Non-Random Assignment of Individual Identifiers and Selection into Linked Data: Implications for Research

by

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CES 26-06 **January 2026**

Abstract

The U.S. Census Bureau's Person Identification Validation System facilitates anonymous linkages between survey and administrative records by assigning Protected Identification Keys (PIKs) to person records. While PIK assignment is generally accurate, some person records are not successfully assigned a PIK, which can lead to sample selection bias in analyses of linked data. Using the American Community Survey (ACS) and the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) between 2005 and 2022, we corroborate and extend existing findings on the drivers of PIK assignment, showing that the rate of PIK assignment varies widely across socio-demographic subgroups. Using earnings as a test case, we then show that limiting a survey sample of wage earners to person records with PIKs or successful linkages to W-2 wage records tends to overestimate self-reported wage earnings, on average, indicative of linkage-induced selection bias. In a validation exercise, we demonstrate that reweighting methods, such as inverse probability weighting or entropy balancing, can mitigate this bias.

Keyword: Linkage error, sample selection bias, inverse probability weighting, inverse probability tilting, entropy balancing

JEL Classification: C81, C83

[*] We are grateful to Jonathan Eggleston, Jennifer Bernard, Brad Foster, Rachel Shattuck, Sonya Porter, Denise Flanagan-Doyle, Ashley Erceg, Charles Hokayem, Yerís Mayol-García, J. David Brown, Joshua Mitchell, Mark Klee, Shalise Ayromloo, and participants at the Federal Committee on Statistical Methodology 2024 Research and Policy Conference for their valuable insights and constructive feedback. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (Project 7506072: CBDRB-FY24-CES027-002, CBDRB-FY24-CES027-006, CBDRB-FY25-0190, CBDRB-FY26-017).

1 Introduction

Methodological advances in the ability to link data across sources have generated wide-ranging benefits for survey operations, population statistics, and causal inference. Survey administrators leverage administrative records to reduce response burden (National Academies of Sciences, Engineering, and Medicine 2016), improve the coverage of sampling frames (Brown et al. 2023; Rastogi and O'Hara 2012), and understand non-response bias (Bollinger et al. 2019). Meanwhile, users of survey data have incorporated administrative records to reduce measurement error in population statistics, including program participation rates (Meyer, Mittag, and Goerge 2022), earnings inequality (Bollinger et al. 2019), and sex-based wage gaps (Foster et al. 2020). The ability to link individuals longitudinally and across generations has also facilitated the production of novel population statistics on intergenerational mobility (Chetty, Hendren, Kline, Saez, and Turner 2014; Chetty, Hendren, Kline, and Saez 2014; Chetty et al. 2017, 2020) and causal inference on the long-run impacts of public policies and social programs (Isen, Rossin-Slater, and Walker 2017; Bailey et al. 2024).

Integral to these advances is the assignment of unique and anonymous identifiers to person records. However, not all person records can be assigned such identifiers due to limitations in the available identifying information and in the probabilistic methods involved in the assignment process.

At the Census Bureau, the Person Identification Validation System (PVS) assigns Protected Identification Keys (PIKs) to person records in household surveys, administrative records, and third-party data files to facilitate record linkage. PVS employs a series of cascading and probabilistic modules that rely on name, sex, date of birth, address, and Social Security Number (SSN) or Individual Taxpayer Identification Number (ITIN) information (Wagner and Layne 2014). The accuracy of PIK assignment by PVS is high, but not all records can be assigned a PIK (Layne, Wagner, and Rothhaas 2014).

Importantly, records that cannot be assigned a PIK are not represented in linked data sets. Prior research shows that the likelihood of being assigned a PIK by PVS varies across data sources as well as between socioeconomic and demographic subgroups (Meyer, Mittag, and Goerge 2022; Mulrow et al. 2011; Rastogi and O'Hara 2012; Bond et al. 2014; Bollinger et al. 2019; Bernard, Drotning, and Genadek 2024). Most studies do not correct for this. Those that do typically reweight linked samples by the inverse probability of PIK assignment. However, there are documented shortcomings with this approach in some contexts. For example, estimates are unstable when selection probabilities (e.g., rates of PIK assignment) are close to zero or one (Busso, DiNardo, and McCrary 2014).

In this paper, we characterize selection into PIK assignment, estimate the magnitude of the resulting bias in linked data sets, and validate the performance of reweighting methods. We first provide an overview of the PVS process and decompose an expression for linkage-induced selection bias. The decomposition highlights the importance of both (i) imbalances between records that have and have not been assigned an identifier and (ii) the proportion of records that have been assigned an identifier. We estimate both components in the context of PIK assignment using two major household surveys: the American Community Survey (ACS) and the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC). By linking these surveys to administrative records from the Internal Revenue Service (IRS), we then quantify linkage-induced selection bias using wage and salary earnings as a test case. Finally, we review several reweighting methods and evaluate their performance in our setting.

In addition to providing comprehensive documentation of non-random PIK assignment in the ACS and the CPS ASEC from 2005 to 2022, we build upon existing evidence by estimating the resulting selection bias in an economic outcome of interest. With few exceptions, our estimates of the linkage-induced selection bias in average wage earnings are non-negligible in both surveys throughout the sample period, which suggests that selection into PIK assignment should be accounted for in analyses of linked data. Our validation exercise suggests that commonly used reweighting techniques, such as inverse probability weighting or entropy balancing, tend to perform well in mitigating the bias, especially when many covariates are available for modeling selection into PIK assignment or specifying moment constraints. Although our study focuses on the Census Bureau's PVS, our findings may also apply to other record linkage systems that rely on probabilistic methods.

2 Background

2.1 Person Identification Validation System

The Census Bureau and the Social Security Administration developed the Person Identification Validation System (PVS) in 1999 to assign Protected Identification Keys (PIKs) to person records (Wagner and Layne 2014). A PIK is a unique and anonymous identifier that can be used to link person records. The PVS assigns PIKs by probabilistically matching each person record from an incoming file to a reference file wherein every Social Security Number (SSN) and Individual Taxpayer Identification Number (ITIN)[1] holder has been assigned a PIK. The reference file is an enhanced version of the Social Security Administration Numerical Identification (SSA Numident) file that includes information on an individual's sex and all variants of their name, date of birth, and address from federal sources. The incoming file (or input file) may include administrative, survey, or third party data with data fields standardized to match that of the reference file.

To match an incoming file to the reference file, the PVS employs a series of cascading and probabilistic modules. The specific modules employed depend on the version of the PVS, which changes over time, and on the data fields contained in the incoming file. For example, incoming records that contain SSNs start with the Verification module, which searches for a match using SSN, name, and date of birth fields. If there is an exact match on SSN and the name and date of birth sufficiently agree, the record is assigned a PIK. If not, the record may pass through the module again using a less restrictive match probabilistic cut-off or proceed to the next module. Each pass in a module is also defined by a blocking strategy for computational efficiency, and the module is allotted a certain number of passes to find a match. All records from the incoming file are assigned a PVS flag indicating which module was used to assign the PIK or the reason for the inability to assign a PIK. Wagner and Layne (2014) provide a detailed overview of each PVS module.

A person record may not receive a PIK due to coverage deficiencies in the reference file or data quality issues in the incoming file. Examples of person records whose SSN or ITIN may not be incorporated into the reference file at the time of PVS processing include newborns, recent immigrants, and undocumented people. Even if a person exists in the reference file, records in the incoming file may contain insufficient identifying information to uniquely match a record in the reference file (e.g., due to limited collection of dates of birth or other identifying fields, missing values among collected fields, common names, or shared addresses) or incorrect identifying information

[1] An ITIN is a tax processing number issued by the IRS to individuals who are required to file taxes but are not eligible to receive a SSN from SSA.

(e.g., due to confusion, inattention, proxy reporting, or mistrust). Alternatively, the identifying information may be complete and accurate but differ from that on the reference file (e.g., name mismatches due to recent changes in last name, different addresses due to recent moves, etc.).

The PVS has undergone changes since its inception to improve the quantity and quality of PIK assignment. In the late 2000s, ITINs were incorporated into the reference file, which facilitated higher rates of PIK assignment among non-citizens (Bond et al. 2014). New modules have been introduced temporarily or permanently, including DOB Search, Household Composition, and ZIP Code Adjacency. Some evidence suggests these additions improved PIK assignment for younger children and frequent movers in the ACS (Bond et al. 2014). Despite these improvements, however, the characteristics of those who are assigned a PIK continue to differ systematically from those who are not assigned a PIK (Bond et al. 2014).

2.2 Selection into PIK assignment

Existing research documents variation in PIK rates across a range of socioeconomic characteristics and geography. Residentially mobile individuals, people of Hispanic origin or Some Other Race alone, non-citizens, and those with limited English proficiency are particularly under-represented in PIKed samples (Meyer, Mittag, and Goerge 2022; Mulrow et al. 2011; Rastogi and O'Hara 2012; Bond et al. 2014; Bollinger et al. 2019). These groups of individuals likely experience problems related to reference file coverage and data quality as discussed in Section 2.1. For example, non-citizens may not have the SSNs or ITINs necessary for inclusion in the reference file, while individuals who move frequently may be included in the reference file with out-of-date addresses. Similarly, individuals from ethnic groups with more complex naming structures, such as multiple last names and spelling variation, may not report their name in the way that aligns with that recorded in the reference file, and data processing may distort their names (Bernard, Drotning, and Genadek 2024; Bond et al. 2014). Individuals who have difficulties speaking English may misreport identifying information in surveys due to confusion.

Research also shows that individuals who lack health insurance coverage, are younger, have lower income, are unemployed, have a proxy reporter, or have lower educational attainment are also less likely to receive a PIK (Meyer, Mittag, and Goerge 2022; Mulrow et al. 2011; Rastogi and O'Hara 2012; Bond et al. 2014). Additionally, Mulrow et al. (2011) document substantial differences in PIK rates across states.

While these findings suggest that selection into PIK assignment is non-random, uncertainty remains about the consequences of this selection for analyses of linked data and how researchers ought to correct for it. In addition to corroborating existing findings over a longer sample period, we contribute to the literature by quantifying the bias from selection into PIK assignment and empirically validating the efficacy of commonly used reweighting methods in adjusting for linkage-induced sample selection.

3 Conceptual framework

Linking records across different sources of data can facilitate novel inferences about a population of interest, but false-positive or false-negative linkages can lead to biased inference. A false-positive linkage occurs when an individual's record in one data source is linked to a different individual's record in another data source (e.g., assigning the same PIK to different individuals across data sources). A false-negative linkage occurs when the linkage process fails to link records for an individual who does, in fact, have a record in each data source (e.g., by failing to assign a PIK to the individual in at least one of the data sources). Previous validation efforts suggest that the PVS produces relatively few false-positive linkages. For example, Layne, Wagner, and Rothhaas (2014) compare PIK assignment across PVS runs with or without SSNs and find that the rate of false-positive PIK assignment is generally less than 1% across modules for federal data sources. This finding reflects the design of the PVS, wherein probabilistic thresholds are set high to reduce the likelihood of false-positive linkages (Wagner and Layne 2014). We therefore focus our attention on the consequences of false-negative linkages and, for ease of exposition, assume that there are no false-positive linkages.

Our interest is in illustrating how conditioning a target sample on linkable records can induce selection bias. We define the bias as the difference between what a researcher would observe in the subset of a target sample that is capable of being linked and what they would observe in the unconditioned target sample. If the researcher's objective is to estimate a population mean of a response variable y and the target sample is representative of the population of interest, then

$$\text{Linkage-induced selection bias} \equiv \mathbb{E}(y_i|l_i = 1) - \mathbb{E}(y_i) \ ,$$

where

- y_i is the response of respondent $i \in \{1, ..., n\}$,
- $l_i = 1$ if i is linkable (e.g., assigned a PIK) or successfully links,
- $l_i = 0$ if i is not linkable (e.g., not assigned a PIK) or fails to link, and
- $\mathbb{E}(l_i = 1) \in (0, 1)$.

In the context of the PVS, records with missing PIKs can generate linkage-induced selection bias, and we can decompose the bias into a function of the PIK rate and the imbalance between the responses of respondents who have been assigned a PIK ("PIKed" respondents) and those of respondents who have not been assigned a PIK ("unPIKed" respondents):

$$\begin{aligned}
\text{Missing PIK bias} &\equiv \mathbb{E}(y_i|l_i = 1) - \mathbb{E}(y_i) \\
&= \mathbb{E}(y_i|l_i = 1) - (\mathbb{E}(y_i|l_i = 1)\mathbb{E}(l_i = 1) + \mathbb{E}(y_i|l_i = 0)\mathbb{E}(l_i = 0)) \\
&= \mathbb{E}(y_i|l_i = 1) - \mathbb{E}(y_i|l_i = 1)\mathbb{E}(l_i = 1) - \mathbb{E}(y_i|l_i = 0)(1 - \mathbb{E}(l_i = 1)) \\
&= \mathbb{E}(y_i|l_i = 1)(1 - \mathbb{E}(l_i = 1)) - \mathbb{E}(y_i|l_i = 0)(1 - \mathbb{E}(l_i = 1)) \\
&= \left(1 - \underbrace{\mathbb{E}(l_i = 1)}_{\text{PIK rate}}\right) \underbrace{\left(\underbrace{\mathbb{E}(y_i|l_i = 1)}_{\substack{\text{Mean response of} \\ \text{PIKed respondents}}} - \underbrace{\mathbb{E}(y_i|l_i = 0)}_{\substack{\text{Mean response of} \\ \text{unPIKed respondents}}}\right)}_{\text{Imbalance between PIKed and unPIKed respondents}}
\end{aligned} \tag{1}$$

This decomposition formalizes what we expect are widely held intuitions about linkage-induced selection bias from missing PIKs:

1. Holding the imbalance constant, a lower PIK rate leads to larger bias.
2. Holding the PIK rate constant, a larger imbalance between PIKed and unPIKed respondents leads to larger bias.

A less obvious implication is that a low PIK rate does not necessarily imply high linkage-induced selection bias. If PIKed and unPIKed respondents are similar on average, there would be negligible bias regardless of the PIK rate.

The same intuition applies when further conditioning the target sample on records that successfully link to an external sample. In this setting, the linkage-induced selection bias is a function of the linkage rate and the imbalance between respondents who do and do not successfully link. Because PIK assignment is a prerequisite for record linkage, the magnitude of linkage-induced selection bias from non-linkages will be at least as large as that from missing PIKs for the same target sample.

4 Data

4.1 American Community Survey

Sampling 3.5 million addresses annually, the American Community Survey (ACS) is the largest household survey in the United States and a primary source of information on a wide range of social, demographic, economic, and housing characteristics. The ACS was implemented nationally in 2005 for the household population and in 2006 for the group quarters population. Since 2010, the ACS has replaced the decennial census long-form.

Our ACS sample consists of 81,500,000 respondents from the 50 states and District of Columbia in 2005-2019 and 2021-2022. We exclude 2020 due to above average non-response in the wake of the COVID-19 pandemic (Rothbaum and Bee 2021). To determine which respondents were assigned a PIK, we link each year of the ACS to its corresponding PIK crosswalk. In 2011, synthetic interviews were introduced as part of the group quarters data collection, producing wholly imputed respondents. These wholly imputed respondents cannot be assigned a PIK because they are not actual people who could exist in the PVS reference files, so we drop them from the 2011-2022 samples and adjust the survey weights following Meyer, Wyse, and Corinth (2023).

The PVS modules used in each year of our sample are listed in Table A1. Because the ACS does not collect SSNs, the Verification module (V flag) is never included in the PVS processing of ACS data. ITINs were incorporated into the reference file used in assigning PIKs to the 2010 ACS (Bond et al. 2014).

4.2 Current Population Survey

The Current Population Survey Annual Social and Economic Supplement (CPS ASEC) is a nationally representative household survey that serves as the official source of national poverty estimates and a primary source of information on income and labor force characteristics. Each year it surveys more than 75,000 households, including both the civilian non-institutional population living in housing units and members of the Armed Forces living off post or living with their families on post.

Our CPS ASEC sample consists of 3,305,000 respondents from 2005-2019 and 2021-2022. As with the ACS, we exclude 2020 due to above average non-response in the wake of the COVID-19 pandemic and link each year of our sample to a consolidated PIK crosswalk.

As shown in Table A1, the Verification module (V flag) was only used by the PVS in the processing of the 2005 CPS ASEC data. Through 2005, the CPS ASEC collected SSNs and respondents had to agree to let their data be linked to administrative records via an "opt-in" consent regime. Starting in 2006, SSNs were no longer collected by the CPS ASEC and the consent process for linking respondents to administrative records changed to "opt-out" consent such that respondents had to refuse being linked to administrative data.

4.3 Internal Revenue Service Form W-2

To study the linked sample of survey respondents who are both assigned a PIK and linked to an administrative record, we use Wage and Tax Statements (or W-2) from the IRS. Every employer who pays an employee at least $600 for their services must file a W-2 with the Internal Revenue Service (IRS) on the employee's behalf. The form details income earned from the employer and the amount of taxes withheld from the employee's paycheck. The full criteria for filing a W-2 are detailed on the IRS website (Internal Revenue Service 2025).

We include W-2s from 2005-2019 and 2021-2022 that were assigned a PIK. W-2s are filed by the employer, which ensures near full coverage of formally employed workers because the sample of W-2s is not limited to tax filers. The identifying information used to assign a PIK is typically self-reported by the employee in the Employee's Withholding Certificate (or W-4).

4.4 PIK de-duplication

The PVS can produce inconsistencies in PIK assignment whereby multiple person records in an incoming file are assigned the same PIK. This issue is less likely when SSNs are included in the incoming file but still quite rare in the absence of SSNs due to the conservative approach to probabilistic matching in the PVS.

We resolve duplicate PIKs in the ACS using a cascading set of business rules. These business rules rely on information about the PVS module in which a respondent was assigned a PIK, as indicated by the PVS verification flag, as well as the number of passes it took for the respondent to be assigned a PIK in the module indicated on the verification flag, and a PVS score for the final pass. Modules processed earlier in the PVS are more reliable, so when multiple respondents are assigned the same PIK but different verification flags, we prioritize the respondent who was assigned the PIK in the earlier module.[2] If multiple respondents have the same PIK and the same verification flag, we prioritize the respondent with the smallest number of passes through the module. If multiple respondents have the same PIK, the same verification flag, and the same number of passes, we prioritize the respondent with the highest PVS score. To resolve any remaining ties among respondents with the same PIK, verification flag, number of passes, and PVS score, we select one respondent at random to retain in the analytic sample.

[2] Prior to 2012, the modules were ordered from first to last as follows: Verification (V flag), GeoSearch (S flag), Zip3 Adjacency Search (J flag), Movers Search (K flag), Name Search (T flag), DOB Search (D flag), HHComp Search (U flag) . Beginning from 2012, the order changed to: Verification (V flag), GeoSearch (S flag), Movers Search (K flag), Name Search (T flag), DOB Search (D flag), HHComp Search (U flag), Zip3 Adjacency Search (J flag).

For the CPS ASEC, duplicate PIK assignment is resolved by Census Bureau staff in a consolidated crosswalk. The consolidation follows a similar logic for de-duplication as outlined above for the ACS.

In the IRS, duplicate records for a single person are expected. In W-2 filings, multiple employers may submit W-2s on behalf of an employee. Duplicate PIKs observed in IRS tax data could be explained by different people being assigned the same PIK in the PVS, but those instances would be impossible to differentiate from a unique person with multiple employers. For these reasons, we assume "duplicate" PIKs observed in the IRS tax data are the same person appearing twice.

5 Evidence of PIK-induced selection

We explore two dimensions of selection into PIK assignment that shape the degree of linkage-induced selection bias, as we show in Equation 1: how often records "select" into PIK assignment, as measured by the PIK rate, and whether the selection process is non-random, as indicated by the imbalance between PIKed and unPIKed records.

We calculate imbalances for survey-based characteristics and outcomes of interest. The specific measures are tailored to data availability in each survey. First, we calculate the difference in the unconditional mean of characteristics between the PIKed and unPIKed samples. We present this difference in absolute and relative terms, where the baseline group for the relative estimate is the unPIKed sample. Then, we conduct a statistical test of whether the difference is significantly different from zero. Throughout, we estimate differences by regressing the value of a characteristic on an indicator equal to one if a record was assigned a PIK and zero if otherwise and make inference using heteroskedasticity-consistent standard errors.

The degree to which an imbalance drives linkage-induced selection bias depends on the PIK rate of the sample. We define the PIK rate to be the proportion of person records who were assigned a PIK, excluding any observation assigned a duplicate PIK. As we show in Equation 1, the PIK rate operates as a scaling factor in which lower PIK rates magnify the bias from an imbalance. To examine how this scaling factor varies between subgroups of interest, we calculate the PIK rate within each survey year and across subgroups defined by discrete demographic, socioeconomic, and geographic characteristics and based on data availability in each survey.

5.1 PIK rate

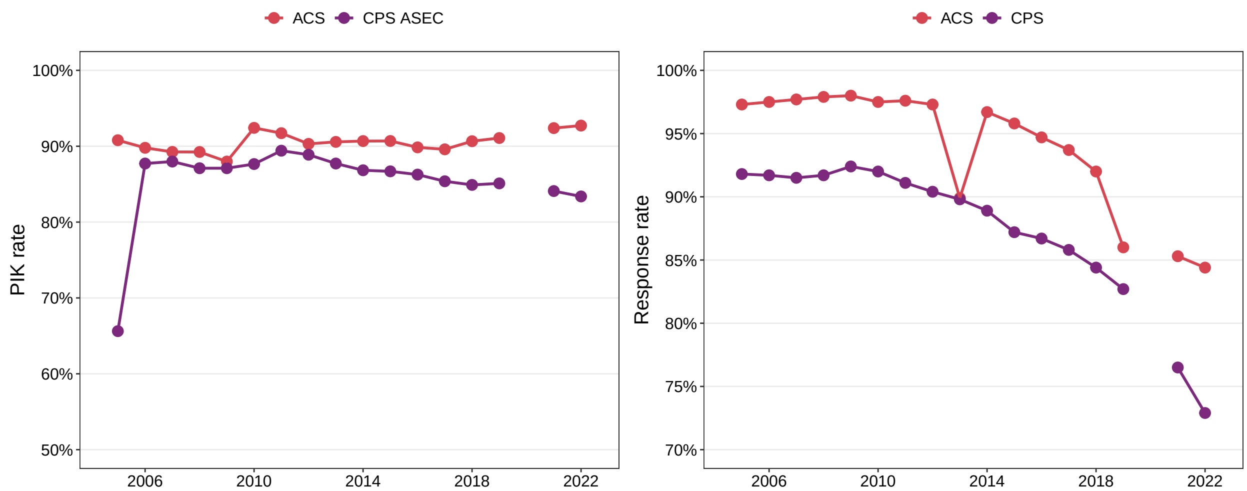
In Figure 1a, we observe higher PIK rates in the ACS (88-93%) than in the CPS ASEC (66-89%) in every year of our study. For example, in 2022 the PIK rate was 10 percentage points higher in the ACS than in the CPS ASEC. This differential cannot be explained by differences in identifying information that informs PVS processing because both surveys have collected the same non-SSN identifying information from respondents since 2006.

Major discontinuities in PIK rates over time can largely be explained by changes in the PVS and survey data collection. In the ACS, PIK rates fell through 2009 when they reached their lowest level in our sample period, 88%. In 2010, ACS PIK rates achieved their largest single-year increase (4 percentage points) due to the addition of three PVS modules[3] and the inclusion of ITIN-holders in

[3] Namely, the Household Composition module, the DOBSearch module, and the ZIP3 Adjacency module.

Figure 1: PIK and survey response rates

(a) PIK rate (b) Survey response rate



Notes: Panel A shows the percentage of respondents from each survey who were assigned a PIK by survey year. Panel B shows the percentage of household units or group quarter persons sampled for the survey who participated in the survey by survey year. PIK estimates are produced using survey-specific person weights. 2020 is omitted due to high survey non-response. Lines represent linear interpolation of survey year statistics. *Data sources:* ACS, CPS ASEC, U.S. Census Bureau (n.d.), Bureau of Labor Statistics (n.d.).

the PVS reference file. After 2010, ACS PIK rates plateaued through 2017 and gradually increased thereafter.

In the CPS ASEC, PIK rates jumped from 66% in 2005 to 88% in 2006. In 2006, the survey stopped collecting SSNs from respondents, which would, other things being equal, lead to lower PIK rates. However, the simultaneous change from an opt-in to opt-out consent for linking survey responses to administrative records more than offset any such negative effect. The PIK rate peaked in 2011 at 90% and has fallen in every year since except 2019.

Recent trends in ACS and CPS ASEC PIK rates do not seem to be explained by changes in survey response rates. In theory, declining response rates could: (a) positively select participants who would were more willing to participate and share accurate and complete identifying information, or (b) reflect a broader decline in willingness to share identifying information which offsets any positive selection on participation willingness. However, both ACS and CPS ASEC response rates have fallen by 13 and 24 percentage points, respectively, since 2010 (see Figure 1b). It is unlikely that falling response rates alone could simultaneously explain increasing PIK rates in the ACS and decreasing PIK rates in the CPS ASEC.

Across surveys and years, we find extensive evidence of imbalance between the PIKed and unPIKed groups that suggests the PIK assignment observed in Figure 1a is non-random. We first discuss imbalances that point to specific drivers of selection into PIK assignment followed by those with non-specific drivers.

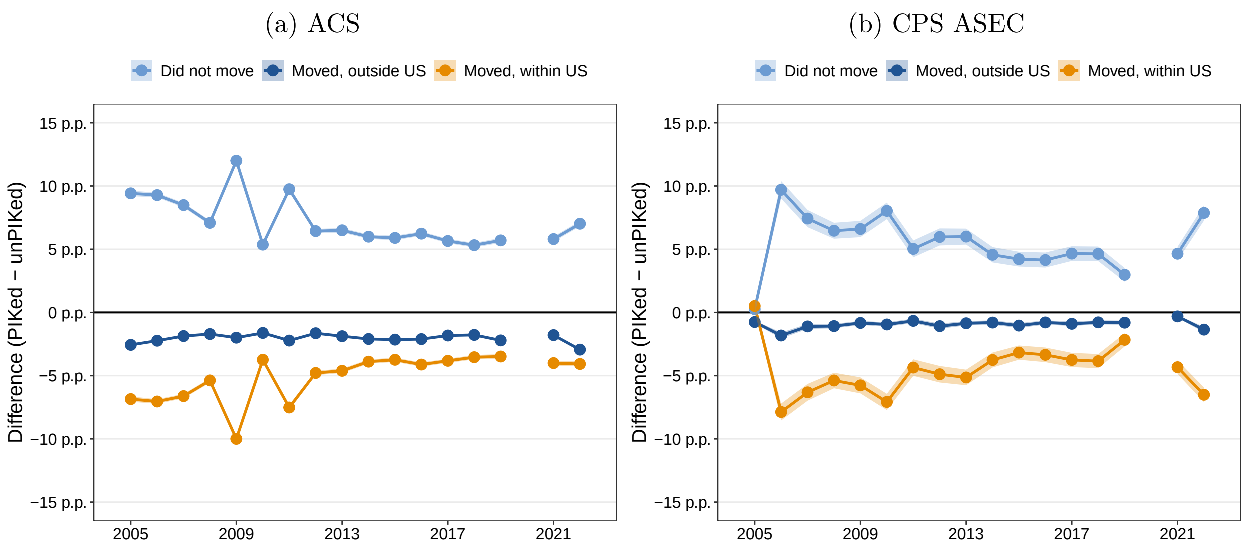
5.2 Selection driver 1: Outdated residential information in the reference file

Residential mobility could matter for PIK assignment if a survey respondent reports an accurate and complete current address, but their latest address is not (or not yet) captured in the PVS reference file. In the ACS and CPS ASEC, PIKed respondents were 7-8 percentage points less likely to have moved within the past year than PIKed respondents in 2022 (Figure 2).

We observe similar imbalances in other residentially mobile populations. Renters, for example, tend to be more residentially mobile than their home-owning counterparts. In the ACS, we observe an under-representation of renters in the PIKed group compared to the unPIKed group (Table A2). Young adulthood is also a relatively mobile life stage when many people transition to independent living (e.g., by entering college). In both surveys, PIKed respondents were older on average than unPIKed respondents and young adults were the most under-represented age group among PIKed respondents (Figure 3).

People living in group quarters are likely to have outdated residential information in the reference file for reasons including, but not limited to, residential mobility. For example, residing in university student housing or emergency shelters may indicate mobility whereas people living in a correctional facility may not be mobile but could have limited contact with SSA and related government agencies that would allow for their residential address to be updated in the reference file.

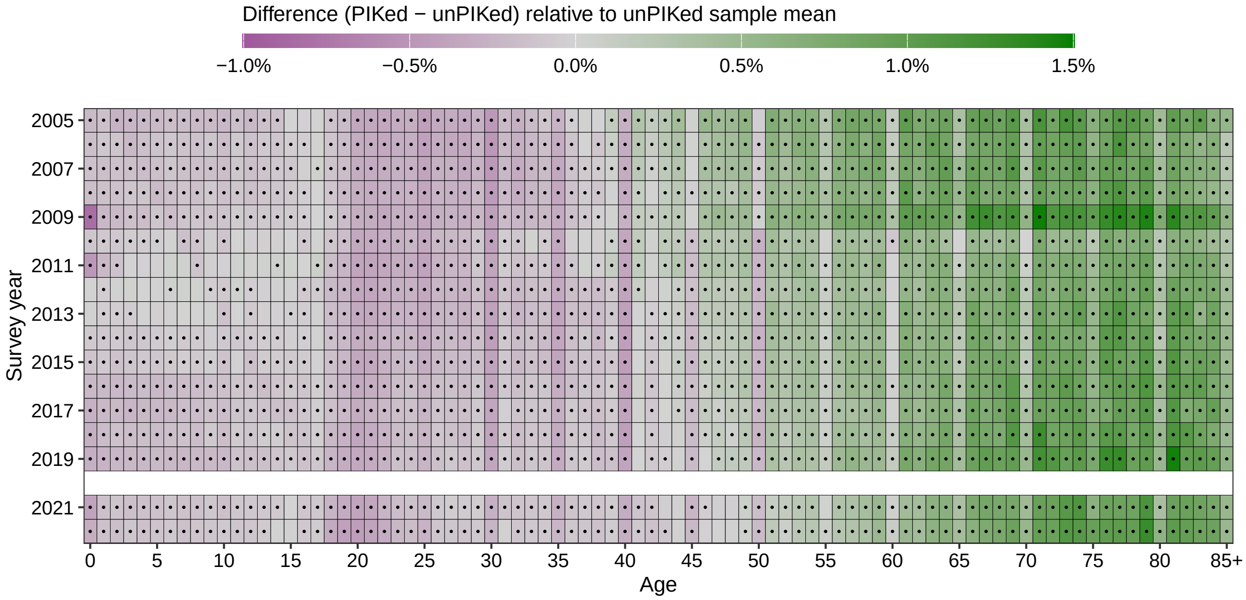
Figure 2: Past-year mobility balance test



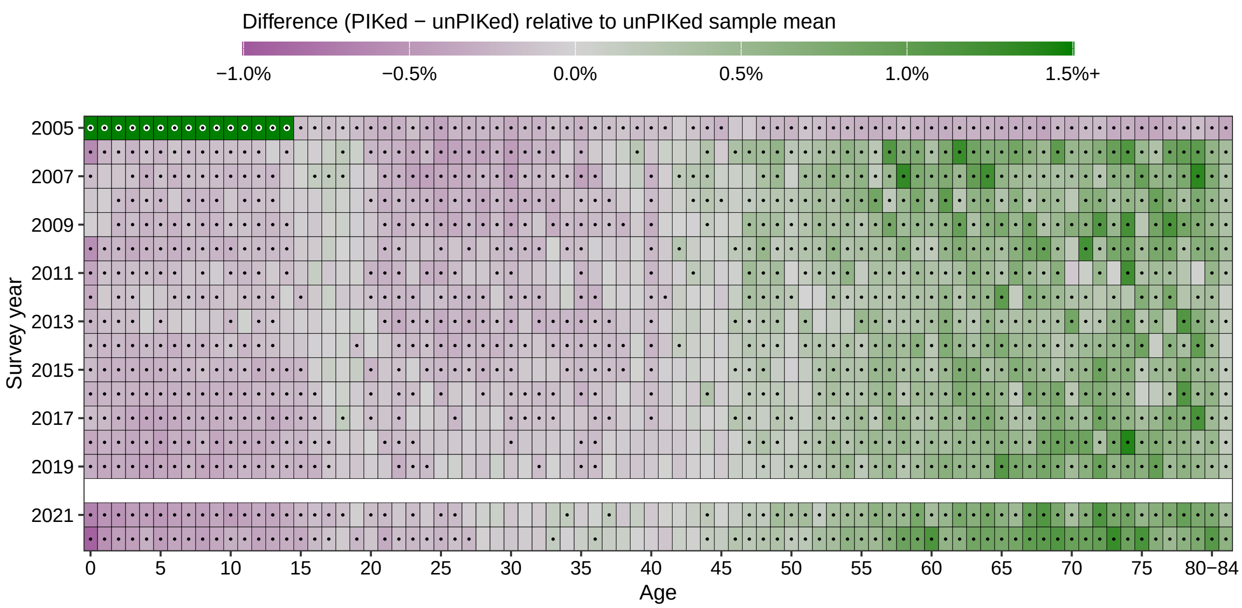
Notes: These figures show differences in mobility status between respondents aged 1 year and older who were and were not assigned a PIK. 2020 is omitted due to high survey non-response. All estimates are produced using survey-specific person weights. Shaded regions represent 95% confidence intervals. Lines represent linear interpolation of survey year statistics. *Data sources:* ACS, CPS ASEC.

Figure 3: Age balance test

(a) ACS



(b) CPS ASEC



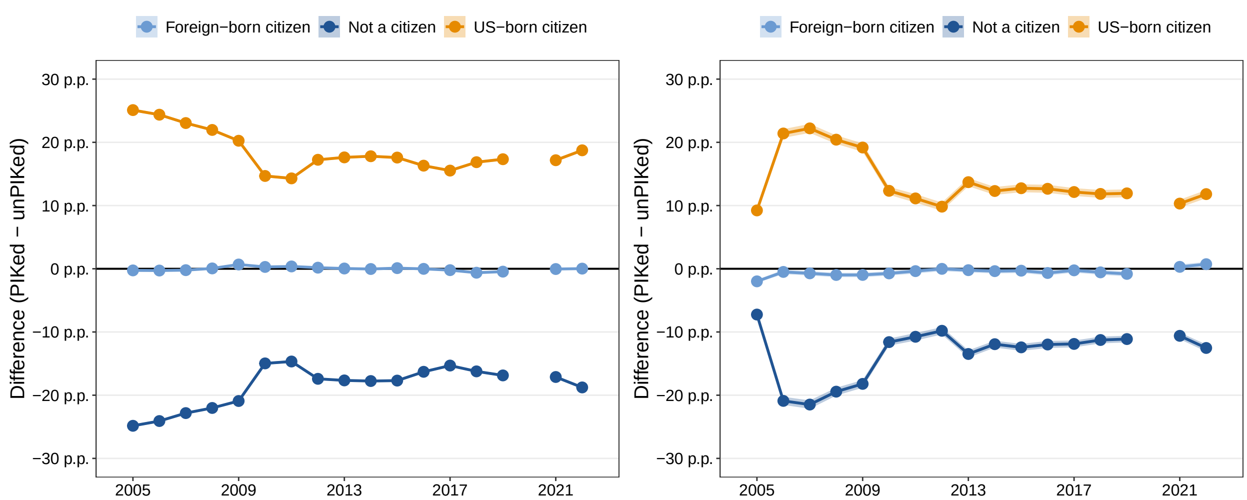
Notes: These figures show differences in age between respondents who were and were not assigned a PIK. All estimates are produced using survey-specific person weights. 2020 is omitted due to high survey non-response. Black dots represent statistical significance at the 5% level. White circles in Panel B highlight top-coded estimates. *Data sources:* ACS, CPS ASEC.

5.3 Selection driver 2: Absence in reference file

An individual who is not present in the reference file at the time of PVS processing cannot be assigned a PIK. This issue is most relevant to people without an SSN or ITIN, like some non-citizens, and those with a recently assigned SSN or ITIN, like some newborns. In line with previous research, we find large imbalances in citizenship status across all years and surveys. In 2022, the percentage of non-citizens was 19 percentage points higher among unPIKed ACS respondents than among PIKed ACS respondents (Figure 4a) and 13 percentage points higher among unPIKed CPS ASEC respondents than among PIKed CPS ASEC respondents (Figure 4b). In the CPS ASEC, children under age one were acutely underrepresented in the PIKed sample in the years after the COVID-19 pandemic. If insufficient time has passed between time of the survey data collection and PIK assignment in the PVS, newborns reported on a household roster may not be captured in the SSA data that is used to update the reference file. Changes in workflow related to the pandemic led to errors and delays in SSN assignment which exacerbated this risk (Office of Audit 2022). Between 2019 and 2020, the disparity in the representation of children under age one between the PIKed and unPIKed groups grew by 50% (Figure 3b). We don't find evidence of the same in the ACS, perhaps due to differences in the timing of PVS processing relative to data collection.

Figure 4: Citizenship balance test

(a) ACS (b) CPS ASEC

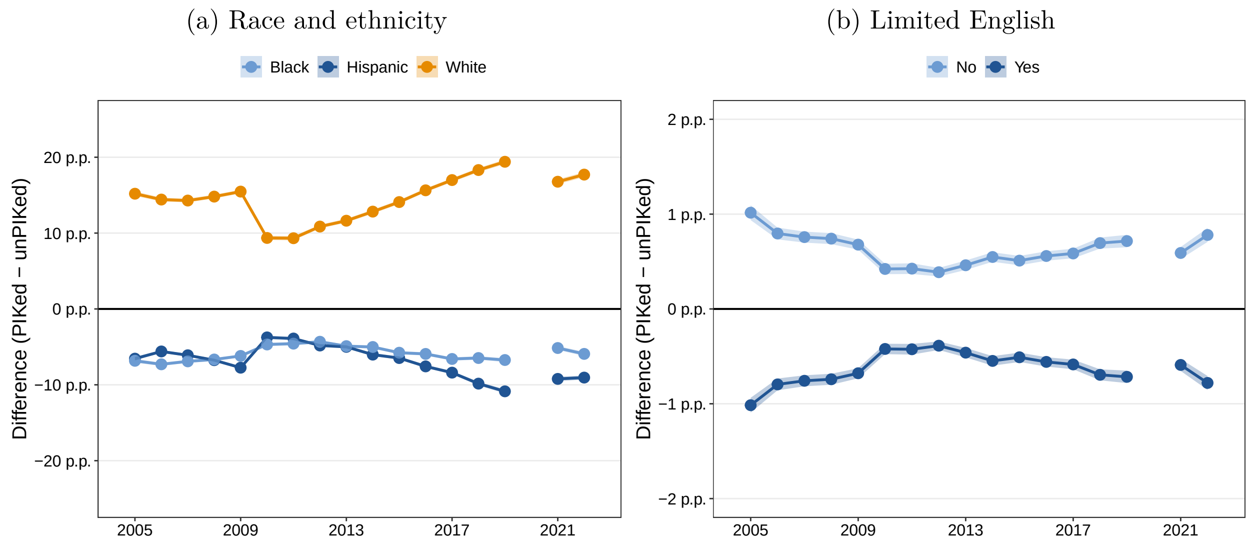


Notes: These figures show the differences in citizenship status between respondents who were and were not assigned a PIK. All estimates are produced using survey-specific person weights. 2020 is omitted due to high survey non-response. Shaded regions represent 95% confidence intervals. Lines represent linear interpolation of survey year statistics. *Data sources:* ACS, CPS ASEC.

5.4 Selection driver 3: Complex naming structures

Complex naming structures could lead to lower PIK rates if such names are inconsistently reported or difficult to parse for PVS processing (Bernard, Drotning, and Genadek 2024; Bond et al. 2014). In both surveys, we document imbalances of racial and ethnic groups between the PIKed and unPIKed respondents. Previous research has argued that the under-representation of some racial-ethnic groups (e.g., Hispanic) in PIKed samples is explained by citizenship status and reference file coverage (Bollinger et al. 2019). When we restrict our attention to to US-born citizens, however, we still observe a racial-ethnic imbalance that supports the complex naming structure theory. Figure 5a demonstrates that US-born citizens who are assigned a PIK in the ACS are less likely to be Native Hawaiian, Pacific Islander, American Indian, Alaskan Native, or Some Other Race than those who are not assigned a PIK.

Figure 5: Racial group and English ability balance test among US-born citizens in the ACS



Notes: These figures show differences in racial-ethnic composition and English speaking status between US-born respondents who were and were not assigned a PIK. All estimates are produced using ACS person weights. 2020 is omitted due to high survey non-response. Shaded regions represent 95% confidence intervals. Lines represent linear interpolation of survey year statistics. *Data source:* ACS.

5.5 Selection driver 4: Confusion in survey response

Any confusion in responding to survey questions that solicit the identifying information used in PVS processing could lead to incomplete or inaccurate responses. Confusion could stem from a wide range of circumstances, including inattention, illiteracy, or language familiarity. In the ACS, the percentage of respondents with limited English ability was at least 10 percentage points higher among unPIKed respondents than among PIKed respondents in every year of our study. Similar to racial and ethnic groups, verbal language ability is likely correlated with citizenship. Figure 5b shows that after conditioning the sample on US-born citizens, ACS respondents with limited English verbal language ability are still under-represented in the PIKed sample.

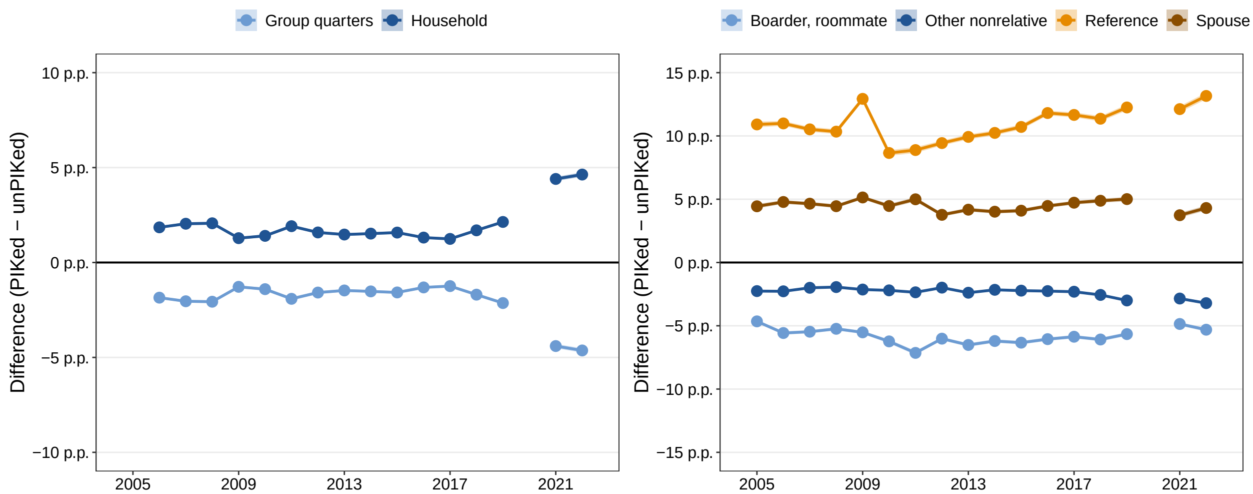
5.6 Selection driver 5: Proxy reporting

Proxy reporting, whereby survey responses are provided by a respondent about another member of the sampled unit, could lead to mistakes in the identifying information reported for persons other than oneself. Proxy reporting affects respondents residing in both group quarters and household units. In the ACS, the imbalance in the likelihood of group quarter residence between PIKed and unPIKed groups doubled between 2019 and 2021 (see Figure 6a). Due to COVID-19 restrictions, in-person operations were suspended and data collection in group quarters relied more heavily on proxy reporting (Reese, Scanniello, and Ross 2021). For ACS respondents residing in a household, one member is designated as the reference person and the relationship of all other household members to the reference person is reported. Where applicable, the reference person is one of the people in whose name the home is owned, being bought, or rented. Otherwise, any household member over age 15 may be designated the reference person (U.S. Census Bureau 2022). Figure 6b shows the reference person and their spouse are over-represented in the PIKed group, while those less closely related to the reference person and non-relatives are under-represented. In 2022, for example, reference persons accounted for 13 percent more of the PIKed sample than the unPIKed sample, while their spouses accounted for 4 percent more. Given the common practice of reference persons proxy reporting for other household members, this suggests that proxy reporting negatively affects PIK assignment.

Figure 6: ACS balance tests related to proxy reporting

(a) Housing type

(b) Relationship to reference person



Notes: These figures shows the differences in housing type (Panel A) and relationship to reference person (Panel B) between respondents who were and were not assigned a PIK. All estimates are produced using survey-specific person weights. 2020 is omitted due to high survey non-response. Shaded regions represent 95% confidence intervals. Lines represent linear interpolation of survey year statistics. *Data source:* ACS.

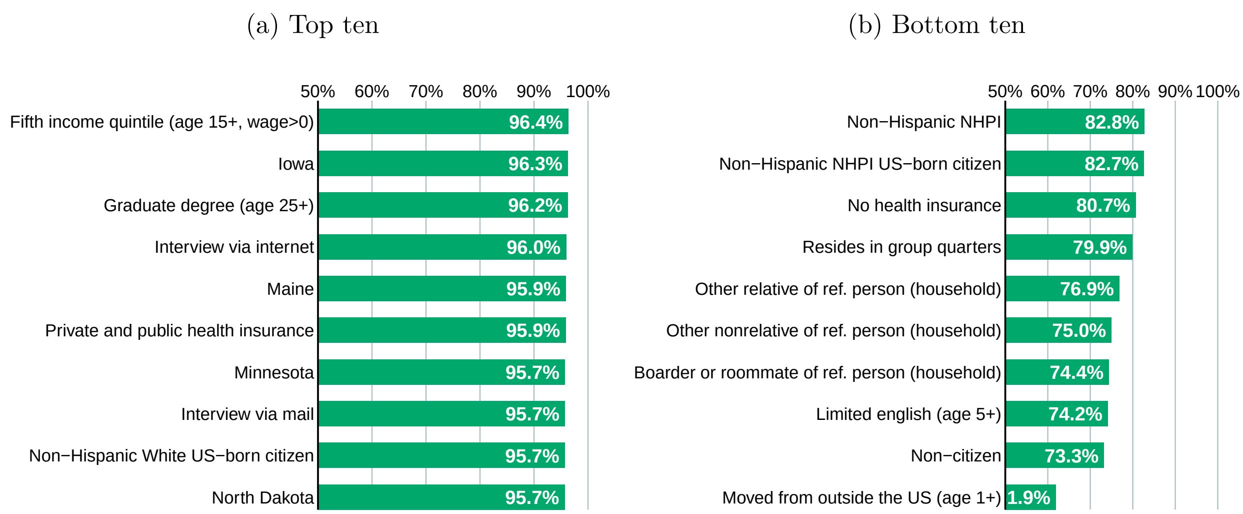
5.7 Non-specific drivers

We document several other imbalances in PIK assignment that do not pinpoint a specific PVS or survey operations-related driver of PIK assignment. Some of these imbalances are consistent with previous literature, such as those across levels of educational attainment, employment, income, health insurance, welfare receipt, state of residence, and urbanicity. We also find evidence of other imbalances that have not been previously documented, including the under-representation of never married adults and over-representation of government workers and respondents with a cognitive disability in the PIKed group.

5.8 Subgroup PIK rate

Our main analysis focuses the full sample for each survey-year, except where variable definitions require a conditioned sample. However, if the PIK imbalance for a given characteristic does not vary across subgroups, it follows from Equation 1 that the magnitude of bias will be larger in subgroups where the PIK rate is lower. Figure 7 summarizes the ten subgroups with the highest and lowest PIK rates in the 2022 ACS. Racial and ethnic subgroups feature among the subgroups with the highest and lowest PIK rate, so we quantify bias and evaluate performance of statistical corrections within racial and ethnic subgroups in secondary analyses. Table A5 and Table A6 detail subgroup PIK rates across all years for both surveys.

Figure 7: Subgroup PIK rates in the 2022 ACS



Notes: These figures show the proportion of respondents from each sub group who were assigned a PIK in 2022. Panel A shows the subgroups with the highest PIK rates. Panel B shows the subgroups with the lowest PIK rates. All estimates are produced using survey-specific person weights. *Data source:* ACS.

6 Statistical adjustments for linkage-induced selection

6.1 Quantifying bias

To quantify the consequences of linkage-induced selection evidenced in Section 5, we estimate the bias induced by conditioning a target sample (e.g., the full ACS or the full CPS ASEC) on PIK assignment. The resulting "missing PIK bias" is the average difference in an outcome between a PIKed sample and the full target sample (Equation 1), which we can interpret as a direct consequence of false-negative PVS linkages.

While focusing on PIK assignment in a single sample allows us to attribute the estimated bias to missing PIKs, this may oversimplify the problem faced by researchers. In practice, researchers often condition a target sample on PIK assignment in order to link to an external sample. In the resulting linked sample, missing PIK bias from both the target sample and external sample compound. Assuming similar patterns of selection in the external sample, we expect the missing PIK bias to understate the bias induced by conditioning the target sample on successful linkage.

To quantify the consequences of further conditioning a target sample on successful linkage to an external sample, we also estimate "linkage bias," which we define as the average difference in an outcome between a linked sample and the full target sample (an extension of Equation 1). This difference captures the impact of missing PIKs in the target and external sample, though it may also contain other linkage-related biases, such as those from coverage error or measurement error in either the target or external samples.[4]

We seek to isolate the portion of linkage bias due to false-negative PVS linkages, so we choose an empirical setting that minimizes other sources of non-linkage. Specifically, we define survey-based target samples so as to maximize the likelihood that each person record exists in the IRS W-2 sample. To create target samples of likely W-2 holders, we restrict each survey sample (ACS and CPS ASEC) to respondents aged 15-64 who were employed in the government or private sector and reported non-zero wages and salary in the prior year. In doing so, we acknowledge that some coverage error is unavoidable. For example, wage and salary reference periods may be misaligned across data sources and some employers may fail to comply with IRS reporting requirements, resulting in missing W-2 records for some workers in the ACS or CPS ASEC. Additionally, there may be measurement error in the survey responses used to condition the target sample if, for example, survey respondents misreport their wage and salary earnings or sector of employment. While these additional sources of linkage error are specific to our setting, the potential for such errors is universal to all empirical analyses of linked data. A conservative interpretation of linkage bias estimates is that they reflect some combination of PVS-induced linkage errors and other causes of non-linkage that are unrelated to the PVS process.

We express the magnitude of both types of linkage-induced selection bias in terms of wage and salary earnings ("wage earnings"), a common outcome of interest. We cannot express bias in terms of wage earnings from external sources (e.g., tax data) because external measures are only observable for the subset of the target sample that successfully links to the external sample. We therefore express the bias in terms of self-reported wage earnings from the ACS and CPS ASEC, which are available for all individuals in each target sample regardless of PIK assignment or successful linkage. Throughout the analysis wage earnings are inflated to 2022 dollars using the Consumer Price Index for all Urban Consumers (CPI-U).

For each survey and year, we define a stacked estimation sample that appends a conditioned sample (i.e., either the PIKed sample or the linked sample) to the unconditioned sample (i.e., the full target sample) and estimate a regression model that compares the wage earnings of the conditioned sample to those of the unconditioned sample:

$$y_{ij} = \alpha + \beta \ \mathbb{1}(j = \text{conditioned sample}) + \varepsilon_{ij} \ , \tag{2}$$

where y_{ij} is the wage earnings of survey respondent $i \in \{1, ..., N\}$ in sample $j \in \{$conditioned sample, unconditioned sample$\}$ and $\mathbb{1}(j =$ conditioned sample$)$ is an indicator equal to one if respondent i was assigned a PIK (linked) and in the conditioned sample and zero if otherwise. In this setup, each respondent with a PIK (linkage) appears in the estimation sample twice—once for

[4] Linkage-related coverage error arises when an external sample is misaligned with the target sample, such as when person records from the target sample are not present in the external sample, regardless of PIK assignment status. Researchers can mitigate this type of coverage error by selecting an external sample that captures a larger share of individuals in the target sample or by restricting the target sample to individuals who are likely to appear in the external sample. However, measurement error in the variables used to restrict the target sample can limit the efficacy of this approach, potentially substituting one source of misalignment for another.

$j =$ conditioned sample and once for $j =$ unconditioned sample. In this way, α represents expected wage earnings in the full sample and β represents missing PIK bias (linkage bias). Positive values of β indicate that the conditioned sample overstates average earnings, negative values indicate that the conditioned sample understates average earnings, and a value of zero indicates that the conditioned sample yields unbiased estimates of average wage earnings. To account for the repeated observations of respondents in the estimation sample, we allow the error term ε_{ij} to be correlated within respondents.

To incorporate sampling weights w_{it} from the ACS and the CPS ASEC, we estimate the parameters of Equation 2 by minimizing the weighted sum of squares:

$$\min_{\hat{\alpha},\hat{\beta}} \sum_i \sum_j w_{ij} \left(y_{ij} - \hat{\alpha} - \hat{\beta}\, \mathbb{1}(j = \text{conditioned sample}) \right)^2 . \tag{3}$$

6.2 Reweighting methods

After expressing the magnitude of missing PIK and linkage biases in the ACS and the CPS ASEC in terms of wage earnings, we evaluate the efficacy of reweighting methods in ameliorating those biases. In our evaluation, we consider inverse probability weighting (IPW), inverse probability tilting (IPT), and entropy balancing, and apply each method using the `WeightIt R` package (Greifer 2025).[5]

Inverse probability weighting

Inverse probability weighting (IPW) is the most commonly used reweighting method among Census Bureau working papers that attempt to adjust for selection into PIK assignment. Initially conceived as a way to adjust for observable confounders in causal inference settings (Rosenbaum and Rubin 1983), IPW consists of modeling selection into "treatment" and reweighting each observation in an analysis sample by the inverse of their modeled propensity to receive their realized exposure to the treatment. IPW has since been used to address a variety of missing data problems, including unit non-response (e.g., Abraham, Maitland, and Bianchi 2006), item non-response (e.g., Bollinger and Hirsch 2006), and false-negative record linkage (e.g., Cerf Harris 2014; Meyer and Mittag 2015; Andersson et al. 2016; Groen, Kutzbach, and Polivka 2016; Kucko, Rinz, and Solow 2017; Voorheis 2017; Brummet et al. 2018; Sandler and Szembrot 2019; Ziliak, Hokayem, and Bollinger 2020; Foster et al. 2020; Banzhaf and Banzhaf 2022; Meyer, Mittag, and Goerge 2022).

In the context of record linkage, the "treatment" is PIK assignment or successful linkage to an external sample. The first step in this application of IPW is to estimate a person-weighted binary choice model of the conditional probability of PIK assignment (or successful linkage) using either a probit (e.g., Cerf Harris 2014; Meyer and Mittag 2015; Voorheis 2017; Brummet et al. 2018; Ziliak, Hokayem, and Bollinger 2020; Foster et al. 2020; Banzhaf and Banzhaf 2022; Meyer, Mittag, and

[5] For ease of exposition, we omit results for covariate-balancing propensity score reweighting (CBPS, Imai and Ratkovic 2014) and gradient-boosted IPW (Cefalu et al. 2024), which are available upon request. CBPS is conceptually similar to IPT, and it performs similarly to IPT in our validation exercise. Gradient-boosted IPW performs similarly to IPW when adjusting for a limited set of covariates (i.e., age, sex, and race/ethnicity), but we find that it often fails to converge when attempting to adjust for a larger set of covariates. As a practical matter, the software implementations we use for CBPS and gradient-boosted IPW are less computationally efficient than those we use for IPW, IPT, and entropy balancing.

Goerge 2022) or logit (e.g., Andersson et al. 2016; Groen, Kutzbach, and Polivka 2016; Kucko, Rinz, and Solow 2017; Sandler and Szembrot 2019) link:

$$P(l_i = 1|X_i) = g^{-1}(X_i'\Gamma) \ ,$$

where $l_i = 1$ indicates that respondent i was assigned a PIK assignment (or successfully linked), $g^{-1}(\cdot)$ is the inverse link function,[6] X_i is a vector of observable covariates, and Γ is a vector of coefficients.

The second step is to calculate an IPW weight for each respondent in the PIKed (linked) sample as the inverse of their estimated propensity score:

$$\hat{w}_i^{\text{IPW}} = \frac{1}{\hat{P}(l_i = 1|X_i)} \ .$$

The final step before analysis is to calculate an adjusted weight for each respondent in the PIKed (linked) sample as the product of their IPW weight and their original sampling weights.

The validity of this approach hinges on the assumption that $P(l_i = 1|y_i, X_i) = P(l_i = 1|X_i)$, where y_i is a variable of interest that can only be observed in the linked sample. This is akin to a selection-on-observations assumption (Wooldridge 2007). Successful applications of IPW require researchers to specify a model of PIK assignment for which the selection-on-observables assumption is defensible. In other words, researchers must include all relevant drivers of selection into PIK assignment (or linkage) using the "correct" functional form. This is easier said than done, however, as accommodating complex forms of selection can be difficult in practice. For example, IPW weights derived from binary choice models with many covariates, non-linear effects, and interactions can yield statistically and numerically unstable estimates (Ridgeway et al. 2024), and extreme propensity scores near 0 or 1 can also lead IPW to yield unstable estimates (Busso, DiNardo, and McCrary 2014). Moreover, when there is poor overlap in propensity scores (e.g., between PIKed and unPIKed respondents), IPW can exacerbate existing covariate imbalances (Li, Morgan, and Zaslavsky 2018).

For our evaluation of IPW, we consider a logistic regression specification, which we describe in Section 6.3.

Inverse probability tilting

Over the past two decades, several methods have been proposed that borrow the same intuition from IPW with extensions to directly target balance on observables. One such method is inverse probability tilting (IPT), which augments IPW by replacing standard regression score equations with moment constraints (Graham, Pinto, and Egel 2012). By directly targeting covariate balance, IPT features a double robustness property that relaxes the selection-on-observables assumption of IPW; namely, a misspecified model for the propensity score can still yield consistent estimates if the appropriate unconditional moments are chosen as moment constraints (Graham, Pinto, and Egel 2012).

For our evaluation of IPT, we consider logistic regression specifications with moment constraints that target covariate balance between the PIKed (linked) sample and the full target sample.

[6] For example, $g^{-1}(z) = \dfrac{1}{1+\exp(-z)}$ for a logit link or $g^{-1}(z) = \Phi(x)$ for a probit link, where $\Phi(\cdot)$ is the standard normal cumulative density function.

Entropy balancing

Entropy balancing uses an optimization model to select weights that achieve covariate balance while minimizing the negative entropy of the resulting weights (Hainmueller 2012). Without explicitly modeling selection, this delivers exact balance while stabilizing the values of the weights used to achieve that balance. Relative to IPW, entropy balancing can better adapt to a high dimensional vector of moment constraints with more computational efficiency, which in turn can reduce bias at the expense of precision (Harvey et al. 2017). Like IPW, the credibility of entropy balancing rests on a selection-on-observables assumption (Hainmueller 2012; Zhao and Percival 2017; Källberg and Waernbaum 2023). Entropy balancing has been used to adjust survey-based samples for selection into linked data (Bee et al. 2023; Rothbaum and Bee 2021; Rothbaum et al. 2021) as well as coverage error (Watson and Elliot 2016).

For our evaluation of entropy balancing, we consider moment constraints that target covariate balance between the PIKed (linked) sample and the full target sample using the approach described by Källberg and Waernbaum (2023) and implemented by Greifer (2025). In this way, the approach we evaluate differs from the original entropy balancing approach proposed by Hainmueller (2012) and further analyzed by Zhao and Percival (2017), which in our setting would target covariate balance between the PIKed sample and the unPIKed sample.

6.3 Evaluating the performance of reweighting methods

To evaluate the performance of each reweighting method, we re-estimate missing PIK and linkage biases by replacing the weights in Equation 3 with adjusted weights $\tilde{w}_{ij}$:

$$\tilde{w}_{ij} = \begin{cases} w_{ij} & \text{if } \; j = \text{Unconditioned sample} \\ w_{ij} \times \hat{w}_{ij} & \text{if } \; j = \text{Conditioned sample} \end{cases},$$

where $\hat{w}_{ij}$ is either an inverse probability weight, an inverse probability tilting weight, or an entropy balancing weight.

We evaluate the performance of reweighting methods in samples with varying covariate availability and varying PIK or linkage rates, which allows us to consider how the efficacy of reweighting varies across commonly encountered empirical settings. Other things being equal, we expect reweighting methods to perform better in settings with many available covariates than in settings with relatively few available covariates, as additional covariates can capture additional drivers of selection (Hypothesis 1: Covariate Availability). We also expect reweighting to yield lower bias in settings with high PIK (linkage) rates than in settings with low PIK (linkage) rates, as indicated by the decomposition in Equation 1 (Hypothesis 2: Linkability). We test these hypotheses by comparing the linkage-induced biases after applying each method under different covariate availability and PIK (linkage) rate scenarios.

To test the covariate availability hypothesis, we apply each reweighting method twice using different sets of covariate adjustments:

- A "limited" adjustment for sex, race/ethnicity, and a quartic in age.
- A "full" adjustment for the "limited" set of covariates in addition to citizenship, English ability, interview mode, migration in the last year, educational attainment, marital status, disability status, region, and urbanicity.

The limited adjustment is meant to simulate target samples with relatively few available covariates, such as those derived from administrative records, whereas the full adjustment uses a broader set of covariates inspired by specifications that have been used in the existing literature to model selection into PIK assignment (e.g., Bollinger et al. 2019; Meyer, Mittag, and Goerge 2022). Although wage earnings are observed in the full target sample, our objective is to simulate a research application in which a researcher measures an outcome using an external sample. In such an application, a researcher would not be able to observe the outcome for the full target sample, preventing them from including the outcome as a covariate when modeling selection into PIK assignment. Moreover, adjusting for wage earnings would mechanically attenuate our estimates of linkage-induced selection bias toward zero. For reweighting methods that enforce balance, like IPT or entropy balancing, adjusting for wage earnings would trivially eliminate the bias. We therefore exclude wage earnings as a covariate.

To test the second hypothesis, we leverage differences in PIK and linkage rates across racial and ethnic groups and provide group-specific estimates of the bias for each reweighting method. Due to small sample sizes, we omit the three smallest racial-ethnic groups from the CPS ASEC subgroup analysis (namely, non-Hispanic American Indian or Alaska Native, non-Hispanic Native Hawaiian or Pacific Islander, and non-Hispanic two or more races).[7]

We do not view our full adjustment as a universally applicable specification that fully accounts for linkage-induced selection in all applications. Indeed, as we will show in Section 6.5, the performance of the full adjustment varies across samples, subgroups, and reweighting methods. In practice, the successful application of reweighting methods requires contextual knowledge to defend the assumption that all relevant variables driving selection are observed in the data and modeled correctly. Having access to additional covariates may increase the likelihood of observing the drivers of selection, but invoking selection-on-observables still requires researchers to specify which covariates drive selection and take a stand on the appropriate functional form (e.g., interactions, non-linearities, etc.).

6.4 Estimates of bias before reweighting

We find evidence of positive linkage-induced selection bias for average wage earnings in PIKed samples and linked samples (Figure 8). In other words, restricting the target sample to PIKed or linked respondents overestimates average wage earnings during the study period. The direction of bias is consistent with results from Section 5 which suggest that PIKed respondents are positively selected on wage earnings, on average (see Table A7).[8]

The gray points in Figure 8 illustrate estimates of linkage-induced selection bias without reweighting. In the ACS sample, the missing PIK bias estimates range from \$686 to \$1,647 over 2005-2022, while the linkage bias estimates range from \$2,266 to \$3,509. Relative to the target sample of private and government wage earners aged 15-64, missing PIK bias amounts to 1.3-3.1% of average wage earnings and linkage bias amounts to 4.1-6.5% of average wage earnings. In the CPS ASEC sample, bias estimates tend to be smaller in magnitude and—reflecting the smaller sample size–less precise than those in the ACS sample. Missing PIK bias in the CPS ASEC amounts to 0.5-2.8% of average

[7] Unlike the ACS, the CPS ASEC does not define “some other race” as a category, so we also omit the “non-Hispanic some other race” group by default.

[8] Wage earnings estimates in Section 5 are based on the population of non-zero wage earners who are at least 15 years old, while the estimates in Section 6.4 are based on the population of non-zero wage earners in the private or government sectors who are 15-64 years old.

wage earnings in the target sample, while the estimated linkage bias amounts to 1.8-4.1%. In 2005, the missing PIK bias is not significantly distinguishable from zero.

In both surveys, we find that linkage bias exceeds missing PIK bias throughout the study period. This is at least partially driven by linkage rates that fall below PIK rates. Table A7 shows the rate of successful record linkage lags behind that of PIK assignment by 5.9-8.9 percentage points annually in the ACS target sample and 3.4-6.9 percentage points annually in the CPS ASEC target sample. Recall that the linkage rate is shaped by the PIK rate in both the target and external samples, as well as other sources of non-linkage, and will never be greater than the PIK rate in the target sample alone. The decomposition in Equation 1 indicates that, holding constant any difference in the underlying imbalances in wage earnings, the positive differential between PIK rates and linkage rates would on its own lead to more linkage bias than missing PIK bias. While we do not directly test for equal PIK-based and linkage-based imbalances, the overall pattern of results suggests that any difference in the degree of imbalance fails to offset the effect of the rate differential on bias estimates.

We find a similar pattern of results when we estimate each type of bias separately by demographic groups with high (non-Hispanic White) and low (Hispanic) rates of PIK assignment and successful record linkage. The estimates in Figure 9 suggest that missing PIK bias and linkage bias increase as PIK rates and linkage rates decrease. As above, this does not necessarily imply that imbalance is constant across non-Hispanic White and Hispanic groups, but it shows that the PIK-based and linkage-based imbalances are similar enough for the negative correlation between PIK or linkage rates and bias to hold.

Bias estimates are relatively stable over time except for years in which major changes to the PVS were implemented. In the ACS sample, the 2010 change in PVS processing that led to higher PIK rates appears to have reduced the bias from missing PIKs. In the CPS ASEC, by contrast, the 2006 changes to data collection and PVS processing that led to higher PIK rates appears to have increased the bias from missing PIKs. Compared to the point estimate of the missing PIK bias in 2005, which is statistically indistinguishable from zero, the bias estimates in 2006 and subsequent years are unambiguously positive. This suggests that the transition from opt-in consent to opt-opt consent and the termination of SSN collection induced positive selection on wage earnings that more than offset the impact of higher PIK rates. Indeed, imbalances in earnings and other characteristics increase after 2005 (see Table A3 and Table A4).

6.5 Estimates of bias after reweighting

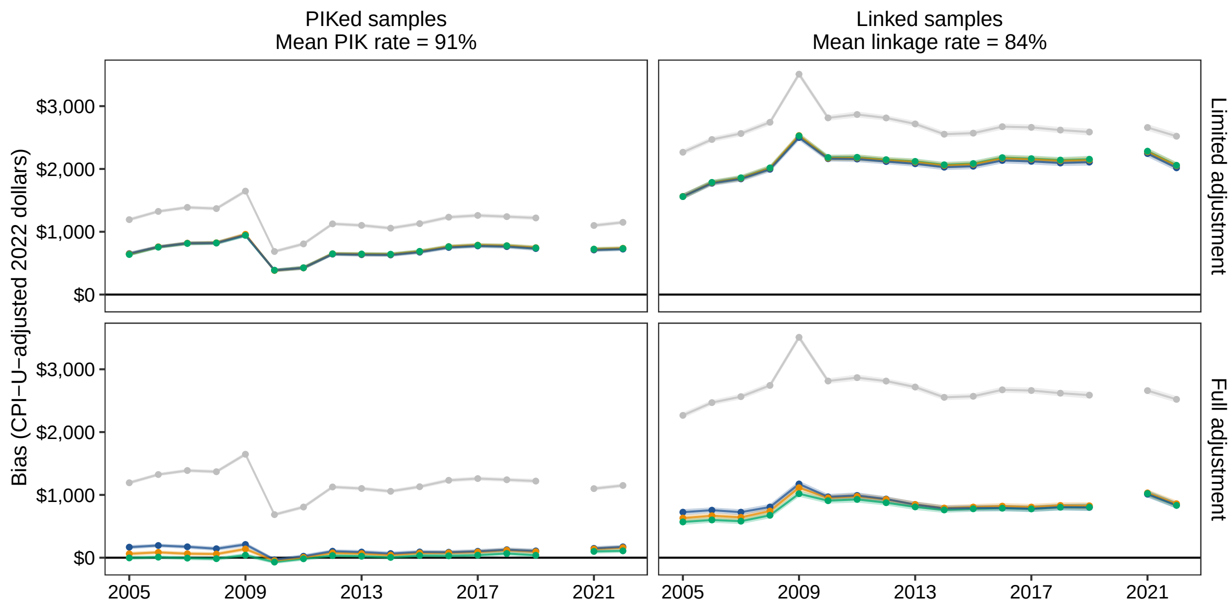
Figure 8 shows bias estimates where observations are reweighted using propensity-based (IPW), balance-targeted (entropy balancing), and hybrid (IPT) techniques. In the full sample, all three reweighting techniques reduce the magnitude of linkage-induced bias in estimates of average wage earnings. This holds true for estimates of missing PIK and linkage bias in both surveys, where weights are derived using full and limited covariate adjustments. Further, we observe little meaningful difference in performance across reweighting techniques.

We find that the full adjustment consistently performs better than the limited adjustment meant to mimic covariates typically observed in administrative records (Figure 8). On average, the full adjustment reduces the magnitude of bias by 78% (range: 11-100%), while the limited adjustment reduces the magnitude of bias by 33% (range: 13-80%).

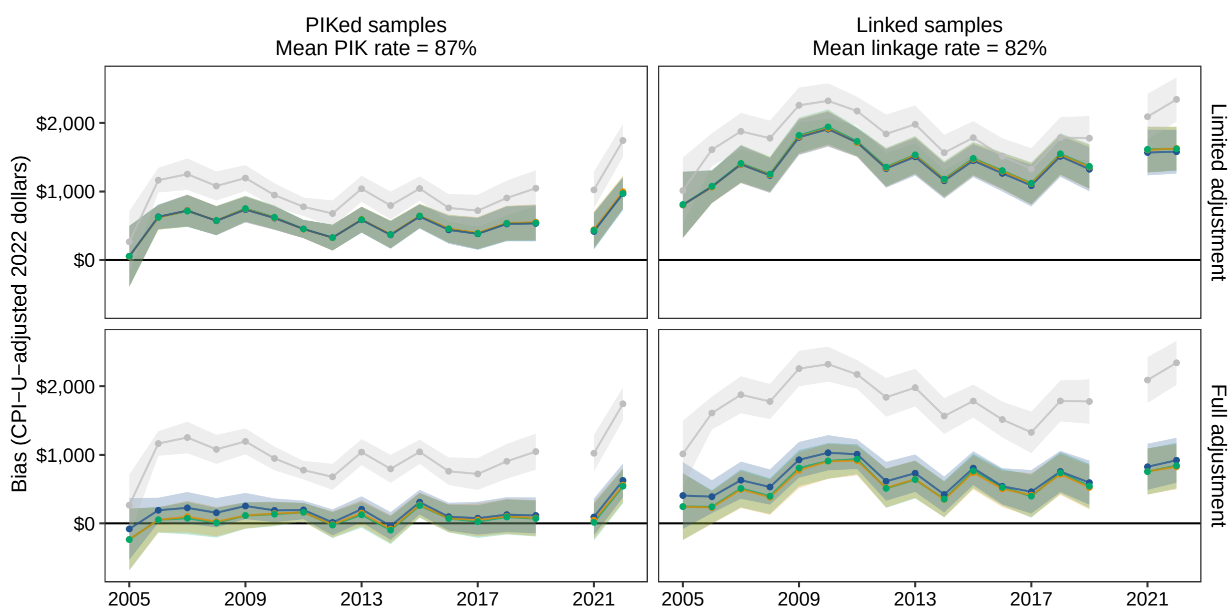
Figure 8: Missing PIK and linkage bias

Reweighting method: None IPW IPT Entropy balancing

(a) ACS

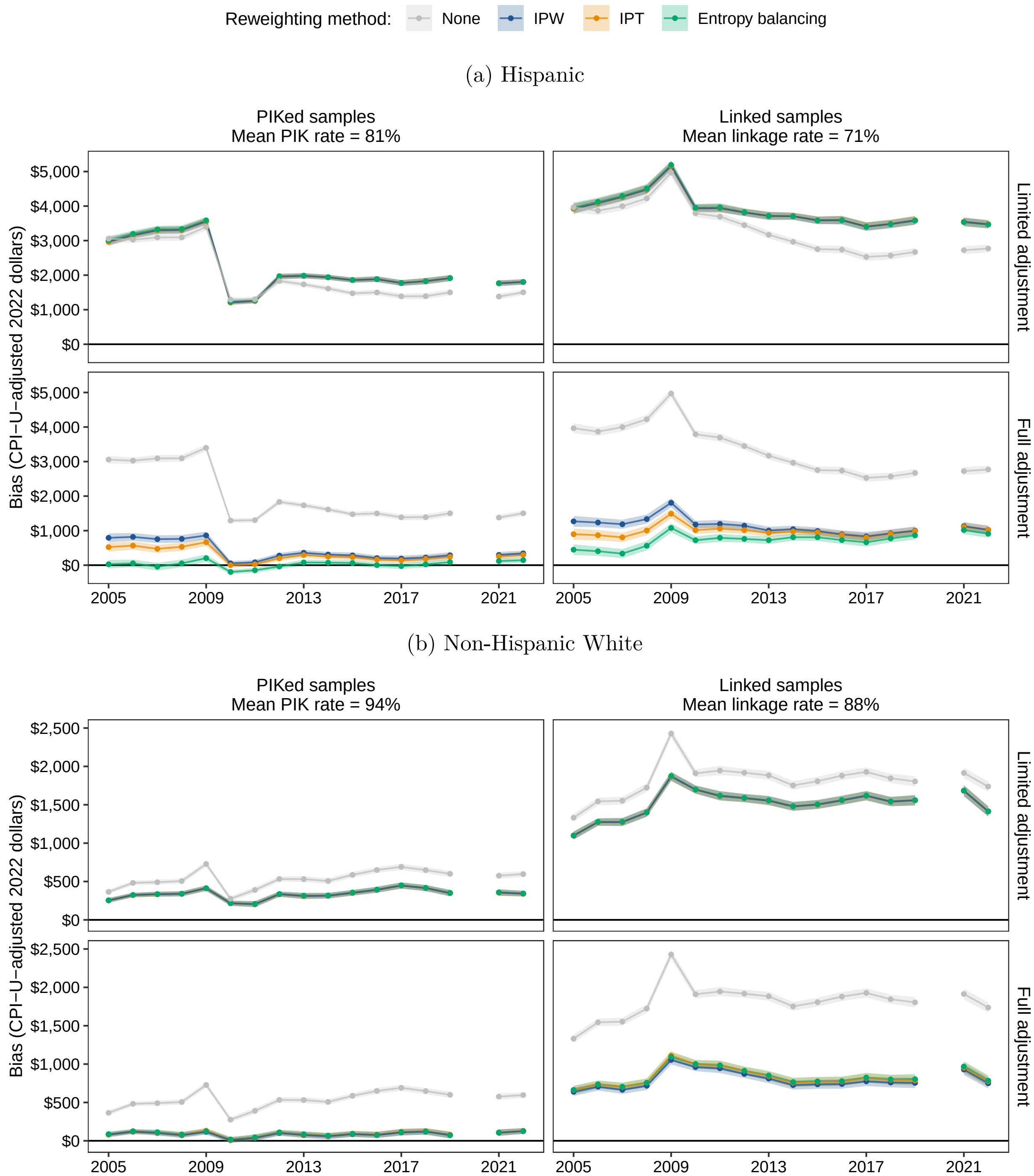


(b) CPS ASEC



Notes: These figures show differences in average wage earnings between the target sample of non-zero wage earners aged 15-64 and employed in the government or private sector and a restricted sample of those assigned a PIK (missing PIK bias) or linked to a W-2 record (linkage bias). Each panel compares baseline to adjusted bias estimates, where adjustments are produced using a limited or full set of covariates. All estimates are produced using survey-specific person weights. 2020 is omitted due to high survey non-response. Shaded regions represent 95% confidence intervals. Lines represent linear interpolation of survey year statistics. *Data sources:* ACS, CPS ASEC, IRS W-2s.

Figure 9: Missing PIK and linkage bias by selected ACS racial groups

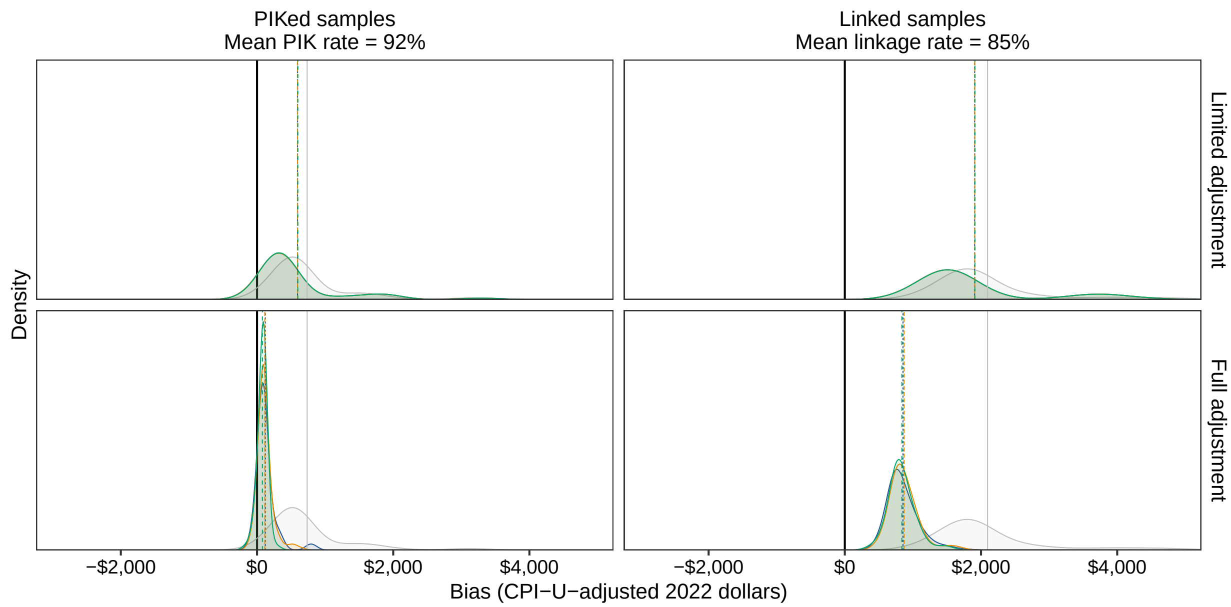


Notes: These figures show differences in average wage earnings between the target sample of non-zero wage earners aged 15-64 and employed in the government or private sector and a restricted sample of those assigned a PIK (missing PIK bias) or linked to a W-2 record (linkage bias). Each panel compares baseline to adjusted bias estimates, where adjustments are produced using a limited or full set of covariates. Panel A shows bias estimates among the Hispanic population. Panel B shows bias estimates among the non-Hispanic White population. All estimates are produced using survey-specific person weights. 2020 is omitted due to high survey non-response. Shaded regions represent 95% confidence intervals. Lines represent linear interpolation of survey year statistics. *Data sources:* ACS, IRS W-2s.

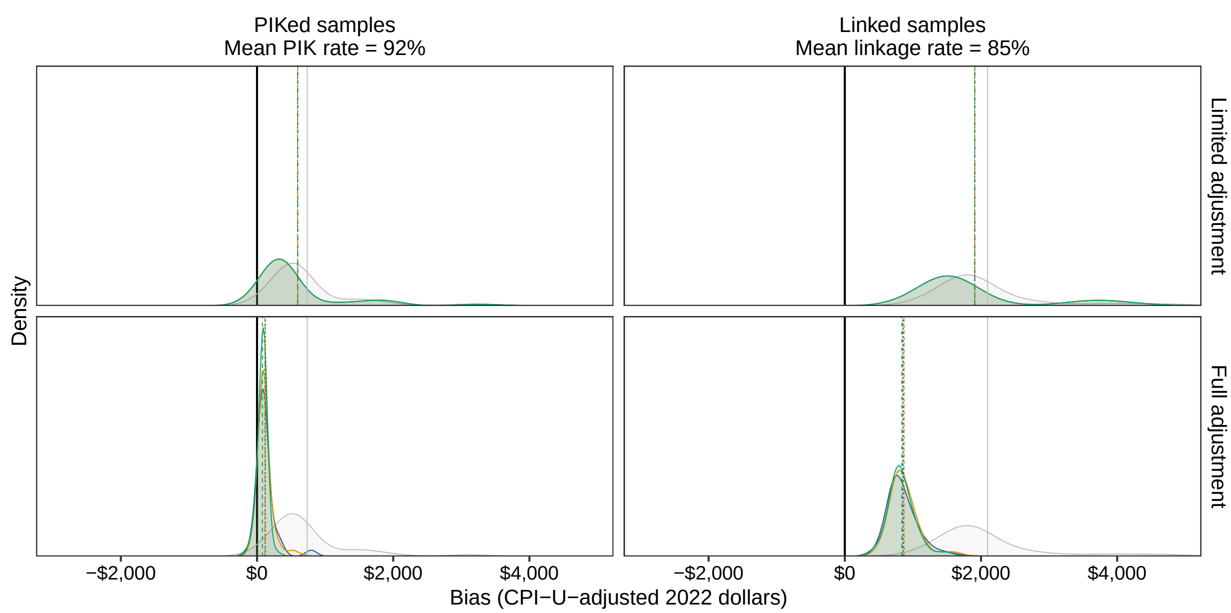
Figure 10: Density of missing PIK and linkage bias estimates at the subgroup-by-year level

Reweighting method: None IPW IPT Entropy balancing

(a) ACS



(b) CPS ASEC



Notes: These figures show kernel density estimations of the distribution of bias within all survey-years and racial-ethnic subgroups. Bias is estimated as the difference in average wage earnings between the target sample of non-zero wage earners aged 15-64 and employed in the government or private sector and a restricted sample of those assigned a PIK (missing PIK bias) or linked to a W-2 record (linkage bias). All bias estimates are produced using survey-specific person weights. Each bias estimate is then weighted by its sample size. 2020 is omitted due to high survey non-response. *Data sources:* ACS, CPS ASEC, IRS W-2s.

To test the performance of reweighting techniques in high and low linkability settings, we leverage differences in PIK and linkage rates between non-Hispanic White wage earners (94% and 88%, respectively) and Hispanic wage earners (81% and 71%, respectively) in the ACS (Figure 9). Among the more linkable non-Hispanic White wage earners, reweighting generally performs similar to the combined sample of racial-ethnic groups. Among the less linkable Hispanic wage earners, we find that the full adjustment performs well, but the limited adjustment yields bias estimates that exceed the baseline bias estimates in most years, regardless of the reweighting method. This suggests that model and moment misspecification is particularly problematic in low PIK-rate settings.

Using the full-adjustment in low linkability settings reveals some meaningful variation in the performance of reweighting techniques. Among Hispanic wage earners, we find that full-adjustment entropy balancing tends to outperform full-adjustment IPT, which in turn tends to outperform full-adjustment IPW. However, these differences diminish over time. Before 2010, entropy balancing reduces linkage (missing PIK) bias by 87% (98%) on average, compared to 68% (75%) using IPW. After 2010, the difference in performance for missing PIK (linkage) bias falls from 19 to 7 (23 to 10) percentage points, on average. By 2022, the difference in linkage bias between full-adjustment entropy balancing and IPW is statistically indistinguishable from zero.

We extend this subgroup analysis in Figure 10 by plotting the distribution of bias estimates for every racial-ethnic group and survey-year using kernel density estimation. One takeaway is that the distribution of bias estimates for entropy balancing exhibits less variance than that for IPW or IPT. We also observe smaller variance for the full adjustment than for the limited adjustment for all reweighting techniques.

7 Conclusion

In this paper, we comprehensively document patterns of selection into PIK assignment and provide evidence of linkage-induced selection bias in an outcome of broad interest to researchers—wage earnings—as well as the efficacy of reweighting techniques in mitigating that bias. A key takeaway from our analysis is that researchers ought to adjust for linkage-induced sample selection when estimating population statistics from linked data.

Imbalances across the PIKed and unPIKed samples suggest that reference file coverage and data quality are key drivers of selection into linked data. Because the PVS reference file is developed from the Numident and periodically updated, recent movers, young children, and non-citizens are less likely to have their full and updated records reflected in the reference file. Data quality matters in terms of both the information provided directly by respondents, as well as the way in which that information is processed into standardized data fields. Confusion, proxy reporting, and name parsing methods can impair the identifying information on which the PVS relies. Although PIK rates in major national surveys are generally high (93% in 2022 ACS and 83% in 2022 CPS), we observe PIK rates as low as 50% in ACS subgroups and 39% in CPS subgroups. Such deviations can exacerbate the effect of sample imbalance on selection bias in outcomes of interest.

We find statistically significant and economically meaningful levels of bias in estimates of wage earnings, which can be mitigated with sufficient information to model selection or specify moment constraints. Using a target sample of ACS wage earners linked to W-2 records as a test case, we find that linkage bias amounts to 4.1-6.5% of percent of average wage earnings over 2005-2019 and 2021-2022. By leveraging differences in linkage rates across racial-ethnic groups, we show that bias estimates in low linkage-rate settings exceed those in high linkage-rate settings. We consider propensity-based (IPW), balance-targeted (entropy balancing), and hybrid (IPT) reweighting techniques, and find that all three approaches tend to reduce linkage-induced selection bias in average wage earnings, especially when weights are estimated using the full set of covariates. While the differences are modest, IPT tends to perform no worse, on average, than IPW and entropy balancing tends to perform no worse, on average, than IPT. In this sense, entropy balancing weakly dominates the other two approaches in our validation exercise.

While we focus our attention on how false-negative linkages lead to sample-selection bias, false-negative linkages can also lead to measurement error, particularly in applications where linkages themselves define outcomes. For example, in an application linking survey data to criminal records as a source of criminal-justice outcomes (e.g., arrests, convictions, or incarceration), false-negative linkages would produce false-negative outcomes (Tahamont et al. 2021), leading to non-classical measurement error (Aigner 1973) in addition to linkage-induced sample selection. We leave an analysis of linkage-induced measurement error for future research.

The forefront of social science research increasingly relies on novel data linkage. We document a source of selection bias that is universal to samples that rely on PVS processing or other probabilistic linkage methodologies. Based on our analysis, we offer the following practical guidance to researchers using linked data:

1. If an analysis sample is conditioned on PIK assignment or successful linkage, reweight it.
2. Consider using entropy balancing as an alternative to inverse probability weighting.
3. If feasible, invest in access to datasets with a rich set of available covariates for reweighting.

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Appendix

Table A1: PVS modules used in processing of ACS and CPS ASEC

	Survey Year																
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022
ACS																	
DOB Search (D flag)						✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Geo Search (S flag)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
HHComp Search (U flag)						✓	✓	✓	✓	✓	✓			✓	✓	✓	✓
Movers Search (K flag)								✓	✓								
Name Search (T flag)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ZIP3 Adjacency Search (J flag)						✓	✓	✓									
CPS ASEC																	
DOB Search (D flag)							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Geo Search (S flag)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
HHComp Search (U flag)							✓	✓	✓	✓	✓	✓					
Name Search (T flag)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Verification (V flag)	✓																
ZIP3 Adjacency Search (J flag)							✓										

Notes: This table shows the PVS modules used to assign PIKs to survey respondents in each survey year. 2020 is omitted due to high non-response. *Data sources:* ACS, CPS ASEC.

Table A2: Balance tests among ACS respondents

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Gender																		
Female	2.0	2.4	2.7	2.3	1.7	2.4	2.5	1.8	2.2	2.0	2.0	1.3	1.2	1.8	1.6	2.7	2.6	All
	4%	5%	6%	5%	3%	5%	5%	4%	4%	4%	4%	3%	2%	4%	3%	6%	5%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Male	-2.0	-2.4	-2.7	-2.3	-1.7	-2.4	-2.5	-1.8	-2.2	-2.0	-2.0	-1.3	-1.2	-1.8	-1.6	-2.7	-2.6	All
	-4%	-5%	-5%	-4%	-3%	-5%	-5%	-4%	-4%	-4%	-4%	-3%	-2%	-4%	-3%	-5%	-5%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Race and ethnicity																		
White, non-Hisp.	27.4	26.5	25.6	25.1	24.6	16.5	16.1	19.1	19.6	20.4	21.1	21.6	22.1	23.6	24.7	23.0	24.0	All
	65%	63%	60%	58%	57%	34%	33%	42%	44%	47%	50%	52%	54%	61%	66%	63%	68%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
2+ races, non-Hisp.	0.2	0.3	0.4	0.3	0.2	0.3	0.4	0.0	0.2	0.3	0.3	0.2	0.3	0.4	0.5	0.5	0.4	All
	19%	26%	28%	25%	15%	16%	21%	2%	8%	13%	15%	10%	13%	20%	24%	13%	10%	
	***	***	***	***	***	***	***		***	***	***	***	***	***	***	***	***	
Black, non-Hisp.	-2.1	-2.5	-2.5	-2.5	-2.5	-2.2	-2.3	-1.4	-1.8	-1.9	-2.5	-2.8	-3.5	-3.1	-3.3	-2.0	-2.2	All
	-15%	-17%	-17%	-17%	-17%	-15%	-16%	-10%	-13%	-14%	-17%	-19%	-23%	-20%	-21%	-15%	-16%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Hispanic	-23.3	-22.0	-21.5	-21.1	-20.4	-12.8	-12.0	-15.4	-15.4	-15.9	-15.8	-15.7	-15.8	-17.9	-19.1	-18.9	-19.3	All
	-65%	-64%	-63%	-62%	-61%	-45%	-43%	-50%	-50%	-50%	-49%	-49%	-49%	-52%	-53%	-52%	-52%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Asian, non-Hisp.	-1.5	-1.6	-1.4	-1.3	-1.4	-1.3	-1.7	-1.5	-1.7	-1.9	-2.2	-2.2	-1.9	-2.0	-1.7	-0.9	-1.2	All
	-27%	-28%	-24%	-23%	-25%	-23%	-27%	-24%	-26%	-28%	-30%	-30%	-26%	-27%	-24%	-14%	-18%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
AIAN, non-Hisp.	-0.3	-0.3	-0.2	-0.3	-0.3	-0.2	-0.1	-0.3	-0.4	-0.5	-0.5	-0.6	-0.6	-0.6	-0.5	-0.6	-0.5	All
	-31%	-33%	-23%	-34%	-29%	-20%	-18%	-34%	-39%	-45%	-47%	-52%	-51%	-51%	-43%	-56%	-53%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
NHPI, non-Hisp.	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.3	-0.2	-0.3	-0.3	All
	-31%	-34%	-37%	-35%	-39%	-38%	-40%	-60%	-62%	-57%	-58%	-57%	-57%	-64%	-61%	-64%	-62%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Other race, non-Hisp.	-0.3	-0.3	-0.3	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3	-0.4	-0.8	-0.8	All
	-59%	-60%	-59%	-53%	-54%	-49%	-59%	-59%	-56%	-56%	-56%	-56%	-55%	-52%	-64%	-62%	-61%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Race and ethnicity, among US-born citizens																		
White, non-Hisp.	15.2	14.4	14.3	14.8	15.5	9.4	9.3	10.9	11.6	12.8	14.1	15.6	17.0	18.3	19.4	16.8	17.7	US-born cit.
	25%	24%	24%	25%	27%	15%	15%	18%	20%	22%	25%	29%	32%	36%	39%	34%	37%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
2+ races, non-Hisp.	-0.2	-0.1	-0.0	-0.1	-0.2	0.0	0.2	-0.3	-0.2	-0.1	-0.0	-0.1	-0.0	0.1	0.2	0.1	0.0	US-born cit.
	-13%	-7%	-3%	-4%	-12%	1%	8%	-13%	-7%	-4%	-1%	-5%	-2%	3%	7%	2%	1%	
	***	***		**	***		***	***	***	**		***		*	***			
Black, non-Hisp.	-6.8	-7.3	-6.9	-6.7	-6.2	-4.7	-4.6	-4.3	-4.9	-5.0	-5.8	-5.9	-6.6	-6.5	-6.7	-5.1	-5.9	US-born cit.
	-36%	-37%	-36%	-35%	-34%	-27%	-26%	-25%	-28%	-28%	-31%	-32%	-35%	-34%	-35%	-30%	-33%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Hispanic	-6.6	-5.6	-6.1	-6.8	-7.7	-3.8	-3.9	-4.8	-5.0	-6.0	-6.5	-7.6	-8.4	-9.8	-10.9	-9.2	-9.0	US-born cit.
	-42%	-38%	-39%	-41%	-44%	-25%	-25%	-29%	-30%	-33%	-35%	-38%	-40%	-44%	-46%	-40%	-39%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Asian, non-Hisp.	-0.5	-0.4	-0.4	-0.4	-0.5	-0.4	-0.4	-0.4	-0.4	-0.4	-0.5	-0.6	-0.5	-0.6	-0.6	-0.4	-0.7	US-born cit.
	-26%	-22%	-21%	-21%	-23%	-18%	-19%	-16%	-19%	-19%	-21%	-22%	-21%	-21%	-21%	-14%	-23%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
AIAN, non-Hisp.	-0.8	-0.7	-0.5	-0.7	-0.6	-0.4	-0.3	-0.6	-0.7	-0.9	-0.9	-1.0	-1.0	-1.1	-0.9	-1.0	-0.9	US-born cit.
	-51%	-51%	-43%	-50%	-45%	-33%	-31%	-47%	-50%	-56%	-57%	-60%	-60%	-60%	-54%	-64%	-63%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	

Table A2: Balance tests among ACS respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
NHPI, non-Hisp.	-0.1 -50% ***	-0.1 -50% ***	-0.1 -55% ***	-0.1 -52% ***	-0.1 -56% ***	-0.1 -45% ***	-0.1 -51% ***	-0.2 -69% ***	-0.2 -71% ***	-0.2 -67% ***	-0.2 -68% ***	-0.2 -66% ***	-0.2 -67% ***	-0.3 -71% ***	-0.3 -71% ***	-0.3 -72% ***	-0.3 -71% ***	US-born cit.
Other race, non-Hisp.	-0.2 -53% ***	-0.1 -49% ***	-0.2 -56% ***	-0.1 -47% ***	-0.2 -52% ***	-0.1 -49% ***	-0.2 -59% ***	-0.2 -59% ***	-0.2 -58% ***	-0.2 -55% ***	-0.2 -57% ***	-0.2 -57% ***	-0.2 -50% ***	-0.2 -53% ***	-0.3 -62% ***	-0.9 -64% ***	-0.9 -64% ***	US-born cit.
Citizenship																		
US-born citizen	25.1 39% ***	24.4 38% ***	23.1 35% ***	22.0 33% ***	20.2 30% ***	14.7 20% ***	14.3 20% ***	17.2 25% ***	17.6 25% ***	17.8 26% ***	17.6 25% ***	16.3 23% ***	15.5 22% ***	16.9 24% ***	17.3 25% ***	17.2 25% ***	18.7 28% ***	All
Foreign-born citizen	-0.3 -4% ***	-0.3 -4% ***	-0.2 -3% ***	0.1 1%	0.7 11% ***	0.3 4% ***	0.4 5% ***	0.2 2% ***	0.0 1%	-0.0 -1%	0.1 1% *	-0.0 0%	-0.2 -3% ***	-0.6 -7% ***	-0.5 -5% ***	-0.0 0%	0.0 0%	All
Not a citizen	-24.8 -84% ***	-24.1 -83% ***	-22.8 -83% ***	-22.0 -82% ***	-20.9 -82% ***	-15.0 -71% ***	-14.7 -71% ***	-17.4 -76% ***	-17.7 -77% ***	-17.8 -77% ***	-17.7 -77% ***	-16.3 -75% ***	-15.3 -74% ***	-16.2 -76% ***	-16.9 -77% ***	-17.1 -77% ***	-18.8 -78% ***	All
Marital status																		
Married	7.9 16% ***	9.0 20% ***	8.7 19% ***	8.6 19% ***	8.9 20% ***	9.9 23% ***	11.4 28% ***	9.5 23% ***	10.2 25% ***	9.6 23% ***	9.8 24% ***	9.6 23% ***	10.1 24% ***	10.8 27% ***	10.7 27% ***	10.2 25% ***	11.6 29% ***	Age 18+
Separated	-1.1 -33% ***	-1.2 -34% ***	-1.1 -32% ***	-0.8 -26% ***	-0.9 -30% ***	-0.5 -19% ***	-0.6 -20% ***	-0.6 -21% ***	-0.8 -26% ***	-0.6 -23% ***	-0.7 -24% ***	-0.6 -24% ***	-0.8 -29% ***	-0.8 -30% ***	-0.8 -30% ***	-0.8 -32% ***	-0.8 -34% ***	Age 18+
Divorced	1.8 20% ***	1.8 19% ***	1.8 18% ***	1.8 18% ***	2.1 22% ***	1.3 12% ***	1.3 13% ***	1.7 17% ***	1.5 15% ***	1.8 18% ***	2.1 21% ***	1.7 17% ***	1.6 16% ***	1.7 17% ***	2.0 21% ***	2.0 21% ***	2.0 22% ***	Age 18+
Widowed	1.4 27% ***	1.1 20% ***	1.1 19% ***	1.3 24% ***	1.6 33% ***	0.7 12% ***	1.0 19% ***	1.2 24% ***	1.2 24% ***	1.2 23% ***	1.2 25% ***	1.3 27% ***	1.2 24% ***	1.2 24% ***	1.4 30% ***	1.2 27% ***	1.3 30% ***	Age 18+
Never married	-10.0 -30% ***	-10.7 -30% ***	-10.5 -29% ***	-10.9 -29% ***	-11.7 -30% ***	-11.3 -29% ***	-13.1 -32% ***	-11.8 -29% ***	-12.2 -30% ***	-11.9 -29% ***	-12.4 -30% ***	-11.9 -29% ***	-12.0 -29% ***	-12.9 -30% ***	-13.3 -31% ***	-12.5 -29% ***	-14.1 -32% ***	Age 18+
Limited English																		
Yes	-17.2 -84% ***	-16.5 -84% ***	-15.7 -83% ***	-14.8 -82% ***	-14.1 -82% ***	-10.5 -73% ***	-9.8 -72% ***	-10.5 -75% ***	-10.7 -76% ***	-11.0 -76% ***	-10.7 -75% ***	-10.3 -75% ***	-9.7 -74% ***	-10.3 -76% ***	-10.6 -77% ***	-10.8 -76% ***	-11.8 -78% ***	Age 5+
No	17.2 22% ***	16.5 21% ***	15.7 19% ***	14.8 18% ***	14.1 17% ***	10.5 12% ***	9.8 11% ***	10.5 12% ***	10.7 12% ***	11.0 13% ***	10.7 13% ***	10.3 12% ***	9.7 11% ***	10.3 12% ***	10.6 12% ***	10.8 13% ***	11.8 14% ***	Age 5+
Limited English, among US-born citizens																		
Yes	-1.0 -65% ***	-0.8 -61% ***	-0.8 -61% ***	-0.7 -60% ***	-0.7 -61% ***	-0.4 -48% ***	-0.4 -49% ***	-0.4 -46% ***	-0.5 -54% ***	-0.5 -59% ***	-0.5 -57% ***	-0.6 -60% ***	-0.6 -62% ***	-0.7 -65% ***	-0.7 -67% ***	-0.6 -59% ***	-0.8 -64% ***	Age 5+, US-born cit.
No	1.0 1% ***	0.8 1% ***	0.8 1% ***	0.7 1% ***	0.7 1% ***	0.4 0% ***	0.4 0% ***	0.4 0% ***	0.5 0% ***	0.5 1% ***	0.5 1% ***	0.6 1% ***	0.6 1% ***	0.7 1% ***	0.7 1% ***	0.6 1% ***	0.8 1% ***	Age 5+, US-born cit.
Urbanicity																		
Urban	-3.3 -4% ***	-3.7 -5% ***	-4.1 -5% ***	-3.7 -5% ***	-4.0 -5% ***	-3.3 -4% ***	-4.5 -6% ***	-3.6 -4% ***	-3.6 -4% ***	-3.9 -5% ***	-4.0 -5% ***	-3.2 -4% ***	-3.4 -4% ***	-5.1 -6% ***	-5.9 -7% ***	-4.0 -5% ***	-4.3 -5% ***	All

Table A2: Balance tests among ACS respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Rural	3.3 17% ***	3.7 19% ***	4.1 22% ***	3.7 18% ***	4.0 20% ***	3.3 16% ***	4.5 22% ***	3.6 23% ***	3.6 23% ***	3.9 26% ***	4.0 26% ***	3.2 20% ***	3.4 22% ***	5.1 36% ***	5.9 42% ***	4.0 25% ***	4.3 27% ***	All
Region																		
Midwest	7.1 45% ***	7.4 47% ***	7.3 47% ***	7.6 51% ***	7.2 46% ***	6.2 39% ***	5.6 34% ***	6.0 37% ***	6.6 42% ***	6.5 43% ***	6.8 45% ***	6.9 47% ***	6.9 47% ***	6.7 45% ***	6.4 43% ***	6.4 43% ***	6.4 43% ***	All
Northeast	1.5 9% ***	1.5 9% ***	1.5 9% ***	1.0 6% ***	1.2 7% ***	-0.8 -4% ***	-0.7 -4% ***	0.1 1%	0.2 1% **	0.1 1% *	0.5 3% ***	0.8 5% ***	0.9 5% ***	1.2 7% ***	1.2 8% ***	1.1 7% ***	0.5 3% ***	All
South	-0.5 -1% ***	-0.7 -2% ***	-0.9 -2% ***	-1.1 -3% ***	-1.1 -3% ***	-0.5 -1% ***	0.1 0%	-0.5 -1% ***	-0.5 -1% ***	-0.4 -1% ***	-1.0 -3% ***	-1.7 -4% ***	-1.6 -4% ***	-0.4 -1% ***	-0.5 -1% ***	-1.7 -4% ***	-2.0 -5% ***	All
West	-8.1 -27% ***	-8.2 -27% ***	-8.0 -26% ***	-7.6 -25% ***	-7.3 -24% ***	-4.9 -18% ***	-5.0 -18% ***	-5.6 -20% ***	-6.2 -21% ***	-6.3 -22% ***	-6.2 -21% ***	-6.0 -21% ***	-6.2 -21% ***	-7.4 -24% ***	-7.2 -24% ***	-5.8 -20% ***	-4.9 -17% ***	All
Cognitive disability																		
Yes	3.4 29% ***	2.7 20% ***	2.9 22% ***	2.3 20% ***	3.1 29% ***	2.2 19% ***	2.7 26% ***	2.7 25% ***	3.1 28% ***	3.2 30% ***	3.3 31% ***	3.2 29% ***	2.7 24% ***	2.9 26% ***	3.3 31% ***	2.4 20% ***	2.4 20% ***	Age 5+
No	-3.4 -4% ***	-2.7 -3% ***	-2.9 -3% ***	-2.3 -3% ***	-3.1 -4% ***	-2.2 -2% ***	-2.7 -3% ***	-2.7 -3% ***	-3.1 -3% ***	-3.2 -4% ***	-3.3 -4% ***	-3.2 -4% ***	-2.7 -3% ***	-2.9 -3% ***	-3.3 -4% ***	-2.4 -3% ***	-2.4 -3% ***	Age 5+
Cash welfare																		
Yes	-1.3 -28% ***	-0.9 -23% ***	-0.8 -22% ***	-0.7 -19% ***	-1.1 -25% ***	-0.3 -8% ***	-0.6 -13% ***	-0.7 -15% ***	-0.9 -19% ***	-0.7 -16% ***	-0.7 -17% ***	-0.9 -21% ***	-1.0 -26% ***	-0.9 -24% ***	-0.5 -16% ***	-0.4 -9% ***	-0.9 -23% ***	Household
No	1.3 1% ***	0.9 1% ***	0.8 1% ***	0.7 1% ***	1.1 1% ***	0.3 0% ***	0.6 1% ***	0.7 1% ***	0.9 1% ***	0.7 1% ***	0.7 1% ***	0.9 1% ***	1.0 1% ***	0.9 1% ***	0.5 1% ***	0.4 0% ***	0.9 1% ***	Household
Health insurance																		
Private	-	-	-	15.3 35% ***	15.2 36% ***	10.2 23% ***	9.5 21% ***	10.8 25% ***	11.1 26% ***	10.6 24% ***	10.2 22% ***	10.3 22% ***	10.9 24% ***	11.2 25% ***	10.7 24% ***	11.7 27% ***	12.0 28% ***	All
Public	-	-	-	-2.6 -14% ***	-3.8 -18% ***	-1.0 -5% ***	-1.0 -5% ***	-0.5 -2% ***	-1.0 -5% ***	-1.5 -6% ***	-2.3 -9% ***	-4.1 -15% ***	-5.2 -18% ***	-5.0 -18% ***	-3.9 -14% ***	-3.3 -12% ***	-2.9 -10% ***	All
Private and public	-	-	-	5.9 94% ***	6.5 121% ***	4.4 64% ***	4.8 75% ***	4.8 73% ***	5.2 83% ***	5.4 85% ***	5.6 88% ***	5.8 88% ***	5.9 91% ***	6.2 100% ***	6.2 100% ***	6.0 88% ***	5.7 82% ***	All
None	-	-	-	-18.6 -59% ***	-17.8 -57% ***	-13.7 -48% ***	-13.3 -48% ***	-15.1 -52% ***	-15.3 -53% ***	-14.5 -57% ***	-13.5 -61% ***	-12.0 -60% ***	-11.6 -59% ***	-12.4 -60% ***	-13.0 -61% ***	-14.4 -65% ***	-14.9 -67% ***	All
Class of worker																		
Private	-5.4 -7% ***	-5.6 -7% ***	-5.4 -7% ***	-4.6 -6% ***	-5.3 -7% ***	-3.4 -4% ***	-3.5 -5% ***	-3.6 -5% ***	-3.4 -4% ***	-3.1 -4% ***	-3.2 -4% ***	-3.1 -4% ***	-2.9 -4% ***	-3.4 -4% ***	-3.9 -5% ***	-3.3 -4% ***	-3.6 -5% ***	Age 16+, empl.
Government	5.7 60% ***	5.6 58% ***	5.5 57% ***	5.1 51% ***	5.5 57% ***	4.2 37% ***	4.1 36% ***	4.2 39% ***	4.3 41% ***	4.0 37% ***	4.0 39% ***	4.0 39% ***	4.0 38% ***	4.4 44% ***	4.6 45% ***	4.3 39% ***	4.5 42% ***	Age 16+, empl.

Table A2: Balance tests among ACS respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Self-employed	-0.2 -2% *	0.1 1%	-0.0 0%	-0.4 -4% ***	-0.2 -2% **	-0.7 -7% ***	-0.5 -5% ***	-0.6 -6% ***	-0.9 -8% ***	-0.8 -8% ***	-0.8 -8% ***	-0.9 -9% ***	-1.0 -10% ***	-1.0 -9% ***	-0.7 -7% ***	-0.9 -8% ***	-0.7 -7% ***	Age 16+, empl.
Unpaid family	-0.2 -31% ***	-0.0 -12% ***	-0.1 -22% ***	-0.1 -24% ***	-0.1 -25% ***	-0.1 -28% ***	-0.0 -12% **	-0.0 -8% *	-0.0 -12% ***	-0.0 -12% ***	-0.1 -14% ***	-0.0 -9% *	-0.0 -10% **	-0.0 -6%	-0.0 -11% **	-0.1 -28% ***	-0.2 -37% ***	Age 16+, empl.
Education																		
Less than HS	-14.5 -50% ***	-14.1 -49% ***	-14.2 -50% ***	-15.0 -53% ***	-14.6 -53% ***	-9.7 -41% ***	-8.9 -40% ***	-11.2 -47% ***	-11.9 -49% ***	-12.0 -50% ***	-12.2 -51% ***	-12.0 -51% ***	-11.7 -52% ***	-12.5 -54% ***	-12.8 -55% ***	-13.9 -59% ***	-14.1 -60% ***	Age 25+
High school	-1.8 -6% ***	-2.9 -9% ***	-3.2 -10% ***	-1.8 -6% ***	-2.0 -7% ***	-2.7 -9% ***	-2.1 -7% ***	-2.4 -8% ***	-2.5 -8% ***	-3.3 -11% ***	-3.4 -11% ***	-4.1 -13% ***	-5.1 -16% ***	-4.9 -16% ***	-4.8 -15% ***	-5.1 -16% ***	-5.6 -18% ***	Age 25+
Some college	8.1 40% ***	8.3 43% ***	8.1 41% ***	7.4 34% ***	6.7 29% ***	5.0 21% ***	4.8 20% ***	5.3 22% ***	5.5 23% ***	5.9 25% ***	6.0 26% ***	5.8 24% ***	5.9 25% ***	5.9 25% ***	6.0 26% ***	6.0 27% ***	6.1 27% ***	Age 25+
Bachelor's degree	4.4 33% ***	4.7 36% ***	4.9 38% ***	5.0 39% ***	5.3 41% ***	3.4 24% ***	2.7 18% ***	4.3 30% ***	4.4 30% ***	4.7 33% ***	4.9 33% ***	5.2 36% ***	5.5 38% ***	5.9 40% ***	5.9 39% ***	6.8 46% ***	7.2 48% ***	Age 25+
Graduate degree	3.9 60% ***	4.0 64% ***	4.5 74% ***	4.4 72% ***	4.7 76% ***	4.0 60% ***	3.5 48% ***	4.1 58% ***	4.5 63% ***	4.7 65% ***	4.8 66% ***	5.0 68% ***	5.5 75% ***	5.7 76% ***	5.8 77% ***	6.1 75% ***	6.4 80% ***	Age 25+
Employment status																		
Employed	2.7 5% ***	3.4 6% ***	2.7 5% ***	3.1 5% ***	3.1 6% ***	3.1 6% ***	3.0 5% ***	3.6 7% ***	3.5 6% ***	4.0 7% ***	4.0 7% ***	4.3 8% ***	4.9 9% ***	4.2 8% ***	3.1 5% ***	5.4 10% ***	5.7 10% ***	Age 16+
Unemployed	-0.8 -16% ***	-0.5 -10% ***	-0.2 -5% ***	-0.5 -12% ***	-1.4 -18% ***	-0.3 -5% ***	-0.4 -5% ***	-1.1 -15% ***	-0.9 -14% ***	-0.7 -13% ***	-0.6 -14% ***	-0.5 -13% ***	-0.6 -16% ***	-0.5 -15% ***	-0.4 -13% ***	-0.4 -9% ***	-0.6 -18% ***	Age 16+
Not in labor force	-1.9 -5% ***	-3.0 -8% ***	-2.5 -7% ***	-2.6 -7% ***	-1.7 -5% ***	-2.8 -7% ***	-2.6 -7% ***	-2.5 -7% ***	-2.6 -7% ***	-3.3 -8% ***	-3.4 -8% ***	-3.7 -9% ***	-4.3 -10% ***	-3.7 -9% ***	-2.7 -7% ***	-5.0 -12% ***	-5.1 -12% ***	Age 16+
Housing type																		
Household unit	-	1.9 2% ***	2.0 2% ***	2.1 2% ***	1.3 1% ***	1.4 1% ***	1.9 2% ***	1.6 2% ***	1.5 2% ***	1.5 2% ***	1.6 2% ***	1.3 1% ***	1.2 1% ***	1.7 2% ***	2.1 2% ***	4.4 5% ***	4.6 5% ***	All
Group quarters	-	-1.9 -43% ***	-2.0 -45% ***	-2.1 -45% ***	-1.3 -34% ***	-1.4 -36% ***	-1.9 -44% ***	-1.6 -40% ***	-1.5 -38% ***	-1.5 -39% ***	-1.6 -40% ***	-1.3 -36% ***	-1.2 -35% ***	-1.7 -42% ***	-2.1 -48% ***	-4.4 -69% ***	-4.6 -69% ***	All
Tenure																		
Owned, mortgage	18.2 51% ***	17.7 49% ***	16.9 46% ***	16.9 46% ***	17.5 50% ***	12.2 32% ***	14.1 40% ***	13.7 39% ***	15.1 47% ***	15.0 48% ***	15.5 50% ***	16.2 54% ***	16.4 53% ***	16.8 57% ***	16.7 56% ***	14.5 45% ***	15.1 48% ***	Household
Owned, no mortgage	5.3 41% ***	5.4 43% ***	5.7 47% ***	5.2 41% ***	6.2 53% ***	3.9 28% ***	4.9 37% ***	4.5 32% ***	5.0 34% ***	5.1 35% ***	5.2 35% ***	5.6 37% ***	5.6 37% ***	5.8 37% ***	6.7 44% ***	5.4 31% ***	5.7 32% ***	Household
Rented, cash	-23.0 -46% ***	-22.7 -46% ***	-22.2 -46% ***	-21.7 -44% ***	-23.3 -46% ***	-15.8 -34% ***	-18.6 -38% ***	-17.8 -36% ***	-19.5 -38% ***	-19.5 -38% ***	-20.1 -39% ***	-21.1 -40% ***	-21.3 -41% ***	-21.9 -42% ***	-22.8 -43% ***	-19.2 -40% ***	-20.1 -41% ***	Household

Table A2: Balance tests among ACS respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Rented, no cash	-0.4 -20% ***	-0.4 -18% ***	-0.4 -19% ***	-0.4 -22% ***	-0.4 -22% ***	-0.3 -16% ***	-0.4 -19% ***	-0.4 -20% ***	-0.6 -27% ***	-0.6 -26% ***	-0.6 -28% ***	-0.7 -32% ***	-0.7 -33% ***	-0.7 -31% ***	-0.6 -29% ***	-0.8 -36% ***	-0.7 -33% ***	Household
Migration in past year																		
Moved, within US	-6.9 -32% ***	-7.0 -31% ***	-6.6 -31% ***	-5.4 -27% ***	-10.0 -42% ***	-3.7 -20% ***	-7.5 -35% ***	-4.8 -25% ***	-4.6 -25% ***	-3.9 -22% ***	-3.7 -21% ***	-4.1 -23% ***	-3.8 -22% ***	-3.5 -21% ***	-3.5 -21% ***	-4.0 -25% ***	-4.1 -26% ***	Age 1+
Moved, outside US	-2.6 -87% ***	-2.2 -84% ***	-1.9 -82% ***	-1.7 -80% ***	-2.0 -87% ***	-1.6 -79% ***	-2.2 -85% ***	-1.6 -80% ***	-1.9 -82% ***	-2.1 -83% ***	-2.1 -83% ***	-2.1 -82% ***	-1.8 -80% ***	-1.8 -82% ***	-2.2 -85% ***	-1.8 -86% ***	-2.9 -87% ***	Age 1+
Did not move	9.4 13% ***	9.3 12% ***	8.5 11% ***	7.1 9% ***	12.0 16% ***	5.4 7% ***	9.7 13% ***	6.4 8% ***	6.5 8% ***	6.0 8% ***	5.9 7% ***	6.2 8% ***	5.6 7% ***	5.3 7% ***	5.7 7% ***	5.8 7% ***	7.0 9% ***	Age 1+
Interview mode																		
Mail	39.0 212% ***	39.6 253% ***	40.4 285% ***	42.1 297% ***	40.4 248% ***	41.5 306% ***	39.1 269% ***	36.7 198% ***	13.6 137% ***	13.1 144% ***	12.5 144% ***	11.6 136% ***	11.2 144% ***	10.9 140% ***	11.2 146% ***	6.2 97% ***	5.6 77% ***	All
Internet	-	-	-	-	-	-	-	-	21.3 174% ***	22.2 169% ***	23.4 162% ***	24.9 156% ***	27.1 164% ***	28.1 152% ***	28.4 156% ***	29.9 93% ***	29.7 86% ***	All
CAPI	-29.0 -48% ***	-29.4 -49% ***	-29.2 -48% ***	-30.6 -49% ***	-31.6 -50% ***	-28.7 -46% ***	-29.7 -46% ***	-28.3 -45% ***	-30.9 -47% ***	-32.9 -49% ***	-33.4 -49% ***	-34.8 -51% ***	-37.1 -53% ***	-37.5 -54% ***	-37.6 -54% ***	-31.8 -58% ***	-30.6 -60% ***	All
CATI	-9.9 -47% ***	-8.4 -43% ***	-9.2 -46% ***	-9.4 -50% ***	-7.5 -45% ***	-11.4 -58% ***	-7.5 -47% ***	-6.8 -47% ***	-2.6 -30% ***	-0.9 -16% ***	-1.0 -18% ***	-0.4 -11% ***	-0.0 0%	0.2 30% ***	0.1 20% ***	0.0 5% *	-0.1 -9% ***	All
GQ personal visit	-	-1.9 -43% ***	-2.0 -45% ***	-2.1 -45% ***	-1.3 -34% ***	-1.4 -36% ***	-1.9 -44% ***	-1.6 -40% ***	-1.5 -38% ***	-1.5 -39% ***	-1.6 -40% ***	-1.3 -36% ***	-1.2 -35% ***	-1.7 -42% ***	-2.1 -48% ***	-4.4 -69% ***	-4.6 -69% ***	All
Relationship to reference person																		
Reference person	10.9 36% ***	11.0 39% ***	10.5 36% ***	10.3 36% ***	12.9 49% ***	8.7 29% ***	8.9 30% ***	9.4 32% ***	9.9 35% ***	10.2 36% ***	10.7 38% ***	11.8 44% ***	11.7 43% ***	11.4 41% ***	12.2 45% ***	12.1 43% ***	13.2 47% ***	Household
Sibling	-1.8 -68% ***	-2.1 -67% ***	-1.8 -64% ***	-1.8 -63% ***	-1.5 -58% ***	-1.3 -52% ***	-1.3 -52% ***	-1.3 -54% ***	-1.3 -53% ***	-1.4 -53% ***	-1.3 -51% ***	-1.3 -53% ***	-1.3 -52% ***	-1.3 -52% ***	-1.3 -51% ***	-1.3 -54% ***	-1.4 -57% ***	Household
Parent	-0.5 -36% ***	-0.6 -34% ***	-0.6 -32% ***	-0.6 -33% ***	-0.5 -29% ***	-0.4 -26% ***	-0.4 -24% ***	-0.6 -34% ***	-0.8 -38% ***	-0.8 -38% ***	-0.8 -37% ***	-0.8 -38% ***	-0.9 -38% ***	-0.9 -40% ***	-0.9 -41% ***	-0.9 -42% ***	-1.0 -46% ***	Household
Spouse	4.4 28% ***	4.8 32% ***	4.6 31% ***	4.4 30% ***	5.1 36% ***	4.5 31% ***	5.0 36% ***	3.8 25% ***	4.2 29% ***	4.0 28% ***	4.1 28% ***	4.5 32% ***	4.7 34% ***	4.9 35% ***	5.0 37% ***	3.7 25% ***	4.3 29% ***	Household
In-law	-1.3 -69% ***	-1.5 -67% ***	-1.4 -64% ***	-0.6 -49% ***	-0.7 -51% ***	-0.5 -43% ***	-0.6 -46% ***	-0.6 -47% ***	-0.6 -47% ***	-0.6 -46% ***	-0.7 -48% ***	-0.8 -50% ***	-0.7 -48% ***	-0.7 -47% ***	-0.7 -48% ***	-0.8 -52% ***	-0.8 -55% ***	Household
Unmarried partner	-0.7 -25% ***	-0.6 -22% ***	-0.6 -22% ***	-0.6 -22% ***	-0.7 -25% ***	-0.4 -15% ***	-0.6 -21% ***	-0.7 -25% ***	-0.8 -26% ***	-0.8 -26% ***	-0.7 -24% ***	-0.5 -19% ***	-0.4 -16% ***	-0.6 -21% ***	-0.5 -18% ***	-0.6 -18% ***	-0.8 -22% ***	Household
Child	0.2 1%	0.9 3% ***	0.2 1% **	0.0 0%	-2.2 -7% ***	1.6 5% ***	2.2 8% ***	1.4 5% ***	1.6 5% ***	0.9 3% ***	0.5 2% ***	-0.8 -3% ***	-1.1 -4% ***	-0.7 -2% ***	-1.4 -4% ***	-0.5 -2% ***	-0.1 0%	Household

Table A2: Balance tests among ACS respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Foster child	-0.2 -67% ***	-0.2 -70% ***	-0.1 -63% ***	-0.1 -60% ***	-0.2 -69% ***	-0.1 -64% ***	-0.1 -64% ***	-0.1 -59% ***	-0.1 -59% ***	-0.1 -58% ***	-0.1 -54% ***	-0.1 -59% ***	-0.1 -53% ***	-0.1 -53% ***	-0.1 -55% ***	-0.1 -51% ***	-0.1 -57% ***	Household
Grandchild	-1.2 -40% ***	-0.7 -27% ***	-0.6 -24% ***	-0.7 -26% ***	-1.4 -40% ***	-0.3 -13% ***	-0.5 -19% ***	-0.4 -15% ***	-0.3 -10% ***	-0.3 -13% ***	-0.4 -15% ***	-0.8 -26% ***	-0.9 -27% ***	-0.7 -22% ***	-0.9 -28% ***	-1.1 -32% ***	-1.3 -36% ***	Household
Boarder, roommate	-4.7 -78% ***	-5.6 -78% ***	-5.5 -77% ***	-5.2 -76% ***	-5.5 -77% ***	-6.2 -76% ***	-7.1 -80% ***	-6.0 -77% ***	-6.5 -78% ***	-6.2 -76% ***	-6.3 -76% ***	-6.1 -74% ***	-5.9 -74% ***	-6.1 -76% ***	-5.7 -75% ***	-4.9 -76% ***	-5.3 -78% ***	Household
Other nonrelative	-2.3 -75% ***	-2.3 -73% ***	-2.0 -71% ***	-1.9 -71% ***	-2.1 -74% ***	-2.2 -72% ***	-2.4 -72% ***	-2.0 -68% ***	-2.4 -70% ***	-2.2 -68% ***	-2.2 -68% ***	-2.3 -70% ***	-2.3 -71% ***	-2.6 -72% ***	-3.0 -74% ***	-2.8 -75% ***	-3.2 -78% ***	Household
Other relative	-2.9 -74% ***	-3.2 -73% ***	-2.9 -72% ***	-3.3 -74% ***	-3.4 -74% ***	-3.2 -69% ***	-3.1 -68% ***	-2.8 -67% ***	-2.9 -67% ***	-2.8 -65% ***	-2.7 -68% ***	-2.8 -69% ***	-2.8 -69% ***	-2.7 -69% ***	-2.8 -70% ***	-2.9 -72% ***	-3.4 -75% ***	Household
Person number																		
1	11.2 38% ***	11.1 39% ***	10.6 37% ***	10.5 36% ***	13.1 49% ***	8.9 30% ***	9.2 31% ***	9.4 32% ***	10.1 35% ***	10.4 37% ***	10.9 39% ***	12.2 45% ***	12.0 44% ***	11.7 42% ***	12.7 47% ***	12.7 46% ***	13.8 51% ***	Household
2	0.5 2% ***	0.4 1% ***	0.3 1% ***	0.0 0%	1.1 4% ***	0.9 3% ***	0.5 2% ***	-0.4 -1% ***	-0.6 -2% ***	-0.7 -2% ***	-0.6 -2% ***	-0.4 -1% ***	-0.2 -1% **	-0.1 0%	0.0 0%	-0.3 -1% **	-0.2 -1%	Household
3	-2.1 -12% ***	-2.2 -12% ***	-2.4 -13% ***	-2.5 -14% ***	-3.2 -17% ***	-1.8 -10% ***	-1.8 -10% ***	-2.5 -13% ***	-2.7 -14% ***	-2.9 -15% ***	-3.1 -16% ***	-3.5 -18% ***	-3.5 -18% ***	-3.5 -18% ***	-3.8 -19% ***	-3.7 -19% ***	-4.1 -21% ***	Household
4	-1.9 -18% ***	-2.0 -18% ***	-1.9 -17% ***	-2.2 -19% ***	-3.1 -25% ***	-1.9 -17% ***	-1.9 -17% ***	-1.9 -17% ***	-2.0 -18% ***	-2.1 -18% ***	-2.4 -20% ***	-2.8 -23% ***	-2.7 -23% ***	-2.7 -23% ***	-3.0 -25% ***	-2.7 -23% ***	-3.2 -26% ***	Household
5	-1.9 -35% ***	-2.0 -35% ***	-1.8 -32% ***	-1.9 -33% ***	-2.7 -42% ***	-1.7 -30% ***	-1.7 -30% ***	-1.6 -29% ***	-1.7 -31% ***	-1.8 -32% ***	-1.9 -32% ***	-2.2 -36% ***	-2.2 -37% ***	-2.2 -37% ***	-2.4 -39% ***	-2.3 -37% ***	-2.5 -40% ***	Household
6+	-5.7 -75% ***	-5.2 -73% ***	-4.9 -71% ***	-3.9 -65% ***	-5.2 -71% ***	-4.4 -63% ***	-4.2 -64% ***	-3.1 -56% ***	-3.0 -55% ***	-3.0 -55% ***	-3.0 -54% ***	-3.3 -58% ***	-3.3 -58% ***	-3.2 -57% ***	-3.5 -59% ***	-3.6 -60% ***	-3.8 -62% ***	Household

Notes: This table shows differences in social and demographic characteristics between respondents who were and were not assigned a PIK. Each cell contains an absolute difference and relative difference, where respondents who were not assigned a PIK serve as the reference group. All estimates are produced using ACS person weights. Significance at the 10%, 5%, and 1% levels is indicated by *, **, ***, respectively. 2020 is omitted due to high survey non-response. *Acronyms:* Hisp. = Hispanic; AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander; HS = high school; CAPI = Computer-Assisted Personal Interview; CATI = Computer-Assisted Telephone Interview. *Data source:* ACS.

Table A3: Balance tests among CPS ASEC respondents

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Gender																		
Male	0.3 1%	-2.3 -5% ***	-2.1 -4% ***	-2.3 -4% ***	-2.2 -4% ***	-1.7 -3% ***	-2.6 -5% ***	-2.2 -4% ***	-1.5 -3% ***	-1.0 -2% **	-0.9 -2% **	-0.4 -1%	-0.7 -1% *	-0.7 -1% *	-0.9 -2% **	-0.4 -1%	-0.5 -1%	All
Female	-0.3 -1%	2.3 5% ***	2.1 4% ***	2.3 5% ***	2.2 5% ***	1.7 4% ***	2.6 5% ***	2.2 4% ***	1.5 3% ***	1.0 2% **	0.9 2% **	0.4 1%	0.7 1% *	0.7 1% *	0.9 2% **	0.4 1%	0.5 1%	All
Race and ethnicity																		
White, non-Hisp.	3.4 5% ***	24.3 53% ***	24.7 56% ***	22.6 49% ***	22.0 47% ***	17.8 36% ***	14.5 28% ***	13.3 26% ***	15.7 32% ***	14.7 30% ***	15.0 31% ***	15.2 32% ***	16.2 34% ***	16.2 35% ***	17.7 39% ***	17.5 39% ***	17.1 38% ***	All
Black, non-Hisp.	0.9 8% ***	-2.3 -16% ***	-2.9 -20% ***	-2.5 -17% ***	-2.0 -14% ***	-3.1 -21% ***	-2.7 -18% ***	-2.7 -18% ***	-1.9 -14% ***	-2.4 -17% ***	-1.2 -9% ***	-1.2 -9% ***	-1.9 -14% ***	-2.4 -17% ***	-1.5 -11% ***	-1.7 -12% ***	-1.3 -10% ***	All
Asian, non-Hisp.	-1.0 -21% ***	-3.8 -50% ***	-3.9 -50% ***	-3.2 -45% ***	-3.0 -44% ***	-3.4 -46% ***	-3.3 -44% ***	-3.3 -42% ***	-2.8 -37% ***	-2.6 -35% ***	-3.5 -41% ***	-4.3 -46% ***	-4.6 -48% ***	-4.3 -45% ***	-4.7 -47% ***	-3.5 -40% ***	-3.1 -36% ***	All
AIAN, non-Hisp.	0.2 55% ***	-0.3 -34% ***	-0.0 -6%	0.0 1%	-0.0 -5%	-0.1 -9%	0.1 23% **	0.1 15%	0.0 4%	0.1 23% **	0.1 8%	0.2 34% ***	-0.0 -5%	-0.1 -16% **	0.1 19% **	0.1 16% **	0.0 6%	All
NHPI, non-Hisp.	-0.0 -7%	-0.0 -8%	-0.0 -10%	-0.0 -15%	-0.1 -32% ***	-0.1 -28% **	-0.1 -25% **	-0.2 -39% ***	-0.1 -30% ***	-0.2 -38% ***	-0.1 -30% ***	-0.2 -37% ***	-0.3 -48% ***	-0.1 -17%	-0.4 -60% ***	-0.0 -4%	-0.1 -16%	All
2+ races, non-Hisp.	0.9 99% ***	0.7 73% ***	0.7 77% ***	0.4 40% ***	0.5 43% ***	0.2 12% **	0.6 54% ***	0.5 34% ***	0.7 52% ***	0.6 45% ***	0.5 35% ***	0.4 29% ***	0.6 44% ***	0.4 24% ***	0.2 9%	0.1 4%	0.3 16% ***	All
Hispanic	-4.4 -26% ***	-18.6 -60% ***	-18.4 -59% ***	-17.3 -57% ***	-17.3 -56% ***	-11.3 -44% ***	-9.2 -37% ***	-7.8 -33% ***	-11.5 -42% ***	-10.3 -39% ***	-10.7 -40% ***	-10.2 -38% ***	-10.0 -38% ***	-9.7 -37% ***	-11.5 -41% ***	-12.4 -42% ***	-13.0 -43% ***	All
Citizenship																		
US-born citizen	9.2 11% ***	21.4 31% ***	22.2 33% ***	20.4 29% ***	19.2 27% ***	12.3 16% ***	11.1 14% ***	9.8 13% ***	13.7 18% ***	12.3 16% ***	12.7 17% ***	12.6 17% ***	12.1 16% ***	11.8 16% ***	11.9 16% ***	10.3 13% ***	11.8 16% ***	All
Foreign-born citizen	-2.0 -33% ***	-0.5 -10% ***	-0.7 -13% ***	-1.0 -17% ***	-1.0 -16% ***	-0.7 -12% ***	-0.4 -6% *	-0.0 0%	-0.2 -4%	-0.4 -6% **	-0.3 -5%	-0.7 -10% ***	-0.2 -4%	-0.6 -8% ***	-0.8 -11% ***	0.3 4%	0.7 11% ***	All
Not a citizen	-7.2 -59% ***	-20.9 -81% ***	-21.5 -81% ***	-19.4 -80% ***	-18.2 -79% ***	-11.6 -67% ***	-10.8 -65% ***	-9.8 -62% ***	-13.5 -71% ***	-11.9 -69% ***	-12.4 -70% ***	-12.0 -68% ***	-11.9 -68% ***	-11.3 -67% ***	-11.1 -67% ***	-10.6 -68% ***	-12.5 -71% ***	All
Marital status																		
Married	2.1 4% ***	6.4 13% ***	5.9 12% ***	5.7 11% ***	6.3 13% ***	7.7 16% ***	7.8 17% ***	7.1 15% ***	5.7 12% ***	7.0 15% ***	5.6 12% ***	5.2 11% ***	5.6 12% ***	6.3 13% ***	6.0 12% ***	6.7 14% ***	6.2 13% ***	Age 18+
Divorced/separated/widowed	0.5 3% *	1.5 9% ***	2.4 15% ***	2.3 13% ***	2.2 13% ***	1.3 7% ***	2.2 13% ***	1.7 10% ***	2.3 14% ***	1.8 10% ***	2.3 14% ***	2.8 18% ***	2.7 17% ***	2.8 17% ***	3.7 25% ***	3.0 19% ***	4.0 28% ***	Age 18+
Never married	-2.6 -10% ***	-7.9 -25% ***	-8.4 -26% ***	-8.0 -24% ***	-8.5 -25% ***	-9.0 -26% ***	-10.0 -28% ***	-8.8 -25% ***	-8.0 -23% ***	-8.7 -24% ***	-7.9 -22% ***	-8.1 -23% ***	-8.3 -23% ***	-9.0 -25% ***	-9.6 -26% ***	-9.6 -25% ***	-10.2 -26% ***	Age 18+

Table A3: Balance tests among CPS ASEC respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Region																		
Northeast	-1.0	2.7	2.3	1.8	1.3	1.0	0.1	1.1	2.2	1.4	1.6	0.9	0.8	-0.0	1.5	1.4	1.2	All
	-5%	17%	14%	11%	8%	6%	0%	6%	14%	9%	10%	6%	5%	0%	10%	9%	7%	
	***	***	***	***	***	***		***	***	***	***	***	***		***	***	***	
Midwest	2.4	7.6	7.0	6.3	7.6	6.2	4.8	4.0	4.6	6.0	6.2	6.2	5.9	6.9	7.3	6.2	7.0	All
	12%	49%	44%	39%	50%	38%	27%	22%	26%	37%	39%	40%	37%	46%	50%	40%	47%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
South	2.0	-0.1	0.1	1.1	0.8	-0.6	1.5	1.4	0.2	0.5	0.9	0.2	1.2	0.8	0.5	0.2	-1.0	All
	6%	0%	0%	3%	2%	-2%	4%	4%	1%	1%	3%	1%	3%	2%	1%	1%	-2%	
	***			***	**		***	***			**		***	**			**	
West	-3.4	-10.2	-9.4	-9.3	-9.6	-6.6	-6.3	-6.5	-6.9	-7.9	-8.7	-7.4	-7.9	-7.6	-9.3	-7.8	-7.2	All
	-13%	-32%	-30%	-29%	-30%	-22%	-22%	-22%	-23%	-26%	-28%	-25%	-26%	-25%	-29%	-26%	-24%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Tenure																		
Owned	2.9	23.0	20.1	19.2	20.2	18.2	14.2	12.9	14.9	14.5	13.1	13.9	15.5	15.9	15.3	16.2	16.4	All
	4%	45%	38%	36%	39%	35%	26%	23%	28%	27%	24%	26%	30%	30%	28%	30%	30%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Rented	-3.0	-22.8	-20.0	-19.2	-20.2	-18.1	-14.1	-12.8	-15.1	-14.6	-13.3	-13.9	-15.2	-15.8	-15.1	-15.8	-16.4	All
	-10%	-48%	-44%	-43%	-43%	-39%	-32%	-30%	-33%	-32%	-30%	-31%	-33%	-35%	-34%	-36%	-37%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
No cash rent	0.1	-0.2	-0.0	0.0	0.0	-0.0	-0.1	-0.1	0.2	0.0	0.2	0.0	-0.3	-0.1	-0.1	-0.4	0.0	All
	9%	-12%	-2%	3%	2%	-2%	-9%	-10%	23%	4%	22%	1%	-20%	-6%	-12%	-27%	5%	
	*	*							***		***		***			***		
Migration in past year																		
Moved, within US	0.5	-7.9	-6.3	-5.4	-5.8	-7.1	-4.4	-4.9	-5.1	-3.8	-3.2	-3.4	-3.8	-3.9	-2.2	-4.3	-6.5	Age 1+
	4%	-39%	-34%	-33%	-34%	-38%	-29%	-31%	-32%	-26%	-23%	-25%	-27%	-30%	-19%	-37%	-48%	
	**	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Moved, outside US	-0.8	-1.8	-1.1	-1.1	-0.8	-1.0	-0.7	-1.1	-0.9	-0.8	-1.0	-0.8	-0.9	-0.8	-0.8	-0.3	-1.4	Age 1+
	-66%	-89%	-80%	-81%	-76%	-83%	-70%	-81%	-79%	-75%	-72%	-73%	-77%	-76%	-78%	-69%	-87%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Did not move	0.3	9.7	7.4	6.5	6.6	8.0	5.0	6.0	6.0	4.6	4.2	4.1	4.7	4.6	3.0	4.6	7.9	Age 1+
	0%	12%	9%	8%	8%	10%	6%	7%	7%	5%	5%	5%	5%	5%	3%	5%	9%	
		***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Education																		
Less than HS	-1.7	-11.6	-12.4	-11.4	-12.4	-8.7	-6.0	-5.8	-8.4	-7.9	-7.9	-8.1	-7.8	-7.7	-8.0	-8.1	-7.4	Age 25+
	-11%	-47%	-49%	-49%	-51%	-42%	-34%	-33%	-44%	-42%	-43%	-45%	-45%	-45%	-47%	-51%	-49%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
High school	-2.0	-1.3	-1.6	-2.7	-0.7	-2.8	-2.4	-1.8	-1.3	-2.2	-2.2	-1.8	-2.8	-3.1	-3.2	-3.2	-2.7	Age 25+
	-6%	-4%	-5%	-8%	-2%	-8%	-7%	-6%	-4%	-7%	-7%	-6%	-9%	-10%	-10%	-10%	-9%	
	***	***	***	***		***	***	***	***	***	***	***	***	***	***	***	***	
Some college	3.2	7.5	7.2	7.5	6.7	5.9	4.8	4.3	4.5	5.1	5.4	5.1	6.0	5.9	5.6	6.3	4.6	Age 25+
	13%	39%	38%	39%	33%	28%	22%	19%	20%	23%	25%	23%	28%	28%	27%	32%	22%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Bachelor's degree	0.1	2.5	4.1	3.7	3.3	2.8	1.4	1.5	2.3	2.2	2.0	2.9	2.5	2.2	2.6	2.2	2.2	Age 25+
	0%	16%	27%	23%	20%	17%	7%	8%	13%	12%	11%	16%	13%	11%	13%	10%	10%	
		***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Graduate degree	0.5	3.0	2.6	2.8	3.2	2.8	2.2	1.8	2.9	2.7	2.6	2.0	2.0	2.7	3.0	2.7	3.3	Age 25+
	6%	42%	34%	36%	41%	34%	24%	19%	32%	29%	27%	18%	18%	25%	27%	22%	29%	
	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	
Labor force status																		

Table A3: Balance tests among CPS ASEC respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Employed	2.0 3% ***	4.0 7% ***	3.5 6% ***	4.4 8% ***	4.2 8% ***	4.5 8% ***	3.6 7% ***	4.3 8% ***	4.2 8% ***	4.5 8% ***	4.7 9% ***	4.9 9% ***	6.5 12% ***	5.2 9% ***	3.9 7% ***	4.4 8% ***	2.2 4% ***	Age 15+
Unemployed	1.0 34% ***	-0.1 -3%	0.1 3%	-0.1 -3%	-0.4 -7% **	-0.2 -3%	0.3 5%	-0.2 -4%	0.3 6%	0.0 1%	0.1 2%	0.5 18% ***	0.3 12% **	0.3 11% *	0.1 4%	-0.1 -3%	-0.2 -7%	Age 15+
Not in labor force	-3.1 -8% ***	-3.9 -10% ***	-3.6 -9% ***	-4.3 -11% ***	-3.8 -10% ***	-4.3 -11% ***	-3.9 -10% ***	-4.0 -10% ***	-4.5 -11% ***	-4.5 -11% ***	-4.8 -11% ***	-5.4 -13% ***	-6.8 -15% ***	-5.5 -13% ***	-4.0 -10% ***	-4.3 -10% ***	-2.0 -5% ***	Age 15+
Class of worker																		
Private	-1.2 -2% ***	-6.3 -8% ***	-6.7 -8% ***	-4.3 -5% ***	-4.9 -6% ***	-2.7 -4% ***	-2.5 -3% ***	-1.8 -2% ***	-1.8 -2% ***	-3.3 -4% ***	-2.3 -3% ***	-3.2 -4% ***	-2.6 -3% ***	-2.3 -3% ***	-2.5 -3% ***	-2.6 -3% ***	-3.6 -5% ***	Age 15+
Government	1.6 12% ***	6.0 69% ***	6.2 73% ***	5.5 58% ***	5.3 56% ***	3.7 33% ***	3.3 29% ***	3.3 30% ***	3.6 33% ***	3.5 34% ***	3.4 32% ***	4.2 42% ***	3.8 37% ***	3.3 31% ***	3.1 29% ***	3.9 39% ***	3.7 36% ***	Age 15+
Self-employed	-0.4 -3%	0.4 3%	0.5 5%	-1.2 -10% ***	-0.4 -3%	-0.9 -8% **	-0.8 -8% **	-1.5 -14% ***	-1.7 -15% ***	-0.2 -3%	-1.0 -10% ***	-0.9 -8% **	-1.1 -10% ***	-0.9 -9% **	-0.5 -5%	-1.3 -12% ***	0.0 0%	Age 15+
Unpaid	-0.0 -18%	-0.0 -30%	-0.1 -42%	-0.1 -49% *	-0.1 -56% **	-0.1 -48%	0.0 48%	0.0 3%	-0.0 -26%	-0.0 -12%	-0.0 -40%	-0.0 -33%	-0.0 -31%	-0.1 -68% **	-0.1 -59% *	-0.0 -33%	-0.1 -55%	Age 15+
Public assistance																		
Yes	1.0 64% ***	-0.8 -28% ***	-0.4 -17% ***	-0.8 -30% ***	-0.8 -29% ***	-1.0 -32% ***	-0.6 -22% ***	-0.3 -13% ***	-0.5 -19% ***	-0.8 -28% ***	-0.3 -14% ***	-0.6 -26% ***	-0.7 -28% ***	-0.7 -33% ***	-0.5 -25% ***	-0.6 -29% ***	-0.8 -37% ***	All
No	-1.0 -1% ***	0.8 1% ***	0.4 0% ***	0.8 1% ***	0.8 1% ***	1.0 1% ***	0.6 1% ***	0.3 0% ***	0.5 0% ***	0.8 1% ***	0.3 0% ***	0.6 1% ***	0.7 1% ***	0.7 1% ***	0.5 0% ***	0.6 1% ***	0.8 1% ***	All

Notes: This table shows differences in social and demographic characteristics between respondents who were and were not assigned a PIK. Each cell contains an absolute difference and relative difference, where respondents who were not assigned a PIK serve as the reference group. All estimates are produced using CPS ASEC person weights. Significance at the 10%, 5%, and 1% levels is indicated by *, **, ***, respectively. 2020 is omitted due to high survey non-response. *Acronyms:* Hisp. = Hispanic; AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander; HS = high school. *Data source:* CPS ASEC.

Table A4: Wage balance tests among ACS and CPS ASEC respondents

	Survey Year									
	2005	2006	2007	2008	2009	2010	2011	2012	2013	Universe
CPS ASEC	-246 0%	9,760 21% **	10,470 22% **	8,942 19% **	9,298 19% **	8,987 19% **	7,760 16% **	6,472 13% **	7,414 15% **	Age 15+, wage>0
ACS	14,520 34% **	14,280 34% **	14,000 33% **	13,710 32% **	15,280 37% **	9,600 21% **	10,230 23% **	11,990 28% **	12,290 29% **	Age 15+, wage>0

	Survey Year								
	2014	2015	2016	2017	2018	2019	2021	2022	Universe
CPS ASEC	6,237 12% **	7,524 15% **	6,044 11% **	4,655 8% **	4,760 8% **	6,860 12% **	7,581 14% **	12,280 24% **	Age 15+, wage>0
ACS	12,180 28% **	12,880 29% **	13,350 30% **	13,480 29% **	14,380 31% **	14,890 32% **	15,400 32% **	16,880 37% **	Age 15+, wage>0

Notes: This table shows differences in average wage earnings between respondents who were and were not assigned a PIK. Each cell contains an absolute difference and relative difference, where respondents who were not assigned a PIK serve as the reference group. All estimates are produced using survey-specific person weights. Significance at the 10%, 5%, and 1% levels is indicated by *, **, ***, respectively. 2020 is omitted due to high survey non-response. *Data sources:* ACS, CPS ASEC.

Table A5: PIK rates among ACS respondents

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Overall																		
Full sample	90.79	89.79	89.25	89.24	87.98	92.42	91.72	90.31	90.57	90.68	90.69	89.85	89.59	90.66	91.08	92.39	92.72	All
Gender																		
Female	91.11	90.22	89.76	89.67	88.33	92.76	92.09	90.62	90.94	91.01	91.02	90.09	89.80	90.96	91.35	92.76	93.07	All
Male	90.45	89.34	88.72	88.79	87.61	92.07	91.34	89.99	90.20	90.33	90.35	89.61	89.37	90.35	90.81	92.01	92.36	All
Race and ethnicity																		
White, non-Hisp.	94.22	93.46	92.98	92.93	91.99	94.23	93.65	92.97	93.26	93.46	93.59	93.08	92.99	93.99	94.44	95.18	95.53	All
2+ races, non-Hisp.	92.16	91.69	91.37	91.17	89.35	93.42	93.07	90.51	91.20	91.65	91.82	90.66	90.64	92.07	92.68	93.20	93.34	All
Black, non-Hisp.	89.33	87.88	87.28	87.28	85.79	91.18	90.33	89.32	89.31	89.36	89.00	87.80	86.92	88.54	88.95	91.21	91.44	All
Hispanic	77.36	76.16	75.52	76.09	74.29	86.94	86.28	82.32	82.90	82.94	83.11	81.80	81.43	82.39	82.66	85.35	85.88	All
Asian, non-Hisp.	87.78	86.36	86.25	86.40	84.64	90.42	88.94	87.63	87.62	87.58	87.25	86.08	86.41	87.67	88.62	91.24	91.30	All
AIAN, non-Hisp.	87.18	85.54	86.45	84.48	83.85	90.66	90.07	85.94	85.48	84.25	83.86	81.09	80.78	82.55	85.25	84.22	85.67	All
NHPI, non-Hisp.	87.12	85.21	83.96	84.43	81.71	88.28	86.83	78.97	78.41	80.80	80.51	79.34	78.75	77.91	79.94	81.45	82.78	All
Other race, non-Hisp.	80.25	77.66	77.12	79.47	77.20	86.06	82.11	79.31	81.03	81.13	80.98	79.45	79.64	82.25	78.72	82.27	83.31	All
Race and ethnicity, among US-born citizens																		
White, non-Hisp.	94.52	93.76	93.29	93.24	92.32	94.41	93.85	93.21	93.52	93.74	93.87	93.36	93.28	94.26	94.69	95.31	95.70	US-born cit.
2+ races, non-Hisp.	92.27	91.89	91.60	91.35	89.35	93.70	93.49	90.97	91.83	92.18	92.35	91.21	91.16	92.56	93.17	93.93	94.25	US-born cit.
Black, non-Hisp.	89.81	88.42	87.81	87.73	86.31	91.48	90.71	89.66	89.68	89.78	89.36	88.12	87.29	88.84	89.28	91.42	91.63	US-born cit.
Hispanic	88.82	88.28	87.16	86.73	84.25	91.64	90.81	89.13	89.43	89.06	88.88	87.10	86.28	87.19	87.41	90.05	90.79	US-born cit.
Asian, non-Hisp.	91.02	90.39	89.81	89.73	88.00	92.30	91.46	90.66	90.67	90.85	90.65	89.45	89.19	90.48	90.97	92.91	92.63	US-born cit.
AIAN, non-Hisp.	87.13	85.67	86.55	84.65	83.86	90.76	90.10	86.08	85.64	84.34	83.97	81.18	80.87	82.67	85.38	84.43	85.90	US-born cit.
NHPI, non-Hisp.	87.35	85.94	83.38	84.24	80.83	88.91	86.76	78.02	77.80	80.23	79.40	78.63	77.71	78.02	78.95	80.84	82.68	US-born cit.
Other race, non-Hisp.	86.58	86.08	83.26	85.39	81.98	88.18	84.54	82.68	83.64	84.66	83.86	82.54	83.90	85.09	83.02	84.39	85.44	US-born cit.
Citizenship																		
US-born citizen	93.22	92.38	91.82	91.68	90.47	93.62	92.99	92.07	92.33	92.44	92.44	91.60	91.30	92.34	92.75	93.82	94.22	All
Foreign-born citizen	90.45	89.39	88.93	89.32	89.02	92.71	92.10	90.52	90.62	90.63	90.79	89.84	89.34	90.03	90.66	92.36	92.73	All
Not a citizen	61.87	59.42	59.05	59.57	56.63	77.99	76.15	68.78	69.03	69.37	69.50	68.57	69.03	70.35	70.46	73.59	73.26	All
Marital status																		
Married	92.47	91.66	91.20	91.17	90.64	93.88	93.54	92.00	92.39	92.44	92.53	92.03	91.92	92.80	93.26	94.05	94.45	Age 18+
Separated	87.64	85.77	85.47	86.51	85.03	90.98	90.02	88.07	87.77	88.44	88.41	87.67	86.64	87.71	88.36	89.52	89.74	Age 18+
Divorced	92.67	91.62	91.15	91.13	90.80	93.32	92.72	91.61	91.76	92.13	92.38	91.61	91.37	92.27	92.94	93.88	94.15	Age 18+
Widowed	93.06	91.67	91.16	91.47	91.48	93.28	93.08	92.07	92.34	92.46	92.59	92.24	91.88	92.66	93.41	94.15	94.50	Age 18+
Never married	88.06	86.59	86.06	85.98	84.87	89.81	88.48	86.85	87.20	87.57	87.53	86.94	86.64	87.63	88.29	89.94	90.00	Age 18+
Limited English																		
Yes	61.21	58.78	58.33	59.71	58.22	76.80	76.12	70.11	70.22	70.48	70.87	69.52	69.43	70.45	70.94	74.39	74.15	Age 5+
No	92.45	91.48	90.94	90.83	90.06	93.23	92.61	91.28	91.55	91.69	91.70	90.97	90.69	91.68	92.13	93.27	93.62	Age 5+
Limited English, among US-born citizens																		
Yes	83.48	83.25	81.85	82.01	80.60	88.64	87.57	86.33	85.04	83.82	84.33	81.82	80.62	81.34	81.52	86.43	85.63	Age 5+
No	93.61	92.72	92.18	92.03	91.38	93.77	93.23	92.21	92.49	92.63	92.64	91.90	91.62	92.61	93.05	94.03	94.41	Age 5+
Urbanicity																		
Urban	90.44	89.35	88.73	88.78	87.42	92.11	91.27	89.92	90.19	90.27	90.27	89.49	89.19	90.12	90.49	92.04	92.35	All
Rural	92.02	91.30	90.98	90.75	89.80	93.38	93.10	91.98	92.20	92.43	92.47	91.42	91.27	92.93	93.55	93.82	94.17	All

Table A5: PIK rates among ACS respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Region																		
Midwest	93.47	92.84	92.45	92.59	91.47	94.42	93.69	92.75	93.19	93.28	93.40	92.87	92.65	93.37	93.60	94.56	94.80	All
Northeast	91.46	90.55	90.07	89.78	88.71	92.10	91.44	90.36	90.65	90.75	90.91	90.26	90.06	91.23	91.67	92.85	92.93	All
South	90.67	89.61	89.02	88.95	87.65	92.33	91.74	90.20	90.45	90.59	90.46	89.45	89.21	90.57	90.98	92.07	92.37	All
West	87.87	86.55	85.94	86.10	84.68	90.96	90.09	88.22	88.32	88.41	88.47	87.53	87.15	88.01	88.65	90.67	91.31	All
Cognitive disability																		
Yes	92.83	91.44	91.12	90.96	90.93	93.60	93.40	92.11	92.52	92.71	92.79	92.06	91.55	92.56	93.16	93.69	93.92	Age 5+
No	90.64	89.62	89.05	89.09	88.21	92.29	91.61	90.04	90.29	90.41	90.43	89.67	89.48	90.50	90.94	92.30	92.61	Age 5+
Wages and salary																		
Quintile 1	91.05	90.28	90.00	89.71	88.41	92.80	91.73	89.89	90.53	90.84	90.88	90.47	90.41	91.04	91.37	92.18	92.09	Age 15+, wage>0
Quintile 2	87.58	86.15	85.40	85.68	84.47	90.62	89.95	87.69	87.97	88.44	88.35	87.73	87.78	88.69	89.12	90.81	91.06	Age 15+, wage>0
Quintile 3	91.54	89.95	89.36	89.52	88.76	92.78	91.94	90.48	90.62	90.74	90.82	90.14	89.82	90.67	91.04	92.72	93.00	Age 15+, wage>0
Quintile 4	93.89	92.91	92.39	92.33	92.00	94.13	93.60	92.73	92.93	93.09	93.19	92.82	92.63	93.30	93.62	94.81	95.12	Age 15+, wage>0
Quintile 5	95.28	94.59	94.14	94.01	93.94	94.92	94.53	93.97	94.36	94.54	94.66	94.28	94.33	94.95	95.33	96.00	96.39	Age 15+, wage>0
Cash welfare																		
Yes	87.69	87.31	86.91	87.23	84.79	91.91	90.72	88.93	88.76	89.22	89.21	87.58	86.59	88.27	89.76	92.06	91.18	Household
No	90.90	90.05	89.52	89.51	88.24	92.55	91.91	90.51	90.78	90.87	90.88	90.06	89.80	90.88	91.30	92.74	93.10	Household
Health insurance																		
Private	-	-	-	91.80	90.85	93.74	93.05	92.07	92.34	92.32	92.25	91.55	91.43	92.37	92.66	93.91	94.20	All
Public	-	-	-	87.67	85.69	92.07	91.35	90.11	90.14	90.09	89.84	88.27	87.52	88.86	89.73	91.46	91.94	All
Private and public	-	-	-	94.15	94.17	95.24	95.09	94.15	94.62	94.75	94.82	94.34	94.27	95.10	95.35	95.81	95.87	All
None	-	-	-	77.22	75.72	86.33	85.26	81.63	81.85	80.61	79.14	77.78	77.88	79.43	80.11	81.11	80.72	All
Class of worker																		
Private	91.20	90.04	89.51	89.60	88.70	92.68	91.96	90.45	90.82	91.13	91.18	90.67	90.56	91.32	91.68	92.86	93.09	Age 16+, empl.
Government	94.68	93.90	93.51	93.23	92.94	94.79	94.22	93.23	93.59	93.61	93.73	93.34	93.23	94.05	94.38	94.99	95.25	Age 16+, empl.
Self-employed	91.61	90.73	90.16	89.80	89.18	92.51	91.93	90.29	90.45	90.75	90.85	90.24	90.01	90.91	91.55	92.61	92.95	Age 16+, empl.
Unpaid	88.47	89.55	87.78	87.38	86.24	90.51	91.35	90.16	90.06	90.35	90.28	90.22	90.02	91.18	91.17	90.68	89.90	Age 16+, empl.
Education																		
Less than HS	85.04	83.28	82.16	81.35	80.45	88.52	87.94	84.09	84.00	83.98	83.83	82.83	82.22	83.14	83.86	84.69	85.09	Age 25+
High school	91.45	89.91	89.31	89.62	89.01	92.32	91.87	90.18	90.43	90.33	90.39	89.56	88.95	90.07	90.75	91.83	92.11	Age 25+
Some college	94.09	93.34	92.88	92.48	91.82	94.08	93.55	92.39	92.68	92.89	93.00	92.49	92.30	93.09	93.60	94.46	94.77	Age 25+
Bachelor's degree	93.80	93.03	92.72	92.73	92.44	94.21	93.45	92.84	93.06	93.30	93.37	93.07	92.96	93.79	94.18	95.14	95.48	Age 25+
Graduate degree	94.79	94.13	94.15	94.04	93.84	95.46	94.72	94.04	94.36	94.53	94.61	94.33	94.39	95.00	95.36	95.91	96.24	Age 25+
Employment status																		
Employed	91.68	90.65	90.08	90.10	89.43	92.91	92.25	90.87	91.15	91.40	91.46	90.93	90.82	91.58	91.96	93.26	93.53	Age 16+
Unemployed	89.90	89.18	89.16	88.42	86.75	92.21	91.46	88.77	89.24	89.57	89.52	89.00	88.48	89.63	90.42	91.97	91.54	Age 16+
Not in labor force	90.89	89.39	89.00	88.93	88.44	92.01	91.32	89.72	90.05	90.09	90.13	89.42	89.06	90.18	90.98	91.73	92.00	Age 16+
Housing type																		
Household unit	90.79	89.96	89.45	89.44	88.12	92.52	91.87	90.45	90.70	90.81	90.82	89.98	89.71	90.80	91.26	92.71	93.04	All
Group quarters	-	83.48	81.97	81.92	82.95	88.61	86.06	84.89	85.62	85.59	85.38	85.07	84.92	84.85	84.04	79.16	79.93	All
Tenure																		
Owned, mortgage	93.71	93.02	92.50	92.54	91.74	94.23	94.05	92.95	93.47	93.58	93.71	93.25	93.04	93.93	94.21	94.86	95.19	Household
Owned, no mortgage	93.30	92.75	92.56	92.29	91.90	94.07	93.92	92.60	92.90	93.02	93.04	92.49	92.25	93.11	93.75	94.33	94.64	Household

Table A5: PIK rates among ACS respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Rented, cash	84.06	82.75	82.15	82.50	80.12	89.03	87.54	85.79	85.78	85.97	85.87	84.33	83.71	85.16	85.60	88.43	88.73	Household
Rented, no cash	88.75	87.97	87.26	86.90	85.30	91.25	90.11	88.36	87.71	87.94	87.62	85.91	85.34	87.16	88.10	89.09	89.98	Household
Migration in past year																		
Moved, within US	87.13	85.83	85.14	85.82	81.53	90.67	87.94	87.43	87.86	88.39	88.47	87.21	87.04	88.49	88.98	90.18	90.47	Age 1+
Moved, outside US	56.30	57.86	59.89	62.33	50.27	71.92	62.41	65.13	63.30	62.46	62.07	60.97	62.98	64.23	60.00	63.69	61.91	Age 1+
Did not move	91.75	90.83	90.24	90.07	89.86	92.87	92.66	90.97	91.23	91.28	91.29	90.55	90.24	91.22	91.65	92.90	93.29	Age 1+
Interview mode																		
Mail	96.84	96.87	96.96	97.05	96.22	98.02	97.61	96.52	95.79	95.96	95.97	95.44	95.45	95.88	96.18	95.99	95.74	All
Internet	-	-	-	-	-	-	-	-	96.33	96.31	96.22	95.77	95.78	96.08	96.31	95.91	95.95	All
CAPI	83.64	81.85	81.26	80.87	78.54	86.87	85.74	83.73	83.49	83.35	83.12	81.19	80.16	81.66	82.37	83.45	83.55	All
CATI	83.97	83.46	81.89	80.58	80.02	83.77	85.53	83.04	87.12	89.11	88.83	88.75	89.56	92.68	92.46	92.74	92.05	All
GQ personal visit	-	83.48	81.97	81.92	82.95	88.61	86.06	84.89	85.62	85.59	85.38	85.07	84.92	84.85	84.04	79.16	79.93	All
Relationship to reference person																		
Reference person	93.08	92.55	92.04	91.99	91.68	94.10	93.62	92.60	92.92	93.07	93.19	92.80	92.55	93.29	93.81	94.79	95.17	Household
Sibling	75.90	74.66	75.37	75.91	75.50	85.49	84.36	81.48	82.07	82.14	82.84	81.00	80.60	82.56	83.52	85.36	85.08	Household
Parent	86.36	85.46	85.13	85.02	84.08	90.14	89.56	86.25	85.90	86.00	86.23	84.78	84.29	85.53	86.07	88.04	87.79	Household
Spouse	92.67	92.23	91.75	91.67	91.00	94.19	93.91	92.24	92.64	92.66	92.71	92.20	92.10	93.04	93.45	94.07	94.53	Household
In-law	75.46	74.74	75.11	81.15	78.28	87.52	85.85	83.31	83.69	84.13	83.81	81.72	81.78	84.08	84.44	85.88	85.79	Household
Unmarried partner	88.05	87.45	86.81	86.92	84.74	91.35	89.91	87.64	87.85	87.98	88.26	87.85	87.95	88.66	89.59	91.28	91.25	Household
Child	90.84	90.22	89.51	89.45	87.37	92.88	92.40	90.84	91.13	91.05	90.96	89.74	89.36	90.62	90.90	92.59	93.01	Household
Foster child	76.28	72.77	75.84	77.04	69.66	81.69	80.33	79.62	80.12	80.46	81.89	78.76	80.39	82.15	82.39	86.24	85.03	Household
Grandchild	85.50	86.72	86.50	86.32	81.58	91.47	90.14	88.98	89.76	89.61	89.36	86.99	86.39	88.54	88.31	89.66	89.48	Household
Boarder, roommate	68.86	66.66	66.35	67.44	63.19	74.43	69.62	68.85	68.63	70.24	70.39	69.59	68.97	70.44	72.10	75.10	74.45	Household
Other nonrelative	71.44	70.66	70.81	70.73	66.25	77.86	75.75	75.19	74.42	76.10	75.85	73.06	71.97	73.61	73.36	76.27	75.03	Household
Other relative	71.62	70.49	70.30	69.17	65.78	79.51	78.21	75.81	76.14	77.41	75.86	73.69	72.90	75.51	75.95	78.26	76.88	Household
Person number																		
1	93.14	92.56	92.05	92.03	91.72	94.13	93.66	92.58	92.94	93.10	93.21	92.87	92.62	93.36	93.89	94.88	95.28	Household
2	90.93	90.09	89.56	89.45	88.52	92.74	91.99	90.34	90.52	90.62	90.66	89.87	89.64	90.77	91.27	92.63	93.00	Household
3	89.64	88.73	88.09	87.99	86.07	91.75	91.05	89.15	89.31	89.37	89.28	88.06	87.73	89.03	89.40	91.12	91.34	Household
4	89.04	88.05	87.52	87.25	84.68	91.17	90.34	88.69	88.90	88.95	88.73	87.30	87.07	88.40	88.66	90.69	90.76	Household
5	86.57	85.39	85.25	84.92	81.25	89.62	88.79	87.07	87.09	87.11	87.01	85.16	84.68	86.22	86.51	88.83	88.84	Household
6+	70.93	70.87	70.74	74.90	68.01	81.96	80.40	80.74	81.58	81.76	81.86	79.02	78.48	81.00	81.05	83.61	83.62	Household

Notes: This table shows the percentage of respondents from each survey who were assigned a PIK by subgroup and survey year. All estimates are produced using ACS person weights. 2020 is omitted due to high survey non-response. *Acronyms:* Hisp. = Hispanic; AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander; HS = high school; CAPI = Computer-Assisted Personal Interview; CATI = Computer-Assisted Telephone Interview. *Data source:* ACS.

Table A6: PIK rates among CPS ASEC respondents

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Overall																		
Full sample	65.62	87.72	87.98	87.10	87.10	87.65	89.41	88.88	87.72	86.83	86.69	86.26	85.38	84.90	85.10	84.09	83.38	All
Gender																		
Male	65.76	87.21	87.52	86.58	86.60	87.27	88.91	88.44	87.40	86.59	86.48	86.16	85.22	84.72	84.87	83.99	83.23	All
Female	65.49	88.21	88.43	87.60	87.59	88.02	89.90	89.30	88.03	87.06	86.89	86.37	85.54	85.08	85.32	84.19	83.53	All
Race and ethnicity																		
White, non-Hisp.	66.77	91.64	91.93	90.96	90.88	90.62	91.55	90.96	90.41	89.53	89.48	89.21	88.70	88.34	88.84	88.02	87.39	All
Black, non-Hisp.	67.26	85.67	85.43	84.82	85.25	84.93	87.34	86.69	86.00	84.58	85.58	85.10	83.44	82.42	83.60	82.23	81.91	All
Asian, non-Hisp.	60.23	78.15	78.44	78.82	79.24	79.34	82.58	82.33	81.72	81.11	79.25	77.16	75.38	75.43	75.09	76.14	76.23	All
AIAN, non-Hisp.	74.74	82.56	87.34	87.26	86.47	86.64	91.19	90.16	88.12	89.02	87.52	89.37	84.74	82.59	87.13	86.02	84.20	All
NHPI, non-Hisp.	63.97	86.83	86.85	85.22	82.18	83.66	86.37	82.98	83.38	80.30	81.96	79.70	75.08	82.41	69.51	83.51	80.89	All
2+ races, non-Hisp.	79.12	92.50	92.83	90.41	90.63	88.81	92.88	91.46	91.55	90.53	89.78	89.02	89.34	87.46	86.17	84.57	85.39	All
Hispanic	58.68	74.09	75.10	74.46	74.79	80.04	84.09	84.33	80.50	80.02	79.67	79.46	78.44	78.11	77.22	75.27	73.97	All
Citizenship																		
US-born citizen	67.99	90.34	90.67	89.72	89.56	89.18	90.62	89.99	89.41	88.45	88.38	88.00	87.14	86.67	86.86	85.69	85.29	All
Foreign-born citizen	55.95	86.58	86.42	84.91	84.97	86.15	88.77	88.85	87.31	86.13	86.13	85.00	84.90	83.83	83.60	84.67	84.82	All
Not a citizen	43.70	57.35	58.33	57.69	58.13	69.95	74.86	75.29	67.10	67.05	66.48	66.57	65.10	65.09	65.66	63.18	59.57	All
Marital status																		
Married	60.50	89.62	89.59	88.81	89.00	90.12	91.27	90.61	89.25	88.98	88.78	88.43	87.94	87.76	87.92	87.97	87.47	Age 18+
Divorced/separated/widowed	60.22	89.29	89.84	88.96	89.04	89.38	90.99	90.17	89.40	88.60	88.94	89.01	88.39	88.12	88.98	88.41	88.71	Age 18+
Never married	57.14	85.24	85.14	84.37	84.30	85.35	86.64	86.30	85.12	84.18	84.58	84.22	83.37	82.66	82.76	82.73	82.02	Age 18+
Region																		
Northeast	64.39	89.31	89.32	88.23	87.91	88.23	89.44	89.48	89.03	87.74	87.75	86.90	85.96	84.87	86.25	85.22	84.33	All
Midwest	68.06	91.41	91.35	90.34	91.00	90.76	91.50	90.71	90.02	90.05	90.03	89.76	88.91	89.12	89.56	88.07	88.08	All
South	66.84	87.69	88.00	87.45	87.35	87.47	89.80	89.25	87.78	86.99	86.98	86.34	85.77	85.18	85.25	84.17	83.03	All
West	62.35	82.99	83.71	82.64	82.49	84.62	86.86	86.16	84.56	82.99	82.43	82.57	81.25	80.82	80.16	79.75	79.17	All
Tenure																		
Owned	66.53	91.21	90.98	90.16	90.38	90.52	91.40	90.78	90.13	89.33	89.00	88.77	88.33	87.97	88.00	87.27	86.71	All
Rented	63.11	78.91	80.41	79.50	79.37	81.16	85.12	84.92	82.69	81.70	82.09	81.35	79.64	78.63	79.15	77.21	75.95	All
No cash rent	67.63	86.32	87.78	87.47	87.38	87.43	88.53	87.80	89.75	87.27	88.83	86.40	82.39	84.09	83.42	79.45	83.99	All
Migration in past year																		
Moved, within US	66.14	81.61	82.81	81.89	81.77	81.60	85.84	84.78	82.90	83.02	83.42	82.63	81.01	79.95	82.26	77.33	73.33	Age 1+
Moved, outside US	38.78	44.54	59.30	55.92	61.60	55.45	71.56	60.72	60.46	61.91	64.38	63.31	57.15	57.50	56.32	62.37	40.49	Age 1+
Did not move	65.34	89.10	88.92	87.94	87.96	88.79	90.02	89.60	88.49	87.45	87.27	86.87	86.07	85.64	85.58	84.99	85.12	Age 1+
Education																		
Less than HS	56.74	81.00	80.57	79.23	78.45	82.51	86.09	85.36	81.23	80.67	80.72	79.55	78.61	78.14	78.01	76.76	77.08	Age 25+
High school	58.06	88.49	88.53	87.20	87.92	88.20	89.64	89.13	88.02	87.07	87.15	86.95	85.94	85.50	85.83	85.75	85.69	Age 25+
Some college	62.58	91.77	91.82	91.14	90.83	91.27	91.92	91.19	90.20	89.90	90.13	89.70	89.58	89.34	89.54	89.85	88.90	Age 25+
Bachelor's degree	59.67	90.27	91.18	90.14	89.96	90.50	90.93	90.41	89.62	89.04	89.00	89.12	88.36	87.93	88.37	88.10	87.84	Age 25+
Graduate degree	60.91	91.91	91.58	90.99	91.30	91.62	92.07	91.17	91.02	90.34	90.23	89.34	88.81	89.13	89.56	89.15	89.42	Age 25+
Labor force status																		
Employed	60.52	89.09	89.09	88.41	88.47	89.40	90.47	89.98	88.84	88.32	88.39	88.09	87.79	87.18	87.11	87.07	86.13	Age 15+

Table A6: PIK rates among CPS ASEC respondents *(continued)*

	Survey Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021	2022	Universe
Unemployed	66.52	88.07	88.85	87.34	86.88	88.33	90.34	88.83	88.68	87.58	87.75	88.88	87.77	87.38	86.83	85.83	84.78	Age 15+
Not in labor force	57.66	87.28	87.48	86.29	86.56	87.41	88.92	88.22	86.82	86.15	86.16	85.59	84.42	84.42	85.09	84.86	85.04	Age 15+
Class of worker																		
Private	60.51	88.26	88.23	87.77	87.68	88.93	90.18	89.69	88.58	87.82	88.03	87.69	87.41	86.89	86.75	86.64	85.51	Age 15+
Government	63.58	93.24	93.37	92.32	92.22	91.70	92.43	92.05	91.36	90.95	90.92	91.36	90.76	89.98	89.73	90.30	89.39	Age 15+
Self-employed	60.11	89.40	89.59	87.23	88.00	88.48	89.74	88.46	87.10	88.00	87.25	87.18	86.54	86.20	86.51	85.58	86.09	Age 15+
Unpaid	56.02	85.06	82.62	79.45	77.08	81.10	93.33	90.15	85.42	86.90	81.99	83.30	83.25	68.36	73.68	81.84	73.45	Age 15+
Public assistance																		
Yes	75.78	83.78	85.87	82.47	82.80	82.74	86.83	87.45	85.20	82.67	84.84	82.28	80.71	78.92	81.02	78.94	75.85	All
No	65.39	87.81	88.02	87.19	87.19	87.76	89.47	88.91	87.77	86.92	86.73	86.34	85.47	85.00	85.16	84.17	83.49	All
Annual wages																		
Quintile 1	64.36	89.29	89.24	88.52	88.42	89.21	90.82	90.24	89.22	88.69	88.67	88.75	88.11	87.15	86.30	85.73	84.01	Age 15+, wage>0
Quintile 2	58.98	84.62	84.14	83.49	84.36	86.89	88.01	87.53	86.13	85.56	85.80	85.89	85.50	85.65	84.61	84.60	83.87	Age 15+, wage>0
Quintile 3	60.25	89.12	89.01	88.27	87.96	89.13	90.23	89.97	88.82	87.60	87.93	87.93	87.89	86.65	87.55	87.04	86.01	Age 15+, wage>0
Quintile 4	61.10	91.29	91.52	91.02	91.04	91.14	91.89	91.50	90.24	90.11	90.46	89.42	89.23	89.06	88.83	89.50	88.15	Age 15+, wage>0
Quintile 5	61.33	92.84	92.89	92.24	92.01	92.48	92.64	92.21	91.77	90.74	90.94	90.29	89.87	89.62	89.81	89.71	90.53	Age 15+, wage>0

Notes: This table shows the percentage of respondents from each survey who were assigned a PIK by subgroup and survey year. All estimates are produced using CPS ASEC person weights. 2020 is omitted due to high survey non-response. *Acronyms:* Hisp. = Hispanic; AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander; HS = high school. *Data source:* CPS ASEC.

Table A7: Missing PIK and linkage bias estimates among wage earners

	ACS					**CPS ASEC**				
	Target sample	**PIKed sample**		**Linked sample**		**Target sample**	**PIKed sample**		**Linked sample**	
	Mean	Rate	Bias	Rate	Bias	Mean	Rate	Bias	Rate	Bias
Overall										
2005	54,340 (54)	91.67	1,193 (16)	85.68	2,266 (23)	56,200 (291)	61.25	266 (229)	57.81	1,014 (247)
2006	52,950 (49)	90.52	1,324 (14)	84.46	2,469 (21)	56,150 (271)	89.35	1,165 (92)	84.55	1,610 (123)
2007	54,110 (51)	89.98	1,388 (15)	84.04	2,564 (23)	57,740 (322)	89.25	1,253 (118)	84.46	1,877 (138)
2008	54,170 (52)	89.97	1,369 (16)	83.34	2,743 (24)	56,530 (284)	88.82	1,080 (108)	84.03	1,778 (131)
2009	53,590 (52)	89.18	1,647 (16)	81.79	3,509 (25)	57,750 (279)	88.75	1,196 (96)	82.64	2,258 (132)
2010	53,160 (51)	92.91	686 (14)	84.04	2,813 (23)	57,170 (287)	89.83	947 (89)	82.93	2,322 (130)
2011	53,010 (57)	92.17	807 (16)	83.62	2,867 (25)	55,720 (275)	90.93	777 (69)	84.41	2,174 (107)
2012	52,730 (50)	90.73	1,126 (15)	83.67	2,812 (22)	56,900 (305)	90.51	679 (97)	84.26	1,840 (144)
2013	53,280 (53)	91.04	1,102 (17)	83.70	2,717 (24)	57,300 (306)	89.45	1,040 (97)	83.99	1,980 (140)
2014	53,570 (53)	91.29	1,057 (16)	84.27	2,553 (24)	57,160 (297)	88.79	795 (104)	83.59	1,566 (134)
2015	54,880 (54)	91.35	1,130 (16)	84.49	2,570 (24)	59,180 (302)	89.01	1,043 (91)	83.86	1,785 (123)
2016	56,240 (57)	90.81	1,232 (17)	84.26	2,673 (24)	60,690 (321)	88.68	761 (103)	83.75	1,515 (133)
2017	57,180 (58)	90.72	1,260 (17)	84.28	2,662 (25)	61,780 (333)	88.48	721 (119)	83.56	1,328 (155)
2018	57,990 (59)	91.44	1,241 (17)	85.02	2,619 (25)	62,360 (344)	87.86	906 (130)	83.04	1,786 (153)
2019	59,210 (63)	91.79	1,220 (18)	85.09	2,588 (28)	63,670 (349)	87.71	1,047 (134)	82.86	1,778 (165)
2021	61,330 (69)	93.07	1,100 (17)	85.81	2,660 (27)	63,780 (350)	87.64	1,023 (136)	82.62	2,091 (170)
2022	60,940 (68)	93.31	1,150 (16)	86.39	2,521 (26)	62,990 (362)	86.45	1,744 (123)	82.16	2,343 (164)
Hispanic										
2005	38,410 (108)	75.55	3,056 (57)	68.55	3,964 (74)	40,050 (496)	49.24	1,978 (504)	45.34	2,658 (544)
2006	37,870 (91)	73.68	3,026 (48)	66.84	3,866 (63)	39,710 (362)	71.9	2,977 (220)	66.43	3,526 (252)
2007	38,810 (93)	73.10	3,092 (51)	66.42	3,997 (63)	40,870 (486)	71.91	3,317 (261)	65.88	4,048 (312)
2008	39,140 (97)	73.89	3,095 (52)	66.56	4,223 (66)	40,310 (425)	72.39	3,024 (240)	66.51	3,791 (281)
2009	37,860 (90)	72.83	3,398 (49)	64.81	4,969 (63)	41,420 (446)	73.11	3,450 (256)	66.17	4,465 (316)
2010	37,400 (91)	85.75	1,292 (34)	70.17	3,789 (56)	40,320 (478)	80.67	2,027 (179)	67.9	3,917 (330)
2011	37,110 (102)	85.35	1,303 (36)	70.52	3,694 (60)	39,050 (428)	83.69	1,719 (138)	69.97	3,881 (241)
2012	37,120 (90)	80.86	1,832 (38)	70.97	3,450 (53)	39,480 (425)	83.25	1,233 (171)	70.6	3,050 (289)
2013	37,430 (94)	81.62	1,733 (38)	71.56	3,169 (56)	40,200 (444)	79.59	2,036 (196)	70.84	3,595 (248)
2014	37,930 (89)	82.22	1,612 (36)	72.64	2,965 (50)	40,440 (427)	80.02	1,728 (205)	71.7	2,796 (255)
2015	39,030 (94)	82.66	1,475 (37)	73.17	2,754 (53)	42,060 (460)	80.03	1,823 (195)	71.95	2,847 (249)
2016	40,290 (107)	82.18	1,498 (41)	73.07	2,739 (58)	45,080 (621)	80.15	1,410 (280)	72.55	2,259 (362)
2017	41,480 (100)	82.23	1,387 (42)	73.42	2,528 (59)	46,300 (623)	80.22	657 (362)	72.4	1,156 (432)
2018	42,290 (103)	82.90	1,391 (45)	74.26	2,568 (58)	45,210 (504)	80.31	1,570 (196)	72.45	2,451 (276)
2019	43,730 (110)	83.17	1,501 (44)	74.30	2,671 (59)	46,350 (566)	79.01	1,293 (316)	70.98	1,909 (391)
2021	45,680 (123)	85.59	1,380 (41)	76.13	2,723 (60)	44,950 (485)	78.87	2,090 (223)	71.34	3,294 (288)
2022	45,690 (119)	86.06	1,502 (39)	76.76	2,771 (57)	45,880 (546)	76.76	2,699 (263)	69.51	3,302 (365)
White, non-Hispanic										
2005	59,360 (69)	95.07	365 (16)	89.65	1,331 (27)	60,950 (380)	63.4	-476 (289)	60.14	212 (311)
2006	57,890 (64)	94.27	482 (15)	88.75	1,544 (25)	60,980 (360)	93.33	316 (97)	88.78	638 (141)
2007	59,170 (67)	93.82	491 (16)	88.45	1,553 (26)	62,590 (418)	93.54	255 (130)	89.06	784 (158)
2008	59,150 (68)	93.71	506 (17)	87.67	1,723 (28)	61,320 (379)	92.8	216 (127)	88.36	717 (160)
2009	58,600 (69)	93.04	728 (18)	86.27	2,428 (29)	62,730 (369)	92.67	256 (117)	87.09	1,141 (160)
2010	58,330 (67)	94.79	275 (17)	87.84	1,910 (27)	62,150 (377)	92.6	417 (104)	86.98	1,375 (155)
2011	58,340 (75)	94.09	390 (20)	87.41	1,946 (30)	61,110 (374)	93.13	348 (78)	88.33	1,225 (127)
2012	58,170 (66)	93.46	533 (17)	87.48	1,918 (27)	62,760 (417)	92.84	291 (112)	88.16	936 (176)
2013	58,930 (71)	93.79	531 (20)	87.47	1,883 (30)	63,040 (420)	92.35	416 (112)	87.88	984 (175)
2014	59,400 (71)	94.04	507 (19)	87.99	1,752 (29)	62,730 (406)	91.58	265 (124)	87.3	683 (168)
2015	60,980 (73)	94.15	587 (19)	88.20	1,807 (29)	65,180 (415)	91.95	439 (109)	87.58	880 (157)
2016	62,410 (76)	93.76	650 (20)	88.11	1,880 (30)	66,250 (429)	91.72	297 (116)	87.59	858 (159)
2017	63,510 (78)	93.79	690 (21)	88.20	1,928 (31)	67,460 (451)	91.49	382 (132)	87.39	773 (185)
2018	64,320 (80)	94.54	648 (20)	88.94	1,845 (31)	68,600 (484)	90.94	437 (160)	86.99	1,121 (188)
2019	65,460 (84)	94.95	600 (21)	89.02	1,804 (34)	70,420 (502)	91.27	454 (174)	87.35	928 (213)
2021	67,520 (97)	95.67	576 (21)	89.30	1,914 (36)	70,240 (487)	91.15	368 (177)	86.87	1,078 (226)
2022	66,940 (93)	95.99	596 (19)	89.94	1,737 (34)	69,220 (513)	90.18	966 (148)	86.7	1,265 (210)
Black, non-Hispanic										
2005	42,290 (124)	91.36	79 (39)	84.69	935 (57)	44,260 (470)	62.11	-780 (360)	58.69	-189 (390)
2006	40,880 (110)	89.88	149 (36)	83.00	1,139 (48)	45,130 (623)	88.84	-329 (396)	84.18	314 (419)
2007	41,780 (109)	89.22	214 (37)	82.39	1,216 (50)	46,540 (705)	87.83	480 (170)	83.17	915 (228)
2008	42,010 (112)	89.11	182 (39)	81.14	1,479 (54)	46,150 (657)	87.99	47 (173)	83.1	928 (216)
2009	41,750 (116)	88.35	368 (42)	79.30	2,090 (60)	45,770 (610)	87.35	-60 (182)	80.17	1,033 (314)

Table A7: Missing PIK and linkage bias estimates among wage earners *(continued)*

	ACS					CPS ASEC				
	Target sample	PIKed sample		Linked sample		Target sample	PIKed sample		Linked sample	
	Mean	Rate	Bias	Rate	Bias	Mean	Rate	Bias	Rate	Bias
2010	41,830 (116)	92.21	13 (38)	82.61	1,657 (56)	45,390 (628)	87.95	-368 (279)	81.14	614 (341)
2011	41,420 (128)	91.40	116 (37)	81.82	1,755 (60)	43,270 (546)	89.13	-154 (246)	82.66	857 (293)
2012	40,530 (110)	90.03	245 (37)	81.72	1,731 (51)	45,440 (745)	89.05	-435 (345)	83.21	340 (412)
2013	40,550 (121)	90.14	185 (44)	81.84	1,562 (59)	44,510 (654)	88.1	12 (175)	82.63	408 (366)
2014	40,340 (124)	90.43	168 (43)	82.82	1,330 (56)	45,260 (636)	86.95	-75 (207)	82.05	414 (261)
2015	41,350 (125)	90.12	242 (45)	83.06	1,228 (59)	46,800 (708)	88.03	204 (210)	83.29	885 (253)
2016	42,500 (132)	89.49	343 (45)	82.81	1,305 (59)	48,600 (787)	88.07	357 (204)	83.37	656 (276)
2017	42,940 (133)	88.96	480 (42)	82.49	1,309 (61)	49,040 (810)	87.75	-48 (325)	83.15	418 (402)
2018	43,730 (140)	89.78	378 (47)	83.42	1,241 (61)	49,110 (762)	86.76	154 (400)	82.67	479 (432)
2019	44,500 (148)	90.03	389 (52)	83.52	1,285 (67)	48,980 (611)	86.62	307 (208)	82.02	682 (288)
2021	46,470 (163)	92.67	350 (43)	85.20	1,418 (62)	52,490 (994)	86.24	6 (396)	81.29	726 (484)
2022	46,560 (165)	92.58	403 (44)	85.78	1,153 (67)	50,680 (862)	85.19	502 (317)	81.54	888 (377)
Asian, non-Hispanic										
2005	63,820 (284)	91.12	1,222 (87)	82.59	3,178 (128)	66,830 (1,827)	58.53	-172 (1,437)	53.91	1,114 (1,636)
2006	63,220 (267)	89.61	1,490 (84)	81.22	3,391 (127)	66,020 (1,295)	82.95	1,850 (524)	76.53	2,207 (852)
2007	65,220 (285)	88.96	1,869 (90)	80.74	4,051 (135)	73,170 (2,269)	82.85	653 (1,391)	76.8	1,715 (1,486)
2008	65,810 (277)	89.10	1,674 (93)	80.68	4,095 (134)	67,980 (1,462)	83.38	-83 (1,039)	77.01	1,886 (1,093)
2009	66,430 (276)	87.98	2,138 (96)	79.26	4,953 (139)	70,630 (1,422)	83.4	888 (593)	75.58	3,319 (742)
2010	64,900 (265)	92.00	1,022 (82)	81.76	4,162 (130)	71,890 (1,685)	83.08	1,655 (654)	75.68	4,407 (860)
2011	65,470 (305)	90.74	1,569 (90)	81.16	4,725 (137)	66,020 (1,180)	86.31	476 (469)	78.47	3,084 (571)
2012	65,710 (269)	89.83	1,642 (85)	81.67	4,489 (120)	66,930 (1,359)	85.71	713 (729)	78.22	2,651 (927)
2013	67,460 (273)	90.02	1,489 (90)	81.48	4,373 (130)	70,470 (1,287)	86.35	1,591 (378)	78.76	3,992 (555)
2014	67,890 (280)	90.20	1,419 (103)	81.59	4,384 (137)	71,400 (1,566)	85.5	-182 (845)	78.68	1,981 (930)
2015	69,590 (279)	90.10	1,822 (86)	82.10	4,690 (120)	72,830 (1,389)	84.16	1,047 (610)	78.18	2,598 (716)
2016	72,670 (297)	89.06	2,240 (96)	81.11	5,234 (135)	76,460 (1,500)	81.5	30 (765)	75.1	1,987 (868)
2017	73,550 (287)	89.04	1,952 (96)	81.48	4,632 (134)	78,750 (1,500)	82.32	1,012 (646)	76.56	2,498 (779)
2018	75,610 (303)	90.29	2,051 (85)	82.61	4,861 (135)	81,360 (1,631)	80.97	410 (880)	75.11	2,813 (973)
2019	79,080 (350)	90.89	1,834 (98)	83.22	4,516 (192)	82,880 (1,447)	80.53	1,991 (632)	75.04	3,804 (806)
2021	82,970 (331)	93.10	1,634 (80)	85.05	4,869 (130)	84,810 (1,506)	81.7	230 (740)	76.17	3,182 (837)
2022	83,410 (335)	93.17	1,725 (85)	85.79	4,654 (128)	82,870 (1,536)	81.44	2,394 (729)	77.09	3,993 (817)
NHPI, non-Hispanic										
2005	43,640 (956)	88.78	652 (292)	80.53	896 (464)					
2006	42,720 (836)	87.33	525 (330)	80.19	911 (436)					
2007	42,870 (870)	85.25	160 (411)	76.06	1,238 (517)					
2008	43,190 (872)	85.99	1,252 (320)	76.06	2,122 (507)					
2009	43,280 (880)	84.38	664 (337)	72.72	2,356 (521)					
2010	44,900 (1,105)	90.05	-507 (511)	76.88	954 (636)					
2011	42,650 (1,038)	88.76	-246 (610)	75.77	2,107 (721)					
2012	42,640 (1,068)	81.05	-351 (616)	73.42	1,091 (692)					
2013	43,700 (1,482)	78.40	-693 (1,169)	70.90	677 (1,225)					
2014	43,480 (1,010)	81.43	488 (486)	74.48	1,163 (580)					
2015	42,770 (1,066)	82.07	104 (395)	75.32	-180 (838)					
2016	43,620 (860)	79.72	-184 (432)	73.55	279 (510)					
2017	45,910 (1,000)	80.68	-345 (564)	73.69	921 (635)					
2018	45,710 (1,011)	77.90	887 (497)	72.24	878 (596)					
2019	48,310 (1,178)	81.21	-32 (511)	74.59	-65 (830)					
2021	50,850 (1,417)	81.99	-167 (668)	74.79	951 (797)					
2022	50,450 (1,454)	83.61	832 (482)	76.04	2,019 (672)					
AIAN, non-Hispanic										
2005	39,940 (433)	89.50	158 (135)	80.30	1,464 (205)					
2006	38,100 (412)	88.08	469 (134)	78.82	1,681 (202)					
2007	38,210 (404)	88.42	326 (148)	77.49	1,753 (216)					
2008	38,710 (460)	86.63	178 (145)	75.85	1,613 (236)					
2009	38,640 (423)	87.10	556 (160)	75.11	2,612 (243)					
2010	38,430 (432)	92.35	317 (105)	78.88	1,948 (217)					
2011	38,150 (472)	91.13	-174 (237)	78.31	1,649 (294)					
2012	37,830 (379)	86.59	334 (143)	76.60	2,153 (197)					
2013	37,330 (408)	86.53	-202 (160)	76.43	1,386 (228)					
2014	38,620 (440)	85.56	-36 (184)	75.87	1,498 (270)					
2015	38,640 (422)	85.03	129 (178)	75.76	1,501 (258)					
2016	39,940 (457)	83.24	290 (174)	74.19	1,737 (248)					
2017	40,790 (482)	83.48	316 (201)	74.57	1,902 (256)					

Table A7: Missing PIK and linkage bias estimates among wage earners *(continued)*

	ACS					CPS ASEC				
	Target sample	**PIKed sample**		**Linked sample**		**Target sample**	**PIKed sample**		**Linked sample**	
	Mean	Rate	Bias	Rate	Bias	Mean	Rate	Bias	Rate	Bias
2018	40,580 (451)	83.80	369 (194)	74.91	1,953 (259)					
2019	42,910 (661)	86.35	620 (191)	76.89	2,013 (306)					
2021	43,170 (655)	85.45	422 (218)	76.10	1,658 (316)					
2022	42,620 (516)	86.40	-51 (188)	77.19	1,147 (272)					
Two or more races, non-Hispanic										
2005	44,530 (460)	93.56	-30 (136)	84.96	986 (205)					
2006	42,860 (375)	92.71	129 (102)	84.31	1,304 (167)					
2007	44,880 (422)	92.40	319 (104)	84.05	1,578 (213)					
2008	44,780 (427)	92.12	332 (107)	83.41	2,072 (186)					
2009	43,580 (359)	91.24	554 (100)	81.11	2,930 (176)					
2010	44,970 (383)	94.14	143 (102)	83.38	2,473 (164)					
2011	44,310 (423)	93.36	275 (97)	83.76	2,201 (157)					
2012	43,360 (339)	90.96	348 (106)	82.77	2,348 (143)					
2013	45,020 (384)	91.67	537 (100)	83.63	2,149 (167)					
2014	45,540 (371)	92.14	238 (145)	84.34	1,800 (177)					
2015	46,200 (346)	92.57	349 (99)	85.31	1,763 (147)					
2016	47,840 (386)	91.63	546 (101)	84.76	1,951 (202)					
2017	49,190 (378)	91.84	470 (134)	84.98	2,081 (165)					
2018	50,540 (385)	92.75	765 (89)	85.69	2,228 (150)					
2019	51,890 (404)	93.34	432 (138)	86.19	1,694 (207)					
2021	56,380 (325)	93.71	558 (80)	86.12	1,950 (132)					
2022	56,850 (348)	93.96	735 (70)	86.82	2,189 (131)					
Some other race, non-Hispanic										
2005	44,850 (940)	79.42	1,490 (458)	70.30	2,254 (612)					
2006	45,020 (845)	75.29	2,382 (461)	67.87	3,177 (555)					
2007	45,750 (934)	75.72	1,384 (550)	67.11	2,768 (664)					
2008	49,470 (1,071)	79.04	2,166 (538)	71.18	4,093 (653)					
2009	49,890 (1,039)	78.56	1,858 (482)	70.35	3,795 (642)					
2010	51,450 (1,686)	86.75	1,236 (438)	75.13	3,503 (732)					
2011	47,670 (1,374)	81.58	1,386 (563)	67.62	3,610 (971)					
2012	46,760 (962)	78.60	1,264 (463)	68.97	2,850 (627)					
2013	48,140 (1,172)	79.80	924 (519)	70.57	1,279 (860)					
2014	46,440 (1,077)	81.34	323 (472)	72.19	1,817 (657)					
2015	51,430 (2,261)	81.71	-2,221 (2,078)	71.75	-1,001 (2,118)					
2016	45,820 (884)	79.58	276 (444)	71.29	2,037 (536)					
2017	48,660 (1,171)	80.50	1,392 (487)	72.05	3,122 (629)					
2018	51,000 (1,188)	83.15	-336 (625)	74.59	506 (768)					
2019	52,160 (1,110)	79.23	1,502 (504)	71.17	2,503 (669)					
2021	62,700 (1,063)	83.22	745 (595)	73.44	3,093 (731)					
2022	62,100 (1,062)	84.10	1,136 (371)	75.58	2,546 (551)					

Notes: This table shows the difference in average wage earnings between the target sample of non-zero wage earners aged 15-64 and employed in the government or private sector and a restricted sample of those assigned a PIK (missing PIK bias) or linked to a W-2 record (linkage bias) by survey, year, and racial-ethnic group. To facilitate interpretation of theses bias estimates, the table also provides the average wage earnings in the target sample, proportion of the target sample who were assigned a PIK, and the proportion of the target sample who were linked to a W-2 record. All estimates are produced using survey-specific person weights. Standard errors are in parentheses. CPS estimates are omitted for racial-ethnic groups that were not measured or yielded insufficient sample size for bias adjustments. 2020 is omitted due to high survey non-response. *Acronyms:* AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander. *Data sources:* ACS, CPS ASEC, IRS W-2s.

Table A8: IPW-adjusted bias estimates among wage earners

	ACS				CPS ASEC			
	PIKed sample		Linked sample		PIKed sample		Linked sample	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
Overall								
2005	652 (16)	168 (17)	1,561 (24)	725 (25)	52 (227)	-81 (231)	804 (246)	406 (249)
2006	760 (14)	194 (15)	1,772 (21)	757 (22)	631 (92)	192 (93)	1,069 (122)	390 (122)
2007	817 (15)	174 (17)	1,842 (23)	725 (24)	722 (119)	226 (118)	1,395 (140)	630 (138)
2008	821 (16)	143 (17)	1,995 (24)	807 (25)	572 (108)	155 (109)	1,234 (131)	530 (131)
2009	947 (16)	211 (18)	2,500 (25)	1,174 (26)	736 (97)	254 (97)	1,791 (133)	928 (133)
2010	386 (14)	-32 (15)	2,163 (23)	969 (23)	612 (89)	190 (89)	1,910 (131)	1,030 (131)
2011	425 (16)	23 (17)	2,158 (25)	991 (26)	453 (68)	196 (69)	1,715 (107)	1,009 (110)
2012	644 (15)	104 (16)	2,118 (22)	934 (23)	327 (97)	14 (97)	1,335 (143)	614 (145)
2013	635 (17)	90 (17)	2,083 (24)	845 (25)	586 (96)	206 (96)	1,506 (140)	732 (140)
2014	631 (16)	66 (17)	2,028 (24)	785 (24)	366 (103)	-38 (104)	1,156 (133)	421 (134)
2015	675 (16)	91 (17)	2,043 (24)	791 (25)	634 (90)	309 (92)	1,450 (123)	806 (126)
2016	750 (17)	87 (17)	2,135 (25)	792 (25)	440 (104)	97 (104)	1,265 (135)	541 (135)
2017	775 (17)	102 (18)	2,121 (25)	781 (26)	382 (119)	76 (122)	1,086 (156)	461 (162)
2018	764 (17)	128 (18)	2,095 (25)	805 (26)	526 (129)	127 (130)	1,513 (153)	757 (153)
2019	732 (18)	108 (19)	2,109 (29)	801 (29)	534 (134)	116 (134)	1,325 (165)	594 (164)
2021	710 (17)	149 (18)	2,245 (28)	1,011 (28)	417 (136)	93 (138)	1,569 (170)	826 (172)
2022	724 (16)	173 (17)	2,018 (27)	835 (27)	970 (121)	626 (126)	1,580 (163)	921 (168)
Hispanic								
2005	2,968 (59)	792 (65)	3,921 (75)	1,269 (80)	2,235 (522)	819 (538)	2,955 (564)	1,251 (595)
2006	3,154 (50)	818 (58)	4,086 (65)	1,235 (70)	3,004 (227)	757 (229)	3,712 (261)	1,120 (256)
2007	3,297 (54)	753 (57)	4,265 (66)	1,185 (67)	3,678 (291)	1,272 (259)	4,593 (350)	1,723 (301)
2008	3,306 (54)	762 (57)	4,477 (68)	1,335 (68)	3,340 (262)	1,072 (239)	4,194 (312)	1,439 (267)
2009	3,556 (52)	860 (56)	5,159 (65)	1,806 (67)	3,901 (268)	1,362 (268)	5,067 (330)	2,074 (328)
2010	1,209 (34)	54 (34)	3,933 (57)	1,177 (56)	2,144 (178)	645 (173)	4,418 (333)	1,721 (320)
2011	1,253 (36)	84 (37)	3,938 (61)	1,195 (59)	1,650 (137)	602 (142)	4,180 (250)	1,717 (296)
2012	1,958 (39)	279 (38)	3,812 (55)	1,143 (53)	1,305 (175)	290 (176)	3,559 (296)	1,441 (323)
2013	1,980 (39)	358 (43)	3,713 (59)	1,002 (57)	2,310 (210)	583 (191)	4,334 (277)	1,480 (235)
2014	1,937 (37)	308 (37)	3,705 (52)	1,042 (52)	1,953 (209)	475 (210)	3,424 (266)	1,168 (274)
2015	1,855 (38)	283 (44)	3,588 (55)	988 (54)	2,170 (201)	796 (233)	3,667 (261)	1,525 (309)
2016	1,883 (41)	205 (40)	3,593 (61)	895 (57)	2,004 (290)	522 (306)	3,427 (382)	989 (416)
2017	1,772 (43)	192 (44)	3,406 (61)	834 (63)	1,164 (369)	38 (416)	2,283 (447)	511 (542)
2018	1,825 (46)	221 (46)	3,481 (60)	923 (58)	2,063 (201)	827 (209)	3,481 (290)	1,570 (304)
2019	1,914 (45)	287 (46)	3,586 (63)	1,000 (63)	1,673 (317)	119 (310)	2,836 (396)	521 (388)
2021	1,765 (42)	299 (42)	3,544 (63)	1,130 (61)	2,457 (233)	830 (238)	4,199 (311)	1,760 (335)
2022	1,802 (39)	342 (41)	3,473 (60)	1,025 (60)	2,869 (269)	1,270 (309)	3,983 (376)	1,589 (414)
White, non-Hispanic								
2005	254 (16)	80 (17)	1,098 (27)	638 (27)	-260 (291)	-282 (295)	465 (314)	268 (318)
2006	323 (15)	118 (16)	1,274 (25)	705 (25)	224 (97)	86 (98)	533 (141)	219 (142)
2007	334 (16)	101 (17)	1,274 (26)	665 (27)	152 (130)	35 (130)	736 (158)	426 (158)
2008	339 (17)	72 (18)	1,398 (28)	718 (29)	70 (127)	-55 (127)	587 (160)	261 (160)
2009	412 (18)	117 (19)	1,868 (29)	1,054 (30)	137 (117)	-13 (117)	1,082 (161)	626 (161)
2010	216 (17)	8 (18)	1,698 (27)	961 (28)	256 (104)	95 (104)	1,258 (155)	776 (155)
2011	204 (20)	36 (21)	1,615 (30)	945 (31)	298 (78)	201 (78)	1,217 (128)	857 (129)
2012	334 (17)	100 (18)	1,586 (27)	872 (28)	208 (112)	59 (112)	844 (177)	498 (179)
2013	311 (20)	75 (20)	1,553 (30)	811 (30)	235 (112)	167 (112)	822 (176)	536 (176)
2014	314 (19)	58 (19)	1,478 (29)	726 (30)	71 (124)	-73 (124)	574 (168)	254 (168)
2015	352 (19)	87 (19)	1,502 (30)	736 (30)	244 (108)	170 (109)	784 (158)	556 (160)
2016	391 (19)	75 (20)	1,557 (30)	740 (31)	48 (116)	-30 (117)	651 (159)	378 (160)
2017	447 (21)	109 (21)	1,617 (31)	775 (31)	121 (131)	60 (134)	602 (185)	363 (188)
2018	413 (20)	119 (21)	1,541 (31)	760 (32)	176 (159)	80 (160)	998 (188)	668 (188)
2019	348 (21)	76 (22)	1,558 (34)	754 (35)	139 (174)	57 (175)	687 (213)	500 (215)
2021	356 (21)	105 (21)	1,683 (36)	929 (36)	-76 (176)	-88 (177)	741 (226)	486 (226)
2022	341 (19)	126 (19)	1,413 (34)	750 (35)	403 (147)	326 (149)	745 (209)	499 (213)
Black, non-Hispanic								
2005	74 (39)	8 (40)	921 (57)	537 (58)	-580 (362)	-496 (378)	56 (395)	-234 (404)
2006	136 (36)	-25 (37)	1,181 (49)	505 (49)	-317 (397)	-302 (398)	360 (420)	91 (419)
2007	220 (37)	7 (37)	1,276 (51)	522 (51)	346 (171)	196 (178)	905 (230)	495 (233)
2008	184 (39)	-12 (40)	1,483 (55)	711 (55)	79 (175)	64 (185)	898 (215)	634 (228)
2009	258 (42)	5 (42)	1,827 (60)	911 (60)	-67 (182)	-104 (182)	1,083 (318)	656 (317)
2010	-12 (38)	-109 (38)	1,503 (56)	764 (56)	-245 (279)	-274 (281)	842 (342)	507 (345)

Table A8: IPW-adjusted bias estimates among wage earners *(continued)*

	ACS				CPS ASEC			
	PIKed sample		Linked sample		PIKed sample		Linked sample	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
2011	48 (37)	-31 (38)	1,627 (60)	824 (60)	-272 (246)	-296 (246)	721 (292)	429 (291)
2012	138 (37)	58 (38)	1,616 (51)	860 (51)	-544 (344)	-548 (344)	284 (412)	-36 (413)
2013	99 (44)	-60 (45)	1,566 (60)	716 (61)	-59 (174)	-116 (177)	471 (366)	162 (368)
2014	63 (43)	-93 (44)	1,337 (57)	555 (57)	-183 (205)	-296 (208)	388 (259)	42 (265)
2015	112 (45)	-60 (46)	1,270 (60)	533 (60)	50 (211)	72 (219)	905 (257)	713 (268)
2016	175 (45)	-59 (46)	1,301 (60)	523 (61)	290 (202)	409 (208)	760 (277)	679 (278)
2017	327 (42)	40 (43)	1,313 (61)	501 (61)	-119 (326)	-16 (328)	516 (407)	372 (407)
2018	230 (46)	-8 (47)	1,218 (62)	503 (62)	-59 (399)	-193 (401)	442 (432)	122 (436)
2019	241 (52)	-4 (53)	1,289 (67)	547 (68)	0 (207)	-33 (207)	575 (290)	354 (288)
2021	262 (43)	34 (43)	1,462 (63)	759 (63)	-391 (393)	-449 (393)	544 (481)	140 (479)
2022	266 (44)	5 (45)	1,094 (67)	410 (67)	103 (317)	174 (322)	539 (377)	505 (382)
Asian, non-Hispanic								
2005	1,139 (87)	304 (91)	2,954 (128)	1,272 (133)	39 (1,424)	439 (1,481)	1,500 (1,644)	726 (1,623)
2006	1,333 (84)	247 (87)	3,116 (127)	1,107 (130)	1,970 (527)	429 (523)	2,498 (857)	110 (854)
2007	1,637 (89)	294 (94)	3,631 (134)	1,205 (140)	586 (1,388)	-1,027 (1,379)	2,080 (1,489)	-327 (1,456)
2008	1,511 (93)	234 (97)	3,630 (133)	1,266 (137)	44 (1,040)	-745 (1,040)	2,099 (1,095)	311 (1,089)
2009	1,716 (96)	322 (108)	4,155 (138)	1,553 (151)	857 (594)	89 (588)	3,277 (743)	1,371 (729)
2010	865 (82)	41 (86)	3,690 (130)	1,449 (134)	1,870 (658)	420 (644)	4,853 (877)	2,228 (840)
2011	1,207 (90)	179 (97)	3,973 (136)	1,529 (143)	625 (472)	-152 (471)	3,545 (586)	1,819 (574)
2012	1,243 (85)	199 (89)	3,742 (120)	1,419 (124)	514 (729)	144 (732)	2,520 (928)	1,158 (924)
2013	1,119 (90)	124 (93)	3,575 (130)	1,264 (133)	1,507 (378)	844 (390)	3,843 (555)	2,175 (553)
2014	1,136 (103)	107 (107)	3,697 (137)	1,366 (140)	-207 (848)	-484 (859)	1,986 (937)	688 (953)
2015	1,439 (86)	318 (90)	3,896 (120)	1,480 (125)	967 (608)	744 (608)	2,808 (719)	1,487 (703)
2016	1,737 (95)	337 (101)	4,383 (134)	1,579 (141)	-249 (762)	10 (775)	1,523 (864)	708 (858)
2017	1,577 (95)	187 (101)	3,788 (133)	1,120 (140)	1,223 (646)	777 (663)	2,771 (782)	1,222 (776)
2018	1,558 (85)	358 (92)	4,028 (134)	1,446 (140)	73 (879)	-825 (876)	2,709 (977)	709 (970)
2019	1,417 (97)	235 (106)	3,821 (192)	1,152 (196)	1,541 (633)	1,310 (660)	3,317 (812)	1,763 (806)
2021	1,190 (80)	294 (83)	3,916 (130)	1,568 (133)	-206 (741)	-174 (754)	2,678 (840)	1,267 (833)
2022	1,215 (85)	409 (88)	3,686 (128)	1,549 (132)	1,548 (721)	785 (722)	3,230 (811)	1,330 (806)
NHPI, non-Hispanic								
2005	746 (292)	660 (308)	1,111 (466)	966 (471)				
2006	372 (329)	151 (333)	791 (437)	522 (444)				
2007	59 (412)	190 (438)	1,099 (517)	1,072 (550)				
2008	584 (320)	556 (344)	1,294 (516)	1,213 (538)				
2009	492 (333)	346 (352)	1,875 (519)	1,706 (546)				
2010	-754 (510)	-688 (522)	437 (634)	654 (656)				
2011	-556 (610)	-604 (614)	1,542 (721)	1,150 (724)				
2012	-414 (616)	-569 (621)	986 (693)	525 (691)				
2013	-983 (1,162)	-1,022 (1,170)	424 (1,221)	357 (1,226)				
2014	155 (486)	546 (528)	876 (580)	945 (606)				
2015	-254 (390)	-28 (384)	-619 (836)	-462 (837)				
2016	-42 (434)	-42 (451)	490 (514)	400 (540)				
2017	-341 (564)	-54 (580)	517 (635)	900 (686)				
2018	691 (491)	654 (498)	698 (598)	622 (612)				
2019	-492 (506)	-438 (538)	-543 (827)	-562 (841)				
2021	-418 (677)	-85 (703)	484 (814)	656 (850)				
2022	650 (483)	658 (499)	1,503 (664)	1,333 (678)				
AIAN, non-Hispanic								
2005	193 (135)	-85 (136)	1,277 (205)	724 (206)				
2006	464 (134)	59 (138)	1,695 (203)	887 (202)				
2007	335 (148)	141 (153)	1,668 (217)	917 (218)				
2008	282 (145)	-121 (149)	1,693 (238)	790 (235)				
2009	394 (160)	50 (163)	2,298 (244)	1,429 (244)				
2010	378 (105)	203 (108)	1,952 (218)	1,289 (215)				
2011	-27 (237)	-155 (239)	1,570 (296)	900 (295)				
2012	227 (142)	187 (146)	1,989 (198)	1,312 (198)				
2013	-272 (160)	-216 (164)	1,359 (228)	856 (230)				
2014	-29 (185)	-105 (185)	1,614 (273)	870 (272)				
2015	-36 (177)	-51 (188)	1,445 (260)	789 (264)				
2016	240 (174)	37 (173)	1,800 (253)	825 (243)				
2017	233 (201)	29 (201)	1,873 (257)	1,038 (251)				
2018	240 (194)	106 (204)	1,918 (259)	1,145 (265)				

Table A8: IPW-adjusted bias estimates among wage earners *(continued)*

	ACS				**CPS ASEC**			
	PIKed sample		**Linked sample**		**PIKed sample**		**Linked sample**	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
2019	535 (191)	407 (198)	2,053 (312)	1,081 (309)				
2021	367 (216)	193 (215)	1,645 (318)	916 (314)				
2022	-123 (188)	-118 (193)	1,198 (275)	661 (285)				
Two or more races, non-Hispanic								
2005	21 (136)	-111 (137)	918 (205)	528 (207)				
2006	158 (102)	79 (106)	1,229 (167)	715 (170)				
2007	292 (104)	147 (108)	1,423 (213)	797 (213)				
2008	259 (107)	42 (110)	1,837 (187)	997 (184)				
2009	450 (99)	206 (103)	2,362 (176)	1,440 (176)				
2010	266 (102)	89 (104)	2,426 (165)	1,490 (162)				
2011	211 (97)	96 (102)	1,958 (156)	1,230 (159)				
2012	274 (106)	-19 (107)	2,239 (144)	1,225 (141)				
2013	404 (100)	169 (101)	1,925 (168)	1,034 (165)				
2014	179 (145)	-85 (146)	1,761 (178)	834 (178)				
2015	334 (99)	48 (100)	1,833 (148)	912 (147)				
2016	471 (101)	140 (103)	1,864 (203)	897 (204)				
2017	348 (134)	-21 (135)	1,965 (166)	1,034 (166)				
2018	605 (89)	203 (90)	2,031 (151)	983 (151)				
2019	365 (138)	30 (138)	1,624 (207)	752 (207)				
2021	451 (80)	158 (83)	2,007 (132)	1,101 (135)				
2022	637 (70)	292 (73)	2,053 (132)	1,154 (135)				
Some other race, non-Hispanic								
2005	1,492 (466)	79 (568)	2,442 (625)	1,239 (691)				
2006	2,452 (461)	510 (489)	3,342 (555)	992 (572)				
2007	1,714 (561)	-27 (614)	3,262 (679)	743 (728)				
2008	2,183 (532)	282 (550)	3,832 (643)	1,193 (652)				
2009	2,092 (500)	196 (534)	3,803 (660)	1,125 (687)				
2010	1,329 (457)	646 (464)	3,636 (776)	2,017 (706)				
2011	1,804 (572)	1,078 (600)	4,246 (989)	1,883 (1,006)				
2012	1,590 (466)	890 (478)	3,137 (631)	1,667 (644)				
2013	1,305 (525)	673 (537)	2,030 (879)	484 (885)				
2014	876 (490)	115 (506)	2,663 (685)	1,127 (737)				
2015	-2,467 (2,076)	-3,243 (2,080)	-1,004 (2,119)	-2,141 (2,124)				
2016	780 (451)	276 (486)	2,706 (553)	1,638 (613)				
2017	1,630 (488)	1,469 (945)	3,455 (633)	2,984 (1,211)				
2018	-79 (628)	-659 (644)	1,015 (779)	-160 (804)				
2019	1,578 (506)	999 (567)	2,986 (686)	1,992 (735)				
2021	262 (593)	-280 (597)	2,239 (727)	1,019 (735)				
2022	1,023 (372)	344 (371)	2,446 (550)	1,308 (542)				

Notes: This table shows the IPW-adjusted difference in average wage earnings between the target sample of non-zero wage earners aged 15-64 and employed in the government or private sector and a restricted sample of those assigned a PIK (missing PIK bias) or linked to a W-2 record (linkage bias) by survey, year, and racial-ethnic group. Adjustments are estimated using a limited or full set of covariates. All estimates are produced using survey-specific person weights. Standard errors are in parentheses. CPS estimates are omitted for racial-ethnic groups that were not measured or yielded insufficient sample size for bias adjustments. 2020 is omitted due to high survey non-response. *Acronyms:* AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander. *Data sources:* ACS, CPS ASEC, IRS W-2s.

Table A9: IPT-adjusted bias estimates among wage earners

	ACS				CPS ASEC			
	PIKed sample		Linked sample		PIKed sample		Linked sample	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
Overall								
2005	645 (16)	62 (17)	1,562 (24)	631 (25)	53 (227)	-234 (230)	805 (246)	245 (249)
2006	760 (14)	85 (16)	1,782 (21)	668 (23)	620 (92)	50 (93)	1,064 (122)	231 (123)
2007	818 (16)	64 (17)	1,854 (23)	643 (24)	720 (119)	97 (119)	1,398 (140)	496 (139)
2008	825 (16)	58 (17)	2,014 (24)	743 (25)	577 (108)	24 (109)	1,245 (131)	382 (132)
2009	959 (16)	139 (18)	2,532 (25)	1,114 (26)	744 (97)	115 (98)	1,802 (133)	777 (134)
2010	384 (14)	-47 (15)	2,173 (23)	953 (23)	617 (89)	143 (89)	1,922 (131)	906 (131)
2011	426 (16)	6 (17)	2,177 (25)	977 (26)	450 (68)	161 (69)	1,716 (107)	916 (111)
2012	650 (15)	76 (16)	2,142 (22)	928 (23)	327 (97)	-16 (97)	1,346 (143)	518 (145)
2013	644 (17)	66 (17)	2,111 (24)	848 (25)	592 (96)	150 (96)	1,527 (140)	645 (140)
2014	640 (16)	42 (17)	2,056 (24)	791 (24)	373 (103)	-83 (104)	1,172 (133)	348 (134)
2015	687 (16)	76 (17)	2,075 (24)	807 (25)	645 (90)	269 (92)	1,470 (123)	742 (126)
2016	764 (17)	78 (17)	2,169 (25)	821 (25)	457 (104)	74 (104)	1,296 (136)	504 (136)
2017	787 (17)	91 (18)	2,155 (25)	806 (26)	395 (119)	50 (123)	1,113 (156)	412 (163)
2018	778 (17)	119 (18)	2,130 (25)	832 (26)	539 (130)	102 (130)	1,537 (153)	716 (153)
2019	747 (18)	96 (19)	2,142 (29)	826 (29)	551 (134)	78 (133)	1,357 (165)	526 (164)
2021	722 (17)	139 (18)	2,273 (28)	1,032 (28)	442 (136)	46 (137)	1,607 (170)	758 (172)
2022	737 (16)	160 (17)	2,052 (27)	858 (27)	995 (122)	557 (126)	1,628 (163)	827 (168)
Hispanic								
2005	2,965 (59)	523 (68)	3,922 (75)	897 (84)	2,236 (523)	306 (547)	2,957 (565)	702 (609)
2006	3,156 (50)	567 (61)	4,091 (65)	868 (75)	2,989 (227)	497 (234)	3,693 (261)	776 (263)
2007	3,297 (54)	473 (60)	4,271 (66)	805 (70)	3,680 (292)	1,083 (260)	4,585 (351)	1,529 (304)
2008	3,311 (54)	532 (59)	4,487 (68)	1,003 (71)	3,332 (262)	869 (240)	4,189 (312)	1,167 (270)
2009	3,558 (52)	666 (58)	5,165 (65)	1,489 (70)	3,903 (268)	1,049 (271)	5,061 (330)	1,685 (334)
2010	1,206 (34)	2 (35)	3,933 (57)	1,015 (57)	2,142 (178)	520 (173)	4,414 (333)	1,423 (322)
2011	1,252 (36)	26 (37)	3,946 (61)	1,059 (60)	1,646 (137)	516 (142)	4,169 (249)	1,579 (310)
2012	1,960 (39)	198 (39)	3,822 (55)	1,015 (54)	1,309 (175)	239 (176)	3,577 (296)	1,270 (323)
2013	1,981 (39)	296 (43)	3,719 (59)	938 (58)	2,322 (210)	491 (190)	4,361 (278)	1,353 (234)
2014	1,938 (37)	246 (38)	3,711 (52)	977 (52)	1,960 (209)	403 (210)	3,441 (267)	1,069 (271)
2015	1,858 (38)	236 (47)	3,594 (55)	950 (54)	2,172 (202)	742 (236)	3,671 (261)	1,455 (310)
2016	1,887 (41)	164 (40)	3,600 (61)	875 (57)	2,008 (290)	489 (314)	3,432 (382)	964 (440)
2017	1,776 (43)	143 (45)	3,415 (62)	803 (63)	1,169 (369)	24 (424)	2,286 (447)	514 (561)
2018	1,828 (46)	185 (46)	3,489 (60)	909 (58)	2,068 (201)	805 (214)	3,485 (290)	1,549 (309)
2019	1,917 (45)	242 (46)	3,592 (63)	985 (63)	1,678 (317)	74 (310)	2,848 (397)	480 (392)
2021	1,767 (42)	255 (42)	3,546 (63)	1,109 (61)	2,461 (233)	757 (236)	4,203 (311)	1,673 (333)
2022	1,804 (39)	301 (41)	3,477 (60)	1,024 (60)	2,871 (269)	1,206 (316)	3,991 (377)	1,508 (418)
White, non-Hispanic								
2005	253 (16)	81 (17)	1,099 (27)	662 (27)	-268 (291)	-288 (294)	457 (314)	261 (317)
2006	323 (15)	120 (16)	1,274 (25)	735 (25)	224 (97)	80 (98)	532 (141)	214 (142)
2007	334 (16)	106 (17)	1,274 (26)	702 (27)	152 (130)	29 (130)	736 (158)	417 (158)
2008	339 (17)	78 (18)	1,398 (28)	756 (29)	70 (127)	-66 (127)	587 (160)	247 (160)
2009	412 (18)	132 (19)	1,868 (29)	1,111 (30)	137 (117)	-17 (117)	1,081 (161)	620 (161)
2010	216 (17)	11 (18)	1,697 (27)	997 (27)	256 (104)	88 (104)	1,257 (155)	761 (155)
2011	204 (20)	42 (21)	1,616 (30)	982 (31)	298 (78)	197 (78)	1,217 (128)	848 (129)
2012	334 (17)	107 (18)	1,586 (27)	913 (28)	208 (112)	52 (112)	840 (177)	487 (179)
2013	310 (20)	81 (20)	1,553 (30)	844 (30)	235 (112)	165 (112)	822 (176)	531 (176)
2014	314 (19)	63 (19)	1,478 (29)	757 (30)	71 (124)	-76 (124)	573 (168)	250 (168)
2015	351 (19)	92 (19)	1,503 (30)	769 (30)	244 (108)	170 (109)	783 (158)	556 (160)
2016	391 (19)	81 (20)	1,557 (30)	773 (31)	48 (116)	-34 (117)	649 (159)	369 (160)
2017	446 (21)	118 (21)	1,617 (31)	818 (31)	121 (131)	59 (134)	600 (185)	352 (188)
2018	413 (20)	126 (21)	1,541 (31)	794 (32)	177 (159)	82 (160)	999 (188)	666 (188)
2019	348 (21)	80 (22)	1,558 (34)	788 (35)	140 (174)	52 (175)	688 (213)	488 (215)
2021	356 (21)	109 (21)	1,684 (36)	954 (36)	-76 (176)	-89 (177)	741 (226)	486 (226)
2022	341 (19)	130 (19)	1,414 (34)	776 (35)	402 (147)	337 (149)	744 (209)	509 (212)
Black, non-Hispanic								
2005	74 (39)	6 (40)	920 (57)	547 (58)	-581 (362)	-529 (376)	51 (395)	-261 (403)
2006	136 (36)	-22 (37)	1,181 (49)	514 (49)	-317 (397)	-302 (398)	360 (420)	95 (419)
2007	220 (37)	9 (37)	1,276 (51)	539 (51)	347 (171)	183 (177)	907 (231)	486 (233)
2008	184 (39)	-7 (40)	1,482 (55)	734 (55)	79 (175)	55 (185)	898 (215)	620 (229)
2009	258 (42)	14 (42)	1,828 (60)	939 (60)	-67 (182)	-106 (182)	1,084 (318)	656 (317)

Table A9: IPT-adjusted bias estimates among wage earners *(continued)*

	ACS				**CPS ASEC**			
	PIKed sample		**Linked sample**		**PIKed sample**		**Linked sample**	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
2010	-12 (38)	-108 (38)	1,502 (56)	777 (56)	-246 (279)	-282 (281)	842 (342)	498 (345)
2011	48 (37)	-28 (38)	1,626 (60)	851 (60)	-273 (246)	-295 (246)	720 (292)	430 (291)
2012	138 (37)	63 (38)	1,616 (51)	886 (52)	-543 (344)	-551 (344)	286 (412)	-40 (413)
2013	100 (44)	-54 (45)	1,566 (60)	740 (62)	-58 (174)	-116 (177)	471 (366)	163 (368)
2014	63 (43)	-90 (44)	1,337 (57)	568 (57)	-184 (205)	-294 (208)	389 (259)	42 (265)
2015	112 (45)	-53 (46)	1,272 (60)	550 (60)	50 (211)	82 (219)	904 (257)	724 (268)
2016	175 (45)	-53 (46)	1,303 (60)	544 (61)	286 (202)	406 (208)	752 (277)	682 (278)
2017	327 (42)	48 (43)	1,313 (61)	518 (61)	-119 (326)	-14 (328)	512 (407)	373 (408)
2018	230 (46)	0 (47)	1,218 (62)	523 (62)	-60 (399)	-195 (401)	434 (432)	116 (435)
2019	241 (52)	2 (53)	1,291 (67)	573 (68)	-2 (207)	-28 (207)	574 (290)	370 (288)
2021	262 (43)	37 (43)	1,463 (63)	772 (63)	-390 (393)	-459 (393)	539 (481)	127 (479)
2022	266 (44)	11 (45)	1,097 (67)	434 (68)	98 (317)	143 (323)	535 (377)	477 (382)
Asian, non-Hispanic								
2005	1,138 (87)	304 (91)	2,953 (128)	1,306 (133)	33 (1,424)	484 (1,487)	1,493 (1,643)	749 (1,621)
2006	1,332 (84)	242 (87)	3,117 (127)	1,128 (130)	1,965 (527)	427 (523)	2,492 (857)	116 (853)
2007	1,636 (89)	285 (94)	3,631 (134)	1,240 (140)	585 (1,388)	-1,125 (1,379)	2,073 (1,489)	-405 (1,458)
2008	1,510 (93)	223 (97)	3,633 (133)	1,336 (137)	45 (1,040)	-858 (1,041)	2,089 (1,095)	186 (1,090)
2009	1,714 (96)	326 (107)	4,155 (138)	1,626 (150)	857 (594)	139 (588)	3,272 (744)	1,362 (728)
2010	864 (82)	36 (86)	3,692 (130)	1,506 (134)	1,872 (658)	400 (644)	4,850 (877)	2,188 (839)
2011	1,205 (90)	218 (96)	3,974 (136)	1,661 (142)	627 (472)	-219 (471)	3,538 (586)	1,767 (576)
2012	1,243 (85)	215 (89)	3,746 (120)	1,543 (124)	506 (729)	119 (732)	2,512 (928)	1,094 (924)
2013	1,119 (90)	141 (92)	3,578 (130)	1,391 (132)	1,505 (378)	865 (390)	3,833 (555)	2,187 (554)
2014	1,136 (103)	122 (107)	3,701 (137)	1,492 (140)	-206 (848)	-481 (860)	1,967 (937)	696 (954)
2015	1,439 (86)	337 (90)	3,901 (120)	1,618 (124)	968 (608)	741 (608)	2,805 (719)	1,499 (703)
2016	1,735 (95)	360 (101)	4,386 (134)	1,764 (140)	-251 (762)	-3 (775)	1,514 (865)	740 (858)
2017	1,576 (95)	189 (101)	3,790 (133)	1,260 (139)	1,222 (646)	733 (663)	2,770 (782)	1,224 (777)
2018	1,557 (85)	389 (91)	4,034 (134)	1,590 (140)	69 (879)	-797 (877)	2,701 (977)	730 (971)
2019	1,415 (97)	252 (106)	3,824 (192)	1,292 (196)	1,538 (633)	1,328 (661)	3,319 (813)	1,829 (807)
2021	1,190 (80)	291 (83)	3,926 (130)	1,638 (132)	-207 (741)	-135 (755)	2,675 (840)	1,320 (833)
2022	1,216 (85)	409 (88)	3,695 (128)	1,630 (132)	1,549 (721)	834 (722)	3,235 (812)	1,436 (805)
NHPI, non-Hispanic								
2005	750 (292)	645 (307)	1,108 (466)	980 (472)				
2006	368 (329)	164 (333)	790 (437)	575 (443)				
2007	61 (412)	276 (443)	1,099 (517)	1,138 (556)				
2008	589 (320)	525 (342)	1,311 (515)	1,297 (543)				
2009	493 (333)	402 (354)	1,885 (519)	1,762 (550)				
2010	-754 (510)	-697 (522)	445 (634)	693 (658)				
2011	-554 (610)	-609 (614)	1,554 (721)	1,217 (725)				
2012	-415 (616)	-579 (619)	969 (693)	528 (692)				
2013	-984 (1,162)	-1,025 (1,170)	426 (1,221)	351 (1,224)				
2014	154 (486)	568 (531)	874 (580)	950 (608)				
2015	-257 (390)	-11 (384)	-622 (836)	-477 (837)				
2016	-43 (434)	-21 (453)	486 (514)	450 (547)				
2017	-342 (564)	-58 (579)	514 (635)	934 (678)				
2018	691 (491)	682 (498)	693 (598)	670 (609)				
2019	-498 (506)	-428 (536)	-558 (827)	-554 (839)				
2021	-417 (677)	-96 (695)	455 (817)	582 (848)				
2022	646 (483)	663 (503)	1,464 (665)	1,331 (685)				
AIAN, non-Hispanic								
2005	194 (135)	-82 (136)	1,276 (205)	722 (205)				
2006	464 (134)	67 (138)	1,694 (203)	907 (202)				
2007	335 (148)	143 (153)	1,670 (217)	946 (218)				
2008	282 (145)	-128 (148)	1,694 (238)	784 (235)				
2009	394 (160)	62 (163)	2,302 (244)	1,508 (244)				
2010	377 (105)	199 (108)	1,951 (218)	1,306 (215)				
2011	-26 (237)	-154 (239)	1,571 (296)	931 (295)				
2012	228 (142)	185 (146)	1,987 (198)	1,362 (198)				
2013	-272 (160)	-220 (164)	1,358 (228)	868 (230)				
2014	-29 (185)	-113 (185)	1,614 (273)	893 (272)				
2015	-36 (177)	-67 (187)	1,443 (261)	828 (264)				
2016	240 (174)	32 (173)	1,793 (253)	856 (243)				
2017	232 (201)	21 (201)	1,872 (257)	1,046 (251)				

Table A9: IPT-adjusted bias estimates among wage earners *(continued)*

	ACS				CPS ASEC			
	PIKed sample		Linked sample		PIKed sample		Linked sample	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
2018	241 (194)	110 (203)	1,914 (259)	1,181 (262)				
2019	535 (191)	413 (199)	2,050 (312)	1,140 (309)				
2021	366 (216)	200 (215)	1,640 (318)	956 (316)				
2022	-123 (188)	-110 (193)	1,198 (275)	720 (287)				
Two or more races, non-Hispanic								
2005	21 (136)	-110 (138)	917 (205)	531 (207)				
2006	158 (102)	81 (106)	1,227 (167)	750 (170)				
2007	292 (104)	141 (108)	1,420 (213)	799 (213)				
2008	259 (107)	45 (110)	1,835 (187)	1,028 (185)				
2009	449 (99)	210 (103)	2,360 (176)	1,485 (176)				
2010	266 (102)	90 (104)	2,420 (165)	1,506 (163)				
2011	211 (97)	93 (102)	1,957 (156)	1,250 (159)				
2012	274 (106)	-7 (107)	2,236 (144)	1,262 (141)				
2013	404 (100)	153 (101)	1,922 (168)	1,047 (165)				
2014	180 (145)	-80 (146)	1,761 (178)	864 (177)				
2015	334 (99)	58 (100)	1,831 (148)	955 (147)				
2016	471 (101)	148 (103)	1,861 (203)	942 (204)				
2017	348 (134)	-32 (135)	1,963 (166)	1,052 (166)				
2018	605 (89)	210 (90)	2,030 (151)	1,024 (151)				
2019	364 (138)	39 (138)	1,621 (207)	787 (207)				
2021	451 (80)	144 (84)	2,007 (132)	1,118 (135)				
2022	638 (70)	291 (73)	2,051 (132)	1,208 (134)				
Some other race, non-Hispanic								
2005	1,474 (466)	391 (530)	2,440 (625)	1,098 (694)				
2006	2,423 (461)	201 (504)	3,309 (555)	546 (583)				
2007	1,706 (561)	-216 (622)	3,258 (679)	694 (730)				
2008	2,174 (532)	128 (549)	3,823 (643)	1,053 (647)				
2009	2,082 (500)	78 (533)	3,791 (660)	1,077 (683)				
2010	1,330 (457)	639 (468)	3,644 (777)	1,991 (712)				
2011	1,810 (572)	1,016 (599)	4,263 (989)	1,882 (996)				
2012	1,601 (466)	767 (478)	3,151 (632)	1,447 (643)				
2013	1,304 (525)	637 (538)	2,021 (879)	528 (887)				
2014	884 (490)	97 (507)	2,669 (685)	1,112 (724)				
2015	-2,472 (2,076)	NA	-1,007 (2,119)	-2,345 (2,125)				
2016	778 (451)	282 (489)	2,691 (553)	1,701 (617)				
2017	1,633 (488)	1,403 (949)	3,468 (634)	2,947 (1,187)				
2018	-77 (628)	-758 (643)	1,023 (778)	-138 (794)				
2019	1,575 (506)	841 (564)	2,971 (686)	1,781 (735)				
2021	258 (593)	-304 (599)	2,240 (727)	1,038 (738)				
2022	1,027 (372)	232 (374)	2,449 (550)	1,232 (548)				

Notes: This table shows the IPT-adjusted difference in average wage earnings between the target sample of non-zero wage earners aged 15-64 and employed in the government or private sector and a restricted sample of those assigned a PIK (missing PIK bias) or linked to a W-2 record (linkage bias) by survey, year, and racial-ethnic group. Adjustments are estimated using a limited or full set of covariates. All estimates are produced using survey-specific person weights. Standard errors are in parentheses. CPS estimates are omitted for racial-ethnic groups that were not measured or yielded insufficient sample size for bias adjustments. 2020 is omitted due to high survey non-response. *Acronyms:* AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander. *Data sources:* ACS, CPS ASEC, IRS W-2s.

Table A10: Entropy balancing-adjusted bias estimates among wage earners

	ACS				CPS ASEC			
	PIKed sample		Linked sample		PIKed sample		Linked sample	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
Overall								
2005	638 (16)	-3 (17)	1,560 (24)	570 (25)	56 (227)	-236 (230)	810 (247)	245 (249)
2006	755 (14)	9 (15)	1,786 (21)	601 (22)	623 (92)	52 (95)	1,075 (122)	242 (124)
2007	814 (16)	-7 (17)	1,859 (23)	582 (24)	714 (119)	75 (120)	1,409 (140)	510 (141)
2008	822 (16)	-16 (17)	2,017 (24)	675 (25)	578 (108)	9 (110)	1,254 (131)	397 (133)
2009	942 (16)	40 (18)	2,526 (25)	1,019 (26)	751 (97)	114 (98)	1,819 (133)	807 (134)
2010	388 (14)	-70 (15)	2,183 (23)	907 (23)	624 (89)	134 (89)	1,942 (131)	910 (132)
2011	427 (16)	-17 (17)	2,185 (25)	928 (26)	454 (69)	162 (70)	1,731 (107)	937 (112)
2012	649 (15)	33 (16)	2,148 (22)	876 (23)	327 (97)	-25 (97)	1,357 (144)	511 (146)
2013	646 (17)	24 (17)	2,120 (24)	809 (25)	589 (96)	126 (96)	1,535 (140)	639 (140)
2014	642 (16)	5 (17)	2,066 (24)	761 (24)	373 (103)	-98 (104)	1,181 (133)	354 (135)
2015	688 (16)	35 (17)	2,086 (24)	779 (25)	643 (90)	261 (92)	1,482 (124)	765 (127)
2016	763 (17)	30 (17)	2,180 (25)	788 (25)	455 (104)	71 (104)	1,305 (136)	526 (136)
2017	784 (17)	40 (18)	2,164 (25)	777 (26)	388 (119)	26 (121)	1,120 (156)	397 (160)
2018	777 (17)	67 (18)	2,141 (25)	804 (26)	536 (130)	93 (130)	1,550 (153)	738 (154)
2019	743 (18)	38 (19)	2,154 (29)	804 (29)	542 (134)	70 (134)	1,366 (165)	544 (165)
2021	723 (17)	100 (18)	2,283 (28)	1,022 (28)	432 (136)	15 (137)	1,615 (170)	756 (172)
2022	734 (16)	109 (17)	2,058 (27)	833 (27)	971 (122)	542 (127)	1,622 (163)	842 (169)
Hispanic								
2005	3,007 (59)	27 (63)	3,955 (75)	448 (79)	2,241 (523)	216 (540)	2,961 (565)	584 (598)
2006	3,195 (50)	55 (55)	4,122 (65)	404 (70)	3,068 (228)	234 (228)	3,754 (262)	525 (257)
2007	3,324 (54)	-44 (57)	4,293 (66)	335 (68)	3,725 (291)	842 (260)	4,615 (351)	1,317 (306)
2008	3,335 (54)	53 (56)	4,507 (68)	562 (69)	3,355 (261)	634 (242)	4,206 (311)	931 (272)
2009	3,586 (52)	203 (55)	5,191 (65)	1,078 (68)	3,939 (269)	913 (276)	5,091 (331)	1,590 (339)
2010	1,225 (34)	-196 (34)	3,952 (57)	723 (56)	2,165 (179)	394 (179)	4,428 (334)	1,194 (325)
2011	1,269 (37)	-147 (36)	3,960 (61)	792 (60)	1,662 (138)	394 (144)	4,180 (250)	1,379 (296)
2012	1,970 (39)	-38 (39)	3,828 (55)	760 (54)	1,312 (175)	131 (176)	3,563 (296)	1,097 (319)
2013	1,986 (39)	78 (43)	3,718 (59)	723 (58)	2,321 (209)	340 (194)	4,345 (276)	1,226 (243)
2014	1,941 (37)	73 (38)	3,705 (52)	810 (52)	1,960 (208)	292 (217)	3,425 (265)	966 (285)
2015	1,859 (38)	63 (40)	3,585 (55)	809 (54)	2,175 (202)	636 (228)	3,659 (261)	1,396 (311)
2016	1,886 (42)	2 (40)	3,589 (61)	727 (58)	2,007 (290)	404 (299)	3,421 (383)	893 (400)
2017	1,774 (43)	-25 (44)	3,402 (61)	662 (62)	1,165 (369)	-81 (404)	2,268 (446)	402 (529)
2018	1,827 (46)	24 (46)	3,477 (60)	774 (58)	2,072 (202)	745 (215)	3,479 (290)	1,500 (314)
2019	1,914 (45)	89 (46)	3,577 (63)	863 (63)	1,670 (317)	-32 (311)	2,826 (396)	353 (392)
2021	1,765 (42)	119 (43)	3,533 (63)	1,017 (62)	2,461 (232)	690 (239)	4,193 (310)	1,603 (333)
2022	1,803 (39)	145 (41)	3,465 (59)	910 (60)	2,878 (269)	1,103 (310)	3,989 (376)	1,426 (416)
White, non-Hispanic								
2005	255 (16)	88 (17)	1,100 (27)	663 (27)	-268 (291)	-285 (295)	458 (314)	263 (317)
2006	325 (15)	126 (16)	1,277 (25)	736 (25)	228 (97)	82 (98)	537 (141)	220 (142)
2007	336 (16)	112 (17)	1,278 (26)	706 (27)	152 (130)	24 (130)	738 (158)	423 (159)
2008	341 (17)	83 (18)	1,400 (28)	756 (29)	70 (127)	-66 (127)	587 (160)	257 (161)
2009	412 (18)	124 (19)	1,875 (29)	1,095 (30)	139 (117)	-16 (117)	1,085 (161)	637 (161)
2010	218 (17)	17 (18)	1,699 (27)	1,001 (28)	259 (104)	86 (104)	1,261 (155)	769 (155)
2011	207 (20)	45 (21)	1,620 (30)	984 (31)	301 (78)	200 (78)	1,218 (128)	859 (129)
2012	337 (17)	110 (18)	1,590 (27)	912 (28)	209 (112)	52 (112)	839 (177)	491 (178)
2013	315 (20)	86 (20)	1,558 (30)	852 (30)	238 (112)	166 (112)	825 (176)	532 (176)
2014	318 (19)	68 (19)	1,481 (29)	766 (30)	72 (124)	-77 (124)	575 (168)	256 (169)
2015	356 (19)	91 (19)	1,506 (30)	775 (30)	246 (108)	173 (109)	784 (158)	562 (160)
2016	394 (19)	77 (20)	1,561 (30)	778 (31)	50 (116)	-33 (117)	651 (159)	378 (160)
2017	450 (21)	113 (21)	1,620 (31)	825 (31)	121 (131)	49 (133)	601 (185)	347 (187)
2018	417 (20)	122 (21)	1,544 (31)	800 (32)	178 (159)	79 (160)	1,000 (188)	674 (188)
2019	352 (21)	73 (22)	1,560 (34)	803 (35)	141 (174)	51 (175)	688 (213)	487 (215)
2021	358 (21)	108 (21)	1,684 (36)	968 (36)	-73 (176)	-86 (177)	746 (226)	492 (226)
2022	344 (19)	127 (19)	1,414 (34)	784 (35)	400 (147)	339 (150)	743 (209)	509 (214)
Black, non-Hispanic								
2005	73 (39)	5 (40)	922 (57)	544 (58)	-581 (362)	-524 (376)	50 (395)	-254 (402)
2006	136 (36)	-26 (37)	1,182 (49)	518 (49)	-317 (397)	-300 (398)	362 (420)	97 (420)
2007	220 (37)	7 (37)	1,277 (51)	552 (51)	348 (171)	181 (176)	907 (230)	493 (233)
2008	184 (39)	-7 (40)	1,484 (55)	743 (55)	78 (175)	48 (184)	898 (215)	615 (228)
2009	258 (42)	5 (42)	1,832 (60)	929 (60)	-66 (182)	-106 (182)	1,086 (318)	668 (318)

Table A10: Entropy balancing-adjusted bias estimates among wage earners *(continued)*

	ACS				CPS ASEC			
	PIKed sample		Linked sample		PIKed sample		Linked sample	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
2010	-12 (38)	-112 (38)	1,505 (56)	776 (56)	-245 (279)	-281 (281)	843 (342)	511 (346)
2011	49 (37)	-31 (38)	1,628 (60)	858 (60)	-272 (246)	-292 (246)	722 (292)	428 (291)
2012	139 (37)	60 (38)	1,620 (51)	887 (52)	-542 (344)	-541 (345)	288 (412)	-35 (414)
2013	101 (44)	-56 (45)	1,567 (60)	755 (61)	-58 (174)	-119 (177)	471 (366)	167 (368)
2014	64 (43)	-93 (44)	1,338 (57)	579 (57)	-184 (205)	-287 (209)	390 (260)	56 (266)
2015	113 (45)	-60 (46)	1,273 (60)	565 (60)	49 (211)	81 (219)	904 (257)	723 (267)
2016	176 (45)	-63 (46)	1,304 (60)	553 (61)	286 (202)	406 (208)	751 (277)	681 (279)
2017	328 (42)	39 (43)	1,314 (61)	528 (61)	-116 (326)	-11 (328)	513 (407)	376 (408)
2018	232 (46)	-16 (47)	1,220 (62)	527 (62)	-59 (399)	-203 (401)	435 (432)	114 (435)
2019	241 (52)	-11 (53)	1,292 (67)	582 (68)	-2 (207)	-25 (208)	576 (290)	377 (289)
2021	263 (43)	38 (43)	1,463 (63)	793 (63)	-388 (393)	-460 (393)	541 (481)	128 (478)
2022	268 (44)	6 (45)	1,097 (67)	448 (68)	102 (317)	145 (323)	539 (377)	484 (384)
Asian, non-Hispanic								
2005	1,139 (87)	249 (91)	2,951 (128)	1,233 (133)	29 (1,424)	509 (1,490)	1,489 (1,643)	775 (1,622)
2006	1,335 (84)	178 (87)	3,116 (127)	1,066 (130)	1,966 (527)	435 (526)	2,491 (857)	142 (853)
2007	1,639 (89)	177 (94)	3,628 (134)	1,119 (140)	588 (1,388)	-1,088 (1,382)	2,077 (1,489)	-356 (1,461)
2008	1,515 (93)	159 (97)	3,631 (133)	1,221 (137)	46 (1,040)	-836 (1,043)	2,089 (1,095)	184 (1,092)
2009	1,717 (96)	198 (104)	4,151 (138)	1,488 (148)	854 (594)	132 (589)	3,263 (743)	1,387 (732)
2010	867 (82)	-27 (86)	3,685 (130)	1,391 (134)	1,873 (658)	440 (648)	4,849 (877)	2,270 (846)
2011	1,214 (90)	112 (95)	3,973 (136)	1,488 (140)	626 (472)	-140 (473)	3,528 (586)	1,866 (579)
2012	1,248 (85)	139 (89)	3,739 (120)	1,404 (124)	503 (729)	151 (732)	2,511 (928)	1,156 (926)
2013	1,122 (90)	70 (93)	3,572 (130)	1,251 (132)	1,507 (378)	871 (389)	3,831 (555)	2,200 (554)
2014	1,143 (103)	64 (107)	3,698 (137)	1,386 (140)	-208 (848)	-482 (857)	1,962 (937)	713 (947)
2015	1,443 (86)	262 (90)	3,896 (120)	1,490 (124)	968 (608)	748 (609)	2,804 (719)	1,526 (705)
2016	1,740 (95)	241 (101)	4,380 (134)	1,594 (140)	-248 (762)	0 (775)	1,511 (865)	750 (859)
2017	1,580 (95)	96 (101)	3,785 (133)	1,104 (138)	1,221 (646)	719 (662)	2,774 (782)	1,217 (777)
2018	1,562 (85)	318 (92)	4,029 (134)	1,452 (140)	74 (879)	-791 (878)	2,700 (977)	725 (969)
2019	1,421 (97)	173 (108)	3,822 (192)	1,140 (196)	1,533 (633)	1,363 (658)	3,314 (813)	1,874 (808)
2021	1,193 (80)	227 (83)	3,918 (130)	1,488 (132)	-201 (741)	-116 (754)	2,679 (840)	1,330 (835)
2022	1,224 (85)	348 (88)	3,688 (128)	1,496 (130)	1,544 (721)	790 (722)	3,236 (812)	1,402 (806)
NHPI, non-Hispanic								
2005	752 (292)	659 (307)	1,109 (466)	989 (473)				
2006	366 (329)	156 (333)	791 (437)	550 (442)				
2007	61 (412)	209 (434)	1,100 (517)	1,122 (547)				
2008	586 (320)	519 (339)	1,320 (514)	1,278 (539)				
2009	491 (333)	385 (352)	1,882 (519)	1,771 (548)				
2010	-753 (510)	-658 (521)	442 (634)	698 (658)				
2011	-552 (610)	-610 (614)	1,553 (721)	1,211 (725)				
2012	-416 (616)	-569 (619)	966 (693)	532 (694)				
2013	-986 (1,162)	-992 (1,170)	427 (1,221)	351 (1,225)				
2014	157 (486)	538 (523)	878 (580)	929 (606)				
2015	-259 (390)	-14 (386)	-624 (836)	-474 (838)				
2016	-44 (434)	-32 (450)	487 (514)	425 (541)				
2017	-341 (564)	-53 (579)	512 (635)	926 (676)				
2018	693 (492)	668 (501)	695 (598)	670 (613)				
2019	-498 (506)	-387 (540)	-554 (827)	-499 (842)				
2021	-416 (677)	-61 (696)	455 (819)	645 (873)				
2022	646 (483)	653 (505)	1,459 (665)	1,338 (691)				
AIAN, non-Hispanic								
2005	194 (135)	-52 (137)	1,274 (205)	704 (205)				
2006	464 (134)	68 (137)	1,694 (203)	912 (203)				
2007	335 (148)	148 (153)	1,670 (217)	959 (219)				
2008	284 (145)	-87 (150)	1,693 (238)	813 (238)				
2009	393 (160)	67 (163)	2,304 (244)	1,506 (244)				
2010	377 (105)	214 (108)	1,952 (218)	1,312 (216)				
2011	-26 (237)	-137 (239)	1,572 (296)	942 (295)				
2012	227 (142)	187 (146)	1,988 (198)	1,361 (198)				
2013	-271 (160)	-221 (163)	1,359 (228)	876 (230)				
2014	-29 (185)	-103 (185)	1,614 (273)	908 (272)				
2015	-36 (177)	-76 (184)	1,445 (260)	835 (263)				
2016	240 (174)	43 (172)	1,793 (253)	890 (243)				
2017	232 (201)	30 (202)	1,873 (257)	1,052 (252)				

Table A10: Entropy balancing-adjusted bias estimates among wage earners *(continued)*

	ACS				**CPS ASEC**			
	PIKed sample		**Linked sample**		**PIKed sample**		**Linked sample**	
	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment	Limited adjustment	Full adjustment
2018	240 (194)	92 (199)	1,914 (259)	1,189 (261)				
2019	535 (191)	421 (201)	2,053 (312)	1,184 (316)				
2021	366 (216)	208 (216)	1,640 (318)	956 (315)				
2022	-124 (188)	-101 (194)	1,199 (275)	715 (286)				
Two or more races, non-Hispanic								
2005	20 (136)	-98 (138)	916 (205)	541 (208)				
2006	158 (102)	72 (105)	1,227 (167)	742 (170)				
2007	292 (104)	142 (108)	1,421 (213)	805 (213)				
2008	259 (107)	40 (110)	1,838 (187)	1,026 (185)				
2009	449 (99)	190 (103)	2,364 (176)	1,453 (176)				
2010	265 (102)	106 (104)	2,419 (165)	1,534 (163)				
2011	211 (97)	80 (101)	1,956 (156)	1,235 (160)				
2012	274 (106)	-9 (107)	2,238 (144)	1,263 (141)				
2013	405 (100)	146 (101)	1,924 (168)	1,049 (165)				
2014	181 (145)	-78 (146)	1,761 (178)	872 (177)				
2015	334 (99)	52 (100)	1,829 (148)	958 (147)				
2016	471 (101)	150 (104)	1,861 (203)	937 (204)				
2017	348 (134)	-46 (135)	1,963 (166)	1,060 (166)				
2018	606 (89)	206 (91)	2,032 (151)	1,045 (152)				
2019	365 (138)	34 (138)	1,619 (207)	803 (207)				
2021	452 (80)	153 (84)	2,006 (132)	1,168 (138)				
2022	640 (70)	279 (72)	2,051 (132)	1,199 (133)				
Some other race, non-Hispanic								
2005	1,509 (467)	201 (508)	2,455 (626)	909 (675)				
2006	2,420 (461)	-43 (494)	3,309 (556)	400 (581)				
2007	1,707 (561)	-239 (598)	3,254 (680)	683 (714)				
2008	2,175 (531)	-15 (558)	3,829 (643)	918 (657)				
2009	2,090 (499)	194 (564)	3,805 (660)	1,155 (704)				
2010	1,327 (456)	651 (475)	3,643 (776)	2,005 (720)				
2011	1,809 (572)	1,059 (600)	4,265 (989)	1,890 (996)				
2012	1,592 (466)	696 (476)	3,150 (632)	1,423 (640)				
2013	1,294 (525)	533 (536)	2,000 (878)	504 (888)				
2014	885 (490)	83 (502)	2,665 (684)	1,039 (697)				
2015	-2,479 (2,076)		-1,007 (2,119)	-2,284 (2,124)				
2016	770 (451)	283 (483)	2,686 (552)	1,739 (605)				
2017	1,632 (488)	1,285 (864)	3,470 (634)	3,063 (1,245)				
2018	-79 (628)	-774 (645)	1,018 (778)	-118 (801)				
2019	1,573 (506)	958 (557)	2,966 (686)	1,928 (732)				
2021	258 (593)	-293 (598)	2,235 (727)	1,018 (739)				
2022	1,029 (372)	184 (373)	2,450 (550)	1,186 (546)				

Notes: This table shows the entropy balancing-adjusted difference in average wage earnings between the target sample of non-zero wage earners aged 15-64 and employed in the government or private sector and a restricted sample of those assigned a PIK (missing PIK bias) or linked to a W-2 record (linkage bias) by survey, year, and racial-ethnic group. Adjustments are estimated using a limited or full set of covariates. All estimates are produced using survey-specific person weights. Standard errors are in parentheses. CPS estimates are omitted for racial-ethnic groups that were not measured or yielded insufficient sample size for bias adjustments. 2020 is omitted due to high survey non-response. *Acronyms:* AIAN = American Indian, Alaska Native; NHPI = Native Hawaiian, Pacific Islander. *Data sources:* ACS, CPS ASEC, IRS W-2s.