## Appendix A.

## **Census of Agriculture Methodology**

The purpose of a census is to enumerate all objects with a defined characteristic. For the census of agriculture, that goal is to account for "any place from which \$1,000 or more of agricultural products were produced and sold, or normally would have been sold, during the census year." To do this, NASS creates a Census Mail List (CML) of agricultural operations that potentially meet the farm definition, collects agricultural information from those operations, reviews the data, corrects or completes the requested information, and combines the data to provide information on the characteristics of farm operations and farm producers at the national, State, and county levels. In this appendix, these census processes are described.

#### THE CENSUS POPULATION

#### The Census Mail List

The National Agricultural Statistics Service (NASS) maintains a list of farmers and ranchers from which the CML is compiled. The goal is to build as complete a list as possible of agricultural places that meet the farm definition. The CML compilation begins with the list used to define sampling populations for NASS surveys conducted for the agricultural estimates program. Each record on the list includes name, address, telephone number, and email plus additional information that is used to efficiently administer the census of agriculture and agricultural estimates programs.

NASS builds and improves the list on an ongoing basis by obtaining outside source lists. Sources include State and federal government lists, producer association lists, seed grower lists, pesticide applicator lists, veterinarian lists, marketing association lists, and a variety of other agriculture-related lists. NASS also obtains special commodity lists to address specific list deficiencies. These outside source lists are matched to the NASS list using record linkage programs. Most names on newly acquired

sources are already on the NASS list. Records not on the NASS list are treated as potential farms until NASS can confirm their existence as a qualifying farm. Staff in NASS regional and field offices routinely contact these potential farms to determine whether they meet the farm definition. For the 2017 Census of Agriculture, NASS made a concerted effort to work with community-based organizations not only to improve list coverage for minorities but also to increase census awareness and participation.

List building activities for developing the 2017 CML started in 2014 by updating list information from respondents to the 2012 Census of Agriculture. Between 2015 and 2017, NASS conducted a series of National Agricultural Classification Surveys (NACS) on approximately 1.6 million records, which included nonrespondents from the 2012 census and newly added records from outside list sources. The NACS report forms collected information that was used to determine whether an operation met the farm definition. If the definition was met, the operation was added to the NASS list and subsequently to the CML. Addressees that were nonrespondents to a NACS were also added to the CML and identified with a special status code.

Measures were taken to improve name and address quality. Additional record linkage programs were run to detect and remove duplicate records both within each State and across States. List addresses were processed through software programs that utilize the United States Postal Service's National Change of Address System and the Locatable Address Conversion System to improve mail delivery. Records on the list with missing or invalid phone numbers were matched against a nationally available telephone database to obtain as many phone numbers as possible. To reduce costs, operations with characteristics that indicated they were unlikely to be farms, according to the farm definition, were removed from the list.

The official CML for the 2017 Census of Agriculture was established on September 3, 2017. The list contained 2,999,098 records. Of these, 2,259,750 records were thought to meet the NASS farm definition and 739,348 were potential farm records, which included NACS nonrespondents, other records added to the CML by the NASS regional field offices after the record linkage process, and late adds to the CML that were not included in any previous NACS or State screening survey.

### Not on the Mail List (NML)

Extensive efforts are directed toward developing a CML that includes all farms in the U.S. However, some farms are not on the list, and some agricultural operations on the list are not farms. NASS uses its June Area Survey (JAS) to quantify the number and types of farms not on the CML. The records in the JAS that are not on the CML are said to be in the Noton-the-Mail List (NML) domain. If a JAS record in the NML domain is determined to be a farm during the census, it is an NML farm. The NML farms are used to measure coverage associated with the census.

The JAS is based on an area frame, which covers all land in the U.S. and includes all farms. The land in the U.S. is stratified by characteristics of the land. A probability sample of segments is drawn within each stratum for the JAS. Segments of approximately equal size are delineated within each stratum and designated on aerial photographs. The JAS sample of segments is allocated to strata to provide accurate measures of acres planted to widely grown crops, farm numbers, and inventories of cattle. Sampled segments in the JAS are personally enumerated. Each operation identified within a segment boundary is known as a tract.

The 2017 JAS sample was increased to improve the farm counts for operations that produced specialty commodities or had socially disadvantaged or minority producers. The total JAS sample consisted of 13,972 segments of which 3,012 were additional segments. This set of additional segments is referred to as the Agricultural Coverage Evaluation Survey (ACES) segments. The ACES segments were selected using a multivariate sampling design that targeted specific items at the U.S. level. The 2017 JAS

consisted of sample segments from all States, with the exception of Alaska where NASS does not maintain an area frame.

During the JAS/ACES enumeration process, each tract is identified as either agricultural or nonagricultural. Each JAS/ACES agricultural tract is identified as a farm or non-farm in June based on the farm definition of \$1,000 of sales or potential sales of agricultural products. Non-agricultural tracts are further classified into categories: with farm potential, with unknown farm potential, or with no farm potential. The names and addresses collected in the 2017 JAS/ACES were matched to the CML. Those from the 2017 JAS/ACES that did not match were determined to be in the NML domain and sent a yellow census report form so that they could be differentiated from the green report form sent to those addressees on the CML. Instructions on the census report form directed any respondent who received duplicate forms to complete the CML form and to mail all duplicate forms back together. Those who returned a CML and an NML form had been misclassified as NML and were removed from the NML domain.

The initial NML mailout consisted of 42,430 records. A total of 41,787 NML records were summarized of which 2,799 records were confirmed to be NML and in-scope.

The farm/nonfarm status of each NML domain operation was determined based on the reported data in the census form. An operation in the NML domain that was determined to be a farm is referred to as an NML farm. Characteristics of NML farms and their producers provided a measure of the undercoverage of farms on the CML. The percentage of farms not represented on the CML varied by State. In general, NML farms tended to be small in acreage, production, and sales of agricultural products. Farm operations were missing from the CML for various reasons, including the possibility that the operation started after development of the CML, the operation was so small that it did not appear in any agriculture-related source list, or the operation was misclassified as a nonfarm prior to census mailout. The CML was used with the NML in a capture-recapture framework to represent all farming operations across all States in the JAS sample.

## DATA COLLECTION OUTREACH AND PROMOTIONAL EFFORTS

NASS planned and executed a multi-phase strategic communications campaign for the 2017 Census of Agriculture, to increase the level of awareness and response among all U.S. agricultural producers.

- Phase 1 ran from December 2016 June 2017. It raised awareness about the census and list building, encouraged producers to sign up in response to NASS mailings and at community, association, and other stakeholder meetings where NASS partners reached out.
- Phase 2 ran from July 2017 December 2017. It notified farm producers and agricultural organizations that the census would be mailed in December, and encouraged communications regarding the census.
- Phase 3 ran from December 2017 July 2018. It focused on census data collection with messaging urging response, reminding producers that it was not too late to respond.
- Phase 4 ran from August 2018 February 2019. It thanked producers for their participation and NASS partners for their support, and informed all of the February 2019 data release plan.

The communications campaign focused on these primary areas: partnership building, local-level outreach, public relations, media relations, paid media, and social media. Some external support was provided by a private communications agency (i.e. primarily assistance with paid media/advertising strategy and ad creation) and a freelance writer.

The unifying force behind the 2017 communications campaign was the theme "Your Voice. Your Future. Your Opportunity." This was accompanied by supporting messages and artwork that created a census consistent look and feel for all communications. All messages and materials served the purpose of inspiring action: Grow Your Farm Future - Shape Your Farm Programs - Boost Your Rural Services - Fill out your Census of Agriculture -Do your part to be counted - The Census of Agriculture is Your Voice, Your Future, Your Opportunity.

### Partnership and Local-Level Outreach

At the national level, NASS officials met with leaders from dozens of agricultural organizations, State Departments of Agriculture, and other USDA agencies to successfully secure their support in promoting the census among their constituencies. Stakeholders partnered with NASS to promote the 2017 Census of Agriculture through publications (e.g. newsletters), special mailings, speeches, social media, websites, and other communications. In addition, through grassroots-level outreach and efforts, NASS partnered with a number of community-based organizations to reach minority and limited-resource farmers and ranchers. National-level outreach was encouraged and mirrored at the regional, State, and local levels. Among the highlights of these partnership efforts was the production of multiple television and radio public service announcements featuring the U.S. Secretary of Agriculture, State secretaries, directors, and commissioners agriculture and leaders from community-based organizations.

# **Coverage of American Indian and Alaska Native Farm Producers**

To maximize coverage of American Indian and Alaska Native agricultural producers, special procedures were followed in the census. A concerted effort was made to get individual reports from every American Indian and Alaska Native farm or ranch producer in the country. If this was not possible within some reservations, a single reservation-level census report was obtained from knowledgeable reservation officials. These reports covered agricultural activity on the entire reservation. NASS staff reviewed these data and removed duplication with any data reported by American Indian or Alaska Native producers who responded on an individual census report form. Additionally NASS obtained, from knowledgeable reservation officials, the count of American Indian and Alaska Native producers (on reservations) who were not counted through individual census report forms, but whose agricultural activity was included in the reservation-level report form.

Table D, American Indian and Alaska Native **Producers: 2017** provides the number of producers (1) reported as American Indian or Alaska Native in the race category, either as a single race or in combination with other races, on the individual census report forms (for up to four per farm) and (2) identified as American Indian or Alaska Native producers farming on reservations by reservation officials. The count from the individual report forms is summarized in the "Individually reported" column. It includes up to four producers on or off reservations. The "Other" column provides counts of producers on reservations as reported by a reservation or tribal official. The "Total" column is simply a sum of the "Individually reported" and the "Other" columns. Tables in other parts of the publication count the reservation-level reports as single farms.

#### **Public Relations**

In the public relations arena, NASS worked with internal and external stakeholders to equip them with communications tools and resources to deliver the census communications message to their audiences. NASS utilized its Intranet and the Partner Tools page on the census website to deliver materials to the 12 regional and 46 field offices as well as to external stakeholders. The materials included but were not limited to: customizable news releases, public service announcement scripts, and a PowerPoint template; Secretary of Agriculture video public service announcements, and drop-in advertisements; informational, instructional, and testimonial videos; website buttons and banners; brochures in multiple languages; flyers; posters; FAQ sheets, talking points, and more. In addition, at the national level, NASS issued six news releases during data collection (three more were produced before data collection to inform and prepare producers) citing department and agency spokespeople, published half a dozen timely and relevant pieces to the USDA blog highlighting the census, and conducted three social media campaigns. These public relations efforts at the national and locallevels helped ensure that NASS' message about the census was continually in the media, including print and online publications, a variety of social media, radio, and some television programs. Media outlets included both those specializing in agriculture and more general outlets.

#### Paid Media

Even with increasingly limited budgets and resources, NASS was able to apply a small portion of funds toward paid media. For the 2017 Census of Agriculture, NASS strategically advertised in regional print publications, online, and with national agriculture news services (i.e. TV, radio) to bolster reach both in general and within geographically-specific, previously under-represented populations and lower response areas.

#### **DATA COLLECTION**

#### **Method of Enumeration**

Data collection was accomplished primarily by mail, Computer-Assisted Self Interview (CASI) on the Internet, and personal enumeration for special classes of records in the census operations. Personal enumeration (interviewing) involved the use of both Computer-Assisted Telephone Interview (CATI) and Computer-Assisted Personal Interview (CAPI) data collection instruments. Enumerators at the five NASS Data Collection Centers conducted CATI data collection. In addition, enumerators under contract with NASS through the National Association of State Departments of Agriculture (NASDA) conducted phone and personal interviews with respondents. For the 2017 Census of Agriculture, NASS implemented a pre-notification strategy in an effort to increase awareness, improve overall responses, and encourage respondents to report early to avoid continued correspondence. All records with an e-mail address received an e-mail message marketing the improved web form and announcing the census mail packets were coming.

## **Report Forms**

Four versions of report forms were used for the 2017 Census of Agriculture:

- General form (17-A100)
- Short form (17-A200)
- Hawaii form (17-A101)
- American Indian form (17-A300)

The general form facilitated reporting crops and livestock most commonly grown and raised in the U.S. The short form expedited reporting specific crops or livestock for pre-identified farms and ranches in the U.S. The Hawaii form targeted crops and

livestock specifically grown or raised on farms and ranches in Hawaii. The American Indian form focused on crops and livestock for farms and ranches on reservations in Arizona, New Mexico, and Utah. All of the report forms allowed respondents to write in specific commodities that were not prelisted on their report form.

## **Report Form Mailings**

Pre-notification of census data collection began on November 17, 2017. Approximately producers with an active e-mail address on the census mail list received a message informing them of the upcoming census data collection period and encouraging them to utilize the new census web form. Between November 27 and November 30, 2017, approximately 1 million producers received a letter with their survey code and instructions for completing their census online. The letter encouraged producers to report online early to avoid receiving mail and phone follow-up. Approximately 3 million mail packets were mailed in December 2017 and January 2018. Each packet contained a cover letter, instruction sheet, a labeled report form, and a return envelope. The Census Bureau's National Processing Center (NPC) in Jeffersonville, IN was contracted to perform mail packet preparation, initial mailout, and two follow-up mailings to nonrespondents.

The initial mailout was followed by a thank-you reminder postcard that was delivered in January 2018 to all operations that received mail packets. First follow-up mail packets were mailed in mid-February 2018 to approximately 1.5 million nonrespondents. Second follow-up mail packets were mailed in mid-March 2018 to approximately 1 million nonrespondents.

### Nonresponse Follow-up

Operating concurrently with NPC's mail data collection efforts, NASS Data Collection Centers targeted selected groups of census nonrespondents for telephone enumeration. NASS regional field offices targeted selected groups of census nonrespondents for in-person enumeration. These efforts were referred to as:

• Must Case Follow-up

- American Indian Producer Follow-up
- National Nonresponse Follow-up
- Not on Mail List (NML) Follow-up

Must Case Follow-up. Must cases are known large or unique operations, the absence of which could have significantly affected the accuracy of census results. For the 2017 Census of Agriculture, 125,697 records were categorized as Must cases. Each active Must operation was accounted for by mail receipt, phone interview, or personal enumeration; if an operation was no longer in business, its nonfarm status was documented. Call centers conducted CATI calling of nonrespondent Must cases from March 2018 through May 2018, after the initial and first follow-up mailings. Following the CATI calling, the remaining nonresponse Must cases were assigned to regional field offices for personal enumeration. Because of the potential importance of Must cases, they were all accounted for and therefore not eligible for nonresponse weighting adjustment.

American Indian Producer Follow-up. The American Indian report form (17-A300) was mailed to all operations in Arizona, New Mexico and Utah thought to have an American Indian producer. It was included in the initial mailout, but due to poor mail response, a personal enumeration data collection strategy was utilized with no additional mail followup. A concerted effort was made to get individual reports from every American Indian farm producer in the country. If this was not possible within a reservation, a single reservation-level census report was obtained from knowledgeable reservation officials. These reports covered agricultural activity on the entire reservation. NASS staff reviewed these data and removed any duplicate data reported by American Indian producers from that reservation who responded on an individual census report form. Additionally NASS obtained, from knowledgeable reservation officials, the count of American Indian farm producers (on the reservations) who were not counted through individual census report forms, but whose agricultural activity was included in the reservation-level report form.

National Nonresponse Follow-up (Excludes Must Records). The National Nonresponse follow-up activity was designed to focus nonresponse follow-up in a manner that would both reflect the characteristics

of the nonresponders and increase response rates. In April 2018, a sample of 249,521 nonrespondents was selected from the remaining 864,260 nonrespondents using a stratified random design. The strata were based on State, county, size of farm, type of farm, producer race, and propensity to respond. Beginning in mid-April 2018 and continuing through July 2018, extensive efforts were made to collect data for the sampled records, including an additional CASI push, autodial calls, CATI, and CAPI. Records in the same stratum received the same set of collection methods. Of the 80,504 responses, 51,846 records were identified as being in-scope, resulting in a weighted farm count of 143,847 from the sample.

Not-on-the-Mail List (NML) Follow-up. To account for farming operations not on the CML, NASS used its 2017 JAS sample from the NASS area frame, augmented with the ACES segments. Because the NASS area frame covers all land in the U.S. with the exception of Alaska, it includes all farms. As previously described, NASS conducted a record linkage operation between the CML records and the records from the 2017 JAS/ACES. Those 2017 JAS records that did not match records on the CML were designated as "Not-on-the-Mail List" (NML) records. These records were mailed a yellow census form so that it could be differentiated from the green forms mailed to CML records. The NML records were mailed at the same time as the census mailing and received the same follow-up procedures as the census mailing through the first follow-up in mid-February 2018. Beginning in March 2018, CATI was used for nonresponse follow-up for NML nonrespondents.

#### REPORT FORM PROCESSING

#### **Data Capture**

The Census Bureau's National Processing Center (NPC) in Jeffersonville, IN was contracted to process returned mail packets. NASS staff on site at the NPC provided technical guidance and monitored NPC processing activities. All report forms returned to the NPC were immediately checked in, using bar codes printed on the mailing label, and removed from follow-up report form mailings. All forms with any data were scanned and an image was made of each page of a report form. Optical Mark Recognition (OMR) was used to capture categorical responses and to identify the other answer zones in which some type

of mark was present.

Data entry operators keyed data from the scanned images using OMR results that highlighted the areas of the report forms with respondent entries. The keyer evaluated the contents and captured pertinent responses. Ten percent of the captured data were keyed a second time for quality control. If differences existed between the first keyed value and the second, an adjudicator handled resolution. The decision of the adjudicator was used to grade the performance of the keyers, who were required to maintain a certain accuracy level.

The images and the captured data were transferred to NASS's centralized network and became available to NASS analysts on a flow basis. The images were available for use in all stages of review.

## **Editing Data**

Captured data were processed through a computer formatting program that verified that records were valid – that the record ID number was on the list of census records, that the reported counties of operation and production were valid, and other related criteria. Rejected records were referred to analysts for correction. Accepted records were sent to a complex computer batch edit process. Each execution of the computer edit in batch mode consisted of records from only one State and flowed as the data were received from NPC, the NASS Computer-Assisted Self Interview (CASI), or the Computer-Assisted Telephone Interview (CATI) applications.

The computer edit determined whether a reporting operation met the qualifying criteria to be counted as a farm (in-scope). The edit examined each in-scope record for reasonableness and completeness and determined whether to accept the recorded value for each data item or take corrective action. Such corrective actions included removing erroneously reported values, replacing an unreasonable value with one consistent with other reported data, or providing a value for an item omitted by the respondent. To the extent possible, the computer edit determined a replacement value. Strategies for determining replacement values are discussed in the next section. Operations failing to meet the qualifying criteria for being classified as a farm were categorized as out-ofscope for the census. Records that NASS had reason

to believe might have been erroneously classified as out-of-scope (indications of recent and/or significant agricultural activity reported on NASS surveys, for example) were referred to analysts for verification.

The edit systematically checked reported data sectionby-section with the overall objective of achieving an internally consistent and complete report. NASS subject-matter experts had previously defined the criteria for acceptable data. Problems that could not be resolved within the edit were referred to an analyst for intervention. Prior to the census mail-out, NASS established a group of analysts in a Census Editing Unit in the National Operations Center in St. Louis, MO who examined the scanned images, consulted additional sources of information, and determined an appropriate action. Regional field office analysts also participated using an interactive version of the edit program to submit corrected data and immediately reedit the record to ensure a satisfactory solution.

## **Short Form Editing**

From the CML, 400,000 records were selected to receive a short form; this short form was derived from the full census report form by reducing a number of sections to a 'total' question – for example, instead of asking the respondent to report the acreage for each specific type of fruit or vegetable, the short form only asked for total fruit acreage or total vegetable acreage. In some cases, the same questions were asked on the general form, in which case the edit treated the short form responses as though they were incomplete general forms, as described in the previous paragraphs. In other cases, several items on the general form were collapsed – for example, total acres of Christmas trees and short rotation woody crops were asked as a single item on the short form, instead of separately as on the general form. In such cases, different approaches were taken in the edit to create a general form item or items from the short-form specific items. Any short form record that reported values above a certain threshold (in practice this threshold was 0 for almost all items) for these shortform-specific questions was 'flagged' by the edit; these records were later called back and the respondent asked for additional information about the items reported – for example, a producer reporting 10 acres of fruit on the short form was called back and asked for the total, bearing, and nonbearing acres for each type of fruit grown, as was asked on the general form. If the producer was successfully contacted and these additional data collected, the information was added to the record as additional reported data, and the edit was 'reset to original' - that is, the effects of the previous edit were undone – and the record was reedited with the new additional information. A flag was passed to the edit so that the short form record was not flagged for callback in such cases. In many cases, of course, it was not possible to recontact the respondent. In such cases, a flag was passed to the edit system, and the record was unlocked and available for review.

## **Imputing Data**

The edit determined the best value to impute for reported responses that were deemed unreasonable and for required responses that were absent. If an item could not be calculated directly from other current responses, the edit determined whether acreage, production, or inventory items had been reported for that farm on a recent NASS crop or livestock survey. For producers who had not changed in five years, demographics such as race and gender were taken from the previous census. Administrative data from the Farm Service Agency were used for a few items, such as Conservation Reserve Program acreage. When deterministic edit logic and previouslyreported data sources were unable to provide a current value, data from a reporting farm of similar type, size, and location were considered. In cases where automated imputation was unable to provide a consistent report, the record was referred to an analyst for resolution.

Separate system processes were established to efficiently provide data from a similar farm to the edit when donor imputation was required. The farm characteristics used to define similarity between a recipient record and its donor record were determined dynamically by the edit logic. Euclidean distance was used for similarity computations, with each contributing similarity characteristic scaled appropriately. The most similar farm based on this criterion (the "nearest neighbor") was identified and returned to the edit for use as a donor. The calculated distance between the centroids of the principal counties of production of the donor and recipient was always included as one of the measures of similarity.

To provide donors to the automated edit, a pool of successfully edited records was maintained for each section of the report form. These donor pools began with 2012 census data, reconfigured to emulate 2017 data and then edited using 2017 logic. Data from the 2015 Census Content Test were similarly remapped and edited before being added to the original donor pools. As 2017 records were successfully processed, they were added to the donor pools, which maintained the most recent data for each farm. Donor pools were updated approximately every other week, as determined by edit processing schedules. After several updates, all initial data records were dropped, leaving only 2017 records in the donor pools. After each update, donor pool records were grouped into strata containing farms in the same State of similar type and size, using a data-driven algorithm to define strata. Certain American Indian farms were treated as a separate group, effectively having their own donor pool.

In response to each donor request issued by the edit, a dedicated system process would search the appropriate stratum and respond with the most similar donor, while giving preference to more recent donors. In relatively rare instances where it was unable to provide a donor, the donor selection process issued an appropriate failure message to the edit. Imputation failures occurred for several different reasons. The requirement that an imputed value be positive could have ruled out all available donors, as could have the necessity for the donor record to satisfy a particular constraint – say, that the donor record has cattle, but no milk cows. In general, an imputation failure occurred if there were no satisfactory donors in the same profile as the report being edited. Records with imputation failures were either held until more records were available in the donor pool or referred to an analyst. In addition, when such a failure occurred in finding a donor for expenditure data, donor pool averages were provided in lieu of an individual donor, wherever possible. This "failover" utility was first introduced for the 2012 census imputation process, and significantly reduced the number of imputation failures among the expenditure and labor variables. During the early stages of editing, records requiring imputation for production (and hence yields) of field crops or hay, land values, or certain expenditure variables, were set aside or "parked." These records were edited when the donor pools contained only 2017 records, ensuring that 2017 data were used in the

imputations for the variables.

After receiving a donor's data, the edit substituted the values into the edited record. In many cases, the donor record's data value was scaled using another data field specified in the edit logic. In such cases, the size of the auxiliary field's value in the edited record, relative to its value in the donor record, was used to appropriately scale the donor record's value for the field to be imputed. The imputed data were then validated by the same edit logic to which reported data were subject. Since imputation was conducted independently for each occurrence, reports requiring multiple imputations may have drawn from multiple donors.

Substantial changes were introduced to the Personal Characteristics section of the form in 2017. Information on an additional (fourth) producer was collected, and several new questions were added for each producer - specifically, whether or not the person was considered a "principal producer," whether the person was a spouse of a principal producer, and whether the person was involved in any of five types of decisions with respect to the operation. These changes necessitated a new imputation process for records reporting three or more persons as producers. Records with one or two persons reported as producers had these data edited and imputed using the decision logic table edit and donor pool imputation process. Records with three or more persons reported as producers, and for which it was determined that these data were inconsistent or missing, had these data imputed using a fully conditional specification method. During the edit for records reporting three or more producers, the items needing imputation were marked, and the record was flagged. Periodically the data for these records (both the items needing to be imputed and the other variables needed by the model) were pulled and run through the imputation program. The resulting imputed values were loaded back to the records, and the records were made available for review. This process was conducted 19 times for the CML, and 6 times for the NML, during census production editing.

## **Data Analysis**

The complex edit ensured the full internal consistency of the record. Successfully completing the edit did not provide insight as to whether the report was reasonable compared to other reports in the county. Analysts were provided an additional set of tools, in the form of listings and graphs, to review record-level data across farms. These examinations revealed extreme outliers, large and small, or unique data distribution patterns that were possibly a result of reporting, recording, or handling errors. Potential problems were investigated and, when necessary, corrections were made and the record interactively edited again.

When NASS summarizes data from the census of agriculture, each individual report is typically assigned to a single "principal" county. The principal county is the county in which the majority of an operation's agricultural products are produced, as reported by the producer. For large operations that have significant production in multiple counties, their reports may be broken up into multiple source counties to more accurately summarize the data. Similarly, for large farms operating in more than one State, separate report forms are completed by State in order to assign the proper portion of the farm's total agricultural production to each State in which the farm operates.

## ACCOUNTING FOR UNDERCOVERAGE, NONRESPONSE, AND MISCLASSIFICATION

Although much effort was expended making the CML as complete as possible, the CML did not include all U.S. farms, resulting in list undercoverage. Some farm producers who were on the CML did not respond to the census, despite numerous attempts to contact them. In addition, although each operation was classified as a farm or a nonfarm based on the responses to the census report form, some were misclassified; that is, some nonfarms were classified as farms and some farms were classified as nonfarms. NASS's goal was to produce agricultural census totals for publication at the county level that were fully adjusted for list undercoverage, nonresponse, and misclassification.

In 2012 NASS used capture-recapture methodology to adjust for undercoverage, nonresponse, and misclassification. This same methodology was implemented for the 2017 Census of Agriculture. To implement capture-recapture methods. independent surveys were required. The 2017 Census of Agriculture (based on the CML) and the 2017 JAS

(based on the area frame) were those two surveys. Historically, NASS has been careful to maintain the independence of these two surveys.

A second assumption was that the proportion of JAS farms with a given set of characteristics captured by the census was equal to the proportion of U.S. farms with those same characteristics captured by the census.

For a farm to be identified as a farm, and thus captured by the census, it must be on the CML, respond to the census report form and, based on the census response, be classified as a farm. Only those nonrespondents included in the nonresponse sample had an opportunity to be captured and had a probability  $\pi_s$  of being included in the sample; respondents prior to drawing the nonresponse sample had  $\pi_s = 1$ . Thus, the capture probability  $\pi_c$  is of interest:

 $\pi_{\rm C} = \pi({\rm CML, Responded, Farm on Census|Farm}) \, \pi_{\rm S}$ 

Two types of classification error can occur. First, a farm can be misclassified as a nonfarm. This type of misclassification is accounted for in determining the probability of capture  $\pi_c$ . The second type of classification error results when a response to the census is classified as a farm operation when it does not meet the definition of a farm. That is, some farms on the CML may be misclassified from their census report response and may be nonfarms. To account for the misclassification of nonfarms as farms, the probability of a farm on the census being classified correctly must be estimated; that is,

 $\pi_{CCFC} = \pi(Farm \mid Farm \text{ on Census})$ 

where CCFC represents Correct Census Farm Classification. To adjust for undercoverage, nonresponse, and misclassification, each CML record classified as a farm based on its response to the census report form was given a weight of the ratio of the estimated probability of correct classification of a farm on the census and the estimated probability of capture  $(\hat{\pi}_{CCFC}/\hat{\pi}_C)$  where the hat symbol (^) denotes an estimate). To estimate the number of farms with a given set of characteristics, the weights of CML records responding as farms on the census and having that set of characteristics were summed. This

estimator is referred to as the capture-recapture estimator (CR):

$$CR = \sum_{i \in F} \frac{\hat{\pi}_{CCFC,i}}{\hat{\pi}_{C,i}}$$

where *F* is the set of all CML records classified as farms based on their responses to the census report form.

To estimate the capture and correct census farm classification probabilities, a matched dataset consisting of JAS records and census records was created. Records in the 2017 JAS sample were matched to the 2017 census using probabilistic record linkage. The CML records that matched with JAS tracts represent the Census Sample.

Note: The Census Sample is a subset of the CML records and includes only those records matching a JAS tract. Both agricultural and non-agricultural tracts were included in the matched dataset.

## **Resolving Farm Status**

The farm status based on census responses to either the CML or NML census data collection and the JAS agreed in most cases; these records are referred to as having resolved farm status. However, in other cases, a record was identified as a farm (nonfarm) on the JAS and as a nonfarm (farm) by the census through either the CML or the NML. Such records are said to have conflicting or unresolved farm status. An operation identified as a farm is referred to as inscope; an operation identified as a nonfarm is referred to as out-of-scope. From the set of matched records, two groups with conflicting farm status were identified: 1) in-scope JAS records that were out-ofscope on the census and 2) census in-scope and JAS out-of-scope records. The records with conflicting farm status were sent to NASS regional field offices for review. In each case, efforts were made to determine whether (1) the status had changed between June and December when the census was conducted, (2) the JAS farm status was correct, (3) the census farm status was correct, (4) the records were incorrectly matched, or (5) the farm status could not be resolved. Not all of the records with conflicting farm status could be resolved. In 2017, 8.1 percent of the records in the Census Sample had unresolved farm status.

The probability an operation is a farm was estimated for the records with unresolved farm status. Using the 2017 matched dataset, a logistic model of the probability an operation is a farm based on the records with resolved farm status was developed; that is, the operations where the farm (or nonfarm) status agreed between the JAS and the census were used to develop a missing data model, which was then used to resolve farm status. The final missing data model was used to impute the probability that each of the agricultural operations with unresolved farm status is a farm. For the resolved farms and nonfarms, the probability of the operation being a farm was 1 and 0, respectively. Five-fold cross-validation was used to develop and to compare competing models. The accuracy of the model was thereby not overstated due to fitting and evaluating the model on the same set of data. To ensure that each of the cross-validation samples covered the U.S., the five cross-validation samples of JAS segments were drawn within State-stratum combinations. Characteristics of the JAS tracts were considered as potential covariates in the model. Because limited information is available for JAS nonfarm tracts, other covariates considered included county-level socio-demographic variables from the most recent U.S. population census, segment-level data from the Cropland Data Layer, the county-level rural-urban code, state-level response rates, an indicator for records that are thought to be out-ofbusiness, and an indicator for records in the national nonresponse sample. The sample weight associated with each JAS tract was multiplied by the probability of being a farm. This adjusted weight was used in all subsequent modeling.

## **Capture Probabilities**

Recall that, for a farm to be identified as a farm, and thus captured, by the census, it must be on the CML, respond to the census report form and, based on the census response, be classified as a farm. These adjustments are dependent. Further, those nonrespondents at the time the nonresponse sample was drawn had a known probability  $\pi_S$  of being included in the sample; respondents before the sample was drawn had  $\pi_S = 1$ . Therefore, the probability of capture  $\pi_C$  may be written as

 $\pi_c = \pi(\text{CML}, \text{Responded}, \text{Farm on Census}|\text{Farm}) \pi_s$  $=\pi(\text{CML}|\text{Farm})\pi(\text{Responded}|\text{CML},\text{Farm})\pi(\text{Farm})$ on Census CML, Responded, Farm)  $\pi_s$ 

The probability of being included in the sample  $\pi_s$  is known for all responding farms. The other terms in the probability of capturing a farm depend on the characteristics of the farm. Using five-fold crossvalidation, three logistic models were developed based on the matched dataset. The first model estimated the probability of a farm being on the CML. The second model estimated the probability that a farm on the CML responded to the census report form. The final model estimated the probability that a farm that was on the CML and responded to the census was identified as a farm based on its response. The probability that a farm is captured by the census of agriculture is then the product of the three conditional probabilities that a farm is on the CML, responds, and is identified as a farm.

Note 1: Responses were required for Must cases. These operations were only excluded in modeling the probability of a farm responding given that it was on the CML.

Note 2: Because Alaska is not included in the JAS and thus has no area frame, the Alaskan agricultural operations were not included in the capture-recapture process. No adjustments were made undercoverage or misclassification. To account for nonresponse, the CML records were divided into three groups: (1) the Must records, (2) the Criteria Records, and (3) the remaining CML records. The must records received a weight of one, thereby receiving no adjustment for nonresponse. The probability of response for each of the other two groups was the proportion of responders within the group. Each record within the group was then given a weight equal to the reciprocal of the probability of response.

#### Misclassification

An operation is misclassified if: (1) it meets the definition of a farm, but is classified as a nonfarm on the census or (2) it does not meet the definition of a farm, but is classified as a farm on the census. The first type of misclassification is accounted for when modeling the probability of capture. An adjustment is

still needed for the misclassification of nonfarms as farms. As with farm status and capture, the probability of this misclassification depends on an operation's characteristics. Thus, a final logistic model was developed. Given that an operation was classified as a farm on the CML, the probability of its being a farm was modeled based on its characteristics. Five-fold cross-validation was used to ensure that the model was not over-fitted.

#### **CALIBRATION**

Each operation identified as being in-scope on the CML was given a weight equal to the probability of misclassification divided by the probability of capture. This weight accounted for undercoverage, nonresponse, both types of misclassification, and the nonresponse sample.

The record weighting processes were initially applied at the State level to produce adjusted estimates of farm numbers and land in farms for 63 different categories of 8 characteristics of the farm operation or the farm producer -- value of agricultural sales (9); age (2); female; race (3); Hispanic origin of principal farm producer; 4 sales categories for each of 10 major commodities (40); and farm type groups (7). The State-level number of farms and land in farms were two additional adjusted estimates, resulting in 65 categories. To reduce the intercensal variation at the State level, the State targets were smoothed by averaging the 2017 estimates from capture-recapture and the published 2012 State estimates with the restrictions that the smoothed targets were within two standard errors of the capture-recapture estimates. The smoothed State targets were rescaled so that they summed to the national capture-recapture estimates.

These State estimates were general purpose in that they did not provide any control over expected levels of commodity production of the individual farm operation. As a result of this limitation, the procedures could have over-adjusted or under-adjusted for commodity production. To address this, a second set of variables, known as commodity targets, was added to the calibration algorithm. These targets were commodity totals from administrative sources or from NASS surveys of nonfarm populations (e.g. USDA Farm Service Agency program data, Agricultural Marketing Service market orders, livestock slaughter data, cotton ginning data). The introduction of these

commodity coverage targets strengthened the overall adjustment procedure by ensuring that major commodity totals remained within reasonable bounds of established benchmarks.

Each State was calibrated separately. The calibration algorithm addressed commodity coverage. The algorithm was controlled by the 65 State farm operation coverage targets and the State commodity coverage targets. Because calibration targets are estimates subject to uncertainty, NASS allowed some tolerance in the determination of the adjusted weights. Rather than forcing the total for each calibration variable computed using the adjusted weights to equal a specific amount, NASS allowed the estimated total to fall within a tolerance range.

Tolerance ranges for the farm operation coverage targets were determined differently from the commodity targets. The tolerance range for the 65 State farm operation coverage targets was the estimated smoothed State total for the variable plus or minus one standard error of the capture-recapture estimate. This choice limited the cumulative deviation from the estimated total for a variable when State totals were summed to a U.S. total. Commodity coverage targets with acceptable ranges were established based on the administrative source for each State. Ranges were not necessarily symmetric around the target value.

To ensure that all subdomains for which NASS publishes summed to their grand total, integer weights were produced by a discrete calibration algorithm. This eliminated the need for rounding individual cell values and ensured that marginal totals always added correctly to the grand total. If a weight was initially not in the interval [1,6], it was trimmed so that in was in that interval. That is, adjusted weights less than 1 were set to 1, and those greater than 6 were set to 6. The remaining non-integer weights were then rounded sequentially to reduce the distance of the estimated totals from the targets.

Calibration adjustments began with the computation of a priority index for each record. The priority index was the absolute value of the gradient of the relative error associated with increasing or decreasing a record's weight by one. The record with the highest priority index was then selected as a candidate to increase or decrease its weight by one to reduce the

cumulative distance from the targets as measured by the relative error. If the new value produced an improvement and satisfied the range restrictions, the weight was updated and new priorities were assigned; otherwise, the record with the next highest priority index was processed. This process was iteratively performed until convergence was attained. Because census data collection was assumed to be complete for very large and unique farms, their weights were controlled to 1 during the calibration adjustment process. For all other farms, the final census record weights were forced to be an integer number in the interval [1, 6]. The calibration process considered all targets simultaneously through the priority index. Although calibration was seldom able to adjust weights so that all State targets were met, all targets were brought collectively as close to the targets as possible.

The proportions of selected census data items that were due to coverage, response, and classification adjustments are displayed in Tables A and C.

#### **DISCLOSURE REVIEW**

After tabulation and review of the aggregates, a comprehensive disclosure review was conducted. NASS is obligated to withhold, under Title 7, U.S. Code, any total that would reveal an individual's information or allow it to be closely estimated by the public. Farm counts are not considered sensitive and are not subject to disclosure controls. Cell suppression was used to protect the cells that were determined to be sensitive to a disclosure of information.

Based on agency standards, data cells were determined to be sensitive to a disclosure of information if they failed either of two rules. The threshold rule failed if the data cell contained less than three operations. For example, if only one farmer produced turkeys in a county, NASS could not publish the county total for turkey inventory without disclosing that individual's information. dominance rule failed if the distribution of the data within the cell allowed a data user to estimate any respondent's data too closely. For example, if there are many farmers producing turkeys in a county and some of them were large enough to dominate the cell total, NASS could not publish the county total for turkey inventory without risking disclosing an individual respondent's data. In both of these

situations, the data were suppressed and a "(D)" was placed in the cell in the census publication table. These data cells are referred to as primary suppressions.

Since most items were summed to marginal totals, primary suppressions within these summation relationships were protected by ensuring that there were additional suppressions within the linear relationship that provided adequate protection for the primary. A detailed computer routine selected additional data cells for suppression to ensure all primary suppressions were properly protected. These data cells are referred to as complementary suppressions. These cells are not themselves sensitive to a disclosure of information but were suppressed to protect other primary suppressions. A "(D)" was also placed in the cell of the census publication table to indicate a complementary suppression. A data user cannot determine whether a cell with a (D) represents a primary or a complementary suppression.

Regional field office analysts reviewed all complementary suppressions to ensure no cells had been withheld that were vital to the data users. In instances where complementary suppressions were deemed critically important to a State or county, analysts requested an override and a different complementary cell was chosen.

## **CENSUS QUALITY**

The purpose of the census of agriculture is to account for "any place from which \$1,000 or more of agricultural products were produced and sold, or normally would have been sold, during the census year." To accomplish this, NASS develops a CML that contains identifying information for operations that have an indication of meeting the census definition, develops procedures to collect agricultural information from those records, establishes criteria for analyst review of the data, creates computer routines to correct or complete the requested information, and provides census estimates of the characteristics of farms and farm producers with associated measures of uncertainty.

It is not likely that either the CML includes all operations that meet the definition of a farm or that all those that do meet the definition of a farm respond to the census inquiry. The goal is to publish data with a

high level of quality. The quality of a census may be measured in many ways. One of the first indicators used is a measure of the response to the census data collection as it has generally been thought that a high response rate indicates more complete coverage of the population of interest. This is a valid assumption if the enumeration list, the CML here, has complete coverage of the population of interest. In the case of the census of agriculture, the definition requiring advance knowledge of sales makes achieving a high level of coverage difficult. To ensure that the census of agriculture is as complete as possible, records are included that might not meet the census definition of a farm – in fact, almost 50 percent more records than the anticipated number of qualifying farm operations were included in the 2017 CML. A second indicator of quality then is the coverage of the farm population by the CML. Other indicators of quality relate to the accuracy and completeness of the data, and the validity of the procedures used in processing the data.

In some cases, NASS was able to produce measures of quality – such as the response rate to the data collection, the coverage of the census mail list, and the variability of the final adjusted estimates. In other cases, measures were not produced but descriptions of procedures that NASS used to reduce errors from the procedures were subsequently provided.

#### **Census Response Rate**

The response rate is one indicator of the quality of a data collection. It is generally assumed that if a response rate is close to a full participation level of 100 percent, the potential for nonresponse bias is small, although this has been questioned in the literature. The response rate for the 2017 Census of Agriculture CML was 71.8 percent, as compared with the 2012 Census of Agriculture's response rate of 74.6 percent and 78.2 percent for the 2007 Census of Agriculture.

The 2017 Census of Agriculture's response rate used the fourth response rate formula (RR4) from the American Association of Public Opinion Research's Response Rate Standard Definitions manual:

$$RR4 = \frac{C_{adj}}{C_{adj} + R + NC + O + Replicated + e(U)} (100)$$

where

 $C_{adj}$  = number of fully and partially completed records, excluding replicated records

R = number of explicit refusals

NC = number of non-contacted operations known to be eligible

O = number of other types of nonrespondents Replicated = number of replicated records U = number of operations of unknown eligibility e(U) = estimated number of operations of unknown eligibility assumed to be eligible

Records were classified into the above variables based on the combination of their active status (AS) codes, in-scope status, and replication status. Active status refers to the eligibility status of records for selection on the CML. All replicated records were considered to be a form of nonresponse and were classified into other nonrespondents; in-scope status was considered immaterial.

Certain active status classifications indicated records of unknown agricultural status. These classifications included records to be removed from the CML but had data from outside sources indicating agricultural activity, new records from outside data sources, nonrespondents and refusals to the NACS, records for regional office handling only, and records with Farm Service Agency or Conservation Reserve Program data on operations that are not owned by the principal producer. These records were stratified (grouped) based on their probabilities of being in-scope had they responded. The estimated number of in-scope nonrespondents was calculated for the *h*th stratum (group) by the following formula:

$$e(U_h) = \left(\frac{C_{in-scope,h}}{C_h}\right) U_h$$

where

 $e(U_h)$  = estimated number of operations of unknown eligibility assumed to be eligible in the hth group  $C_{in\text{-}scope,h}$  = the number of completed and in-scope census records in the hth group

 $C_h$  = the number of completed census records in the hth group

 $U_h$  = number of operations of unknown eligibility in the hth group

### **Census Coverage**

As a side-product of the statistical adjustment used to account for undercoverage, nonresponse of farms on the CML, and misclassification of responses to the census, the proportion of the adjustments due to each of those factors can be derived. The percentages of final census estimates due to adjustments for undercoverage, nonresponse, and misclassification as well as the total percent adjustment for selected items are displayed in Tables A and C.

## MEASURED ERRORS IN THE CENSUS PROCESS

Although the census of agriculture does not inherently rely on a sample, NASS used a national nonresponse sample as part of its follow-up efforts in 2017. In addition to the uncertainty introduced by the sample, NASS nonresponse uses statistical procedures in compiling the CML, in its data collection procedures, in data editing and processing, and in compiling the final data. Additionally, it uses statistical procedures to both measure errors in the various processes and in making adjustments for those errors in the final data. One example is the statistical process used to account for undercoverage, nonresponse of farms on the CML, misclassification of responses to the census. The basis of the undercoverage adjustment is the capturerecapture procedure that uses the area sample enumeration from the JAS. The largest contributors to error in the census estimates are due to the adjustments for nonresponse, undercoverage. misclassification, calibration, and integerization.

# Variability in Census Estimates due to Statistical Adjustment

In conducting the 2017 Census of Agriculture, efforts were initiated to measure error associated with the adjustments for farm operations that were not on the CML, for farm operations that were on the CML but did not respond to the census report form, and for farms and nonfarms that were misclassified as nonfarms and farms, respectively, for calibration. These error measurements were developed from the standard error of the estimates at the national, State, and county levels and were expressed as coefficients of variation (CVs) at the national and State levels and

as generalized coefficients of variation (GCVs) at the county levels.

The standard error of an estimate is an estimate of the standard deviation of the sampling distribution of the estimator. Because Alaska was modeled separately from the other States, the variances of a national-level data item for this State was computed separately and added to the variance of that data item for the rest of the U.S. The standard error was then the square root of the total variance. In each case, standard errors were computed using an approach based on a combination of group jackknife and bootstrap methodologies. To conduct the jackknifing, k = 10mutually exclusive and exhaustive groups of JAS segments were formed. The groups were selected using a stratified random design so that each group reflected the survey design, including State and agricultural strata within a State. The weight of record *i* in jackknife group *j* is  $CR_i^{(j)}$  for j = 1, 2, ..., k. Based on these weights, a group jackknife estimator to estimate the variance would account for the uncertainty associated with modeling the capturerecapture probabilities. To account for the additional uncertainty due to calibration, the weights within each jackknife group were transformed through bootstrap simulation; these transformed weights are called calibration-adjusted-jackknife weights. The full dataset, which is composed of the records of all responding farms on the CML, is calibrated as described in the Calibration section, and the final calibration-adjusted weight of record i is denoted by  $\hat{w}_i$ . For each record i in jackknife group k, the calibration-adjusted-jackknife weights of that record can be approximated as  $w_i^{(j)} = a_i^{(j)} C R_i^{(j)}$  where  $a_i^{(j)} \sim$  $N(1,(\hat{w}_i-1)/\hat{w}_i)$ . The bootstrap process simulated the value of the adjustment  $a_i^{(j)}$  for each record on the CML to obtain the calibration-adjusted-jackknife weights. For a given data item, such as the number of farms, the estimate  $T^{(j)}$  was computed at the specified geographical level, such as nation, State, or county, using the (k-1) groups remaining after deleting the calibration-adjusted jackknife group i. Estimates of the variance and standard error associated with the estimator  $T_i$  are then, respectively,

$$\sigma_i^2 = \frac{k-1}{k} \sum_{j=1}^k \left( T_i^{(j)} - \sum_{l=1}^k \frac{T_i^{(l)}}{k} \right)^2; \quad SE(T_i) = \sqrt{\sigma_i^2}$$

Increasing k improves the estimate of the variance but, as k increases, the observations become too sparse to reflect the survey design and to provide countrywide coverage. Ten (10) calibration-adjusted jackknife groups were used to provide standard errors for 2017 State and national estimates. For the estimate of the number of farms with a given set of characteristics, only the CML records with those characteristics were used to obtain the overall estimate as well as the estimates from each calibration-adjusted jackknife

Note that the calibrated jackknife groups were only constructed once, and different subsets of the records were used to compute estimates and standard errors for the data items.

The CV is a measure of the relative amount of error associated with the sample estimate:

$$CV_i = \frac{SE(T_i)}{T_i} 100\%$$

where  $SE(T_i)$  is the standard error of the capturerecapture estimate for data item i. This relative measure allows the reliability of a range of estimates to be compared. For example, the standard error is often larger for large population estimates than for small population estimates, but the large population estimates may have a smaller CV, indicating a more reliable estimate. For county-level estimates, a generalized coefficient of variation (GCV) was determined for each estimate within a State. A generalized variance function relates a function of the variance of an estimator to a function of the estimator. Within a State, the standard error of an estimate for a data item was often found to be linearly related to the estimate of that item with an intercept of zero. Based on this modeled relationship, the GCV is the slope of the line relating the standard error to the estimate, multiplied times 100 to represent the GCV as a percentage.

The standard error is the product of the CV (or GCV for county estimates) and the estimate divided by 100. As an example, if the GCV for a State is 25 percent and a county's estimate is 4, then the standard error is 25(4)/100 = 1. The standard error of an estimated data item from the census provides a measure of the error variation in the value of that estimated data item based on the possible outcomes of the census collection,

including variants as to who was on the CML, who returned a census form, who was misclassified either as a farm or as a nonfarm, and the uncertainty associated with calibration and integerization. With 95 percent confidence, an estimate is within two standard errors of the true value being estimated. For this example, with 95 percent confidence, the estimate of 4 is within 2(1) = 2 of the true county value.

Table B presents the fully adjusted estimates with the coefficient of variation for selected items.

## NONMEASURED ERRORS IN THE CENSUS PROCESS

As noted in the previous section, sampling errors can be introduced from the coverage, nonresponse and misclassification adjustment procedures. This error is measureable. However, nonsampling errors are imbedded in the census process that cannot be directly measured as part of the design of the census but must be contained to ensure an accurate count. Extensive efforts were made to compile a complete and accurate mail list for the census, to elicit response to the census, to design an understandable report form with clear instructions, to minimize processing errors through the use of quality control measures, to reduce matching error associated with the capture-recapture estimation process, and to minimize error associated with identification of a respondent as a farm operation (referred to as classification error). The weight adjustment and tabulation processes recognize the presence of nonsampling errors; however, it is assumed that these errors are small and that, in total, the net effect is zero. In other words, the positive errors cancel the negative errors.

### **Respondent and Enumerator Error**

Incorrect or incomplete responses to the census report form or to the questions posed by an enumerator can introduce error into the census data. Steps were taken in the design and execution of the census of agriculture to reduce errors from respondent reporting. Poor instructions and ambiguous definitions lead to misreporting. Respondents may not remember accurately, may estimate responses, or may record an item in the wrong cell. To reduce reporting and recording errors, the report form was tested prior to the census using industry accepted cognitive testing procedures. Detailed instructions for completing the

report form were provided to each respondent. Questions were phrased as clearly as possible based on previous tests of the report form. Computer-assisted telephone interviewing software included immediate integrity checks of recorded responses so suspect data could be verified or corrected. In addition, each respondent's answers were checked for completeness and consistency by the complex edit and imputation system.

## **Processing Error**

Processing of each census report form was another potential source of nonsampling error. All mail returns that included multiple reports, respondent remarks, or that were marked out of business and report forms with no reported data were sent to an analyst for verification and appropriate action. Integrity checks were performed by the imaging system and data transfer functions. Standard quality control procedures were in place that required that randomly selected batches of data keyed from image be re-entered by a different operator to verify the work and evaluate key entry operators. All systems and programs were thoroughly tested before going on-line and were monitored throughout the processing period.

Developing accurate processing methods complicated by the complex structure of agriculture. Among the complexities are the many places to be included, the variety of arrangements under which farms are operated, the continuing changes in the relationship of producers to the farm operated, the expiration of leases and the initiation or renewal of leases, the problem of obtaining a complete list of agriculture operations, the difficulty of contacting and identifying some types of contractor/contractee relationships, the producer's absence from the farm during the data collection period, and the producer's opinion that part or all of the operation does not qualify and should not be included in the census. During data collection and processing of the census, all operations underwent a number of quality control checks to ensure results were as accurate as possible.

### **Item Nonresponse**

All item nonresponse actions provide another opportunity to introduce measurement errors. Regardless of whether it was previously reported data, administrative data, the nearest neighbor algorithm,

the fully conditional specification method, or manually imputed by an analyst, some risk exists that the imputed value does not equal the actual value. Previously reported and administrative data were used only when they related to the census reference period. A new nearest neighbor was randomly selected for each incident to eliminate the chance of a consistent bias

## **Record Matching Error**

The process of building and expanding the CML involves finding new list sources and checking for names not on the list. An automated processing system compared each new name to the existing CML names and "linked" like records for the purpose of preventing duplication. New names with strong links to a CML name were discarded and those with no links were added as potential farms. Names with weak links, possible matches, were reviewed by staff to determine whether the new name should be added. Despite this thorough review, some new names may have been erroneously added or deleted. Additions could contribute to duplication (overcoverage) whereas deletions could contribute to undercoverage. As a result, some names received more than one report form, and some farm producers did not receive a report form. Respondents were instructed to complete one form and return all forms so the duplication could be removed.

Another chance for error came when comparing June Area Survey tract producer names to the CML. Area producers whose names were not found on the CML were part of the measure of list incompleteness, or NML. Mistakes in determining overlap status resulted in overcounts (including a tract whose producer was on the CML) or undercounts (excluding a tract whose producer was not on the CML). All tracts determined to not be on the list were triple checked to eliminate, or at least minimize, any error. NML tract producers were mailed a report form printed in a different color. In order to attempt to identify duplication, all respondents who received multiple report forms were instructed to complete the CML version and return all forms so duplication could be removed.

Records in the 2017 JAS were matched to the 2017 census using probabilistic record linkage. The records of operations with differing farm status were sent out to be reviewed by NASS regional field offices. If farm status could not be resolved, the probability of an operation being a farm was imputed using a missing data model. The uncertainty associated with this estimate, with the exception of model uncertainty, was accounted for, but errors not found through this process were not.

Table A. Summary of State Coverage, Nonresponse, and Misclassification Adjustments: 2017 [For meaning of abbreviations and symbols, see introductory text.]

[For meaning of abbreviations and symbols, see introductory text.]	Total	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
Farmsnu Land in farms			32.2 20.6	13.8 5.7	10.8 10.6	7.5 4.4
Farms by size: 1 to 9 acres	arms 10,333	3 1,284	53.1	25.2	14.6	13.3
	acres 53,998	9,306	53.7 36.0	24.1 16.8	14.7 11.2	14.9 8.1
	acres 668,842	45,797	35.2 27.1	15.8 11.6	10.7 9.7	8.6 5.7
	acres 359,679	25,902	27.1 27.4	11.7 10.4	9.7 10.5	5.8 6.4
	acres 597,049	20,104	27.3 24.1	10.4	10.4	6.4 6.7
	acres 732,87	66,982	24.0 21.0	8.4 7.7	8.9 6.5	6.7 6.8
	acres 629,73	29,067	21.0 19.4	7.7 6.1	6.5 9.9	6.8 3.5
	acres 547,67	27,784	19.5 20.4	6.1 6.0	9.9 10.4	3.5 3.9
	acres 468,099	42,063	20.3 26.8	6.0 6.4	10.4 14.2	3.9 6.3
500 to 999 acres	acres 2,093,233 arms 3,955		27.4 27.2	6.2 4.6	14.7 19.3	3.9 6.3 6.5 3.3 3.2
	acres 2,728,843		26.9 19.0	4.3 1.4	19.4 15.0	3.2 2.6
	acres 2,631,900	153,129	18.0 3.6	1.4 1.1	14.0 1.4	2.6 1.0
	acres 2,453,379	40,611	2.8	0.9	1.0	0.9
Irrigated land use: Harvested cropland			29.8	13.8	11.3	4.6
Pastureland and other land	acres 48,555 arms 275 acres 2,110	167	11.6 50.2 43.2	3.8 21.6 18.5	5.6 15.4 16.4	2.2 13.1 8.3
Market value of agricultural products sold (see text)\$	9,341,229	147,955	16.9	3.9	9.7	3.4
Farms by value of sales: Less than \$1,000 (see text)			47.9	21.2	13.0	13.7
\$1,000 to \$2,499	1,000 4,03 arms 7,57 1,000 12,64	683	58.7 37.8 37.9	26.6 17.7 17.4	16.5 12.4 12.6	15.7 7.8 7.9
\$2,500 to \$4,999		392	32.6 32.4	17.4 17.1 17.0	9.6 9.5	5.9 5.9
\$5,000 to \$9,999		529	28.8 28.4	14.9 14.7	8.6 8.5	5.3 5.2
\$10,000 to \$19,999		379	22.8 22.4	9.0 8.8	9.2 9.0	4.7 4.6
\$20,000 to \$24,999		258	22.1 22.2	7.3 7.3	10.2 10.3	4.6 4.6
\$25,000 to \$39,999	arms 4,042 1,000 128,21	2 227	18.1 18.0	5.8 5.8	8.2 8.2	4.0 4.0
\$40,000 to \$49,999\$	1,000 82,064	138	18.2 18.2	5.7 5.7	8.3 8.2	4.2 4.3
	1,000 388,640		22.8 22.9	6.5 6.4	11.5 11.7	4.9 4.8
	,000 987,38	33,502	28.2 29.0	5.0 5.1	16.8 17.2	6.4 6.6
\$250,000 to \$499,999\$	1 232 45	62,628	25.5 25.8	3.3 3.3	18.6 18.9	3.6 3.6
\$500,000 to \$999,999	L000 L 1 675 168	82,295	22.2 22.1	2.3 2.4	17.4 17.1	3.6 2.4 2.5
\$1,000,000 or more\$	arms 1,90 1,000 4,594,775		13.7 9.2	3.6 3.1	6.8 3.3	3.3 2.8
Legal status for tax purposes (see text): Family or individual	arms 68,02°		32.9	14.4	10.8	7.7
Partnership	acres 9,957,709 arms 4,780	278	22.3 26.0	6.6 9.0	11.1 10.9	4.7 6.1
Corporation: Family held	acres 2,392,000 arms 2,960		15.2 26.7	2.8	9.3	3.1
	acres 1,200,384	81,411	16.9 27.7	3.2 8.0	10.5 10.6 11.4	5.6 3.2 8.3
	acres 83,96		14.6	5.3	5.3	4.0
American Indian Reservation, etc	arms 1,68 acres 331,22		29.1 23.9	12.2 8.1	9.5 9.6	7.4 6.2
Tenure: Full owners	arms 54,750	2.017	34.2	15.3	10.5	8.4
	arms 34,736 acres 4,175,393 arms 19,49	149,090	25.4 26.1	9.6 8.5	9.3 12.5	6.4 5.1
	acres 8,987,054 arms 3,556	1 219,773	18.7 33.9	3.1 14.6	12.4 14.5	3.2 4.8
	acres 802,84		17.9	4.8	10.5	2.5
All principal producer characteristics by <sup>1</sup> - Sex of operator: Male			31.1	13.0	11.1	6.9
Female		1,762	20.3 36.9 22.7	5.3 15.4 6.5	10.9 11.9 10.8	4.1 9.6 5.4
Primary occupation:	acres 3,104,45	141,009	22.1	6.5	10.8	5.4
Farming		7 1,703 3,335	27.7 35.5	10.3 15.0	10.3 12.3	7.1 8.2
	51,000	3,300	55.0	.5.0	.2.0	

See footnote(s) at end of table. --continued

Table A. Summary of State Coverage, Nonresponse, and Misclassification Adjustments: 2017 (continued) [For meaning of abbreviations and symbols, see introductory text.]

[For meaning of abbreviations and symbols, see introductory text.]						
Item	Total	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
All principal producer characteristics by ¹ Con.				-		
Hispanic, Latino, or Spanish origin (see text)	669	124	45.1	24.9	11.6	8.6
	82,391	8,609	14.5	7.3	3.8	3.3
Race: American Indian or Alaska Nativefarms	134	94	41.0	12.7	14.1	14.2
Asian	16,088	3,260	13.5	4.7	4.2	4.6
	123	92	48.0	13.4	24.8	9.7
acres Black or African American	8,715	1,200	14.6	6.3	4.4	3.8
	147	81	28.8	10.7	9.8	8.3
	9,661	3,559	17.7	5.2	7.5	5.0
Native Hawaiian or Other Pacific Islanderfarms	16	(H)	56.3	6.2	32.4	17.6
Whitefarms	847	(H)	16.5	3.9	7.2	5.5
	77,271	2,409	32.1	13.9	10.8	7.5
More than one race reported	13,921,607	270,277	20.7	5.7	10.6	4.4
	404	138	33.2	15.5	10.7	7.1
	39,847	15,162	16.9	5.4	7.6	3.9
Military service (see text): Never servedproducers	91,501	3,689	32.8	13.4	11.8	7.7
Servedproducers	11,189	816	28.9	11.7	9.3	7.9
All producers by age group <sup>1</sup> : Under 25 yearsfarms	2,473	317	41.5	17.1	15.0	9.5
25 to 34 years farms 35 to 44 years farms	10,760	1,547	46.9	19.9	16.7	10.3
	17,023	1,268	40.7	18.1	16.8	5.8
45 to 54 years farms	24,303	1,252	35.0	13.2	13.6	8.2
55 to 64 years farms	36,416	1,254	29.6	13.2	9.7	6.7
65 to 74 yearsfarms	24,707	1,412	27.2	11.1	7.2	8.9
75 years and overfarms	13,004	740	23.4	8.7	7.3	7.3
Net cash farm income of operations (see text): Farms with gains of <sup>2</sup> - Less than \$1,000farms	2,595	338	31.0	15.1	9.6	6.3
\$1,000	1,202	181	30.0	14.5	9.5	6.1
\$1,000 to \$4,999farms	6,718	392	24.9	11.2	8.4	5.4
\$1,000	18,554	1,352	25.4	10.6	9.2	5.6
\$5,000 to \$9,999	4,588	172	21.5	8.8	8.0	4.7
\$1,000 \$10,000 to \$24,999	33,461 6,918 114,472	1,462 402 7,019	21.3 21.3 21.6	8.6 7.8 7.7	8.0 8.4 8.7	4.7 5.1 5.2
\$25,000 to \$49,999	5,098	324	23.6	6.8	11.5	5.3
	181,626	11,154	23.8	6.8	11.7	5.3
\$50,000 or more	10,974 2,595,273	276 61,888	23.4 17.5	4.3 3.4	11.7 14.7 10.9	4.4 3.3
Farms with losses of - Less than \$1,000farms	3,339	398	36.2	16.5	11.3	8.4
\$1,000 to \$4,999farms	1,703	244	36.4	16.4	11.5	8.4
	13,018	770	40.7	18.6	12.3	9.8
\$1,000	37,595	2,366	41.1	19.1	12.2	9.8
\$5,000 to \$9,999farms	9,876	567	43.2	21.4	11.9	10.0
\$1,000	71,207	4,144	43.1	21.1	11.9	10.0
\$10,000 to \$24,999farms	9,454	1,203	39.9	17.0	12.6	10.3
\$1,000	145,963	19,876	39.7	16.6	12.6	10.5
\$25,000 to \$49,999farms	3,173	398	35.2	16.0	10.3	8.9
\$1,000 \$50,000 or more	109,205 2,054 270,154	11,846 287 35,552	34.6 31.8 28.5	15.7 13.0 10.2	10.2 11.7 11.1	8.7 7.1 7.2
Livestock and poultry: Cattle and calves inventory	25,224	1,141	32.8	13.7	13.3	5.7
number Beef cows inventoryfarms	1,284,240	49,347	26.5	6.1	15.9	4.5
	17,733	833	31.6	13.4	12.4	5.8
number Milk cows inventory farms	300,681	12,124	27.0	7.7	14.1	5.2
	3,346	161	33.1	11.8	18.0	3.3
number Hog and pigs inventoryfarms	269,069	10,335	12.3	2.5	8.4	1.4
	3,484	414	38.7	14.9	15.5	8.2
number Layers inventory farms	2,561,252	135,687	20.9	6.5	6.5	7.9
	10,274	628	46.5	21.6	15.5	9.3
number Broilers sold	28,868,147	1,026,526	2.8	1.3	0.6	1.0
	1,408	380	48.7	22.5	15.7	10.6
Aquaculture soldfarms	97,878,519	11,122,391	43.6	17.0	16.9	9.7
	130	43	29.5	15.7	8.2	5.6
\$1,000 Selected crops harvested:	9,305	890	8.7	5.9	0.8	2.0
Corn for grain	21,339	590	23.0	6.6	12.0	4.5
	3,286,205	62,951	15.7	2.3	10.7	2.7
Durum wheat for grain	-	-	- -	- -	- -	-
Other spring wheat for grain (see text) acres  Winter wheat for grain farms	7,861	269	22.4	5.4	12.4	4.5
acres Sorghum for grain	462,579	16,648	18.7	3.2	11.9	3.7
	14	4	28.6	18.4	4.1	6.2
acres Soybeans for beans farms	196	33	9.2	4.2	2.0	2.9
	25,636	740	23.7	7.3	11.7	4.7
acres Ricefarms	5,090,532	158,363	19.0	3.0	12.7	3.3
acres Cotton farms	-	-	-	-	-	-
Peanutsfarms	- -	-	-	-	-	-
acres	-	-	-	-	-	-

See footnote(s) at end of table. --continued

Table A. Summary of State Coverage, Nonresponse, and Misclassification Adjustments: 2017 (continued)

[For meaning of abbreviations and symbols, see introductory text.]

[1 of meaning of abbreviations and symbols, see introductory text.]						
ltem	Total	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
Selected crops harvested: - Con.						
Barley         farms           Oats         farms           acres         acres	167	29	24.0	9.7	9.8	4.4
	3,994	433	15.9	4.5	7.6	3.9
	1,276	139	34.8	10.8	16.5	7.5
	18,093	1,752	33.1	9.3	17.1	6.7
Forage - land used for all hay and all haylage, grass silage, and						
greenchop (see text)	34,230	1,304	33.4	14.0	11.1	8.3
	1,116,016	30,417	25.6	9.1	10.8	5.7
Land in vegetables (see text)	2,916	344	31.8	13.5	13.7	4.7
	33.118	2,359	10.2	2.9	5.8	1.5
Potatoes	613	152	33.4	13.0	16.7	3.7
	2.111	1,050	20.1	2.0	16.2	2.0
Tomatoes in the openfarms	1,278	192	31.5	13.5	14.4	3.5
Sweet cornfarms	4,636	290	9.1	2.3	5.6	1.2
	1,085	204	29.3	12.2	13.1	4.1
acres Lettucefarms	7,908	829	9.9	3.4	4.9	1.6
	337	69	31.6	17.4	9.7	4.5
Land in orchards (see text)farms	429	24	7.4	3.9	1.9	1.6
	1,801	213	32.7	15.7	12.2	4.8
Applesfarms	8,984	770	12.0	5.4	4.2	2.4
	1,137	137	32.2	15.0	12.2	5.0
Grapes acres Grapes acres	4,849	346	10.8	4.3	4.2	2.2
	525	101	31.4	15.7	11.1	4.6
	1,745	360	7.2	3.6	2.2	1.4
Oranges	-	-	-	-	-	-
Almondsfarms	11	(H)	63.6	44.5	8.8	10.3
Land in berriesacres acres acres acres acres	1,309 1,584	(H) 219 185	35.0 34.2 19.4	23.3 17.9 9.1	5.3 11.4 7.3	6.4 4.9 3.0

<sup>1</sup> Data were collected for a maximum of four producers per farm.
2 Farms with total production expenses equal to market value of agricultural products sold, government payments, and farm-related income are included as farms with gains of less than \$1,000.

# Table B. Reliability Estimates of State Totals: 2017 [For meaning of abbreviations and symbols, see introductory text.]

Item		Total	Coefficient of variation (percent)	ltem	Total	Coefficient of variation (percent)
FarmsLand in farms		77,805 13,965,295	3.1 2.0	All principal producer characteristics by <sup>1</sup> Con.		
Farms by size:		10,000,200	2.0	Hispanic, Latino, or Spanish origin (see text)farms	669	18.5
1 to 9 acres		10,333	12.4	acres		10.4
10 to 49 acres	acres farms	53,998 26,533	17.2 6.6	Race:		
50 to 69 acres	acres	668,842 6,156	6.8	American Indian or Alaska Nativefarms	124	70.3
	acres	359,679	7.8 7.2	acres	16.088	20.3
70 to 99 acres	farms acres	7,222 597,045	3.6 3.4	Asian		74.6 13.8
100 to 139 acres	farms	6,289	9.1	Black or African Americanfarms	147	55.3
140 to 179 acres	acres farms	732,875 4,004	9.1 4.6	Native Hawaiian or	-,	36.8
180 to 219 acres	acres	629,735 2,772	4.6 4.9	Other Pacific Islander		(H) (H)
	acres	547,671	5.1	Whitefarms	77,271	3.1
220 to 259 acres	acres	1,958 468,095	9.0 9.0	More than one race reported	404	1.9 34.1
260 to 499 acres	farms acres	5,844 2,093,233	3.8 4.1	acres		38.1
500 to 999 acres	farms	3,955	2.7	Military service (see text):	04 504	4.0
1,000 to 1,999 acres	acres farms	2,728,843 1,958	3.2 5.9	Never served producers Served producers		4.0 7.3
2,000 acres or more	acres	2,631,900 781	5.8 1.7	All producers by age group 1:		
2,000 4000 0	acres	2,453,379	1.7	Under 25 years farms		12.8
Irrigated land use:				25 to 34 years		14.4 7.5
Harvested cropland	farms acres	2,710 48,555	12.0 5.7	45 to 54 years		5.2 3.4
Pastureland and other land	farms	275	60.9	65 to 74 yearsfarms	24,707	5.7
	acres	2,110	53.6	75 years and overfarms	13,004	5.7
Market value of agricultural products sold (see text)	\$1,000	9,341,225	1.6	Net cash farm income of operations (see text): Farms with gains of <sup>2</sup> - Less than \$1,000	2.505	42.0
Farms by value of sales:				\$1,000	1 202	13.0 15.1
Less than \$1,000 (see text)	¢1 000	19,592 4,037	6.7 13.4	\$1,000 to \$4,999	18 554	5.8 7.3
\$1,000 to \$2,499	farms	7,572	9.0	\$5,000 to \$9,999	4,588	3.8
\$2,500 to \$4,999	\$1,000 farms	12,643 7,998	10.5 4.9	\$1,000 \$10,000 to \$24,999farms	6,918	4.4 5.8
\$5,000 to \$9,999	\$1,000 farms	28,420 8,171	5.4 6.5	\$1,000 \$25,000 to \$49,999farms	114,472 5,098	6.1 6.4
\$10,000 to \$19,999	\$1,000	58,269	6.2	\$1,000 \$50,000 or more	191626	6.1
	\$1.000	7,120 101,008	5.3 5.4	\$50,000 or more\$1,000	10,974 2,595,273	2.5 2.4
\$20,000 to \$24,999	farms \$1,000	2,164 48,152	11.9 11.2	Farms with losses of -		
\$25,000 to \$39,999	farms	4,042	5.6	Less than \$1,000farms		11.9
\$40,000 to \$49,999	\$1,000 farms	128,211 1,847	5.9 7.5	\$1,000 to \$4,999	13,018	14.3 5.9
\$50,000 to \$99,999	\$1,000 farms	82,064 5,460	7.5 5.1	\$1,000 \$5,000 to \$9,999farms	37,595 9,876	6.3 5.7
	\$1,000	388,640	5.5	\$1,000	71,207	5.8
\$100,000 to \$249,999	\$1,000	6,105 987,385	3.0 3.4	\$10,000 to \$24,999	145,963	12.7 13.6
\$250,000 to \$499,999	farms \$1.000	3,456 1,232,454	5.7 5.1	\$25,000 to \$49,999	100 205	12.6 10.8
\$500,000 to \$999,999	farms	2,371	5.0	\$50,000 or more farms	2,054	14.0
\$1,000,000 or more		1,675,168 1,907	4.9 2.9	\$1,000	270,154	13.2
	\$1,000	4,594,775	2.2	Livestock and poultry:  Cattle and calves inventoryfarms	25,224	4.5
Legal status for tax purposes (see text): Family or individual		60.007	2.2	number Beef cows inventory farms	4 204 240	3.8
·	acres	68,027 9,957,709	3.3 2.5	number	300,681	4.7 4.0
Partnership	farms acres	4,786 2,392,008	5.8 4.7	Milk cows inventory		4.8 3.8
Corporation:				Hog and pigs inventoryfarms	3,484	11.9
Family held	acres	2,960 1,200,384	7.7 6.8	number Layers inventory farms	10,274	5.3 6.1
Other than family held	farms acres	351 83,967	92.8 46.1	Broilers sold		3.6 27.0
Other - estate or trust, prison farm, grazing association	n,			number	97,878,519	11.4
American Indian Reservation, etc	acres	1,681 331,227	10.4 13.5	Aquaculture sold		32.8 9.6
Tenure:				Selected crops harvested:		
Full owners		54,750	3.7	Corn for grainfarms	21,339	2.8
Part owners	acres farms	4,175,393 19,497	3.6 3.4	Durum wheat for grain		1.9
Tenants	acres farms	8,987,054 3,558	2.4 7.8	Other spring wheat for grain (see text)		
	acres	802,848	6.6	acres	-	- 2.4
All principal producer characteristics by 1-				Winter wheat for grain	462,579	3.4 3.6
Sex of operator:  Male	farms	69,661	3.3	Sorghum for grain		25.2 16.8
	acres	13,357,983	2.0	Soybeans for beansfarms	25,636	2.9
Female	acres	25,609 3,104,458	6.9 4.5	Rice	-	3.1
Primary occupation:				Cottonfarms	-	-
Farming Other		41,097 61,593	4.1 5.4	acres	-	-
See feetnete(s) at and of table			1		-1	continued

See footnote(s) at end of table.

## Table B. Reliability Estimates of State Totals: 2017 (continued)

[For meaning of abbreviations and symbols, see introductory text.]

Item	Total	Coefficient of variation (percent)	ltem	Total	Coefficient of variation (percent)
Selected crops harvested: - Con.			Selected crops harvested: - Con. Land in vegetables (see text) - Con.		
Peanutsfarms	-	-			
acres	-	-	Sweet cornfarms	1,085	18.8
Barleyfarms	167	17.1	acres	7,908	10.5
acres	3,994	10.8	Lettucefarms	337	20.4
Oatsfarms	1,276	10.9	acres	429	5.7
acres	18,093	9.7	Land in orchards (see text)farms	1,801	11.8
	,		acres	8,984	8.6
Forage - land used for all hay and all			Applesfarms	1,137	12.1
haylage, grass silage, and			acres	4,849	7.1
greenchop (see text)farms	34,230	3.8	Grapesfarms	525	19.1
acres	1,116,016	2.7	acres	1.745	20.6
Land in vegetables (see text)farms	2,916	11.8	Orangesfarms	1,7 45	20.0
	33,118	7.1			-
Potatoes	613		Almonds acres	- 11	(11)
		24.7		11	(H)
acres	2,111	49.8	acres	2	(H)
Tomatoes in the openfarms	1,278	15.0	Land in berriesfarms	1,309	16.7
acres	4,636	6.3	acres	1,584	11.7

Data were collected for a maximum of four producers per farm.
Farms with total production expenses equal to market value of agricultural products sold, government payments, and farm-related income are included as farms with gains of less than \$1,000.

Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2017 [For meaning of abbreviations and symbols, see introductory text.]

Counties		Percent of total adjustment from nonresponse	Percent of total adjustment from coverage	Adjustment as percent of total	Standard error	Total (number)	Geographic area
Chemister   Chem							ALL FARMS (NUMBER)
Counties  Adams .							State Total
Aden	7.5	10.8	13.8	32.2	2,385	77,805	Ohio
Adams							Counties
Asen.	7.0	0.0	40.0	20.0	400	4.404	
Ashland		9.2 9.3					
Alberts		10.5 13.1					Ashtahula
Befmont	.3 8.0	11.3	13.1	32.4	89	687	Athens
Brown		7.7 10.2					Auglaize
B86   299   30.0   12.9   1.0	0.9 7.2	10.9	15.4	33.5	133	1,237	Brown
Clark		13.9 14.4					
Clark	3.3 7.2	13.3	11 0	22.2	225	960	Champaign
Circle	0.2 8.4	10.2	15.3	33.9	244	742	Clark
Columbiana		13.6 9.8					
Crawford	0.4 7.5	10.4	16.6	34.5	173	1,227	Columbiana
Cuyahoga         111         54         39.9         23.0         11           Deflance         907         155         21.2         8.1         1.4         Deflance         803         111         36.6         17.9         1         1.1		9.4 13.0					Coshocton
Defiance   907   153   21.2   8.1	0.6 6.3	10.6					Cuyahoga
Elie		9.1 8.1					
Elie	.4 7.4	11.4	17 0	36.6	111	803	Delaware
Fayette	7.8 6.0	7.8	15.7	29.6	60	382	Erie
Franklin		9.0 8.1					FairfieldFavette
Galla 990 192 33.6 14.2 19.6 19.6 19.2 33.6 14.2 19.5 19.1 19.1 19.1 19.1 19.1 19.1 19.1	8.6	13.9	17.4	40.0	130	408	Franklin
Geauga   1,049   213   41,5   19,1   19,1   10,000   10,0		6.8 10.3					
Guerneey		11.9 7.5					Geauga
Hancock		8.0					
Hancock	10.0	14.9	15.7	40.5	71	318	Hamilton
Harrison	7.1 5.1	7.1	10.7	22.8	151	887	Hancock
Henry		12.1 9.9					
Höcking	3.6 4.7	8.6	8.4	21.8	111	841	Henry
Huron		10.4 13.0			144		
Jackson		9.2 11.0					
Knox		10.4					
Knox	2.7 10.7	12.7	14.7	38.1	206	599	Jefferson
Lawrence	0.2 6.8	10.2	15.6	32.7	254	1,338	Knox
Logan         1,009         121         32.5         13.3         1           Lorain         1,001         160         35.6         16.0         1           Lucas         386         172         30.5         10.1         1           Madison         789         122         34.3         14.7         1         1           Madison         774         136         38.6         18.3         1		9.0 11.6					
Lorain         1,001         160         35.6         16.0         1.1           Lucas         386         172         30.5         10.1         1.1           Madison         789         122         34.3         14.7         1.1           Marion         615         187         26.7         10.2         1.1           Merion         615         187         26.7         10.2         1.1           Meigia         1,149         278         36.1         15.8         11           Meigis         515         137         29.3         14.5         14.5         14.5         14.5         12.2         14.5         14.5         16.0         12.2         1.2         16.0         26.5         10.8         14.5         10.8         14.5         14.5         14.5         14.5         10.8         14.5 <td< td=""><td></td><td>9.1 11.5</td><td></td><td></td><td></td><td></td><td></td></td<>		9.1 11.5					
Madison     789     122     34.3     14.7     1.       Mahoning     774     136     38.6     18.3     1.       Marion     615     187     26.7     10.2     1       Medina     1,149     278     36.1     15.8     11.       Meigs     515     137     29.3     14.5     1.       Mercer     1,231     106     26.5     10.8     6       Miami     1,037     184     32.3     14.1     1.       Monroe     808     164     33.5     15.3     1.       Montgomery     781     320     38.4     12.9     1.       Morgan     530     81     30.8     11.2     1.       Morow     865     78     38.7     19.6     1       Muskingum     1,263     169     29.0     13.1     1       Noble     593     80     34.5     14.5     1       Ottawa     551     81     22.9     12.3     1       Paulding     622     65     19.0     7.7       Perry     762     117     37.2     16.5     1       Pickaway     805     55     27.9     11.9     1	.4 8.1	11.4	16.0	35.6	160	1,001	Lorain
Mahoning     774     136     38.6     18.3     13       Marion     615     187     26.7     10.2     1       Medina     1,149     278     36.1     15.8     11       Meigs     515     137     29.3     14.5     1       Merce     1,231     106     26.5     10.8       Miami     1,037     184     32.3     14.1       Monroe     808     164     33.5     15.3       Morgan     808     164     33.5     15.3       Morgan     530     81     30.8     11.2     11       Morrow     865     78     38.7     19.6     1       Muskingum     1,263     169     29.0     13.1     1       Noble     593     80     34.5     14.5     1       Ottawa     551     81     22.9     12.3     1       Perry     622     65     19.0     7.7       Perry     762     117     37.2     16.5     11       Pike     511     169     36.1     11.4     1       Pickaway     805     55     27.9     11.9     1       Pike     511     169     36.1 <td></td> <td>13.4 12.9</td> <td></td> <td></td> <td></td> <td></td> <td></td>		13.4 12.9					
Medina     1,149     278     36.1     15.8     11.8       Meigs     515     137     29.3     14.5     14.5       Mercer     1,231     106     26.5     10.8     10.8       Miami     1,037     184     32.3     14.1     14.1       Monroe     808     164     33.5     15.3     15.3       Montgomery     781     320     38.4     12.9     1       Morgan     530     81     30.8     11.2     1       Morrow     865     78     38.7     19.6     1       Muskingum     1,263     169     29.0     13.1     1       Noble     593     80     34.5     14.5     1       Ottawa     551     81     22.9     12.3     1       Perry     762     117     37.2     16.5     1       Pickaway     805     55     27.9     11.9     1       Pike     511     169     36.1     11.4     1       Portage     1,118     256     40.9     14.6     1       Portage     1,118     256     40.9     14.6     1       Putnam     1,335     131     23.2     8.1		12.4					Mahoning
Meigs     515     137     29.3     14.5       Mercer     1,231     106     26.5     10.8       Miami     1,037     184     32.3     14.1       Montone     808     164     33.5     15.3       Montgomery     781     320     38.4     12.9     1.       Morgan     530     81     30.8     11.2     1.       Morrow     865     78     38.7     19.6     1       Muskingum     1,263     169     29.0     13.1     1       Noble     593     80     34.5     14.5     1       Ottawa     551     81     22.9     12.3       Paulding     622     65     19.0     7.7       Perry     762     117     37.2     16.5     1       Pike     805     55     27.9     11.9     1       Pike     511     169     36.1     11.4     1       Portage     1,118     256     40.9     14.6     1       Preble     1,055     101     31.2     17.2     1       Putnam     1,335     131     23.2     8.1       Richland     1,160     122     35.6     17.1		11.1	10.2	26.7			Marion
Mercer         1,231         106         26.5         10.8         9           Miami         1,037         184         32.3         14.1         1           Mornoe         808         164         33.5         15.3         9           Morgan         781         320         38.4         12.9         1           Morgan         530         81         30.8         11.2         1           Morrow         865         78         38.7         19.6         1           Muskingum         1,263         169         29.0         13.1         1           Noble         593         80         34.5         14.5         1           Noble         593         80         34.5         14.5         1           Ottawa         551         81         22.9         12.3         2           Perry         622         65         19.0         7.7         7           Perry         762         117         37.2         16.5         1           Pike         9         36.5         55         27.9         11.9         1           Pike         11         169         36.1		12.0 7.8					
Montoe         808         164         33.5         15.3         15.3           Montgomery         781         320         38.4         12.9         1.           Morgan         530         81         30.8         11.2         1.           Morrow         865         78         38.7         19.6         1           Muskingum         1,263         169         29.0         13.1         6           Noble         593         80         34.5         14.5         1           Ottawa         551         81         22.9         12.3         1           Paulding         622         65         19.0         7.7         1           Perry         762         117         37.2         16.5         1           Pike         805         55         27.9         11.9         1           Pike         511         169         36.1         11.4         1           Portage         1,118         256         40.9         14.6         1           Preble         1,055         101         31.2         17.2         1           Putnam         1,335         131         23.2         8	5.9	9.8	10.8	26.5	106	1,231	Mercer
Montgomery     781     320     38.4     12.9     1.       Morgan     530     81     30.8     11.2     1.       Morrow     865     78     38.7     19.6     1       Muskingum     1,263     169     29.0     13.1     1       Noble     593     80     34.5     14.5     1.       Ottawa     551     81     22.9     12.3     1.       Paulding     622     65     19.0     7.7       Perry     762     117     37.2     16.5     1       Pike     511     169     36.1     11.4     1       Portage     1,118     256     40.9     14.6     1       Portage     1,118     256     40.9     14.6     1       Putnam     1,335     131     23.2     8.1     1       Richland     1,160     122     35.6     17.1     1       Ross     1,121     134     30.8     15.0       Sandusky     688     194     40.8     14.3     14.3		9.0 9.9					Miami
Morrow.         865         78         38.7         19.6         1           Muskingum.         1,263         169         29.0         13.1         1           Noble.         593         80         34.5         14.5         1.           Ottawa.         551         81         22.9         12.3         1.           Paulding.         622         65         19.0         7.7         7.           Perry.         762         117         37.2         16.5         11         11.9         11.1         11.9         11.9	.2 11.2	14.2	12.9	38.4	320	781	Montgomery
Muskingum     1,263     169     29.0     13.1       Noble     593     80     34.5     14.5     12.0       Ottawa     551     81     22.9     12.3     12.3       Paulding     622     65     19.0     7.7       Perry     762     117     37.2     16.5     11       Pickaway     805     55     27.9     11.9     11       Pike     511     169     36.1     11.4     11       Portage     1,118     256     40.9     14.6     11       Preble     1,055     101     31.2     17.2       Putnam     1,335     131     23.2     8.1       Richland     1,160     122     35.6     17.1     1       Ross     1,121     134     30.8     15.0       Sandusky     768     85     28.8     13.3     1       Scioto     688     194     40.8     14.3     14.3	.8 7.3	12.5 11.8					Morrow
Ottawa         551         81         22.9         12.3         9           Paulding         622         65         19.0         7.7         9           Perry         762         117         37.2         16.5         11           Pickaway         805         55         27.9         11.9         11           Pike         511         169         36.1         11.4         11           Portage         1,118         256         40.9         14.6         11           Preble         1,055         101         31.2         17.2         1           Putnam         1,335         131         23.2         8.1         9           Richland         1,160         122         35.6         17.1         1           Ross         1,121         134         30.8         15.0         3           Sandusky         768         85         28.8         13.3         5           Scioto         688         194         40.8         14.3         14		8.7	13.1		169	1,263	Muskingum
Paulding         622         65         19.0         7.7         7.7           Perry         762         117         37.2         16.5         1           Pickaway         805         55         27.9         11.9         1           Pike         511         169         36.1         11.4         1           Portage         1,118         256         40.9         14.6         1           Preble         1,055         101         31.2         17.2         0           Putnam         1,335         131         23.2         8.1         9           Richland         1,160         122         35.6         17.1         1           Ross         1,121         134         30.8         15.0         3           Sandusky         768         85         28.8         13.3         5           Scioto         688         194         40.8         14.3         14		12.4					
Perry _         762         117         37.2         16.5         11           Pickaway .         805         55         27.9         11.9         11           Pike .         511         169         36.1         11.4         11           Portage .         1,118         256         40.9         14.6         11           Preble .         1,055         101         31.2         17.2         11           Putnam .         1,335         131         23.2         8.1         1           Richland .         1,160         122         35.6         17.1         1           Ross .         1,121         134         30.8         15.0         3           Sandusky .         768         85         28.8         13.3         5           Scioto .         688         194         40.8         14.3         14		5.6 7.1					
Pike     511     169     36.1     11.4     11       Portage     1,118     256     40.9     14.6     11       Preble     1,055     101     31.2     17.2     0       Putnam     1,335     131     23.2     8.1     9       Richland     1,160     122     35.6     17.1     1       Ross     1,121     134     30.8     15.0     3       Sandusky     768     85     28.8     13.3     5       Scioto     688     194     40.8     14.3     14	10.0	10.7	16.5	37.2	117	762	Perry
Portage         1,118         256         40,9         14,6         16           Preble         1,055         101         31,2         17,2         6           Putnam         1,335         131         23,2         8,1         9           Richland         1,160         122         35,6         17,1         1           Ross         1,121         134         30,8         15,0         8           Sandusky         768         85         28,8         13,3         9           Scioto         688         194         40,8         14,3         11	5.6 8.2	10.1 16.6	11.4	36.1	169		Pike
Putnam     1,335     131     23.2     8.1     9       Richland     1,160     122     35.6     17.1     1       Ross     1,121     134     30.8     15.0     8       Sandusky     768     85     28.8     13.3     9       Scioto     688     194     40.8     14.3     14	5.5 9.9	16.5	14.6	40.9	256	1,118	Portage
Richland     1,160     122     35.6     17.1     1       Ross     1,121     134     30.8     15.0     1       Sandusky     768     85     28.8     13.3     9       Scioto     688     194     40.8     14.3     11	0.9 5.2	6.5 9.9	8.1	23.2	131	1,335	Putnam
Sandusky         768         85         28.8         13.3         9           Scioto         688         194         40.8         14.3         15	.6 7.0	11.6	17.1	35.6	122	1,160	Richland
Scioto		8.2					
		9.7 15.9					
	2.5 7.0	12.5	10.7	30.2	137	1,156	Seneca
Stark         1,547         376         38.6         13.3         14	.0 11.3	9.9 14.0	13.3	38.6	376	1,547	Stark
Summit		5.9 11.4					Summit
Tuscarawas	5.5 7.8	13.5	13.1	34.4	232	1,155	Tuscarawas
	7.4	10.3	15.3	32.9	112	997	
		9.0					
		15.8 11.6					
		9.2					

Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2017 (continued) [For meaning of abbreviations and symbols, see introductory text.]

[For meaning of abbreviations and symbols, see introductory text.]  Geographic area	Total (number)	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
ALL FARMS (NUMBER) - Con.						
Counties - Con.						
Wayne	2,034	523	38.3	15.0	13.9	9.4
Williams	881	150	24.9	10.0	9.7	5.2
Wood	1,069	151	22.9	8.8	8.7	5.4
Wyandot	649	95	27.2	9.8	11.9	5.4
LAND IN FARMS (ACRES)						
State Total	40,005,005	070.004	20.0	5.7	40.0	
Ohio	13,965,295	278,984	20.6	5.7	10.6	4.4
Adams	165,947	32,395	28.5	10.9	11.7	5.9
Allen	186,623	37,647	20.4	3.8	13.3	3.4
Ashland	160,698	12,774	26.9	9.9	11.4	5.6
AshtabulaAthens	153,654 98,742	19,111 21,915	26.5 24.7	10.2 5.8	10.6 13.2	5.7 5.8
Auglaize	210,018	20,316	20.4	4.0	12.4	3.9
Belmont	129,364 207,957	15,820 54,542	19.2 31.7	7.3	6.8	5.1 5.0
Brown	123,916	26,208	27.6	6.5 6.8	20.2 13.3	7.5
Carroll	110,672	12,813	15.3	5.8	5.4	4.1
Champaign	188,997	21,469	14.6	3.3	8.2	3.2
Clark	170,987	28,233	17.7	4.3	10.3	3.2
Clermont	97,342 212,769	13,509 49,990	23.5 22.3	8.8 3.4	9.1 15.5	5.6 3.3
Columbiana	142,422	11,783	22.4	9.6	7.7	5.1
CoshoctonCrawford	182,555 238,233	13,249 33,166	28.8 18.6	11.7 2.6	10.0 12.9	7.1 3.1
Cuyahoga	2,248	883	18.3	11.2	3.0	4.0
Darke	343,774 228,465	35,306 38,968	18.0 26.9	3.5 4.4	11.1 18.9	3.3 3.6
Deliance					10.9	
Delaware	132,875 86,440	35,743 8,900	22.6 16.4	4.1 3.3	15.2 10.3	3.3 2.8
Fairfield	188,407	49,055	18.3	4.3	10.5	3.5
Fayette	204,254	39,770	12.4	1.6	9.0	1.8
FranklinFulton	52,356 196,306	9,243 18,143	25.5 14.6	6.5 3.1	13.0 8.6	6.0 2.8
Gallia	118,630	10,562	30.5	12.5	11.5	6.6
GeaugaGreene	69,907 167,701	16,899 43,894	28.6 15.6	11.0 2.6	11.6 10.6	6.0 2.4
Guernsey	151,837	16,383	29.8	13.2	8.2	8.4
Hamilton	17,970	6,351	35.4	12.1	12.5	10.8
Hancock	240,017	22,064	15.3	3.7	8.4	3.2
Hardin Harrison	261,744 99,340	29,141 23,091	17.7 22.2	2.8 7.9	11.3 9.6	3.7 4.7
Henry	234,876	47,157	12.4	1.5	8.4	2.5
Highland	287,973	33,964	28.1	5.7	18.2	4.2
HockingHolmes	38,357 173,925	12,067 26,749	31.2 26.7	12.4 11.5	9.1 9.8	9.7 5.4
Huron	240,519	43,845	19.5	3.0	13.1	3.3
Jackson	67,446	10,600	15.5	5.2	6.3	4.0
Jefferson	76,987 194,445	15,112 31,113	31.9 20.9	13.8	9.1	9.0
KnoxLake	13,098	1,107	23.6	7.6 13.8	8.5 4.0	4.7 5.9
Lawrence	62,009	11,132	32.9	14.1	11.2	7.6
Licking Logan	220,486 211,281	11,106 61,499	20.1 18.4	7.5 3.5	7.1 11.4	5.5 3.5
Lorain	125,721	34,552	22.0	5.0	12.2	4.8
Lucas	65,558 252,392	12,972 30,571	16.9 19.1	3.8 3.6	9.7 12.3	3.4 3.2
Mahoning	74,560	15,442	22.9	8.5	9.2	5.2
Marion	203,860	21,911	17.0	4.2	8.6	4.2
MedinaMeigs	99,325 78,449	11,588 9,249	18.1 24.6	6.2 13.2	8.1 5.4	3.8 6.0
Mercer	268,958	40,604	16.7	2.8	10.4	3.5
Miami	173,159 107,724	24,599 13,130	19.2 28.3	4.9 11.0	10.6 10.2	3.7 7.1
Montgomery	113,109	22,877	14.6	4.4	5.4	4.7
Morgan	99,210 165,235	13,256 23,053	18.5 14.8	6.8 4.6	7.5 6.9	4.1 3.3
Muskingum	189,022	17,963	15.9	5.9	6.0	4.0
	80,124	15,499	26.8	9.0	10.7	7.1
NobleOttawa	121,498	10,544	24.2	8.1	9.7	7.1 6.5
Paulding	219,663	30,817	21.2	3.9	13.6	3.7
Perry Pickaway	101,130 296,988	8,134 34,930	22.8 18.6	8.2 2.4	8.7 13.7	5.8 2.5
Pike	97,809	13,828	22.9	8.3	8.8	5.9
Portage Preble	85,877 213,476	12,367 29,133	23.6 21.4	8.1 5.0	9.6 12.5	5.9 4.0
Putnam	304,862	32,933	20.6	3.7	12.6	4.3
Richland	155,844	18,864	21.7	6.1	11.7	4.0
Ross	247,903	12,507	21.7	7.0	10.0	4.8
Sandusky	178,761 91,414	38,206 8,685	15.4 36.1	3.2 12.4	9.3 13.8	2.9 9.8
Seneca	266,896	16,473	21.3	4.1	13.5	3.6
ShelbyStark	214,966 132,896	9,868 15,171	16.0 16.7	3.3 5.2	9.7 7.0	3.0 4.5
	102,000	13,171	10.7	5.2	1.0	т.5

Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2017 (continued) [For meaning of abbreviations and symbols, see introductory text.]

1970   1970	Geographic area	Total (number)	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
Summer   18   722	LAND IN FARMS (ACRES) - Con.						-
Trumbale   12,065   12,065   16,7   7,7   5,5   5,5   5,5   5,5   5,5   1,5	Counties - Con.						
Trumbale   12,065   12,065   16,7   7,7   5,5   5,5   5,5   5,5   5,5   1,5	Summit	18.752	13.826	34.1	11.8	15.6	6.8
Tright	Trumbull	123,654	18,255	18.7	7.5	5.7	5.5
Van Word.    248,344   25,445   16.4   21   16.8   25							
Warrengen	Van Wert						
Washington	Vinton						
Wayne 251-396 2 26.07 10.1 3.3 10.3 4.6 10.7 10.5 10.5 10.5 10.5 10.5 10.5 10.5 10.5							
Word	Wayne	251,996	26,227	22.4	6.9	10.9	4.6
Wymets	Williams	210,592	23,895	16.7	3.5	9.9	3.3
State Total Onco State Total Onco Countes	Wood						3.2
Same	Wyandot	224,603	29,726	17.6	2.6	12.1	3.0
Sample	SALES (\$1,000)						
Adams	State Total						
Adams	Ohio	9,341,225	147,955	16.9	3.9	9.7	3.4
Allen	Counties						
Allen	Adams	40,118	5,949	26.2	6.6	15.3	4.3
Ashtabula   97,897   5,861   15,9   5,6   6,8   3,8   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6   6,8   3,6	Allen	139,911	25,157	19.3	4.3	10.6	4.4
Albers   11.432   7.248   24.8   0.0   16.4   5.5   Albers   2.5.557   2.5.557   2.5.557   2.5.557   2.5.557   Albers   2.5.557   A	AshlandAshtahula						
Aughière	Ashtabula	11,432				18.4	5.5
Property	Auglaize	206,904	23,894	21.3	4.9	11.9	4.5
Buller	Brown						
Claim   119,086   12,476   13,6   27   6.3   2.5   2.5   12.6	Butler	54,903	19,243	23.9	3.2	16.7	4.1
Clark.   126.488   15.225   12.3   3.0   6.9   2.3   Clark.   37.788   33.896   15.3   3.0   6.9   2.3   Columbaina   37.788   33.896   15.3   3.0   6.9   3.0   Columbaina   37.788   33.896   15.3   3.1   6.6   3.5   Columbaina   39.114   9.527   26.1   3.1   1.2   4   8.3   Columbaina   39.114   9.527   26.1   3.2   1.0   1.1   Columbaina   39.114   9.527   26.1   3.2   1.0   Columbaina   39.114   9.527   26.1   3.2   1.0   Columbaina   39.114   9.527   26.1   Columbaina   39.114   37.7   2.7   8.7   2.3   Columbaina   38.886   16.7   6.3   8.8   3.6   Columbaina   38.886   16.7   6.5   8.8   3.8   Columbaina   38.886   16.7   6.5   8.8   3.8   Columbaina   38.886   16.7   6.5   8.8   3.8   Columbaina   38.886   16.1   6.5   6.5   Columbaina   38.886   16.7   6.5   8.8   1.8   Columbaina   38.886   16.7   6.5   8.8   Columbaina   38.886   16.7	Carroll	48,627	2,174	11.5	4.7	4.5	2.3
Clark.   120,468   15,225   12.3   3.0   6.9   2.3   Delmont.   31,527   32,666   16.3   3.0   6.9   2.3   Delmont.   31,527   32,666   16.3   3.0   6.9   2.3   Delmont.   31,527   32,666   16.5   3.0   6.9   2.3   Delmont.   32,527   26.3   3.1   12.4   6.5   Delmont.   39,118   32,527   32.3   3.1   1.1   Darke.   516,133   35,666   16.7   3.3   8.8   3.6   Delmont.   35,666   16.7   3.3   8.8   3.6   Delmont.   35,666   16.7   3.3   3.8   3.5   Delmont.   35,666   16.7   3.3   3.5   Delmont.   35,666   16.7   3.5   Delmont.   35,666   16.7   3.5   Delmont.   35,666   16.7   3.5   Delmont.   35,666   3.5   3.5   Delmont.   35,666   3.5   3.5   Delmont.   35,666   3.5   Delmo	Champaign	119,586	12,476	13.6	2.7	8.3	
Clinton	Clark	126,468		12.3			
Columbinian							
Crawford	Columbiana	106,666	9,883	24.8	8.8	10.0	6.0
Coyaboga         6,224         368         5.2         3.2         1.0         1.11           Date         516,193         35,680         18.7         6.3         8.8         3.6           Defrace         107,279         16,150         24.3         2.5         19.7         2.8           Delaware         86,862         14,744         13.7         2.7         8.7         2.3           Efe         42,050         5,040         6.8         1.8         1.3         1.2         1.3           Efe         42,050         5,040         6.8         1.5         7.0         1.4           Feyette         127,188         23,024         9.8         1.5         7.0         1.4           Feyette         127,188         23,024         9.8         1.5         7.0         1.4           Feyette         13,186         7.113         18.5         4.0         10.3         4.3           Guld         13,187         2.1         1.3         4.0         10.3         4.3           George         37,086         2.2,015         1.2         4.0         10.3         4.3           Hamillon         22,028         5,355         33	Coshocton						
Definace   516,193   35,680   18.7   6.3   8.8   3.6   Definace   86,862   14,784   13.7   2.7   8.7   2.3   Element   94,205   5,040   6.9   1.7   3.3   1.9   Farifield   94,205   5,040   6.9   1.7   3.3   1.9   Farifield   95,758   24,224   19.8   3.5   12.0   3.3   Farifield   15,758   24,224   19.8   3.5   12.0   3.3   Farifield   173,103   24,711   12.9   3.9   6.5   24   Gallia   18,975   19.00   3.0   7.7   3.9   6.5   24   Gallia   18,975   19.00   3.0   7.7   3.9   6.5   24   Gallia   18,975   19.00   3.0   7.7   3.9   General   27,086   23,015   12.4   1.8   8.6   2.0   General   27,086   23,015   12.4   1.8   8.6   2.0   General   23,037   1.352   1.352   1.3   Hamilton   22,2865   13,085   9.9   3.0   4.4   2.5   Harrion   222,865   13,085   9.9   3.0   4.4   2.5   Harrion   222,865   13,085   9.9   3.0   4.4   2.5   Harrion   18,535   25,535   20.9   5.5   3.0   Harrion   19,988   25,685   22.0   7.5   9.9   4.6   Harrion   19,988   25,865   22.0   7.5   9.9   4.6   Harrion   18,574   10,977   1.7   1.7   1.7   1.7   1.7   1.7   Harrion   18,574   10,977   1.7   1.7   1.7   1.7   1.7   Harrion   19,988   25,865   22.0   7.5   9.9   4.6   Harrion   19,988   2							
Delaware	Darke	516,193	35,680	18.7	6.3	8.8	3.6
Efe. 94,205 5,040 6.9 1.7 3.3 1.9 Farmfuld. 99,750 24,225 18.8 3.8 12.2 3.8 4.0 10.0 10.3 4.3 1.9 Farmfuld. 99,750 24,225 18.8 3.8 12.2 3.8 4.0 10.0 10.3 4.3 1.9 Farmfuld. 173,103 24,711 12.9 3.9 6.5 2.4 4.0 10.3 4.3 1.0 173,103 24,711 12.9 3.9 6.5 2.4 4.0 10.3 4.3 1.0 1.0 10.3 1.0 10.0 10	Defiance	107,279	16,150	24.9	2.5	19.7	2.8
Fairfield	Delaware					8.7	
Fayetle.   127,198   23,024   9.8   1.5   7.0   1.4   Fayetle.   127,198   23,024   9.8   1.5   7.0   1.3   Farnklin   152,158   7,113   18.5   4.0   10.3   4.3   Fulton   173,103   24,712   12.9   9.8   1.6   6.5   2.4   Fulton   173,103   24,712   12.9   9.8   1.8   Fulton   18,613   6.180   23.9   23.9   7.3   12.3   4.0   Fulton   26,6789   5.365   33.0   11.3   13.4   Fulton   23,037   1.352   5.1   3.0   1.1   Fulton   155,792   10,987   142   3.3   7.7   3.2   Fulton   18,635   3.867   2.9   3.0   4.4   2.5   Fulton   18,635   3.867   2.9   5.7   10.4   4.8   Fulton   133,371   2.50,98   1.9   3.0   4.4   2.5   Fulton   133,371   2.50,98   1.9   3.0   4.4   2.5   Fulton   133,371   2.50,98   1.9   3.0   4.4   2.5   Fulton   18,635   3.867   2.9   5.7   10.4   4.8   Fulton   18,635   3.867   2.9   5.7   10.4   Fulton   18,635   3.867   2.9   5.7   5.9   Fulton   18,635   3.867   2.9   5.7   5.9   Fulton   18,635   3.867   2.9   5.7   5.9   Fulton   18,635   3.867   2.9   Fulton   18,635   3	Erie						
Frinklin         52,158         7,113         18.5         4.0         10.3         4.3           Fillon         173,103         24,711         12.9         3.9         6.5         2.4           Gallia         18,973         1,820         30.4         7.8         15.7         6.0           George         37,088         1,015         2.4         7.8         15.7         6.0           Guerneay         26,789         1,015         2.4         7.8         15.7         6.0           Guerneay         28,789         1,015         2.4         7.3         13.4         8.3           Hamilton         23,037         1,352         5.1         3.0         1.1         1.0           Hancock         135,792         10,95         14.2         3.0         1.1         1.0           Harrison         186,55         3,857         2.9         5.7         10.4         4.8           Harrison         186,65         3,857         2.9         5.7         10.4         4.8           Harrison         180,69         3,857         2.9         5.7         10.4         4.8           Harrison         180,69         3,857         2.9 <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>							
Gallia         18,875         1,820         30.4         7,8         15,7         6.9           Gaugua         36,103         6,190         23,5         7,3         12.3         4.0           Greene         97,086         22,015         12.4         1.8         8.6         2.0           Gerene         25,785         330         11.3         13.4         8.5           Hamilton         23,037         1,352         5.1         3.0         11.1         1.0           Hancock         135,792         10,987         14.2         3.3         7.7         3.2           Hardin         222,2865         13,085         9.9         3.0         1.4         2.5           Hariston         13,333         3.085         9.9         3.0         4.4         2.5           Hariston         13,333         3.085         9.9         3.0         4.4         2.5           Hariston         13,333         3.085         9.9         3.0         4.4         2.5           Highland         122,902         12,541         2.8         3.8         20.7         3.5           Hocking         5,090         648         16.4         8.3	Franklin	52,158	7,113	18.5	4.0	10.3	4.3
Geauga         36,103         6,190         23,5         7,3         12,3         4,0           Greene         97,086         23,015         12,4         1,8         8,6         2,0           Guerney         26,789         5,355         33,0         11,3         13,4         8,3           Hamilton         23,037         1,352         5,1         3,0         1,1         1,0           Hamilton         22,3037         1,957         14,2         3,3         7,7         3,2           Hardin         222,865         13,088         9,9         3,0         4,4         2,5           Hardin         222,865         13,088         9,9         3,0         4,4         2,5           Hardin         25,088         1,9         3,3         7,5         10,4         4,8           Heron         18,23,279         25,088         10,9         1,3         7,5         12,2           Horon         18,208         2,565         20,0         7,5         9,9         4,6           Holding         1,500         6,48         16,4         3,3         3,0         12,0         3,3           Jackson         11,042         1,22							
Guernsey. 26,789 5,355 33.0 11.3 13.4 8.3 Hamilton. 23,037 1,352 5.1 3.0 1.1 Hamilton. 23,037 1,352 5.1 4.2 3.0 1.1 Hamilton. 24,035 7.1 1.4 3.0 1.1 Hamilton. 25,030 1.0 1.0 1.1 Hamilton. 26,036 1.0 1.0 1.0 1.0 1.1 Hamilton. 26,036 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0	Geauga						
Hamilton	Greene						
Hancock	Guernsey	26,789	5,355	33.0	11.3	13.4	8.3
Hardin	Hamilton						
Harrison							
Henry	Harrison						
Höcking.         5,090         648         164         8.3         3.7         4.4           Holmes         182,088         25,265         22,0         7.5         9.9         4.6           Huron.         199,958         26,416         18.3         3.0         12.0         3.3           Jackson.         11,042         1,221         18.7         5.7         8.7         4.3           Jefferson.         9,195         1,500         26.1         10.8         8.0         7.2           Knox         135,144         10,872         27.8         11.2         9.9         6.8           Lake         73,622         8,216         9.7         4.0         3.9         1.7           Lawrence         4,035         905         19.2         7.9         6.9         4.5           Logan.         121,724         37.471         14.0         1.8         9.9         2.5         3.1           Logan.         121,724         37.471         14.0         1.8         9.9         2.4           Loras.         50,677         7.7         2.3         2.2         2.6         2.6           Loras.         50,677         7.7         1	Henry						
Holmes   182,088   25,265   22.0   7.5   9.9   4.6     Huron   199,988   26,416   18.3   3.0   12.0   3.3     Jackson   11,042   1,221   18.7   5.7   8.7   4.3     Jefferson   9,195   1,500   26.1   10.8   8.0   7.2     Jefferson   135,144   10,872   27.8   11.2   9.9   6.8     Lake   73,622   8,216   9.7   4.0   3.9   1.7     Lawrence   4,035   905   19.2   7.9   6.9   4.5     Licking   185,397   6.82   8.5   2.9   2.5   3.1     Lorain   121,724   37,471   14.0   1.8   9.9   2.4     Lorain   133,901   10,599   7.7   2.3   2.8   2.6     Lorain   133,901   10,599   7.7   2.3   2.8   2.6     Madison   159,255   25,575   17.8   2.5   12.5   2.8     Madison   159,255   25,575   17.8   2.5   12.5   2.8     Madison   135,923   9,767   14.0   3.1   7.6   3.3     Madison   14,944   14,945   14,945   14,945   14,945     Madison   14,945   14,945   14,945   14,945   14,945     Madison   14,945   14,945   14,945   14,945   14,945   14,945     Madison   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945   14,945	Highland						
Jackson     11,042   1,221   18.7   5.7   8.7   4.3     Jefferson     9,195   1,500   26.1   10.8   8.0   7.2     Krox     135,144   10,872   27.8   11.2   9.9   6.8     Lake     73,622   8,216   9.7   4.0   3.9   1.7     Lawrence     4,035   905   19.2   7.9   6.9   4.5     Licking     185,397   6,822   8.5   2.9   2.5   3.1     Logan     121,724   37,471   14.0   1.8   9.9   2.4     Lorain     133,901   10,599   7.7   2.3   2.8   2.6     Lucas     50,677   7,177   14.5   3.4   8.5   2.7     Madison     159,255   25,575   17.8   2.5   12.5   2.8     Mahoning     68,599   12,698   27.2   9.0   12.9   5.3     Marion     135,923   9,767   14.0   3.1   7.6   3.3     Macina     140,94   140,94   140,94   140,94     Macina     140,94   140,94   140,94   140,94     Macina     140,94   140,94   140,9	Holmes	182,088	25,265		7.5	9.9	4.6
Jefferson         9,195         1,500         26.1         10.8         8.0         7.2           Knox         135,144         10,872         27.8         11.2         9.9         6.8           Lake         73,622         8.216         9.7         4.0         3.9         1.7           Lawrence         4,035         905         19.2         7.9         6.9         4.5           Licking         185,397         6.822         8.5         2.9         2.5         3.1           Logan         121,724         37,471         14.0         1.8         9.9         2.4           Lorain         133,901         10,599         7.7         2.3         2.8         2.6           Lucas         50,677         7,177         14.5         3.4         8.5         2.7           Macison         159,255         25,575         17.8         2.5         12.5         2.8           Mahoning         135,923         9,767         14.0         3.1         7.6         3.3           Macina         135,923         9,967         14.0         3.1         7.6         3.3           Macina         135,923         9,967         14.0	Huron						3.3
Knox         135,144         10,872         27,8         11.2         9.9         6.8           Lake         73,622         8,216         9.7         4,0         3.9         1.7           Lawrence         4,035         905         19.2         7.9         6.9         4.5           Loking         185,397         6,822         8.5         2.9         2.5         3.1           Logan         121,724         37,471         14.0         1.8         9.9         2.4           Lorain         133,901         10,599         7.7         2.3         2.8         2.6           Madison         50,677         7,177         14.5         3.4         8.5         2.7           Madison         159,255         25,575         17.8         2.5         12.5         2.8           Marion         135,923         9,767         14.0         3.1         7.6         3.3           Merion         135,923         9,767         14.0         3.1         7.6         3.3           Medina         135,923         9,767         14.0         3.1         7.6         3.3           Merion         135,923         9,767         14.0         <	UUUNOUII		1,221	10.7	-		4.3
Lake       73.622       8,216       9.7       4.0       3.9       1.7         Lawrence       4,035       905       192       7.9       6.9       4.5         Licking       185,397       6,822       8.5       2.9       2.5       3.1         Logan       121,724       37,471       14.0       1.8       9.9       2.4         Lorain       50,677       7,177       14.5       3.4       8.5       2.7         Madison       50,677       7,177       14.5       3.4       8.5       2.7         Madison       159,255       25,575       17.8       2.5       12.5       2.8         Mahoning       159,255       25,575       17.8       2.5       12.5       2.8         Mahoning       135,923       9,767       14.0       3.1       7.6       3.3         Merion       135,923       9,767       14.0       3.1       7.6       3.3         Medina       15,523       2,931       12.2       4.0       5.6       2.7         Merion       16,611       3,510       16.7       8.0       5.2       3.5         Merer       631,612       45,817       17.0 </td <td>Jefferson</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	Jefferson						
Lawrence       4,035       905       19.2       7.9       6.9       4.5         Licking       185.397       6.822       8.5       2.9       2.5       3.1         Logan       121,724       37,471       14.0       1.8       9.9       2.4         Lorain       133,901       10,599       7.7       2.3       2.8       2.6         Lucas       50,677       7,177       14.5       3.4       8.5       2.7         Madison       159,255       25,575       17.8       2.5       12.5       2.8         Mahoning       68,599       12,698       27.2       9.0       12.9       5.3         Marion       135,923       9,767       14.0       3.1       7.6       3.3         Medina       135,923       9,767       14.0       3.1       7.6       3.3         Medina       135,923       2,931       12.2       4.0       5.6       2.7         Meigs       16,611       3,510       16.7       8.0       5.2       3.5         Mercer       631,612       45,817       17.0       4.5       8.5       4.0         Misami       106,66       30,636       20.8		135,144 73,622					
Licking       185,397       6,822       8.5       2.9       2.5       3.1         Logan       121,724       37,471       14.0       1.8       9.9       2.4         Lorain       133,901       10,599       7.7       2.3       2.8       2.6         Lucas       50,677       7,177       14.5       3.4       8.5       2.7         Madison       195,255       25,575       17.8       2.5       12.5       2.8         Mahoning       135,923       9,767       14.0       3.1       7.6       3.3         Medina       135,923       9,767       14.0       3.1       7.6       3.3         Medina       15,523       2,931       12.2       4.0       5.6       2.7         Meigs       16,611       3,510       16.7       8.0       5.2       3.5         Mercer       63,1812       45,817       17.0       4.5       8.5       4.0         Monrow       13,961       3,004       2.76       6.7       14.9       6.0         Montgomery       78,711       6,764       6.3       2.4       2.2       1.8         Morgan       18,005       5,573       2.0	Lawrence	4,035	905	19.2	7.9	6.9	4.5
Lorain	Licking			8.5		2.5	
Lucas         50,677         7,177         14.5         3.4         8.5         2.7           Madison         159,255         25,575         17.8         2.5         12.5         2.8           Marion         135,923         9,767         14.0         3.1         7.6         3.3           Merion         135,923         9,767         14.0         3.1         7.6         3.3           Merion         51,523         2,931         12.2         4.0         5.6         2.7           Meige         51,523         2,931         12.2         4.0         5.6         2.7           Mercer         631,612         45,817         17.0         4.5         8.5         4.0           Miami         106,696         30,636         20.8         2.3         16.0         2.5           Morrow         13,961         3,004         27.6         6.7         14.9         6.0           Morrow         78,711         6,764         6.3         2.4         2.2         1.8           Morrow         84,194         9,363         8.7         2.2         3.9         2.7           Muskingum         70,074         6,143         27.3							
Mahoning     68,599     12,698     27.2     9.0     12.9     5.3       Marion     135,923     9,767     14.0     3.1     7.6     3.3       Medina     51,523     2,931     12.2     4.0     5.6     2.7       Meige     16,611     3,510     16.7     8.0     5.2     3.5       Mercer     631,612     45,817     17.0     4.5     8.5     4.0       Miami     106,696     30,636     20.8     2.3     16.0     2.5       Monroe     13,961     3,004     27.6     6.7     14.9     6.0       Morgan     78,711     6,764     6.3     2.4     2.2     1.8       Morgan     81,805     5,573     20.0     3.6     13.7     2.7       Morrow     84,194     9,363     8.7     2.2     3.9     2.7       Muskingum     70,074     6,143     27.3     8.3     12.5     6.6       Ottawa     59,220     6,438     23.4     6.8     10.3     6.3       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Perry     <	Lucas	50,677	7,177	14.5	3.4	8.5	2.7
Marion.         135,923         9,767         14,0         3.1         7,6         3.3           Medina         51,523         2,931         12.2         4,0         5,6         2.7           Meigs         16,611         3,510         16.7         8.0         5.2         3.5           Mercer         631,612         45,817         17,0         4,5         8.5         4,0           Miami         106,696         30,636         20.8         2.3         16,0         2.5           Monroe         13,961         3,004         27.6         6.7         14,9         6.0           Mortgomery         78,711         6,764         6.3         2.4         2.2         1.8           Morgan         18,005         5,573         20.0         3.6         13,7         2.7           Muskingum         70,074         6,143         27.3         8.3         12.5         6.6           Noble         7,296         670         22.9         8.8         7.6         6.6           Ottawa         59,220         6,438         23.4         6.8         10.3         6.3           Perry         33,831         6,067         17.7		159,255 68,599					
Medina     51,523     2,931     12.2     4.0     5.6     2.7       Meigs     16,611     3,510     16.7     8.0     5.2     3.5       Mercer     631,612     45,817     17.0     4.5     8.5     4.0       Miami     106,696     30,636     20.8     2.3     16.0     2.5       Monroe     13,961     3,004     27.6     6.7     14.9     6.0       Morgan     78,711     6,764     6.3     2.4     2.2     1.8       Morgan     84,194     9,363     8.7     2.2     3.9     2.7       Morrow     84,194     9,363     8.7     2.2     3.9     2.7       Muskingum     70,074     6,143     27.3     8.3     12.5     6.6       Noble     7,296     670     22.9     8.8     7.6     6.6       Ottawa     59,220     6,438     23.4     6.8     10.3     6.3       Paulding     173,451     18,516     13.0     2.2     8.0     2.8       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Pickaway     162,649     21,434     18.3     1.8     14.4     2.1       Picke <t< td=""><td>·</td><td></td><td></td><td></td><td></td><td></td><td></td></t<>	·						
Meigs.     16,611     3,510     16,7     8,0     5,2     3,5       Mercer.     631,612     45,817     17,0     4.5     8.5     40       Miami.     106,696     30,636     20.8     2.3     16.0     2.5       Montore.     13,961     3,004     27.6     6.7     14,9     6.0       Morgan.     18,005     5,573     20.0     3.6     13,7     2,7       Morrow.     84,194     9,363     8.7     2.2     3.9     2,7       Morkingum     7,074     6,143     27.3     8.3     12.5     6.6       Noble.     7,296     670     22.9     8.8     7.6     6.6       Ottawa     59,220     6,438     23.4     6.8     10.3     6.3       Paulding.     173,451     18,516     13.0     2.2     8.0     2.8       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Pickaway     162,649     21,434     18.3     1.8     14.4     2.1       Picke.     5,072     2,982     8.2     1.6     4.2     2.4       Protage     34,489     2,586     12.4     4.9     4.3     3.2       Preble </td <td>Medina</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>3.3 2.7</td>	Medina						3.3 2.7
Miami     106,696     30,636     20.8     2.3     16.0     2.5       Monroe     13,961     3,004     27.6     6.7     14.9     6.0       Montgomery     78,711     6,764     6.3     2.4     2.2     1.8       Morgan     18,005     5,573     20.0     3.6     13.7     2.7       Muskingum     8,7     2.2     3.9     2.7       Muskingum     6,143     27.3     8.3     12.5     6.6       Noble     7,296     670     22.9     8.8     7.6     6.6       Ottawa     59,220     6,438     23.4     6.8     10.3     6.3       Paulding     173,451     18,516     13.0     2.2     8.0     2.8       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Pick     162,649     21,434     18.3     1.8     14.4     2.1       Pike     5,072     2,982     8.2     1.6     4.2     2.4       Preble     146,273     16,396     18.9     3.4     12.0     3.4	Meigs	16,611	3,510	16.7	8.0	5.2	3.5
Monroe         13,961         3,004         27.6         6.7         14,9         6.0           Montgomery.         18,005         5,573         20.0         3.6         13,7         2.7           Morgan         18,005         5,573         20.0         3.6         13,7         2.7           Morrow         84,194         9,363         8.7         2.2         3.9         2.7           Muskingum         70,074         6,143         27.3         8.3         12.5         6.6           Noble         7,296         670         22.9         8.8         7.6         6.6           Ottawa         59,220         6,438         23.4         6.8         10.3         6.3           Paulding         173,451         18,516         13.0         2.2         8.0         2.8           Perry         33,831         6,067         17.7         4.6         8.1         4.9           Pickaway         162,649         21,434         18.3         1.8         14.4         2.1           Pike         5,072         2,982         8.2         1.6         4.2         2.4           Preble         146,273         16,396         18.9	Mercer						
Montgomery.     78,711     6,764     6.3     2.4     2.2     1.8       Morgan     18,005     5,573     20.0     3.6     13.7     2.7       Morrow     84,194     9,363     8.7     2.2     3.9     2.7       Muskingum     70,074     6,143     27.3     8.3     12.5     6.6       Noble     7,296     670     22.9     8.8     7.6     6.6       Ottawa     59,220     6,438     23.4     6.8     10.3     6.3       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Pickaway     162,649     21,434     18.3     1.8     14.4     2.1       Pike     55,072     2,982     8.2     1.6     4.2     2.4       Portage     34,489     2,586     12.4     4.9     4.3     3.2       Preble     146,273     16,396     18.9     3.4     12.0     3.4	Monroe						
Morrow         84,194         9,363         8.7         2.2         3.9         2.7           Muskingum         70,074         6,143         27.3         8.3         12.5         6.6           Noble         7,296         670         22.9         8.8         7.6         6.6           Ottawa         59,220         6,438         23.4         6.8         10.3         6.3           Paulding         173,451         18,516         13.0         2.2         8.0         2.8           Perry         33,831         6,067         17.7         4.6         8.1         4.9           Pickaway         162,649         21,434         18.3         1.8         14.4         2.1           Pike         55,072         2,982         8.2         1.6         4.2         2.4           Protage         34,489         2,586         12.4         4.9         4.3         3.2           Preble         146,273         16,396         18.9         3.4         12.0         3.4	Montgomery	78,711	6,764	6.3	2.4	2.2	1.8
Muskingum         70,074         6,143         27.3         8.3         12.5         6.6           Noble         7,296         670         22.9         8.8         7.6         6.6           Ottawa         59,220         6,438         23.4         6.8         10.3         6.3           Paulding         173,451         18,516         13.0         2.2         8.0         2.8           Perry         33,831         6,067         17.7         4.6         8.1         4.9           Pickaway         162,649         21,434         18.3         1.8         14.4         2.1           Pike         55,072         2,982         8.2         1.6         4.2         2.4           Portage         34,489         2,586         12.4         4.9         4.3         3.2           Preble         146,273         16,396         18.9         3.4         12.0         3.4							
Ottawa     59,220     6,438     23.4     6.8     10.3     6.3       Paulding.     173,451     18,516     13.0     2.2     8.0     2.8       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Pickaway     162,649     21,434     18.3     1.8     14.4     2.1       Pike.     55,072     2,982     8.2     1.6     4.2     2.4       Portage     34,489     2,586     12.4     4.9     4.3     3.2       Preble     146,273     16,396     18.9     3.4     12.0     3.4	Muskingum						
Ottawa     59,220     6,438     23.4     6.8     10.3     6.3       Paulding.     173,451     18,516     13.0     2.2     8.0     2.8       Perry     33,831     6,067     17.7     4.6     8.1     4.9       Pickaway     162,649     21,434     18.3     1.8     14.4     2.1       Pike.     55,072     2,982     8.2     1.6     4.2     2.4       Portage     34,489     2,586     12.4     4.9     4.3     3.2       Preble     146,273     16,396     18.9     3.4     12.0     3.4	Noble	7 296	670	22 Q	8.8	76	66
Paulding.     173,451     18,516     13.0     2.2     8.0     2.8       Perry.     33,831     6,067     17.7     4.6     8.1     4.9       Pickaway.     162,649     21,434     18.3     1.8     14.4     2.1       Pike.     55,072     2,982     8.2     1.6     4.2     2.4       Portage.     34,489     2,586     12.4     4.9     4.3     3.2       Preble.     146,273     16,396     18.9     3.4     12.0     3.4	Ottawa	59,220	6,438	23.4	6.8	10.3	6.3
Pickaway     162,649     21,434     18.3     1.8     14.4     2.1       Pike     55,072     2,982     8.2     1.6     4.2     2.4       Portage     34,489     2,586     12.4     4.9     4.3     3.2       Preble     16,396     18.9     3.4     12.0     3.4	Paulding	173,451	18,516	13.0	2.2	8.0	2.8
Pike     55,072     2,982     8.2     1.6     4.2     2.4       Portage     34,489     2,586     12.4     4.9     4.3     3.2       Preble     16,396     18.9     3.4     12.0     3.4							
Portage         34,489         2,586         12.4         4.9         4.3         3.2           Preble         16,396         18.9         3.4         12.0         3.4	Pike	55,072	2,982	8.2	1.6	4.2	2.4
	Portage	34,489	2,586	12.4	4.9		
continued	rieule	146,273	16,396	18.9	3.4	12.0	

Table C. Summary of Coverage, Nonresponse, and Misclassification Adjustments by County: 2017 (continued)

[For meaning of abbreviations and symbols, see introductory text.]

Geographic area	Total (number)	Standard error	Adjustment as percent of total	Percent of total adjustment from coverage	Percent of total adjustment from nonresponse	Percent of total adjustment from misclassification
SALES (\$1,000) - Con.						
Counties - Con.						
Putnam Richland Ross Sandusky Scioto Seneca Shelby Stark Summit Trumbull	214,481 135,144 77,745 101,038 17,841 140,877 178,239 95,843 12,605 56,058	20,241 20,997 3,410 20,395 4,127 12,596 9,920 11,862 6,841 11,070	21.4 26.5 15.9 12.7 34.1 19.5 18.9 12.9 14.6 13.5	4.2 7.0 3.0 2.2 9.3 3.1 3.5 3.8 7.4 5.0	12.5 14.9 10.6 8.3 17.4 13.0 12.0 7.0 5.4 4.7	4.7 4.6 2.2 2.2 7.4 3.3 2.1 1.8 3.8
Tuscarawas. Union. Van Wert. Vinton. Warren Washington Wayne. Williams. Wood. Wyandot.	125,183 209,324 191,295 5,693 47,671 42,049 327,890 122,782 159,265 157,309	28,594 24,383 12,706 2,302 2,327 41,591 27,778 7,855 16,962 15,624	26.8 11.3 16.9 21.3 13.7 21.0 19.2 15.8 12.9 12.8	6.1 2.4 2.8 11.6 6.1 3.1 5.5 3.6 2.5 2.7	16.2 6.5 10.9 5.5 3.3 15.3 10.3 9.0 7.5 6.0	4.6 2.4 3.1 4.2 4.2 2.6 3.5 3.2 2.8 4.1

Table D. American Indian or Alaska Native Producers: 2017

Geographic area	Total	Individually reported <sup>1</sup>	Other <sup>2</sup>	Geographic area		Individually	
					Total	reported 1	Other <sup>2</sup>
hi.				Counties - Con.			
hio	530	530	-	Jefferson	1 10	1	
ounties				Lawrence	6	6	
dams	10	10	-	Licking Logan	17 9	17 9	
lenshland	4 3	4 3	-	Lorain	16	16	
htabula	10	10	-	Mahoning	2	2	
hensuglaize	8 3	8 3	-	Marion	15	5 15	
elmontown	7 4	7 4	-	Meigs	8	8	
ıtlerarroll	13	13	-	Miami Monroe	6	6	
	7	7		Montgomery	1	1	
nampaignark	9	9	-	Morrow	6	6	
ermontinton	15 6	15 6		Muskingum Noble	8   3	8 3	
olumbianaoshocton	5 5	5	-	Paulding	2 11	2 11	
awford	2	2 5	-			2	
arke efiance	3	3	Ξ.	Pickaway	11	11	
elaware	9	9	-	Portage	12	12 6	
ieifield	2 17	2 17	-	PutnamRichland	2 7	2 7	
yette	6	6	-	Ross	22	22	
anklinllton	1 1	1 1		Scioto	21 3	21 3	
alliaeauga	13 5	13	-	Shelby	6	6	
reeneuernsey	2 14	2 14	-	StarkSummit	3 7	3 7	
ancock	2	2	-	Trumbull	8	8	
ardin	3	3	-	Tuscarawas	14 12	14 12	
arrison	1 4	1	-	Van Wert Warren	2 11	2 11	
ghlandocking	2	2	-	WashingtonWayne	15	15	
olmes	4	4		Williams	2	2	
uron	1 10	1 10	-	Wood	4	4	

Data were collected for a maximum of four producers per farm.
 Data represent American Indian or Alaska Native farm or ranch producers on reservations who did not report individually. Data obtained by reservation officials.