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IN THIS ISSUE:

- ▶ **Evaluating a New Process for Assigning Geographic Residence Codes and Identifying Demographic Information for Workers in a Given Tax Year**
- ▶ **Work Overpayments Among New Social Security Disability Insurance Beneficiaries**

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Article

1 Evaluating a New Process for Assigning Geographic Residence Codes and Identifying Demographic Information for Workers in a Given Tax Year

by Michael Compson

The Social Security Administration’s Office of Research, Evaluation, and Statistics (ORES) produces annual statistical publications that estimate the employment and earnings of U.S. workers. This article evaluates a new methodology developed by ORES to assign a state and county of residence code and identify the date of birth and sex of nearly all workers, rather than a 1-percent sample of workers, for whom tax records provide earnings data for a given year. The evaluation compares the estimates generated by the current methodology with those of the new methodology using microdata for tax year 2017. The results align with preevaluation expectations and highlight the importance of using a much larger sample of workers, which the new process enables, to generate the annual employment and earnings estimates.

Perspectives

49 Work Overpayments Among New Social Security Disability Insurance Beneficiaries

by Denise Hoffman, Monica Farid, John T. Jones, Serge Lukashanets, and Michael T. Anderson

In this article, the authors track the experiences of working Disability Insurance beneficiaries who received benefit overpayments because of work during their first 10 years after award. They describe the antecedents to overpayments and compare the likelihoods of continued benefit receipt for working beneficiaries who did and did not receive overpayments.

EVALUATING A NEW PROCESS FOR ASSIGNING GEOGRAPHIC RESIDENCE CODES AND IDENTIFYING DEMOGRAPHIC INFORMATION FOR WORKERS IN A GIVEN TAX YEAR

by Michael Compson*

The Social Security Administration’s Office of Research, Evaluation, and Statistics (ORES) produces annual statistical publications that estimate the employment and earnings of U.S. workers. This article evaluates a new methodology developed by ORES to assign a state and county of residence code and identify the date of birth and sex of nearly all workers, rather than a 1-percent sample of workers, for whom tax records provide earnings data for a given year. The evaluation compares the estimates generated by the current methodology with those of the new methodology using microdata for tax year 2017. The results align with preevaluation expectations and highlight the importance of using a much larger sample of workers, which the new process enables, to generate the annual employment and earnings estimates.

Introduction

In 2021, the Office of Research, Evaluation and Statistics (ORES) in the Social Security Administration (SSA) completed development of a new methodology for assigning geographic residence codes and identifying demographic information for nearly all workers with earnings in a given year. Compson (2022) describes the new methodology in detail, and this article evaluates it by comparing it to the methodology SSA currently uses to generate the comprehensive earnings and employment estimates it publishes in its annual statistical publications. ORES has applied the new methodology to tax information for tax years 2014 through 2020,¹ producing a standalone Master Geographic and Demographic (MGD) data file for each year. For that reason, the terms “new methodology” and “MGD process” are used interchangeably throughout this article. ORES considers the development and evaluation of the new methodology to be the first and second steps, respectively, in a multistep process that will result in a dramatic expansion of the sample size used to generate the estimates for its statistical publications.

The evaluation of the MGD methodology consists of two distinct assessments. The first, a procedural assessment, uses internal audit reports to assess the completeness and accuracy of the new methodology in processing tax records for a 7-year span. It involves looking at the number of records processed, the number of unique Social Security numbers (SSNs) represented, the sources of the tax information, the methodology used to assign state and county codes (SCCs), and the results of various imputations used in populating missing data fields. The second assessment compares the MGD-assigned SCCs and demographic identifiers with those assigned under the current

Selected Abbreviations

ASA	Assigned State_SE_Active (merged data file)
CWHS	Continuous Work History Sample
IRS	Internal Revenue Service
MEF	Master Earnings File
MGD	Master Geographic and Demographic
Numident	Numerical Identification System

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Selected Abbreviations—Continued

OASDI	Old-Age, Survivors, and Disability Insurance
OEIS	Office of Enterprise Information Systems
ORES	Office of Research, Evaluation, and Statistics
SCC	state and county code
SSA	Social Security Administration
SSN	Social Security number

methodology. Specifically, this assessment involves comparing the estimated numbers of workers with Social Security taxable earnings and the amounts of those earnings by state, sex, age, and type of earnings (wage and salary, self-employment). This assessment also compares the two methodologies' estimated numbers of workers by county.

In general, the procedural assessment finds that the MGD process is consistent and thorough across the 7 years of tax data analyzed, although it raises minor questions, noted later, that ORES is currently investigating. The comparative assessment finds match rates of nearly 99 percent for workers' state code assignments and sex and age identifications. For county code assignments, the match rate is lower, at 94.5 percent. This result was expected because the MGD process uses more detailed geographic identifiers to assign county codes than were available when the current process was developed.² Thus, in this circumstance, the lower match rate might reflect greater accuracy in the new methodology.

This introduction is followed by five sections. The first section highlights the key points of the MGD process for identifying demographic information and assigning geographic codes for the population of workers in a given tax year. The second section details the procedural assessment of the MGD process for the 7 years of tax data currently available. The third section discusses the methodology for conducting the micro-data comparison, presents the preevaluation expectations of the comparisons, and assesses the results for worker counts by type of earnings, sex, age, and state. The fourth section discusses the comparison of the county-level estimates, and the fifth section concludes.

The MGD Process

The MGD process was developed to address the current methodology's limitations in assigning accurate geographic codes to workers' tax records and

its reliance on sample data too small in size for the required scope of the work. The current methodology uses administrative microdata (that is, person-level information) from SSA's 1-percent Continuous Work History Sample (CWHS). For tax year 2017, the sample consists of fewer than 1.7 million workers. By contrast, the new methodology culminates in the creation of a standalone MGD data file containing geographic and demographic information for nearly all workers in a given tax year (179 million in 2017). The process generates 32 audit reports for each year. The reports allow ORES to track and evaluate the results of each step in the process of assigning a single SCC to each worker in a given tax year.

Each year, SSA and the Internal Revenue Service (IRS) share information from IRS tax forms for those agencies' respective programmatic needs. To that end, SSA's Office of Enterprise Information Systems (OEIS) receives hundreds of millions of IRS Forms W-2 and W-2c (filed by employers) and millions of Form 1040 Schedule SE (filed by the self-employed) from the IRS.³ As part of its elaborate annual wage reporting process, OEIS extracts all the information SSA needs to administer its programs. In a separate and distinct process undertaken for ORES and SSA's Office of the Chief Actuary, OEIS extracts the full address information reported on these forms and uses Pitney-Bowes' Finalist software to assign an SCC for each record.⁴ The resulting data files are the basis of the MGD process for assigning geographic residence codes for nearly all workers in a tax year.

The MGD process begins with job-level data—that is, records that contain both the worker's SSN and the employer identification number—and converts them to worker-level data, assigning a single SCC to each SSN as it does so. For this article, "number of records processed in a given tax year" is synonymous with the number of jobs in a given tax year, and "number of SSNs" refers to the number of workers in a given tax year. The number of records for each of the data sources (that is, the tax forms) is always greater than the number of SSNs because many individuals hold multiple jobs during the year.

Audits track the number of records or SSNs throughout each step of the MGD process. For example, the audit reports provide the number of records processed for each type of data source (Forms W-2, W-2c, and 1040 Schedule SE) and the number of unique SSNs associated with each data source, on an annual basis and over time.

In general, the audit reports contain the following information:

- The number of records processed and the corresponding number of unique SSNs.
- The number of records and SSNs associated with each type of tax form.
- The number of SCCs assigned to each worker via the OEIS/Finalist process (one, multiple, none).
- The numbers of workers with valid and invalid SSNs.
- The number of individuals with sex and date of birth information assigned.
- The number of unique SSNs affected by each of the MGD methodology's various imputation processes.
- The data source for the SCC assignment for each worker.
- The number of records for each tax year that were processed in a given calendar year.

Once the underlying OEIS/Finalist data are extracted, the MGD process sorts workers into one of the following mutually exclusive data-source categories:

- W-2 only.
- W-2c only.
- Schedule SE only.
- W-2 and W-2c.
- W-2 and Schedule SE.
- Schedule SE and W-2c.
- W-2, W-2c, and Schedule SE.

The audit reports detail the number of records and the number of unique SSNs for each of these data-source categories and compute the total number of unique SSNs in a given tax year.

The next step in the MGD process uses an administrative data master file called the Numerical Identification System (Numident) to identify valid and invalid SSNs and to supply information on each worker's sex and date of birth.⁵ Any SSN in both the MGD file and the Numident file is deemed to be valid. SSNs in the MGD file but not in the Numident file are deemed to be invalid. ORES can record sex and date of birth only for workers whose SSNs appear in the Numident file. For records with invalid SSNs, ORES enters "Missing" in the sex and date of birth data fields. The MGD process creates a data file containing demographic information that is set aside while the process of assigning a single SCC to each worker in a given tax year, described below, proceeds.

First, the MGD process groups workers by the number of SCCs (one, multiple, none) that the OEIS/Finalist process assigned to them. The records for workers with a single SCC assigned by the OEIS/Finalist step are referred to as the "gold-standard file" and for them, the process of assigning an SCC is complete. For workers who were not assigned an SCC, ORES uses the frequency distribution of SCCs in gold-standard file records that share the worker's ZIP Code to try to impute an SCC.⁶ ORES employs a multistep process (briefly summarized later and detailed in Compson 2022) to assign the "best" SCC to the records of workers that have multiple SCCs after the OEIS/Finalist step. The audit reports show which method ORES used to assign a single SCC for each worker.

Once a single SCC has been assigned to each worker, the resulting file is rejoined with the file containing demographic information to create the standalone MGD file for that tax year. The merged file contains the following data fields for each worker:

- SSN.
- SCC.
- Date of Birth.
- Sex.
- Date of Death.
- Date on which Date of Death was posted on the Numident.
- Method of SCC Assignment.

Researchers and policy analysts using the MGD file must consider several important points. First, as noted earlier, the process that OEIS uses to assign SCCs for each job is based on the full address reported on the tax forms and is separate and distinct from the annual wage reporting process undertaken as part of program operations. As a result, the data used to create the MGD file have not been subjected to the cleaning and evaluation techniques that the tax data must undergo before they can be posted to SSA's Master Earnings File (MEF) for programmatic purposes. One result of using the raw tax data is that the MGD file contains invalid or improperly assigned SSNs. The latter may occur if the employer incorrectly enters an SSN when filling out the worker's Form W-2 or W-2c, or a self-employed individual enters the wrong SSN when filing Form 1040 Schedule SE. There is currently no way for ORES to correct such errors in its files.

Second, because the MGD file does not contain any information on the type or amount of earnings reported on the tax forms,⁷ it cannot, by itself, be used

to estimate earnings covered or taxable under Social Security and Medicare. ORES is currently developing a new process to generate estimates using a much a larger sample of workers extracted from the MEF or even, possibly, the entire population of workers in a tax year. The MEF and the MGD files together would contain the data necessary to generate the annual earnings estimates.

Third, the MGD file for a given tax year y contains data only for tax records that were processed in calendar year $y + 1$. For example, the first MGD file contains data for tax year 2017, but only for forms that were processed in 2018. In turn, for processing year 2018, 2017 is the primary tax year. The 2017 MGD file excludes any data for tax year 2017 that were processed in a calendar year other than 2018, and it excludes data for tax years other than 2017 that were processed in 2018. In developing the MGD methodology, ORES decided to focus on the data for a single tax year that were processed in the single calendar year that followed. ORES chose this method despite knowing that some tax year 2017 earnings were processed in 2017 or would not be processed until after 2018. Whether it was possible to include these data in the 2017 MGD file, and if so, how, was yet to be determined.⁸

To illustrate, the MGD file for 2017 contains records for 178,863,694 workers whose tax forms were processed in 2018. However, an additional 2,618,600 workers had earnings in tax year 2017, but their forms were processed in other years, as follows: 233,222 in 2017; 1,737,114 in 2019; 404,899 in 2020; and 243,365 in 2021. Thus, the 2017 MGD file omits up to 1.44 percent of the population of workers with reported earnings in 2017.

This circumstance raises several critical questions. First, are any of these individuals already in the 2017 MGD file? (This can occur for multiple job holders or those with earnings reported on both a Form W-2 and an amended Form W-2c, or because of filer error in entering the tax year.) Identifying these instances can reduce the number of individuals whose records need to be incorporated into the MGD file. Second, to add the records for workers whose tax forms were not processed in 2018 into the 2017 MGD file, how many processing years should be included, and how reliable will those data be? Experience shows that some data for a given tax year may not be reported for several years. However, over time, the number of workers being added trends to zero so the potential effect on the MGD file becomes inconsequential.

Another concern is the reliability of the address information reported on the tax forms processed in later

years. For example, if a Form W-2 or W-2c for tax year 2017 is not processed until 2021, the individual may no longer reside in the same location. ORES is evaluating the possibility of incorporating the additional tax information reported in subsequent years to the MGD files. This issue is especially pertinent given that the COVID-19 pandemic led to substantial delays in IRS processing of tax returns from 2020 to April 2023.

The Procedural Evaluation

Table 1 presents the number of records extracted in each processing year from 2015 to 2021 and the number of unique SSNs associated with those records, by type of data source (W-2, W-2c, and 1040 Schedule SE). The number of records is analogous to the number of jobs, and the number of SSNs reflects the number of workers. The number of records far exceeds the number of unique SSNs each year because workers may have multiple jobs, each requiring its own tax form. A worker may have tax forms of more than one type in a year, or multiple forms of the same type in a year, or both. The total number of unique SSNs for each year overstates the actual number of workers because it includes duplicates (that is, the SSNs of workers with more than one type of tax form). Note the relatively large volume of W-2c records processed in 2017, the decrease in the number of Schedule SE records processed in 2020, and the drop in the numbers of W-2s and associated SSNs in 2021. It is not clear if the lower numbers of Schedule SE records processed in 2020 and W-2s processed in 2021 reflect fewer jobs in the economy or the effect of COVID-19 on employers' ability to timely file W-2s or W-2cs for their employees and the IRS' ability to process Schedule SEs.⁹

As mentioned earlier, data for nonprimary tax years are included in a calendar year's processing workload. Table 2 shows the prevalence of primary-year and nonprimary-year data for each type of tax form in 2015–2021. The number of W-2s processed dropped by nearly 12 million from 2020 to 2021, which is likely due to COVID-19's effect on the labor market and employers' W-2 filings.

The number of W-2cs processed nearly doubled in 2017 and increased sharply in 2021. Part of the increase in W-2c processing in 2017 reflects a large payroll service provider's issuance of corrections to approximately 500,000 records (SSA 2017). The increase in 2021 is most likely a rebound after COVID-19 limited W-2c processing in 2020. The steep increase in 2021 processing of 1040 Schedule

Table 1.**ORES data extraction volume: Numbers of tax records processed and unique SSNs contained therein, by type of form, 2015–2021**

Processing year	Primary tax year	Total		Form W-2		Form W-2c		Form 1040 Schedule SE	
		Records	Unique SSNs ^a	Records	Unique SSNs	Records	Unique SSNs	Records	Unique SSNs
2015	2014	259,791,044	181,523,762	237,765,591	160,795,805	3,243,285	2,538,180	18,782,168	18,189,777
2016	2015	269,436,834	186,400,337	245,528,242	163,550,439	3,227,003	2,799,543	20,681,589	20,050,355
2017	2016	278,488,758	191,098,053	251,509,338	166,219,172	6,214,674	4,695,964	20,764,746	20,182,917
2018	2017	279,435,723	191,637,671	254,788,713	168,297,764	3,452,217	2,840,058	21,194,793	20,499,849
2019	2018	284,888,320	194,365,647	259,798,529	170,468,612	3,709,345	3,179,679	21,380,446	20,717,356
2020	2019	286,651,734	195,429,463	262,691,363	172,374,107	3,428,934	3,024,076	20,531,437	20,031,280
2021	2020	276,478,907	194,970,016	250,693,566	170,750,781	4,167,226	3,760,955	21,618,115	20,458,280

SOURCE: Author's calculations based on SSA data processing audit reports.

a. Because some workers have more than one type of tax form in a given year, the total number of unique SSNs includes duplicates.

Table 2.**ORES extraction volume for primary and nonprimary tax year data: Numbers of tax records processed and unique SSNs contained therein, by type of form, 2015–2021**

Processing year	Primary tax year	Records processed						Number of unique SSNs	
		Number			Percent			For primary tax year	For other tax year
		Total	For primary tax year	For other tax year	Total	For primary tax year	For other tax year		
Form W-2									
2015	2014	237,765,591	235,615,820	2,149,771	100.00	99.10	0.90	160,535,225	2,007,148
2016	2015	245,528,242	243,723,231	1,805,011	100.00	99.26	0.74	163,366,783	1,704,720
2017	2016	251,509,338	249,530,278	1,979,060	100.00	99.21	0.79	166,000,893	1,839,742
2018	2017	254,788,713	253,365,171	1,423,542	100.00	99.44	0.56	168,108,594	1,329,548
2019	2018	259,798,529	258,510,183	1,288,346	100.00	99.50	0.50	170,275,487	1,217,177
2020	2019	262,691,363	261,583,557	1,107,806	100.00	99.58	0.42	172,238,245	1,041,896
2021	2020	250,693,566	249,832,215	861,351	100.00	99.66	0.34	170,623,150	812,196
Form W-2c									
2015	2014	3,243,285	2,179,694	1,063,591	100.00	67.21	32.79	1,870,493	814,835
2016	2015	3,227,003	2,000,757	1,226,246	100.00	62.00	38.00	1,886,081	996,142
2017	2016	6,214,674	3,699,613	2,515,061	100.00	59.53	40.47	3,443,782	1,840,675
2018	2017	3,452,217	2,591,048	861,169	100.00	75.05	24.95	2,192,494	709,762
2019	2018	3,709,345	2,785,824	923,521	100.00	75.10	24.90	2,532,575	723,700
2020	2019	3,428,934	2,695,360	733,574	100.00	78.61	21.39	2,517,683	584,314
2021	2020	4,167,226	3,474,898	692,328	100.00	83.39	16.61	3,253,048	557,342
Form 1040 Schedule SE									
2015	2014	18,782,168	17,813,779	968,389	100.00	94.84	5.16	17,812,721	728,932
2016	2015	20,681,589	19,664,474	1,017,115	100.00	95.08	4.92	19,663,466	780,799
2017	2016	20,764,746	19,804,112	960,634	100.00	95.37	4.63	19,803,275	750,329
2018	2017	21,194,793	20,050,718	1,144,075	100.00	94.60	5.40	20,050,006	908,497
2019	2018	21,380,446	20,278,455	1,101,991	100.00	94.85	5.15	20,277,674	859,115
2020	2019	20,531,437	19,601,328	930,109	100.00	95.47	4.53	19,601,024	795,290
2021	2020	21,618,115	19,308,932	2,309,183	100.00	89.32	10.68	19,308,531	2,031,568

SOURCE: Author's calculations based on SSA data processing audit reports.

SEs for nonprimary tax years most likely reflects IRS efforts to reduce the backlog caused by the pandemic.

As noted earlier, the MGD process uses data from the Numident master file to identify valid and invalid SSNs and to provide information on each worker’s sex and date of birth, yet the tax data used in the OEIS process are not subject to the cleaning and verification associated with the programmatic annual wage reporting process. As a result, some of the SSNs in the data extracted for the new process are not in the Numident file and are deemed to be invalid.¹⁰ Table 3 shows the number of valid and invalid SSNs and expresses both numbers as a percentage of the unique SSNs contained in the records processed each year. The percentage of SSNs that are valid is stable over the years.

In the next step of the MGD process, ORES identifies the demographic information for each worker using data from the Numident file. Table 4 shows the volume of records processed for this step and the breadth of the demographic information the records contained, which enabled ORES to identify, in each

tax year, the sex and date of birth of nearly 99 percent of workers whose records include a valid SSN.

Table 5 shows, for unique SSNs associated with worker records processed, the number to which the OEIS/Finalist process assigned either one SCC, multiple SCCs, or no SCCs. The number of workers for whom the OEIS/Finalist process assigned a single SCC is dramatically lower for 2015 than all other years and is reflected in the aberrantly high number of workers with no SCC assigned in that year. In addition, the number of workers with multiple assigned SCCs is much lower for 2015 than all other years. These results raise concerns about the quality of the processing-year 2015 MGD data and ORES will carefully evaluate the distribution of the state and county assignments for that year. The record-processing results for the other years are consistent over time.

ZIP Code imputation is the first of several steps ORES takes to assign a single SCC for records that were not assigned an SCC in the OEIS/Finalist process. Table 6 shows that ZIP Code imputation

Table 3.
Unique SSNs in records processed by ORES, by whether valid, 2015–2021

Processing year	Primary tax year	Number			Percent		
		Total	Valid	Invalid	Total	Valid	Invalid
2015	2014	170,260,465	168,962,452	1,298,013	100.00	99.24	0.76
2016	2015	174,002,077	172,610,971	1,391,106	100.00	99.20	0.80
2017	2016	176,723,136	175,237,389	1,485,747	100.00	99.16	0.84
2018	2017	178,863,694	177,339,293	1,524,401	100.00	99.15	0.85
2019	2018	181,131,038	179,553,005	1,578,033	100.00	99.13	0.87
2020	2019	182,622,507	181,050,599	1,571,908	100.00	99.14	0.86
2021	2020	181,232,792	179,465,649	1,767,143	100.00	99.02	0.98

SOURCE: Author’s calculations based on SSA data processing audit reports.

Table 4.
Number and percentage of tax records processed that include populated demographic data fields, by type of demographic information, 2015–2021

Processing year	Primary tax year	Number			Percentage		
		Sex	Date of—		Sex	Date of—	
			Birth	Death ^a		Birth	Death ^a
2015	2014	168,147,105	168,082,142	5,175,248	98.76	98.72	3.04
2016	2015	171,808,654	171,745,301	4,547,893	98.74	98.70	2.61
2017	2016	174,446,485	174,385,193	3,948,451	98.74	98.70	2.61
2018	2017	176,571,242	176,512,242	2,003,789	98.72	98.69	1.12
2019	2018	178,801,354	178,744,349	2,696,883	98.71	98.68	1.49
2020	2019	180,317,027	180,262,406	2,128,766	98.74	98.71	1.17
2021	2020	178,765,797	178,714,205	1,566,516	98.64	98.61	0.86

SOURCE: Author’s calculations based on SSA data processing audit reports.

a. Lags in posting death date information result in apparent annual declines in deaths that do not reflect actual annual mortality.

Table 5.
Unique SSNs in records processed by ORES, by number of SCCs assigned in the OEIS/Finalist process, 2015–2021

Processing year	Primary tax year	Total	One SCC	Multiple SCCs	No SCC
<i>Number</i>					
2015	2014	170,260,465	58,018,347	1,025,466	111,216,652
2016	2015	174,002,077	163,954,526	8,674,681	1,372,870
2017	2016	176,723,136	166,415,923	9,099,500	1,207,713
2018	2017	178,863,694	168,338,342	9,304,745	1,220,607
2019	2018	181,131,038	170,390,900	9,532,040	1,208,098
2020	2019	182,622,507	171,744,208	9,673,477	1,204,822
2021	2020	181,232,792	171,189,181	8,835,307	1,208,304
<i>Percent</i>					
2015	2014	100.00	34.08	0.60	65.32
2016	2015	100.00	94.23	4.99	0.79
2017	2016	100.00	94.17	5.15	0.68
2018	2017	100.00	94.12	5.20	0.68
2019	2018	100.00	94.07	5.26	0.67
2020	2019	100.00	94.04	5.30	0.66
2021	2020	100.00	94.46	4.88	0.67

SOURCE: Author's calculations based on SSA data processing audit reports.

NOTE: Rounded components of percentage distributions do not necessarily sum to 100.00.

Table 6.
Unique SSNs in records processed by ORES, by number of SCCs assigned after ZIP Code imputation, 2015–2021

Processing year	Primary tax year	Total	One SCC	Multiple SCCs	No SCC
<i>Number</i>					
2015	2014	170,260,465	163,623,449	4,883,072	1,753,944
2016	2015	174,002,077	165,122,626	8,678,490	200,961
2017	2016	176,723,136	167,433,007	9,104,367	185,762
2018	2017	178,863,694	169,358,474	9,308,397	196,823
2019	2018	181,131,038	171,373,714	9,535,314	222,010
2020	2019	182,622,507	172,723,721	9,676,552	222,234
2021	2020	181,232,792	172,172,586	8,836,639	223,567
<i>Percent</i>					
2015	2014	100.00	96.10	2.87	1.03
2016	2015	100.00	94.90	4.99	0.12
2017	2016	100.00	94.74	5.15	0.11
2018	2017	100.00	94.69	5.20	0.11
2019	2018	100.00	94.61	5.26	0.12
2020	2019	100.00	94.58	5.30	0.12
2021	2020	100.00	95.00	4.88	0.12

SOURCE: Author's calculations based on SSA data processing audit reports.

NOTE: Rounded components of percentage distributions do not necessarily sum to 100.00.

dramatically affects the distribution for 2015, converting many worker records from zero to one assigned SCC. Yet for 2015, the number of workers with multiple SCCs is still much lower than in subsequent years and the number of workers with no SCC is much higher than in later years. The high volume of records that were subject to imputation because they were not assigned an SCC in the OEIS/Finalist process probably accounts for the anomalous 2015 figures. The results for the other years are consistent.

The next step in the MGD process determines, for workers with multiple SCCs, which one is the best to assign. For this, ORES first generates a file containing all the SSNs that have multiple SCCs and extracts the earnings data for each worker from the MEF. The SCC for the location of the worker’s highest-paying job is assigned, when that information is available. For the remaining workers, ORES applies one of several additional imputation techniques (detailed in Compson 2022) that involve matching the frequency distribution of employer location and worker SCCs in the gold-standard file to select the best SCC.

Table 7 quantifies the methods by which records received a single SCC assignment. Excluding processing year 2015, the volume of records having a single SCC assigned via each method is consistent over time. The OEIS/Finalist process produces most of the single-SCC assignments, with the resulting gold-standard file constituting at least 94 percent of workers each year. Using the highest-paying job to assign a single SCC for workers with multiple SCCs accounts for at least 4.7 percent and as much as 5.1 percent of workers in a given year. Combined, these techniques enabled ORES to assign a single SCC to at least 99 percent of workers with a valid SSN in 2016–2021. The frequencies of the other imputation techniques are also consistent over time, as is the percentage of SSNs for which ORES could not assign an SCC.

The procedural evaluation of the MGD process shows consistency over time and provides evidence that the process is stable and robust. However, some observations warrant further investigation. Why did so many records have no SCC assigned in 2015, and did that affect the assumed geographic distribution of workers for that year? Why did the number of W-2c records processed increase sharply in 2017? What accounts for the drop, shown in Table 4, in the number of records with a date of death from 5.18 million (3.0 percent of records processed) in 2015 to 1.57 million (0.9 percent) in 2021? Comparing the following

tabulation, which shows all U.S. deaths for 2014–2022, with the number of worker records containing a value in the date of death field shown in Table 4 suggests that many deaths from earlier years were not posted until 2015, 2016, and 2017, and that many deaths occurring in 2018 or later have not been posted yet.

Year	Number
2014	2,626,418
2015	2,712,630
2016	2,744,248
2017	2,813,503
2018	2,839,205
2019	2,854,838
2020	3,390,079
2021	3,471,742
2022	3,289,236

SOURCE: Centers for Disease Control and Prevention (2022, 2023).

The Comparative Evaluation

This section describes the steps ORES took in preparing to compare the current-methodology and new-process estimates, summarizes the results that ORES staff expected the evaluation would produce, and describes the construction and characteristics of the data files used in the evaluation. Then, it discusses the differences between the two methodologies in the estimated number of workers with covered earnings and the amounts of those earnings by state, sex, and age.

Comparison of Current-Methodology and MGD-Process Geographic Estimates

The current methodology provides the estimates that ORES publishes in annual statistical publications. ORES publishes covered employment and earnings estimates by state in the *Annual Statistical Supplement to the Social Security Bulletin* (hereafter, the *Annual Statistical Supplement*; see <https://www.ssa.gov/policy/docs/statcomps/supplement/index.html>) and by state and county in *Earnings and Employment Data for Workers Covered Under Social Security and Medicare, by State and County* (hereafter, *Earnings and Employment*; see https://www.ssa.gov/policy/docs/statcomps/eedata_sc/index.html). This evaluation uses the microdata and the estimation methods currently used for those publications (with slight modifications, described later) to generate a data file that allows comparison with the MGD process used for assigning SCCs and identifying demographic information. The

Table 7.
Unique SSNs in records processed by ORES, by number of SCCs assigned and method of assignment, 2015–2021

Processing year	Primary tax year	Total	Number of SCCs assigned after OEIS/Finalist process						Missing data; cannot assign SCC
			One (gold-standard records)	None (single SCC assigned via ZIP Code imputation)	More than one: Single SCC assigned based on imputation of MEF data on location of highest-paying job				
					MEF data identify a single highest-paying job	Highest-paying job has multiple locations ^a	No highest-paying job ^a	No earnings data in MEF ^a	
Number									
2015	2014	170,260,465	58,018,347	105,605,102	4,706,334	13,536	692	137,444	1,779,010
2016	2015	174,002,077	163,954,526	1,168,100	8,364,726	29,937	1,886	280,216	202,686
2017	2016	176,723,136	166,415,923	1,017,084	8,757,866	40,532	1,745	302,377	187,609
2018	2017	178,863,694	168,338,342	1,020,132	8,995,263	31,444	1,939	277,928	198,646
2019	2018	181,131,038	170,390,900	982,814	9,230,337	26,826	1,912	274,257	223,992
2020	2019	182,622,507	171,744,208	979,513	9,369,156	25,673	2,070	277,695	224,192
2021	2020	181,232,792	171,189,181	983,405	8,532,308	25,240	2,112	274,689	225,857
Percent									
2015	2014	100.00	34.08	62.03	2.76	0.01	(L)	0.08	1.04
2016	2015	100.00	94.23	0.67	4.81	0.02	(L)	0.16	0.12
2017	2016	100.00	94.17	0.58	4.96	0.02	(L)	0.17	0.11
2018	2017	100.00	94.12	0.57	5.03	0.02	(L)	0.16	0.11
2019	2018	100.00	94.07	0.54	5.10	0.01	(L)	0.15	0.12
2020	2019	100.00	94.04	0.54	5.13	0.01	(L)	0.15	0.12
2021	2020	100.00	94.46	0.54	4.71	0.01	(L)	0.15	0.12

SOURCE: Author's calculations based on SSA data processing audit reports.

NOTES: Rounded components of percentage distributions do not necessarily sum to 100.00.

(L) = less than 0.005.

a. Imputations involve matching the frequency distributions of employer location and worker SCC combinations in the gold-standard file with data available in the MEF.

evaluation comprises two distinct comparisons. The first comparison focuses solely on estimates of the number of workers and their taxable earnings amounts by state, sex, and age. The second comparison focuses on county-level estimates. It is addressed in a separate section because it is significantly more complex than the state-level comparison.

Chart 1 diagrams the steps ORES currently takes to generate the state- and county-level earnings estimates in its statistical publications.¹¹ The process begins by merging the contents of three distinct component files in the 1-percent CWHS file system: the Assigned State file, the Active file, and the SE file. The Assigned State file contains annual earnings and geographic data at the job level, with one record for each SSN/employer identification number combination. The Active file contains time-series earnings and demographic data at the SSN level for each worker with reported earnings over time. The SE file contains job-level earnings and geographic data for self-employed individuals for a given year. The resulting merged microdata file is called the Assigned State_SE_Active (ASA) file. After various manipulations, this merged file contains worker-level data and includes the following data fields:

- SSN;
- Social Security taxable earnings;
- Medicare taxable earnings;
- Year of birth;
- Sex;
- Employment type (wage and salary, self-employed); and
- SCC (in ASA, the SCC is a strictly numeric code; that is, it does not contain state or county names).

ORES currently uses the merged ASA file to create several summarized data files from which it generates state- and county-level employment and earnings estimates. Generating the county-level estimates requires an extra step because the microdata do not contain the county names associated with the SCCs. Specifically, the summarized county-level data must be joined with a separate data file called the LABELS file that contains both the numeric SCCs and the corresponding county names. Further details are provided below in the section on county-level estimates.

Comparing the current and MGD methodologies involves joining the ASA and MGD files, linking the two files' records by SSN. The resulting joined ASA-MGD file—the evaluation file—contains all the information needed to generate two versions of the

earnings tables with state-level estimates. This allows a direct comparison between the current and MGD processes of the estimated number of workers and total earnings amounts by sex, age, and type of earnings.

The ASA microdata file that is used to generate the tax year 2017 earnings tables by state and county contains 1,758,471 SSNs (Table 8). Of those, 1,751,807 SSNs are found in both files and 6,664 are in the ASA but not in the MGD file. Given that the MGD file represents the entire population of workers in a tax year, what explains the 6,664 workers represented in the ASA but not in the MGD file? There are two possible answers.

Recall that the MGD file for a given tax year excludes records for earnings that were not processed in the calendar year following that tax year. For example, in 2018, the MGD process excluded all records containing information for tax years other than 2017. Therefore, some of the MGD file's "missing" SSNs for tax year 2017 were processed in a year other than 2018.¹² As previously noted, tax year 2017 data for 2,618,600 individuals were processed in 2017, 2019, 2020, and 2021, and were therefore omitted from the tax year 2017 MGD file.

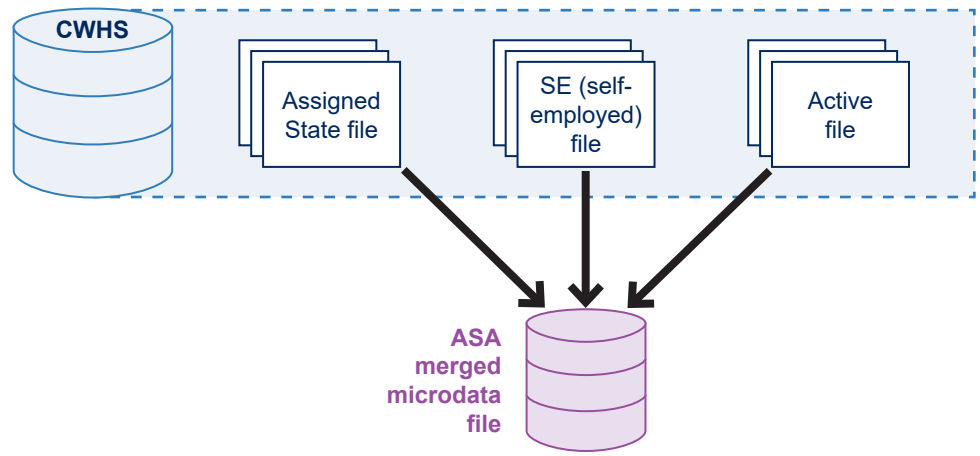
Of the 6,664 individuals with a 2017 ASA record but no MGD record, ORES identified 1,001 whose records were processed in 2017, 50 whose records were processed in 2019, and 8 whose records were processed in 2020 or 2021. ORES did not attempt to assign a geographic code or identify the sex and date of birth for the 1,059 individuals whose tax year 2017 information was not processed in 2018.

A second explanation for the "missing" individuals is the possibility that incorrect SSNs were entered on the tax forms. Recall that the MGD process for assigning location codes and identifying sex and date of birth is separate and distinct from the OEIS process that cleans and verifies the information before posting the data to the MEF. For example: In compiling its annual wage reports, OEIS matches the name and SSN shown on Form W-2 to that worker's administrative records. If one of the digits in the SSN was entered incorrectly, OEIS undertakes one or more procedures to assign the W-2 information to the correct worker. However, the MGD process does not have this capability. Instead, ORES simply takes the SSN as given and uses it to assign a geographic code and identify the worker's sex and date of birth using the Numident file. As a result, the record for a worker whose information was incorrectly reported on Form W-2 could be

Chart 1.
ORES current-methodology process for estimating state- and county-level covered earnings and employment for its statistical publications

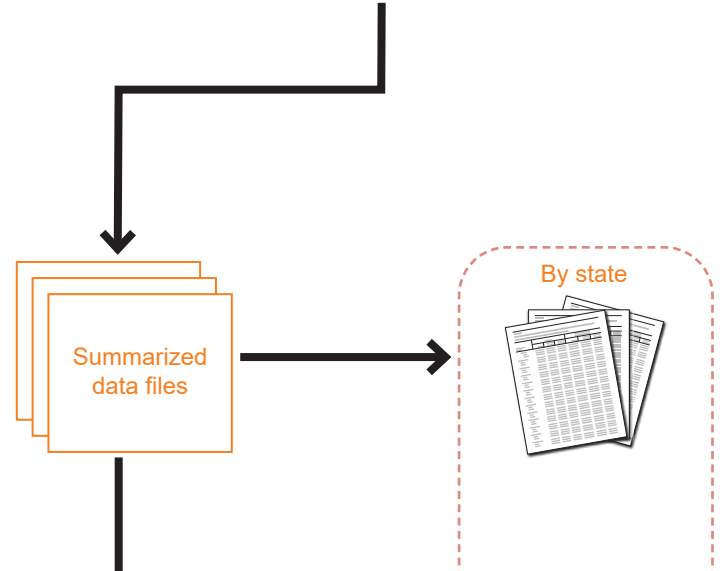
Step 1

Extract geographic and demographic data elements from the CWHS component data files that house them and create a new data file to hold the combined data.



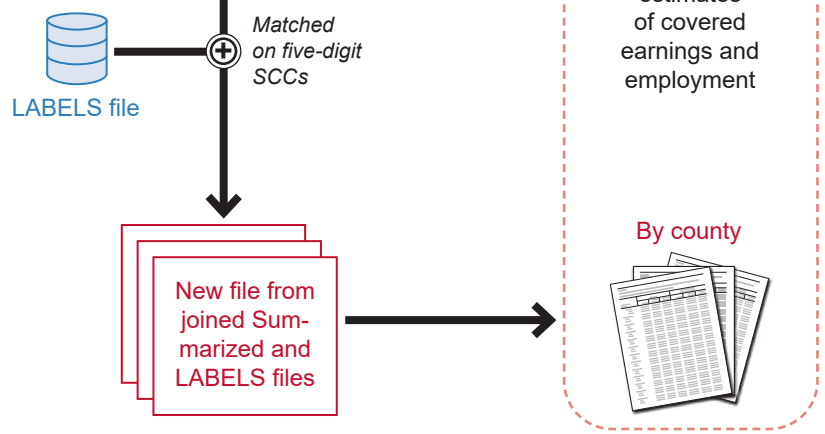
Step 2

Create summarized data files that include the SCC data available in the ASA file. Use the first two digits of the five-digit SCC to identify state names.



Step 3

For county-level estimates, merge the SCC data in the summarized data files with the geographic identifiers contained in the LABELS data file, which links the five-digit SCCs with the corresponding county names.



SOURCE: ORES.

Table 8.
Characteristics of the 2017 ASA microdata file and the merged ASA-MGD evaluation file

Criterion	Number	Percent
ASA microdata file		
Workers represented	1,758,471	100.00
With records used in evaluating MGD	1,751,807	99.62
With records not in the MGD file	6,664	0.38
Merged ASA-MGD evaluation file		
Total	1,751,807	100.00
Workers with Social Security–taxable earnings ^a	1,687,544	96.33
Wage and salary	1,580,879	90.24
Self-employment	186,697	10.66
Workers with earnings not covered for Social Security	64,263	3.67
Workers with Medicare-taxable earnings ^a	1,726,916	98.58
Wage and salary	1,622,793	92.64
Self-employment	194,288	11.09
Workers with earnings not covered for Medicare	24,891	1.42

SOURCE: Author's calculations using 2017 ASA and merged ASA-MGD files.

a. Because some workers accrued both wage and salary and self-employment earnings, the sum of those two categories exceeds the total number of workers with taxable earnings.

retained in the ASA file but would not be included in the MGD file.

Whatever the cause of the discrepancy, the 6,664 individuals with records missing from the MGD file represent less than 0.4 percent of the 1,758,471 workers in the 2017 ASA file. Therefore, ORES removed them from the merged ASA-MGD file that was used in evaluating the MGD process results.

Table 8 shows the number of workers represented in the ASA microdata file and in the large subgroup who comprise the MGD evaluation file, with detail by earnings type (wage and salary, self-employment). It also distinguishes between workers whose earnings are taxable and are not taxable for Social Security and Medicare.

The evaluation begins by comparing MGD-process estimates with slightly modified versions of those published in *Annual Statistical Supplement* Tables 4.B10 and 4.B12, which respectively show Social Security– and Medicare-covered workers and taxable earnings, by state.¹³ In the next step, MGD-process estimates are compared with the worker counts and earnings amounts by sex and state found in the modified versions of *Earnings and Employment* Tables 1 and 4. The third step involves comparing the MGD-process estimates with worker counts and earnings amounts by sex, age, and state,

as published in *Earnings and Employment* Tables 2 and 5. After comparing the state-level estimates, the MGD file's county-level estimates of workers by sex are compared with those in *Earnings and Employment* Tables 3 and 6.

Preevaluation Expectations

Prior to comparing the estimates produced by the current and MGD processes, ORES expected the outcomes to include larger percentage differences between the methodologies' worker counts and earning amounts for less populous states than for larger ones. To provide a deliberately exaggerated example, consider two hypothetical states: SSA statistical publications estimate that state A has 10,000 workers and state B has 50,000 workers. If the MGD process assigns 2,000 more workers to each state, the estimated number of workers differs by 20 percent in state A but only 4 percent in state B. In such a scenario, the estimated amounts of taxable earnings reported in the states would be similarly affected. In addition, because there are far fewer self-employed individuals (186,697) than wage and salary workers (1,580,879) in the CWHS microdata that underlie the current methodology, smaller absolute changes will likewise generate larger percentage differences for the self-employed than for other workers. ORES expected a similar effect in the estimates by age for the

age groups that include comparatively few workers in the CWHS.

ORES also expected match rates between the current methodology and the MGD process to be higher for state assignments than for county assignments. Any worker whose state code does not match in the two files will also have a nonmatching county code, even before considering the several reasons why county assignments within a state may differ between the files. The current methodology assigns state and county codes based on abbreviated geographic identifiers (the first five letters of the city name and the five-digit ZIP Codes reported on tax forms). Although the same abbreviated city name can appear in multiple states, the fact that few (if any) ZIP Codes cross state lines indicates that the current methodology generates reasonably accurate state code assignments.

For county code assignments, however, abbreviated geographic information can be problematic. ZIP Codes speed the flow of mail by designating efficient postal delivery zones which, at the five-digit level, may cross county boundaries. Thus, using only the first five letters of a city name and the five-digit ZIP Code can lead to occasional county code inaccuracies.

Furthermore, under the current methodology, an SCC assigned for a worker with both wage and salary and self-employment earnings might be based on data reported on Form 1040 Schedule SE and on either or both of Forms W-2 or W-2c. When the current methodology was developed more than 30 years ago, the SCC corresponding with the self-employment income was typically assigned because the address reported on Schedule SE was viewed as more reliable than a conflicting address reported on another form. However, the MGD process has revealed that millions of individuals are assigned multiple SCCs in a given tax year and there is no reason to believe that the address reported on Schedule SE is more reliable than the address on the W-2 or W-2c. The MGD process provides several options for assigning an SCC and ORES has determined that the best option is to use the SCC corresponding with the highest-paying job regardless of the type of earnings. For these reasons, differences between the current methodology and the MGD process are more likely in county assignments than in state assignments.

Third, ORES expected very high match rates between the current methodology and the MGD process for worker sex and age. Where discrepancies emerged, ORES expected that the MGD process would be more accurate than the current process.

This is because the Numident master file is the sole source of the sex and age information used in the MGD process, while in the current methodology, that information may be drawn from either of two files that are derived from the Numident, rather than from the source file itself.

Evaluating Worker Counts

Of the 1,751,807 individuals represented in the full MGD evaluation file, which includes those with noncovered earnings as well as those with earnings covered by Social Security or Medicare, 98.87 percent have the same state code assigned by the current and MGD processes (not shown). Thus, only 19,875 workers (1.13 percent) have nonmatching state codes. However, among those workers with nonmatching state codes are 2,511 to whom the current methodology assigns one of the following location categories: Armed Forces, International Operations, Other, and Reserves, categories that are not included in the MGD process.¹⁴ Because those categories do not represent a state or U.S. territory, calculating a “true” match rate—one that accounts only for cases in which it is possible for the two state codes to match—requires removing those 2,511 individuals from the total of 1,751,807 workers. The resulting “true” match rate is 99.26 percent, which leaves only 17,364 of 1,749,296 workers whose MGD-process and current-methodology state codes do not match. This result aligns with ORES expectations of high state code match rates given that few ZIP Codes, if any, cross state lines.

The tables that follow compare the numbers of workers and the taxable earnings amounts estimated using the current and the MGD processes for assigning geographic and demographic information. Recall that the current-methodology estimates are slightly modified so that the estimates for both processes are based on the same unadjusted and unweighted raw data from the microdata file derived from the 1-percent CWHS.

Table 9 shows the estimated number of workers with earnings taxable for Social Security—that is, Old-Age, Survivors, and Disability Insurance (OASDI)—by state or other area (as assigned using the current methodology) and type of earnings. It also shows the number and percentage of workers who are assigned the same state codes using the MGD process. Note that these estimates include the workers for whom the current methodology assigned the codes Armed Forces, International Operations, Other, and Reserves. As a result, the state-code match rates are slightly understated.

Table 9.

Number of workers with Social Security (OASDI) taxable earnings, by state or other area as assigned under the current methodology; and number and percent of workers with matching state codes in the MGD file; by type of earnings, tax year 2017

Current-methodology assigned state or area	All			Wage and salary			Self-employed		
	Total	Workers with matching state code in MGD file		Total	Workers with matching state code in MGD file		Total	Workers with matching state code in MGD file	
		Number	Percent		Number	Percent		Number	Percent
All areas	1,687,544	1,669,082	98.91	1,580,879	1,563,528	98.90	186,697	183,118	98.08
Alabama	23,856	23,657	99.17	22,531	22,340	99.15	2,411	2,374	98.47
Alaska	3,791	3,760	99.18	3,561	3,531	99.16	417	410	98.32
Arizona	33,785	33,553	99.31	31,847	31,629	99.32	3,455	3,374	97.66
Arkansas	14,690	14,428	98.22	13,774	13,516	98.13	1,608	1,578	98.13
California	189,421	188,343	99.43	173,786	172,769	99.41	25,134	24,829	98.79
Colorado	29,337	29,041	98.99	27,275	26,995	98.97	3,647	3,568	97.83
Connecticut	19,621	19,452	99.14	18,326	18,164	99.12	2,228	2,189	98.25
Delaware	5,199	5,120	98.48	4,984	4,905	98.41	422	416	98.58
District of Columbia	4,155	3,986	95.93	3,939	3,775	95.84	437	415	94.97
Florida	104,426	103,565	99.18	96,427	95,607	99.15	13,431	13,164	98.01
Georgia	52,577	52,067	99.03	49,197	48,709	99.01	6,020	5,916	98.27
Hawaii	7,715	7,652	99.18	7,183	7,124	99.18	867	854	98.50
Idaho	8,866	8,745	98.64	8,325	8,208	98.59	951	931	97.90
Illinois	66,450	65,557	98.66	62,455	61,585	98.61	7,220	7,096	98.28
Indiana	36,500	36,229	99.26	34,895	34,643	99.28	3,119	3,062	98.17
Iowa	17,681	17,516	99.07	16,723	16,565	99.06	1,847	1,817	98.38
Kansas	15,798	15,670	99.19	14,921	14,799	99.18	1,641	1,612	98.23
Kentucky	22,194	22,006	99.15	20,975	20,793	99.13	2,177	2,143	98.44
Louisiana	21,612	21,339	98.74	20,175	19,909	98.68	2,537	2,491	98.19
Maine	7,164	7,096	99.05	6,631	6,563	98.97	913	898	98.36
Maryland	33,296	32,996	99.10	31,493	31,206	99.09	3,385	3,322	98.14
Massachusetts	36,585	36,209	98.97	34,164	33,799	98.93	4,154	4,095	98.58
Michigan	52,165	51,845	99.39	49,353	49,040	99.37	5,206	5,142	98.77
Minnesota	32,585	32,310	99.16	30,920	30,650	99.13	3,220	3,191	99.10
Mississippi	14,298	14,229	99.52	13,406	13,340	99.51	1,691	1,660	98.17
Missouri	31,759	31,517	99.24	30,041	29,808	99.22	3,196	3,142	98.31
Montana	6,098	5,688	93.28	5,723	5,318	92.92	671	651	97.02
Nebraska	11,127	10,801	97.07	10,525	10,202	96.93	1,151	1,129	98.09
Nevada	13,930	13,851	99.43	13,095	13,021	99.43	1,459	1,422	97.46
New Hampshire	8,055	7,983	99.11	7,548	7,478	99.07	826	816	98.79
New Jersey	49,423	49,059	99.26	46,467	46,124	99.26	5,287	5,200	98.35
New Mexico	9,740	9,690	99.49	9,198	9,150	99.48	932	910	97.64
New York	105,970	104,884	98.98	98,858	97,849	98.98	12,494	12,260	98.13
North Carolina	52,577	52,238	99.36	49,529	49,199	99.33	5,482	5,401	98.52
North Dakota	4,469	4,337	97.05	4,222	4,092	96.92	510	501	98.24
Ohio	58,397	57,740	98.87	54,935	54,288	98.82	5,895	5,839	99.05
Oklahoma	19,624	19,513	99.43	18,488	18,384	99.44	2,038	2,008	98.53
Oregon	21,674	21,547	99.41	20,326	20,207	99.41	2,287	2,240	97.94
Pennsylvania	68,886	68,531	99.48	65,408	65,070	99.48	6,426	6,334	98.57
Rhode Island	5,964	5,885	98.68	5,650	5,573	98.64	587	574	97.79

(Continued)

Table 9.
Number of workers with Social Security (OASDI) taxable earnings, by state or other area as assigned under the current methodology; and number and percent of workers with matching state codes in the MGD file; by type of earnings, tax year 2017—Continued

Current-methodology assigned state or area	All			Wage and salary			Self-employed		
	Total	Workers with matching state code in MGD file		Total	Workers with matching state code in MGD file		Total	Workers with matching state code in MGD file	
		Number	Percent		Number	Percent		Number	Percent
South Carolina	25,479	25,336	99.44	24,176	24,040	99.44	2,450	2,398	97.88
South Dakota	5,470	5,131	93.80	5,158	4,822	93.49	612	600	98.04
Tennessee	34,994	34,754	99.31	32,637	32,409	99.30	4,124	4,045	98.08
Texas	134,668	133,888	99.42	124,891	124,142	99.40	16,667	16,438	98.63
Utah	16,305	16,206	99.39	15,631	15,535	99.39	1,481	1,464	98.85
Vermont	3,786	3,747	98.97	3,553	3,514	98.90	434	428	98.62
Virginia	46,057	45,662	99.14	43,680	43,312	99.16	4,510	4,409	97.76
Washington	39,559	39,303	99.35	37,498	37,252	99.34	3,629	3,571	98.40
West Virginia	8,378	8,327	99.39	7,992	7,941	99.36	683	677	99.12
Wisconsin	32,812	32,663	99.55	31,346	31,207	99.56	2,742	2,712	98.91
Wyoming	3,217	3,180	98.85	3,036	3,001	98.85	357	343	96.08
Outlying areas ^a	10,197	10,019	98.25	9,424	9,248	98.13	997	985	98.80
Other and unknown	5,162	1,231	23.85	4,578	1,178	25.73	632	74	11.71

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

NOTE: Because some workers accrued both wage and salary and self-employment earnings, the sum of those two categories exceeds the number of all workers with taxable earnings.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

The match rate for all workers with OASDI taxable earnings is 98.9 percent. It is at least 99 percent in 34 states, at least 98 percent in 46 states, and at least 97 percent in 48 states.¹⁵ The lowest match rates are those for the District of Columbia (95.9 percent), South Dakota (93.8 percent), and Montana (93.3 percent)—states with relatively few workers.

The match rate for all wage and salary workers with OASDI taxable earnings is also 98.9 percent.¹⁶ The match rate is at least 99 percent in 34 states and at least 98 percent in 47 states. The lowest match rates are 96.9 percent for North Dakota, 95.8 percent for the District of Columbia, and around 93 percent for Montana and South Dakota.

The match rate for all self-employed individuals with OASDI taxable earnings is 98.1 percent. In most states, the match rate for self-employed individuals tends to be lower than that for wage and salary workers, likely because self-employed individuals are far less numerous than wage and salary workers in the CWS. Only three states have a match rate of at least 99 percent, although 39 states have a match rate of at least 98 percent and 49 have a match rate of at least

97 percent. The match rate for Wyoming is 96.1 percent and for the District of Columbia it is 95.0 percent.

Results of the same analysis for workers with earnings covered under the Medicare programs were similar to those for workers covered under OASDI, and this pattern recurred for all subsequent comparisons between the two methodologies. Therefore, the results for Medicare-covered workers are not shown in separate tables and are not discussed hereafter unless they diverge from those for OASDI-covered workers.

Differences in Estimated Worker Counts

Table 10 shows the number of workers for whom the current methodology and the MGD process assigned a state code, by the assigned state or area. For all workers with OASDI taxable earnings, the difference in the number of state assignments ranges from 420 fewer workers estimated in the MGD file for Illinois to 1,331 additional workers estimated in the MGD file for California. For only seven states does the percentage differ by more than 1 percent, with the MGD file assigning fewer workers for six of them: Montana (–6.1 percent), South Dakota (–5.1 percent), the District of Columbia

Table 10.**Number of workers with Social Security (OASDI) taxable earnings for whom a state was assigned using the current methodology and the MGD process, by state or other area and type of earnings, tax year 2017**

State or area	All				Wage and salary				Self-employed			
	Current methodology	MGD process	Difference		Current methodology	MGD process	Difference		Current methodology	MGD process	Difference	
			Number	Percent			Number	Percent			Number	Percent
All areas	1,687,544	1,687,544	0	0.00	1,580,879	1,580,879	0	0.00	186,697	186,697	0	0.00
Alabama	23,856	23,874	18	0.08	22,531	22,547	16	0.07	2,411	2,420	9	0.37
Alaska	3,791	3,805	14	0.37	3,561	3,576	15	0.42	417	420	3	0.72
Arizona	33,785	33,912	127	0.38	31,847	31,975	128	0.40	3,455	3,442	-13	-0.38
Arkansas	14,690	14,637	-53	-0.36	13,774	13,716	-58	-0.42	1,608	1,610	2	0.12
California	189,421	190,752	1,331	0.70	173,786	175,077	1,291	0.74	25,134	25,170	36	0.14
Colorado	29,337	29,420	83	0.28	27,275	27,328	53	0.19	3,647	3,682	35	0.96
Connecticut	19,621	19,609	-12	-0.06	18,326	18,312	-14	-0.08	2,228	2,231	3	0.13
Delaware	5,199	5,142	-57	-1.10	4,984	4,926	-58	-1.16	422	423	1	0.24
District of Columbia	4,155	4,044	-111	-2.67	3,939	3,829	-110	-2.79	437	447	10	2.29
Florida	104,426	104,990	564	0.54	96,427	96,911	484	0.50	13,431	13,450	19	0.14
Georgia	52,577	52,601	24	0.05	49,197	49,234	37	0.08	6,020	6,010	-10	-0.17
Hawaii	7,715	7,709	-6	-0.08	7,183	7,181	-2	-0.03	867	869	2	0.23
Idaho	8,866	8,816	-50	-0.56	8,325	8,279	-46	-0.55	951	949	-2	-0.21
Illinois	66,450	66,030	-420	-0.63	62,455	62,024	-431	-0.69	7,220	7,199	-21	-0.29
Indiana	36,500	36,608	108	0.30	34,895	35,014	119	0.34	3,119	3,135	16	0.51
Iowa	17,681	17,630	-51	-0.29	16,723	16,671	-52	-0.31	1,847	1,852	5	0.27
Kansas	15,798	15,790	-8	-0.05	14,921	14,912	-9	-0.06	1,641	1,643	2	0.12
Kentucky	22,194	22,153	-41	-0.18	20,975	20,939	-36	-0.17	2,177	2,165	-12	-0.55
Louisiana	21,612	21,468	-144	-0.67	20,175	20,036	-139	-0.69	2,537	2,520	-17	-0.67
Maine	7,164	7,213	49	0.68	6,631	6,670	39	0.59	913	916	3	0.33
Maryland	33,296	33,296	0	0.00	31,493	31,496	3	0.01	3,385	3,378	-7	-0.21
Massachusetts	36,585	36,491	-94	-0.26	34,164	34,057	-107	-0.31	4,154	4,168	14	0.34
Michigan	52,165	52,213	48	0.09	49,353	49,391	38	0.08	5,206	5,204	-2	-0.04
Minnesota	32,585	32,598	13	0.04	30,920	30,927	7	0.02	3,220	3,245	25	0.78
Mississippi	14,298	14,326	28	0.20	13,406	13,435	29	0.22	1,691	1,691	0	0.00
Missouri	31,759	32,121	362	1.14	30,041	30,391	350	1.17	3,196	3,216	20	0.63
Montana	6,098	5,728	-370	-6.07	5,723	5,358	-365	-6.38	671	659	-12	-1.79
Nebraska	11,127	10,854	-273	-2.45	10,525	10,253	-272	-2.58	1,151	1,147	-4	-0.35
Nevada	13,930	14,037	107	0.77	13,095	13,204	109	0.83	1,459	1,470	11	0.75
New Hampshire	8,055	8,092	37	0.46	7,548	7,580	32	0.42	826	842	16	1.94

(Continued)

Table 10.
Number of workers with Social Security (OASDI) taxable earnings for whom a state was assigned using the current methodology and the MGD process, by state or other area and type of earnings, tax year 2017—Continued

State or area	All				Wage and salary				Self-employed			
	Current methodology		Difference		Current methodology	MGD process	Difference		Current methodology	MGD process	Difference	
			Number	Percent			Number	Percent			Number	Percent
New Jersey	49,423	49,543	120	0.24	46,467	46,589	122	0.26	5,287	5,306	19	0.36
New Mexico	9,740	9,806	66	0.68	9,198	9,264	66	0.72	932	927	-5	-0.54
New York	105,970	106,741	771	0.73	98,858	99,672	814	0.82	12,494	12,500	6	0.05
North Carolina	52,577	52,579	2	0.00	49,529	49,533	4	0.01	5,482	5,480	-2	-0.04
North Dakota	4,469	4,414	-55	-1.23	4,222	4,166	-56	-1.33	510	516	6	1.18
Ohio	58,397	58,066	-331	-0.57	54,935	54,599	-336	-0.61	5,895	5,904	9	0.15
Oklahoma	19,624	19,657	33	0.17	18,488	18,517	29	0.16	2,038	2,053	15	0.74
Oregon	21,674	21,712	38	0.18	20,326	20,368	42	0.21	2,287	2,276	-11	-0.48
Pennsylvania	68,886	69,062	176	0.26	65,408	65,573	165	0.25	6,426	6,438	12	0.19
Rhode Island	5,964	5,929	-35	-0.59	5,650	5,615	-35	-0.62	587	587	0	0.00
South Carolina	25,479	25,648	169	0.66	24,176	24,338	162	0.67	2,450	2,452	2	0.08
South Dakota	5,470	5,192	-278	-5.08	5,158	4,881	-277	-5.37	612	614	2	0.33
Tennessee	34,994	34,976	-18	-0.05	32,637	32,624	-13	-0.04	4,124	4,101	-23	-0.56
Texas	134,668	135,072	404	0.30	124,891	125,224	333	0.27	16,667	16,702	35	0.21
Utah	16,305	16,384	79	0.48	15,631	15,707	76	0.49	1,481	1,498	17	1.15
Vermont	3,786	3,792	6	0.16	3,553	3,558	5	0.14	434	434	0	0.00
Virginia	46,057	46,235	178	0.39	43,680	43,844	164	0.38	4,510	4,516	6	0.13
Washington	39,559	39,797	238	0.60	37,498	37,724	226	0.60	3,629	3,648	19	0.52
West Virginia	8,378	8,410	32	0.38	7,992	8,020	28	0.35	683	692	9	1.32
Wisconsin	32,812	32,907	95	0.29	31,346	31,436	90	0.29	2,742	2,758	16	0.58
Wyoming	3,217	3,211	-6	-0.19	3,036	3,028	-8	-0.26	357	352	-5	-1.40
Outlying areas ^a	10,197	10,137	-60	-0.59	9,424	9,362	-62	-0.66	997	1009	12	1.20
Other and unknown	5,162	2,315	-2,847	-55.15	4,578	1,988	-2,590	-56.57	632	361	-271	-42.88

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

NOTE: Because some workers accrued both wage and salary and self-employment earnings, the sum of those two categories exceeds the number of all workers with taxable earnings.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

(-2.7 percent), Nebraska (-2.5 percent), North Dakota (-1.2 percent), Delaware (-1.1 percent), and Missouri (1.1 percent). These states all have relatively few workers.

For wage and salary workers with OASDI taxable earnings, the difference in the number of state assignments ranges from 431 fewer workers in the MGD file for Illinois to 1,291 additional workers in the MGD file for California. Because wage and salary workers far outnumber self-employed individuals, their results in Table 10 are similar to those for all workers: MGD assignments for the same seven states differ by more than 1 percent from those of the current methodology (Montana, -6.4 percent; South Dakota, -5.4 percent; the District of Columbia, -2.8 percent; Nebraska, -2.6 percent; North Dakota, -1.3 percent; Delaware, -1.2 percent; and Missouri, 1.2 percent).

For self-employed individuals, the differences in the numbers of state assignments range from 23 fewer workers in the MGD file for Tennessee to 36 additional workers in the MGD file for California. The MGD state code assignments differ by more than 1 percent from the current-methodology assignments in seven states: the District of Columbia (2.3 percent), New Hampshire (1.9 percent), West Virginia (1.3 percent), North Dakota (1.2 percent), Utah (1.2 percent), Wyoming (-1.4 percent), and Montana (-1.8 percent). In a notable departure from the pattern for wage and salary workers, MGD code assignments for the self-employed are more than 1 percent higher than those in the current methodology for five states.

A parallel analysis for workers with Medicare-taxable earnings produced very similar results, with one difference worth noting. The MGD process assigned the District of Columbia code to 1.3 percent more individuals with Medicare-covered self-employment income than the current methodology did (not shown), compared with 2.3 percent more for self-employed individuals with OASDI taxable earnings.

Differences in Estimated Taxable Earnings Amounts

Given the high match rates in the estimated numbers of workers with OASDI taxable earnings for both earnings types, one might expect the estimated taxable earnings amounts by state to be similar under the two methodologies as well. However, some of the workers with different state codes assigned by the MGD process could have earnings that are high enough to alter some of the estimated state-level earnings. Potential state-level shifts in estimated Medicare-covered

earnings amounts could be even greater because unlike OASDI-covered earnings, there is no cap on the amount of Medicare earnings subject to the payroll tax.

Table 11 compares the estimated amounts of Social Security taxable earnings for workers whose state code was assigned under the current methodology with those whose state code was assigned under the MGD process.

For all workers, the MGD earnings estimate differs by at least 1 percent from that of the current methodology in 10 states. The MGD estimate is lower in seven of those states: Montana (-5.0 percent), South Dakota (-4.2 percent), the District of Columbia (-3.8 percent), Nebraska (-1.9 percent), Delaware (-1.5 percent), Louisiana (-1.2 percent), and North Dakota (-1.0 percent). The MGD estimate is higher in three states: Missouri (1.3 percent) and New Mexico and Maine (1.1 percent).

For wage and salary workers, the MGD estimate differs by at least 1 percent from that of the current methodology in 11 states. The MGD estimate is lower in eight of those states: Montana (-5.2 percent), South Dakota (-4.3 percent), the District of Columbia (-3.9 percent), Nebraska (-2.0 percent), Delaware (-1.6 percent), Louisiana (-1.2 percent), North Dakota (-1.1 percent), and Ohio (-1.0 percent). In three states, the MGD estimate is at least 1 percent higher than the current-methodology estimate: Missouri (1.4 percent), New Mexico (1.1 percent), and Maine (1.0 percent).

For self-employed individuals, the MGD estimate differs by at least 1 percent from that of the current methodology in 12 states. The MGD estimate is higher for eight of them: the District of Columbia (2.7 percent); Nevada (1.5 percent); Alaska, Indiana, and North Dakota (1.4 percent); Washington and West Virginia (1.1 percent); and Colorado (1.0 percent). The MGD estimate is lower for four states: Montana (-2.3 percent), Wyoming (-1.7 percent), Arkansas (-1.1 percent), and Louisiana (-1.0 percent).

The percentage changes in the estimated amounts of OASDI taxable earnings between the two methodologies are generally small, as was expected; but are the percentage changes in estimated earnings proportional with the percentage changes in the estimated numbers of workers? That is, if the MGD estimate of workers in a given state is 1.5 percent lower than the current-methodology estimate, is there a corresponding decrease in the estimated amount of taxable OASDI earnings?

Table 11.

Earnings of workers with Social Security (OASDI) taxable earnings for whom a state was assigned using the current methodology and the MGD process, by state or other area and type of earnings, tax year 2017 (in 2017 dollars)

State or area	Current methodology	MGD process	Difference	
			Amount	Percent
<i>All</i>				
All areas	68,423,438,380	68,423,438,380	0	0.00
Alabama	857,716,152	858,592,612	876,460	0.10
Alaska	153,874,120	154,421,206	547,086	0.36
Arizona	1,302,959,209	1,306,516,111	3,556,902	0.27
Arkansas	491,163,014	489,982,217	-1,180,797	-0.24
California	8,433,766,110	8,481,973,766	48,207,656	0.57
Colorado	1,238,763,159	1,243,011,623	4,248,464	0.34
Connecticut	921,093,226	919,812,262	-1,280,964	-0.14
Delaware	216,156,133	212,893,943	-3,262,190	-1.51
District of Columbia	231,648,128	222,967,504	-8,680,624	-3.75
Florida	3,791,556,468	3,812,600,272	21,043,804	0.56
Georgia	1,993,330,826	1,991,930,932	-1,399,894	-0.07
Hawaii	319,080,649	318,270,329	-810,320	-0.25
Idaho	302,386,845	301,788,771	-598,074	-0.20
Illinois	2,748,333,915	2,727,070,643	-21,263,272	-0.77
Indiana	1,352,562,930	1,360,357,123	7,794,193	0.58
Iowa	665,729,171	662,820,670	-2,908,501	-0.44
Kansas	598,835,629	598,542,985	-292,644	-0.05
Kentucky	762,050,270	760,602,506	-1,447,764	-0.19
Louisiana	773,282,923	764,287,215	-8,995,708	-1.16
Maine	248,549,671	251,190,221	2,640,550	1.06
Maryland	1,630,296,173	1,631,735,995	1,439,822	0.09
Massachusetts	1,748,735,103	1,747,889,863	-845,240	-0.05
Michigan	2,042,364,653	2,042,894,366	529,713	0.03
Minnesota	1,404,270,994	1,405,178,905	907,911	0.06
Mississippi	467,146,390	467,671,454	525,064	0.11
Missouri	1,143,533,770	1,158,822,712	15,288,942	1.34
Montana	200,619,056	190,604,753	-10,014,303	-4.99
Nebraska	418,010,730	410,128,643	-7,882,087	-1.89
Nevada	503,719,119	507,489,173	3,770,054	0.75
New Hampshire	362,380,857	362,902,978	522,121	0.14
New Jersey	2,418,851,606	2,424,681,320	5,829,714	0.24
New Mexico	337,908,949	341,565,374	3,656,425	1.08
New York	4,771,907,899	4,804,933,827	33,025,928	0.69
North Carolina	1,974,284,037	1,976,214,801	1,930,764	0.10
North Dakota	180,947,605	179,144,543	-1,803,062	-1.00
Ohio	2,139,409,841	2,119,620,918	-19,788,923	-0.92
Oklahoma	694,532,355	693,883,937	-648,418	-0.09
Oregon	871,808,720	873,599,440	1,790,720	0.21
Pennsylvania	2,849,416,932	2,855,317,004	5,900,072	0.21
Rhode Island	243,885,478	243,124,171	-761,307	-0.31
South Carolina	919,022,725	925,946,911	6,924,186	0.75
South Dakota	186,155,770	178,413,757	-7,742,013	-4.16
Tennessee	1,277,836,973	1,276,286,028	-1,550,945	-0.12
Texas	5,403,455,636	5,423,910,900	20,455,264	0.38
Utah	611,070,284	614,279,890	3,209,606	0.53

(Continued)

Table 11.

Earnings of workers with Social Security (OASDI) taxable earnings for whom a state was assigned using the current methodology and the MGD process, by state or other area and type of earnings, tax year 2017 (in 2017 dollars)—Continued

State or area	Current methodology	MGD process	Difference	
			Amount	Percent
<i>All (cont.)</i>				
Vermont	142,580,658	142,886,697	306,039	0.21
Virginia	2,088,562,332	2,099,671,869	11,109,537	0.53
Washington	1,862,102,324	1,871,095,019	8,992,695	0.48
West Virginia	293,519,718	295,441,183	1,921,465	0.65
Wisconsin	1,292,637,852	1,295,553,320	2,915,468	0.23
Wyoming	122,145,345	121,929,576	-215,769	-0.18
Outlying areas ^a	237,340,154	235,879,261	-1,460,893	-0.62
Other and unknown	180,139,794	65,106,881	-115,032,913	-63.86
<i>Wage and salary</i>				
All areas	65,799,740,190	65,799,740,190	0	0.00
Alabama	827,957,923	828,946,232	988,309	0.12
Alaska	147,351,844	147,905,856	554,012	0.38
Arizona	1,260,295,968	1,263,843,879	3,547,911	0.28
Arkansas	473,254,737	471,965,870	-1,288,867	-0.27
California	8,023,239,762	8,070,405,328	47,165,566	0.59
Colorado	1,184,284,373	1,187,477,629	3,193,256	0.27
Connecticut	875,217,959	874,178,633	-1,039,326	-0.12
Delaware	210,174,607	206,902,502	-3,272,105	-1.56
District of Columbia	222,607,680	213,946,772	-8,660,908	-3.89
Florida	3,650,205,329	3,670,244,169	20,038,840	0.55
Georgia	1,925,737,777	1,924,700,902	-1,036,875	-0.05
Hawaii	305,121,578	304,328,035	-793,543	-0.26
Idaho	290,087,661	289,567,847	-519,814	-0.18
Illinois	2,652,242,379	2,631,031,675	-21,210,704	-0.80
Indiana	1,314,385,276	1,322,446,028	8,060,752	0.61
Iowa	641,044,554	638,025,174	-3,019,380	-0.47
Kansas	574,789,255	574,751,422	-37,833	-0.01
Kentucky	737,285,458	735,928,648	-1,356,810	-0.18
Louisiana	742,800,185	733,968,962	-8,831,223	-1.19
Maine	235,689,047	238,101,805	2,412,758	1.02
Maryland	1,581,885,107	1,583,384,514	1,499,407	0.09
Massachusetts	1,675,437,348	1,674,458,736	-978,612	-0.06
Michigan	1,975,784,546	1,976,301,140	516,594	0.03
Minnesota	1,357,964,358	1,358,654,929	690,571	0.05
Mississippi	448,508,759	449,122,191	613,432	0.14
Missouri	1,104,700,118	1,119,716,148	15,016,030	1.36
Montana	191,194,586	181,294,921	-9,899,665	-5.18
Nebraska	402,459,145	394,582,716	-7,876,429	-1.96
Nevada	484,192,411	488,181,527	3,989,116	0.82
New Hampshire	345,023,243	345,473,658	450,415	0.13
New Jersey	2,321,913,541	2,327,899,404	5,985,863	0.26
New Mexico	326,703,029	330,365,888	3,662,859	1.12
New York	4,592,694,595	4,626,594,435	33,899,840	0.74
North Carolina	1,906,929,140	1,908,884,471	1,955,331	0.10
North Dakota	172,882,650	170,998,260	-1,884,390	-1.09

(Continued)

Table 11.

Earnings of workers with Social Security (OASDI) taxable earnings for whom a state was assigned using the current methodology and the MGD process, by state or other area and type of earnings, tax year 2017 (in 2017 dollars)—Continued

State or area	Current methodology	MGD process	Difference	
			Amount	Percent
Wage and salary (cont.)				
Ohio	2,062,139,701	2,042,274,693	-19,865,008	-0.96
Oklahoma	671,254,262	670,515,050	-739,212	-0.11
Oregon	835,388,680	837,410,794	2,022,114	0.24
Pennsylvania	2,754,547,086	2,760,069,736	5,522,650	0.20
Rhode Island	235,265,798	234,450,170	-815,628	-0.35
South Carolina	890,369,058	896,951,561	6,582,503	0.74
South Dakota	178,287,749	170,632,577	-7,655,172	-4.29
Tennessee	1,209,383,919	1,208,427,144	-956,775	-0.08
Texas	5,173,321,386	5,192,270,975	18,949,589	0.37
Utah	596,024,683	599,105,522	3,080,839	0.52
Vermont	137,165,055	137,460,528	295,473	0.22
Virginia	2,025,521,370	2,036,073,995	10,552,625	0.52
Washington	1,799,128,895	1,807,248,859	8,119,964	0.45
West Virginia	283,313,293	285,180,695	1,867,402	0.66
Wisconsin	1,256,046,557	1,258,873,867	2,827,310	0.23
Wyoming	117,372,594	117,079,703	-292,891	-0.25
Outlying areas ^a	224,617,215	223,109,020	-1,508,195	-0.67
Other and unknown	168,546,961	58,024,995	-110,521,966	-65.57
Self-employed				
All areas	5,799,361,603	5,799,361,603	0	0.00
Alabama	66,648,167	66,545,016	-103,151	-0.15
Alaska	14,519,740	14,719,815	200,075	1.38
Arizona	100,645,843	100,315,372	-330,471	-0.33
Arkansas	40,949,914	40,505,569	-444,345	-1.09
California	797,303,016	797,260,291	-42,725	-0.01
Colorado	120,265,806	121,486,330	1,220,524	1.01
Connecticut	89,875,562	89,283,750	-591,812	-0.66
Delaware	14,895,078	14,902,505	7,427	0.05
District of Columbia	20,949,978	21,524,978	575,000	2.74
Florida	317,106,454	315,124,001	-1,982,453	-0.63
Georgia	156,585,224	156,027,875	-557,349	-0.36
Hawaii	28,383,465	28,535,683	152,218	0.54
Idaho	28,006,004	28,077,951	71,947	0.26
Illinois	218,901,727	217,987,027	-914,700	-0.42
Indiana	97,753,666	99,101,243	1,347,577	1.38
Iowa	60,342,164	60,399,916	57,752	0.10
Kansas	56,259,390	56,278,057	18,667	0.03
Kentucky	61,320,285	61,070,243	-250,042	-0.41
Louisiana	68,502,378	67,810,281	-692,097	-1.01
Maine	26,088,892	26,075,417	-13,475	-0.05
Maryland	124,010,332	124,322,266	311,934	0.25
Massachusetts	153,009,485	153,360,152	350,667	0.23
Michigan	157,817,436	157,261,359	-556,077	-0.35
Minnesota	113,550,586	114,494,480	943,894	0.83
Mississippi	42,668,082	42,780,374	112,292	0.26

(Continued)

Table 11.

Earnings of workers with Social Security (OASDI) taxable earnings for whom a state was assigned using the current methodology and the MGD process, by state or other area and type of earnings, tax year 2017 (in 2017 dollars)—Continued

State or area	Current methodology	MGD process	Difference	
			Amount	Percent
Self-employed (cont.)				
Missouri	94,816,194	95,176,683	360,489	0.38
Montana	20,833,803	20,360,948	-472,855	-2.27
Nebraska	38,648,035	38,576,907	-71,128	-0.18
Nevada	42,495,330	43,113,267	617,937	1.45
New Hampshire	32,061,866	32,339,105	277,239	0.86
New Jersey	205,454,248	206,256,749	802,501	0.39
New Mexico	26,110,321	25,969,312	-141,009	-0.54
New York	413,468,918	414,833,661	1,364,743	0.33
North Carolina	156,079,879	156,247,750	167,871	0.11
North Dakota	20,229,337	20,502,566	273,229	1.35
Ohio	168,884,200	169,135,108	250,908	0.15
Oklahoma	58,331,043	58,587,588	256,545	0.44
Oregon	75,262,265	74,820,957	-441,308	-0.59
Pennsylvania	223,224,904	223,504,490	279,586	0.13
Rhode Island	19,783,599	19,866,812	83,213	0.42
South Carolina	71,291,266	71,880,825	589,559	0.83
South Dakota	20,107,307	20,077,426	-29,881	-0.15
Tennessee	137,155,734	136,201,945	-953,789	-0.70
Texas	487,609,948	486,965,031	-644,917	-0.13
Utah	49,916,410	50,305,835	389,425	0.78
Vermont	12,999,807	12,964,845	-34,962	-0.27
Virginia	154,147,599	154,729,247	581,648	0.38
Washington	134,758,092	136,214,362	1,456,270	1.08
West Virginia	22,225,842	22,463,427	237,585	1.07
Wisconsin	90,998,522	91,812,978	814,456	0.90
Wyoming	12,254,030	12,040,548	-213,482	-1.74
Outlying areas ^a	20,637,445	20,776,379	138,934	0.67
Other and unknown	13,216,985	8,386,901	-4,830,084	-36.54

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

NOTE: Because some workers accrued both wage and salary and self-employment earnings, the sum of the earnings in those two categories exceeds the amount shown for all workers with taxable earnings.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

Table 12 shows the percentage differences between the current-methodology estimates and the MGD-process estimates of both the number of workers with OASDI taxable earnings (from Table 10) and the amounts of those earnings (from Table 11), and presents the percentage-point differences between those two measures. For all workers, the percentage-point difference between the two measures exceeds 0.5 in only four states: Montana and the District of Columbia (1.1 percentage points), South Dakota (0.9 percentage point), and Nebraska (0.6 percentage point). The results for wage and salary workers are similar.

For self-employed individuals, the two measures differ by 0.5 percentage point or more in nine states: Arkansas (1.2 percentage points); New Hampshire (1.1 percentage points); Indiana (0.9 percentage point); Connecticut, Florida, and South Carolina (0.8 percentage point); Nevada and Alaska (0.7 percentage point); and Washington (0.6 percentage point).

Estimates by State and Sex

The evaluation continues by comparing the results of the current methodology and the MGD process for identifying the sex of workers. Table 13 shows that the match rate of the reported sex for all workers is 99.3 percent. However, the MGD file includes two categories of incomplete data, Missing and Unknown, that are not duplicated in the CWHS microdata file. If the records for the 5,237 workers with Missing values and the 648 workers with Unknown values for sex are removed from the MGD file, the match rate is 99.6 percent (not shown).

Table 13 shows that the sex identified in the current methodology and the MGD process matches for at least 99 percent of all workers and for wage and salary workers in all states except Iowa, which has a 98.9 percent match rate. For self-employed individuals, the match rate by sex is lower than 99 percent in seven states. However, the match rate for all seven of those states exceeds 98.4 percent.

Table 14 repeats Table 12 with detail by sex; that is, it shows the percentage differences between the current-methodology estimates and the MGD-process estimates of both the number of workers with OASDI taxable earnings and the amounts of those earnings, and presents the percentage-point differences between those two measures. For all workers, the percentage-point difference between the number of workers and the amount of taxable OASDI earnings exceeds 0.5 in only nine states (Louisiana, Ohio, South Dakota, and Wyoming, for women; the District of Columbia,

Maine, Nebraska, and Oklahoma, for men; and Montana, for both).

Estimates by State and Age

Earnings and Employment includes tables showing the numbers of workers with taxable Social Security and Medicare earnings by state or other area, sex, and age. Table 15 compares the worker ages identified using the current methodology and the MGD process and shows that the ages assigned by the MGD process match those identified under the current methodology for 98.9 percent of workers overall. However, the records for 5,734 workers in the MGD file are missing an age value and therefore cannot match the current-methodology age value. Removing these records from consideration would produce a “true” match rate of 99.2 percent. Further, for an additional 0.6 percent of all workers, the age assigned in the MGD file is within 2 years (plus or minus) of the age assigned by the current methodology. Combining the true match rate and the share of workers whose ages are within 2 years of the current-methodology assigned age would result in a 99.8 percent match rate for all workers.

Estimates by age in *Earnings and Employment* are shown for each of nine age groups. In many states, some of those categories contain relatively few workers. Specifically, five of the age groups (under 20, 60–61, 62–64, 65–69, and 70 or older) contain far fewer workers than the other four. As previously noted, lower numbers of workers in these categories are likely to result in larger percentage differences in the estimates by age between the current methodology and the MGD process. Comparing the differences between the two processes is therefore problematic because many of the larger percentage changes may reflect relatively small changes in the number of workers.

Table 16 shows how the MGD-estimated counts of workers with OASDI taxable earnings by sex and age differ from the current-methodology estimates (after removing the MGD records for 5,734 workers with a missing value for age). Because the differences are slight, the MGD assignment of age requires no further evaluation.

Estimates by County

Earnings and Employment includes 102 tables showing county-level statistics: 51 (one for each state plus one for Puerto Rico) for workers covered under Social Security and 51 for those covered under Medicare. Each table presents worker counts, taxable earnings, and

Table 12.

Percentage difference between current-methodology and MGD-process estimates of the number of workers with Social Security (OASDI) taxable earnings and their taxable earnings amounts, and the percentage-point difference between those two estimates, by state or other area and type of earnings, tax year 2017

State or area	All			Wage and salary			Self-employed		
	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference
	Number of workers	Taxable earnings		Number of workers	Taxable earnings		Number of workers	Taxable earnings	
All areas	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alabama	0.08	0.10	0.02	0.07	0.12	0.05	0.37	-0.15	0.52
Alaska	0.37	0.36	0.01	0.42	0.38	0.04	0.72	1.38	0.66
Arizona	0.38	0.27	0.11	0.40	0.28	0.12	-0.38	-0.33	0.05
Arkansas	-0.36	-0.24	0.12	-0.42	-0.27	0.15	0.12	-1.09	1.21
California	0.70	0.57	0.13	0.74	0.59	0.15	0.14	-0.01	0.15
Colorado	0.28	0.34	0.06	0.19	0.27	0.08	0.96	1.01	0.05
Connecticut	-0.06	-0.14	0.08	-0.08	-0.12	0.04	0.13	-0.66	0.79
Delaware	-1.10	-1.51	0.41	-1.16	-1.56	0.40	0.24	0.05	0.19
District of Columbia	-2.67	-3.75	1.08	-2.79	-3.89	1.10	2.29	2.74	0.45
Florida	0.54	0.56	0.02	0.50	0.55	0.05	0.14	-0.63	0.77
Georgia	0.05	-0.07	0.12	0.08	-0.05	0.13	-0.17	-0.36	0.19
Hawaii	-0.08	-0.25	0.17	-0.03	-0.26	0.23	0.23	0.54	0.31
Idaho	-0.56	-0.20	0.36	-0.55	-0.18	0.37	-0.21	0.26	0.47
Illinois	-0.63	-0.77	0.14	-0.69	-0.80	0.11	-0.29	-0.42	0.13
Indiana	0.30	0.58	0.28	0.34	0.61	0.27	0.51	1.38	0.87
Iowa	-0.29	-0.44	0.15	-0.31	-0.47	0.16	0.27	0.10	0.17
Kansas	-0.05	-0.05	0.00	-0.06	-0.01	0.05	0.12	0.03	0.09
Kentucky	-0.18	-0.19	0.01	-0.17	-0.18	0.01	-0.55	-0.41	0.14
Louisiana	-0.67	-1.16	0.49	-0.69	-1.19	0.50	-0.67	-1.01	0.34
Maine	0.68	1.06	0.38	0.59	1.02	0.43	0.33	-0.05	0.38
Maryland	0.00	0.09	0.09	0.01	0.09	0.08	-0.21	0.25	0.46
Massachusetts	-0.26	-0.05	0.21	-0.31	-0.06	0.25	0.34	0.23	0.11
Michigan	0.09	0.03	0.06	0.08	0.03	0.05	-0.04	-0.35	0.31
Minnesota	0.04	0.06	0.02	0.02	0.05	0.03	0.78	0.83	0.05
Mississippi	0.20	0.11	0.09	0.22	0.14	0.08	0.00	0.26	0.26
Missouri	1.14	1.34	0.20	1.17	1.36	0.19	0.63	0.38	0.25
Montana	-6.07	-4.99	1.08	-6.38	-5.18	1.20	-1.79	-2.27	0.48
Nebraska	-2.45	-1.89	0.56	-2.58	-1.96	0.62	-0.35	-0.18	0.17
Nevada	0.77	0.75	0.02	0.83	0.82	0.01	0.75	1.45	0.70
New Hampshire	0.46	0.14	0.32	0.42	0.13	0.29	1.94	0.86	1.08
New Jersey	0.24	0.24	0.00	0.26	0.26	0.00	0.36	0.39	0.03
New Mexico	0.68	1.08	0.40	0.72	1.12	0.40	-0.54	-0.54	0.00
New York	0.73	0.69	0.04	0.82	0.74	0.08	0.05	0.33	0.28
North Carolina	0.00	0.10	0.10	0.01	0.10	0.09	-0.04	0.11	0.15
North Dakota	-1.23	-1.00	0.23	-1.33	-1.09	0.24	1.18	1.35	0.17

(Continued)

Table 12.

Percentage difference between current-methodology and MGD-process estimates of the number of workers with Social Security (OASDI) taxable earnings and their taxable earnings amounts, and the percentage-point difference between those two estimates, by state or other area and type of earnings, tax year 2017—Continued

State or area	All			Wage and salary			Self-employed		
	Percentage difference in estimated—		Percent-age point difference	Percentage difference in estimated—		Percent-age point difference	Percentage difference in estimated—		Percent-age point difference
	Number of workers	Taxable earnings		Number of workers	Taxable earnings		Number of workers	Taxable earnings	
Ohio	-0.57	-0.92	0.35	-0.61	-0.96	0.35	0.15	0.15	0.00
Oklahoma	0.17	-0.09	0.26	0.16	-0.11	0.27	0.74	0.44	0.30
Oregon	0.18	0.21	0.03	0.21	0.24	0.03	-0.48	-0.59	0.11
Pennsylvania	0.26	0.21	0.05	0.25	0.20	0.05	0.19	0.13	0.06
Rhode Island	-0.59	-0.31	0.28	-0.62	-0.35	0.27	0.00	0.42	0.42
South Carolina	0.66	0.75	0.09	0.67	0.74	0.07	0.08	0.83	0.75
South Dakota	-5.08	-4.16	0.92	-5.37	-4.29	1.08	0.33	-0.15	0.48
Tennessee	-0.05	-0.12	0.07	-0.04	-0.08	0.04	-0.56	-0.70	0.14
Texas	0.30	0.38	0.08	0.27	0.37	0.10	0.21	-0.13	0.34
Utah	0.48	0.53	0.05	0.49	0.52	0.03	1.15	0.78	0.37
Vermont	0.16	0.21	0.05	0.14	0.22	0.08	0.00	-0.27	0.27
Virginia	0.39	0.53	0.14	0.38	0.52	0.14	0.13	0.38	0.25
Washington	0.60	0.48	0.12	0.60	0.45	0.15	0.52	1.08	0.56
West Virginia	0.38	0.65	0.27	0.35	0.66	0.31	1.32	1.07	0.25
Wisconsin	0.29	0.23	0.06	0.29	0.23	0.06	0.58	0.90	0.32
Wyoming	-0.19	-0.18	0.01	-0.26	-0.25	0.01	-1.40	-1.74	0.34
Outlying areas ^a	-0.59	-0.62	0.03	-0.66	-0.67	0.01	1.20	0.67	0.53
Other and unknown	-55.15	-63.86	54.53	-56.57	-65.57	9.00	-42.88	-36.54	6.34

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

Table 13.

Number of workers with Social Security (OASDI) taxable earnings, by state or other area as assigned under the current methodology; and number and percent of workers with matching sex identifiers in the MGD file; by type of earnings, tax year 2017

Current-methodology assigned state or area	All			Wage and salary			Self-employed		
	Total	Workers with matching sex identifier in MGD file		Total	Workers with matching sex identifier in MGD file		Total	Workers with matching sex identifier in MGD file	
		Number	Percent		Number	Percent		Number	Percent
All areas	1,687,544	1,675,898	99.31	1,580,879	1,570,114	99.32	186,697	185,287	99.24
Alabama	23,856	23,710	99.39	22,531	22,391	99.38	2,411	2,397	99.42
Alaska	3,791	3,763	99.26	3,561	3,534	99.24	417	414	99.28
Arizona	33,785	33,585	99.41	31,847	31,659	99.41	3,455	3,434	99.39
Arkansas	14,690	14,598	99.37	13,774	13,687	99.37	1,608	1,599	99.44
California	189,421	187,988	99.24	173,786	172,497	99.26	25,134	24,921	99.15
Colorado	29,337	29,178	99.46	27,275	27,129	99.46	3,647	3,628	99.48
Connecticut	19,621	19,487	99.32	18,326	18,201	99.32	2,228	2,209	99.15
Delaware	5,199	5,168	99.40	4,984	4,954	99.40	422	421	99.76
District of Columbia	4,155	4,121	99.18	3,939	3,909	99.24	437	432	98.86
Florida	104,426	103,726	99.33	96,427	95,778	99.33	13,431	13,337	99.30
Georgia	52,577	52,176	99.24	49,197	48,832	99.26	6,020	5,968	99.14
Hawaii	7,715	7,673	99.46	7,183	7,146	99.48	867	861	99.31
Idaho	8,866	8,821	99.49	8,325	8,286	99.53	951	944	99.26
Illinois	66,450	65,964	99.27	62,455	61,995	99.26	7,220	7,171	99.32
Indiana	36,500	36,330	99.53	34,895	34,740	99.56	3,119	3,100	99.39
Iowa	17,681	17,478	98.85	16,723	16,536	98.88	1,847	1,818	98.43
Kansas	15,798	15,727	99.55	14,921	14,855	99.56	1,641	1,634	99.57
Kentucky	22,194	22,076	99.47	20,975	20,866	99.48	2,177	2,164	99.40
Louisiana	21,612	21,463	99.31	20,175	20,051	99.39	2,537	2,504	98.70
Maine	7,164	7,134	99.58	6,631	6,604	99.59	913	908	99.45
Maryland	33,296	33,112	99.45	31,493	31,321	99.45	3,385	3,365	99.41
Massachusetts	36,585	36,388	99.46	34,164	33,980	99.46	4,154	4,127	99.35
Michigan	52,165	51,676	99.06	49,353	48,900	99.08	5,206	5,153	98.98
Minnesota	32,585	32,417	99.48	30,920	30,761	99.49	3,220	3,204	99.50
Mississippi	14,298	14,210	99.38	13,406	13,322	99.37	1,691	1,681	99.41
Missouri	31,759	31,563	99.38	30,041	29,857	99.39	3,196	3,178	99.44
Montana	6,098	6,063	99.43	5,723	5,691	99.44	671	665	99.11
Nebraska	11,127	11,072	99.51	10,525	10,474	99.52	1,151	1,145	99.48
Nevada	13,930	13,839	99.35	13,095	13,011	99.36	1,459	1,448	99.25
New Hampshire	8,055	8,017	99.53	7,548	7,512	99.52	826	822	99.52
New Jersey	49,423	49,045	99.24	46,467	46,107	99.23	5,287	5,254	99.38
New Mexico	9,740	9,675	99.33	9,198	9,139	99.36	932	922	98.93
New York	105,970	105,455	99.51	98,858	98,388	99.52	12,494	12,414	99.36
North Carolina	52,577	52,141	99.17	49,529	49,127	99.19	5,482	5,430	99.05
North Dakota	4,469	4,445	99.46	4,222	4,199	99.46	510	507	99.41
Ohio	58,397	57,902	99.15	54,935	54,468	99.15	5,895	5,850	99.24
Oklahoma	19,624	19,502	99.38	18,488	18,373	99.38	2,038	2,028	99.51
Oregon	21,674	21,542	99.39	20,326	20,207	99.41	2,287	2,268	99.17
Pennsylvania	68,886	68,274	99.11	65,408	64,842	99.13	6,426	6,360	98.97
Rhode Island	5,964	5,925	99.35	5,650	5,612	99.33	587	585	99.66

(Continued)

Table 13.

Number of workers with Social Security (OASDI) taxable earnings, by state or other area as assigned under the current methodology; and number and percent of workers with matching sex identifiers in the MGD file; by type of earnings, tax year 2017—Continued

Current-methodology assigned state or area	All			Wage and salary			Self-employed		
	Total	Workers with matching sex identifier in MGD file		Total	Workers with matching sex identifier in MGD file		Total	Workers with matching sex identifier in MGD file	
		Number	Percent		Number	Percent		Number	Percent
South Carolina	25,479	25,325	99.40	24,176	24,029	99.39	2,450	2,434	99.35
South Dakota	5,470	5,445	99.54	5,158	5,135	99.55	612	608	99.35
Tennessee	34,994	34,780	99.39	32,637	32,434	99.38	4,124	4,109	99.64
Texas	134,668	133,380	99.04	124,891	123,713	99.06	16,667	16,499	98.99
Utah	16,305	16,242	99.61	15,631	15,571	99.62	1,481	1,476	99.66
Vermont	3,786	3,771	99.60	3,553	3,538	99.58	434	434	100.00
Virginia	46,057	45,803	99.45	43,680	43,445	99.46	4,510	4,475	99.22
Washington	39,559	39,230	99.17	37,498	37,185	99.17	3,629	3,601	99.23
West Virginia	8,378	8,339	99.53	7,992	7,956	99.55	683	678	99.27
Wisconsin	32,812	32,676	99.59	31,346	31,218	99.59	2,742	2,729	99.53
Wyoming	3,217	3,200	99.47	3,036	3,019	99.44	357	356	99.72
Outlying areas ^a	10,197	10,136	99.40	9,424	9,371	99.44	997	987	99.00
Other and unknown	5,162	5,142	99.61	4,578	4,559	99.58	632	631	99.84

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

NOTE: Because some workers accrued both wage and salary and self-employment earnings, the sum of those two categories exceeds the number of all workers with taxable earnings.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

Table 14.

Percentage difference between current-methodology and MGD-process estimates of the number of workers with Social Security (OASDI) taxable earnings and their taxable earnings amounts, and the percentage-point difference between those two estimates, by sex, state or other area, and type of earnings, tax year 2017

State or area	All			Wage and salary			Self-employed		
	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference
	Number of workers	Taxable earnings		Number of workers	Taxable earnings		Number of workers	Taxable earnings	
All areas	-0.33	-0.41	-0.08	-0.32	-0.41	-0.08	-0.40	-0.50	-0.10
Men	-0.33	-0.42	-0.09	-0.32	-0.42	-0.10	-0.40	-0.46	-0.06
Women	-0.33	-0.39	-0.06	-0.33	-0.39	-0.06	-0.42	-0.45	-0.03
Alabama									
Men	0.06	0.28	0.22	0.08	0.31	0.23	-0.08	-0.45	-0.37
Women	-0.28	-0.69	-0.41	-0.29	-0.69	-0.40	0.27	-0.05	-0.32
Alaska									
Men	0.25	0.31	0.06	0.32	0.33	0.02	1.63	1.37	-0.26
Women	-0.17	-0.32	-0.15	-0.12	-0.33	-0.21	-1.16	1.34	2.50
Arizona									
Men	0.10	-0.05	-0.14	0.11	-0.06	-0.17	-0.11	0.03	0.14
Women	0.26	0.13	-0.13	0.29	0.15	-0.14	-1.07	-1.59	-0.51
Arkansas									
Men	-0.67	-0.71	-0.03	-0.79	-0.78	0.00	0.00	-1.76	-1.76
Women	-0.47	-0.14	0.33	-0.49	-0.13	0.36	0.00	-0.63	-0.63
California									
Men	0.70	0.30	-0.40	0.81	0.36	-0.45	-0.19	-0.43	-0.23
Women	-0.03	-0.24	-0.20	-0.03	-0.25	-0.22	-0.45	-0.75	-0.30
Colorado									
Men	-0.09	-0.09	0.00	-0.17	-0.20	-0.03	0.40	0.66	0.26
Women	0.15	0.19	0.04	0.05	0.14	0.09	1.15	1.18	0.03
Connecticut									
Men	-0.17	-0.25	-0.08	-0.17	-0.18	-0.01	-0.24	-1.04	-0.80
Women	-0.62	-0.77	-0.15	-0.62	-0.80	-0.17	-0.52	-1.03	-0.51
Delaware									
Men	-1.18	-1.62	-0.44	-1.28	-1.67	-0.40	0.00	-0.33	-0.33
Women	-1.36	-1.81	-0.45	-1.41	-1.86	-0.45	0.52	0.55	0.04
District of Columbia									
Men	-2.09	-4.42	-2.33	-2.42	-4.72	-2.31	5.99	4.93	-1.06
Women	-3.55	-3.52	0.02	-3.44	-3.51	-0.07	-1.82	-0.44	1.38
Florida									
Men	0.36	0.28	-0.09	0.33	0.28	-0.06	0.23	-0.55	-0.78
Women	0.17	0.07	-0.10	0.12	0.05	-0.06	-0.54	-1.85	-1.31
Georgia									
Men	-0.37	-0.57	-0.19	-0.33	-0.55	-0.22	-0.43	-0.47	-0.05
Women	-0.29	-0.50	-0.21	-0.24	-0.47	-0.23	-0.84	-1.28	-0.44
Hawaii									
Men	-0.73	-0.72	0.01	-0.65	-0.74	-0.09	-0.43	0.39	0.82
Women	0.00	-0.18	-0.18	0.06	-0.16	-0.22	0.00	0.04	0.04
Idaho									
Men	-1.13	-0.68	0.45	-1.11	-0.68	0.43	-1.14	-0.19	0.95
Women	-0.31	0.15	0.46	-0.23	0.19	0.42	0.00	0.99	0.99

(Continued)

Table 14.

Percentage difference between current-methodology and MGD-process estimates of the number of workers with Social Security (OASDI) taxable earnings and their taxable earnings amounts, and the percentage-point difference between those two estimates, by sex, state or other area, and type of earnings, tax year 2017—Continued

State or area	All			Wage and salary			Self-employed		
	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference
	Number of workers	Taxable earnings		Number of workers	Taxable earnings		Number of workers	Taxable earnings	
Illinois									
Men	-1.12	-1.36	-0.24	-1.18	-1.42	-0.24	-0.91	-0.73	0.19
Women	-0.91	-1.04	-0.13	-0.98	-1.04	-0.06	-0.40	-0.78	-0.38
Indiana									
Men	0.10	0.48	0.37	0.18	0.54	0.35	-0.11	0.68	0.79
Women	0.17	0.31	0.13	0.22	0.34	0.11	0.67	2.31	1.64
Iowa									
Men	-1.33	-1.67	-0.34	-1.27	-1.61	-0.34	-1.45	-1.76	-0.31
Women	-1.11	-1.28	-0.17	-1.13	-1.34	-0.20	-0.81	-1.58	-0.77
Kansas									
Men	-0.26	-0.38	-0.12	-0.25	-0.30	-0.05	-0.31	-0.61	-0.30
Women	-0.25	-0.34	-0.09	-0.27	-0.35	-0.08	0.45	0.97	0.52
Kentucky									
Men	-0.17	-0.06	0.11	-0.09	-0.02	0.07	-1.31	-1.20	0.11
Women	-0.47	-0.67	-0.21	-0.51	-0.71	-0.20	-0.21	0.16	0.37
Louisiana									
Men	-1.03	-1.51	-0.49	-1.00	-1.54	-0.53	-1.69	-1.53	0.17
Women	-0.85	-1.51	-0.67	-0.83	-1.47	-0.63	-1.02	-2.66	-1.64
Maine									
Men	0.38	0.91	0.54	0.24	0.83	0.59	-0.39	-0.59	-0.21
Women	0.72	0.87	0.15	0.68	0.88	0.20	1.01	0.82	-0.19
Maryland									
Men	-0.22	-0.41	-0.20	-0.20	-0.39	-0.19	-0.51	0.11	0.62
Women	-0.15	0.16	0.30	-0.15	0.15	0.30	-0.19	-0.14	0.04
Massachusetts									
Men	-0.32	-0.07	0.25	-0.37	-0.07	0.30	0.17	-0.14	-0.31
Women	-0.51	-0.45	0.06	-0.57	-0.47	0.10	-0.06	-0.32	-0.26
Michigan									
Men	-0.60	-0.74	-0.14	-0.60	-0.72	-0.12	-1.07	-1.35	-0.28
Women	-0.51	-0.61	-0.11	-0.50	-0.61	-0.10	-0.42	-0.45	-0.03
Minnesota									
Men	-0.12	-0.13	0.00	-0.14	-0.16	-0.01	0.64	0.81	0.17
Women	-0.30	-0.37	-0.07	-0.31	-0.36	-0.05	0.45	0.31	-0.14
Mississippi									
Men	0.00	-0.25	-0.25	0.02	-0.20	-0.22	0.00	-0.48	-0.48
Women	0.01	0.09	0.07	0.04	0.09	0.05	-0.47	0.77	1.25
Missouri									
Men	0.86	0.96	0.10	0.93	1.00	0.07	0.00	-0.35	-0.35
Women	0.86	0.97	0.11	0.86	1.01	0.15	0.82	0.65	-0.16
Montana									
Men	-6.17	-5.57	0.59	-6.55	-5.81	0.73	-2.36	-2.42	-0.06
Women	-6.48	-4.50	1.98	-6.67	-4.64	2.02	-2.43	-2.30	0.13

(Continued)

Table 14.

Percentage difference between current-methodology and MGD-process estimates of the number of workers with Social Security (OASDI) taxable earnings and their taxable earnings amounts, and the percentage-point difference between those two estimates, by sex, state or other area, and type of earnings, tax year 2017—Continued

State or area	All			Wage and salary			Self-employed		
	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference
	Number of workers	Taxable earnings		Number of workers	Taxable earnings		Number of workers	Taxable earnings	
Nebraska									
Men	-2.73	-2.01	0.72	-2.86	-2.09	0.77	-0.84	-0.25	0.58
Women	-2.52	-2.09	0.43	-2.65	-2.14	0.50	-0.46	-0.46	0.00
Nevada									
Men	0.39	0.24	-0.15	0.48	0.34	-0.15	0.40	1.12	0.72
Women	0.62	0.77	0.15	0.69	0.81	0.12	0.14	1.22	1.07
New Hampshire									
Men	-0.02	-0.14	-0.12	0.00	-0.10	-0.10	1.82	0.99	-0.83
Women	0.62	0.18	-0.44	0.57	0.14	-0.43	1.21	-0.50	-1.71
New Jersey									
Men	-0.19	-0.16	0.03	-0.19	-0.16	0.03	-0.23	0.06	0.29
Women	-0.16	-0.39	-0.22	-0.14	-0.37	-0.22	0.31	-0.22	-0.54
New Mexico									
Men	0.59	0.86	0.27	0.64	0.95	0.31	-1.12	-2.36	-1.24
Women	0.25	0.58	0.33	0.33	0.62	0.29	-1.03	-0.58	0.45
New York									
Men	1.12	0.83	-0.29	1.29	0.90	-0.38	-0.01	-0.14	-0.12
Women	0.07	0.15	0.08	0.13	0.18	0.06	-0.29	0.48	0.77
North Carolina									
Men	-0.42	-0.46	-0.03	-0.41	-0.44	-0.03	-0.41	-0.82	-0.41
Women	-0.38	-0.27	0.11	-0.34	-0.27	0.07	-0.83	-0.01	0.82
North Dakota									
Men	-1.07	-0.92	0.16	-1.15	-1.03	0.12	0.00	0.44	0.44
Women	-1.86	-1.38	0.48	-1.93	-1.41	0.53	2.82	3.89	1.06
Ohio									
Men	-1.00	-1.33	-0.33	-1.04	-1.38	-0.33	-0.49	-0.43	0.05
Women	-1.15	-1.78	-0.62	-1.20	-1.82	-0.62	-0.19	-0.40	-0.21
Oklahoma									
Men	-0.21	-0.75	-0.54	-0.15	-0.72	-0.58	-0.27	-0.90	-0.63
Women	-0.06	-0.25	-0.19	-0.13	-0.32	-0.19	1.19	1.47	0.28
Oregon									
Men	-0.18	-0.24	-0.07	-0.14	-0.20	-0.06	-0.68	-0.93	-0.25
Women	0.05	-0.10	-0.15	0.09	-0.02	-0.11	-0.99	-1.33	-0.33
Pennsylvania									
Men	-0.22	-0.32	-0.09	-0.17	-0.29	-0.12	-0.68	-0.48	0.20
Women	-0.52	-0.72	-0.21	-0.55	-0.76	-0.21	-0.23	-0.52	-0.30
Rhode Island									
Men	-0.50	-0.42	0.08	-0.57	-0.48	0.09	0.00	0.18	0.18
Women	-1.31	-1.01	0.29	-1.30	-1.04	0.26	-0.78	0.59	1.37
South Carolina									
Men	0.46	0.53	0.06	0.49	0.51	0.02	0.08	1.12	1.05
Women	0.42	0.50	0.08	0.40	0.48	0.08	-0.51	-0.51	0.00

(Continued)

Table 14.

Percentage difference between current-methodology and MGD-process estimates of the number of workers with Social Security (OASDI) taxable earnings and their taxable earnings amounts, and the percentage-point difference between those two estimates, by sex, state or other area, and type of earnings, tax year 2017—Continued

State or area	All			Wage and salary			Self-employed		
	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference	Percentage difference in estimated—		Percentage point difference
	Number of workers	Taxable earnings		Number of workers	Taxable earnings		Number of workers	Taxable earnings	
South Dakota									
Men	-4.65	-4.19	0.46	-4.92	-4.32	0.61	0.00	-0.33	-0.33
Women	-5.93	-4.73	1.20	-6.16	-4.85	1.30	-0.44	-1.75	-1.30
Tennessee									
Men	-0.41	-0.43	-0.02	-0.37	-0.39	-0.01	-1.24	-0.91	0.33
Women	-0.30	-0.66	-0.37	-0.32	-0.64	-0.31	-0.06	-0.92	-0.86
Texas									
Men	-0.26	-0.35	-0.09	-0.26	-0.33	-0.06	-0.69	-1.42	-0.73
Women	-0.18	-0.25	-0.07	-0.22	-0.28	-0.06	-0.15	-0.17	-0.02
Utah									
Men	0.45	0.47	0.02	0.46	0.43	-0.03	1.08	1.15	0.07
Women	0.26	0.12	-0.13	0.25	0.18	-0.07	1.08	-0.16	-1.24
Vermont									
Men	-0.16	-0.04	0.11	-0.17	-0.05	0.12	0.00	0.12	0.12
Women	0.22	0.14	-0.08	0.17	0.12	-0.05	0.00	-0.72	-0.72
Virginia									
Men	0.00	0.05	0.04	0.00	0.04	0.04	-0.62	-0.52	0.11
Women	0.27	0.46	0.20	0.28	0.48	0.20	0.14	0.32	0.18
Washington									
Men	0.11	-0.12	-0.23	0.10	-0.18	-0.28	0.10	0.91	0.81
Women	0.14	-0.09	-0.23	0.16	-0.07	-0.23	-0.12	-0.07	0.06
West Virginia									
Men	0.31	0.71	0.40	0.35	0.74	0.39	-0.26	0.42	0.67
Women	0.05	0.09	0.04	-0.03	0.06	0.09	2.41	1.92	-0.49
Wisconsin									
Men	-0.07	-0.11	-0.04	-0.09	-0.12	-0.03	0.50	0.71	0.21
Women	0.27	0.16	-0.12	0.28	0.15	-0.13	0.00	0.45	0.45
Wyoming									
Men	0.00	-0.48	-0.48	0.00	-0.51	-0.51	-0.49	-1.98	-1.49
Women	-0.59	0.08	0.67	-0.76	-0.07	0.69	-2.63	-1.34	1.29
Outlying areas ^a									
Men	-0.74	-0.59	0.15	-0.78	-0.60	0.18	0.46	-1.04	-1.51
Women	-0.71	-0.91	-0.21	-0.75	-1.00	-0.26	1.43	4.43	3.00
Other and unknown									
Men	-62.44	-70.79	-8.36	-64.88	-72.96	-8.08	-34.64	-28.96	5.68
Women	-42.53	-47.14	-4.61	-40.76	-46.82	-6.06	-50.61	-46.50	4.12

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

Table 15.

Number of workers with Social Security (OASDI) taxable earnings, by state or other area as assigned under the current methodology; and number and percent of workers with matching ages in the MGD file; tax year 2017

Current-methodology assigned state or area	Total	Workers with matching age in MGD file	
		Number	Percent
All areas	1,687,544	1,668,449	98.87
Alabama	23,856	23,613	98.98
Alaska	3,791	3,748	98.87
Arizona	33,785	33,442	98.98
Arkansas	14,690	14,529	98.90
California	189,421	187,067	98.76
Colorado	29,337	29,054	99.04
Connecticut	19,621	19,369	98.72
Delaware	5,199	5,148	99.02
District of Columbia	4,155	4,110	98.92
Florida	104,426	103,209	98.83
Georgia	52,577	51,900	98.71
Hawaii	7,715	7,652	99.18
Idaho	8,866	8,782	99.05
Illinois	66,450	65,572	98.68
Indiana	36,500	36,201	99.18
Iowa	17,681	17,436	98.61
Kansas	15,798	15,659	99.12
Kentucky	22,194	22,005	99.15
Louisiana	21,612	21,381	98.93
Maine	7,164	7,102	99.13
Maryland	33,296	32,942	98.94
Massachusetts	36,585	36,246	99.07
Michigan	52,165	51,468	98.66
Minnesota	32,585	32,323	99.20
Mississippi	14,298	14,119	98.75
Missouri	31,759	31,419	98.93
Montana	6,098	6,042	99.08
Nebraska	11,127	11,048	99.29
Nevada	13,930	13,769	98.84
New Hampshire	8,055	7,979	99.06
New Jersey	49,423	48,800	98.74
New Mexico	9,740	9,627	98.84
New York	105,970	104,947	99.03
North Carolina	52,577	51,945	98.80
North Dakota	4,469	4,433	99.19
Ohio	58,397	57,662	98.74
Oklahoma	19,624	19,401	98.86
Oregon	21,674	21,490	99.15
Pennsylvania	68,886	67,960	98.66
Rhode Island	5,964	5,901	98.94

(Continued)

Table 15.

Number of workers with Social Security (OASDI) taxable earnings, by state or other area as assigned under the current methodology; and number and percent of workers with matching ages in the MGD file; tax year 2017—Continued

Current-methodology assigned state or area	Total	Workers with matching age in MGD file	
		Number	Percent
South Carolina	25,479	25,145	98.69
South Dakota	5,470	5,421	99.10
Tennessee	34,994	34,612	98.91
Texas	134,668	133,007	98.77
Utah	16,305	16,193	99.31
Vermont	3,786	3,750	99.05
Virginia	46,057	45,543	98.88
Washington	39,559	39,114	98.88
West Virginia	8,378	8,306	99.14
Wisconsin	32,812	32,557	99.22
Wyoming	3,217	3,181	98.88
Outlying areas ^a	10,197	9,999	98.06
Other and unknown	5,162	5,121	99.21

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

Table 16.
Difference from the current-methodology estimates of the number of workers with Social Security (OASDI) taxable earnings when using the MGD process, by age, sex, and state or other area, tax year 2017

State or area	All ages	Under 20	20–29	30–39	40–49	50–59	60–61	62–64	65–69	70 or older
All areas	-6,070	1	42	-214	-755	-2,956	-1,213	-462	-321	-192
Men	-3,147	-9	29	-176	-442	-1,494	-531	-267	-87	-170
Women	-2,923	10	13	-38	-313	-1,462	-682	-195	-234	-22
Alabama										
Men	1	3	7	-2	23	-21	0	4	-10	-3
Women	-33	6	-12	-8	-3	-3	-4	-7	1	-3
Alaska										
Men	5	-1	2	6	-2	-2	2	0	1	-1
Women	-4	0	3	-2	2	-3	-4	0	-1	1
Arizona										
Men	13	3	7	17	-1	-5	-3	-9	3	1
Women	35	6	16	12	9	-15	0	3	5	-1
Arkansas										
Men	-51	0	-2	1	-7	-30	-4	-4	-5	0
Women	-36	5	2	-8	-4	-10	-4	-8	-9	0
California										
Men	673	55	562	249	-19	-76	-49	-22	0	-27
Women	-46	22	144	31	2	-150	-49	-12	-39	5
Colorado										
Men	-21	0	15	-8	0	-20	-1	-1	2	-8
Women	16	-1	10	0	16	8	-16	-7	4	2
Connecticut										
Men	-21	2	-6	0	-1	1	-15	-4	0	2
Women	-64	-1	7	-1	-7	-32	-6	-4	-13	-7
Delaware										
Men	-31	-2	-3	-8	-10	-2	-3	-1	-2	0
Women	-35	-1	-12	-9	-3	-6	-1	-2	-2	1
District of Columbia										
Men	-42	-1	11	-17	-20	-10	-5	1	0	-1
Women	-76	-3	-24	-7	-18	-17	-5	-1	-2	1
Florida										
Men	174	17	54	47	77	-12	-16	-16	12	11
Women	76	11	38	41	-11	3	-13	-3	-1	11
Georgia										
Men	-112	10	12	-16	-2	-53	-27	-18	-4	-14
Women	-80	15	13	8	-8	-61	-16	-18	-8	-5
Hawaii										
Men	-32	-6	-15	-4	-4	-1	0	3	1	-6
Women	0	1	2	10	-4	-5	-3	3	-5	1
Idaho										
Men	-55	-2	-13	-13	-14	-6	-6	-1	0	0
Women	-15	-5	-1	4	-2	-7	-3	0	-1	0
Illinois										
Men	-389	-19	-29	-69	-41	-148	-40	-22	-10	-11
Women	-301	-4	-35	-25	-25	-120	-54	-6	-17	-15
Indiana										
Men	15	-1	4	13	11	-6	-7	9	-6	-2
Women	25	5	3	17	16	-5	-4	-11	4	0

(Continued)

Table 16.
Difference from the current-methodology estimates of the number of workers with Social Security (OASDI) taxable earnings when using the MGD process, by age, sex, and state or other area, tax year 2017—Continued

State or area	All ages	Under 20	20–29	30–39	40–49	50–59	60–61	62–64	65–69	70 or older
Iowa										
Men	-121	-2	-1	-11	-32	-66	-7	-3	4	-3
Women	-98	0	-4	-6	-27	-45	-11	-2	-2	-1
Kansas										
Men	-22	-2	2	-12	-1	-9	1	1	-1	-1
Women	-21	-1	-2	2	-5	-14	-1	1	-1	0
Kentucky										
Men	-24	0	5	-2	-14	-1	5	-8	-5	-4
Women	-52	-8	-7	-7	-7	-14	-1	-7	-3	2
Louisiana										
Men	-119	-7	-7	-16	-28	-32	-11	-3	-7	-8
Women	-93	0	-13	-22	-33	-18	3	-7	-3	0
Maine										
Men	13	1	4	3	4	1	-1	2	-1	0
Women	25	-2	-2	3	12	12	2	2	-1	-1
Maryland										
Men	-42	3	21	6	-11	-37	-9	-6	-5	-4
Women	-34	-4	-10	6	9	-32	-5	5	-9	6
Massachusetts										
Men	-66	-11	-6	-26	-20	7	-4	0	-5	-1
Women	-98	-2	-2	-14	-17	-25	-13	-17	0	-8
Michigan										
Men	-172	3	7	-5	15	-119	-54	-10	1	-10
Women	-132	1	7	4	1	-96	-46	5	-4	-4
Minnesota										
Men	-28	1	-12	4	-1	-7	4	-2	-10	-5
Women	-50	4	2	-14	-5	-27	-4	-3	-2	-1
Mississippi										
Men	-3	5	11	-7	0	-9	4	-7	-1	1
Women	-3	-2	-4	9	-3	-14	-3	7	3	4
Missouri										
Men	136	19	48	16	44	1	-8	-2	12	6
Women	131	29	20	32	12	36	-10	11	-1	2
Montana										
Men	-201	-26	-36	-50	-29	-44	0	-7	-6	-3
Women	-187	-27	-48	-40	-24	-19	-4	-7	-7	-11
Nebraska										
Men	-159	-12	-35	-45	-23	-30	-1	-7	-4	-2
Women	-134	-25	-27	-27	-15	-20	-13	-1	-5	-1
Nevada										
Men	27	1	21	-1	11	0	-5	5	0	-5
Women	39	6	9	26	5	-4	-3	3	-2	-1
New Hampshire										
Men	-3	3	2	4	-2	0	-2	-3	-2	-3
Women	22	7	2	7	2	4	-1	-1	2	0

(Continued)

Table 16.
Difference from the current-methodology estimates of the number of workers with Social Security (OASDI) taxable earnings when using the MGD process, by age, sex, and state or other area, tax year 2017—Continued

State or area	All ages	Under 20	20–29	30–39	40–49	50–59	60–61	62–64	65–69	70 or older
New Jersey										
Men	-54	-1	22	11	-2	-44	-23	-7	4	-14
Women	-44	0	34	8	-1	-48	-45	1	-1	8
New Mexico										
Men	28	5	12	5	10	-1	-3	1	0	-1
Women	10	-1	2	9	-1	0	-5	6	2	-2
New York										
Men	575	9	332	191	73	-8	-12	-12	1	1
Women	21	7	80	36	16	-64	-10	-15	-25	-4
North Carolina										
Men	-120	8	-2	-19	-35	-64	-11	7	-4	0
Women	-104	2	5	7	9	-61	-34	-20	-11	-1
North Dakota										
Men	-26	1	8	-3	-9	-11	-5	-5	1	-3
Women	-39	-5	-10	-6	-4	-4	0	-4	1	-7
Ohio										
Men	-317	-1	-37	-33	-66	-106	-42	-27	4	-9
Women	-327	-15	-13	-17	-80	-99	-63	-22	-18	0
Oklahoma										
Men	-23	1	0	-6	-8	-5	-4	0	5	-6
Women	-9	1	10	-6	8	-19	-1	4	-9	3
Oregon										
Men	-23	-2	-20	7	0	-7	2	4	-4	-3
Women	3	3	19	-8	1	-5	3	-9	2	-3
Pennsylvania										
Men	-93	11	3	12	26	-92	-40	-3	-20	10
Women	-176	10	27	21	-9	-98	-67	-39	-19	-2
Rhode Island										
Men	-20	-4	-6	0	1	-3	-1	-1	-2	-4
Women	-39	-3	-8	-7	-5	-8	-7	1	-2	0
South Carolina										
Men	55	4	32	27	8	-27	3	2	-2	8
Women	47	12	11	12	3	-5	2	9	2	1
South Dakota										
Men	-130	-8	-33	-23	-25	-25	-3	-5	-5	-3
Women	-160	-21	-37	-33	-25	-31	-4	-5	-3	-1
Tennessee										
Men	-78	8	-7	2	-22	-27	-9	-13	-7	-3
Women	-56	10	-11	-19	10	-30	-21	2	-1	4
Texas										
Men	-197	16	-2	62	-55	-145	-50	-33	1	9
Women	-127	28	30	45	-17	-134	-78	16	-16	-1
Utah										
Men	38	4	15	20	16	-10	-1	-6	3	-3
Women	17	3	9	5	4	-4	-1	-3	2	2

(Continued)

Table 16.
Difference from the current-methodology estimates of the number of workers with Social Security (OASDI) taxable earnings when using the MGD process, by age, sex, and state or other area, tax year 2017—Continued

State or area	All ages	Under 20	20–29	30–39	40–49	50–59	60–61	62–64	65–69	70 or older
Vermont										
Men	-4	-1	-5	-2	3	4	-2	0	1	-2
Women	4	0	-3	5	6	-3	0	-2	0	1
Virginia										
Men	-5	7	3	-23	25	-2	-13	-8	9	-3
Women	51	1	18	53	12	-9	-17	-3	-2	-2
Washington										
Men	15	5	31	22	9	-28	-13	-4	-5	-2
Women	25	11	19	24	24	-36	-28	-4	6	9
West Virginia										
Men	13	1	3	10	2	2	-1	1	0	-5
Women	0	-1	6	5	1	-6	2	-1	-4	-2
Wisconsin										
Men	-17	-2	6	14	-2	-10	-9	-1	-3	-10
Women	39	0	21	18	4	-3	-5	2	-1	3
Wyoming										
Men	0	1	-1	1	-1	-2	-3	2	3	0
Women	-10	3	-6	-6	-3	4	1	-4	0	1
Outlying areas ^a										
Men	-41	0	-9	-2	-7	-16	-4	-6	8	-5
Women	-38	-2	-8	-14	-5	0	-8	1	-6	4
Other and unknown										
Men	-2,066	-105	-946	-503	-286	-131	-25	-22	-27	-21
Women	-788	-65	-257	-192	-126	-100	-4	-22	-12	-10

SOURCE: Author's calculations using 2017 merged ASA-MGD file.

a. Most of the workers in this category are assigned a Puerto Rico state code. Other outlying areas are American Samoa, Guam, Northern Mariana Islands, and U.S. Virgin Islands.

trust fund contributions, by sex, for all workers, wage and salary workers, and self-employed individuals.

Evaluating the results of the MGD process at the county level is much more complex than assessing the estimates shown by state, sex, and age for three primary reasons. First, the current methodology and the MGD process use distinct sets of county codes and names. The current methodology uses SSA-designated SCCs while the MGD process uses Federal Information Processing Standards SCCs. As a result, ORES must confirm the consistency of the county names used in the two methodologies and determine if any counties are identified in one process and not the other. For example, some states recognize independent cities as well as counties.¹⁷ *Earnings and Employment* includes estimates for those independent cities. Are each of those independent cities also identified in the MGD file?

Second, data nondisclosure requirements significantly affect the quantity of county-level estimates that SSA may publish. More than one-half of the cells showing county-level data in the *Earnings and Employment* tables are suppressed to comply with disclosure restrictions. Primary cell suppression rules require any unweighted estimate of fewer than 10 workers to be suppressed. For tables that include sex, age, or type-of-earnings breakdowns, SSA must also apply secondary cell suppression. Consider a small county with an unweighted count of 25 workers. If 13 are men and 12 are women, SSA can publish estimates for the total number of workers and workers by sex for this county. However, if 16 of the workers are women and only nine are men, secondary data disclosure rules require SSA to suppress the estimates by sex and publish only the total number of workers for the county (because suppressing only the number of men would leave that value open to computation). Estimates with breakdowns by age and type of earnings only increase the instances that require cell suppression. More than one-half of the estimates of self-employed individuals are subject to primary cell suppression, which requires SSA to apply secondary cell suppression to the corresponding estimates for wage and salary workers.

Third, evaluating county-level estimates is complicated by their sheer volume. In the 2017 edition of *Earnings and Employment*, the tables showing county-level data for Social Security–covered workers contain 88,182 discreet estimates, as do the tables for Medicare-covered workers.

The comparison of the SCCs assigned via the current methodology and the MGD process takes place in

two steps. The first step involves aligning the universe of geographic identifiers: comparing all possible state and county combinations in the two methodologies irrespective of the actual distribution of workers. This step ensures that the SCCs include all possible state and county combinations in both methodologies and not just the combinations found in the CWHS micro-data file. This first step allows a direct comparison between the resulting distribution of workers under both methodologies. The second step simply extends the first step by directly comparing the numbers of workers estimated under each methodology.

Identifying All Possible State and County Combinations and Removing Incomplete or Incompatible Records

The universe of state and county combinations is drawn from the current methodology’s LABELS file (Chart 1) and the MGD file. Box 1 shows an excerpt from the LABELS file and provides examples of the geographic coding it contains. For example, row 1 shows the codes that designate workers with a missing value for both the state and county, row 2 shows the codes for workers with an “unknown” state code and a missing county value, and row 3 contains the codes for workers with the Alabama state code and a missing county value. Rows 4 through 10 and 69–70 show the data fields that apply when state and county codes are assigned. Row 71 applies the “Statewide” identifier in the county name field and indicates data for all workers in Alabama.

To focus the evaluation on counties, ORES removed LABELS file records with the values American Samoa, Armed Forces, District of Columbia, Guam, International Operations, Northern Mariana Islands, Other, Reserves, UNKNOWN, or Virgin Islands in the STATE_NAME field; and with Statewide or no value in the COUNTY_NAME field. ORES used the resulting adjusted LABELS file in comparing the current methodology with the MGD process.

The 2017 MGD file contains records for 178,863,694 workers. To limit the file to records that are relevant for comparison, ORES removed the records of workers with the values American Samoa, District of Columbia, Federated State of Micronesia, Guam, Marshall Islands, Northern Mariana Islands, Palau, UNKNOWN, or Virgin Islands in the STATE_NAME field; and UNKNOWN in the COUNTY_NAME field.

This step removed records for 1,031,176 workers from the file, leaving 177,832,518 workers represented

Box 1.
Sample data fields from current methodology’s LABELS file

ROW	STATE_SCC	COUNTY_SCC	COUNTY_NAME	STATE_ABBR	STATE_NAME	SCC
1	00	000		Nn		00000
2	00			Aa		00
3	64			AL	Alabama	64
4	64	000	Autagua	AL	Alabama	64000
5	64	010	Baldwin	AL	Alabama	64010
6	64	020	Barbour	AL	Alabama	64020
7	64	030	Bibb	AL	Alabama	64030
8	64	040	Blount	AL	Alabama	64040
9	64	050	Bullock	AL	Alabama	64050
10	64	060	Butler	AL	Alabama	64060
69	64	660	Wilcox	AL	Alabama	64650
70	64	660	Winston	AL	Alabama	64660
71	64	990	Statewide	AL	Alabama	64990

SOURCE: SSA LABELS file, derived from 2017 CWHS.

in the modified MGD file. Those records were then exported to a separate data file that sorts the workers across the U.S. counties, which can be compared with the data from the current methodology’s modified LABELS file. In both files, the county-level records are arranged by state.

The comparison begins by ensuring that the entries in the state name data fields are consistent in both files and confirming that the number of observations (that is, counties) in the state tables match. For the tax year 2017 data, this process revealed duplicate entries for Waukesha County in Wisconsin (with the same SCC) and two different SCCs associated with Teton County in Wyoming, enabling ORES to remove the duplicate records from the LABELS file.

Next, ORES compared the county names in the two files and identified nonmatching names. This review revealed mismatches caused by variant spellings of the county names, such as the following:

State	County name from—	
	LABELS file (current methodology)	MGD file
Illinois	De Witt	Dewitt
Indiana	LaGrange	Lagrange
Indiana	LaPorte	La Porte
Louisiana	St. Bernard	Saint Bernard
Missouri	St. Clair	Saint Clair
New York	St. Lawrence	Saint Lawrence

After standardizing the spelling of county names, ORES identified the following counties (or county equivalents) in the LABELS file but not the MGD file:

State	County name
Alaska	Kusilvak
Puerto Rico	Puerto Rico
Montana	Yellowstone National Park
South Dakota	Oglala Lakota
Virginia	Clifton Forge City
Virginia	Emporia City
Virginia	Nansemond City
Virginia	South Boston City

Kusilvak Census Area in Alaska and Oglala Lakota County in South Dakota were, until 2015, named Wade Hampton Census Area and Shannon County, respectively. The part of Yellowstone National Park located in Montana was a county equivalent until 1978, when the area was absorbed by two adjacent counties.¹⁸ Administrative districts called municipalities are the Puerto Rican equivalent of counties, but because no municipality is named “Puerto Rico,” that term’s appearance in the county-name data field seems to be similar to “Statewide,” or a proxy for the entire territory. Of the four independent cities in Virginia named in LABELS but not in the MGD file, Clifton Forge and South Boston voluntarily dissolved their charters as independent cities (in 2001 and 1994, respectively), and became part of their surrounding counties; Nansemond merged with Suffolk

Independent City in 1974; and Emporia remains an independent city. ORES is in the process of standardizing the county names in the two files.

Comparing County Assignments

The final step in compiling the data that allows a comparison of the two methodologies' county assignments is to compare the number of counties allocated to each state via the two processes. The number of allocated counties differed in six states: The current methodology allocated one more county to Alaska, South Dakota, and Virginia than the MGD process did, and the MGD process allocated one more county to Montana, Puerto Rico, and Texas, and two more counties to Virginia, than the current methodology did.

Regarding the counties that are identified in the current methodology but not the MGD process, 35 workers were assigned by the current process to Kusilvak Census Area in Alaska, 54 were assigned to Oglala Lakota County in South Dakota, and 66 were assigned to the independent city of Emporia in Virginia. Conversely, the MGD process assigned 1 worker to Wibaux County in Montana, 2 workers to Aibonito Municipality in Puerto Rico, 4 workers to Borden County in Texas, and 91 workers to Manassas Park Independent City and 79 workers to Poquoson Independent City in Virginia; the current methodology assigned no workers to those areas. The records for these 332 workers in 8 areas were removed from the merged county-comparison file because the evaluation requires the state and county names to align across the two methodologies. The resulting file contains records for 1,731,546 workers and 3,202 counties.

Evaluating the County-Level Estimates

With the preliminary processes complete, the resulting merged file allows a comparison of current-methodology and MGD-process county-level estimates of worker counts by type of earnings. Note that the MGD process, unlike the current methodology, does not generate any county-level estimates if the microdata file has no workers with a given type of earnings in that county. This has a pronounced effect on the number of counties to which self-employed individuals are assigned.

Table 17 shows the numbers and percentages of workers whose records have matching and nonmatching county assignments by type of earnings. More than 97 percent of the individuals represented in the county-comparison file have earnings that are taxable under Social Security. Among all workers with taxable earnings, the county-assignment match rate is 94.5 percent. Workers with OASDI taxable wage and salary earnings account for 90.3 percent of the workers in the county-comparison file. For them, the match rate for county assignments is also 94.5 percent.

Nearly 11 percent of workers represented in the county-comparison file have OASDI taxable self-employment income. Among them, the match rate for county assignments is 92.3 percent. Note that because the number of self-employed individuals is far less than that of wage and salary workers, 62 counties have at least one of the latter but none of the former, resulting in fewer counties assigned for self-employed individuals (3,140) than for wage and salary workers

Table 17.
County assignment match rates between the current methodology and the MGD process, by type of earnings, tax year 2017

Records in microdata file	All workers		Worker records with—				Counties represented
	Number	Percent of workers in microdata file	Matching county assignments		Nonmatching county assignments		
			Number	Percent	Number	Percent	
Total	1,731,546	100.00	3,202
Workers with taxable earnings	1,688,819	97.53	1,596,103	94.51	92,716	5.49	3,202
Wage and salary	1,563,334	90.29	1,477,184	94.49	86,150	5.51	3,202
Self-employed	184,978	10.68	170,637	92.25	14,341	7.75	3,140

SOURCE: Author's calculations using 2017 LABELS, MGD, and merged ASA-MGD files.

NOTES: Because some workers accrued both wage and salary and self-employment earnings, the sum of those two categories exceeds the numbers of all workers with taxable earnings (and all workers represented in the microdata file).

... = not applicable.

(3,202). Table 18 shows the county-assignment match rates by state.¹⁹ The match rates for all workers range from a high of 99.3 percent for Hawaii to a low of 80.3 percent for Virginia.

As noted earlier, the critical limitation of the current methodology is that data disclosure restrictions require some estimates to be suppressed, and estimates based on a 1-percent sample of self-employed individuals fall under that rule in many counties. Table 19 shows, for each state, the percentage distribution of counties by the number of self-employed workers with Social Security taxable earnings who have records assigned by the current methodology to that county. Nearly 30 percent of Alabama's 67 counties, for example, have fewer than 10 self-employed individuals assigned to them in the current methodology, and primary cell suppression rules require SSA to suppress the estimates for those counties in *Earnings and Employment*. Although the estimated number of wage and salary workers exceeds 10 in most if not all of those counties, secondary cell suppression rules require SSA to suppress those estimates as well. In total, more than 37 percent of the county estimates for self-employed individuals (and, therefore, also for wage and salary workers) must be suppressed.

Further, as noted earlier, publishing county-level estimates by worker sex requires that a county contain a minimum of 20 self-employed individuals to meet the data disclosure threshold. Adding this restriction requires SSA to suppress more than 60 percent of the county-level estimates for self-employed individuals, and secondary cell suppression applies to the corresponding county estimates for wage and salary workers. Given the complexity of incorporating data disclosure procedures into the large number of county-level estimates that would have to be generated, ORES decided to forgo any attempt to compare the estimates of the amount of taxable OASDI earnings for the two methodologies. These circumstances highlight the importance of using a much larger sample of workers to generate the annual employment and earnings estimates.

Conclusion

This article presents two distinct assessments of the MGD process: a procedural evaluation of the completeness and consistency of the MGD data produced over time and a comparison of current-methodology and MGD-process assignment of residential location

and demographic data for earners in tax year 2017. The procedural evaluation shows very consistent outcomes for the MGD process across tax years 2015–2020. Although the procedural evaluation identified some minor issues that ORES is investigating, it found that the MGD process is robust and working as expected. In comparing the estimated number of all workers with taxable earnings, the state code assigned in the MGD process matched that of the current methodology for 98.9 percent of the records (Table 9). As was expected prior to the evaluation, the match rate for county assignments was lower, at 94.5 percent (Table 17). The primary reason for occasional disagreement between the two methodologies is a difference in the level of detail with which geographic information is recorded. The current methodology assigns county codes using only the first five letters of the city name and the five-digit ZIP Codes reported on the workers' tax forms. Additionally, the current process uses the SCCs generated for two different data files within the CWHS system and does not consistently select the code from only one of those files. ORES believes that the MGD process is more accurate because it relies on more recently developed software that uses the full address information reported on workers' tax forms to assign SCCs.

Worker sex and age identified in the MGD process match those identified in the current methodology at very high rates (99.3 percent and 98.9 percent, respectively; Tables 13 and 15). The current methodology extracts age and sex information from either of two different CWHS files. In theory, the values in these files should match. Although the nonmatch rates for sex and age are low, ORES believes that the MGD process is the more accurate of the two methodologies because it assigns sex and age identifiers based on a single authoritative source.

The evaluation's results are encouraging. ORES will continue developing the MGD process to provide a streamlined, modern method of generating its annual earnings estimates using a much larger sample of earners. Using a larger sample will eliminate the need for cell suppression in many instances and enable ORES statistical publications to report county-level estimates with much greater depth and accuracy.

Table 18.**Number of workers with Social Security (OASDI) taxable earnings for whom the county assigned using the current methodology and the MGD process matches, by state or other area and type of earnings, tax year 2017**

State or area	All				Wage and salary				Self-employed			
	Worker records	County code matches		Number of counties	Worker records	County code matches		Number of counties	Worker records	County code matches		Number of counties
		Number	Percent			Number	Percent			Number	Percent	
All areas	1,668,819	1,577,202	94.51	3,202	1,563,334	1,477,184	94.49	3,202	184,978	170,637	92.25	3,140
Alabama	23,818	22,233	93.35	67	22,493	21,007	93.39	67	2,410	2,160	89.63	67
Alaska	3,657	3,623	99.07	22	3,438	3,405	99.04	22	395	384	97.22	21
Arizona	33,700	32,810	97.36	15	31,764	30,922	97.35	15	3,450	3,283	95.16	15
Arkansas	14,478	13,750	94.97	75	13,562	12,887	95.02	75	1,608	1,466	91.17	75
California	188,006	183,290	97.49	58	172,485	168,093	97.45	58	24,969	23,862	95.57	56
Colorado	28,982	23,907	82.49	63	26,933	22,170	82.32	63	3,626	2,927	80.72	61
Connecticut	19,587	19,060	97.31	8	18,293	17,804	97.33	8	2,225	2,118	95.19	8
Delaware	5,177	5,075	98.03	3	4,962	4,862	97.98	3	422	411	97.39	3
District of Columbia
Florida	104,227	99,721	95.68	67	96,233	92,008	95.61	67	13,422	12,526	93.32	67
Georgia	52,187	46,476	89.06	159	48,814	43,474	89.06	159	6,010	5,176	86.12	155
Hawaii	7,461	7,405	99.25	4	6,939	6,886	99.24	4	850	836	98.35	4
Idaho	8,798	8,499	96.60	44	8,258	7,976	96.59	44	950	893	94.00	42
Illinois	66,187	61,773	93.33	102	62,195	58,023	93.29	102	7,214	6,623	91.81	101
Indiana	36,428	35,043	96.20	92	34,827	33,540	96.30	92	3,115	2,878	92.39	92
Iowa	17,645	16,826	95.36	99	16,687	15,950	95.58	99	1,844	1,662	90.13	98
Kansas	15,738	15,315	97.31	105	14,861	14,465	97.34	105	1,640	1,558	95.00	104
Kentucky	22,161	21,157	95.47	120	20,943	20,002	95.51	120	2,171	2,009	92.54	118
Louisiana	21,576	20,338	94.26	64	20,140	18,973	94.21	64	2,534	2,350	92.74	62
Maine	7,133	6,994	98.05	16	6,600	6,465	97.95	16	912	883	96.82	16
Maryland	33,182	30,384	91.57	24	31,388	28,732	91.54	24	3,368	3,003	89.16	24
Massachusetts	36,422	35,445	97.32	14	34,006	33,083	97.29	14	4,144	3,951	95.34	14
Michigan	51,993	49,248	94.72	83	49,183	46,586	94.72	83	5,202	4,816	92.58	83
Minnesota	32,227	29,958	92.96	87	30,575	28,425	92.97	87	3,198	2,912	91.06	87
Mississippi	14,291	13,452	94.13	82	13,399	12,600	94.04	82	1,691	1,562	92.37	81

(Continued)

Table 18.**Number of workers with Social Security (OASDI) taxable earnings for whom the county assigned using the current methodology and the MGD process matches, by state or other area and type of earnings, tax year 2017—Continued**

State or area	All				Wage and salary				Self-employed			
	Worker records	County code matches		Number of counties	Worker records	County code matches		Number of counties	Worker records	County code matches		Number of counties
		Number	Percent			Number	Percent			Number	Percent	
Missouri	31,474	28,454	90.40	115	29,766	26,905	90.39	115	3,183	2,802	88.03	115
Montana	5,715	5,622	98.37	55	5,343	5,261	98.47	55	664	626	94.28	53
Nebraska	10,846	10,228	94.30	93	10,245	9,676	94.45	93	1,142	1,047	91.68	84
Nevada	13,924	13,775	98.93	17	13,090	12,953	98.95	17	1,453	1,407	96.83	15
New Hampshire	8,025	7,928	98.79	10	7,518	7,424	98.75	10	825	806	97.70	10
New Jersey	49,323	48,086	97.49	21	46,376	45,192	97.45	21	5,278	5,041	95.51	21
New Mexico	9,730	9,297	95.55	33	9,189	8,771	95.45	33	931	875	93.98	30
New York	105,544	102,894	97.49	62	98,464	95,944	97.44	62	12,456	11,900	95.54	61
North Carolina	52,259	49,334	94.40	100	49,224	46,479	94.42	100	5,460	5,007	91.70	100
North Dakota	4,364	4,233	97.00	53	4,118	4,001	97.16	53	505	475	94.06	50
Ohio	58,197	54,923	94.37	88	54,742	51,646	94.34	88	5,885	5,498	93.42	88
Oklahoma	19,579	17,637	90.08	77	18,444	16,616	90.09	77	2,037	1,774	87.09	76
Oregon	21,652	19,965	92.21	36	20,306	18,729	92.23	36	2,284	2,048	89.67	35
Pennsylvania	68,629	65,547	95.51	67	65,159	62,255	95.54	67	6,410	5,963	93.03	67
Rhode Island	5,925	5,851	98.75	5	5,611	5,540	98.73	5	587	564	96.08	5
South Carolina	25,448	23,533	92.47	46	24,147	22,327	92.46	46	2,448	2,195	89.67	46
South Dakota	5,100	4,743	93.00	65	4,789	4,455	93.03	65	606	545	89.93	63
Tennessee	34,939	33,201	95.03	95	32,584	30,962	95.02	95	4,121	3,789	91.94	95
Texas	133,970	124,157	92.68	252	124,227	115,108	92.66	252	16,603	14,957	90.09	240
Utah	16,266	15,992	98.32	29	15,592	15,328	98.31	29	1,481	1,417	95.68	28
Vermont	3,757	3,614	96.19	14	3,524	3,389	96.17	14	433	406	93.76	14
Virginia	45,625	36,642	80.31	130	43,268	34,768	80.35	130	4,468	3,392	75.92	128
Washington	39,425	38,303	97.15	39	37,367	36,298	97.14	39	3,623	3,444	95.06	39
West Virginia	8,358	7,984	95.53	55	7,972	7,620	95.58	55	681	631	92.66	53
Wisconsin	32,506	31,108	95.70	72	31,055	29,734	95.75	72	2,714	2,531	93.26	72
Wyoming	3,205	3,161	98.63	23	3,026	2,984	98.61	23	355	340	95.77	23
Puerto Rico	9,973	9,208	92.33	77	9,210	8,481	92.08	77	975	908	93.13	75

SOURCE: Author's calculations using 2017 LABELS, MGD, and merged ASA-MGD files.

NOTES: Because some workers accrued both wage and salary and self-employment earnings, the sum of those two categories exceeds the number of all workers with taxable earnings.

... = not applicable.

Table 19.**Percentage distribution of counties by the number of self-employed individuals with Social Security (OASDI) taxable earnings identified under the current methodology, by state or other area, tax year 2017**

State or area	Total	0-9	10-19	20-29	30-49	50-99	100-249	250-499	500-999	1,000 or more
All areas	100.00	37.36	22.90	11.11	9.59	8.38	5.92	2.61	1.43	0.70
Alabama	100.00	29.85	26.87	13.43	8.96	13.43	5.97	1.49	0.00	0.00
Alaska	100.00	66.67	9.52	4.76	4.76	9.52	4.76	0.00	0.00	0.00
Arizona	100.00	13.33	6.67	6.67	13.33	33.33	13.33	0.00	6.67	6.67
Arkansas	100.00	41.33	32.00	10.67	8.00	4.00	4.00	0.00	0.00	0.00
California	100.00	7.14	12.50	5.36	7.14	12.50	21.43	12.50	8.93	12.50
Colorado	100.00	45.90	18.03	8.20	6.56	6.56	4.92	8.20	1.64	0.00
Connecticut	100.00	0.00	0.00	0.00	0.00	37.50	25.00	25.00	12.50	0.00
Delaware	100.00	0.00	0.00	0.00	0.00	33.33	66.67	0.00	0.00	0.00
District of Columbia
Florida	100.00	17.91	13.43	8.96	5.97	14.93	17.91	11.94	4.48	4.48
Georgia	100.00	41.94	25.16	7.74	7.74	10.97	3.87	0.00	2.58	0.00
Hawaii	100.00	0.00	0.00	0.00	0.00	25.00	50.00	0.00	25.00	0.00
Idaho	100.00	57.14	16.67	11.90	4.76	4.76	2.38	2.38	0.00	0.00
Illinois	100.00	34.65	27.72	11.88	8.91	6.93	4.95	2.97	0.99	0.99
Indiana	100.00	28.26	33.70	9.78	11.96	9.78	5.43	0.00	1.09	0.00
Iowa	100.00	38.78	42.86	8.16	3.06	5.10	1.02	1.02	0.00	0.00
Kansas	100.00	67.31	19.23	5.77	2.88	2.88	0.96	0.96	0.00	0.00
Kentucky	100.00	54.24	24.58	11.02	5.08	3.39	0.85	0.85	0.00	0.00
Louisiana	100.00	24.19	35.48	8.06	8.06	12.90	8.06	3.23	0.00	0.00
Maine	100.00	6.25	0.00	37.50	18.75	25.00	6.25	6.25	0.00	0.00
Maryland	100.00	0.00	12.50	16.67	20.83	12.50	20.83	12.50	4.17	0.00
Massachusetts	100.00	0.00	0.00	7.14	14.29	7.14	28.57	28.57	7.14	7.14
Michigan	100.00	21.69	27.71	13.25	13.25	13.25	6.02	2.41	2.41	0.00
Minnesota	100.00	26.44	39.08	11.49	9.20	8.05	3.45	1.15	1.15	0.00
Mississippi	100.00	34.57	38.27	9.88	7.41	7.41	2.47	0.00	0.00	0.00
Missouri	100.00	40.87	30.43	13.04	7.83	2.61	2.61	2.61	0.00	0.00
Montana	100.00	73.58	11.32	1.89	5.66	7.55	0.00	0.00	0.00	0.00
Nebraska	100.00	66.67	19.05	9.52	2.38	0.00	1.19	1.19	0.00	0.00
Nevada	100.00	53.33	6.67	13.33	13.33	0.00	6.67	0.00	0.00	6.67
New Hampshire	100.00	0.00	0.00	0.00	20.00	40.00	10.00	10.00	0.00	0.00
New Jersey	100.00	0.00	0.00	0.00	9.52	19.05	28.57	33.33	9.52	0.00
New Mexico	100.00	36.67	30.00	10.00	13.33	0.00	6.67	3.33	0.00	0.00
New York	100.00	3.28	11.48	16.39	26.23	13.11	13.11	4.92	6.56	4.92
North Carolina	100.00	19.00	20.00	17.00	17.00	16.00	8.00	1.00	2.00	0.00
North Dakota	100.00	74.00	14.00	4.00	6.00	2.00	0.00	0.00	0.00	0.00
Ohio	100.00	10.23	19.32	23.86	18.18	13.64	10.23	1.14	3.41	0.00
Oklahoma	100.00	44.74	26.32	15.79	7.89	1.32	1.32	2.63	0.00	0.00
Oregon	100.00	25.71	22.86	8.57	20.00	2.86	17.14	0.00	2.86	0.00
Pennsylvania	100.00	10.45	16.42	14.93	17.91	17.91	11.94	5.97	4.48	0.00
Rhode Island	100.00	0.00	0.00	0.00	20.00	60.00	0.00	20.00	0.00	0.00

(Continued)

Table 19.**Percentage distribution of counties by the number of self-employed individuals with Social Security (OASDI) taxable earnings identified under the current methodology, by state or other area, tax year 2017—Continued**

State or area	Total	0–9	10–19	20–29	30–49	50–99	100–249	250–499	500–999	1,000 or more
South Carolina	100.00	23.91	19.57	13.04	13.04	10.87	15.22	4.35	0.00	0.00
South Dakota	100.00	69.84	23.81	3.17	0.00	1.59	1.59	0.00	0.00	0.00
Tennessee	100.00	28.42	26.32	16.84	11.58	9.47	4.21	1.05	2.11	0.00
Texas	100.00	44.58	18.33	9.58	10.42	6.25	5.42	2.50	1.25	1.67
Utah	100.00	53.57	10.71	10.71	3.57	10.71	3.57	3.57	3.57	0.00
Vermont	100.00	14.29	7.14	42.86	21.43	7.14	7.14	0.00	0.00	0.00
Virginia	100.00	41.41	21.88	10.16	11.72	6.25	7.81	0.00	0.78	0.00
Washington	100.00	20.51	17.95	20.51	12.82	7.69	12.82	5.13	0.00	2.56
West Virginia	100.00	60.38	18.87	7.55	11.32	1.89	0.00	0.00	0.00	0.00
Wisconsin	100.00	20.83	27.78	18.06	12.50	16.67	1.39	2.78	0.00	0.00
Wyoming	100.00	56.52	8.70	21.74	13.04	0.00	0.00	0.00	0.00	0.00
Puerto Rico	100.00	66.67	20.00	4.00	2.67	5.33	0.00	0.00	0.00	0.00

SOURCE: Author's calculations using 2017 LABELS, MGD, and merged ASA-MGD files.

NOTE: . . . = not applicable.

Notes

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¹ A tax year is the calendar year in which wage, salary, or self-employment income is earned.

² The current methodology was developed in the 1990s, when limited computer storage capacity required ORES to abbreviate city names to their first five letters and use five-digit (rather than nine-digit) ZIP Codes in its geographic data fields.

³ IRS Form W-2 is the annual wage and tax statement that employers file on behalf of employees. Form W-2c, “Corrected Wage and Tax Statement,” is filed when a worker’s original W-2 contained any errors or otherwise needs to be updated.

⁴ Finalist is capable of assigning SCCs using full addresses with nine-digit ZIP Codes rather than relying on the five-digit ZIP Codes, which sometimes cross county lines, and the abbreviated city names that the current methodology uses to assign SCCs.

⁵ The Numident contains records for all SSNs ever issued. The information is derived from SSA Form SS-5,

the application for an SSN, which contains the individual’s name, place and date of birth, and sex.

⁶ For all tax years except 2015, the percentage of workers who were not assigned an SCC by the OEIS/Finalist process was less than 1 percent. The lack of an assigned SCC may be caused by an incomplete address on the worker’s tax form or the absence of an address in the underlying Finalist database that contains every U.S. postal delivery address. (The software cross-references the address reported on tax sources with the postal delivery data file to assign SCCs.)

⁷ This information is included on the tax forms but the OEIS process uses only the address information because its sole focus is on assigning an SCC for each job.

⁸ I discuss the results of those determinations later.

⁹ The COVID-19 pandemic led to a significant backlog in Schedule SE processing in 2021.

¹⁰ The invalid SSNs can be used in the process of assigning a single SCC to each worker and their use enables ORES to have a complete picture of the geographic location of the worker population in a given tax year. As previously noted, the sex and date of birth for these workers cannot be identified.

¹¹ Compson (2022) discusses the limitations of the methodology currently used to assign geographic codes to workers in the CWHS.

¹² The timing of the processing depends on the timing of the tax form submissions by employers and self-employed workers. In SSA, the processing year typically runs through December 15th, meaning that some forms are likely to be

submitted and processed early. In addition, the COVID-19 pandemic led to delays in submitting and processing some tax forms.

¹³ Modifications are necessary because the published estimates are weighted and adjusted to reflect a nationwide population of workers based on a 1-percent sample. To enable a comparison of statistically compatible estimates, the modification entails using the unweighted and unadjusted raw data from the 1-percent CWHS that underlie the published estimates rather than the published estimates themselves.

¹⁴ These workers are included in the “Other” category in *Earnings and Employment* and the “Other and unknown” category in the *Annual Statistical Supplement*.

¹⁵ For brevity, the District of Columbia is referred to as a state throughout the discussion to follow.

¹⁶ Because wage and salary workers vastly outnumber self-employed individuals, similarity in the match rates for all workers and for wage and salary workers is a recurring pattern in the evaluation.

¹⁷ Hereafter, “counties” can be assumed to include county equivalents such as independent cities, parishes, and census areas.

¹⁸ Although Montana dissolved the area as a standalone county equivalent in 1978, the Census Bureau continued to recognize the area as a county equivalent until 1997.

¹⁹ Because the District of Columbia does not have county-equivalent subdistricts, it is included among the *Earnings and Employment* tables showing statistics by state but not among those showing statistics by county. Therefore, Tables 18 and 19 omit values for the District of Columbia (and include those for Puerto Rico, which is covered in the *Earnings and Employment* tables showing statistics by county).

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WORK OVERPAYMENTS AMONG NEW SOCIAL SECURITY DISABILITY INSURANCE BENEFICIARIES

by Denise Hoffman, Monica Farid, John T. Jones, Serge Lukashanets, and Michael T. Anderson*

We study the longitudinal experiences of the 2008 cohort of first-time Disability Insurance (DI) beneficiaries who were at risk of benefit overpayment because of work activity. Less than 4 percent of these beneficiaries ever met the criteria for benefit suspension or termination for work within 10 years of award, yet 82 percent of this at-risk subsample were overpaid during those 10 years. Nearly all overpayments (89 percent) began in the first month after work incentives were exhausted. About 16 percent of beneficiaries received employment support services before being overpaid, representing a potential point for intervention to avoid overpayments. We also find that overpaid beneficiaries were less likely than other working beneficiaries to have benefits terminated for work in the 10 years after DI award. Understanding the beneficiary pathways that lead to overpayments might help policy-makers design policies that minimize overpayments or, if they occur, help beneficiaries maintain employment.

Introduction

A work-related overpayment occurs when the Social Security Administration (SSA) issues a monthly Social Security Disability Insurance (DI) benefit to which an individual is not entitled because of his or her substantial work activity. A beneficiary can appeal an overpayment, but if the appeal is unsuccessful, he or she is required to repay the overpayment debt. SSA-funded resources are available to help beneficiaries navigate overpayments, including the Work Incentives Planning and Assistance program, which provides benefits counseling; and the Protection and Advocacy for Beneficiaries of Social Security program, which provides legal support, advocacy, and information to help beneficiaries resolve employment-related issues.

Not all benefit overpayments are caused by work activity. However, this article focuses on work-related overpayments to DI disabled-worker beneficiaries and uses the terms “overpayments” and “overpaid beneficiaries” in that specific context. Work-related overpayments are prevalent among DI beneficiaries who work. For example, 71 percent of beneficiaries who

were at risk of a work-related overpayment because of sustained substantial earnings were overpaid during 2010–2012. The median overpayment amount accrued was more than \$9,000 and overpayments lasted for a median of 9 months (Hoffman and others 2019). Overpayments are also prevalent among DI beneficiaries participating in Ticket to Work, an SSA-funded program designed to help beneficiaries establish and maintain employment. The Government Accountability Office (GAO) estimated that approximately 96 percent of Ticket to Work participants who had substantial earnings received overpayments during 2002–2010 (GAO 2021).

Selected Abbreviations

DAF	Disability Analysis File
DBAD	Disabled Beneficiaries and Dependents
DI	Disability Insurance
EN	employment network
EPE	extended period of eligibility
FRA	full retirement age

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Selected Abbreviations—Continued

GAO	Government Accountability Office
MEF	Master Earnings File
SGA	substantial gainful activity
SSA	Social Security Administration
SSI	Supplemental Security Income
SVRA	state vocational rehabilitation agency
TWP	trial work period

Overpayments can cause financial and other challenges for DI beneficiaries and for SSA. For beneficiaries, repaying overpayments can create economic hardship and stress (O’Day and others 2016; Hoffman and others 2017). Overpayments can also cause a decline in the proportion of beneficiaries who continue to work and earn substantial amounts (Anand and others 2022; Shenk and Livermore 2021). For SSA, recouping overpaid benefits creates fiscal and administrative challenges (SSA 2015). Minimizing overpayments is one of SSA’s primary program integrity goals (SSA 2020c).

Despite the adverse implications of overpayments on DI beneficiaries and SSA, little is known about the beneficiary’s program-participation milestones that lead to overpayment. Previous literature describes work-related milestones and longitudinal work outcomes for a broad population of beneficiaries without distinguishing overpaid beneficiaries from correctly paid beneficiaries (Hennessey and Muller 1994; Liu and Stapleton 2011; Ben-Shalom and Mamun 2015; Anand and Ben-Shalom 2018).

This article documents beneficiaries’ experiences preceding overpayments among those who received a new DI award in 2008. We describe beneficiaries’ overpayment experiences by documenting temporal aspects of overpayments, including the time between the initial DI award and the first overpayment, the duration of the overpayment, and the number of overpayment spells. We focus on beneficiaries who are at risk of an overpayment and compare the experiences of beneficiaries who are overpaid with those who are not. We describe differences in the attainment rates and the timing of their work-related milestones, which include employment support service receipt, earnings, use of SSA work incentives, and suspension or termination of benefits because of work activity. Understanding the differences in the program-participation and work-related milestones and comparing the milestone

pathways taken by those who are and are not overpaid could highlight potential services or intervention points to help avoid overpayments. It could also suggest the extent to which overpayments lead to differing program participation outcomes such as benefit continuation versus termination because of work activity.

Background

DI benefits are an important safety net for people who meet the program eligibility requirements. In 2019, 8.4 million people received DI disabled-worker benefits, and the average monthly benefit amount was \$1,258 (SSA 2020b). For more than 80 percent of beneficiaries, DI benefits account for more than half of their income (Bailey and Hemmeter 2015). To qualify for DI disabled-worker benefits, a person must be unable to engage in substantial gainful activity (SGA) because he or she has a medically determinable physical or mental impairment that has lasted or is expected to last for at least 12 continuous months or result in death (SSA 2022a). Disabled-worker beneficiaries, who account for 86 percent of all disabled DI beneficiaries, must also have a sufficient work history to be eligible for benefits (SSA 2020b). Children, widows, and widowers of SSA beneficiaries may qualify for benefits because of their own medical impairment even if they have limited or no work experience.

After a waiting period, DI beneficiaries can receive cash benefits and public health insurance coverage. There is generally a 5-month waiting period between disability onset and the date DI benefits can begin.¹ After beneficiaries are entitled to DI benefits for 24 months, they are also eligible for Medicare coverage. Because the process for adjudicating DI applications can be complex and because beneficiaries may appeal a denied claim, some beneficiaries are eligible for both cash benefits (including retroactive benefits) and Medicare coverage at the time of DI award. Once enrolled, to continue receiving DI benefits, beneficiaries must continue to have a medical impairment that prevents them from engaging in SGA. SGA is defined as earnings exceeding an annually adjusted monthly threshold. In 2024, the SGA level is \$1,550 per month for non-blind individuals and \$2,590 per month for blind individuals (SSA 2024). After an initial period in which SSA work incentives allow beneficiaries to test their ability to work without forfeiting benefits, beneficiaries are generally not entitled to benefits for months in which they have earnings above the SGA threshold.

DI eligibility continues until a beneficiary dies, transitions to the Social Security retirement program, or has his or her benefits terminated for SGA or medical improvement. However, even with DI benefits, about 20 percent of beneficiaries live in poverty (Messel and Trenkamp 2022). Earned income could help these beneficiaries maintain their connection to the labor force and improve their financial stability. Many DI beneficiaries have work-related goals, and some beneficiaries are employed. A recent study found that 45 percent of DI beneficiaries considered employment a personal goal or a near-term expectation (Livermore, Shenk, and Sevak 2020). Among beneficiaries awarded DI benefits in 1996, 28 percent returned to work and earned more than \$1,000 in at least 1 of the 10 years after award (Liu and Stapleton 2011). Among 2001 DI awardees who exhausted all SSA work incentives that allow benefits to continue despite work activity, 4.3 percent engaged in SGA for at least 1 month in the 10 years after award (Anand and Ben-Shalom 2018).

SSA's Ticket to Work program offers supports to help beneficiaries achieve work-related goals. Ticket to Work allows DI beneficiaries to receive employment support services from two types of organizations, state vocational rehabilitation agencies (SVRAs) and employment networks (ENs). SSA pays those organizations if a beneficiary uses their services and achieves certain employment milestones or outcomes.² SVRAs provide customized services in line with an individual's employment goals, interests, and abilities. Services can include career counseling, work-based learning experiences, financial support for vocational training and postsecondary education, rehabilitation technology, transportation, and other services and supports (Department of Education 2020). An EN is a private or public individual or organization that provides or coordinates employment-related services. ENs have reported that Ticket to Work can help beneficiaries avoid overpayments (GAO 2021). However, a Ticket to Work blog (SSA 2017) indicated that some participants fail to report their earnings, resulting in overpayments, because of a misconception that employment service providers automatically report their earnings for them.

SSA work incentives allow beneficiaries to test their ability to work. For example, during a trial work period (TWP), DI beneficiaries can work and earn at any level with no effect on their DI benefits. The TWP consists of 9 months (which need not be consecutive) in which earnings exceed an annually

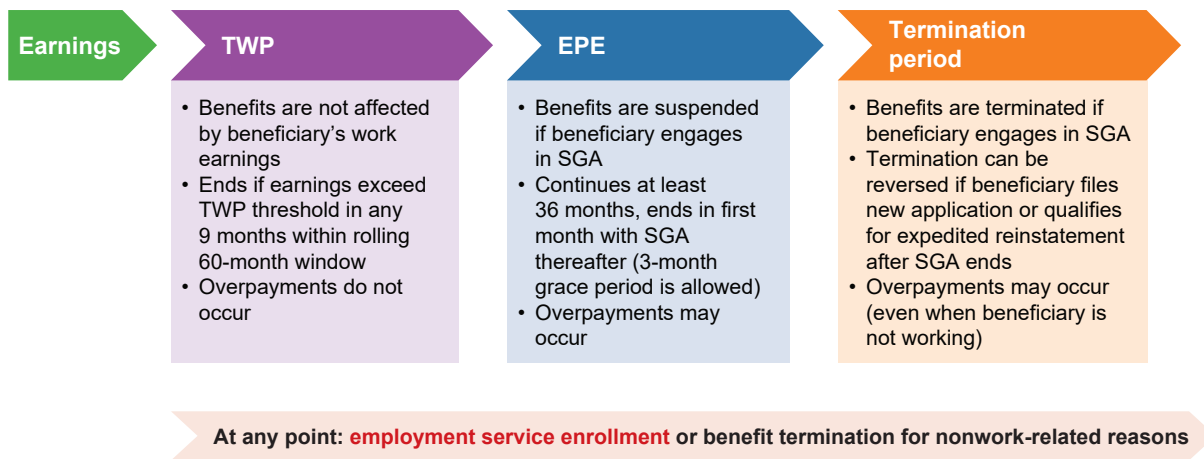
adjusted monthly threshold (\$1,110 in 2024) in a rolling 60-month window.³ An extended period of eligibility (EPE) immediately follows the TWP and lasts at least 36 consecutive months. During the first 36 months, beneficiaries are ineligible for DI benefits in any month in which they engage in SGA, except for a grace period comprising the first month of SGA and the following 2 months. After the grace period, benefits are suspended for any months in which the beneficiary engages in SGA. We refer to SGA after the grace period as meeting the criteria for benefit suspension because of work. Beneficiaries are eligible for benefits in months in which earnings are below the SGA threshold during the 36-month EPE. Starting with the 37th month, if a beneficiary engages in SGA, his or her DI benefits terminate immediately or, if available, after the grace period (the benefit termination period). We refer to SGA after the 37th month and after the grace period as meeting the criteria for benefit termination because of work.

Chart 1 summarizes the work-related milestones a beneficiary may encounter following award. A beneficiary who works may sequentially experience substantial earnings, a TWP, an EPE, and—eventually, if still entitled to benefits—a benefit termination period. The chart also reports the potential for overpayments in the TWP, EPE, and benefit termination periods, which are described in more detail below. Beneficiaries can choose to receive employment services in any of the phases shown in Chart 1.⁴ They also might experience benefit termination at any time for no longer meeting nonwork-related eligibility criteria.

Overpayments may occur after beneficiaries complete the TWP and grace period when they meet the criteria for benefit suspension or termination because of work. During the EPE, work-related overpayments can occur when a beneficiary engages in SGA and meets the conditions for which benefits should be suspended according to program rules. If SSA does not revise the beneficiary's records to change his or her eligibility status and continues to pay cash benefits, then the beneficiary is overpaid. Overpayments can accrue from the month that benefit eligibility terminates through the month in which SSA takes corrective administrative action to discontinue benefit payments.

Overpayments generally occur because of delays in transmitting earnings information to SSA and in agency processing of earnings information. Most DI beneficiaries who work do not report their earnings timely, even though they are expected to report earnings right away when they start or stop work

Chart 1.
Work-related milestones experienced by DI beneficiaries



SOURCE: Authors' compilation of SSA program descriptions.

NOTE: DI beneficiaries with earnings above certain thresholds for certain durations are subject to varying work incentive rules governing how earnings affect benefit amounts. They are also subject to medical and age-based DI eligibility criteria.

or experience a change in their work or earnings (SSA 2024). In 2012, an estimated 65 percent of work-related overpayment dollars were attributable to beneficiary reporting failures (SSA 2018). This is likely in part because beneficiaries are unaware of or do not understand the consequences of failing to meet reporting requirements (Hoffman, Deutsch, and Seifert 2023). Beneficiary interviews revealed that some overpaid beneficiaries were completely unaware of earnings reporting requirements or pending overpayments until they were notified of an overpayment (Kregel 2018). Shenk and Livermore (2021) found that the anticipation of benefit suspension is associated with a lower likelihood of overpayment.

For beneficiaries who do not report earnings timely, SSA must wait to receive earnings information from other sources. Historically, SSA's primary alternative source of earnings information has been annual data provided by the Internal Revenue Service, which can take months or years to become available (SSA 2011). SSA has recently established more timely sources of earnings information, including quarterly earnings data from the Department of Health and Human Services' Office of Child Support Services.

Additionally, SSA does not timely process the earnings information in every case. Earnings processing involves confirming alleged work incentives, verifying wages, gathering additional evidence as needed, and applying the complex rules to individual cases.

Historically, SSA has prioritized processing for self-reported earnings ahead of earnings identified from other sources (SSA 2018). Overpayments may continue to accrue with each month of delayed beneficiary reporting or SSA processing. An audit report by the SSA Office of the Inspector General noted that once beneficiaries report earnings, they may—sometimes mistakenly—presume that SSA is correctly paying benefits (SSA 2018).

Previous research has documented differences between beneficiaries who are overpaid and those who are not overpaid. Using survey data, Shenk and Livermore (2021) found that, among recently employed beneficiaries, work-related overpayments were highest among DI beneficiaries who were 55 or younger, had some college education, and were more than 10 years beyond their initial award, and that work-related overpayments were lowest among DI beneficiaries with a sensory disorder or intellectual disability. Using administrative data, Hoffman and others (2019) documented differences in overpayment rates among beneficiaries who are at risk of a work-related overpayment, which is a smaller subgroup than those who were recently employed. The authors conducted a multivariate analysis, which indicated that after controlling for observable characteristics, statistically significant predictors of an overpayment include being younger than 55, Black, or Hispanic; having less than a high school education; having a mental

disorder; receiving concurrent DI benefits and Supplemental Security Income (SSI) payments; and receiving a monthly DI benefit of less than \$1,000.

As mentioned earlier, overpayments can cause financial and other challenges. Overpayments can create economic hardship and stress on beneficiaries and can act as a disincentive to work (O'Day and others 2016; Hoffman and others 2017; Smalligan and Boyens 2023). Kregel (2018) conducted a qualitative study that provided additional context about beneficiary experiences with overpayments and documented negative reactions among affected beneficiaries. According to survey data, nearly one-quarter of overpaid beneficiaries reported changing their employment because of an overpayment (Shenk and Livermore 2021). Other research has documented a causal effect between overpayments and reduced work activity (Anand and others 2022).

Overpayments are also problematic for SSA. In fiscal year 2022, SSA recovered less than 18 percent of overpayment debt at an administrative cost of \$0.06 for every \$1 recovered (SSA 2022b). A longitudinal analysis suggested ongoing challenges with overpayment recovery: of all the overpayment debt SSA identified in 2004, nearly half was waived, canceled, or outstanding 10 years later (SSA 2015). A recent article summarized many of the challenges with overpayments and noted that the prevalence of overpayments “feeds a perception that work doesn’t pay and creates confusion, heartache, hardship and hassle for both the individual and the Social Security Administration” (Smalligan and Boyens 2023).

Data and Methods

In this section, we describe the data sources and sample selection criteria used in this analysis. We then describe how we identified beneficiaries at risk of overpayment and those who were overpaid. Finally, we describe our approach to identifying program milestones and pathways.

Data

For this analysis, we used the 2019 version of SSA’s Disability Analysis File (DAF), a restricted-access data file that combines data from multiple Social Security administrative data sources and is the agency’s largest longitudinal database of DI beneficiaries. The DAF is recreated every year with updated data. We used the DAF to identify all beneficiaries who were first awarded DI benefits in 2008. Because the data are longitudinal, we can follow the milestones

that the 2008 award cohort achieved over a 10-year period. The DAF contains comprehensive information on beneficiary characteristics, monthly earnings, and the program milestones we study, including TWP completion, use of EN or SVRA services, benefit suspension because of work, work-related and medical benefit terminations, reaching full retirement age (FRA), and death.

To identify overpayments, we used data from the December 2020 Disabled Beneficiaries and Dependents (DBAD) file, which is a monthly extract of the Master Beneficiary Record (MBR), the primary repository of data used to administer the DI program. When SSA is apprised of a beneficiary’s work activity, the agency updates the MBR to reflect the revised status. Each MBR update supersedes all previous iterations, and historical records are not retained. The DBAD files, however, capture historical information by preserving monthly snapshots of the MBR. The DBAD file’s preservation of historical records allows us to identify overpayments by comparing the benefits a beneficiary received while working with the benefits he or she should or should not have received.

We supplemented the DAF and DBAD data with information from the Master Earnings File (MEF). The MEF contains annual earnings data derived from Internal Revenue Service Form W-2, filed by employers, and Form 1040 Schedule SE, filed by self-employed workers. The DAF also includes monthly earnings information derived from SSA’s Disability Control File. However, the Disability Control File includes only earnings identified through continuing disability reviews, which affect a fraction of beneficiaries in a given year and is not the comprehensive source of earnings data that the MEF is.

Analysis Sample

We began by identifying the cohort of beneficiaries who were first awarded DI benefits in 2008 (also referred to as 2008 DI awardees). Hence, our results may not generalize to other award-year cohorts because of differences in economic circumstances, SSA policies or procedures, or beneficiary characteristics.

Our analysis is centered on the DI award date—the date SSA first sent a payment to the beneficiary. This approach follows previous literature tracking work-related milestones (Liu and Stapleton 2011; Ben-Shalom and Mamun 2015; Anand and Ben-Shalom 2018). We focused on the award date rather than on the entitlement date (the date a beneficiary first met the DI eligibility criteria) because the entitlement date may

occur before the award date, and beneficiaries have not engaged with the program until they are notified of their award and have received their first cash benefit.

Box 1 shows the additional selection criteria we imposed on the 830,271 beneficiaries awarded DI benefits in 2008. We did not include the 780 beneficiaries who were enrolled in the Benefit Offset National Demonstration (BOND), a project that changed their benefit payment formula during the analysis period; the 909 beneficiaries whose records did not merge to the December 2020 DBAD file or for whom the DBAD did not record information for the full analysis period; or the 768 beneficiaries whose records were missing key analysis variables. This yielded a sample of 827,814 beneficiaries. We retained beneficiaries regardless of age at award because overpayments can occur among DI beneficiaries nearing retirement age, and a notable portion of our analysis sample (about 38 percent) reached FRA within our 10-year analysis period. We also produced statistics for those who did not reach FRA within 10 years of award (516,307 beneficiaries). These statistics will be explained in more detail later in this article.

Next, among the 827,814 beneficiaries who met the additional sample selection criteria, we identified the beneficiaries who were at risk of an overpayment (that is, those who met the criteria for benefit suspension or termination because of work) and those who were overpaid using an algorithm originally developed and used in the BOND evaluation (Hoffman and others 2017). The same algorithm has since been used to produce overpayment statistics for DI beneficiaries who are not a part of the BOND evaluation (Hoffman and others 2019). Specifically, we identified the months in which beneficiaries were at risk of a work-related overpayment; that is, any months after the TWP and grace period in which they engaged in SGA. Over the 10-year analysis period, 31,520 beneficiaries met that criterion and were at risk of an overpayment—this is our final analysis sample.

After determining the analysis sample, we identified overpayments in months after the grace period in which beneficiaries engaged in SGA and SSA paid benefits (and later retroactively suspended or terminated benefits). We identified 25,846 beneficiaries (3.1 percent of the award cohort) with overpayments in the 10-year period following award. The algorithm detects the overwhelming majority of overpayments but does not include all overpayments. For example, if SSA was already withholding a beneficiary’s monthly benefits to repay a prior overpayment debt,

Box 1. Sample selection	
Total 2008 DI awardees	830,271
Enrolled in benefit offset demonstration	<u>-780</u>
	829,491
Did not merge to DBAD or missing information for analysis period	<u>-909</u>
	828,582
Missing key analysis variables	<u>-768</u>
	827,814
No SGA after the TWP and grace period (not at risk of an overpayment)	<u>-796,294</u>
	Final analysis sample → 31,520
SOURCE: Authors’ calculations based on 2019 DAF and December 2020 DBAD.	

that beneficiary could accrue additional overpayment debt by engaging in SGA, and our algorithm would not capture those overpayments. However, SSA case reviews suggest close alignment with our algorithm in aggregate (Hoffman and others 2019).

We also produced descriptive statistics related to overpayments: the overpayment rate, timing, duration, and dollar amount. We report the nominal dollar amount of the overpayment because SSA reports, tracks, and collects overpayments in nominal dollars. For example, if SSA overpaid a beneficiary \$1,000 in 2010, in future years, the overpayment debt will be \$1,000 minus any amount repaid and is not adjusted for inflation.

Identifying Program Milestones and Pathways

We used administrative data to document program milestones that beneficiaries encounter along the pathway to overpayment. Given the sheer volume of all milestones that might occur during a 10-year period, and the nature of the data (described below), we streamlined the analysis by documenting only the first month a beneficiary met a particular milestone. This approach may overlook some nuances in beneficiary experiences but allows for summary and comparison of experiences.

The members of our sample—beneficiaries who were at risk of an overpayment—must have reached two milestones: earnings and TWP completion. When needed, we imputed these milestone dates. We identified the first instance of earnings after award using

monthly earnings information from the DAF when available. If the MEF, which records annual earnings, reported earnings in a particular year and the DAF did not, we used earnings information from the MEF and imputed the earnings date in one of three ways, depending on beneficiary circumstances and data availability. First, we assigned the midpoint of the calendar year reported in the MEF as the first month of earnings for the year (for 2008, we assigned the midpoint between month of award and December; for all years thereafter, we assigned June). Second, for beneficiaries who received EN or SVRA services in the same calendar year in which first earnings were reported in the MEF only, we revised the imputed date of first earnings to the end of the first month of employment service receipt. Third, in some cases, the administrative data indicated first earnings after the TWP completion date, which is illogical because earnings must occur before TWP completion. In those cases, we imputed that the first earnings occurred 9 months before the TWP completion date. In total, 14.6 percent of our sample had an imputed value for the first month of earnings: 8.6 percent received the first imputation, 0.3 percent received the second, and 5.7 percent received the third. The overall earnings date imputation rates were similar for beneficiaries who were and were not overpaid (14.7 percent versus 14.3 percent), although the rates for each of the three imputation types varied by overpayment status. We recognize that imputing nearly 15 percent of the earnings dates could affect the precision of the dates, but given the nature of the data, we believe the approach provides a solid foundation for analysis. In addition, the administrative data for 0.9 percent of the beneficiaries in our analysis sample did not have a TWP completion date. For these beneficiaries, we imputed a TWP completion month as the month before the benefit suspension date (even if the suspension date was retroactive).

We used the DAF to identify the remaining milestones that occurred within the 10-year period after award, including use of employment services, benefit suspension or termination because of work, benefit terminations for medical reasons, retirement, or death. We define benefit suspension and termination dates as the dates in which beneficiaries met the programmatic criteria for benefit suspension or termination because of work, even if the determination was made retroactively. Following recent literature, we used data derived from SSA's continuing disability review (CDR) Waterfall file to identify benefit terminations

for medical reasons (Hemmeter and Bailey 2016). This file includes information on the full medical reviews conducted by the state Disability Determination Services and was added to the DAF for 2019. We define the date of benefit termination for medical reasons as that corresponding with the CDR final action.

We produced statistics on the prevalence of each milestone and the time from DI benefit award to each milestone among overpaid beneficiaries. Then, we compared these outcomes with those of correctly paid beneficiaries who were at risk of an overpayment by showing the common milestone pathways of a DI beneficiary. As mentioned, we documented the *first* occurrence of work- and program-related milestones. We followed beneficiaries from award until work-related benefit termination or program exit for a non-work reason (medical determination, retirement, or death). We omitted the pathways in which the administrative data indicate that a first milestone occurred before award (but after eligibility) or an impossible sequence of events (for example, a benefit termination for work that preceded the first benefit suspension for work). Nearly 9.0 percent of the overpaid-beneficiary analysis sample (2,315 of 25,846 beneficiaries) was excluded, as was 3.2 percent of the sample of working beneficiaries who were not overpaid (183 of 5,674).

Results

A relatively small portion of 2008 DI awardees in our sample were at risk of an overpayment. Specifically, less than 4 percent of those beneficiaries met the criteria for benefit suspension or termination for work within 10 years of award. Among that group, however, 82.0 percent would be overpaid and 18.0 percent would not. The latter subgroup comprised beneficiaries for whom SSA withheld the correct benefit amount in real time. In this section, we first present statistics related to overpayments. Then we compare the characteristics and program experiences of beneficiaries at risk of overpayment who were and were not overpaid.

Overpayment Characteristics During the 10 Years After DI Award

Table 1 presents statistics on overpayments. Nearly all first overpayment spells (98.7 percent) began when beneficiaries met the criteria for benefit suspension because of work. The remaining 1.3 percent of overpayments began when beneficiaries met the criteria for benefit termination because of work. Most overpayments (89.0 percent) began during the first month beneficiaries met the criteria for benefit suspension

Table 1.
Characteristics of the 2008 DI awardee population and measures of overpayments among overpaid beneficiaries

Characteristic or measure	All awardees	Awardees who did not reach FRA during analysis period
<i>Population characteristics</i>		
Number of awardees		
Total	827,814	516,307
At risk of overpayment	31,520	28,164
Overpaid	25,846	23,274
Percentage of all awardees who are—		
At risk of overpayment	3.8	5.5
Overpaid	3.1	4.5
Percentage of at-risk awardees who are overpaid	82.0	82.6
<i>Overpayment measures</i>		
First overpaid when criteria for suspension met because of work (%)	98.7	98.6
Overpaid in first month of SGA after grace period (%)	89.0	88.8
Duration of overpayment (months)		
Average	12.2	12.5
1st percentile	1.0	1.0
25th percentile	4.0	4.0
50th percentile	9.0	9.0
75th percentile	17.0	18.0
99th percentile	49.0	49.0
Time to first overpayment spell (months)		
Average	53.2	55.2
50th percentile	49.0	52.0
Multiple overpayment spells (%)	38.8	39.2
Duration of first overpayment spell (months)		
Average	7.8	7.9
50th percentile	5.0	5.0
Duration between overpayment spells (months)		
Average	8.7	9.0
50th percentile	4.0	4.0
Overpayment amount (\$)		
Average	13,556	13,614
1st percentile	660	660
25th percentile	3,934	3,943
50th percentile	9,206	9,258
75th percentile	18,337	18,486
99th percentile	64,205	64,428

SOURCE: Authors' calculations based on 2019 DAF and December 2020 DBAD.

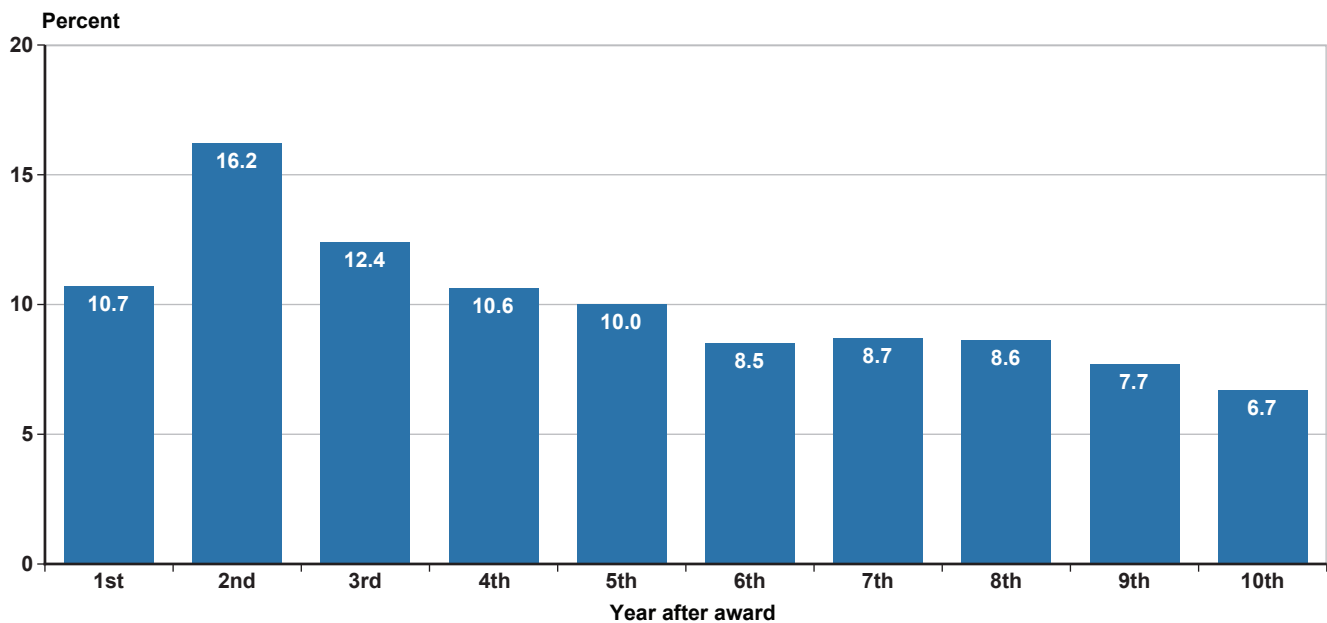
because of work. The other 11.0 percent of overpaid beneficiaries received the correct benefit amount in their first SGA month after the grace period, and then were overpaid for a later SGA month.

There was notable variation in the time between DI award and an overpayment. Chart 2 shows that across each of the first 10 years after DI award, 6.7–16.2 percent of beneficiaries in our sample experienced their first overpayment. Almost half of all overpayments observed in our 10-year analysis period occurred in the first 4 years after award, with a median duration from award to first overpayment of 49 months. Overpayments were most prevalent in the second and third years after award, when 16.2 percent and 12.4 percent, respectively, of overpayments observed in our sample occurred. Thereafter, overpayments were generally less common in each year. Notably, it is possible for beneficiaries to be overpaid in the first year after award (the first year in which a beneficiary received DI benefits) if there was a gap between DI entitlement and DI award. Beneficiaries can complete TWP months as soon as they are entitled to DI, so they could have completed some or all of their TWP months upon DI award. Beneficiaries in our analysis sample were overpaid for a median of 9 months, with

durations ranging from 1 month to more than 4 years (Table 1). For some, these months were spread across multiple overpayment spells—almost 39 percent of beneficiaries experienced more than one spell. The median length of a first or only overpayment spell was 5 months and, among those with multiple spells, the median period between overpayment spells was 4 months. Multiple overpayment spells could be experienced as distinct events triggering separate overpayment notifications from SSA. However, a beneficiary could also experience multiple spells as one overpayment (triggering one overpayment notice) if earnings fluctuated above and below SGA while earnings information was unreported or unprocessed. The median overpayment amount was \$9,206. Because some beneficiaries had very high overpayment amounts, the average overpayment amount was even higher (\$13,556).

Table 1 shows that the overpayment experiences of the 2008 DI awardees, excluding beneficiaries who reached FRA within 10 years of award, were broadly similar to those of the entire cohort of 2008 DI awardees. The most notable difference was the relatively higher rate of engagement in SGA after the grace period: 5.5 percent of those who did not reach FRA within 10 years of award were at risk of an

Chart 2.
Percentage distribution of initial overpayments, by years since award



SOURCE: Authors' calculations based on 2019 DAF and December 2020 DBAD.

NOTE: Sample size = 25,846 overpaid beneficiaries.

overpayment, relative to 3.8 percent of the full sample. Among those at risk, the overpayment rates, duration, and amounts were similar for the full analysis sample and the nonretirement subsample.

The longitudinal experiences of our sample of beneficiaries with overpayments align with previous cross-sectional research (Hoffman and others 2019) describing the median duration (9 months) and the amount (over \$9,000) of overpayments but suggest an even higher prevalence rate of 82 percent. In addition, our results suggest that, once awarded benefits, many overpaid beneficiaries initially rely solely on benefits and then begin a return-to-work journey during which overpayments begin to accrue as soon as they are at risk of overpayment. In the next subsection, we provide additional information about beneficiary pathways and compare the experiences of overpaid beneficiaries with those of at-risk beneficiaries who are not overpaid.

Beneficiary Characteristics by Overpayment Status

Table 2 compares the characteristics of at-risk beneficiaries who were overpaid with those of beneficiaries who were not overpaid. Beneficiaries who were overpaid were more likely than at-risk beneficiaries who were not overpaid to be female (48.3 percent versus 44.3 percent) and younger than 45 (65.0 percent versus 56.4 percent). They were also more likely to have 12 or fewer years of education (52.6 percent versus 44.7 percent). Lower educational levels could be associated more with hourly employment than salaried employment, leading to more variable earnings and more difficulty in tracking the use of work incentives. Overpaid beneficiaries were also more likely than beneficiaries who were not overpaid to have mental disorders (33.8 percent versus 28.4 percent) or intellectual disabilities (5.5 percent versus 1.9 percent), have Medicare eligibility at first award (21.8 percent versus 15.0 percent), and receive SSI payments at the time of DI award (16.5 percent versus 9.5 percent). Several of these characteristics may be associated with difficulty understanding and fulfilling earnings reporting requirements.

These findings are consistent with a comparison of a cross-section of beneficiaries who were overpaid and those who were at risk but not overpaid during 2010–2012 (Hoffman and others 2019). In that study, a multivariate analysis showed some of these characteristics to be statistically significantly associated with a higher likelihood of overpayment, including: aged 54

or younger, less than high school education, mental disorder diagnoses (relative to several other impairment groups), and concurrent SSI receipt. Intellectual disability did not differ significantly from mental disorders in predicting overpayment, implying an increased likelihood of overpayment relative to several other impairments. The difference by sex in overpayment likelihood was not statistically significant, and the effect of Medicare eligibility at first award was not analyzed.

Comparison of Program Experiences of At-Risk Beneficiaries by Overpayment Status

Chart 3 compares the shares of at-risk beneficiaries who reach each of four program milestones by overpayment status. Overpaid beneficiaries were less likely to meet the criteria for benefit suspension (94.1 percent) than at-risk beneficiaries who were not overpaid (99.0 percent). Theoretically, all beneficiaries at risk of overpayment meet the criteria for benefit suspension. However, a beneficiary need not meet the criteria for benefit suspension if he or she completes the TWP and first engages in SGA after the completion of the 36-month EPE, at which point benefits are terminated.

Program exit reasons also varied by overpayment status. Overpaid beneficiaries were less likely than correctly paid beneficiaries to exit the DI program because of work-related benefit termination (55.4 percent versus 63.0 percent). They were also less likely to have their DI eligibility terminate for nonwork reasons (23.7 percent) than those who were not overpaid (26.1 percent). Specifically, overpaid beneficiaries were more likely to experience benefit termination for medical reasons than at-risk beneficiaries who were not overpaid (9.4 percent versus 6.2 percent) but less likely to retire (10.2 percent versus 14.0 percent) or die (5.8 percent versus 8.6 percent) (not shown). Some of these differences might be related to the relatively younger age, lower education, and different mix of medical conditions of overpaid beneficiaries. Relative to beneficiaries who were not overpaid, overpaid beneficiaries were more likely to have received EN or SVRA services (20.8 percent versus 18.3 percent).

We also examined the sequencing of the program milestones that overpaid beneficiaries experienced and compared their pathways to those of at-risk beneficiaries who were not overpaid. Chart 4 summarizes the five most common milestone pathways. Appendix Chart A-1 expands on Chart 4 to provide a more complete depiction of pathways. In both charts, we document the first observance of each milestone.

Table 2.
DI beneficiaries at risk of overpayment because of work: Percentage distributions by characteristics at time of initial award in 2008, by overpayment status

Characteristic	Overpaid	Not overpaid	Percentage-point difference
Number of beneficiaries	25,846	5,674	...
Sex			
Women	48.3	44.3	4.0***
Men	51.7	55.7	-4.0***
Age			
18–24	17.7	13.1	4.5***
25–34	22.4	20.3	2.1***
35–44	24.9	23.0	1.8***
45–54	22.6	26.8	-4.3***
55–64	12.5	16.7	-4.2***
Education level			
0–11 years	14.9	9.2	5.7***
12 years	37.7	35.5	2.3***
13–15 years	21.9	24.6	-2.8***
16 years or more	12.2	22.1	-9.8***
Missing	13.3	8.7	4.6***
Impairment type			
Musculoskeletal and connective tissue disease	19.9	18.6	1.3**
Nervous system and sense organs disease	8.9	8.1	0.8*
Neoplasm	7.0	16.6	-9.6***
Other physical disorder	24.9	26.5	-1.6**
Mental disorder	33.8	28.4	5.4***
Intellectual disability	5.5	1.9	3.6***
Eligible for Medicare			
Yes	21.8	15.0	6.8***
No	77.1	84.1	-7.0***
Missing	1.1	0.8	0.2
Awarded concurrent DI and SSI benefits			
Yes	16.5	9.5	7.0***
No	83.5	90.5	-7.0***

SOURCE: Authors' calculations based on 2019 DAF and December 2020 DBAD.

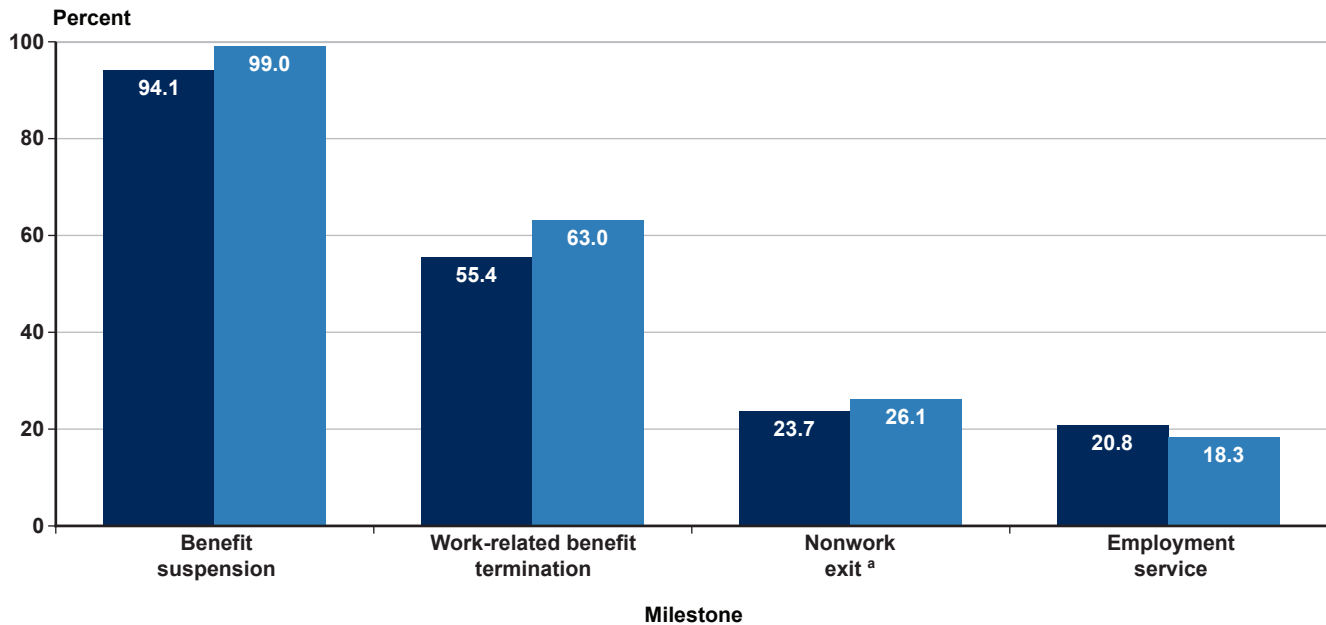
NOTES: Rounded components of percentage distributions do not necessarily sum to 100.0.

... = not applicable.

* = statistically significant at the 0.05 level; ** = statistically significant at the 0.01 level; *** = statistically significant at the 0.001 level (*t*-test comparisons of means across overpayment status categories).

Chart 3.
Share of at-risk beneficiaries reaching program milestones, by overpayment status

■ Ever overpaid ■ Not overpaid



SOURCE: Authors' calculations based on 2019 DAF and December 2020 DBAD.

NOTES: Sample sizes = 25,846 overpaid beneficiaries and 5,674 at-risk beneficiaries who were not overpaid.

T-tests indicate that, for all milestones shown, differences between overpaid and not overpaid beneficiaries are significant at the $p < 0.01$ level.

a. Retired, died, or no longer medically eligible.

For example, although most beneficiaries engaged in SGA in multiple months after the grace period, we include only the first month in which a beneficiary met the criteria for benefit suspension because of work. We did not indicate when the overpayments occurred for ease of presentation. However, as previously mentioned, nearly 90 percent of overpaid beneficiaries were overpaid the first time they engaged in SGA after the EPE grace period (at the beginning of the benefit suspension milestone).

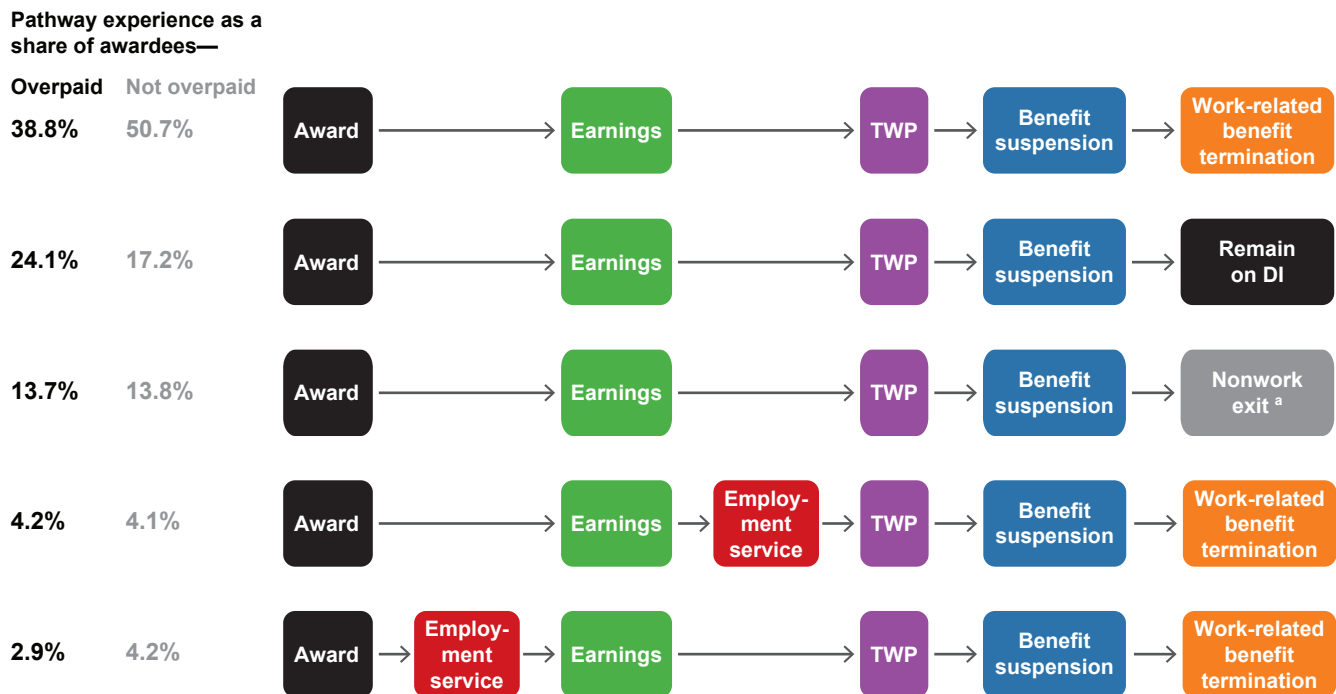
More than three-quarters of overpaid beneficiaries in our sample followed one of the three most prevalent overpayment paths (Chart 4). The most common overpayment pathway, experienced by 38.8 percent of overpaid beneficiaries in our sample, was award, earnings, TWP completion, meeting the criteria for benefit suspension because of work, and meeting the criteria for benefit termination because of work. An additional 24.1 percent followed that same pathway through the first four milestones but then remained entitled to DI benefits, and 13.7 percent followed that pathway through four milestones but then left the program because of medical determination, retirement, or

death, rather than for work. The remaining pathways were much less common. For example, the fourth most prevalent pathway (award, earnings, employment service, TWP completion, meeting the criteria for benefit suspension, then termination because of work) was taken by 4.2 percent of the overpaid subsample.

The three most common pathways for correctly paid beneficiaries—each beginning with award, earnings, TWP completion, and meeting the criteria for benefit suspension because of work—were the same as those for overpaid beneficiaries. However, the shares of awardees differed: a higher proportion of correctly paid beneficiaries had their eligibility terminated because of work (50.7 percent, compared with 38.8 percent of overpaid beneficiaries) and a lower share continued receiving DI benefits (17.2 percent, compared with 24.1 percent of overpaid beneficiaries). These findings align with existing research documenting that overpayments can cause beneficiaries to reduce work activity (Anand and others 2022).

Notably, when beneficiaries receive employment services after resuming work and before completing the TWP, similar shares of overpaid and correctly paid

Chart 4.
Five most common pathways among at-risk beneficiaries, by overpayment status



SOURCE: Authors' calculations based on 2019 DAF, December 2020 DBAD, and MEF.

NOTES: Sample sizes = 23,531 overpaid beneficiaries and 5,491 beneficiaries at risk of overpayment who were not overpaid.

Includes only beneficiaries who had a first milestone of award and had a logical sequence of milestones.

a. Retired, died, or no longer medically eligible.

beneficiaries experience benefit termination because of work. Although we cannot be certain about the mechanisms underlying any similarities or differences, the findings could suggest that overpayments can act as a disincentive to continued SGA when ENs or SVRAs are not involved to help beneficiaries understand and navigate overpayments. However, it is also important to note that there are observable differences in overpaid and correctly paid beneficiaries at risk of overpayment that could affect benefit termination.

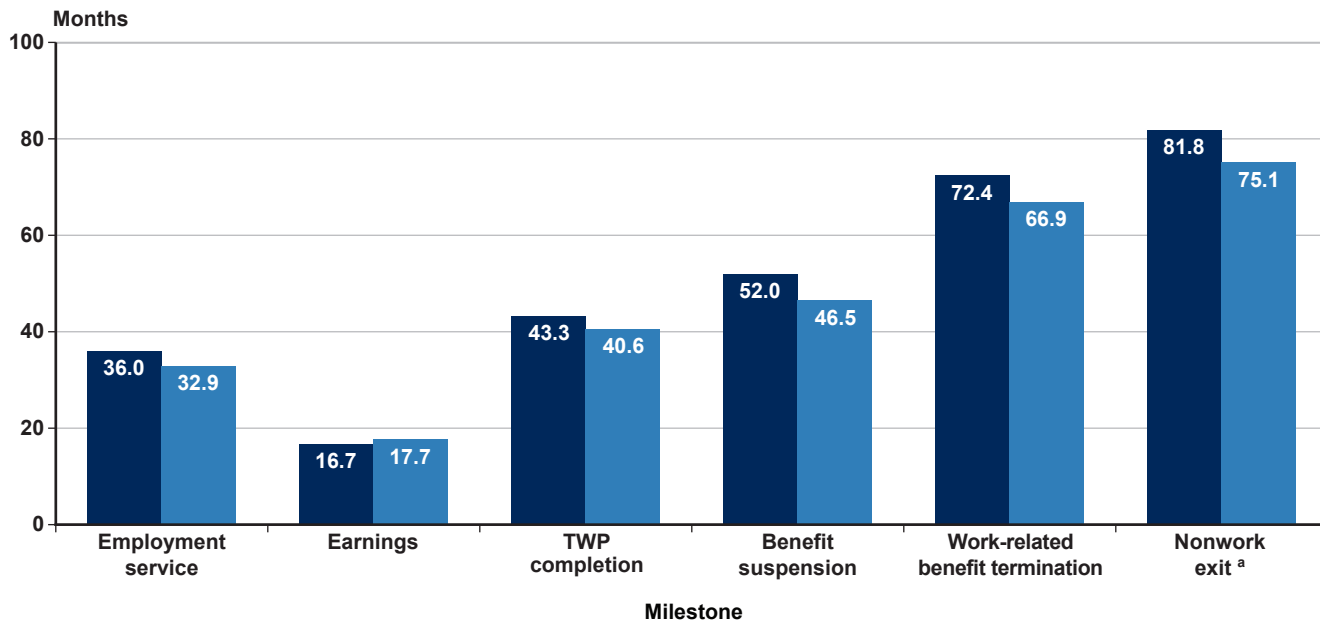
Overpaid beneficiaries were less likely to seek employment services before receiving earnings than correctly paid beneficiaries (Appendix Chart A-1). Specifically, 6.5 percent of overpaid beneficiaries received EN or SVRA services before working for earnings, compared with 8.0 percent of correctly paid beneficiaries. However, a slightly higher share of overpaid beneficiaries (9.2 percent) received EN or SVRA services after returning to work than did correctly paid beneficiaries (8.2 percent). Receipt of employment services before returning to work could help beneficiaries avoid overpayments if ENs and SVRAs educate

beneficiaries about earnings reporting requirements and best practices. It is possible that the same EN or SVRA guidance, if provided shortly before completing the TWP, is too late to prevent an overpayment.

To complement the differences by overpayment status in beneficiary pathways shown in Chart 4, Chart 5 shows the differences by overpayment status in the average time from award to each milestone among those who achieved them. Overpaid beneficiaries had their first month of earnings about 1 month sooner than those who were not overpaid (16.7 versus 17.7 months after DI award). Although this difference is statistically significant, recall that 14 percent of earnings dates were imputed, and the type of imputation differed across the two groups, so it is difficult to assert that this is a meaningful difference. Relative to beneficiaries who were overpaid, those at risk but not overpaid achieved all other milestones sooner. Notably, those who were not overpaid met the criteria for TWP completion, benefit suspension, and benefit termination for work sooner than overpaid beneficiaries did. The period between TWP completion and the first

Chart 5.
Average months from award to each milestone, by beneficiaries' overpayment status

■ Ever overpaid ■ Not overpaid



SOURCE: Authors' calculations based on 2019 DAF, December 2020 DBAD, and MEF.

NOTES: Sample sizes for overpaid beneficiaries (25,846 total) and at-risk beneficiaries who were not overpaid (5,674 total) for each milestone: employment service = 1,548 overpaid and 312 not overpaid; earnings and TWP completion = 25,846 overpaid and 5,674 not overpaid; benefit suspension = 24,321 overpaid and 5,617 not overpaid; work-related benefit termination = 14,329 overpaid and 3,753 not overpaid; and nonwork exit = 6,131 overpaid and 1,481 not overpaid.

T-tests indicate that, for all milestones shown, differences between overpaid and not overpaid beneficiaries are significant at the $p < 0.01$ level.

a. Retired, died, or no longer medically eligible.

month of benefit suspension was also shorter among those who were not overpaid—almost 6 months versus nearly 9 months. This is perhaps surprising because quickly achieving milestones that lead to benefit adjustment requires prompt earnings reporting and benefits processing to avoid overpayments. Hence, this finding suggests that beneficiaries who were not overpaid likely met reporting requirements timely. As mentioned earlier, SSA processes self-reported earnings more quickly than earnings identified from other sources (SSA 2018).

Discussion and Conclusion

This analysis provides new details on the benefit overpayment-related experiences of 2008 DI awardees. We find that nearly 4 percent of DI disabled-worker beneficiaries were at risk of a work-related overpayment because they engaged in SGA after the TWP and grace period and, within that group, 82.0 percent of beneficiaries were overpaid in the first 10 years after award. These results provide additional evidence that

overpayments were the norm for beneficiaries who engaged in SGA after the TWP and grace period. A previous study found that, among a representative cross-section of beneficiaries, 71.0 percent of those at risk of overpayment were overpaid in 2010–2012 (Hoffman and others 2019). The higher overpayment prevalence reported in this study likely reflects the longer analysis period (10 years versus 3), among other differences. Both the previous and current study estimated a median overpayment duration of 9 months and median overpayment amounts of about \$9,300.

The predominance of overpayments among beneficiaries with sustained substantial earnings and the negative effects of those overpayments point to a system in need of reform (Smalligan and Boyens 2023). Our analysis provides additional details that may help inform future modifications or reforms.

This study offers new insight into the timing of overpayments, which do not align with existing processes for timely benefit adjustment. Notably, nearly all overpayment spells (89.0 percent) began in the first

month that beneficiaries met the programmatic criteria for benefit suspension because of work. The current DI work incentive rules and administrative approaches to identifying and processing earnings information are not designed, and do not provide sufficient resources, to properly adjust benefits within the 3-month grace period to avoid overpayments.

This study also illuminates potential gains from a more efficient system for processing earnings reports. Although earlier identification of earnings and more rapid processing are likely beneficial in reducing overpayments, they could also help prevent subsequent overpayment spells. We found that 38.8 percent of overpaid beneficiaries experienced more than one overpayment spell, with a median period of 4 months between spells (Table 1). Earlier identification of overpayments could help prevent overpayments in future months.

Despite the prevalence of overpayments, some beneficiaries avoid them. This could be related to beneficiary characteristics. Relative to beneficiaries who avoid overpayments, overpaid beneficiaries were more likely to exhibit characteristics associated with inconsistent earnings (which are likely more challenging to track and report) and with difficulty in understanding reporting requirements. Research suggests that anticipation of benefit suspension is associated with a lower likelihood of overpayment (Shenk and Livermore 2021). Indeed, the relatively faster pace at which beneficiaries who were not overpaid completed the TWP and had benefits suspended for work, documented here, suggest that those who avoid overpayments are more likely to comply with earnings reporting requirements.

Beneficiaries at risk of overpayments who are not overpaid are also more likely to exit the DI program because of work. This is true in aggregate and among the most common milestone pathways beginning with award, earnings, TWP completion, and meeting the criteria for benefit suspension because of work, without receipt of EN or SVRA services. Research has found that overpayments can cause decreased earnings (Anand and others 2022; Shenk and Livermore 2021). Although the current study is not meant to demonstrate causal evidence, it is possible that overpayments can further lead to a lower likelihood of benefit termination because of work, which emphasizes the importance of preventing overpayments. Our findings on the patterns of program milestones attainment—the differences in program pathways by overpayment status—are also generally consistent

with the theory that employment service receipt can help beneficiaries avoid overpayments or help mediate their negative effects.

Because most overpayments result from beneficiary reporting failures (SSA 2018), efforts to expedite SSA's access to earnings information are critical. SSA is currently working to access more timely earnings information from data exchanges with payroll data providers. If paired with timely processing, this has the potential to prevent overpayments for many beneficiaries. However, data from one or several payroll data companies will not include all disabled workers and no payroll data will include self-employed workers.

The findings of this report suggest two possible points of intervention to prevent or minimize overpayments within the current system. Because a substantial share of overpayments occur in the first years after DI award, well-formatted earnings-reporting reminders sent in the first 4 years after award might encourage timely reporting and reduce the likelihood or amount of overpayments. Zhang and others (2020) found that earnings reporting reminders sent to SSI recipients with disabilities helped reduce the incidence of overpayments. Although the SSI and DI programs have different reporting requirements, it is possible that sending earnings reporting reminders would also be effective for DI beneficiaries. Hoffman, Deutsch, and Seifert (2023) reviewed written materials on earnings reporting that SSA provides to DI beneficiaries. They found that beneficiaries were infrequently notified of the earnings reporting requirements and that the earnings reporting information was often located at the end of a document or amid dense text. The authors note that similar communication deficiencies have been identified in research on tax compliance, which finds that reminders, particularly those using best design practices that account for human behavior, can increase compliance.

A second possible intervention could occur in partnership with employment service providers. ENs and SVRAs could issue earnings reporting reminders or directly assist their clients with reporting their earnings. These efforts could help beneficiaries navigate or even avoid overpayments. Under the Ticket to Work program, ENs and SVRAs that receive client milestone- or outcome-based payments from SSA have an incentive to collect earnings information from their clients. However, the providers do not collect that information automatically, and some beneficiaries in the Ticket to Work program do not understand their reporting responsibilities (SSA 2017).

GAO (2021) estimated that overpayments are more prevalent among Ticket to Work participants than nonparticipants, but our research finds that, in some cases, EN or SVRA services may help beneficiaries avoid or respond to overpayments. Clearly describing the potential consequences of overpayments to clients or creating client incentives to report earnings could improve reporting rates in a way that benefits both clients and providers.

This analysis is subject to several limitations. First, the overpayment algorithm we used might not capture all work-related overpayments. However, an SSA case review of beneficiary records with overpayments found that the algorithm estimated the overpayment amounts within 0.3 percent of SSA's calculations (Hoffman and others 2019). Second, to streamline the numerous combinations of all DI program-participation milestones that might occur during a 10-year period, and to align with the capabilities of the data, we documented only the first occurrence of each milestone that beneficiaries experience. We did this with the recognition that nuanced details in beneficiary experience may be sacrificed, but the fact that many of the findings comport with other research eases these concerns.

Another limitation is that our analysis focuses on beneficiaries awarded DI benefits in 2008. Therefore, the results may not generalize to beneficiaries awarded benefits in other years. This is particularly true if the recession that started in late 2007 affected the employment opportunities and experiences of beneficiaries. It is also possible that overpayment experiences will differ for beneficiaries in more recent award cohorts because SSA has increased its efforts to prevent or minimize overpayments in recent years. In 2017, after an initial pilot period, SSA began to draw on quarterly

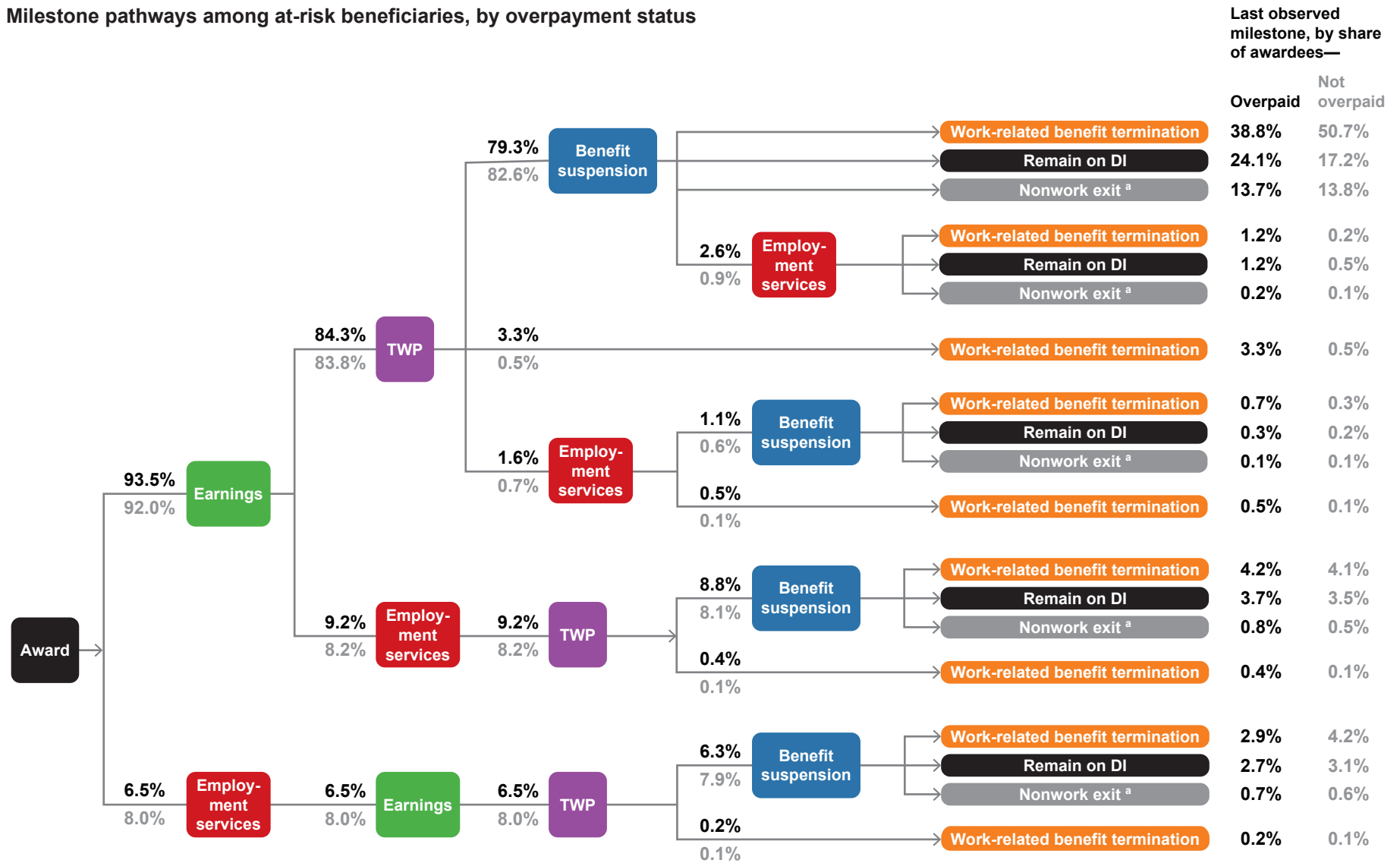
earnings data from the Office of Child Support Services' National Directory of New Hires when reviewing earnings for all DI beneficiaries. As of 2020, SSA was also in the process of working with payroll data providers to access timely earnings data for beneficiaries paid through those providers (SSA 2020c).

Despite these limitations, this study adds to the evidence on beneficiaries' experiences with overpayments and yields some insight into approaches that might help to reduce beneficiaries' overpayments. Future research could attempt to uncover more details about the mechanisms behind why beneficiaries are overpaid and the extent to which certain entities—such as ENs or SVRAs, SSA-funded benefits counselors, SSA field offices and payment service centers, or the centralized SSA toll-free number—might be able to prevent or minimize overpayments. The beneficiary pathways examined in this study may remain important even as SSA pursues initiatives to reduce overpayments, such as establishing information exchange agreements with payroll data providers. Although there is reason to be optimistic that timely information on wages from payroll providers will reduce overpayments, these agreements would not cover all working beneficiaries.

Appendix

Chart A-1 illustrates the sequencing of program milestones for overpaid beneficiaries and at-risk beneficiaries who were not overpaid, including the share of individuals at each milestone.

Chart A-1.
Milestone pathways among at-risk beneficiaries, by overpayment status



SOURCE: Authors' calculations based on 2019 DAF, December 2020 DBAD, and MEF.

NOTES: Sample sizes = 23,531 overpaid beneficiaries and 5,491 beneficiaries at risk of overpayment who were not overpaid.

Includes only beneficiaries who had a first milestone of award and had a logical sequence of milestones.

a. Retired, died, or no longer medically eligible.

Notes

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¹ If a beneficiary's disability results from amyotrophic lateral sclerosis, there is no waiting period before DI benefits begin (SSA 2022a).

² SVRAs may opt for employment service cost reimbursements in lieu of milestone- or outcome-based payments.

³ The rolling 60-month window can allow for longer than 60 months to complete the TWP. For example, the first month of the TWP is month 1. If a beneficiary exceeds the monthly earnings threshold during 9 TWP months between months 1–60, he or she has completed the TWP. However, if a beneficiary has not completed his or her TWP as of month 60, the span of months in consideration will shift from months 1–60 to months 2–61 and so on.

⁴ A summary of employment supports for DI beneficiaries is also available in the SSA Red Book (SSA 2020a).

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