic x South) | 0.0032 | -0.0093 | -0.0125* |
| | (0.0062) | (0.0078) | (0.0074) |
| (Hispanic x West) | 0.0078 | -0.0119 | -0.0197*** |
| | (0.0057) | (0.0073) | (0.0069) |
| Census Divisions | | | |
| Middle Atlantic | 0.0042 | 0.0064 | 0.0022 |
| | (0.0039) | (0.0049) | (0.0036) |
| East North Central | -0.0061* | -0.0077* | -0.0017 |
| | (0.0036) | (0.0046) | (0.0035) |
| West North Central | -0.0155*** | -0.0255*** | -0.0100*** |
| | (0.0036) | (0.0046) | (0.0034) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.0234*** | -0.0231*** | 0.0003 |
| | (0.0034) | (0.0045) | (0.0035) |
| East South Central | -0.0202*** | -0.0277*** | -0.0075* |
| | (0.0040) | (0.0051) | (0.0039) |
| West South Central | -0.0258*** | -0.0382*** | -0.0124*** |
| | (0.0037) | (0.0047) | (0.0035) |
| Mountain | -0.0144*** | -0.0175*** | -0.0031 |
| | (0.0037) | (0.0048) | (0.0036) |
| Pacific | 0.0015 | 0.0059 | 0.0045 |
| | (0.0038) | (0.0049) | (0.0036) |
| Education Level | | | |
| <HS Grad | 0.0080*** | 0.0141*** | 0.0061** |
| | (0.0026) | (0.0032) | (0.0026) |
| HS Grad | 0.0170*** | 0.0280*** | 0.0111*** |
| | (0.0019) | (0.0025) | (0.0018) |
| Some College | 0.0138*** | 0.0272*** | 0.0134*** |
| | (0.0018) | (0.0024) | (0.0017) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.0205*** | 0.0033 | 0.0239*** |
| | (0.0022) | (0.0033) | (0.0027) |
| Income 1-2x FPL | 0.0137*** | 0.0299*** | 0.0162*** |
| | (0.0023) | (0.0029) | (0.0023) |
| Income 2-3x FPL | 0.0192*** | 0.0335*** | 0.0143*** |
| | (0.0023) | (0.0028) | (0.0021) |
| Income 3-4x FPL | 0.0093*** | 0.0189*** | 0.0096*** |
| | (0.0023) | (0.0028) | (0.0021) |
| Age | | | |
| Age <25 | 0.0006 | 0.0057 | 0.0052* |
| | (0.0030) | (0.0036) | (0.0031) |
| Age 25-34 | 0.0376*** | 0.0640*** | 0.0264*** |
| | (0.0033) | (0.0042) | (0.0035) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.0451*** | 0.0679*** | 0.0228*** |
| | (0.0035) | (0.0042) | (0.0036) |
| Age 45-54 | 0.0502*** | 0.0698*** | 0.0196*** |
| | (0.0034) | (0.0040) | (0.0034) |
| Age 55-64 | 0.0375*** | 0.0524*** | 0.0150*** |
| | (0.0033) | (0.0039) | (0.0033) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0275*** | 0.0329*** | 0.0054 |
| | (0.0044) | (0.0051) | (0.0038) |
| Single Non-Elderly Childless | 0.0045 | 0.0096** | 0.0051 |
| | (0.0032) | (0.0041) | (0.0032) |
| Multiple Non-Elderly Childless | -0.0044* | -0.0009 | 0.0035 |
| | (0.0026) | (0.0033) | (0.0026) |
| Elderly | -0.0102** | -0.0094* | 0.0007 |
| | (0.0040) | (0.0048) | (0.0042) |
| <u>Industry Type</u> | | | |
| Retail | 0.0180*** | 0.0136*** | -0.0045 |
| | (0.0035) | (0.0050) | (0.0031) |
| Heavy Industry | 0.0418*** | 0.0511*** | 0.0093*** |
| | (0.0035) | (0.0050) | (0.0031) |
| Financial & Professional Services | 0.0225*** | 0.0199*** | -0.0026 |
| | (0.0036) | (0.0051) | (0.0033) |
| Education & Health | 0.0009 | -0.0094* | -0.0102*** |
| | (0.0037) | (0.0052) | (0.0033) |
| Other | -0.0008 | -0.0159*** | -0.0151*** |
| | (0.0043) | (0.0059) | (0.0037) |
| Unemployed, not in Labor Force | -0.1390*** | -0.1680*** | -0.0292*** |
| | (0.0031) | (0.0041) | (0.0028) |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference Person | 0.0127*** | 0.0078*** | -0.0050*** |
| | (0.0016) | (0.0021) | (0.0017) |
| Non-Citizen | -0.0226*** | -0.0302*** | -0.0077*** |
| | (0.0021) | (0.0028) | (0.0024) |
| Male | 0.0101*** | 0.0156*** | 0.0055*** |
| | (0.0015) | (0.0019) | (0.0015) |
| Metropolitan | -0.0024 | -0.0041** | -0.0017 |
| | (0.0015) | (0.0019) | (0.0014) |
| Number of Adults | -0.0014 | 0.0016 | 0.0029*** |
| | (0.0010) | (0.0012) | (0.0010) |
| Number of Children | -0.0009 | -0.0033** | -0.0025** |
| | (0.0010) | (0.0013) | (0.0011) |
| Weeks Worked (in Past Year) | -0.0034*** | -0.0040*** | -0.0006*** |
| | (0.0001) | (0.0001) | (0.0000) |
| Full Time Job (in Past Year) | 0.0168*** | 0.0230*** | 0.0062*** |
| | (0.0025) | (0.0031) | (0.0021) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | 0.0063*** | 0.0271*** | 0.0208*** |
| | (0.0024) | (0.0032) | (0.0027) |
| Asian, Non-Hispanic | -0.0095*** | -0.0091** | 0.0004 |
| | (0.0031) | (0.0038) | (0.0031) |
| Other, Non-Hispanic | -0.0016 | 0.0024 | 0.0040 |
| | (0.0039) | (0.0051) | (0.0041) |
| Hispanic | -0.0018 | 0.0144*** | 0.0161*** |
| | (0.0022) | (0.0029) | (0.0024) |
| Sample Size | 116,500 | 116,500 | 116,500 |

Source: 2011 CPS ASEC, IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+. Survey weights are adjusted for non-PIKing and whole imputes using inverse probability weighting.

## Table A5b. Determinants of UI Take-Up, CPS (Sample: Survey-Only Eligible)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, | -0.0505 | -0.0183 | 0.0323 |
| Non-Hispanic | (0.0444) | (0.0485) | (0.0317) |
| Asian, | -0.0833*** | -0.0793** | 0.0040 |
| Non-Hispanic | (0.0308) | (0.0331) | (0.0243) |
| Other, | -0.0439 | -0.0403 | 0.0036 |
| Non-Hispanic | (0.0315) | (0.0320) | (0.0172) |
| Hispanic | -0.0595 | -0.0684 | -0.0089 |
| | (0.0444) | (0.0452) | (0.0474) |
| (Black, non-Hispanic | -0.0494 | -0.0339 | 0.0155 |
| x Midwest) | (0.0612) | (0.0628) | (0.0484) |
| (Black, non-Hispanic | 0.1070** | 0.1000* | -0.0073 |
| x South) | (0.0512) | (0.0545) | (0.0347) |
| (Black, non-Hispanic | 0.0587 | 0.0012 | -0.0575 |
| x West) | (0.0731) | (0.0767) | (0.0440) |
| (Hispanic x Midwest) | 0.0751 | 0.0499 | -0.0253 |
| | (0.0613) | (0.0614) | (0.0537) |
| (Hispanic x South) | -0.0288 | 0.0022 | 0.0310 |
| | (0.0536) | (0.0541) | (0.0502) |
| (Hispanic x West) | 0.0516 | 0.0907* | 0.0391 |
| | (0.0503) | (0.0508) | (0.0499) |
| Census Divisions | | | |
| Middle | -0.0292 | -0.0402 | -0.0110 |
| Atlantic | (0.0310) | (0.0313) | (0.0215) |
| East | -0.0753** | -0.0718** | 0.0035 |
| North Central | (0.0303) | (0.0307) | (0.0217) |
| West | -0.1180*** | -0.1420*** | -0.0237 |
| North Central | (0.0312) | (0.0312) | (0.0217) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.1530*** | -0.1550*** | -0.0020 |
| | (0.0298) | (0.0302) | (0.0210) |
| East South Central | -0.1130*** | -0.1490*** | -0.0366 |
| | (0.0363) | (0.0367) | (0.0244) |
| West South Central | -0.1560*** | -0.1920*** | -0.0355* |
| | (0.0330) | (0.0334) | (0.0206) |
| Mountain | -0.0932*** | -0.1140*** | -0.0204 |
| | (0.0317) | (0.0317) | (0.0211) |
| Pacific | -0.0702** | -0.0759** | -0.0057 |
| | (0.0304) | (0.0306) | (0.0204) |
| Education Level | | | |
| <HS Grad | 0.0225 | 0.0399* | 0.0174 |
| | (0.0233) | (0.0240) | (0.0153) |
| HS Grad | 0.0609*** | 0.0721*** | 0.0111 |
| | (0.0177) | (0.0182) | (0.0107) |
| Some College | 0.0433** | 0.0833*** | 0.0400*** |
| | (0.0169) | (0.0174) | (0.0098) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.3100*** | -0.2550*** | 0.0548*** |
| | (0.0213) | (0.0235) | (0.0162) |
| Income 1-2x FPL | -0.1280*** | -0.0973*** | 0.0303** |
| | (0.0193) | (0.0197) | (0.0125) |
| Income 2-3x FPL | -0.0421** | -0.0092 | 0.0330*** |
| | (0.0197) | (0.0197) | (0.0113) |
| Income 3-4x FPL | -0.0529** | -0.0402* | 0.0127 |
| | (0.0210) | (0.0211) | (0.0117) |
| Age | | | |
| Age <25 | -0.1310** | -0.1300** | 0.0017 |
| | (0.0549) | (0.0546) | (0.0384) |
| Age 25-34 | 0.0161 | 0.0414 | 0.0254 |
| | (0.0537) | (0.0537) | (0.0379) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.0790 | 0.1190** | 0.0400 |
| | (0.0534) | (0.0532) | (0.0376) |
| Age 45-54 | 0.1380*** | 0.1650*** | 0.0273 |
| | (0.0529) | (0.0528) | (0.0370) |
| Age 55-64 | 0.1530*** | 0.1750*** | 0.0218 |
| | (0.0543) | (0.0542) | (0.0375) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0442 | 0.0360 | -0.0082 |
| | (0.0281) | (0.0281) | (0.0166) |
| Single Non-Elderly Childless | -0.0375 | -0.0422 | -0.0047 |
| | (0.0270) | (0.0271) | (0.0178) |
| Multiple Non-Elderly Childless | -0.0631*** | -0.0557** | 0.0074 |
| | (0.0224) | (0.0226) | (0.0155) |
| Elderly | -0.0682* | -0.0442 | 0.0240 |
| | (0.0381) | (0.0384) | (0.0270) |
| <u>Industry Type</u> | | | |
| Retail | -0.0515*** | -0.0437** | 0.0077 |
| | (0.0186) | (0.0193) | (0.0128) |
| Heavy Industry | 0.0618*** | 0.0578*** | -0.0039 |
| | (0.0179) | (0.0188) | (0.0123) |
| Financial & Professional Services | | | |
| Education & Health | -0.1080*** | -0.1080*** | -0.0002 |
| | (0.0203) | (0.0208) | (0.0123) |
| Other | -0.0618** | -0.0578** | 0.0040 |
| | (0.0259) | (0.0265) | (0.0154) |
| Unemployed, not in Labor Force | | | |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference | 0.0788*** | 0.0644*** | -0.0144 |
| Person | (0.0153) | (0.0157) | (0.0099) |
| Non-Citizen | -0.1270*** | -0.1420*** | -0.0149 |
| | (0.0218) | (0.0232) | (0.0163) |
| Male | -0.0186 | -0.0027 | 0.0159* |
| | (0.0135) | (0.0139) | (0.0084) |
| Metropolitan | -0.0136 | -0.0181 | -0.0045 |
| | (0.0128) | (0.0130) | (0.0077) |
| Number of | -0.0208** | -0.0205** | 0.0003 |
| Adults | (0.0082) | (0.0085) | (0.0057) |
| Number of | 0.0152* | 0.0045 | -0.0107 |
| Children | (0.0091) | (0.0090) | (0.0066) |
| Weeks Worked | -0.0033*** | -0.0030*** | 0.0004 |
| (in Past Year) | (0.0005) | (0.0005) | (0.0003) |
| Full Time Job | 0.1450*** | 0.1570*** | 0.0119 |
| (in Past Year) | (0.0139) | (0.0142) | (0.0089) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, | 0.0064 | 0.0312 | 0.0248* |
| Non-Hispanic | (0.0196) | (0.0200) | (0.0129) |
| Asian, | -0.0859*** | -0.0833** | 0.0026 |
| Non-Hispanic | (0.0302) | (0.0325) | (0.0240) |
| Other, | -0.0464 | -0.0438 | 0.0026 |
| Non-Hispanic | (0.0311) | (0.0317) | (0.0170) |
| Hispanic | -0.0386** | -0.0243 | 0.0143 |
| | (0.0186) | (0.0190) | (0.0137) |
| Sample Size | 7,500 | 7,500 | 7,500 |

Source: 2011 CPS ASEC, IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+ classified as being eligible using survey data alone. Survey weights are adjusted for non-PIKing and whole imputes using inverse probability weighting.

## Table A5c. Determinants of UI Take-Up, CPS (Sample: Admin-Only Eligible)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | -0.0051 | 0.0712** | 0.0762*** |
| | (0.0209) | (0.0308) | (0.0267) |
| Asian, Non-Hispanic | -0.0368*** | -0.0165 | 0.0202 |
| | (0.0132) | (0.0159) | (0.0125) |
| Other, Non-Hispanic | 0.0047 | 0.0221 | 0.0174 |
| | (0.0155) | (0.0197) | (0.0157) |
| Hispanic | -0.0480*** | 0.0401 | 0.0880*** |
| | (0.0181) | (0.0269) | (0.0245) |
| (Black, non-Hispanic x Midwest) | -0.0150 | -0.0113 | 0.0037 |
| | (0.0290) | (0.0373) | (0.0326) |
| (Black, non-Hispanic x South) | 0.0527** | 0.0142 | -0.0386 |
| | (0.0235) | (0.0316) | (0.0271) |
| (Black, non-Hispanic x West) | -0.0021 | -0.0218 | -0.0197 |
| | (0.0338) | (0.0423) | (0.0352) |
| (Hispanic x Midwest) | 0.0085 | 0.0265 | 0.0180 |
| | (0.0301) | (0.0388) | (0.0368) |
| (Hispanic x South) | 0.0438* | -0.0047 | -0.0485* |
| | (0.0248) | (0.0307) | (0.0283) |
| (Hispanic x West) | 0.0309 | -0.0179 | -0.0488* |
| | (0.0231) | (0.0292) | (0.0273) |
| Census Divisions | | | |
| Middle Atlantic | -0.0011 | 0.0199 | 0.0210 |
| | (0.0157) | (0.0185) | (0.0138) |
| East North Central | -0.0442*** | -0.0432** | 0.0010 |
| | (0.0151) | (0.0178) | (0.0132) |
| West North Central | -0.0563*** | -0.0770*** | -0.0207 |
| | (0.0153) | (0.0179) | (0.0133) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.0820*** | -0.0735*** | 0.0085 |
| | (0.0143) | (0.0171) | (0.0131) |
| East South Central | -0.0694*** | -0.0658*** | 0.0036 |
| | (0.0171) | (0.0208) | (0.0162) |
| West South Central | -0.0776*** | -0.0932*** | -0.0157 |
| | (0.0157) | (0.0184) | (0.0135) |
| Mountain | -0.0384** | -0.0320* | 0.0065 |
| | (0.0156) | (0.0186) | (0.0139) |
| Pacific | -0.0136 | 0.0029 | 0.0165 |
| | (0.0155) | (0.0181) | (0.0136) |
| Education Level | | | |
| <HS Grad | 0.0287** | 0.0632*** | 0.0346*** |
| | (0.0114) | (0.0140) | (0.0110) |
| HS Grad | 0.0401*** | 0.0675*** | 0.0274*** |
| | (0.0080) | (0.0097) | (0.0069) |
| Some College | 0.0287*** | 0.0617*** | 0.0330*** |
| | (0.0074) | (0.0092) | (0.0066) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.0789*** | -0.0233* | 0.0556*** |
| | (0.0091) | (0.0130) | (0.0103) |
| Income 1-2x FPL | 0.0234** | 0.0562*** | 0.0327*** |
| | (0.0093) | (0.0111) | (0.0084) |
| Income 2-3x FPL | 0.0380*** | 0.0729*** | 0.0349*** |
| | (0.0091) | (0.0108) | (0.0081) |
| Income 3-4x FPL | 0.0183* | 0.0374*** | 0.0191** |
| | (0.0097) | (0.0113) | (0.0081) |
| Age | | | |
| Age <25 | 0.0180 | -0.0043 | -0.0223 |
| | (0.0148) | (0.0198) | (0.0162) |
| Age 25-34 | 0.0720*** | 0.0819*** | 0.0098 |
| | (0.0141) | (0.0192) | (0.0153) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.1160*** | 0.1270*** | 0.0116 |
| | (0.0147) | (0.0196) | (0.0157) |
| Age 45-54 | 0.1370*** | 0.1470*** | 0.0095 |
| | (0.0148) | (0.0193) | (0.0153) |
| Age 55-64 | 0.0882*** | 0.0881*** | -0.0001 |
| | (0.0141) | (0.0188) | (0.0148) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0749*** | 0.0755*** | 0.0006 |
| | (0.0157) | (0.0178) | (0.0133) |
| Single Non-Elderly Childless | 0.0137 | 0.0351** | 0.0215* |
| | (0.0128) | (0.0159) | (0.0124) |
| Multiple Non-Elderly Childless | -0.0172* | -0.0088 | 0.0084 |
| | (0.0101) | (0.0127) | (0.0101) |
| Elderly | -0.0229 | -0.0236 | -0.0006 |
| | (0.0164) | (0.0192) | (0.0157) |
| <u>Industry Type</u> | | | |
| Retail | -0.0455*** | -0.1220*** | -0.0761*** |
| | (0.0133) | (0.0180) | (0.0119) |
| Heavy Industry | 0.0178 | -0.0277 | -0.0455*** |
| | (0.0137) | (0.0185) | (0.0120) |
| Financial & Professional Services | -0.0263* | -0.0954*** | -0.0691*** |
| | (0.0139) | (0.0187) | (0.0121) |
| Education & Health | -0.0970*** | -0.1730*** | -0.0763*** |
| | (0.0138) | (0.0183) | (0.0118) |
| Other | -0.0729*** | -0.1650*** | -0.0924*** |
| | (0.0167) | (0.0216) | (0.0137) |
| Unemployed, not in Labor Force | -0.3280*** | -0.3520*** | -0.0239** |
| | (0.0104) | (0.0139) | (0.0099) |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference Person | 0.0324*** | 0.0164** | -0.0160** |
| | (0.0067) | (0.0083) | (0.0064) |
| Non-Citizen | -0.0337*** | -0.0578*** | -0.0241** |
| | (0.0110) | (0.0131) | (0.0112) |
| Male | 0.0129** | 0.0247*** | 0.0117** |
| | (0.0061) | (0.0074) | (0.0056) |
| Metropolitan | 0.0030 | 0.0020 | -0.0010 |
| | (0.0059) | (0.0073) | (0.0054) |
| Number of Adults | -0.0053 | 0.0011 | 0.0064 |
| | (0.0038) | (0.0046) | (0.0040) |
| Number of Children | -0.0005 | -0.0040 | -0.0035 |
| | (0.0041) | (0.0052) | (0.0043) |
| Weeks Worked (in Past Year) | -0.0073*** | -0.0071*** | 0.0001 |
| | (0.0002) | (0.0002) | (0.0001) |
| Full Time Job (in Past Year) | 0.0351*** | 0.0551*** | 0.0200*** |
| | (0.0084) | (0.0101) | (0.0071) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | 0.0228** | 0.0753*** | 0.0525*** |
| | (0.0097) | (0.0123) | (0.0100) |
| Asian, Non-Hispanic | -0.0354*** | -0.0145 | 0.0209* |
| | (0.0128) | (0.0159) | (0.0124) |
| Other, Non-Hispanic | 0.0039 | 0.0237 | 0.0198 |
| | (0.0150) | (0.0197) | (0.0155) |
| Hispanic | -0.0223*** | 0.0337*** | 0.0560*** |
| | (0.0081) | (0.0109) | (0.0092) |
| Sample Size | 19,000 | 19,000 | 19,000 |

Source: 2011 CPS ASEC, IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+ classified as being eligible using administrative data alone. Survey weights are adjusted for non-PIKing and whole imputes using inverse probability weighting.

## Table A5d. Determinants of UI Take-Up, CPS (Sample: Combined Survey-Admin Eligible)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | -0.0392 | -0.0240 | 0.0152 |
| | (0.0447) | (0.0462) | (0.0328) |
| Asian, Non-Hispanic | -0.0789** | -0.0497 | 0.0292 |
| | (0.0324) | (0.0324) | (0.0240) |
| Other, Non-Hispanic | -0.0749** | -0.0841*** | -0.0092 |
| | (0.0317) | (0.0317) | (0.0199) |
| Hispanic | -0.0896** | -0.0683 | 0.0213 |
| | (0.0415) | (0.0460) | (0.0420) |
| (Black, non-Hispanic x Midwest) | -0.0125 | -0.0012 | 0.0113 |
| | (0.0610) | (0.0620) | (0.0478) |
| (Black, non-Hispanic x South) | 0.0521 | 0.0466 | -0.0056 |
| | (0.0511) | (0.0528) | (0.0363) |
| (Black, non-Hispanic x West) | 0.0267 | 0.0091 | -0.0176 |
| | (0.0748) | (0.0757) | (0.0497) |
| (Hispanic x Midwest) | 0.0736 | 0.0375 | -0.0361 |
| | (0.0628) | (0.0645) | (0.0484) |
| (Hispanic x South) | 0.0075 | 0.0277 | 0.0202 |
| | (0.0522) | (0.0553) | (0.0459) |
| (Hispanic x West) | 0.0529 | 0.0722 | 0.0193 |
| | (0.0476) | (0.0509) | (0.0452) |
| Census Divisions | | | |
| Middle Atlantic | -0.0178 | -0.0320 | -0.0142 |
| | (0.0298) | (0.0287) | (0.0219) |
| East North Central | -0.0712** | -0.0849*** | -0.0137 |
| | (0.0297) | (0.0287) | (0.0221) |
| West North Central | -0.1280*** | -0.1560*** | -0.0274 |
| | (0.0307) | (0.0295) | (0.0227) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.1430*** | -0.1530*** | -0.0093 |
| | (0.0296) | (0.0287) | (0.0223) |
| East South Central | -0.1080*** | -0.1490*** | -0.0406 |
| | (0.0359) | (0.0351) | (0.0266) |
| West South Central | -0.1550*** | -0.1840*** | -0.0290 |
| | (0.0330) | (0.0322) | (0.0218) |
| Mountain | -0.1010*** | -0.1280*** | -0.0273 |
| | (0.0306) | (0.0293) | (0.0219) |
| Pacific | -0.0493* | -0.0606** | -0.0114 |
| | (0.0297) | (0.0282) | (0.0216) |
| Education Level | | | |
| <HS Grad | 0.0478* | 0.0480* | 0.0003 |
| | (0.0254) | (0.0253) | (0.0156) |
| HS Grad | 0.0453** | 0.0556*** | 0.0103 |
| | (0.0185) | (0.0187) | (0.0109) |
| Some College | 0.0386** | 0.0638*** | 0.0252** |
| | (0.0176) | (0.0178) | (0.0103) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.3190*** | -0.2210*** | 0.0981*** |
| | (0.0230) | (0.0251) | (0.0165) |
| Income 1-2x FPL | -0.1210*** | -0.0736*** | 0.0472*** |
| | (0.0200) | (0.0202) | (0.0131) |
| Income 2-3x FPL | -0.0110 | 0.0308 | 0.0419*** |
| | (0.0195) | (0.0191) | (0.0117) |
| Income 3-4x FPL | -0.0529** | -0.0348 | 0.0180 |
| | (0.0214) | (0.0215) | (0.0115) |
| Age | | | |
| Age <25 | -0.1770*** | -0.1560*** | 0.0211 |
| | (0.0561) | (0.0561) | (0.0358) |
| Age 25-34 | -0.0519 | -0.0022 | 0.0497 |
| | (0.0537) | (0.0539) | (0.0349) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.0369 | 0.1060** | 0.0687* |
| | (0.0534) | (0.0534) | (0.0355) |
| Age 45-54 | 0.0997* | 0.1500*** | 0.0505 |
| | (0.0529) | (0.0530) | (0.0349) |
| Age 55-64 | 0.1080** | 0.1550*** | 0.0471 |
| | (0.0537) | (0.0537) | (0.0344) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0345 | 0.0351 | 0.0006 |
| | (0.0279) | (0.0276) | (0.0166) |
| Single Non-Elderly Childless | -0.0387 | -0.0526* | -0.0139 |
| | (0.0278) | (0.0277) | (0.0186) |
| Multiple Non-Elderly Childless | -0.0606*** | -0.0347 | 0.0258 |
| | (0.0231) | (0.0230) | (0.0161) |
| Elderly | -0.1240*** | -0.0650* | 0.0591** |
| | (0.0386) | (0.0387) | (0.0292) |
| <u>Industry Type</u> | | | |
| Retail | -0.1090*** | -0.1260*** | -0.0168 |
| | (0.0265) | (0.0263) | (0.0169) |
| Heavy Industry | 0.0152 | -0.0177 | -0.0328* |
| | (0.0275) | (0.0279) | (0.0178) |
| Financial & Professional Services | -0.0776*** | -0.1120 | -0.0340 |
| | (0.0277) | (0.0279) | (0.0178) |
| Education & Health | -0.2030*** | -0.2310*** | -0.0277 |
| | (0.0282) | (0.0282) | (0.0172) |
| Other | -0.1210*** | -0.1580*** | -0.0374* |
| | (0.0357) | (0.0355) | (0.0211) |
| Unemployed, not in Labor Force | | | |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference Person | 0.0931*** | 0.0743*** | -0.0144 |
| | (0.0159) | (0.0163) | (0.0107) |
| Non-Citizen | -0.0952*** | -0.1020*** | -0.0071 |
| | (0.0255) | (0.0264) | (0.0185) |
| Male | 0.0181 | 0.0387*** | 0.0206** |
| | (0.0136) | (0.0137) | (0.0086) |
| Metropolitan | -0.0056 | -0.0070 | -0.0013 |
| | (0.0132) | (0.0132) | (0.0166) |
| Number of Adults | -0.0270*** | -0.0253*** | 0.0003 |
| | (0.0085) | (0.0084) | (0.0057) |
| Number of Children | 0.0158* | 0.0028 | -0.0107 |
| | (0.0095) | (0.0093) | (0.0068) |
| Weeks Worked (in Past Year) | -0.0057*** | -0.0049*** | 0.0008** |
| | (0.0005) | (0.0005) | (0.0003) |
| Full Time Job (in Past Year) | 0.1220*** | 0.1300*** | 0.0077 |
| | (0.0161) | (0.0159) | (0.0100) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | -0.0080 | 0.0037 | 0.0117 |
| | (0.0197) | (0.0197) | (0.0130) |
| Asian, Non-Hispanic | -0.0813** | -0.0537* | 0.0276 |
| | (0.0320) | (0.0322) | (0.0240) |
| Other, Non-Hispanic | -0.0769** | -0.0871*** | -0.0102 |
| | (0.0315) | (0.0316) | (0.0198) |
| Hispanic | -0.0566*** | -0.0247 | 0.0319** |
| | (0.0191) | (0.0194) | (0.0139) |
| Sample Size | 7,300 | 7,300 | 7,300 |

Source: 2011 CPS ASEC, IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+ classified as being eligible using a combination of survey and admin data. Survey weights are adjusted for non-PIKing and whole imputes using inverse probability weighting.

## Table A6a. Determinants of UI Take-Up, SIPP (Sample: All Individuals 18+)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | -0.0068 | 0.0130 | 0.0198** |
| | (0.0073) | (0.0093) | (0.0081) |
| Asian, Non-Hispanic | -0.0200*** | -0.0178*** | 0.0022 |
| | (0.0047) | (0.0058) | (0.0051) |
| Other, Non-Hispanic | -0.0043 | -0.0011 | 0.0032 |
| | (0.0052) | (0.0062) | (0.0052) |
| Hispanic | -0.0004 | 0.0133 | 0.0136 |
| | (0.0097) | (0.0118) | (0.0089) |
| (Black, non-Hispanic x Midwest) | 0.0048 | 0.0130 | 0.0082 |
| | (0.0106) | (0.0120) | (0.0108) |
| (Black, non-Hispanic x South) | 0.0077 | 0.0075 | -0.0002 |
| | (0.0090) | (0.0100) | (0.0092) |
| (Black, non-Hispanic x West) | -0.0090 | -0.0237 | -0.0146 |
| | (0.0132) | (0.0151) | (0.0137) |
| (Hispanic x Midwest) | 0.0072 | 0.0091 | 0.0019 |
| | (0.0129) | (0.0155) | (0.0123) |
| (Hispanic x South) | 0.0084 | 0.0130 | 0.0047 |
| | (0.0112) | (0.0135) | (0.0113) |
| (Hispanic x West) | 0.0094 | 0.0115 | 0.0021 |
| | (0.0108) | (0.0126) | (0.0101) |
| Census Divisions | | | |
| Middle Atlantic | -0.0093 | -0.0009 | 0.0084 |
| | (0.0063) | (0.0074) | (0.0060) |
| East North Central | -0.0146** | -0.0194*** | -0.0048 |
| | (0.0059) | (0.0069) | (0.0056) |
| West North Central | -0.0254*** | -0.0370*** | -0.0116** |
| | (0.0063) | (0.0074) | (0.0059) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.0300*** | -0.0313*** | -0.0014 |
| | (0.0058) | (0.0069) | (0.0058) |
| East South Central | -0.0324*** | -0.0406*** | -0.0082 |
| | (0.0065) | (0.0077) | (0.0062) |
| West South Central | -0.0455*** | -0.0600*** | -0.0146** |
| | (0.0060) | (0.0072) | (0.0060) |
| Mountain | -0.0240*** | -0.0290*** | -0.0050 |
| | (0.0066) | (0.0078) | (0.0064) |
| Pacific | -0.0035 | 0.0004 | 0.0039 |
| | (0.0063) | (0.0076) | (0.0063) |
| Education Level | | | |
| <HS Grad | 0.0093** | 0.0084* | -0.0009 |
| | (0.0043) | (0.0050) | (0.0043) |
| HS Grad | 0.0050* | 0.0201*** | 0.0151*** |
| | (0.0030) | (0.0037) | (0.0031) |
| Some College | 0.0121*** | 0.0227*** | 0.0107*** |
| | (0.0027) | (0.0033) | (0.0027) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.0018 | 0.0312*** | 0.0330*** |
| | (0.0038) | (0.0058) | (0.0050) |
| Income 1-2x FPL | 0.0347*** | 0.0516*** | 0.0169*** |
| | (0.0037) | (0.0042) | (0.0035) |
| Income 2-3x FPL | 0.0294*** | 0.0463*** | 0.0168*** |
| | (0.0032) | (0.0038) | (0.0033) |
| Income 3-4x FPL | 0.0167*** | 0.0259*** | 0.0092*** |
| | (0.0031) | (0.0035) | (0.0031) |
| Age | | | |
| Age <25 | -0.0189*** | -0.0102* | 0.0087* |
| | (0.0047) | (0.0056) | (0.0050) |
| Age 25-34 | 0.0359*** | 0.0520*** | 0.0161*** |
| | (0.0055) | (0.0062) | (0.0056) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.0429*** | 0.0607*** | 0.0179*** |
| | (0.0053) | (0.0062) | (0.0054) |
| Age 45-54 | 0.0556*** | 0.0644*** | 0.0088* |
| | (0.0054) | (0.0059) | (0.0052) |
| Age 55-64 | 0.0380*** | 0.0476*** | 0.0096* |
| | (0.0051) | (0.0056) | (0.0049) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0109* | 0.0159** | 0.0050 |
| | (0.0058) | (0.0073) | (0.0060) |
| Single Non-Elderly Childless | 0.0048 | -0.0009 | -0.0057 |
| | (0.0049) | (0.0062) | (0.0057) |
| Multiple Non-Elderly Childless | 0.0043 | 0.0008 | -0.0034 |
| | (0.0039) | (0.0051) | (0.0047) |
| Elderly | -0.0066 | -0.0091 | -0.0025 |
| | (0.0054) | (0.0071) | (0.0065) |
| <u>Industry Type</u> | | | |
| Retail | 0.0283*** | 0.0109 | -0.0173*** |
| | (0.0049) | (0.0066) | (0.0048) |
| Heavy Industry | 0.0567*** | 0.0617*** | 0.0050 |
| | (0.0050) | (0.0067) | (0.0049) |
| Financial & Professional Services | 0.0439*** | 0.0343*** | -0.0096* |
| | (0.0052) | (0.0070) | (0.0051) |
| Education & Health | 0.0170*** | -0.0115 | -0.0285*** |
| | (0.0052) | (0.0071) | (0.0053) |
| Other | 0.0168*** | -0.0117 | -0.0285*** |
| | (0.0059) | (0.0076) | (0.0056) |
| Unemployed, not in Labor Force | -0.1870*** | -0.1890*** | -0.0017 |
| | (0.0053) | (0.0058) | (0.0051) |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference Person | 0.0013 | 0.0005 | -0.0008 |
| | (0.0025) | (0.0030) | (0.0026) |
| Non-Citizen | -0.0128*** | -0.0045 | 0.0084 |
| | (0.0042) | (0.0058) | (0.0052) |
| Male | 0.0172*** | 0.0180*** | 0.0008 |
| | (0.0022) | (0.0027) | (0.0023) |
| Metropolitan | 0.0039 | -0.0024 | -0.0063** |
| | (0.0026) | (0.0032) | (0.0026) |
| Number of Adults | -0.0045*** | -0.0004 | 0.0041** |
| | (0.0015) | (0.0018) | (0.0017) |
| Number of Children | -0.0018 | -0.0070*** | -0.0052*** |
| | (0.0016) | (0.0021) | (0.0020) |
| Weeks Worked (in Past Year) | -0.0032*** | -0.0030*** | 0.0002* |
| | (0.0001) | (0.0001) | (0.0001) |
| Full Time Job (in Past Year) | -0.0073** | 0.0001 | 0.0074** |
| | (0.0031) | (0.0038) | (0.0031) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | -0.0030 | 0.0171*** | 0.0201*** |
| | (0.0033) | (0.0042) | (0.0037) |
| Asian, Non-Hispanic | -0.0197*** | -0.0171*** | 0.0025 |
| | (0.0045) | (0.0057) | (0.0050) |
| Other, Non-Hispanic | -0.0043 | -0.0009 | 0.0034 |
| | (0.0051) | (0.0061) | (0.0051) |
| Hispanic | 0.0073* | 0.0243*** | 0.0171*** |
| | (0.0039) | (0.0050) | (0.0043) |
| Sample Size | 60,500 | 60,500 | 60,500 |

Source: 2010 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+. Survey weights are adjusted for non-PIKing using inverse probability weighting.

## Table A6b. Determinants of UI Take-Up, SIPP (Sample: Survey-Only Eligible)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | 0.0580 | 0.0194 | -0.0387 |
| | (0.0567) | (0.0564) | (0.0410) |
| Asian, Non-Hispanic | -0.0565 | -0.0769** | -0.0205 |
| | (0.0369) | (0.0383) | (0.0340) |
| Other, Non-Hispanic | -0.0567* | -0.0699** | -0.0132 |
| | (0.0311) | (0.0329) | (0.0256) |
| Hispanic | 0.0834 | 0.1090 | 0.0255 |
| | (0.0663) | (0.0681) | (0.0362) |
| (Black, non-Hispanic x Midwest) | -0.0070 | 0.0367 | 0.0437 |
| | (0.0752) | (0.0756) | (0.0622) |
| (Black, non-Hispanic x South) | -0.0383 | -0.0006 | 0.0377 |
| | (0.0623) | (0.0630) | (0.0483) |
| (Black, non-Hispanic x West) | -0.0723 | 0.0109 | 0.0832 |
| | (0.0937) | (0.0928) | (0.0862) |
| (Hispanic x Midwest) | -0.0204 | -0.0224 | -0.0020 |
| | (0.0864) | (0.0862) | (0.0508) |
| (Hispanic x South) | -0.0291 | 0.0037 | 0.0328 |
| | (0.0762) | (0.0781) | (0.0505) |
| (Hispanic x West) | -0.0990 | -0.0694 | 0.0296 |
| | (0.0721) | (0.0738) | (0.0444) |
| Census Divisions | | | |
| Middle Atlantic | -0.0069 | -0.0272 | -0.0203 |
| | (0.0371) | (0.0369) | (0.0260) |
| East North Central | -0.0345 | -0.0410 | -0.0065 |
| | (0.0340) | (0.0345) | (0.0255) |
| West North Central | -0.0607 | -0.0843** | -0.0236 |
| | (0.0374) | (0.0379) | (0.0261) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.0822** | -0.0954*** | -0.0132 |
| | (0.0353) | (0.0360) | (0.0272) |
| East South Central | -0.1050*** | -0.1130*** | -0.0080 |
| | (0.0401) | (0.0419) | (0.0304) |
| West South Central | -0.1730*** | -0.2070*** | -0.0337 |
| | (0.0369) | (0.0378) | (0.0285) |
| Mountain | -0.0795** | -0.0733* | 0.0062 |
| | (0.0386) | (0.0400) | (0.0300) |
| Pacific | 0.0201 | -0.0116 | -0.0317 |
| | (0.0364) | (0.0370) | (0.0274) |
| Education Level | | | |
| <HS Grad | 0.0889*** | 0.0546* | -0.0342 |
| | (0.0280) | (0.0290) | (0.0227) |
| HS Grad | 0.0446** | 0.0557*** | 0.0111 |
| | (0.0193) | (0.0201) | (0.0153) |
| Some College | 0.0798*** | 0.0614*** | 0.0184 |
| | (0.0176) | (0.0183) | (0.0133) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.1640*** | -0.0728*** | 0.0914*** |
| | (0.0245) | (0.0267) | (0.0208) |
| Income 1-2x FPL | -0.0025 | 0.0355 | 0.0380** |
| | (0.0219) | (0.0220) | (0.0175) |
| Income 2-3x FPL | 0.0562*** | 0.0768*** | 0.0207 |
| | (0.0207) | (0.0208) | (0.0169) |
| Income 3-4x FPL | 0.0463** | 0.0919*** | 0.0456*** |
| | (0.0215) | (0.0223) | (0.0173) |
| Age | | | |
| Age <25 | -0.1860*** | -0.2070*** | -0.0206 |
| | (0.0504) | (0.0544) | (0.0432) |
| Age 25-34 | 0.0462 | 0.0056 | -0.0406 |
| | (0.0508) | (0.0542) | (0.0438) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.1080** | 0.0880 | -0.0196 |
| | (0.0509) | (0.0544) | (0.0441) |
| Age 45-54 | 0.1840*** | 0.1080** | -0.0752* |
| | (0.0508) | (0.0544) | (0.0437) |
| Age 55-64 | 0.1600*** | 0.1210** | -0.0384 |
| | (0.0516) | (0.0549) | (0.0433) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0317 | 0.0115 | -0.0202 |
| | (0.0345) | (0.0355) | (0.0271) |
| Single Non-Elderly Childless | 0.0149 | -0.0368 | -0.0516* |
| | (0.0322) | (0.0320) | (0.0301) |
| Multiple Non-Elderly Childless | -0.0144 | -0.0419* | -0.0275 |
| | (0.0250) | (0.0250) | (0.0225) |
| Elderly | -0.0587 | -0.0889** | -0.0302 |
| | (0.0361) | (0.0368) | (0.0346) |
| <u>Industry Type</u> | | | |
| Retail | -0.0558*** | -0.0712*** | -0.0154 |
| | (0.0201) | (0.0209) | (0.0164) |
| Heavy Industry | 0.0270 | 0.0589*** | 0.0318* |
| | (0.0202) | (0.0214) | (0.0173) |
| Financial & Professional Services | | | |
| Education & Health | -0.1260*** | -0.1470*** | -0.0210 |
| | (0.0218) | (0.0224) | (0.0176) |
| Other | -0.0596** | -0.0765*** | -0.0169 |
| | (0.0276) | (0.0282) | (0.0231) |
| Unemployed, not in Labor Force | | | |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference Person | 0.0160 | 0.0439** | 0.0279** |
| | (0.0168) | (0.0176) | (0.0137) |
| Non-Citizen | -0.0516* | -0.0460 | 0.0056 |
| | (0.0286) | (0.0298) | (0.0259) |
| Male | 0.0157 | -0.0017 | -0.0174 |
| | (0.0148) | (0.0152) | (0.0115) |
| Metropolitan | -0.0082 | -0.0213 | -0.0131 |
| | (0.0168) | (0.0172) | (0.0133) |
| Number of Adults | -0.0342*** | -0.0219** | 0.0123 |
| | (0.0097) | (0.0100) | (0.0099) |
| Number of Children | -0.0007 | -0.0186* | -0.0179* |
| | (0.0101) | (0.0100) | (0.0099) |
| Weeks Worked (in Past Year) | -0.0060*** | -0.0056*** | 0.0005 |
| | (0.0005) | (0.0005) | (0.0004) |
| Full Time Job (in Past Year) | 0.0918*** | 0.0995*** | 0.0078 |
| | (0.0144) | (0.0148) | (0.0113) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | 0.0252 | 0.0226 | -0.0027 |
| | (0.0222) | (0.0223) | (0.0200) |
| Asian, Non-Hispanic | -0.0479 | -0.0697* | -0.0217 |
| | (0.0382) | (0.0389) | (0.0348) |
| Other, Non-Hispanic | -0.0512 | -0.0661** | -0.0149 |
| | (0.0319) | (0.0332) | (0.0260) |
| Hispanic | 0.0316 | 0.0786*** | 0.0469** |
| | (0.0229) | (0.0241) | (0.0195) |
| Sample Size | 5,300 | 5,300 | 5,300 |

Source: 2010 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+ classified as being eligible using survey data alone. Survey weights are adjusted for non-PIKing using inverse probability weighting.

## Table A6c. Determinants of UI Take-Up, SIPP (Sample: Admin-Only Eligible)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, | 0.0072 | 0.0583 | 0.0510 |
| Non-Hispanic | (0.0313) | (0.0363) | (0.0325) |
| Asian, | -0.0498*** | -0.0541** | -0.0043 |
| Non-Hispanic | (0.0184) | (0.0226) | (0.0186) |
| Other, | -0.0015 | 0.0078 | 0.0092 |
| Non-Hispanic | (0.0183) | (0.0222) | (0.0176) |
| Hispanic | 0.0585* | 0.1050** | 0.0470 |
| | (0.0351) | (0.0458) | (0.0367) |
| (Black, non-Hispanic | -0.0047 | 0.0339 | 0.0387 |
| x Midwest) | (0.0422) | (0.0467) | (0.0425) |
| (Black, non-Hispanic | -0.0125 | 0.0143 | 0.0268 |
| x South) | (0.0355) | (0.0387) | (0.0359) |
| (Black, non-Hispanic | -0.0557 | -0.1350** | -0.0788* |
| x West) | (0.0530) | (0.0612) | (0.0452) |
| (Hispanic x Midwest) | -0.0356 | -0.0898 | -0.0542 |
| | (0.0472) | (0.0568) | (0.0399) |
| (Hispanic x South) | -0.0138 | 0.0027 | 0.0165 |
| | (0.0379) | (0.0483) | (0.0395) |
| (Hispanic x West) | -0.0385 | -0.0273 | 0.0111 |
| | (0.0361) | (0.0463) | (0.0378) |
| Census Divisions | | | |
| Middle | -0.0001 | 0.0399 | 0.0400* |
| Atlantic | (0.0234) | (0.0259) | (0.0213) |
| East | -0.0271 | -0.0218 | 0.0053 |
| North Central | (0.0218) | (0.0242) | (0.0194) |
| West | -0.0441* | -0.0713*** | -0.0272 |
| North Central | (0.0239) | (0.0265) | (0.0198) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.0774*** | -0.0704*** | 0.0069 |
| | (0.0215) | (0.0241) | (0.0198) |
| East South Central | -0.0791*** | -0.0737*** | 0.0054 |
| | (0.0239) | (0.0276) | (0.0220) |
| West South Central | -0.1050*** | -0.1310*** | -0.0262 |
| | (0.0225) | (0.0250) | (0.0201) |
| Mountain | -0.0668*** | -0.0715*** | -0.0047 |
| | (0.0237) | (0.0266) | (0.0212) |
| Pacific | -0.0081 | 0.0149 | 0.0230 |
| | (0.0229) | (0.0259) | (0.0213) |
| Education Level | | | |
| <HS Grad | 0.0104 | 0.0034 | -0.0071 |
| | (0.0170) | (0.0188) | (0.0157) |
| HS Grad | -0.0148 | 0.0365*** | 0.0513*** |
| | (0.0115) | (0.0136) | (0.0110) |
| Some College | 0.0171* | 0.0367*** | 0.0196** |
| | (0.0103) | (0.0118) | (0.0094) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.0331** | 0.0243 | 0.0575*** |
| | (0.0138) | (0.0179) | (0.0143) |
| Income 1-2x FPL | 0.0748*** | 0.0861*** | 0.0113 |
| | (0.0129) | (0.0146) | (0.0119) |
| Income 2-3x FPL | 0.0735*** | 0.0910*** | 0.0175 |
| | (0.0121) | (0.0138) | (0.0114) |
| Income 3-4x FPL | 0.0449*** | 0.0520*** | 0.0071 |
| | (0.0122) | (0.0140) | (0.0116) |
| Age | | | |
| Age <25 | -0.0665*** | -0.0822*** | -0.0158 |
| | (0.0215) | (0.0259) | (0.0213) |
| Age 25-34 | 0.0532** | 0.0539** | 0.0007 |
| | (0.0225) | (0.0263) | (0.0217) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.0883*** | 0.1110*** | 0.0224 |
| | (0.0224) | (0.0270) | (0.0228) |
| Age 45-54 | 0.1340*** | 0.1240*** | -0.0106 |
| | (0.0227) | (0.0263) | (0.0220) |
| Age 55-64 | 0.0487** | 0.0473* | -0.0014 |
| | (0.0213) | (0.0251) | (0.0207) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0688*** | 0.0577** | -0.0111 |
| | (0.0228) | (0.0262) | (0.0222) |
| Single Non-Elderly Childless | 0.0277 | 0.0045 | -0.0232 |
| | (0.0180) | (0.0230) | (0.0208) |
| Multiple Non-Elderly Childless | 0.0055 | -0.0087 | -0.0142 |
| | (0.0144) | (0.0187) | (0.0170) |
| Elderly | -0.0275 | -0.0404 | -0.0129 |
| | (0.0199) | (0.0268) | (0.0250) |
| <u>Industry Type</u> | | | |
| Retail | -0.0667*** | -0.1420*** | -0.0757*** |
| | (0.0170) | (0.0207) | (0.0141) |
| Heavy Industry | -0.0042 | -0.0209 | -0.0167 |
| | (0.0173) | (0.0214) | (0.0152) |
| Financial & Professional Services | -0.0221 | -0.0649*** | -0.0428*** |
| | (0.0179) | (0.0219) | (0.0157) |
| Education & Health | -0.1090*** | -0.1860*** | -0.0770*** |
| | (0.0179) | (0.0215) | (0.0152) |
| Other | -0.1180*** | -0.1990*** | -0.0814*** |
| | (0.0200) | (0.0243) | (0.0179) |
| Unemployed, not in Labor Force | -0.3980*** | -0.3940*** | 0.0042 |
| | (0.0177) | (0.0188) | (0.0160) |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference | 0.0007 | -0.0071 | -0.0078 |
| Person | (0.0092) | (0.0108) | (0.0091) |
| Non-Citizen | -0.0458*** | -0.0399** | 0.0059 |
| | (0.0152) | (0.0192) | (0.0163) |
| Male | 0.0355*** | 0.0297*** | -0.0058 |
| | (0.0084) | (0.0097) | (0.0078) |
| Metropolitan | 0.0061 | -0.0064 | -0.0124 |
| | (0.0099) | (0.0118) | (0.0095) |
| Number of | -0.0080 | -0.0027 | 0.0054 |
| Adults | (0.0058) | (0.0064) | (0.0061) |
| Number of | -0.0021 | -0.0087 | -0.0066 |
| Children | (0.0062) | (0.0080) | (0.0074) |
| Weeks Worked | -0.0062*** | -0.0054*** | 0.0009*** |
| (in Past Year) | (0.0002) | (0.0003) | (0.0002) |
| Full Time Job | 0.0079 | 0.0227** | 0.0148* |
| (in Past Year) | (0.0101) | (0.0115) | (0.0089) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, | -0.0070 | 0.0573*** | 0.0643*** |
| Non-Hispanic | (0.0126) | (0.0153) | (0.0132) |
| Asian, | -0.0477** | -0.0504** | -0.0027 |
| Non-Hispanic | (0.0189) | (0.0230) | (0.0190) |
| Other, | 0.0010 | 0.0108 | 0.0099 |
| Non-Hispanic | (0.0187) | (0.0223) | (0.0178) |
| Hispanic | 0.0341** | 0.0888*** | 0.0546*** |
| | (0.0141) | (0.0173) | (0.0145) |
| Sample Size | 9,600 | 9,600 | 9,600 |

Source: 2010 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+ classified as being eligible using administrative data alone. Survey weights are adjusted for non-PIKing using inverse probability weighting.

## Table A6d. Determinants of UI Take-Up, SIPP (Sample: Combined Survey-Admin Eligible)

| | Survey UI (1) | Admin UI (2) | Admin – Survey (3) |
|---|---|---|---|
| ***Panel A: Model with interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, | 0.0159 | 0.0362 | 0.0203 |
| Non-Hispanic | (0.0556) | (0.0546) | (0.0430) |
| Asian, | -0.0806** | -0.1080*** | -0.0270 |
| Non-Hispanic | (0.0385) | (0.0397) | (0.0300) |
| Other, | -0.0258 | -0.0074 | 0.0184 |
| Non-Hispanic | (0.0322) | (0.0338) | (0.0252) |
| Hispanic | 0.0639 | 0.1050* | 0.0414 |
| | (0.0629) | (0.0631) | (0.0414) |
| (Black, non-Hispanic | 0.0449 | 0.0852 | 0.0403 |
| x Midwest) | (0.0734) | (0.0742) | (0.0617) |
| (Black, non-Hispanic | -0.0114 | -0.0058 | 0.0056 |
| x South) | (0.0628) | (0.0617) | (0.0504) |
| (Black, non-Hispanic | a | -0.0798 | a |
| x West) | a | (0.0953) | a |
| (Hispanic x Midwest) | a | -0.0241 | a |
| | a | (0.0823) | a |
| (Hispanic x South) | -0.0572 | -0.0209 | 0.0363 |
| | (0.0738) | (0.0758) | (0.0548) |
| (Hispanic x West) | -0.0446 | -0.0570 | -0.0124 |
| | (0.0698) | (0.0715) | (0.0489) |
| Census Divisions | | | |
| Middle | 0.0240 | 0.0059 | -0.0181 |
| Atlantic | (0.0356) | (0.0357) | (0.0279) |
| East | -0.0337 | -0.0340 | -0.0002 |
| North Central | (0.0331) | (0.0338) | (0.0267) |
| West | -0.0705* | -0.0941** | -0.0236 |
| North Central | (0.0366) | (0.0374) | (0.0268) |

| | | | |
|---|---|---|---|
| South Atlantic | -0.0785** | -0.0865** | -0.0080 |
| | (0.0349) | (0.0356) | (0.0285) |
| East South Central | -0.0999** | -0.0824** | 0.0175 |
| | (0.0399) | (0.0415) | (0.0319) |
| West South Central | -0.1670*** | -0.1900*** | -0.0235 |
| | (0.0372) | (0.0382) | (0.0307) |
| Mountain | -0.1140*** | -0.0855** | 0.0290 |
| | (0.0377) | (0.0391) | (0.0307) |
| Pacific | 0.0113 | -0.0045 | -0.0159 |
| | (0.0351) | (0.0359) | (0.0280) |
| Education Level | | | |
| <HS Grad | 0.0665** | 0.0409 | -0.0257 |
| | (0.0277) | (0.0291) | (0.0225) |
| HS Grad | 0.0321 | 0.0388* | 0.0067 |
| | (0.0199) | (0.0206) | (0.0159) |
| Some College | 0.0611*** | 0.0438** | 0.0173 |
| | (0.0180) | (0.0187) | (0.0135) |
| Family Income Relative to Poverty Line | | | |
| Income 0-1x FPL | -0.1700*** | -0.0992*** | 0.0709*** |
| | (0.0246) | (0.0266) | (0.0199) |
| Income 1-2x FPL | 0.0166 | 0.0426* | 0.0260 |
| | (0.0218) | (0.0222) | (0.0176) |
| Income 2-3x FPL | 0.0701*** | 0.0828*** | 0.0127 |
| | (0.0205) | (0.0210) | (0.0168) |
| Income 3-4x FPL | 0.0531** | 0.0882*** | 0.0351** |
| | (0.0214) | (0.0224) | (0.0172) |
| Age | | | |
| Age <25 | -0.2380*** | -0.2350*** | 0.0032 |
| | (0.0490) | (0.0501) | (0.0388) |
| Age 25-34 | 0.0115 | -0.0200 | -0.0315 |
| | (0.0493) | (0.0496) | (0.0384) |

| | | | |
|---|---|---|---|
| Age 35-44 | 0.0831* | 0.0462 | -0.0369 |
| | (0.0492) | (0.0494) | (0.0388) |
| Age 45-54 | 0.1610*** | 0.0919* | -0.0691* |
| | (0.0488) | (0.0492) | (0.0386) |
| Age 55-64 | 0.1340*** | 0.1070** | -0.0278 |
| | (0.0492) | (0.0491) | (0.0380) |
| <u>Family Type</u> | | | |
| Single Non-Elderly Parent | 0.0245 | 0.0168 | -0.0077 |
| | (0.0332) | (0.0346) | (0.0251) |
| Single Non-Elderly Childless | -0.0279 | -0.0548* | -0.0269 |
| | (0.0308) | (0.0320) | (0.0272) |
| Multiple Non-Elderly Childless | -0.0465* | -0.0558** | -0.0093 |
| | (0.0244) | (0.0249) | (0.0202) |
| Elderly | -0.0897** | -0.0924** | -0.0027 |
| | (0.0357) | (0.0371) | (0.0305) |
| <u>Industry Type</u> | | | |
| Retail | -0.0013 | -0.0371 | -0.0358* |
| | (0.0259) | (0.0268) | (0.0194) |
| Heavy Industry | 0.1000*** | 0.1130*** | 0.0131 |
| | (0.0272) | (0.0284) | (0.0222) |
| Financial & Professional Services | 0.0605** | 0.0460 | -0.0145 |
| | (0.0280) | (0.0291) | (0.0211) |
| Education & Health | -0.1000*** | -0.1460*** | -0.0454** |
| | (0.0288) | (0.0291) | (0.0204) |
| Other | -0.0274 | -0.0662* | -0.0388 |
| | (0.0326) | (0.0339) | (0.0262) |
| Unemployed, not in Labor Force | | | |

| | | | |
|---|---|---|---|
| Other Variables | | | |
| Reference Person | 0.0389** | 0.0556*** | 0.0279** |
| | (0.0169) | (0.0175) | (0.0137) |
| Non-Citizen | -0.0462 | -0.0190 | 0.0272 |
| | (0.0283) | (0.0300) | (0.0247) |
| Male | 0.0254* | 0.0116 | -0.0138 |
| | (0.0144) | (0.0147) | (0.0111) |
| Metropolitan | 0.0087 | 0.0064 | -0.0024 |
| | (0.0163) | (0.0168) | (0.0251) |
| Number of Adults | -0.0400*** | -0.0257*** | 0.0123 |
| | (0.0094) | (0.0096) | (0.0095) |
| Number of Children | -0.0022 | -0.0061 | -0.0179** |
| | (0.0098) | (0.0100) | (0.0087) |
| Weeks Worked (in Past Year) | -0.0068*** | -0.0061*** | 0.0007* |
| | (0.0004) | (0.0005) | (0.0003) |
| Full Time Job (in Past Year) | 0.0855*** | 0.0799*** | -0.0057 |
| | (0.0158) | (0.0161) | (0.0123) |
| ***Panel B: Model with no interaction terms on race*** | | | |
| Race/Ethnicity | | | |
| Black, Non-Hispanic | 0.0148 | 0.0387* | 0.0238 |
| | (0.0219) | (0.0223) | (0.0197) |
| Asian, Non-Hispanic | -0.0786** | -0.1020** | -0.0234 |
| | (0.0387) | (0.0400) | (0.0303) |
| Other, Non-Hispanic | -0.0235 | -0.0027 | 0.0209 |
| | (0.0324) | (0.0338) | (0.0253) |
| Hispanic | 0.0273 | 0.0744*** | 0.0471** |
| | (0.0226) | (0.0232) | (0.0197) |
| Sample Size | 5,600 | 5,600 | 5,600 |

Source: 2010 SIPP Panel (Waves 5-8), IRS Form 1099-G (Tax Year 2010)

Notes: These figures show average partial effects for various determinants of UI receipt. These regressions are run over the sample of all individuals aged 18+ classified as being eligible using a combination of survey and administrative data. Survey weights are adjusted for non-PIKing using inverse probability weighting.

**Table A7. Comparisons of Aggregate UI Benefits Between Form 1040 and Form 1099-G (Robustness Checks Including Processing Year 2012 and Excluding CA and NJ)**

| | Dollars (billions) | | Recipients (millions)* | | |
|---|---|---|---|---|---|
| | Amount ($) | As % of Total | Count | As % of Total | Dollars per Recipient |
| | (1) | (2) | (3) | (4) | (5) |
| | A. Subgroups of 1099-G UI Recipients (including 1040s processed in 2012) | | | | |
| | *1099-G Dollars* | | *1099-G Recipients* | | |
| Link to 1040 with UI Income | 122.40 | 80.55% | 15.55 | 77.16% | 7,871 |
| Link to 1040 without UI Income | 9.81 | 6.46% | 2.20 | 10.93% | 4,455 |
| Does Not Link to 1040 | 19.75 | 13.00% | 2.40 | 11.91% | 8,226 |
| Total | 151.96 | 100.00% | 20.15 | 100.00% | 7,540 |
| | B. Subgroups of 1040 UI Recipients (including 1040s processed in 2012) | | | | |
| | *1040 Dollars* | | *1040 Recipients* | | |
| Link to 1099-G | 121.50 | 99.61% | 14.91 | 99.19% | 8,149 |
| Does Not Link to 1099-G | 0.47 | 0.39% | 0.12 | 0.81% | 3,921 |
| Total | 121.97 | 100.00% | 15.03 | 100.00% | 8,115 |
| | C. Subgroups of 1099-G UI Recipients (excluding CA and NJ) | | | | |
| | *1099-G Dollars* | | *1099-G Recipients* | | |
| Link to 1040 with UI Income | 92.29 | 77.36% | 12.24 | 74.60% | 7,540 |
| Link to 1040 without UI Income | 7.78 | 6.52% | 1.81 | 11.01% | 4,309 |
| Does Not Link to 1040 | 19.23 | 16.12% | 2.36 | 14.39% | 8,145 |
| Total | 119.30 | 100.00% | 16.41 | 100.00% | 7,271 |

* UI recipients are individuals in 1099-Gs and tax units in 1040s.

Source: IRS Forms 1040 (Tax Year 2010 and Calendar Year 2011 Filings) and 1099-G (Tax Year 2010)
Notes: Panel (a) shows total 1099-G dollars and recipient individuals, broken down by various subgroups (i.e., those that link to a 1040 with UI income, those that link to a 1040 without UI income, and those that do not link to a 1040) and including 1040s for tax year 2010 processed in 2012. Table (b) shows total 1040 dollars and recipient tax units, broken down by various subgroups (i.e., those that link to a 1099-G and those that do not link to a 1099-G) and including 1040s for tax year 2010 processed in 2012. Panel (c) shows total 1099-G dollars and recipient individuals, broken down by various subgroups and excluding California and New Jersey (which administered non-UI programs – including paid family leave in both states and Temporary Disability Income in CA – whose amounts are listed in Box 1 on Form 1099-G). Note that recipients in 1040s are tax units while recipients for 1099-Gs are individuals; as a result, the number of 1040 "recipients" by construction is lower than the number of individual recipients because a single tax unit may contain multiple individual recipients.