Estimating the Nonfatal Injury Undercount in Agriculture from 2004 to 2019

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HIGHLIGHTS

- Government estimates of nonfatal occupational injuries and illnesses understate the hazards in U.S. agriculture.
- From 2004 to 2019, government estimates only captured 13% to 26% of the true number of nonfatal injuries.
- Estimates of nonfatal injuries are more accurate for crop production than for animal production.
- Estimates are more accurate over time, with a decline in self-employed and unpaid family labor in agriculture.

ABSTRACT. *The U.S. Bureau of Labor Statistics provides annual estimates of nonfatal occupational injuries and illnesses by U.S. industry sector. We performed a series of corrections to these estimates for each year from 2004 through 2019 to account for institutional and behavioral drivers of the undercount in the sample used to construct these estimates for the U.S. agricultural industry. Institutional factors consisted of the exclusion of small farms and self-employed and family workers, as well as the employment undercount due to the highly seasonal nature of agricultural work. Behavioral factors consisted of willful and negligent underreporting by employers. We updated the estimates using information on the number of people employed in the excluded portions of the agricultural industry and estimates of the underreporting rate from prior work. Over this period, we show that the government estimates only captured 13% to 26% of the true number of nonfatal injuries and illnesses, missing 74% to 87% of the true case counts each year. The government estimates were more accurate for crop production, missing an average of 77% of cases, than for animal production, missing an average of 83% of cases. Willful and negligent underreporting was the largest contributor to the undercount, followed by the exclusion of self-employed and unpaid family workers.*

Keywords. *Agriculture, Nonfatal injuries and illnesses, Occupational injuries, Survey of Occupational Injuries and Illnesses, Undercount.*

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Agriculture is understood to be among the most hazardous industries in the U.S., but available measures understate the true risk. Two metrics commonly used to rank industries by their level of hazard (the rates of occupational fatalities and nonfatal occupational injuries and illnesses) are both estimated by the Bureau of Labor Statistics (BLS). According to the Census of Fatal Occupational Injuries (CFOI), across all sectors, the agriculture, forestry, fishing, and hunting sector is consistently the most hazardous. In 2019, the fatality rate in this sector, which was 23.1 per 100,000 full-time equivalent (FTE) workers, was nearly double the next highest rate, 13.9 per 100,000 FTE in transportation and warehousing (BLS, 2021a). In terms of the rates of nonfatal injuries and illnesses from the Survey of Occupational Injuries and Illnesses (SOII), agriculture is less of an outlier. In 2019, the reported incidence rate of nonfatal occupational injuries and illnesses for workers in agriculture, forestry, and fishing was highest among all U.S. private industry sectors (5.2 per 100 FTE) but was similar to those in other sectors (BLS, 2019a). Here we delineate sectors by the broad two-digit codes of the North American Industry Classification System (NAICS). In 2019, the next highest nonfatal injury and illness rates were 4.4 per FTE for workers in transportation and warehousing and 4.0 per FTE for workers in arts, entertainment, and recreation.

Unlike measures of workplace fatalities from census data, measures of occupational injuries rely on the surveyed sample being representative of the population of firms. This is not the case in the agricultural sector, where estimated injury and illness rates are understood to be undercounts (GAO, 2009; Rautiainen and Reynolds, 2002). The implication is that the risk of becoming injured or ill while working in agriculture is higher than official estimates and might mirror sector fatality rates.

In attempts to improve these government estimates, prior work has examined the rates and prevalence of nonfatal injuries in agriculture using a variety of data sources, including workers compensation claims (Douphrate et al., 2009; Rautiainen and Reynolds, 2002; Karttunen and Rautiainen, 2013), hospital data (Gorucu et al., 2022; Kica and Rosenman, 2020; Scott et al., 2021), data scraped from agricultural news websites (Weichelt and Gorucu, 2019), survey data (Crawford et al., 1998; Johnson et al., 2021; McGwin et al., 2000; Pratt et al., 1992; Rautiainen et al., 2004; Tonozzi and Layne, 2016; Zhou and Roseman, 1994), and meta-analyses of existing work (Jadhav et al., 2016; McCurdy and Carroll, 2000). These studies yield estimates of the nonfatal injury rate for agriculture that range from 2.9 to 16.6 per 100 FTE.

These studies also focus on various subsets of the agricultural workforce, which partially explains the large range of injury estimates. For example, Crawford et al. (1998) administered a survey to farmers in Ohio in 1993 and found a nonfatal injury rate of 5 per 100 persons; Kica and Rosenman (2020) studied impatient-based discharge summaries, outpatient clinic records, and emergency department records for all Michigan hospitals in 2015 and 2016 and found that nonfatal agricultural injuries were highest for dairy farms (40% of injuries) and similar for owners/operators (44%) and hired labor (43%); Tonozzi and Layne (2016) used data from a NIOSH supplement to the National Agricultural Workers Survey and found nonfatal injuries rates of 2.9 to 4.3 among the nationally representative sample of hired crop workers.

In this study, we applied a series of adjustments to the BLS SOII estimates in order to bound the true but unobserved nonfatal injury and illness counts for workers in crop and animal production. The adjustments that we apply are based on those proposed by Leigh et al. (2014), who show that the undercount is driven by both institutional and behavioral factors. Institutional factors include (1) the SOII excludes farms with fewer than eleven employees, self-employed farmers, and family members, and (2) the SOII (and other widely used national data sources) underestimates agricultural employment due to the seasonality of agricultural work and the prevalence of undocumented workers. Behavioral factors account for the remainder of the undercount and include willful and negligent underreporting by workers and employers. Leigh et al. (2014) estimated that the BLS SOII missed 73.7% of injury cases in crop production and 81.9% of injury cases in animal production in 2011, with institutional and behavioral factors each accounting for roughly half of the undercount.

We build on and extend the work of Leigh et al. (2014) along two dimensions. First, we extend estimates of the agricultural injury and illness undercounts beyond a single year to cover the period 2004 to 2019. Our methods can be easily replicated and applied to future data. This allows updates of SOII estimates on an ongoing basis. Our process of computing updated SOII estimates includes uncertainty and constructs upper and lower bounds for the undercount. These bounds incorporate unobservable changes in the BLS data-generating process. Barring significant changes in the underlying population used by BLS to construct SOII estimates, our updated measures are reliable over time, allowing improved policy evaluation and formulation. Changes in any of the following would require updating the parameters or methods to continue producing accurate estimates of agricultural injuries and illnesses: (1) types of operations and workers left out of BLS SOII counts, (2) BLS reporting standards, or (3) penalties for inaccurate or dishonest reporting.

Second, we use a novel simulation approach to compute a reasonable range of estimates, whereas prior work produced point estimates. These ranges account for the uncertainty that is implicit in the adjustment process. Our approach yields a distribution of estimates for nonfatal agricultural injuries and illnesses, which, under a reasonable set of assumptions, can be used to construct bounds for the true but unobserved measure of agricultural injuries and illnesses.

We make three contributions. First, we update prior estimates of the true rates of injuries and illnesses in agriculture. Accurate and up-to-date estimates are vital for developing policies aimed at improving the health and safety of the agricultural workforce (Chari et al., 2018). In addition to these policies having important ramifications for workers, such policies are expensive to implement and enforce, making it even more important to ensure that the policies are impactful. The National Institute for Occupational Safety and Health's Agriculture, Forestry, and Fishing (AgFF) program is allocated $26.5 million annually to address the high rates of fatalities and injuries in agriculture (Harrington et al., 2021). Accurate estimates are necessary to determine where to allocate program funds and to evaluate the efficiency and effectiveness of past initiatives.

Second, we document trends in injuries and illnesses over time. Understanding the dynamics of injuries and illnesses is important for evaluating the effectiveness of past policies aimed at reducing injuries and illnesses in agriculture, ultimately contributing to more effective and efficient policies moving forward. Further, we show that the drivers of undercount are time-varying, ruling out approaches based on a static adjustment factor.

Finally, we propose a systematic approach to incorporating uncertainty in our estimates. Rather than calculating upper and lower bounds on individual adjustment factors, we use a simulation approach that yields a distribution of estimates.

Materials and Methods

Our goal is to construct a range of estimates, incorporating measures of uncertainty, that serve as reasonable bounds on the true number of nonfatal injuries and illnesses in agriculture for each year from 2004 through 2019. We accomplish this by performing a series of adjustments to the BLS SOII estimates for crop and animal production using data from the BLS Quarterly Census of Earnings and Wages (QCEW) and the U.S. Census Current Population Survey (CPS). We list key parameters from each of these data sources in table 1.

We begin our process using information from the BLS SOII injury and illness data for the incidence rate of injuries and illnesses, which is defined as the number of injuries and illnesses per 100 FTE, the number of injury and illness cases, and the percent relative standard errors for detailed industry rates and case counts for 2004 through 2019 (rows 1 to 4 in table 1). We update these baseline numbers to account for the institutional and behavioral drivers of undercount using information on employment and FTE counts in the SOII (rows 5 and 6 in table 1), employment and reliability from the QCEW and CPS (rows 7 to 10 in table 1), and estimates of willful misreporting from the literature.

The SOII does not collect employment data; however, the final measures of injuries and illnesses per 100 FTE require employment estimates. BLS relies on information on employment from the QCEW, excluding farms with fewer than eleven employees (see footnote 5 in BLS, 2019a) and a formula that defines full-time employment for 100 workers as 200,000 work hours per year (BLS, 2020; Leigh et al., 2014; Northwood, 2010).

We outline the algorithm in figure 1. The first box in figure 1 explains our first step: preparing the SOII data by generating employment estimates in the SOII for years they are

Table 1. Data sources.[a]

Parameter	Source
SOII injury and illness: Incidence rate (number of injuries and illnesses per 100 FTE) (2004-2019)	BLS Table 1: Incidence rates - detailed industry level (BLS, 2019a)
SOII injury and illness: Number of cases (2004-2019)	BLS Table 2: Number of cases - detailed industry level (BLS, 2019b)
SOII injury and illness: Percent relative standard errors for industry incidence rates (2004-2019)	BLS Table A1: Percent relative standard errors for detailed industry incidence rates (BLS, 2019c)
SOII injury and illness: Percent relative standard errors for industry case counts (2004-2019)	BLS Table A2: Percent relative errors for detailed industry rates (BLS, 2019d)
SOII employment count (2004-2011)	Personal communication from Henry Reeve, BLS, 24 February 2021
SOII FTE count (2004-2019)	BLS Table 1 and Table 2 (BLS, 2019a, 2019b)
QCEW employment count (2004-2019)	QCEW BLS public data API (BLS, 2021a)
QCEW coverage exclusions for agricultural businesses	QCEW Table A: Coverage exclusions (2004-2019) for selected workers (BLS, 2019e)
CPS employment count for self-employed and unpaid family workers (2004-2019)	CPS Table 4: Employed and experienced unemployed persons by detailed industry and class of worker, annual average (personal communication from Steven Hipple, BLS, 5 February 2021)
CPS reliability parameters for agriculture and related industries	"Calculating approximate standard errors and confidence intervals for CPS estimates" and Table PF-8 from "Parameters and factors for calculating standard errors, tables PF-1 through PF-16" (BLS, 2018, 2021b)

[a] This table provides an overview the key parameters used in the study and details the data source for each parameter. Each parameter is retrieved for NAICS 111 (Crop Production) and NAICS 112 (Animal Production) where possible. Exceptions include QCEW coverage exclusions (which are only available for agricultural businesses as a whole) and CPS reliability measures (which are only available for agriculture and related industries). BLS data were accessed through the BLS API (see Appendix B).

SOII employment data preparation: Our goal is to construct SOII employment estimates that are consistent over time despite a change in data availability. We scale the post-2011 SOII FTE estimates using the mean percentage difference between SOII employment and SOII FTE between 2004 and 2011, i.e., when employment data are available (see Appendix A).

Simulation procedure: Our simulation involves implementing each of the following steps sequentially and repeating for 10,000 iterations.

Step 1: Prepare baseline SOII employment data. We draw baseline injury and illnesses from a normal distribution. The BLS SOII injury and illness estimate is used as the mean, and the BLS SOII percent relative standard error for industry case counts is used as the standard deviation.

Step 2 (Adjustment 1): QCEW adjustment for small farms. This adjustment has two components: the first allows a different incidence rate for farms with fewer than eleven employees, and the second includes small farms by adjusting for the ratio of QCEW employment to SOII employment.

Step 3 (Adjustment 2): QCEW adjustment for government undercount. This adjustment incorporates the QCEW recognized employment undercount. The QCEW publishes an estimate for included and excluded agricultural workers. Uncertainty is incorporated by drawing the excluded worker value from a uniform distribution using the minimum and maximum excluded workers as the bounds. The adjustment is calculated as the ratio of all workers (excluded and included) to included workers.

Step 4 (Adjustment 3): CPS adjustment for self-employed farmers. This adjustment incorporates self-employed farms and those with unpaid family members using the CPS. We draw the CPS total employment and CPS total wage and salary workers from normal distributions using the published CPS estimates as the mean and calculate the standard error using CPS reliability documentation. The adjustment is then calculated as the ratio of the sampled total employed to the sampled wage and salary workers.

Step 5 (Adjustment 4): Willful and negligent underreporting. We assume that the willful and negligent underreporting rate is distributed normally and use 27% as the 2.5th percentile and 57% as the 97.5th percentile of the distribution. These bounds are based on an analysis of nonfatal injury and illness reporting by workers' compensation and the BLS SOII by Boden and Ozonoff (2008). The adjustment is then calculated as one divided by one minus the underreporting rate.

Figure 1. Flowchart of adjustment process. This figure outlines the adjustment process we follow to construct estimates of the nonfatal injury and illness rates for agricultural workers.

missing. The second box in figure 1 documents our simulation procedure, which consists of sequentially applying four adjustments that account for the omission of small farms in the SOII (adjustment 1), the employment undercount in the QCEW (adjustment 2), the omission of self-employed farmers and ranchers and unpaid family members in the SOII (adjustment 3), and willful and negligent underreporting of injuries and illnesses (adjustment 4). We detail each of these steps, including data cleaning and variable creation, in the remainder of this section.

Step 1: Prepare Baseline SOII Employment Data

Our first step uses information from the SOII on employment, FTEs, the incidence rate of injuries and illnesses, the number of injury and illness cases, and the percent relative standard errors for detailed industry incidence rates and case counts for each year from 2004 through 2019. We limit our analysis to agricultural businesses classified according to the North American Industry Classification System (NAICS) codes for crop (NAICS 111) and animal production (NAICS 112).

A limitations is that NAICS classifies businesses based on their primary business activity, which is typically determined by the U.S. Census Bureau using revenue or value of shipments. This implies that businesses categorized as crop producers in our study might also engage in animal production; however, revenues from crop production are larger than revenues from animal production. The analogous holds true for agricultural businesses that are also engaged in non-agricultural activities. This distinction is important for our study because it implies that our findings are specific to businesses categorized according to this system, rather than for all businesses engaged in crop or animal production. For more detail on NAICS classifications, see https://www.census.gov/naics/

The BLS SOII provides employment and FTE estimates from 2004 through 2011. After 2011, the SOII stopped reporting employment estimates but continued to report total FTEs. Employment is a key variable that enables us to link the SOII with other data sources; thus, our adjustment procedure requires a measure of employment in the SOII for each year. Our first step involves imputing an estimate of employment for the missing period (2012 through 2019) using reported FTEs. We calculate the mean percent difference between the SOII FTE count and SOII employment count each year that both are observed, i.e., from 2004 through 2011, and separately for crop and animal production. We then scale the SOII FTE estimates from 2012 to 2019 using this mean percent difference for each sector. The key underlying assumption is that the difference between SOII estimates of employment and FTEs is stable over time.

For the period that SOII provides employment estimates (2004 through 2011), figure 2 shows these reported employment estimates (solid black line) and the SOII FTE estimates

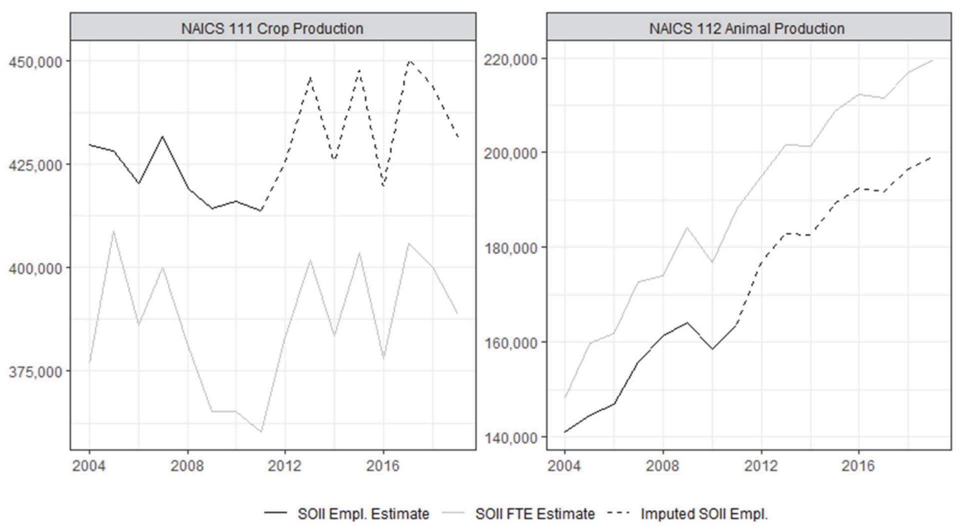

Figure 2. SOII employment estimates. This figure shows BLS SOII employment estimates from 2004 through 2011 (solid lines), SOII FTE estimates from 2004 through 2019, and imputed employment estimates from 2012 through 2019 (dashed lines).

(solid gray line) for crop (left) and animal (right) production. The differences between reported employment and FTE estimates vary over this period but do not exhibit a clear trend. On average, the SOII employment estimates are 10.96% higher than the SOII FTE estimates for crop production and -9.32% lower than the FTE estimates for animal production. This finding is consistent with the characteristics of the two industries. Due to the seasonality of crop production, most employees work fewer than FTE hours each year, whereas in animal production employees often work more than FTE hours (Martin et al., 2016, 2019). The resulting adjustment factors are 1.1096 for crop production and 0.9068 for animal production. Figure 2 shows our imputed employment estimates (dashed black lines) from multiplying these adjustment factors by SOII annual reported FTEs (solid gray lines) for the period after the SOII stopped providing employment estimates (2012 to 2019).

Step 2 (Adjustment 1): QCEW Adjustment for Small Farms

Our second step is to adjust to the SOII injury and illness counts to account for the omission of farms with fewer than eleven employees. We perform this adjustment in two steps. In the first step, we use QCEW employment estimates for crop and animal production to adjust SOII employment estimates to include farms with fewer than eleven employees. In the second step, we extend the sensitivity analysis of Leigh et al. (2014) to account for potential differences in injury and illness incidence rates for these smaller farms.

The QCEW is the most appropriate dataset for implementing this adjustment for two reasons. First, the BLS relies on QCEW employment counts for farms with more than ten employees to develop their sampling technique for the SOII. To ensure that our adjustment for the omission of small farms is consistent with the underlying BLS approach, we adjust BLS numbers using the same dataset used in this sampling technique. Second, to the best of our knowledge, the QCEW is the only publicly available data source with information on employment for crop and animal production establishments with fewer than eleven employees. By contrast, the U.S. Census of Agriculture makes this information available in five-year increments for all agricultural employers (not separated by crop or animal production) with one to nine employees and ten or more employees. However, one limitation to relying on the QCEW for this adjustment is that the QCEW does not include counts of self-employed or unpaid labor. We account for the omission of these types of workers in our next adjustment.

Figure 3 shows the QCEW and SOII employment estimates that we use in the first step of this adjustment. On average over our sample period, the QCEW estimates employment to be 27% and 39% higher than the SOII estimates in crop and animal production, respectively. For the most recent year in our sample (2019), the employment estimate for crop production in the SOII is 431,289, roughly 27% lower than the QCEW estimate of 546,211. For animal production in the same year, the employment estimate in the SOII is 199,164, roughly 33% lower than the QCEW estimate of 265,193.

Note that small farms may experience different injury and illness rates than large farms. To account for this, in the second step of this adjustment we use SOII injury and illness rates for each farm size in each year to construct a small farms incidence rate adjustment. Because the BLS SOII does not publish incidence rates for farms with fewer than eleven employees (the SOII publishes injury and illness rates per 100 FTE for the following groups: 11-49, 50-249, 250-999, and 1000+ employees), we have little prior information on how the incidence rate for small operations compares to that for larger operations.

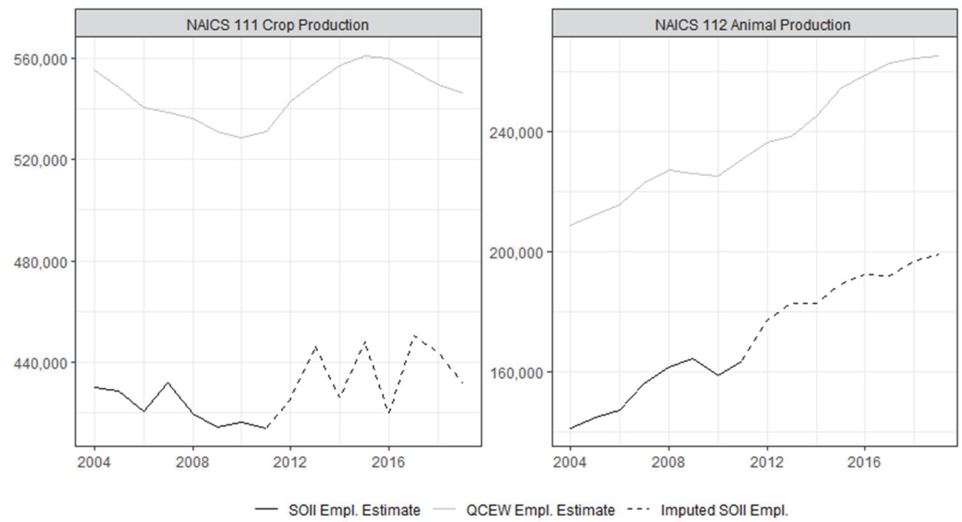

Figure 3. QCEW employment estimates. This figure shows the QCEW employment estimate from 2004 through 2019, the reported SOII employment estimate from 2004 through 2011, and the imputed SOII employment estimate from 2012 through 2019.

For each year of our study period, we construct upper and lower bounds on the small farm incidence rate equal to the normalized maximum and minimum injury and illness rate, respectively, across all farm sizes that year. We assume that the injury and illness rates for farms with fewer than eleven employees fall within the bounds of the rates for larger operations. This assumption is reasonable because there is no clear pattern over time in the injury rates by operation size. For example, injury rates for operations with 250 to 999 employees tend to fall above rates for operations with 11 to 49 employees and below rates for operations with 50 to 249 employees.

We normalize the maximum and minimum injury and illness rates by dividing by the mean incidence rate across all farm sizes. For each iteration in each study year, we draw a small farms incidence rate adjustment from a normal distribution with the 97.5th and 2.5th percentiles of the distribution equal to these normalized maximums and minimums, respectively.

We combine the QCEW employment estimate and the small farms incidence rate adjustment in each iteration i using the following equation:

$$Adjustment1_i = 1 + \frac{QCEW\ Employment - SOII\ Employment}{SOII\ Employment} \times Small\ Farms\ Incidence\ Rate\ Adjustment_i \tag{1}$$

We first calculate the difference between QCEW employment and SOII employment, which captures the number of farms with fewer than eleven employees, i.e., those missed by the SOII. We then divide by the number of farms in the SOII sample to estimate the proportion of farms with fewer than eleven employees relative to the number of farms captured in the SOII sample. Note that this term in the equation is equivalent to (*QCEW Employment* ÷ *SOII Employment*) − 1.

We multiply the small farms incidence rate adjustment by this ratio and add one to obtain our final adjustment factor. We repeat this process 10,000 times for each year and separately for crop and animal production. In each iteration, we draw a random value of the small farms incidence rate adjustment from the distribution described above.

Figure 4 shows the distribution of adjustment factors that we estimate from this process. The median adjustment factor for crop production ranges from a minimum of 1.22 in 2017 to a maximum of 1.34 in 2016. For animal production, the median adjustment factor ranges from a minimum of 1.31 in 2015 to a maximum of 1.51 in 2005. On an annual basis, the small farms adjustment factor is larger for animal production than for crop production, implying that the SOII omission of small farms has a larger impact on the accuracy of injury and illness rates for animal production than crop production. There is no clear trend in the adjustment factors for crop production over time, whereas there is a downward trend for animal production. This suggests that while the omission of small farms in the SOII is more meaningful for the accuracy of incidence rates in animal production, this effect is shrinking over time.

Step 3 (Adjustment 2): QCEW Adjustment for Government Undercount

Our third step is to adjust injury and illness rates to account for the agricultural employment undercount in the QCEW due to the seasonality of agricultural work and the prevalence of undocumented workers (Larson, 2000; Leigh et al., 2014). Our second adjustment factor accounts for this using the ratio of the true number of hired agricultural workers to the QCEW employment count. We construct the true employment count using QCEW estimates of the number of excluded wage and salary workers employed in agriculture each

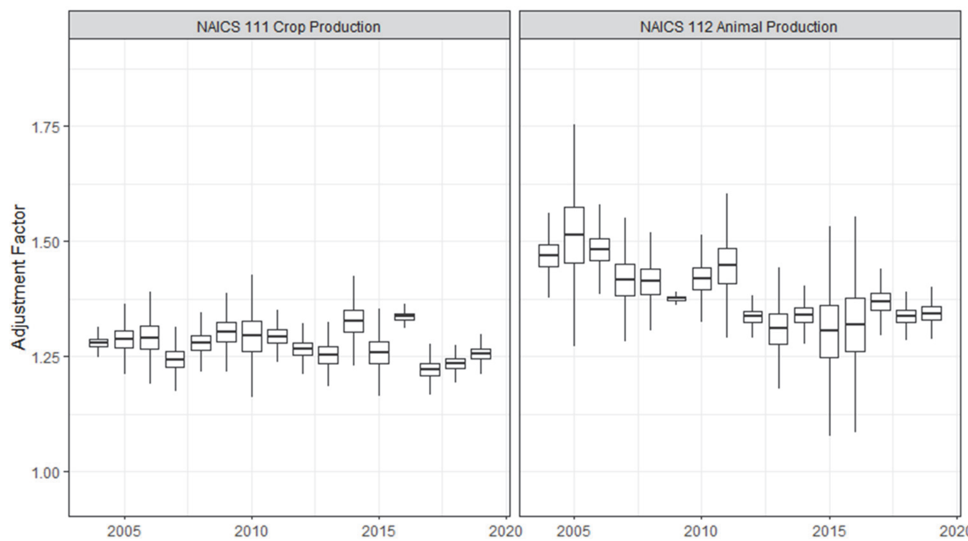

Figure 4. QCEW small farms adjustment factors. This figure shows the distribution of the QCEW small farms adjustment factor, i.e., adjustment 1, using 10,000 iterations for each year and production type. The lower and upper bounds of the boxes correspond to the 25th and 75th percentiles and the mid-line corresponds to the 50th percentile. Data sources: SOII FTE 2012-2019 from BLS SOII Table 1; SOII employment 2004-2011 from Henry Reeve (BLS); SOII incidence rates by employer size from BLS SOII Table Q1; and QCEW employment from BLS API.

year (BLS, 2019e). The QCEW publishes coverage exclusions separately for agricultural businesses and non-agricultural businesses but does not segment these categories further.

We construct the ratio of the true number of hired agricultural workers to the number covered in the QCEW by summing the estimated QCEW excluded count and the QCEW employment count and dividing this total by the QCEW employment count. Because the QCEW excluded count is an estimate, we account for uncertainty in the true value of this parameter by applying a simulation procedure. We assume a uniform distribution for the QCEW excluded count with lower and upper bounds equal to the minimum and maximum QCEW excluded counts over the study period, respectively.

The estimates of the number of excluded workers in the QCEW are provided annually and are rounded to the nearest 100,000. During our sample period, we only observed four distinct values of this estimate ranging from 100,000 to 400,000. Given the lack of information, we chose to use a uniform distribution for this adjustment to capture this uncertainty. This is analogous to using an "uninformative" prior in Bayesian statistics.

We calculate the adjustment factor as:

$$Adjustment\,2_i = \frac{QCEW\ Excluded_i + QCEW\ Included}{QCEW\ Included} \tag{2}$$

where in each iteration i, we draw an estimate of the QCEW excluded count from the described uniform distribution. We repeat this process for 10,000 iterations each year and separately for crop and animal production. Figure 5 shows the distribution of adjustment factors estimated by this procedure. The median adjustment factor for crop production ranges from a minimum of 1.19 in 2017 to a maximum of 1.23 in 2015. For animal production, the median adjustment factor ranges from a minimum of 1.19 in 2018 to 1.23 in 2015.

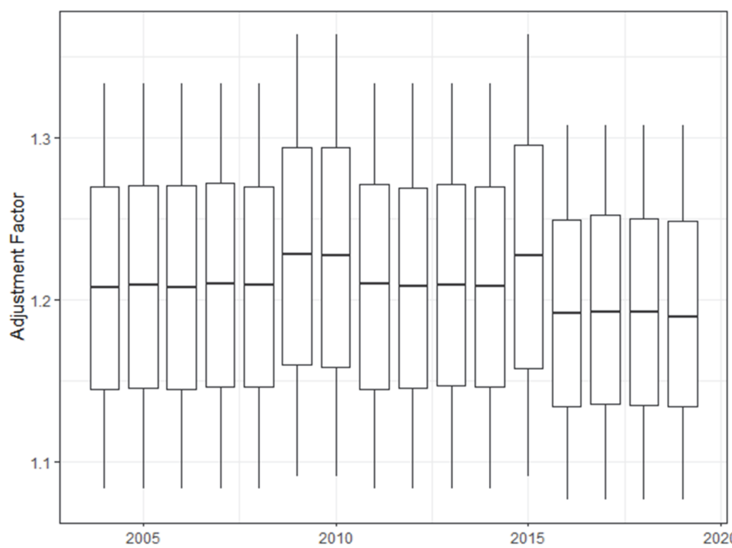

Figure 5. QCEW coverage exclusions adjustment factors. This figure shows the distribution of the QCEW undercount adjustment factor (adjustment 2) for each year. The lower and upper bounds of the boxes correspond to the 25th and 75th percentiles, and the mid-line corresponds to the 50th percentile. Data source: QCEW coverage exclusions from Table A: Coverage exclusions (2004 to 2019) for selected workers.

Step 4 (Adjustment 3): CPS Adjustment for Self-Employed Farmers

Our fourth step is to account for the omission of self-employed farmers and ranchers and unpaid family labor in the SOII. Using data from a survey of farmers and ranchers across seven U.S. states (Iowa, Kansas, Minnesota, Missouri, North Dakota, Nebraska, and South Dakota), Johnson et al. (2021) found that the nonfatal injury rate for self-employed farmers and ranchers was higher than the nonfatal injury rates for workers included in the BLS SOII data.

We use CPS estimates for total employed and total wage and salary workers by industry to construct our third adjustment factor: the ratio of total employed workers to wage and salary workers only. This captures the number of self-employed and unpaid family workers as a proportion of wage and salary workers for both crop and animal production. For this adjustment, we assume that the injury and illness incidence rate for self-employed and unpaid family workers is the same as for wage and salary workers.

Because the CPS employment counts are estimates, we again employ a simulation approach to incorporate uncertainty. We assume that total employment and employment of wage and salary workers alone are normally distributed around the annual CPS estimates. To construct appropriate standard errors for these distributions, we use information from the BLS CPS reliability documentation and parameter and factor tables. We combine this information with the CPS estimates to calculate approximate standard errors using generalized variance functions. The approximate standard errors calculated using the parameter and factor tables are based on the sample design.

The parameter and factor tables in the CPS reliability documentation provide aggregate reliability factors for agriculture and related industries, rather than separating these for crop and animal production. To estimate standard errors for crop and animal production, we calculate the standard errors for the aggregate level of "agriculture and related industries" and then scale the estimated standard error for each crop or animal production industry. For example, the crop production standard error estimate is equivalent to the "agriculture and related industries" standard error multiplied by the fraction of crop production employment over "agriculture and related industry" employment.

We calculate the standard error for each year using the equation recommended in the CPS technical documentation:

$$se(x;\ N;\ f) = f \times se(x; N) = f \times \sqrt{(\alpha + \beta N)\left(x - \frac{x^2}{N}\right)} \tag{3}$$

where

x = annual CPS employment estimate

N = total civilian non-institutional population age 16 years and older

f = annual adjustment factor for workers in agriculture and related industries (i.e., this factor adjusts the monthly standard error to the annual average level)

α and β = adjustment parameters associated with workers in agriculture and related industries.

We calculate the CPS adjustment factor for self-employed and unpaid family members as:

$$Adjustment\,3_i = \frac{Total\ Employed_i}{Wage\ and\ Salary\ Workers_i} \tag{4}$$

where in each iteration *i*, we draw values for total employment and total wage and salary workers from a normal distribution with a mean equal to the relevant CPS employment estimate and a standard error calculated as described above. The adjustment factor for each iteration is equal to the CPS total employment estimate divided by the CPS total wage and salary worker employment estimate. We perform 10,000 iterations of this procedure for each year and separately for crop and animal production.

Figure 6 summarizes the adjustment factors from this procedure. For both crop and animal production, these adjustment factors are shrinking over time, implying that the numbers of self-employed and unpaid family member workers are declining over time relative to the number of hired workers. The median adjustment factor for crop production ranges from a maximum of 1.68 in 2005 to a minimum of 1.42 in 2019. The decline in the adjustment factor is more pronounced in animal production, where the median adjustment factor ranges from a maximum of 2.33 in 2004 to a minimum of 1.72 in 2019.

We use CPS employment counts to construct this adjustment factor because they provide annual counts of self-employed and unpaid family labor for both crop and animal production separately. CPS counts are provided annually and are comparable year over year. One limitation is that some self-employed and unpaid workers might not list crop or animal agriculture as their industry of primary occupation if they were also employed in a different sector. In this case, the adjustment factor will be too small to completely correct the undercount self-employed and unpaid workers.

Note that having a non-farm primary occupation means that these individuals work more hours on the off-farm job than the farm job (BLS, 2021c). For example, farm operators for relatively small farms, those with less than $50,000 in annual sales, who have off-farm jobs spend an average of 35 hours per week working at their off-farm jobs (Brown and Weber, 2013). This reduces the likelihood that they are injured on the farm compared with a full-

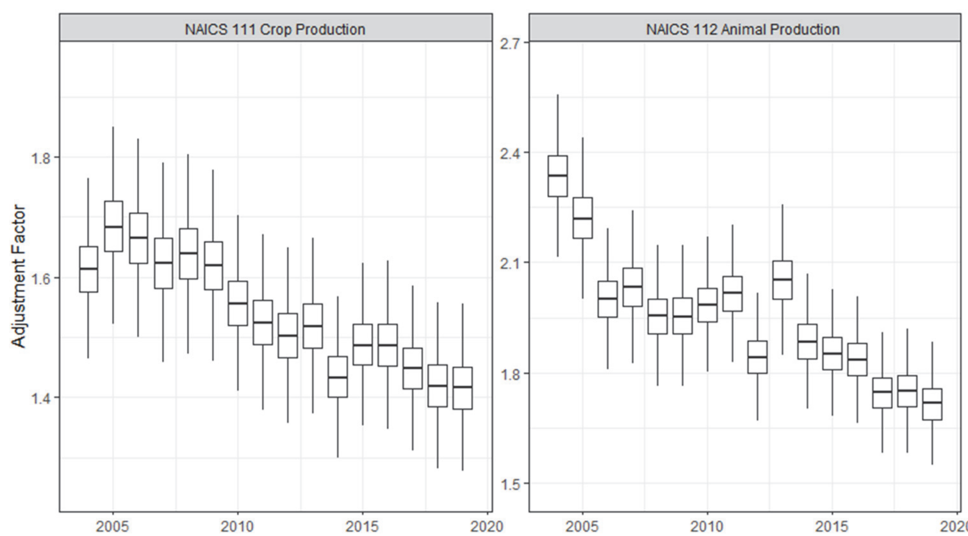

Figure 6. CPS adjustment for self-employed farmers. This figure shows the summary statistics of adjustment 3 across 10,000 simulations for each year. The lower and upper bounds of the boxes correspond to the 25th and 75th percentiles. Data sources: CPS employment data from Steven Hipple (BLS) and BLS reliability estimates.

time worker because they have less exposure. Moreover, jobs with longer hours have higher injury rates (Caruso et al., 2004; Dembe et al., 2005).

An alternative data source for the number of self-employed and unpaid workers is the U.S. Census of Agriculture (CoA), but there are multiple limitations to using these data. First, the CoA is conducted every five years, rather than annually. Second, information on the numbers of hired and unpaid workers in crop and animal production is only available in publicly accessible data for the two most recent censuses (2012 and 2017). This limits our ability to interpolate annual values for earlier years. Third, while the CoA collects information on the number of hired and unpaid workers, there is no information on the number of self-employed operators. For these reasons, we use CPS to compute the adjustment factor. The resulting bias is likely small and within our measures of uncertainty.

Step 5 (Adjustment 4): Willful and Negligent Underreporting

The final adjustment accounts for willful and negligent underreporting. Using worker compensation data, Boden and Ozonoff (2008) found that the BLS SOII missed between 27% and 57% of nonfatal injury and illness cases due to willful and negligent underreporting. Several other studies have either estimated or assumed rates for willful and negligent underreporting. However, apart from Leigh et al. (2014), those studies focused on willful and negligent underreporting across all industries, rather than agriculture alone. Figure 7 shows the rates reported in prior studies. These rates range from 23% for Bonauto et al. (2010) to 74% for Lakdawalla et al. (2007).

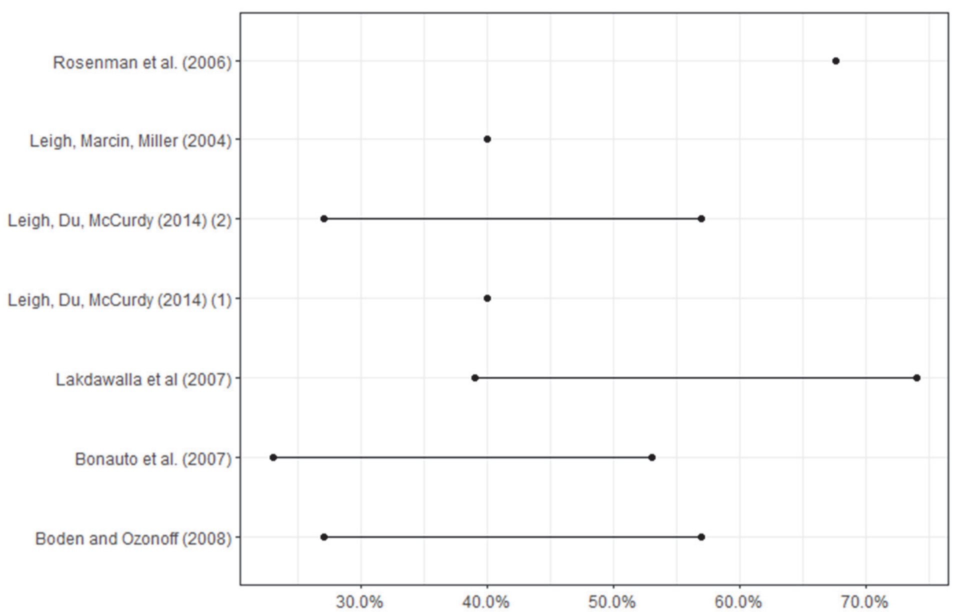

Figure 7. Summary of prior studies on willful and negligent underreporting. This figure shows the upper and lower bounds of willful and negligent underreporting found in prior studies. Studies with a single point provide point estimates rather than ranges of underreporting, whereas some studies provide only a range of reasonable estimates. Leigh et al. (2014) used (1) a single point estimate of 40% in their main analysis and (2) performed a sensitivity analysis with upper and lower bounds of 27% and 57%, respectively.

In our simulation procedure, we assume that the willful and negligent underreporting rate follows a normal distribution, with 2.5th and 97.5th percentiles of the distribution equal to 27% and 57%, respectively. These are the lower and upper bounds estimated by Bonauto et al. (2010) and applied by Leigh et al. (2014). While these values do not match the lowest and highest estimates in the literature, they serve as reasonable values for the lower and upper tails of the distribution. Because these values are not used as strict upper and lower bounds, they allow the possibility of drawing rates outside this range. The final adjustment factor in each iteration *i* is calculated as the inverse of one minus the sampled underreporting rate. In other words, we estimate:

$$Adjustment\,4_i = \frac{1}{1 - Willful\ and\ Negligent\ Underreporting\ Rate_i} \tag{5}$$

The underreporting rates are estimated identically each year for crop and animal production. Estimates of this adjustment factor are stable across time and production type. The median adjustment factor for crop production ranges from a minimum of 1.83 in 2011 to a maximum of 1.85 in 2019. For animal production, the median adjustment factor ranges from a minimum of 1.84 in 2019 to a maximum of 1.85 in 2018.

Results

We sequentially apply each adjustment to the initial draw from the BLS SOII estimates of injuries and illness for each year in each simulation iteration. Here we report summary statistics from repeating this procedure for 10,000 iterations. Figure 8 shows the distribution of estimates of the SOII nonfatal injury and illness undercount rates. We find that the majority of nonfatal illness and injury cases are missed by the SOII counts. In addition, the undercount rates are slightly decreasing over time and are consistently higher for animal

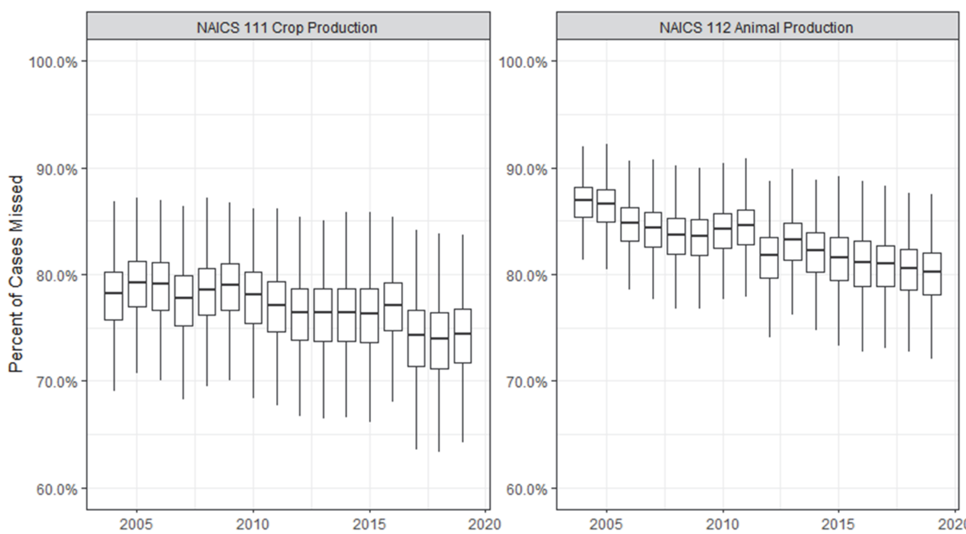

Figure 8. Share of total cases missed by SOII. This figure shows the BLS SOII undercount as a percentage of total cases missed by the BLS SOII.

production than for crop production. For crop production, our preferred range of estimates (from the bottom 2.5% to the upper 97.5% tails of our distribution of estimates) suggests that the SOII counts missed 73.98% to 79.25% of injuries and illnesses each year from 2004 to 2019. For animal production, our findings suggest that the SOII counts missed 80.2% to 86.91% of injuries and illnesses each year.

Figure 9 shows how each adjustment factor contributes to the total injury undercount each year. For both crop and animal production, the adjustment for willful and negligent underreporting is the largest contributor to the SOII injury and illness undercount, accounting for 52.54% to 56.93% of the undercount each year for animal production and 57.57% and 61.78% of the undercount each year for crop production. The CPS adjustment for self-employed and family workers is the second largest contributor to the undercount, accounting for 24.57% and 31.54% of the undercount for crop production and animal production, respectively. The QCEW adjustments for the omission of small farms and government employment account for the remainder of the SOII undercount, accounting for at most 18.59% and 14.90% of the missed SOII cases for crop and animal production, respectively. The relative contribution of these factors is fairly stable across time, with a slight increasing trend in the role of willful and negligent reporting (particularly for animal production) and a slight decreasing trend in the role of excluding self-employed and family labor from the injury counts.

Figure 10 shows the final distribution of our adjusted nonfatal injury and illness counts for crop and animal production. The median estimates of adjusted agricultural injuries and illnesses decline between 2005 and 2010, increase from 2010 through 2015, and begin to decline again after 2015. Overall, the distribution of estimates suggests that 95% of the true annual counts of injuries and illnesses from 2004 to 2019 lie between 60,000 and 150,000 in crop production and between 43,000 and 130,000 in animal production. In 2019, the most recent year in our study, our distribution of estimates suggests that there were between

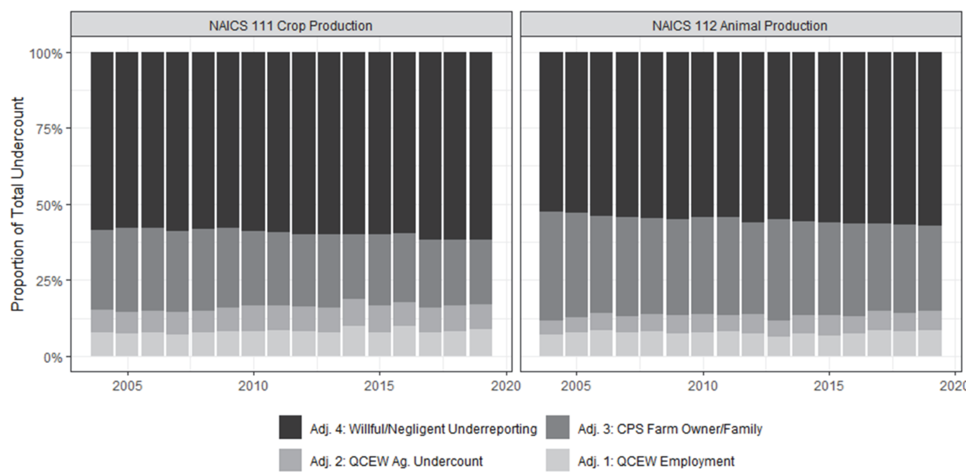

Figure 9. Proportion of total cases missed in BLS SOII by adjustment type. This figure shows the role of each adjustment factor in the total injury undercount each year. Values for each adjustment factor indicate the proportion of the estimated missed injury and illnesses that each factor accounts for in the indicated year. Percentages are calculated using the annual mean of missed injuries and illnesses across our 10,000 simulation iterations.

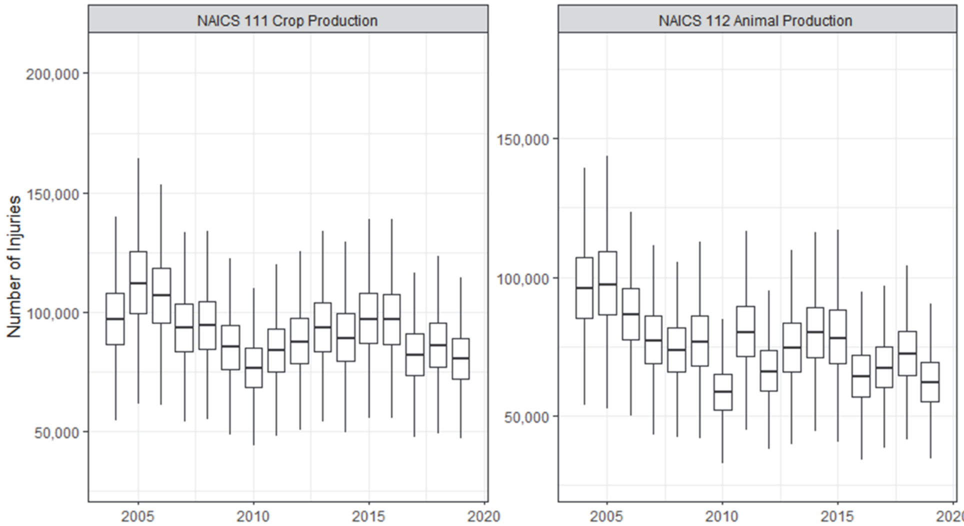

Figure 10. Final adjusted agricultural injury and illness estimates. This figure shows the distributions of the final adjusted injury and illness estimates each year for crop and animal production. The lower and upper bounds of the boxes correspond to the 25th and 75th percentiles, respectively.

61,000 and 102,000 injuries and illnesses in crop production and between 46,000 and 81,000 injuries and illnesses in animal production. By comparison, the 2019 BLS SOII injury and illness point estimates were 21,000 and 12,300 for crop and animal production, respectively.

Discussion and Conclusions

This study constructed adjusted occupational injury and illness estimates for U.S. workers employed in crop and animal production from 2004 through 2019. Our study extends prior work by Leigh et al. (2014) to span a longer period and incorporate uncertainty. We estimate that from 2004 through 2019, the BLS SOII estimates miss an average of 77% of injuries and illnesses in crop production and 83% in animal production. Overall, our distribution of estimates suggests that the true rates of injuries and illnesses during this period range from 60,000 to 150,000 for crop production and from 43,000 to 130,000 for animal production. For both crop and animal production, willful and negligent underreporting accounts for the majority of the total undercount. Over the study period, approximately 60% and 55% of the total undercount is attributed to willful and negligent underreporting for crop and animal production, respectively. We find that the BLS SOII counts become more accurate over our study period and show that this is largely driven by a decline in the prevalence of self-employed and family member workers employed in agriculture, who are a key group omitted from the BLS SOII counts.

This finding is consistent with work by economists at the USDA Economic Research Service. Hoppe et al. (2010), MacDonald and Hoppe (2017), and MacDonald et al. (2018) found that agricultural production has been shifting from relatively smaller scale to larger farms over the period we consider. Technological advancements in agriculture have allowed farms to standardize production, and thus farms can reduce their average cost of production as they increase output, which has led to large farms financially outperforming smaller farms (Burns and MacDonald, 2018). This shift to larger farms is an important driver of the decline in the total number of farms (MacDonald et al., 2018). This decline in the total number of U.S. farms is linked with fewer self-employed, unpaid, and hired workers (Kassel, 2021; Wang et al., 2022). Relevant to our findings, the hours worked by self-employed and unpaid family workers have fallen more than the hours worked by hired workers (Martin, 2022).

Our study produces more accurate estimates of injuries and illnesses in agriculture that are consistent over time. Inaccuracies in the current estimates have multiple important ramifications for social welfare. First, understating the true rates of injuries in the industry will likely result in too few or misdirected policy solutions aimed at reducing workplace health and safety. Accurate estimates are vital for appropriately allocating funds and targeting policy solutions. Misdirected policy solutions can result in preventable injuries and illnesses, with direct negative implications for agricultural workers, consisting of negative health ramifications and lost income, and indirect negative implications for the welfare of society, consisting of the high costs associated with treatment, compensation, and lost productivity (Baidwan et al., 2021; Leigh et al., 2001; NIOSH, 2006). Second, evaluating the effectiveness and economic efficiency of existing worker safety laws requires accurate information on the prevalence of injuries and illnesses. Undercounting the rates of nonfatal injuries may overstate the effectiveness of past government policies at improving working conditions. The estimates developed in this study can be used by researchers to produce better estimates of the impacts of government policies, thereby informing the policy-making process and enhancing the well-being of the U.S. agricultural workforce.

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We thank Henry Reeve and Steven Hipple at the Bureau of Labor Statistics for their help in accessing the measures of employment collected in the CPS and SOII. We also thank Dr. J. Paul Leigh for assisting us in accurately replicating the results from an earlier study and offering contacts and assistance in acquiring data for this study, and we thank Dr. Fadi Fathallah for his feedback and suggestions on the manuscript and methods. This project was supported by the Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health (CDC-NIOSH) Cooperative Agreement #U54 OH00 7550.

References

Baidwan, N. K., Ramirez, M. R., Gerr, F., Boonstra, D., Cavanaugh, J. E., & Casteel, C. (2021). Cost, severity, and prevalence of agricultural-related injury workers' compensation claims in farming operations from 14 U.S. states. *Intl. J. Environ. Res. Public. Health, 18*(8), article 4309. https://doi.org/10.3390/ijerph18084309

BLS. (2018). Calculating approximate standard errors and confidence intervals for current population survey estimates. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/cps/documentation.htm#reliability

BLS. (2019a). Table 1: Incidence rates - Detailed industry level, 2003-2019. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/iif/oshsum.htm#03Summary_Tables

BLS. (2019b). Table 2: Number of cases - Detailed industry level, 2003-2019. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/iif/oshsum.htm#03Summary_Tables

BLS. (2019c). Table A1: Percent relative standard errors for detailed industry rates, 2003-2019. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/iif/oshsum.htm#03Summary_Tables

BLS. (2019d). Table A2: Percent relative standard errors for detailed industry case counts, 2003-2019. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/iif/oshsum.htm#03Summary_Tables

BLS. (2019e). QCEW Table A: Coverage exclusions (2004-2019) for selected workers. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/cew/overview.htm

BLS. (2020). Handbook of methods: Survey of occupational injuries and illnesses. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/opub/hom/soii/calculation.htm

BLS. (2021a). Number and rate of fatal work injuries, by industry sector. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/charts/census-of-fatal-occupational-injuries/number-and-rate-of-fatal-work-injuries-by-industry.htm

BLS. (2021b). Parameter and factor tables. Washington, DC: Bureau of Labor Statistics. Retrieved from http://www.bls.gov/cps/parameters-and-factors-for-calculating-standard-errors.xlsx

BLS. (2021c). Labor force statistics from the current population survey: Concepts and definitions. Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/cps/definitions.htm#mjh

Boden, L. I., & Ozonoff, A. (2008). Capture-recapture estimates of nonfatal workplace injuries and illnesses. *Ann. Epidemiol., 18*(6), 500-506. https://doi.org/10.1016/j.annepidem.2007.11.003

Bonauto, D. K., Fan, J. Z., Largo, T. W., Rosenman, K. D., Green, M. K., Walters, J. K., & Fang, S. (2010). Proportion of workers who were work-injured and payment by workers' compensation systems - 10 states, 2007. *Morbidity Mortality Weekly Report, 59*(29), 897-900. Retrieved from https://www.cdc.gov/mmwr/preview/mmwrhtml/mm5929a1.htm?s_cid=mm5929a1_w

Brown, J. P., & Weber, J. G. (2013). The off-farm occupations of U.S. farm operators and their spouses. Bulletin 117. Washington, DC: USDA Economic Research Service. Retrieved from https://www.ers.usda.gov/webdocs/publications/43789/40009_eib-117.pdf

Burns, C. B., & MacDonald, J. M. (2018). America's diverse family farms: 2018 edition. Bulletin 203. Washington, DC: USDA Economic Research Service. Retrieved from https://www.ers.usda.gov/publications/pub-details/?pubid=90984

Caruso, C. C., Hitchcock, E. M., Dick, R. B., Russo, J. M., & Schmit, J. M. (2004). Overtime and extended work shifts: Recent findings on illnesses, injuries, and health behaviors. Cincinnati, OH: NIOSH. Retrieved from https://www.cdc.gov/niosh/docs/2004-143/pdfs/2004-143.pdf

Chari, R., Kress, A. M., & Madrigano, J. (2018). Injury and illness surveillance of U.S. agricultural workers: Assessment of recommendations and actions. *Rand Health Qtly., 8*(2), article 10. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6183769/

Crawford, J. M., Wilkins III, J. R., Mitchell, G. L., Moeschberger, M. L., Bean, T. L., & Jones, L. A. (1998). A cross-sectional case control study of work-related injuries among Ohio farmers. *American J. Ind. Med., 34*(6), 588-599. https://doi.org/10.1002/(SICI)1097-0274(199812)34:6<588::AID-AJIM7>3.0.CO;2-K

Dembe, A. E., Erickson, J. B., Delbos, R. G., & Banks, S. M. (2005). The impact of overtime and long work hours on occupational injuries and illnesses: New evidence from the United States. *Occup. Environ. Med., 62*(9), 588-597. https://doi.org/10.1136/oem.2004.016667

Douphrate, D. I., Rosecrance, J. C., Stallones, L., Reynolds, S. J., & Gilkey, D. P. (2009). Livestock-handling injuries in agriculture: An analysis of Colorado workers' compensation data. *American J. Ind. Med., 52*(5), 391-407. https://doi.org/10.1002/ajim.20686

GAO. (2009). Workplace safety and health: Enhancing OSHA's records audit process could improve the accuracy of worker injury and illness data. Washington, DC: U.S. Government Accountability Office. Retrieved from https://www.gao.gov/products/gao-10-10

Gorucu, S., Michael, J., & Chege, K. (2022). Nonfatal agricultural injuries treated in emergency departments: 2015-2019. *J. Agromed., 27*(1), 41-50. https://doi.org/10.1080/1059924X.2021.1913271

Harrington, M., Wickman, A., Williams, D., & Lincoln, J. M. (2021). 30 years of the NIOSH agriculture, forestry, and fishing program. *NIOSH Science Blog* (8 Dec. 2021). Retrieved from https://blogs.cdc.gov/niosh-science-blog/2021/12/08/agff/

Hoppe, R. A., MacDonald, J. M., & Korb, P. (2010). Small farms in the United States: Persistence under pressure. Bulletin 63. Washington, DC: USDA Economic Research Service. https://doi.org/10.2139/ssrn.1557208

Jadhav, R., Achutan, C., Haynatzki, G., Rajaram, S., & Rautiainen, R. (2016). Review and meta-analysis of emerging risk factors for agricultural injury. *J. Agromed., 21*(3), 284-297. https://doi.org/10.1080/1059924X.2016.1179611

Johnson, A., Baccaglini, L., Haynatzki, G. R., Achutan, C., Loomis, D., & Rautiainen, R. H. (2021). Agricultural injuries among farmers and ranchers in the central United States during 2011-2015. *J. Agromed., 26*(1), 62-72. https://doi.org/10.1080/1059924X.2020.1845268

Karttunen, J. P., & Rautiainen, R. H. (2013). Distribution and characteristics of occupational injuries and diseases among farmers: A retrospective analysis of workers' compensation claims. *American J. Ind. Med., 56*(8), 856-869. https://doi.org/10.1002/ajim.22194

Kassel, K. (2021). The number of U.S. farms continues to decline slowly. Washington, DC: USDA Economic Research Service. Retrieved from https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=58268

Kica, J., & Rosenman, K. D. (2020). Multisource surveillance for non-fatal work-related agricultural injuries. *J. Agromed., 25*(1), 86-95. https://doi.org/10.1080/1059924X.2019.1606746

Lakdawalla, D. N., Reville, R. T., & Seabury, S. A. (2007). How does health insurance affect workers' compensation filing? *Econ. Inquiry, 45*(2), 286-303. https://doi.org/10.1111/j.1465-7295.2006.00011.x

Larson, A. C. (2000). Migrant and seasonal farmworker enumeration profiles study, 2000. Buda, TX: National Center for Farmworker Health. Retrieved from http://lib.ncfh.org/?plugin=ecomm&content=item&sku=5459

Leigh, J. P., Du, J., & McCurdy, S. A. (2014). An estimate of the U.S. government's undercount of nonfatal occupational injuries and illnesses in agriculture. *Ann. Epidemiol., 24*(4), 254-259. https://doi.org/10.1016/j.annepidem.2014.01.006

Leigh, J. P., Marcin, J. P., & Miller, T. R. (2004). An estimate of the U.S. government's undercount of nonfatal occupational injuries. *J. Occup. Environ. Med., 46*(1), 10-18. https://doi.org/10.1097/01.jom.0000105909.66435.53

Leigh, J. P., McCurdy, S. A., & Schenker, M. B. (2001). Costs of occupational injuries in agriculture. *Public Health Rep., 116*(3), 235-248.

MacDonald, J. M., & Hoppe, R. A. (2017). America's diverse family farms: 2016 edition. Bulletin 164. Washington, DC: USDA Economic Research Service. Retrieved from https://www.ers.usda.gov/publications/pub-details/?pubid=81401

MacDonald, J. M., Hoppe, R. A., & Newton, D. (2018). Three decades of consolidation in U.S. agriculture. Bulletin 189. Washington, DC: USDA Economic Research Service. Retrieved from https://www.ers.usda.gov/webdocs/publications/88057/eib-189.pdf?v=9908

Martin, P. L. (2022). Changes in U.S. farm labor: 1948-2017. *Rural Migration News* (Blog 269, March 2022). Davis, CA: University of California. Retrieved from https://migrationfiles.ucdavis.edu/uploads/rmn/blog/2022/03/Rural%20Migration%20News%20Blog%20269.pdf

Martin, P. L., Hooker, B., Akhtar, M., & Stockton, M. (2016). How many workers are employed in California agriculture? *California Agric., 71*(1), 30-34. https://doi.org/10.3733/ca.2016a0011

Martin, P. L., Hooker, B., & Stockton, M. (2019). Ratio of farmworkers to farm jobs in California increased to 2.3 in 2016. *California Agric., 73*(2), 73-78. https://doi.org/10.3733/ca.2019a0002

McCurdy, S. A., & Carroll, D. J. (2000). Agricultural injury. *American J. Ind. Med., 38*(4), 463-480. https://doi.org/10.1002/1097-0274(200010)38:4<463::AID-AJIM13>3.0.CO;2-N

McGwin, G. J., Enochs, R., & Roseman, J. M. (2000). Increased risk of agricultural injury among African-American farm workers from Alabama and Mississippi. *American J. Epidemiol., 152*(7), 640-650. https://doi.org/10.1093/aje/152.7.640
Myers, J. R. (1990). National surveillance of occupational fatalities in agriculture. *American J. Ind. Med., 18*(2), 163-168. https://doi.org/10.1002/ajim.4700180208
NIOSH. (2006). NIOSH fatal occupational injury cost fact sheet: Agriculture, forestry, and fishing. Publication 2006-151. Cincinnati, OH: NIOSH. Retrieved from https://www.cdc.gov/niosh/docs/2006-151/default.html
Northwood, J. (2010). Change to hours-based fatality rates in the census of fatal occupational injuries. Washington, DC: U.S. Bureau of Labor Statistics. Retrieved from https://www.bls.gov/opub/mlr/cwc/change-to-hours-based-fatality-rates-in-the-census-of-fatal-occupational-injuries.pdf
Pratt, D. S., Marvel, L. H., Darrow, D., Stallones, L., May, J. J., & Jenkins, P. (1992). The dangers of dairy farming: The injury experience of 600 workers followed for two years. *American J. Ind. Med., 21*(5), 637-650. https://doi.org/10.1002/ajim.4700210504
Rautiainen, R. H., & Reynolds, S. J. (2002). Mortality and morbidity in agriculture in the United States. *J. Agric. Saf. Health, 8*(3), 259-276. https://doi.org/10.13031/2013.9054
Rautiainen, R. H., Lange, J. L., Hodne, C. J., Schneiders, S., & Donham, K. J. (2004). Injuries in the Iowa certified safe farm study. *J. Agric. Saf. Health, 10*(1), 51-63. https://doi.org/10.13031/2013.15674
Rosenman, K. D., Kalush, A., Reilly, M. J., Gardiner, J. C., Reeves, M., & Luo, Z. (2006). How much work-related injury and illness is missed by the current national surveillance system? *J. Occup. Environ. Med., 48*(4), 357-365. https://doi.org/10.1097/01.jom.0000205864.81970.63
Scott, E., Hirabayashi, L., Graham, J., Krupa, N., & Jenkins, P. (2021). Using hospitalization data for injury surveillance in agriculture, forestry, and fishing: A crosswalk between ICD10CM external cause of injury coding and the Occupational Injury and Illness Classification System. *Injury Epidemiol., 8*(1), article 6. https://doi.org/10.1186/s40621-021-00300-6
Tonozzi, T. R., & Layne, L. A. (2016). Hired crop worker injuries on farms in the United States: A comparison of two survey periods from the National Agricultural Workers Survey. *American J. Ind. Med., 59*(5), 408-423. https://doi.org/10.1002/ajim.22578
Wang, S. L., Hoppe, R. A., & Hertz, T. (2022). Increases in labor quality contributed to growth in U.S. agricultural output. Washington, DC: USDA Economic Research Service. Retrieved from https://www.ers.usda.gov/amber-waves/2022/february/increases-in-labor-quality-contributed-to-growth-in-u-s-agricultural-output/
Weichelt, B., & Gorucu, S. (2019). Supplemental surveillance: A review of 2015 and 2016 agricultural injury data from news reports on AgInjuryNews.org. *Injury Prev., 25*(3), 228-235. https://doi.org/10.1136/injuryprev-2017-042671
Zhou, C., & Roseman, J. M. (1994). Agricultural injuries among a population-based sample of farm operators in Alabama. *American J. Ind. Med., 25*(3), 385-402. https://doi.org/10.1002/ajim.4700250307

Appendix A

SOII Employment and FTE Estimate Time Trend Analysis

The underlying assumption of the SOII FTE estimate adjustment is that the percent difference between the SOII employment estimates and FTE estimates are relatively constant over time. To evaluate this assumption, we perform a sensitivity analysis by regressing the percent difference between SOII employment and SOII FTE against a time trend. Table A1 presents the results of the time trend analysis for each industry. For crop production, the coefficient on the time trend is not significant, which supports the assumption that the

Table A1. SOII employment and FTE estimate time trend analysis.

	Crop Production (%)	Animal Production (%)
Estimate	0.007928049	-0.007594915
Standard error	0.005107032	0.002596568
t-Statistic	1.552379	-2.924982
p-Value	0.1715588	0.0264592

scaling factor is reasonable. For animal production, there is a negative coefficient on the time trend that is significant at the 5% level.

Appendix B

Detailed Data Sourcing Process

When possible, data were sourced directly from the BLS API (https://www.bls.gov/developers/) using an R script.

SOII Data

Number of injuries and illnesses per 100 full-time workers:

- BLS API Series ID for crop production:
  IIUNRM11100061100 (used for years 2004 to 2013)
  ISUNRM11100061100 (used for years 2014 to 2019)
- BLS API Series ID for animal production:
  IIUNRM11200061100 (used for years 2004 to 2013)
  ISUNRM11200061100 (used for years 2014 to 2019)
- BLS Table 2: Numbers of nonfatal occupational injuries and illnesses by industry and case types, NAICS 111 (crop production) and NAICS 112 (animal production), total recordable cases.

Relative standard errors for number of injuries and illnesses:

- BLS API Series ID for crop production:
  IIUNRM11100060100 (used for years 2004 to 2013)
  ISUNRM11100060100 (used for years 2014 to 2019)
- BLS API Series ID for animal production:
  IIUNRM11200060100 (used for years 2004 to 2013)
  ISUNRM11200060100 (used for years 2014 to 2019)
- BLS Table A-2: Percent relative standard errors for numbers of nonfatal occupational injuries and illnesses by industry, NAICS 111 (crop production) and NAICS 112 (animal production), total recordable cases.

Incidence rates of nonfatal occupational injuries and illnesses by industry and case type:

- BLS API Series ID for crop production:
  IIUNRM11100031100 (used for years 2004 to 2013)
  ISUNRM11100031100 (used for years 2014 to 2019)
- BLS API Series ID for animal production:
  IIUNRM11200031100 (used for years 2004 to 2013)
  ISUNRM11200031100 (used for years 2014 to 2019)
- BLS Table 1: Incidence rates of nonfatal occupational injuries and illnesses by industry and case types, NAICS 111 (crop production) and NAICS 112 (animal production), total recordable cases.

SOII employment data:

- Henry Reeve, BLS, personal communication 5 February 2021

- SOII number of full-time employment: Calculated based on the footnote in BLS Table 1: "The incidence rates represent the number of injuries and illnesses per 100 full-time workers and were calculated as: $(N/EH) \times 200{,}000$, where N = number of injuries and illnesses, EH = total hours worked by all employees during the calendar year, and 200,000 = base for 100 equivalent full-time workers (working 40 hours per week, 50 weeks per year)".

Injury rates by industry size:

- BLS API Series ID for crop production (used for years 2014 through 2019):
  ISUNRM111000E1100 (11-49 employees)
  ISUNRM111000K1100 (50-249 employees)
  ISUNRM111000Q1100 (250-999 employees)
  ISUNRM111000W1100 (1000+ employees)
- BLS API Series ID for animal production (used for years 2014 through 2019):
  ISUNRM112000E1100 (11-49 employees)
  ISUNRM112000K1100 (50-249 employees)
  ISUNRM112000Q1100 (250-999 employees)
  ISUNRM112000W1100 (1000+ employees)
- BLS Table Q1 (used for years 2004 through 2013): Incidence rates of total recordable cases of nonfatal occupational injuries and illnesses by quartile distribution and employment size, private industry, NAICS 111 (crop production) and NAICS 112 (animal production), average incidence rates for all establishments (mean).

QCEW Data

QCEW employment data were sourced from the BLS API. For crop production, the Series ID was ENUUS000105111. For animal production, the Series ID was ENUUS000105112. QCEW coverage exclusion data were sourced from https://www.bls.gov/cew/publications/employment-and-wages-annual-averages/.

CPS Data

CPS employment data:

- Table 4. Employed and experienced unemployed persons by detailed industry and class of worker, provided by Steven Hipple, BLS, personal communication, 24 February 2021.

Sensitivity parameter values:

- Sourced from https://www.bls.gov/cps/parameters-and-factors-for-calculating-standard-errors.xlsx
- Table PF-8 for class of worker "Agriculture and related industries" and "Wage and salary workers" for parameters α and β, and the yearly averages factor value.

Sensitivity, other required values:

- All other required values that go into the standard error formula were sourced from the CPS employment data table provided by Steven Hipple using the industries "Agriculture, forestry, fishing, and hunting" and "Total, 16 years and over".