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Time series, seasonality and trend evaluation of 7 years (2015–2021) of OSHA severe injury data

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ABSTRACT

Problem: Employers are required to report severe work-related injuries (e.g., amputation, inpatient hospitalization, or loss of an eye), to the Occupational Safety and Health Administration (OSHA). This study examined the OSHA severe injury reports (SIRs) public microdata to understand time-related trends and patterns. *Methods:* This study included all SIRs from January 2015 to December 2021 (84 months). We employed time series decomposition models (classical additive and multiplicative, X-11, and X-13ARIMA-SEATS) to evaluate monthly seasonal effect and seasonally adjusted trend of SIRs. We developed data visuals to display trends from different models with the original data series. We compared number of daily SIRs by day of the week, and yearly trends by 2-digit NAICS and separately by 1-digit OIICS injury event. *Results:* There were a total of 70,241 SIRs in this 7 year period; ranging from 8,704 to 11,156 per year, and 600 to 1,100 per month. Seasonally adjusted trend indicated a gradual increase of SIRs over time until October 2018, then a steeper decrease until August 2020, and staying somewhat flat for the rest of the months. Seasonality indicated more SIRs were reported in the summer months (June, July, August). Daily SIRs indicated a weekday average of 34 (SD = 9) and weekend average of 11 (SD = 5). The Manufacturing and Construction industries reported the highest yearly SIRs. Contact with objects and equipment, and falls, slips, trips were the most numerous injury events associated with SIRs. *Discussion:* Although Federal OSHA SIR data do not include SIRs from state-plan jurisdictions, the data provide a timely national trend of SIR. This is the first known time series analysis of SIRs. *Practical Applications:* The findings of this study highlight the ability of researchers to use the SIRs as a timely indicator to understand occupational injury trends by specific industries and injury events.

1. Problem

1.1. Occupational injury in the United States

Nonfatal occupational injuries have a significant cost to workers, their families, and social support system. In 2022, the cost to address the 10 most disabling workplace injuries was $49.18 billion. The highest percentage of the total cost of worker injuries was attributed to overexertion involving outside sources (handling object) (22%), followed by falls on the same level (18%), and struck by object or equipment (9.76%) (Liberty Mutual Institute, 2022). Most recent News Release (November 2022) of the Survey of Occupational Injuries and Illnesses (SOII), reported by the Bureau of Labor Statistics, indicated 2.6 million nonfatal workplace injuries and illnesses in 2021 from the private industry employers, an incidence rate of 2.7 cases per 100 full-time equivalent (FTE) workers (BLS, 2022c).

1.2. Occupational injury surveillance systems

In the United States, occupational safety and health surveillance is distributed among federal, state, and local agencies, employers, professional associations, and labor organizations, among others (NAS, 2018). The major federal partners include the Bureau of Labor Statistics (BLS), OSHA, the Mine Safety and Health Administration within the Department of Labor, and the National Institute for Occupational Safety and Health (NIOSH) in the Centers for Disease Control and Prevention under the Department of Health and Human Services (HHS). These agencies often operate independently, beholden to their mutually exclusive missions of occupational safety and health.

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Although occupational surveillance systems in the United States have recorded a decrease of nonfatal occupational injuries over the last few decades (AFL-CIO, 2021; Bhushan & Leigh, 2011; BLS, 2020b), previous occupational safety and health research may need to assess severe injuries more systematically. Analysis of the National Electronic Injury Surveillance System (NEISS-Work), comprising nonfatal occupational injuries and illnesses from a probability sample of 100 (USCPSC NEISS, 2022a, 2022b) hospital emergency departments, found that the majority of injury-related ED visits were mild in severity (Villaveces, Mutter, Owens, & Barrett, 2013). Sears, Bowman, and Hogg-Johnson (2014) found that implementing a severity threshold allowed for more focused assessment of work-related injuries in hospital discharge data from four states.

The BLS SOII is the closest to a comprehensive national surveillance database of nonfatal occupational injuries in the United States (Wiatrowski, 2014; Bhandari, Marsh, Reichard, & Tonozzi, 2016; Brown, 2020). The BLS SOII is an annual survey, and the estimates were first published in 1974 for the survey year of 1972. The Occupational Safety and Health (OSH) Act of 1970 authorized the Secretary of Labor to "develop and maintain an effective program of collection, compilation, and analysis of occupational safety and health statistics" and the Secretary delegated this responsibility to BLS (Wiatrowski 2014; BLS, 2020d; Brown, 2020). The SOII captures nonfatal occupational injuries and some illnesses from approximately 200,000 employers using a multistage stratified probability sample design (BLS, 2020a, 2021a). Systematic underreporting of work-related injuries makes it difficult to understand the scope of occupational injuries (OSHA, 2015; Spieler & Wagner, 2014). Analysis of the SOII data from 1992-2003 found a consistent decline in reported work-related injuries aligning with changes in OSHA's reporting requirements when correcting for productivity, gross domestic product, number employed in the civilian workforce and average hours of weekly production in the private sector (Friedman & Forst, 2007). Furthermore, fewer than 40% of eligible workers apply for workers' compensation benefits, suggesting that the cost of such injuries is overwhelmingly assumed by the worker, their families, and taxpayer-supported safety-net programs (OSHA, 2015).

Regulatory requirements mandating that employers report severe work-related injuries to the Occupational Safety and Health Administration (OSHA) can supplement and complement our understanding of work-related injury occurrence (OSHA 1904.39, 2014). OSHA revised the *Recording and Reporting Occupational Injuries and Illnesses* rule in 2015 (1904.39 Subpart E) to identify high-hazard employers, target compliance assistance, and enforcement actions and reduce severe injuries to workers in high hazard jobs (OSHA, 2016). The rule requires that an employer report a death of an employee resulting from a work-related incident within 8 hours and an in-patient hospitalization of one or more employees, amputation or loss of an eye within 24 hours to OSHA. Although the promulgation of the 2015 rule only publicizes Severe Injury Reports (SIRs) starting in 2015, work-related injury data dating back to the 1970s are available by Freedom of Information Act Request to OSHA. Prior to this rule, employers were only required to report all work-related fatalities to OSHA within 8-hours and catastrophic incidents involving five or more hospitalizations (OSHA, 2016).

1.3. Measuring occupational injuries

Different data systems for injury surveillance include different data characteristics. A census is a complete enumeration and aims to capture all or most elements of the target population (Groves et al., 2004; Lohr, 2010). The Census of Fatal Occupational Injuries (CFOI) is one such example. BLS uses over 30 data sources to generate CFOI data (BLS, 2020c). In contrast, a probability sample is a scientifically selected sample, representative of the target population. Sample units are selected using a random process from the population frame. Each member of the population has a known nonzero probability of being chosen into the sample. If a probability sample is well designed and implemented, then the sample statistics are unbiased, a small sample could be used to make inference about the large population (Groves et al., 2004; Lohr, 2010). The SOII sample design employs a stratified random sampling method (BLS, 2020a).

OSHA SIRs public microdata is a form of administrative records data that differs from a census or a sample. Administrative records data can be broadly described as microdata, derived from the operation of administrative programs and commercial entities, such as data collected by government agencies for the purposes of registration, transaction, and record keeping. They are typically not designed for research purposes, yet provide benefits, such as attempting to reach a certain population who are required to report based on services received, and limitations such as underreporting of records (Elias, 2014; Connelly, Playford, Gayle, & Dibben, 2016; Penner & Dodge, 2019; U.S. Census Bureau, 2022b). A state-based study of work-related amputations revealed that fewer than half were reported to OSHA in the 17 months following implementation of SIR requirements (Grattan, Laing, Fiore, Pechter, & Davis, 2017). Most recently, Shi, Weaver, Hodgson, and Tustin (2022) used the OSHA SIR to assess possible cases of heat-related acute kidney injury and successfully identified cases despite underreporting and under-ascertainment contributing to an underestimation of the burden. In summary, OSHA SIR microdata is a surveillance system of severe worker injuries data, derived from administrative records based on regulatory requirement that can complement and supplement other occupational injury surveillance systems.

1.4. Study objective

This study examined the OSHA SIR data for the 7-year period (2015–2021) to understand time-related trends and patterns in these injuries, such as differences between days of the week, monthly seasonal effect within a year, trend over time, and trends by industry and injury event. We specifically employed time series decomposition models to evaluate seasonality and trends. This study is the first to assess temporal trends in severe work-related injuries using the OSHA SIR data.

2. Methods

2.1. OSHA severe injury reports (SIR) public microdata

OSHA SIRs public microdata were downloaded from OSHA's website (https://www.osha.gov/severeinjury). This analysis reflects the SIR data downloaded as of August 19, 2022. A severe injury is defined in SIR as any work-related in-patient hospitalization, amputation, or loss of an eye of one or more employees (OSHA, 2016, 2022). Each SIR record is an incident (i.e., injury event) reported by an employer to OSHA under the regulatory requirement.

SIR data only includes the "federal OSHA jurisdiction" data and does not include SIRs under the state plan state jurisdiction (OSHA, 2022). Although SIR data disaggregation reveals injury records from 50 states, the District of Columbia, and five U.S. territories (total 56 states, district, and territories; we will simply refer to this as "states" throughout this paper), there is a caveat on how the data from 56 states are included in this data. Currently, 34 states are under federal OSHA jurisdiction, which covers most private sector workers but do not cover state and local government workers; and 22 states are not under federal OSHA jurisdiction as a state plan covers most private sector, state, and local government workers (i.e., 34 OSHA jurisdiction + 22 no OSHA jurisdiction = 56 states). However, federal OSHA jurisdiction also covers federal government workers including U.S. Postal Service nationwide, military bases, Border Patrol, American Indian or Alaska Native reservations, and certain maritime activities, which is why injury records from all 56 states are found in this SIR data.

Variables included injury event date, employer address, state, latitude, longitude, number of hospitalizations and amputations, text narrative, 6-digit North American Industry Classification System (NAICS) industry codes, and 4-digit Occupational Injury and Illness Classification System (OIICS) codes that characterize the injury event/exposure that precipitated the injury, the source of injury, nature of injury, and body part affected (BLS, 2021b).

2.2. Data processing and aggregation of injury events

First, we employed time-related functions using 'lubridate' R package (Grolemund & Wickham, 2011) to extract and transform the components of date (e.g., 03/16/2016 implies March; 2016; Wednesday) using R software for statistical computing (version 4.1.0; R Core Team, 2021). This enabled aggregation of SIRs by different time units, such as number of SIRs for a specific month or day of the week. We also used the 'stringr' R package (Wickham, 2022) to extract the 2-digit NAICS code and 1-digit OIICS injury event code, followed by joining the narrative descriptions of 2-digit NAICS and 1-digit OIICS event, using the data join procedure. All injury incidents (records) from the SIR microdata for 7 years (84 months) were included from January 1, 2015, through December 31, 2021.

2.3. Trend evaluation with and without seasonal adjustment

The purpose of this study was to examine the SIR data to understand the time-related trends and patterns in these injury events. The analyses assessed month-to-month trend over time *with* and *without* seasonal adjustment, seasonal effect within a year, differences between days of the week, and yearly trends by NAICS industry and OIICS injury event. We employed three methods to evaluate trends of monthly SIRs from January 2015 to December 2021.

2.3.1. Seasonally unadjusted trend using Local Polynomial Regression (LOESS)

To evaluate the trend of the original data series, a *locally estimated scatterplot smoothing* (LOESS) was fitted, a nonparametric regression method for estimating nonlinear trend of monthly SIRs (Cleveland & Devlin, 1988; Cleveland & Grosse, 1991; Cleveland, Devlin, & Grosse, 1988; Cleveland, 1979). LOESS accounts for the moving average of SIRs over time. The smoothing parameter (0 to 1) controls the flexibility of the LOESS regression function (smooth versus wiggle). LOESS regression is essentially the monthly trend in SIR data *without* any seasonal adjustment. The 'ggplot2′ R package (Wickham, 2016) was used to fit the LOESS regression to the monthly SIR data. The optimal smoothing parameter (span = 0.43452) that corresponds to the lowest AICC was used to estimate the trend of the data series.

2.3.2. Seasonally adjusted trend using Time Series Decomposition Models

To evaluate the trend of monthly SIRs *with* seasonal adjustment, we employed two types of time series decomposition models: (a) Classical Additive and Multiplicative decompositions, and (b) X-11 and X-13ARIMA-SEATS decompositions. These methods produce trend after extracting the monthly seasonal effect from the original data series.

2.3.2.1. Classical Additive and Multiplicative Decompositions. In this approach, the original time series data (y_t), is decomposed into seasonal (S_t), trend (T_t) and the remainder or irregular (R_t) components, either in an additive or multiplicative model. That is,

$$\text{Additive Decomposition Model}: \quad y_t = S_t + T_t + R_t$$
$$\text{Multiplicative Decomposition Model}: \quad y_t = S_t \times T_t \times R_t$$

The additive model is useful when the magnitude of the seasonal pattern around the trend does not display variation with the level of the time series, while the multiplicative model is useful when the magnitude of the seasonal pattern around the trend varies with the level of the time series (Hyndman & Athanasopoulos, 2018). Multiplicative models are common with economic time series. We employed decompose( ) function using 'forecast' package to apply both models to our SIR data (Hyndman & Khandakar, 2008; Hyndman et al., 2022).

2.3.2.2. X-13ARIMA-SEATS and X-11 Decompositions. These methods are based on the classical decomposition models with additional improvements, such as estimates are available for all observations including the end points, adjusting for holidays, robust to outliers and level shifts in the time series, and regression model-based F tests for stable seasonal and trading day regressors, etc. U.S. Census Bureau, Statistics Canada, and Bank of Spain are all contributors to these methods. X-13ARIMA-SEATS is an improvement to the initial method of X-11 decomposition (Shiskin, Young, & Musgrave, 1967; U.S. Census Bureau, 2020, 2022). We employed seas( ) function using 'seasonal' package to apply X-11 and X-13ARIMA-SEATS models to our SIR data (Sax & Eddelbuettel, 2018).

2.4. Distribution of daily severe injury reports (SIRs)

To evaluate the distribution of daily SIRs, we aggregated the 7 years of SIRs by day of the week. We plotted the distribution to assess how SIRs vary by different days in a week (e.g., Sunday).

2.5. Yearly severe injury reports (SIRs) by NAICS industry and OIICS injury type

Similar to section 2.4, we aggregated 7 years of SIRs by NAICS and OIICS injury event codes to assess which industry sectors and type of injury share the largest burden.

3. Results

3.1. Yearly severe injury reports (SIRs)

A total of 70,241 SIRs were reported to OSHA between January 1, 2015, through December 31, 2021. Table 1 summarizes the frequency of SIRs by year and associated number of hospitalizations and amputations. Each SIR may include one or more hospitalization and/or amputation. Hence, the total injuries indicate the sum of hospitalizations and amputations. In average, there were 10,034 SIRs per year that included 8,166 hospitalizations and 2,652 amputations per year.

3.2. Trend in monthly severe injury reports (SIRs)

The purpose of this analysis was to evaluate the trend of SIRs *with* and *without* the seasonal adjustment because in some data series, the trend may look very different, or no trend may be observed after extracting the seasonal component. In this SIR anal-

Table 1
Number of severe injury reports (SIRs), hospitalizations, amputations, and total injuries (hospitalizations + amputations) reported to OSHA (2015–2021).

Year	SIRs	Hospitalizations	Amputations	Total Injuries
2015	9,852	7,900	2,701	10,601
2016	10,091	8,186	2,696	10,882
2017	10,448	8,443	2,827	11,270
2018	11,156	9,098	2,872	11,970
2019	11,075	9,069	2,837	11,906
2020	8,915	7,312	2,342	9,654
2021	8,704	7,155	2,286	9,441
7-Year Total	70,241	57,163	18,561	75,724
Average Yearly Total	10,034	8,166	2,652	10,818

ysis, we observed a non-linear trend over the period of 84 months (7 years) *with* and *without* seasonal adjustment. The number of SIRs in a month ranged from 600 to 1,100. The trend evaluation using LOESS moving average regression (seasonally *unadjusted*) suggests a slight overall month-to-month increase in SIRs from January 2015 to November-December 2018, then a steeper decrease until September 2020, and staying somewhat flat until December 2021. Fig. 1a displays the monthly SIR data series with superimposed LOESS regression trend (seasonally *unadjusted*) with 95% confidence band of the trend. Fig. 1b displays the distribution of monthly SIRs by year, corresponding mean (dot inside each box-plot), median and quartiles, and the grand mean (84 month mean, dashed line). Fig. 1b indicates the 12 month mean for each year slightly increased from 2015 up until 2018–2019, then decreased in 2020–2021.

The purpose of using different time series decomposition models was to observe how the adjusted-trends compare after extracting the seasonal effect using different methods. All Time Series Decomposition Models—classical additive, multiplicative, X-13ARIMA-SEATS and X-11—indicate a trend still exists even after adjusting for the seasonal effect (component). Seasonally *adjusted* trend of the classical multiplicative model (green curve) is very similar to *unadjusted* LOESS trend (red curve) and indicates a gradual increase of SIRs over time until October 2018, then a steeper decrease until August 2020, and staying somewhat flat for rest of the months. The X-13ARIMA-SEATS seasonally *adjusted* trend (purple curve) displays a similar pattern except more wiggles and less smooth than classical decomposition model and LOESS. Fig. 2 displays the monthly SIR data series with seasonally *adjusted* trend components (classical multiplicative and X-13ARIMA-SEATS) and *unadjusted* LOESS to compare the patterns among them. Although similar to Fig. 1a, we have magnified the y-axis (Range 600–1,100 SIRs) to highlight the differences in trends between the four different methods.

3.3. Seasonality in monthly severe injury reports (SIRs)

The goal of this analysis was to evaluate whether certain months encompassed higher SIRs than other months (i.e., the presence of seasonal effect). We observed seasonal effect (seasonal fluctuation) in monthly SIRs *with* and *without* trend adjustment. Fig. 3a and 3b show seasonality observed in the SIR data (unadjusted) between 2015 and 2021. In Fig. 3b, each solid-dot represents monthly SIRs of a particular year, the vertical lines connecting these dots represent the range, and the black-open-dot represents the yearly average of that month. Fig. 3c displays the results of classical multiplicative decomposition model (i.e., SIR time series data (y_t), seasonal (S_t), trend (T_t) and remainder (R_t) components). Fig. 3d displays trend-adjusted seasonal components of classical multiplicative and X-13ARIMA-SEATS decompositions. In summary, trend-adjusted (Fig. 3d) and unadjusted (Fig. 3b) seasonality indicate, SIRs gradually decrease from January to April, increase from May to July-August, and then decrease again until to December. Table 2 provides SIR summary statistics for each month (mean, median, standard deviation, range) and related to Fig. 3b. Over the seven-year period, the highest mean SIR counts

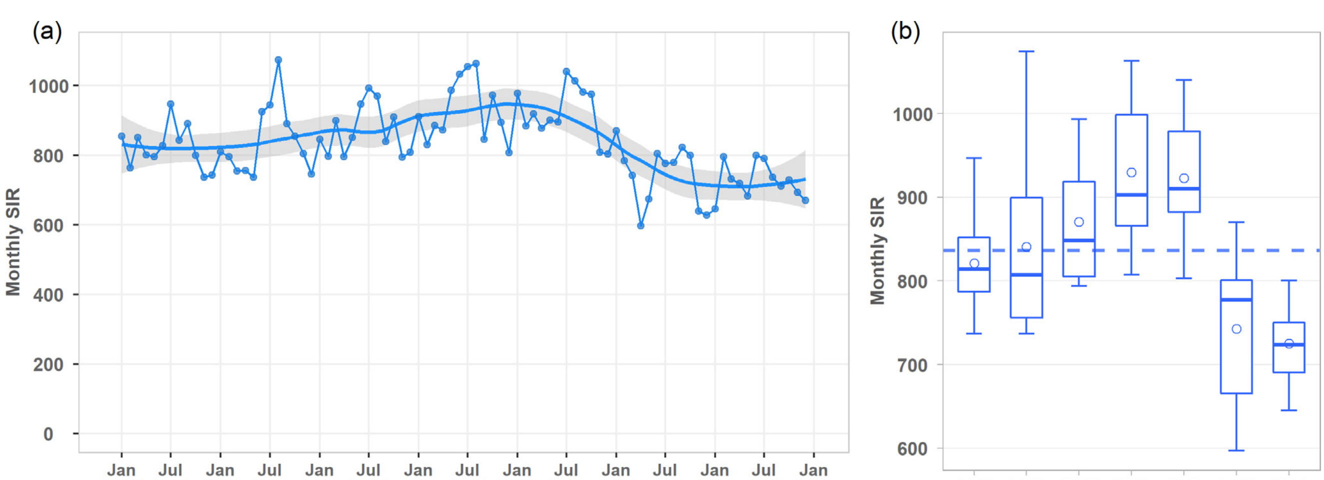

Fig. 1. (a) Monthly SIRs (2015–2021) with LOESS Regression Trend. (b) Distribution of Monthly SIRs for each year.

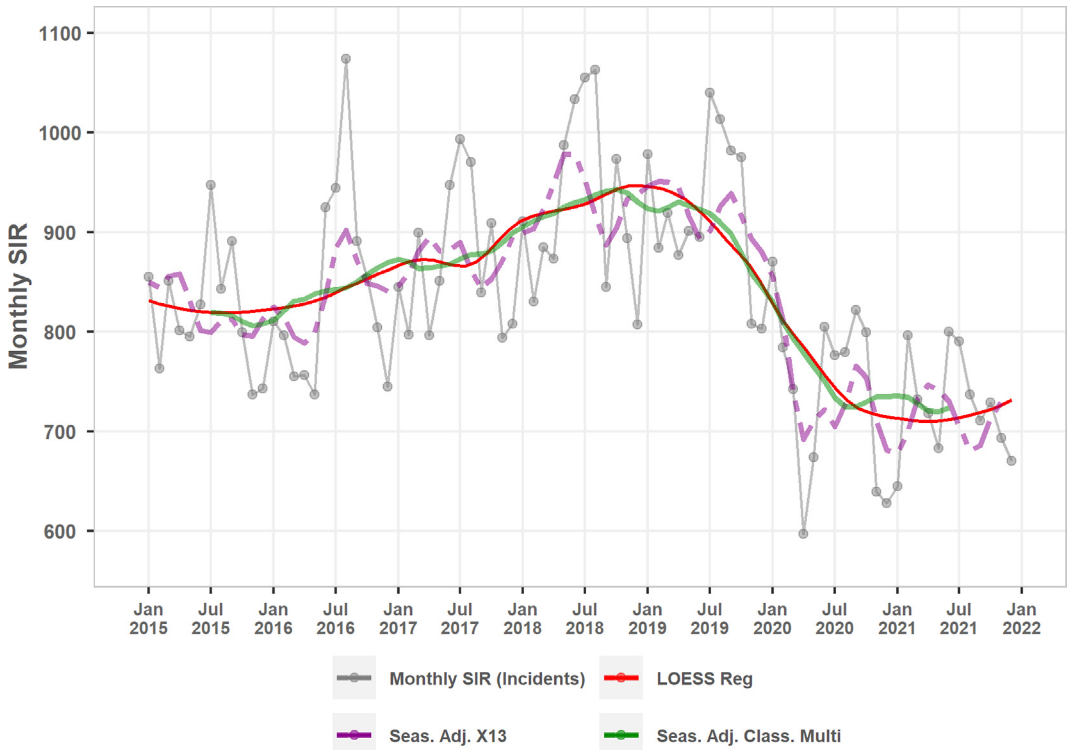

Fig. 2. Monthly SIRs (2015–2021) with seasonally adjusted (X-13 and Classical Multiplicative) and unadjusted (LOESS Regression) Trends.

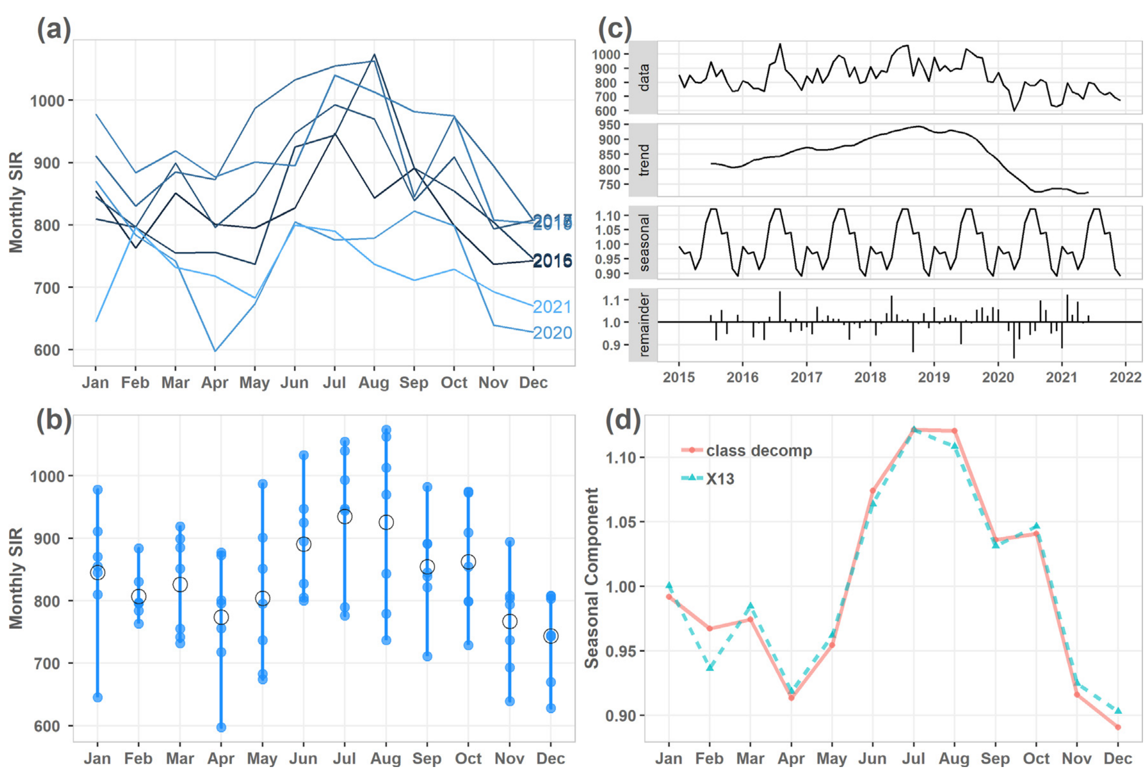

Fig. 3. (a and b) Seasonal plot of monthly SIRs. (c) Classical multiplicative decomposition. (d) Seasonal Components from Decomposition Models (Trend Adjusted).

were in June, July, and August, while the lowest mean SIR counts were in April, November, and December.

3.4. Daily distribution of severe injury reports (SIRs)

The goal of this analysis was to assess whether higher or lower SIRs were reported in certain days of the week in this 7-year data. In our analysis, we observed two unique seasonal patterns—weekdays (Monday – Friday) and weekends (Saturday & Sunday) (Fig. 4). The daily SIRs ranged between 2–68 per day depending on the day of the week, 30–36 on weekdays, and 9–14 on weekends. The daily average is 28 (SD = 13), weekday average is 34 (SD = 9), and weekend average is 11 (SD = 5). Fig. 4 displays the distribution of daily SIRs using boxplots (dot inside a boxplot indicates mean for each day), and the daily mean (28, dashed line). Table 3 provides the SIR summary statistics for each day in a week (mean, median, standard deviation, range).

3.5. Yearly severe injury reports (SIRs) by NAICS industry codes and OIICS injury events

The motivation for this analysis was to identify whether specific industries reported more SIRs than others. In a yearly trend comparison by NAICS industry codes, Manufacturing (2,836–3,614 per year; Mean = 3,304; SD = 293) and Construction (1,528–1,969 per year; Mean = 1,804; SD = 157) incurred the highest yearly number of SIRs compared to other NAICS industries (<1,000 per year) (see Fig. 5a). Similarly, in a yearly injury trend comparison by OIICS injury event, Contact with Objects and Equipment (3,928–5,105 per year; Mean = 4,631; SD = 463), and Falls, Slips, Trips (2,718–3,367 per year; Mean = 3,043; SD = 262) show substantially higher yearly SIRs compared to other OIICS injury events (<1,000 per year) (see Fig. 5b).

4. Discussion

This study described the trends of SIRs reported to OSHA from 2015-2021 by year, month, and day of the week, and specifically evaluated monthly trend using mathematical models with and without seasonal adjustment. Overall, SIRs gradually increased until 2019, with a steep decline in 2020 and staying somewhat flat in 2021. We observed consistent seasonal changes in SIRs, where more SIRs were reported in the summer months (June, July, August) for each year. A recent analysis by Lundstrom et al. (2022) described a linear decrease in work-related injuries treated in a nationally stratified probability sample of U.S. emergency departments. Our study describes, notably, that there was no sharp increase in the SIRs in 2020, which was seen in other occupational injury surveillance systems during the pandemic as a result of increased infection reporting. During the same year, the SOII

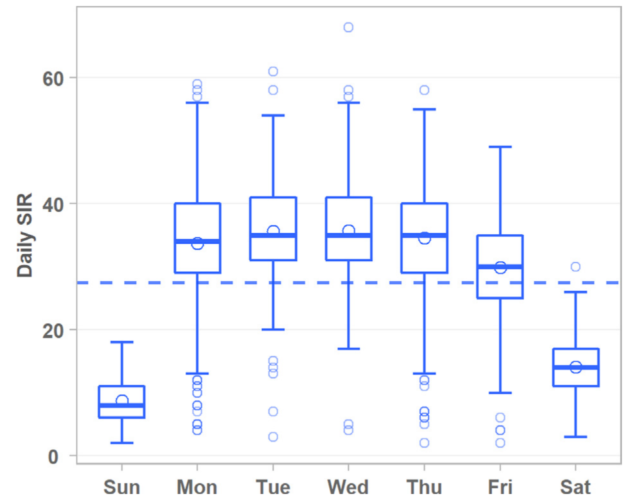

Fig. 4. Distribution of Daily SIRs.

Table 3
Daily Severe Injury Reports (SIRs, 2015–2021, OSHA).

Day	Mean	Median	SD	Max	Min
Sun	8.8	8	3.1	18	2
Mon	33.7	34	9.7	59	4
Tue	35.6	35	7.9	61	3
Wed	35.7	35	8.2	68	4
Thu	34.5	35	8.8	58	2
Fri	29.9	30	7.7	49	2
Sat	14.1	14	4.4	30	3

recorded a marked increase in illnesses events labelled "Exposure to other harmful substance, unspecified" (BLS, 2022a) as a result of the pandemic. This information suggests that changes to the workforce in early 2020 did not substantially increase reported SIRs. Instead, SIRs decreased after 2020.

The manufacturing and construction industry sectors reported the largest number of SIRs. Although these sectors account for about 13% of the overall U.S. workforce (BLS, 2022b), roughly half of the SIRs were reported in these two sectors. The two most common injury events associated with SIRs were contact with objects and equipment, and falls, slips, and trips. In comparison, the largest proportion of fatal work-related injuries resulted from transportation events and falls, slips, and trips (BLS, 2021c). Notably, transportation events are often excluded from reporting requirements depending on the location of the injury event (CFR 1904.39(b)(3)).

In this study, we utilized various time series models to highlight the benefit of these methods in evaluating injury trends overtime.

Table 2
Monthly Severe Injury Reports (SIRs, 2015–2021, OSHA).

Month	Mean	Median	SD	Max	Min
Jan	845	855	103	978	645
Feb	807	796	39	884	763
Mar	826	851	81	919	732
Apr	774	796	97	877	597
May	804	795	116	987	674
Jun	890	895	86	1,033	800
Jul	935	947	112	1,055	776
Aug	926	970	138	1,074	737
Sep	854	845	83	982	711
Oct	863	854	94	975	729
Nov	767	794	84	894	639
Dec	743	745	71	808	628

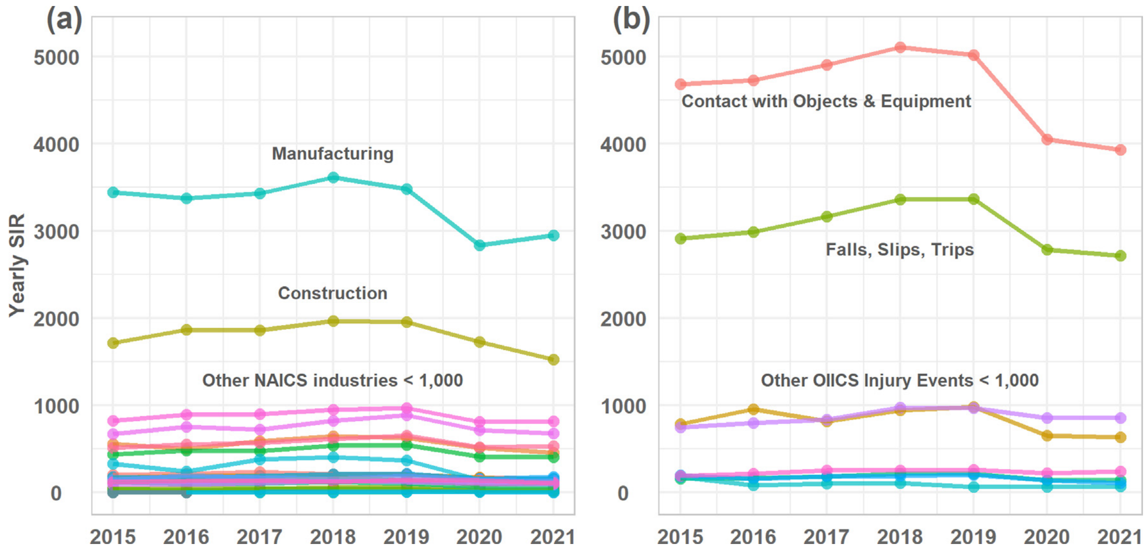

Fig. 5. (a) Yearly sir (2015–2021) by NAICS Industry Sector. (b) Yearly SIR (2015–2021) by OIICS Injury Events.

LOESS generates the empirical trend as it is observed in the data (unadjusted), while all other decomposition models (Additive, Multiplicative, X-13ARIMA-SEATS, and X-11) generate seasonality adjusted trends. Since LOESS accounts for non-linearity of the data and moving average to estimate the trend, it provides a more efficient visual assessment of the trend than a simple linear trend fitted over the data. We also observed different decomposition models generating different levels of smoothness of the seasonally adjusted trend (Fig. 2). In these data, trends from LOESS and seasonally adjusted Multiplicative model were very similar; and Multiplicative model produced smoother trend than the X-13ARIMA-SEATS model that displayed more wiggles. Hence, it is useful to implement more than one decomposition models to evaluate the consistency of the seasonally adjusted trends.

4.1. Limitations

All work-related injury reporting systems are subject to reporting bias. While OSHA does assess a penalty to employers for not reporting a severe injury, the true number of severe injury events among workers covered by Federal OSHA is likely substantially higher (Grattan et al., 2017; OIG, 2018; OSHA & Michaels, 2016). A report by former OSHA Assistant Secretary of Labor, David Michaels, estimates as much as 50% underreporting (OSHA & Michaels, 2016) and was supported by a subsequent Office of Inspector General report (OIG, 2018) and other research (Reilly, Wang, & Rosenman, 2023). The OIG report includes recommendations for OSHA to improve the employer reporting guidance and training, and issue citations for all late reporters to improve employer reporting (OIG, 2018). A recent study of work-related injuries in Michigan revealed that reporting compliance showed nonsignificant changes over a three year study period; however compliance varied by industry (Reilly et al., 2023). Similar to our study of Federal OSHA jurisdiction, Reilly et al. (2023) showed that manufacturing and construction shared the highest burden of hospitalizations, but construction industry employers had a significantly lower reporting compliance compared to manufacturing industry employers. Although our study is limited by underreporting, we do not expect seasonal changes to be confounded by underreporting (e.g., reporting compliance improved in summer months compared to winter months). We would expect variability in worker tasks and hazards may change by season, which could impact the burden of SIRs.

A notable caveat to this dataset, as described in methods section, is that SIRs that occurred in states with state plan jurisdictions are not included in the SIR microdata. Those injuries are still reported to OSHA as required by law but are not available in the public microdata. Therefore, this study did not include a complete, national picture of severe, work-related injuries. Moreover, data are updated multiple times a year and the final numbers may slightly change over time as errors are corrected. The message is that the data included in our study are the lower bound (minimum) of SIRs occurring in the OSHA federal jurisdiction due to underreporting by employers and the lack of publicly available SIRs from state plan states.

Unfortunately, the SIRs are not a good occupational surveillance option to describe work-related injuries by demographic information due to confidentiality, privacy, and ethical considerations (e.g., race/ethnicity, worker age, primary language of injured worker). Other data sources may be more suited to answer questions specific to demographic differences and provide context when presented as a supplement to SIR data. For example, a recent time series analysis of records from the North Carolina Office of the Chief Medical Examiner and death certificate records held by the North Carolina Office of Vital Records found that Latino workers in North Carolina from 2000-2017 experienced the highest rate of fatal occupational injury across race-ethnicity groups (Richey et al., 2022). In order to address such disparities, OSHA might consider collaborating with other federal agencies to post simplified, aggregate demographic reports by OIICS code, or industry sector.

4.2. Future considerations

Improving reporting compliance according to established recommendations (OIG, 2018) and adding state plan jurisdiction SIRs with corresponding OIICS injury variables would greatly increase the value of this dataset for reliable inference and analyses for surveillance activities, specifically, the accuracy of future national level analyses, rate calculations, and allowing state-level comparisons. However, each state plan would be required to release their data publicly or through OSHA under special permission. The dataset could be combined to the federal plan SIR data along with a jurisdiction variable (i.e., flag different jurisdiction data sources) to assist with comparative analyses. Other future improvements to the SIR data release may include a detailed data dictionary for public microdata (with definitions of variables) and version control of the dataset when records are corrected. Currently, the OSHA website only provides the report for the year 2015 ("Year One of OSHA's Severe Injury Reporting Program: An Impact Evaluation," 2016). It may be useful to provide this report for each year as data are released.

SIRs allow occupational safety professionals and other interested partners to gauge the current situation of serious work-related injuries. Despite the limitations, this dataset allows researchers and occupational safety and health professionals to examine a comprehensive picture of serious work-related incidents and identify timely prevention recommendations to reduce severe injuries to workers in high hazard jobs. Another major strength of the analysis is the ongoing update to SIRs and timeliness of the availability of the data. The main strength of this analysis stems from the inclusion of all available administrative records within federal OSHA jurisdiction, and the fact each SIR comes with many structured variables including OIICS codes and event date, allowing for granular level analyses. While we cannot examine this data by all 50 U.S. states, we can use it to consistently estimate severe injuries among workers in federal OSHA jurisdictions across the United States with less than a year of lag time.

4.3. Practical applications

To our knowledge, this is the first known time series analysis of SIRs. The findings of this study highlight the ability of researchers and occupational safety practitioners to use the OSHA SIRs as timely indicator to understand occupational injury trends overall and by specific industries and injury events.

For the federal plan jurisdictions, analyzing SIRs could be a cost-effective way to understand severe injuries experienced by workers and to guide prevention efforts. States with non-federal jurisdiction might consider publishing data in a format consistent with the federal plan jurisdiction data or allow OSHA to publish the full dataset (Federal OSHA Jurisdiction + state plan States) under special permission. Given the brief turnaround in SIR dissemination compared to other national injury surveillance datasets that can take a year or more, OSHA should continue to make this underutilized dataset available for analysis to the public to improve work-related injury prevention.

Disclaimer

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