Veteran Employment Outcomes

Joyce Hahn, Henry Hyatt, Hubert Janicki, Erika McEntarfer,
Seth Murray, Lee Tucker, Andrew Foote, and David Wasser

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1 Background

The challenges faced by military veterans transitioning into the civilian labor force are a subject of ongoing concern to policymakers. In 2019, the Longitudinal Employer-Household Dynamics (LEHD) program created the Veteran Employment Outcomes (VEO) data product, made possible through the creation of new administrative data linkages between employment data from the LEHD program and service member information provided by the U.S. Army. The LEHD program has now released an expanded and revised VEO v2.0 (VEO2). These statistics are generated by linking veteran records provided by the Department of Defense to national administrative data on jobs at the U.S. Census Bureau. Coverage of this new data is all enlisted veterans from five branches of the military–Air Force, Army, Coast Guard, Marine Corps, and Navy– who were discharged between 2002 and 2021. The coverage rules result in a total of 2.8 million veterans.

These new data highlight the broad distribution of labor market outcomes for recent military veterans, highlighting the role of industry and military occupation in post-military earnings outcomes. Some key findings from these new statistics include the following:

1. Private sector earnings upon exit are generally highest for veterans who were drone operators and intelligence specialist while in military service, particularly in the Army, Navy, Air Force, and Marine Corps.

2. Army veterans have a much higher propensity to work in the federal government than veterans of other branches or the civilian workforce at large.

*This paper documents a new version of the Veteran Employment Outcomes experimental statistical product that has been approved for release by the Census Bureau Disclosure Review Board (Release Number: CBDRB-FY25-0058). Any opinions and conclusions expressed in this document are those of the authors and do not represent the views of the U.S. Census Bureau.

3. Industry of employment is an important predictor of earnings outcomes even within broad military occupation groups and service branches.

4. Employment rates fell for veterans exiting during and after the Great Recession across all branches, likely reflecting poor labor market conditions as well as increases in educational benefits for veterans.[1]

The Census Bureau is releasing Veteran Employment Outcomes v2.0 together with an online data exploration tool so that veterans, military personnel, and policy-makers can easily explore these new statistics. As with other Census Bureau experimental statistical products, we seek feedback from users and stakeholders on the quality and usefulness of these data. The VEO may be regularly updated or expanded to include new cohorts if there appears to be sufficient user demand and resources permit. The remainder of this document provides documentation on how the VEO data were constructed and how veteran confidentiality is protected in the released statistics.

2 Data Sources

We use linked employer-employee data from the LEHD program at the U.S. Census Bureau to examine the employment and earnings outcomes of military veterans. The LEHD data consists of quarterly earnings records for individual workers that are submitted by employers for the administration of state unemployment insurance (UI) benefit programs. These records are then linked to establishment-level data collected for the Quarterly Census of Employment and Wages (QCEW) program. As of December, 2024, 48 states along with the District of Columbia and Puerto Rico share UI and QCEW data with the LEHD program as part of the Local Employment Dynamics (LED) federal-state partnership.[2] Their UI data covers the vast majority of private sector, state and local government employment.[3] LEHD data thus covers the vast majority of private sector employment. We also use Office of Personnel Management (OPM) data, which includes earnings records for a large fraction of federal workers. At this time, OPM data are available through 2022, and so VEO v2.0 incorporates OPM data from 2002 through 2022. Since federal employment is a significant source of labor earnings among former service members, we restrict our analysis to this time period.

In addition to LEHD data, we use administrative data from the Department of the Defense, Defense Manpower Data Center (DMDC) and the Military-Civilian Transition Office (MCTO).

[1] The Post-9/11 GI bill, passed in 2009, significantly increased the amount of educational benefits available to veterans who served after 2001.

[2] Note that Puerto Rico availability was limited to the QWI data product during the development of VEO.

[3] See Abowd et al. (2009) for details.

This data allows us to observe service member characteristics, such as branch of service, service start and end dates, occupation, pay grade, characteristics at entry (e.g. education and test scores), and demographic characteristics (e.g. sex, race and ethnicity). We exclude service members that separated from service prior to 2002 due to data quality problems. Each service member is assigned a Protected Identification Key (PIK) that allows for service members to be matched with their employment outcomes in the LEHD data, while obscuring their personally identifiable information.

3 Frame

We take all service members who have been honorably discharged and exclude only those that were dismissed for bad conduct, dishonorable discharge, or any discharge under other than honorable conditions. Service members with multiple career tracks within one service branch or across branches are excluded (for example due to enlisted to officer transitions). We include service members from the Air Force, Army, Coast Guard, Marine Corps, and Navy. Space Force service members are not included due to the availability of only a small number of veteran cohorts. We additionally restrict our sample to service members who have completed any amount of active-duty service following completion of basic training as enlisted service members (not as officers or warrant officers) and have final ranks E01-E09. Moreover, given the availability of DOD data, we focus on service members who separated from the military in 2002 or later. For earnings, we look to the calendar year one, five, and ten years after the year of separation from the active duty service and consider veterans earnings from all UI-covered jobs in all four quarters of that year. When examining veterans earnings by employer characteristics, we identify their dominant employer in the calendar year (defined as the employer with the highest cumulative real earnings in the calendar year) and use that employer's characteristics. For earnings measures, we additionally restrict the sample to veterans who i) work at least three quarters in the calendar year and ii) earn at least the equivalent of working full time at the federal minimum wage. This approach approximates workers who are strongly attached to the labor force and maintains consistency with the original VEO and PSEO methodology.

4 Description of Concepts and Measures

4.1 Concepts

Our primary unit of analysis is a military veteran denoted by subscript i in year t and quarter q.

Employment Status

We denote an earnings record for veteran i at employer j in year t and quarter q as w_{ijtq}. If a worker has positive earnings, we classify their employment status as employed; otherwise, they are considered non-employed. Employment status for worker i is therefore denoted by firm j in year t and quarter q as:

$$m_{ijtq} = \begin{cases} 1, & \text{if } w_{ijtq} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Note that veterans may have earnings records with multiple employers in a given year and quarter. All earnings are adjusted for inflation using the CPI at a quarterly frequency.

Labor Market Attachment

Earnings measures can be sensitive to the inclusion of individuals who are loosely attached to the labor force. Since we do not have measures of hours worked that convey the degree of labor market attachment, we instead impose two sample restrictions when calculating moments of the earnings distribution. First, we require that individuals be employed at any combination of employers for at least three quarters in the calendar year $(m_{it}^{3+} = 1)$. Those employed for two or fewer quarters are denoted as $m_{it}^{3+} = 0$. Second, we require that individuals total annual earnings, w_{it}, exceed a minimum earnings threshold. We set the threshold at the full-time earnings (35 hours times 50 weeks, 12.5 weeks in each quarter) equivalent of the real federal minimum wage. Since the minimum wage varies over our sample, we denote this threshold as $\underline{w_t}$ and require that $w_{it} \geq \underline{w_t}$.

Annual Earnings

Although earnings measures report veterans' real earnings across all employers in a given calendar year, we first generate worker i's annual earnings at firm j in year t by summing the workers quarterly real earnings at the firm:

$$w_{ijt} = \sum_{q \in 1,2,3,4} w_{ijtq} \tag{2}$$

The worker's total annual earnings then aggregate the workers real earnings across all employers in the calendar year:

$$w_{it} = \sum_{j \in J} w_{ijt} \tag{3}$$

where J denotes the set of all possible employers.

Dominant Job

When tabulating workers earnings by employer characteristics, we focus on the characteristics of each worker's dominant job in the calendar year. The dominant job for worker i in year t is the job with the highest annual earnings:

$$d_{ijt} = \begin{cases} 1, \text{if } w_{ijt} > w_{ikt} \forall j \neq k \\ 0, \text{otherwise.} \end{cases} \tag{4}$$

Employer-reported industries can change within a given calendar year. To identify industry for the worker's dominant job in each year (employer j_{it}^{dom} where $d_{ijt} = 1$), we sum up the individual's total earnings at that employer by reported industry. Then, we assign the industry in which the individual earned the most in that job and year.

4.2 Measures

The goal of the VEO2 data product is to release employment and earnings measures.

Employment Counts

We construct two distinct employment counts by strength of labor market attachment. First, the count of strongly attached workers, i.e. the count of all individuals who meet the two sample restrictions in the calendar year:

$$\sum_{(w_{it} \geq \underline{w_t}, m_{it}^{3+}=1, i \in I(m), j_{it}^{dom} \in J(s))} d_{ijt} \tag{5}$$

Second, we produce a count of all other veterans in our data that do not meet our labor market attachment criteria. This includes loosely attached workers, i.e. the count of all individuals with non-zero earnings in the calendar year who fail to meet one or both of the sample restriction criteria (($m_{it}^{3+} = 0$ and/or $w_{it} \geq w_t$) and $w_{it} > 0$), and those with no observed earnings for the calendar year in the LEHD infrastructure files ($w_{it} = 0$). All employment measures are summarized in Table 1.

Earnings Percentiles

VEO2 reports the 25th, 50th, and 75th percentiles from the earnings distribution of veterans who meet the two sample restrictions. We denote the distribution from which these percentiles are calculated as:

Table 1: Summary of Measures for Release

Measure Name	Individual-level Description	Aggregated Description
Annual Earnings Percentiles (25th, 50th, 75th)	$\sum_{j\in J}\sum_{q\in 1,2,3,4} w_{ijtq}$	$F(w_{it}\vert w_{it} \geq \underline{w_t}, m_{it}^{3+} = 1,$ $i \in I(m), j_{it}^{dom} \in J(s))$
"Above-Threshold" Count	$\begin{cases} 1, \text{if } d_{ijt} = 1 \wedge w_{it} > \underline{w_t} \\ 0, \text{otherwise} \end{cases}$	$\sum_{(w_{it}\geq \underline{w_t}, m_{it}^{3+}=1, i\in I(m), j_{it}^{dom}\in J(s))} d_{ijt}$
Unobserved and "Below-Threshold" Counts	$\begin{cases} 1, \text{if } m_{it}^{3+} = 0 \vee (d_{ijt} = 1, w_{it} \leq \underline{w_t}) \\ 0, \text{otherwise} \end{cases}$	$\sum_{i\in I(m)}(1 - m_{it}^{3+}) + \sum_{(w_{it}\leq \underline{w_t}, m_{it}^{3+}=1, i\in I(m), j_{it}^{dom}\in J(s))} d_{ijt}$

$$F(w_{it}|w_{it} \geq \underline{w_t}, m_{it}^{3+} = 1, i \in I(m), j_{it}^{dom} \in J(s)) \tag{6}$$

where $I(m)$ denotes the set of individuals with characteristic of interest m (e.g. sex, race, grade, military occupation, etc.), and $J(s)$ denotes the set of dominant employers with characteristic of interest s (e.g. state or industry).

5 VEO2 Tabulations

Employment and earnings outcomes are tabulated for service members by their branch of service. Outcomes are detailed by the following worker characteristics: separation cohort, sex, race and ethnicity, education at enlistment, AFQT score tercile, pay grade at separation, and military occupation. They are also tabulated by the state and industry of each workers dominant employer. All outcomes are additionally reported one, five, and ten years post separation from the military. All detailed tabulations are detailed in Table 2. Higher-level aggregates are tabulated as appropriate and these are described in Section 6.3.

Separation Cohort

In order for changes in veterans labor market outcomes to be evaluated over time, we group veterans into cohorts based on their year of separation from active-duty service. We retain the same cohort bins that were chosen for the original VEO release. For most tables, we use 2-year cohorts. However, for some tables, data quality constraints limit the extent to which we can provide detailed cohort groups. As a result, these tables are aggregated to 4-year and 8-year cohorts. Statistics for the following separation cohort bins are therefore generated: *Two year bins* - 2002-2003, 2004-2005, 2006-2007, 2008-2009, 2010-2011, 2012-2013, 2014-2015, 2016-2017, 2018-2019,

Table 2: VEO Tabulations

Table Name	Separation Cohort	Characteristics
veoo3	8yr cohort	3-digit DOD Occupation Code by Service Branch
veoo2ns	8yr cohort	2-digit DOD Occupation Code by Sector by Service Branch
veoo2gs	8yr cohort	2-digit DOD Occupation Code by State by Service Branch
veoo2p	4yr cohort	2-digit DOD Occupation Code by Pay Grade by Service Branch
veogs	2yr cohort	State by Service Branch
veos	2yr cohort	Sex by Service Branch
veoe	2yr cohort	Education by Service Branch
veorh	2yr cohort	Race by Ethnicity by Service Branch
veop	2yr cohort	Pay Grade by Service Branch
veons	2yr cohort	Sector by Service Branch
veot	2yr cohort	AFQT Score Tercile by Service Branch
veoa	2yr cohort	Age by Service Branch
veox	2yr cohort	Experience by Service Branch

Note: Each tabulation is available for one, five, and ten years post separation.

and 2020-2021. *Four year bins* - 2004-2007, 2008-2011, 2012-2015, and 2016-2019. *Eight year bins* - 2008-2015.

Note that tables with 4-year bins are suppressed prior to 2004 and tables with 8-year bins are suppressed prior to 2008. This is due to limited DOD data availability before 2002. Likewise, notice that the 2020-2023 4-year bin and the 2016-2023 year bin are also not available because these were not fully populated at the time of product development.

Age, Sex, Race and Ethnicity

Worker demographic information allows for comparison of employment and earnings outcomes by age, sex, race, and ethnicity. Age is defined as age at separation from service and is taken from DOD records. We then create two age bins: age <25 and age 25+. Sex, race, and ethnicity are taken from the LEHD data to allow for representation of race and ethnicity information in a manner that is consistent with the format used by the U.S. Census Bureau, presented in the LEHD schema available at `https://lehd.ces.census.gov/data/schema/latest/lehd_public_use_schema.html`. In a small number of cases when demographic characteristics are not available from the LEHD data, we use the variables from DOD records and recode as necessary to maintain consistency. Sex has two bins: Male and Female. Race has six bins: White Alone, Black or African American alone, American Indian or Alaska Native Alone, Native Hawaiian or Other Pacific Islander Alone, and Two or More Race Groups. Ethnicity has two bins: Hispanic and Not Hispanic.

Education at Enlistment

Eligibility for military enlistment is dependent on meeting certain education thresholds. We use DOD administrative data to generate three education-level categories: GED, High School Graduate, and Some College or Higher. In some service branches, education attainment is missing for some earlier cohorts. In these cases, we create a separate 'UN'–'unknown'–category.

Armed Forces Qualification Test (AFQT) Score

All military recruits take the Armed Forces Vocational Aptitude Battery (ASVAB), which is used to assess their skills at time-of-entry and their fit for any particular military occupation. A subset of the ASVAB is used to calculate the Armed Forces Qualification Test (AFQT) score. This score is reported as a percentile that is relative to a reference group and is comparable across time. We report employment and earnings outcomes by AFQT terciles, with 1 being the lowest scoring tercile and 3 being the highest scoring tercile. In some service branches, AFQT scores are missing for some or all cohorts. In these cases, we create a separate 'UN'–'unknown'–category.

Pay Grade

We use pay grade at separation to capture each service members performance during active-duty service. Due to sparsity of cells, some pay grade categories are aggregated into larger bins. Reported pay grade bins include: E01, E02, E03, E04, E05, E06, and E07-E09, with E01 being the lowest pay grade and E07-E09 being the highest pay grades. Note that when labor market outcomes are reported by pay grade crossed with military occupation, we use a higher level of aggregation and report two grouped pay grade bins, E01-E04 and E05-E09.

Years of Service

We use three bins to capture the distribution of experience or tenure for active-duty service at year of separation. They are: 0-5, 6-19, and 20+ years. Note that most enlisted service members serve less than five years and career personnel are eligible for retirement at 20 years of service.

Military Occupation

Occupation for enlisted personnel is defined within the Department of Defenses Military Occupational Specialty Classification codes at the 2- and 3-digit level. Table 3 lists the 2 digit occupational categories. We do not track veterans who separated from service with an unassigned occupation group (DoD Occupational Group 19).

Table 3: 2-digit Occupation Codes

DOD Occupation Code	Group Title
10X	Infantry, Gun Crews, Seamanship Specialists, or Unknown
11X	Electronic Equipment Repairers
12X	Communications and Intelligence Specialists
13X	Health Care Specialists
14X	Other Allied Professions
15X	Functional Support and Administration
16X	Electrical/Mechanical Equipment Repairers
17X	Craftsworkers
18X	Service and Supply Handlers

The corresponding 3-digit DOD occupation codes are listed in Table 4.

Table 4: 3-digit Occupation Codes

DOD Occupation Code	Title
100	Unknown
101	Infantry, General
102	Armor and Amphibious, General
103	Combat Engineering, General
104	Missile Artillery, Operating Crew
106	Small Boat Operators
108	Unmanned Vehicle System (UVS) Operators, General
110	Navigation, Communication, and Countermeasure, N.E.C.
111	Shipboard and Other Fire Control
112	Missile Guidance and Control
113	Sonar, General
114	Nuclear Weapons, Equipment Repair, General
115	ADP Computers, General
116	Teletype and Cryptographic Equipment, General
117	Cyberspace Maintenance
119	Electronic Instruments, N.E.C.
120	Radio Operators
121	Sonar Operator, General
122	Air Traffic Control
123	Intercept Operators (Code and Non-Code)

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Table 4: 3-digit Occupation Codes

DOD Occupation Code	Title
124	Operational Intelligence
125	Combat Operations Control, General
126	Communications Center Operations,General
127	Cyberspace Operations, General
130	Medical Care and Treatment, General
131	Radiology
132	Diet Therapy
133	Dental Care, General
134	Medical Administration
140	Photography, General
141	Surveying
142	Weather, General
143	EOD/UDT
145	Musicians, General
149	Firefighting and Damage Control
150	Recruiting and Counseling
151	Legal
152	Combined Personnel and Administration, General
153	Operators/Analysts/Programmers
154	Disbursing
155	Supply Administration
156	Chaplain’s Assistants
157	Information and Education, General
160	Aircraft, General
161	Automotive, General
162	Lineman/Central Office
164	Aviation Ordinance
165	Auxiliaries
166	Electric Power
167	Precision Equipment, General
169	Other Mechanical and Electrical Equipment, General
170	Metal Body Repair

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Table 4: 3-digit Occupation Codes

DOD Occupation Code	Title
171	Construction Equipment Operation
172	Utilities, General
174	Lithography, General
176	Fabric, Leather, and Rubber, General
179	Other Craftworkers, N.E.C., General
180	Food Service, General
181	Motor Vehicle Operators
182	Missile Fuel and Petroleum
183	Law Enforcement, General
184	Laundry and Personal Service, General
185	Auxiliary Labor
186	Forward Area Equipment Support, General
187	Other Services, N.E.C.

Employer Geography

Employment and earnings outcomes are available for each of the 50 states and the District of Columbia. However, not all states data are available for all years 2003-2022. Therefore, some veteran cohorts are missing employment and earnings outcomes if state UI data is missing in the relevant year following separation from service. A worker is assigned to a given state if their dominant employer for the calendar year paid for UI coverage for that worker in that state. For federal employees, we use the location of the government agency to establish state. States are identified by their Federal Information Processing Standard (FIPS) state code.

Employer Industry

We provide statistics by the industry of the dominant employer, at the 2-digit NAICS level with the federal government added as a separate category.

6 Confidentiality Protection Procedures

We implement a set of confidentiality protection procedures that follow those used for VEO and PSEO data products.[4] All employment counts are protected by geometric noise infusion while all earnings percentiles use geometric noise infusion in the histogram approach. We summarize implementation of these protection procedures below.

6.1 Disclosure Protection of Employment Counts

Employment counts are a set of count queries that we protect using a geometric mechanism for noise.

Consider a count ($n_{m,s,t,\tau}$) by worker characteristics (e.g. branch of service, cohort, sex, occupation, etc) m, in state and industry s, in table t, τ years after separation. To protect the count, we use the geometric noise mechanism to add noise such that the protected count is:

$$\tilde{n}_{m,s,t,\tau} = n_{m,s,t,\tau} + \eta \tag{7}$$

where $\eta \sim X - Y$, where $X,Y \sim Geometric(p)$ where $p = 1 - \frac{1}{e_t^{\varepsilon}}$. Therefore, $\tilde{n}_{m,s,t,\tau}$ is ε-differentially private.

6.2 Disclosure Protection of Earnings Percentiles

To protect earnings percentiles, we use noise infusion in the histogram approach. Consider the conditional earnings distribution described in Equation (6). We can approximate it by a histogram defined over H bins, such that all observed earnings fall into one of H intervals. These can be denoted $[b_1, b_2), ..., [b_h, b_{h+1}), ..., [b_{H-1} b_H), [b_H, \infty)$. We choose to have an earnings histogram with 21 bins, where the minimum and maximum values are set to \$10,000 and the 99.9th percentile of the earnings distribution, respectively. Each bin represents a 5th percentile increment of a publicly-available lognormal earnings distribution. We base the mean and variance parameters on the earnings distribution of veterans found in the ACS.[5] The corresponding bins are presented in Table 5.

[4] PSEO protections are described in Foote, Machanavajjhala, and McKinney (2019). VEO protections are described in `https://lehd.ces.census.gov/doc/VEO_Tech_Doc.pdf`.

[5] These parameters are estimated using the 2010-2014 5-year ACS Public-Use Microsample for veterans who were on active duty in 1990 onward and reported at least \$10,000 in real earnings. The mean is 10.7814 and standard deviation is 0.71134.

Table 5: ACS Veteran Earnings Histogram

Bin	**Lower Bound**	**Upper Bound**
1	10000	14933
2	14933	19337
3	19337	23021
4	23021	26442
5	26442	29780
6	29780	33136
7	33136	36582
8	36582	40182
9	40182	44003
10	44003	48117
11	48117	52617
12	52617	57619
13	57619	63291
14	63291	69872
15	69872	77745
16	77745	87560
17	87560	100575
18	100575	119733
19	119733	155042
20	155042	193998
21	193998	433482

We also include a bin for workers with zero earnings, or positive earnings but less than the earnings threshold. The count of observations in each bin h is protected by adding noise,

$$\tilde{n}_{h,m,s,t,\tau} = n_{h,m,s,t,\tau} + \eta \tag{8}$$

where $n_{h,m,s,t,\tau}$ is a count of workers in bin h with characteristics (e.g. cohort, sex, occupation, etc) m, in state and industry s, in table t, τ years after separation and $\eta \sim X - Y$, where $X, Y \sim Geometric(p)$ where $p = 1 - \frac{1}{e_t^{\varepsilon}}$. Therefore, $\tilde{n}_{h,m,s,t,\tau}$ is ε-differentially private.

Due to the composition properties of differential privacy established in Hay et al. (2010), the entire histogram is also ε-differentially private. To evaluate the extent to which a change in ε_t impacts the accuracy of the counts associated with the observed empirical distribution approximated by our histogram, we create the following accuracy measure:

$$CA_t = 1 - \frac{1}{100}\sum_{\eta}\frac{1}{2N_t}\sum_{h,m,s,\tau}|\tilde{n}_{h,m,s,t,\tau} - n_{h,m,s,t,\tau}| \tag{9}$$

We define CA_t as the average accuracy of all cells*bins combinations of histograms underlying table t, where the average is defined over 100 draws of η. $N_t = \sum_{h,m,s,\tau} n_{h,m,s,t,\tau}$ is the number of workers contributing to the table. These workers are defined over all possible combinations of (h,m,s,τ) for a table t.

From Equation (8), we can construct an ε-differentially private empirical CDF, from which we construct the percentiles of interest. The empirical CDF is defined as:

$$\tilde{F}(h|m,s,t,\tau) = \frac{\sum_{l=1}^{h}\tilde{n}_{l,m,s,t,\tau}}{\sum_{l=1}^{H}\tilde{n}_{l,m,s,t,\tau}} \tag{10}$$

To construct the percentile of interest from $\tilde{F}(h|m,s,t,\tau)$, we assume earnings are uniformly distributed within a bin. We then use linear interpolation to calculate earnings at any percentile between two estimated bins. The counts associated with the earnings percentiles are then defined over all of the bins, i.e. $\sum_{h=1}^{H}\tilde{n}_{h,m,s,t,\tau}$.

For an approved privacy budget B, we allocate it across tables following the social choice framework detailed in Abowd and Schmutte (2019). Consider the optimal disclosure protection ε-assignment problem for a set of T tables, each with K_t cells, that contains three percentiles (25th, 50th, and 75th). Each table represents a query on the same private database. To evaluate the accuracy of our B-differentially private data product, we consider the average accuracy of I draws of each cell, summed over all tables and percentiles of interest. Formally, this problem can be expressed as:

$$v(B) = \max_{\varepsilon_t}\left\{\sum_{q\in\{25,50,75\}}\sum_{t=1}^{T}\frac{1}{K_t}\sum_{k=1}^{K_t}\frac{1}{I}\sum_{i=1}^{I}\left[1 - \frac{|m^p_{t,i,k,q}(\varepsilon_t) - m^d_{t,k,q}|}{m^d_{t,k,q}}\right]\right\} \tag{11}$$
$$\text{subject to:} \sum_{t=1}^{T}\varepsilon_t \leq B$$

where $v(B)$ represents the total average accuracy across all tables as a function of the underlying privacy budget B. Let $m^p_{t,i,k,q}$ and $m^d_{t,k,q}$ represent the protected and true data moments, respectively. For any approved privacy budget B, we can recover the optimal ε_t for each table t that maximizes our accuracy function.

The degree of suppression of small (protected) cells increases overall accuracy for any value of the privacy budget. Our baseline suppression value is 50, which is slightly higher than the value used in the PSEO data product. The ε values for each individual table have been identified by numerically solving Equation (11).

6.3 Aggregations of Counts and Percentiles

The disaggregated tables shown in Table 2 can be aggregated to total counts and earnings across combined groups of service members. For example, counts of service members for all cohorts by service branch. Many of these aggregations may be repeated across multiple tables with distinct resulting totals and differing earnings estimates due to the application of differential privacy protections and data availability. Note that the original release of VEO maintained consistency in counts across tables. This is no longer possible in v2.0 due to differences in data quality and suppressions of incomplete cohorts. More details on the original aggregation methodology can be found in Graham et al. (2024).

Table 6: Status Flags

Status Flag	Label
-1	Data not available to compute this estimate. For VEO, this is typically due to lack of earnings data for later separation cohorts or lack of state data for earlier separation cohorts
1	OK
5	Value suppressed because it does not meet U.S. Census Bureau publication standards. For VEO, this is typically due to small protected counts.

7 Output

The final data product is composed of 13 files, one for each of the 13 tables described in Table 2. These files contain the following:

- Relevant identifiers
- Protected employment counts of veterans who are above the threshold in one, five, and ten calendar years after separation from active-duty (denoted *y1_emp*, *y5_emp*, and *y10_emp*)
- Protected employment counts of veterans who are below the threshold or unobserved in one, five, and ten calendar years after separation from active-duty (denoted *y1_nonemp*,

y5_nonemp, and *y10_nonemp*).[6]

- Protected employment counts of veterans who are above the threshold are accompanied by three earnings percentiles in one, five, and ten calendar years after separation from active-duty:
  - P25 (denoted *y1_p25_earn*, *y5_p25_earn*, and *y10_p25_earn*)
  - P50 (denoted *y1_p50_earn*, *y5_p50_earn*, and *y10_p50_earn*)
  - P75 (denoted *y1_p75_earn*, *y5_p75_earn*, and *y10_p75_earn*)
- Nine status flags for employment and earnings measures noting suppressions or other data limitations in one, five, and ten calendar years after separation from active-duty (denoted *status_y1_emp*, *status_y5_emp*, and *status_y10_emp*; *status_y1_nonemp*, *status_y5_nonemp*, and *status_y10_nonemp*; and *status_y1_earn*, *status_y5_earn*, and *status_y10_earn*). For example, some states enter the LED partnership after our earliest cohorts separate from the military. As a result, there are state-specific restrictions in the reporting of employment counts and earnings percentiles. Possible values are detailed in Table 6.

References

[1] Abowd, John and Stephens, Bryce and Vilhuber, Lars and Anderson, Fredrik, and McKinney, Kevin and Woodock, Simon (2009) "The LEHD Infastructure Files and the Creation of the Quarterly Workforce Indicators," *NBER Chapters in: Producer Dynamics: New Evidence from Micro Data*, pp. 149-230.

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