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The seasonal variability in surgical site infections and the association with warmer weather: a population-based investigation

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Abstract

OBJECTIVE—To determine if the seasonality of surgical site infections (SSIs) may be explained by changes in temperature.

DESIGN—Retrospective cohort analysis.

SETTING—The National Inpatient Sample.

PATIENTS—All hospital discharges with a primary diagnosis of SSI from 1998–2011 served as cases. Discharges with a primary or secondary diagnosis of specific surgeries commonly associated with SSIs from the previous and current month served as our "at risk" cohort.

METHODS—We modeled the national monthly count of SSI cases both nationally and stratified by region, sex, age, and type of institution. We used data from the National Climatic Data Center to estimate the monthly average temperature for all hospital locations. We modeled the odds of having a primary diagnosis of SSI as a function of demographics, payer, location, patient severity, admission month, year and the average temperature in the month of admission.

RESULTS—SSI incidence is highly seasonal, with the highest SSI incidence in August and the lowest in January. Over the study period, there were 26.5% more cases in August than in January (95% CI: [23.3, 29.7]). Controlling for demographic and hospital-level characteristics, the odds of a primary SSI admission increase by roughly 2.1% per 5°F increase in the average monthly temperature. Specifically, the highest temperature group, 90°F+, was associated with an increase

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in the odds of an SSI admission of 28.9% (95% CI: [20.2–38.3]) compared to temperatures less than 40°F.

CONCLUSIONS—At population level, SSI risk is highly seasonal and associated with warmer weather.

INTRODUCTION

Surgical site infections (SSIs) are among the most common healthcare associated infections[1–3] and represent an important cause of morbidity following surgeries.[4,5] SSIs result in increased use of antimicrobials,[6] increased lengths of hospital stay,[7,8] and increased rates of mortality.[8,9] They are also a leading cause of hospital readmissions[8,10,11] and contributes to excess healthcare costs.[4,5,7,11]

Reports of SSI rates typically vary from 2–5%[2] but lower and higher rates have been reported.[4,5] SSI rates also vary across different procedures. Surgeries following trauma and some procedures (e.g., colorectal surgeries) are much more likely to generate an SSI.[1–3,12] At the patient level, risk factors for SSIs include smoking[13,14], diabetes[14,15], obesity[16], increasing age[14,17] and poor nutrition.[18] In addition to individual and procedure-related risk factors for SSIs, environmental-level risk factors may also exist. At the institutional level, the volume of procedures,[19,20] or institution size[21] may increase SSI risk. In addition, other environmental-level risk factors may also exist. For example, some studies have demonstrated an increased incidence of SSIs for surgeries performed during summer months.[12,22–24]

To date, most reports regarding the seasonality of SSIs are based on investigations in single centers, specific procedures (e.g., spinal surgeries), or specific geographic regions. Furthermore, these specific investigations do not all use the proper time series methods for analyzing auto-correlated data, and do not incorporate local weather patterns across large regions to determine how much of SSI seasonality can be explained by weather effects. The first objective of this study is to determine if, and to what extent, the incidence of SSIs is seasonal using a large, population-based, national sample of hospitalizations. The second objective is to determine to what extent seasonality in the incidence of SSIs can be explained by local weather conditions.

METHODS

Data extraction

All discharge data were extracted from the Nationwide Inpatient Sample (NIS), the largest all-payer database of hospital discharges in the USA. The database is maintained as part of the Healthcare Cost and Utilization Project (HCUP) by the Agency for Healthcare Research and Quality, and contains data from a 20% stratified sample of non-federal acute-care hospitals. Observational studies using de-identified data such as this are deemed exempt by our Institutional Review Board.

We identified every adult hospitalization with a primary diagnosis of SSI from January 1998 to November 2011. For case ascertainment, we used the International Classification of

Diseases, 9th Revision, Clinical Modification (ICD-9-CM) codes 998.51 and 998.59. To estimate a monthly SSI incidence series, we aggregated the number of primary SSI discharges by admission month and year. We applied discharge weights to account for yearly changes in the sampling design, and applied additional weights to account for changes in the number of days per month.

The NIS does not include unique identifiers to allow the tracking of patients across visits to, for example, determine if a surgery in one visit resulted in a readmission in a subsequent visit. Thus, we also extracted adult hospitalizations with a primary or secondary procedure likely to be associated with an SSI to estimate a population "at-risk" for SSIs. We use this series to ensure that any findings on the seasonality of SSIs were not merely a reflection of a lower surgical volume concurrently or in the month prior. Hospitalizations were identified using Clinical Classification software (CCS) codes calculated by HCUP. We included the following codes: 152 (knee arthroplasty), 153 (hip replacement, total and partial), 158 (spinal fusion), 147 (treatment of fracture or dislocation of lower extremity), 78 (colorectal resection), 75 (small bowel resection), 134 (Caesarian section), 85 (inguinal and femoral hernia repair), 86 (another hernia repair), and 87 (exploratory laparotomy). To estimate this monthly surgery incidence series (i.e., the at-risk series), we aggregated cases by admission month and year, applied discharge and days-per-month weights. Finally, we calculated the number of patients at risk for an SSI in a given month by taking an average of the number surgeries in that month and the number of surgeries in the prior month.

Time-series Analysis

The adjusted SSI incidence series was fit with a linear time trend and a collection of fixed effects (i.e. indicator variables) that represent monthly mean deviations from the overall trend. The cyclic nature of the series was captured by the monthly fixed effects. We also explored adding a covariate to this model for the log of the at-risk series. To account for temporal correlation in the residuals, we investigated autoregressive structures of orders 1 through 4. We selected the order for each series based on the Bayesian Information Criterion (BIC) and upon inspection of the autocorrelation function (ACF) and the Partial ACF plots. In the regression equation, the coefficient for the peak month can be interpreted as the "average amplitude of seasonality" adjusted for the other covariates. Similar analyses were performed on the log-transformed series, which allow for a percentage interpretation of model coefficients. An overall test for seasonality was computed using a likelihood ratio test on the 11 monthly fixed effects. All analyses were performed using R 3.1.2 and SAS 9.4.

Subgroup Time-series Analysis

We performed subgroup analyses stratified by region (North, South, East, West), gender, age (grouped by decade), institutional teaching status, and institutional location (teaching/nonteaching, urban/rural). For each subgroup, we calculated the average amplitude of seasonality and the annual trend on the log-transformed count series to allow for easy comparison. The autoregressive structures for all subgroups were individually selected based on BIC.

Weather Data

Hospitals in the study were geolocated using the Google Maps Geocoding API and the American Hospital Association (AHA) address.[25] Weather data were obtained from the Unedited Local Climatological Data (1998–2004) and the Quality Controlled Local Climatological Data (2005–2011). Both data sets were reported by the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA).

Using each hospital's longitude and latitude, we found all weather stations within 100 km of the hospital, then extracted the following monthly summary statistics from these stations: average temperature, minimum temperature, maximum temperature, total precipitation, average dew point, average wet bulb temperature, average heating degree days, average cooling degree days, resultant wind speed, and total monthly precipitation. The summary statistics for hospitals with multiple nearby stations were averaged across stations, while the summary statistics for hospitals with no nearby stations (1.9%) were imputed using k-nearest-neighbors (k = 5) and the `caret` package in R.[26]

Logistic Regression Models

We used logistic regression to estimate the odds of a hospital discharge having a primary diagnosis of SSI using two different models. Our first model is a "demographics-only model", which controls for the following patient-level covariates: age (grouped by decade), sex, primary payer, length-of-stay, Elixhauser Comorbidity Index (30 categories)[27], admission month, and admission year. In addition, at the hospital level, our first model controls for region (Northeast, Midwest, West, South), longitude, and latitude. Our second model is a "weather model" that controls for the same covariates as the demographics model, and adds the average monthly temperature (in 5° steps from 40° to 90°F+). The other weather covariates were very highly correlated with average monthly temperature in the model and were not included.

RESULTS

The NIS contains 108,595,896 hospitalizations from 4,532 hospitals over the course of our study (0.368% with a primary SSI). We observed 9,474,937 discharges with surgeries that could potentially lead to an SSI. In the time-series models, we exclude 65,485 SSIs and 850,510 surgeries due to missing admission month or discharge weight. For our logistic regression models, the sample size was 55,665,828 (2,512 unique hospitals). Exclusion criteria are summarized in Table 1.

In Figure 1, we show the monthly incidence of SSI hospitalizations. We found that the nadir month for SSIs was January and the peak month was August. After controlling for a linear time trend, the average seasonal increase (between January and August) was 2,312 infections (95% CI: [2071–2553]). This corresponds to an increase of 26.5% (95% CI: [23.3–29.7]). The overall test for seasonality was statistically significant ($p < 0.001$). Adjusting for seasonality, the number of SSIs is increasing by 4274 cases per year (95% CI: [3541–5007]), which corresponds to an increase of 3.9% per year (95% CI: [3.0–4.8]). After adding the logged monthly series of SSI-prone surgeries into the model as a covariate, we first note that the seasonality lessens slightly to 23.56% (95% CI: [20.6–26.6]), and the trend becomes less significant at 0.16% growth per year (95% CI: [−0.52–0.85]). Using this model, we can then estimate that a 25% reduction in the average number of at-risk surgeries in the months of August and July would be associated with a decrease of about 1690 SSI cases for the year (a decrease of 20.6% from the observed SSI rate).

The annual trend and the average increase in the peak month for each subgroup considered are presented in Table 2. Seasonality and incidence were similar across all regions, age groups, genders, and hospital teaching categories. The seasonality was greatest among patients in their 40s and 50s. In addition, the seasonality of SSIs was very prominent for both teaching and nonteaching hospitals, and there was no significant difference between the two groups of hospitals: average amplitude of seasonality was 22.89% (95% CI: [19.0, 26.9]) for teaching hospitals and 24.15% (95% CI:[20.5, 27.9]) for non-teaching.

Weather Models

Descriptive statistics for our weather model are presented in Table 3. SSI cases were generally similar to the control group in terms of their mean age, sum of Elixhauser Comorbidities, latitude, longitude, and region. However, cases had a higher mean length of stay (7.15 days vs 4.83 days), and they were admitted during a month with a slightly higher mean temperature than the control group (55.33° F vs 54.39° F). Additionally, although the mean age of cases was similar to the controls (56.88 vs. 56.46), the vast majority of cases are middle-aged, while admissions for older ages are much more likely to be controls. SSI patients had higher rates of diabetes (19.0% vs 14.7%) and obesity (9.5% vs 5.6%) than the controls.

Results from the weather logistic regression model are presented in Table 4. Patients in their 40s were 199% more likely to be a SSI admission (95% CI: [193–205]), compared to the baseline group of 18- to 30-year-old patients. However, admissions for older patients (80+) were 10.4% less likely to be SSI related (95% CI: [8.1, 12.5]). The weather model also indicated a significant time trend over the course of the study: the odds of an SSI admission grew by 2% per year (95% CI: [1.9–2.1]). Higher rates of SSI admission were associated with diabetes, 26.9% higher odds (95% CI: [25.5–28.3]), and obesity, 38.2% higher odds (95% CI: [36.3–40.3]). Finally, the effect of temperature on the odds of SSI admission is presented in Figure 2. The odds of a primary SSI admission increase by roughly 2.1% per 5°F increase in the average monthly temperature, all else held constant. Specifically, the highest temperature group, 90°F+, was associated with an increase in the odds of an SSI admission of 28.9% (95% CI: [20.2–38.3]) when compared to temperatures less than 40°F.

In the demographics-only model, the odds of an SSI discharge increase by 32.1% from January to August (95% CI: [29.5, 34.8]). However, when we control for the effects of temperature and demographics, the odds of an SSI discharge are only 20.7% higher in August (95% CI: [16.4–25.3]). (Figure 3) Thus, by adding average monthly temperature to the model, we were able to explain approximately 35% of the change in the odds of an SSI discharge due to seasonality.

DISCUSSION

Our results show that SSIs are seasonal with 26.5% more SSI-related hospital discharges in the peak month of August compared to the nadir month of January. SSIs are seasonal for men, women, all age groups and all geographic regions. By incorporating weather into our analysis, we demonstrate that the average temperature in the month of a hospitalization is an important risk factor for SSIs; higher temperatures are associated with higher odds of SSI. We observed a slight annual increase in the number of SSIs, though this became insignificant after controlling for the volume of procedures.

The incidence of many infections is seasonal.[28] Respiratory infections peak during winter months and tick- and mosquito-borne infections peak during the summer. Less attention has been focused on the seasonality of healthcare-associated infections. However, reports show evidence of seasonality in the incidence of *Clostridium difficile* infections with cases peaking during winter and spring[29–31] and catheter-related bloodstream infections peaking during summer months[32,33] along with urinary tract infections,[34,35] and cellulitis.[36] A few reports of seasonal SSIs exist, but most of these are either in single centers, over a short time periods, or focused on a specific geographic region, and few incorporate weather data into their analysis. Nevertheless, previous findings are similar to ours. Kane et al. found the highest incidence of SSIs following total joint arthroplasties in August and the majority occurring July-September[23]. Both Durkin et al., and Gruskay et al., found an increased rate of infection after elective spine surgery during the summer months[22,37]. Assessing a more generalized group of patients who underwent various procedures, Durkin et al. also reported a seasonal effect on SSI with summer months demonstrating higher SSI rates[12]. Unlike prior studies, we include a large population – 20% of all hospital discharges over a long period of time and across different geographic regions. In addition to establishing statistical significance in the seasonality of primary admissions for SSI, our results also demonstrate the potential clinical significance of this seasonality. For example, in our multivariate model controlling for patient demographics, severity, and hospital location, the increase in odds of an SSI admission during an especially warm August relative to a cold January reaches a peak of 55.6%, double the effect of diabetes (26.9%). Our results also demonstrate the clinical impact of this seasonality. For example, a 25% reduction in surgical cases in the peak months is associated with over a 20% reduction in SSIs. Thus, if some elective surgeries could be moved from the very warm summer to other months, we may be able to reduce both infections and healthcare cost.

The reason that SSIs peak in the summer is unclear. However, the incidence of other skin and soft tissue infections are reported to be seasonal.[38–40] Elevated levels of bacteria may be found in certain anatomic locations with higher temperatures.[41] Regardless of the specific mechanism, we believe that the seasonality of SSIs is, in large part, driven by weather conditions. In a logistic regression model of the incidence of SSIs, we explained approximately 35% of the seasonal variation by including average monthly temperature data. By including more granular data regarding the incidence of SSIs and weather, we may be able to explain an even larger amount of the seasonality.

Some reports suggest that surgical complications such as SSI could be due to a "July effect" explained by staff turnover at teaching institutions[42]. However, previous authors identified an increase in SSI in patients undergoing spine procedures during the summer months at a regional collection of non-teaching hospitals[22]. Similarly, we found no significant differences in the amplitude of seasonality of SSIs between teaching and non-teaching institutions. In addition, we added an interaction between hospital teaching status and month to our logistic regression model, and the result was non-significant (data not shown.) Thus, the August peak incidence of SSI we report is not likely to be attributable to trainees involved with surgical procedures. Finally, it is possible that the seasonal incidence of SSIs could be due to seasonal variations in surgical volume because most SSIs occur within 30 days of the surgery. However, in our time series model we control for the number surgeries performed in the current and prior month to adjust for surgical volume as a confounding factor in the seasonality of SSIs, yet the seasonality in the series is still highly significant.

Our results are subject to several limitations. First, our analyses were based on the month of the primary admission for SSI, not the procedure that precipitated the SSI. We cannot link admissions for SSIs to admissions for specific procedures because the NIS data do not provide a unique identifier to link patients' visits across hospitalizations. Thus, our analysis considers all SSIs together and we were unable to determine the SSI seasonality for different procedures. Secondary admissions for SSI are also seasonal (data not shown), and some secondary admissions may have occurred during the surgical admission. Second, we used administrative data, e.g,, ICD-9 codes to identify SSIs, and were unable to do chart reviews. Our data does not include microbiology or medication-administration data. Comparisons of SSI codes to traditional forms of SSI highlight the limitations of using ICD-9 codes.[43] However, the sensitivity and specificity of these codes have been reported as 84.1% and 97.3%, respectively.[44] Third, we have only inpatient data, and many SSIs may be treated in outpatient settings. Practice patterns for admitting patients with SSIs may differ during summer months (e.g., due to vacation schedules). Fourth, we only consider weather data aggregated to a monthly level. Although we have more granular weather data, the NIS data set only provides data on a monthly level. More granular discharge data would allow us to estimate the contributions of weather patterns to the seasonality of SSIs more precisely. Finally, we found a small increase in SSI cases over time (2% per year) in contrasts with reports of falling SSI rates.[45,46] However, we only consider inpatients SSIs making it difficult to compare our findings with other reports.

Despite our limitations, we show that the incidence of hospitalizations for SSIs is seasonal and that the seasonality of SSIs can, at least in part, be explained by weather patterns. Our results suggest that further investigation is needed with more granular data including exact surgery dates and specific procedures. Such work will help determine if merely shifting the timing of some surgeries (when feasible) from peak SSI months to non-peak SSI months can help reduce SSIs in specific patients with specific procedures.

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References

1. Centers for Disease Control and Prevention. [Accessed October 15, 2016] Procedure-associated Module: Surgical Site Infection (SSI) Event. 2016. http://www.cdc.gov/nhsn/pdfs/pscmanual/9pscssicurrent.pdf
2. Anderson DJ, Podgorny K, Berrios-Torres SI, et al. Strategies to prevent surgical site infections in acute care hospitals: 2014 update. Infection control and hospital epidemiology. 2014; 35(Suppl 2):S66–88. [PubMed: 25376070]
3. Magill SS, Hellinger W, Cohen J, et al. Prevalence of healthcare-associated infections in acute care hospitals in Jacksonville, Florida. Infection control and hospital epidemiology. 2012; 33:283–291. [PubMed: 22314066]
4. Sandy-Hodgetts K, Leslie GD, Lewin G, Hendrie D, Carville K. Surgical wound dehiscence in an Australian community nursing service: time and cost to healing. Journal of wound care. 2016; 25:377–383. [PubMed: 27410391]
5. de Lissovoy G, Fraeman K, Hutchins V, Murphy D, Song D, Vaughn BB. Surgical site infection: incidence and impact on hospital utilization and treatment costs. American journal of infection control. 2009; 37:387–397. [PubMed: 19398246]
6. Dohmen PM. Antibiotic resistance in common pathogens reinforces the need to minimise surgical site infections. The Journal of hospital infection. 2008; 70(Suppl 2):15–20.
7. Leaper DJ, van Goor H, Reilly J, et al. Surgical site infection - a European perspective of incidence and economic burden. International wound journal. 2004; 1:247–273. [PubMed: 16722874]
8. Kirkland KB, Briggs JP, Trivette SL, Wilkinson WE, Sexton DJ. The impact of surgical-site infections in the 1990s: attributable mortality, excess length of hospitalization, and extra costs. Infection control and hospital epidemiology. 1999; 20:725–730. [PubMed: 10580621]
9. Astagneau P, Rioux C, Golliot F, Brucker G. Morbidity and mortality associated with surgical site infections: results from the 1997–1999 INCISO surveillance. The Journal of hospital infection. 2001; 48:267–274. [PubMed: 11461127]
10. Ramkumar PN, Chu CT, Harris JD, et al. Causes and Rates of Unplanned Readmissions After Elective Primary Total Joint Arthroplasty: A Systematic Review and Meta-Analysis. American journal of orthopedics (Belle Mead, N.J.). 2015; 44:397–405.
11. Whitehouse JD, Friedman ND, Kirkland KB, Richardson WJ, Sexton DJ. The impact of surgical-site infections following orthopedic surgery at a community hospital and a university hospital: adverse quality of life, excess length of stay, and extra cost. Infection control and hospital epidemiology. 2002; 23:183–189. [PubMed: 12002232]
12. Durkin MJ, Dicks KV, Baker AW, et al. Seasonal Variation of Common Surgical Site Infections: Does Season Matter? Infection control and hospital epidemiology. 2015; 36:1011–1016. [PubMed: 26008876]
13. Beitsch P, Balch C. Operative morbidity and risk factor assessment in melanoma patients undergoing inguinal lymph node dissection. American journal of surgery. 1992; 164:462–465. discussion 465–466. [PubMed: 1443370]
14. Harrop JS, Styliaras JC, Ooi YC, Radcliff KE, Vaccaro AR, Wu C. Contributing factors to surgical site infections. Journal of the American Academy of Orthopaedic Surgeons. 2012; 20:94–101. [PubMed: 22302447]
15. Lilienfeld DE, Vlahov D, Tenney JH, McLaughlin JS. Obesity and diabetes as risk factors for postoperative wound infections after cardiac surgery. American journal of infection control. 1988; 16:3–6. [PubMed: 3369746]
16. Nystrom PO, Jonstam A, Hojer H, Ling L. Incisional infection after colorectal surgery in obese patients. Acta chirurgica Scandinavica. 1987; 153:225–227. [PubMed: 3604524]
17. Mishriki SF, Law DJ, Jeffery PJ. Factors affecting the incidence of postoperative wound infection. The Journal of hospital infection. 1990; 16:223–230. [PubMed: 1979572]
18. Casey J, Flinn WR, Yao JS, Fahey V, Pawlowski J, Bergan JJ. Correlation of immune and nutritional status with wound complications in patients undergoing vascular operations. Surgery. 1983; 93:822–827. [PubMed: 6857500]

19. Meyer E, Weitzel-Kage D, Sohr D, Gastmeier P. Impact of department volume on surgical site infections following arthroscopy, knee replacement or hip replacement. BMJ quality & safety. 2011; 20:1069–1074.
20. Muilwijk J, van den Hof S, Wille JC. Associations between surgical site infection risk and hospital operation volume and surgeon operation volume among hospitals in the Dutch nosocomial infection surveillance network. Infection control and hospital epidemiology. 2007; 28:557–563. [PubMed: 17464915]
21. Hughes JM, Culver DH, White JW, et al. Nosocomial infection surveillance, 1980–1982. MMWR. CDC surveillance summaries : Morbidity and mortality weekly report. CDC surveillance summaries. 1983; 32:1ss–16ss.
22. Durkin MJ, Dicks KV, Baker AW, et al. Postoperative infection in spine surgery: does the month matter? Journal of neurosurgery. Spine. 2015; 23:128–134. [PubMed: 25860519]
23. Kane P, Chen C, Post Z, Radcliff K, Orozco F, Ong A. Seasonality of infection rates after total joint arthroplasty. Orthopedics. 2014; 37:e182–186. [PubMed: 24679206]
24. Sagi HC, Cooper S, Donahue D, Marberry S, Steverson B. Seasonal variations in posttraumatic wound infections after open extremity fractures. The journal of trauma and acute care surgery. 2015; 79:1073–1078. [PubMed: 26317814]
25. ggmap: Spatial Visualization with ggplot2 [computer program]. The R Journal. 5(1) 144-1612016.
26. caret: Classification and Regression Training [computer program]. Version 6.0-7.12016.
27. A Elixhauser CS, Harris DR, et al. Comorbidity measures for use with administrative data. Med Care. 1998; 366:8–27.
28. Fisman DN. Seasonality of infectious diseases. Annu. Rev. Public Health. 2007; 28:127–143. [PubMed: 17222079]
29. Polgreen PM, Yang M, Bohnett LC, Cavanaugh JE. A time-series analysis of clostridium difficile and its seasonal association with influenza. Infection control and hospital epidemiology. 2010; 31:382–387. [PubMed: 20175682]
30. Reil M, Hensgens MP, Kuijper EJ, et al. Seasonality of Clostridium difficile infections in Southern Germany. Epidemiology and infection. 2012; 140:1787–1793. [PubMed: 22152928]
31. Brown KA, Daneman N, Arora P, Moineddin R, Fisman DN. The co-seasonality of pneumonia and influenza with Clostridium difficile infection in the United States, 1993–2008. American journal of epidemiology. 2013; 178:118–125. [PubMed: 23660799]
32. Schwab F, Gastmeier P, Meyer E. The warmer the weather, the more gram-negative bacteria-impact of temperature on clinical isolates in intensive care units. PloS one. 2014; 9:e91105. [PubMed: 24599500]
33. Al-Hasan MN, Lahr BD, Eckel-Passow JE, Baddour LM. Seasonal variation in Escherichia coli bloodstream infection: a population-based study. Clinical microbiology and infection : the official publication of the European Society of Clinical Microbiology and Infectious Diseases. 2009; 15:947–950.
34. Anderson JE. Seasonality of symptomatic bacterial urinary infections in women. Journal of epidemiology and community health. 1983; 37:286–290. [PubMed: 6655418]
35. Simmering JE, Tang F, Cavanaugh JE, Polgreen LA, Polgreen PM. The Increase in Hospitalizations for Urinary Tract Infections and the Associated Costs in the United States, 1998–2011. Open Forum Infectious Diseases. 2017; 4:ofw281. [PubMed: 28480273]
36. Peterson RA, Polgreen LA, Cavanaugh JE, Polgreen PM. Increasing Incidence, Cost, and Seasonality in Patients Hospitalized for Cellulitis. Open Forum Infectious Diseases. 2017; 4:ofx008. [PubMed: 28480281]
37. Gruskay J, Smith J, Kepler CK, et al. The seasonality of postoperative infection in spine surgery. Journal of neurosurgery. Spine. 2013; 18:57–62. [PubMed: 23121653]
38. Mermel LA, Machan JT, Parenteau S. Seasonality of MRSA infections. PLoS One. 2011; 6:e17925. [PubMed: 21468350]
39. Wang X, Towers S, Panchanathan S, Chowell G. A population based study of seasonality of skin and soft tissue infections: implications for the spread of CA-MRSA. Plos one. 2013; 8:e60872. [PubMed: 23565281]

40. Leekha S, Diekema DJ, Perencevich EN. Seasonality of staphylococcal infections. Clinical microbiology and infection : the official publication of the European Society of Clinical Microbiology and Infectious Diseases. 2012; 18:927–933.
41. McBride ME, Duncan WC, Knox JM. The environment and the microbial ecology of human skin. Applied and environmental microbiology. 1977; 33:603–608. [PubMed: 16345214]
42. Young JQ, Ranji SR, Wachter RM, Lee CM, Niehaus B, Auerbach AD. "July effect": impact of the academic year-end changeover on patient outcomes: a systematic review. Annals of internal medicine. 2011; 155:309–315. [PubMed: 21747093]
43. Stevenson KB, Khan Y, Dickman J, et al. Administrative coding data, compared with CDC/NHSN criteria, are poor indicators of health care-associated infections. American journal of infection control. 2008; 36:155–164. [PubMed: 18371510]
44. Goto M, Ohl ME, Schweizer ML, Perencevich EN. Accuracy of administrative code data for the surveillance of healthcare-associated infections: a systematic review and meta-analysis. Clinical infectious diseases : an official publication of the Infectious Diseases Society of America. 2014; 58:688–696. [PubMed: 24218103]
45. Baker AW, Dicks KV, Durkin MJ, et al. Epidemiology of Surgical Site Infection in a Community Hospital Network. Infection control and hospital epidemiology. 2016; 37:519–526. [PubMed: 26864617]
46. Centers for Disease Control and Prevention. [Accessed February 27, 2017] Healthcare-associated Infections (HAI) Progress Report. 2016. https://www.cdc.gov/hai/surveillance/progress-report/

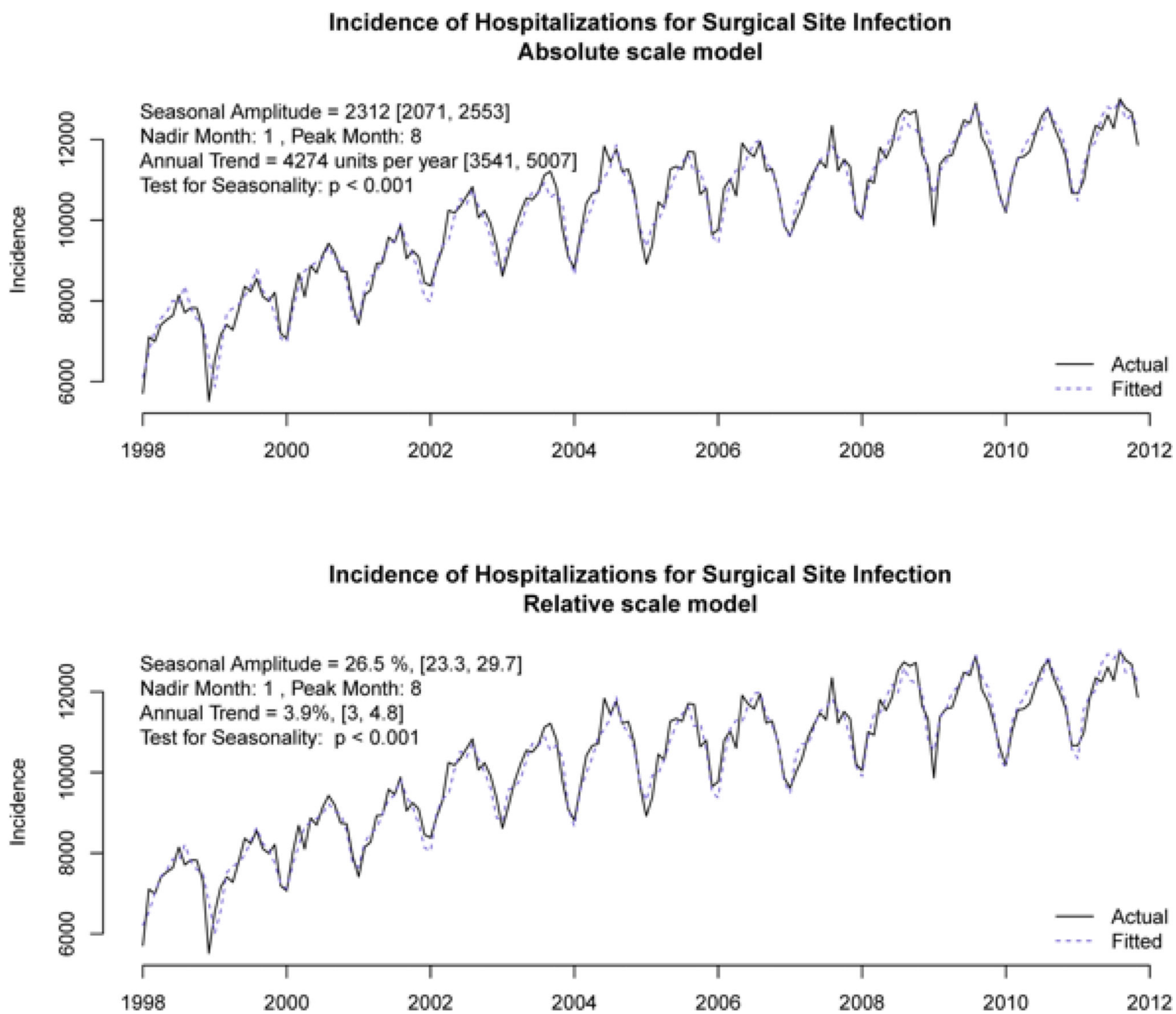

Figure 1.

Hospitalizations with a primary or a secondary diagnosis of a surgical site infection: absolute scale model (top), and relative-scale (log-transformed) model (bottom). The error structure in each model is controlled for using an AR(2) error structure.

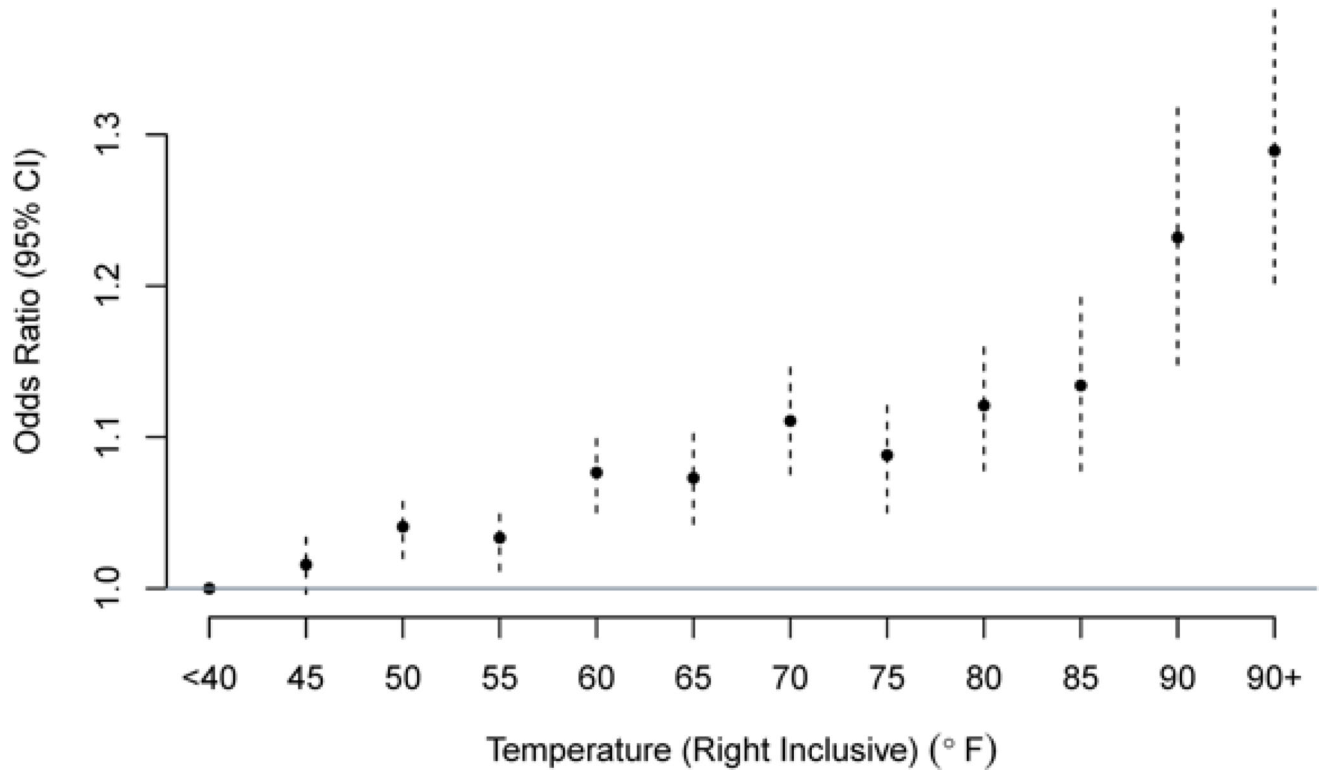

Figure 2.

The effect of monthly average regional temperature on the odds of SSI primary admissions

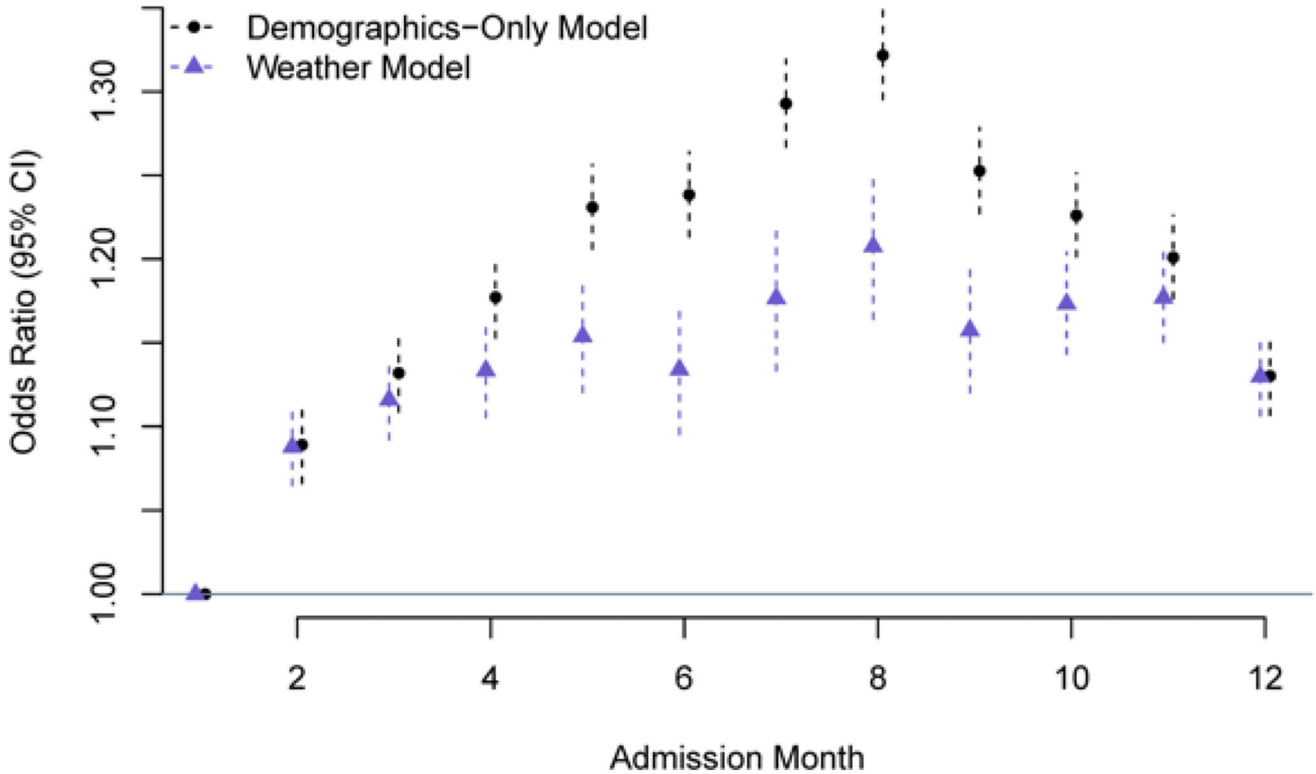

Figure 3.

Monthly odds ratios for a primary SSI for both our demographics-only model and our weather model. Weather explains a portion of the seasonality in primary SSI admissions.

Table 1

Sample Size

Filter	Sample Size	Percent of Initial Sample
None	108,595,896	100%
Non-missing:		
Admission Month	98,435,410	90.64%
Sex	98,252,484	90.48%
Length of Stay	98,246,157	90.47%
Payer	97,971,752	90.22%
Age	97,957,295	90.20%
Age ≥ 18	81,174,170	74.75%
Address Listed	55,665,828	51.26%

Table 2

Subgroup analysis of SSI trends and seasonality, controlling for the number of surgeries in the month of the SSI admission and the prior month within each subgroup.

Subgroup	Annual Trend (%) (95% CI)	Avg. Amplitude of Seasonality (%)[a] (95% CI)
Region		
Northeast	2.15 (0.9, 3.4)	28.10 (22.7, 33.7)
Midwest	1.37 (0.0, 2.8)	23.86 (19.0, 29.0)
South	0.08 (−0.9, 1.1)	22.50 (17.7, 27.5)
West	1.42 (0.5, 2.4)	22.51 (16.7, 28.6)
Age Group		
[18,30)	0.68 (0.1, 1.3)	23.28 (16.1, 30.9)
[30,40)	0.30 (−0.4, 1.0)	27.59 (21.4, 34.1)
[40,50)	0.18 (−0.4, 0.7)	31.44 (25.4, 37.7)
[50,60)	−1.71 (−3.0, −0.5)	36.03 (30.5, 41.8)
[60,70)	1.23 (−1.2, 3.7)	21.81 (16.2, 27.7)
[70,80)	−1.20 (−2.2, −0.2)	23.66 (17.3, 30.4)
80+	0.21 (−0.9, 1.3)	12.58 (4.7, 21.0)
Gender		
Male	1.02 (−0.4, 2.4)	28.24 (24.0, 32.6)
Female	0.60 (−0.2, 1.5)	22.71 (19.4, 26.1)
Hospital[b]		
Teaching	−0.13 (−1.7, 1.5)	22.89 (19.0, 26.9)
Non Teaching	0.17 (−0.5, 0.9)	24.15 (20.5, 27.9)
Urban	−1.59 (−2.0, −1.1)	29.39 (21.8, 37.4)
Rural	0.32 (−0.3, 1.0)	22.77 (19.9, 25.7)

[a] Average amplitude of seasonality is the percentage increase in SSI between the peak and nadir month.

[b] Not mutually exclusive categories in NIS dataset

Table 3

Descriptive Statistics for Variables of Interest in the SSI and Control Groups:mean and standard deviation for continuous variables (top) and number and percentage of patients for categorical variables (bottom)

	Control*	SSI
Number of patients	55,429,859	235,969
Continuous Variables	**Mean (± SD)**	**Mean (± SD)**
Age	56.88 (± 21.1)	56.46 (± 16.8)
LOS	4.83 (± 6.8)	7.15 (± 8.8)
Latitude	39.61 (± 3.4)	39.71 (± 3.5)
Longitude	−91.27 (± 18.0)	−91.47 (± 18.2)
Avg Temp	54.39 (± 16.1)	55.33 (± 16.0)
Elixhauser Sum	1.77 (± 1.6)	1.78 (± 1.6)
Categorical Variables	N (thousands), % of sample	N (thousands), % of sample
Gender		
Female	33,625 (60.7)	131.74 (55.8)
Male	21,805 (39.3)	104.23 (44.2)
Payer		
Medicare	24,172 (43.6)	93.69 (39.7)
Medicaid	7,924 (14.3)	25.81 (10.9)
Private Insurance	18,999 (34.3)	97.3 (41.2)
Self-Pay	2,443 (4.4)	6.82 (2.9)
No Charge	109.5 (0.2)	0.403 (0.17)
Other	1,782 (3.2)	11.92 (5.1)
Region		
Northeast	17,310 (31.2)	73.21 (31.0)
Midwest	11,880 (21.4)	47.51 (20.1)
South	10,068 (18.2)	43.86 (18.6)
West	16,171 (29.2)	71.38 (30.2)
Comorbidity**		
Diabetes	8,149 (14.7)	44.94 (19.0)
Obese	3,106 (5.6)	22.46 (9.5)
Age Group		
[18, 30)	7,544 (13.6)	15.0 (6.3)
[30, 40)	6,977 (12.6)	25.83 (10.9)
[40, 50)	6,588 (11.9)	42.0 (17.8)
[50, 60)	7,422 (13.4)	48.4 (20.5)
[60, 70)	7,954 (14.3)	45.5 (19.3)
[70, 80)	9,358 (16.9)	38.8 (16.4)
80+	9,587 (17.3)	20.4 (8.6)

*All variables were statistically, significantly different between the SSI and control groups (all p<0.001).

** There are 29 Elixhauser Comorbidities, but only DM and Obese are presented in this table.

Table 4

Logistic Regression Model Results. The outcome variable is SSI admission. Estimated odds ratios and associated confidence intervals are presented.

Covariate	Odds Ratio (95% CI)	Covariate	Odds Ratio (95% CI)
Month Effects		**Payer**	
January	Baseline	Medicare	Baseline
February	1.09 (1.07, 1.11)	Medicaid	0.795 (0.78, 0.81)
March	1.12 (1.09, 1.14)	Private Insurance	1.012 (1.00, 1.03)
April	1.13 (1.11, 1.16)	Self-Pay	0.647 (0.63, 0.66)
May	1.15 (1.12, 1.19)	No Charge	0.791 (0.72, 0.87)
June	1.13 (1.10, 1.17)	Other	1.361 (1.33, 1.39)
July	1.18 (1.13, 1.22)		
August	1.21 (1.16, 1.25)	**Age Group**	
September	1.16 (1.12, 1.20)	[18, 30)	Baseline
October	1.17 (1.14, 1.20)	[30, 40)	1.776 (1.74, 1.81)
November	1.18 (1.15, 1.20)	[40, 50)	2.987 (2.93, 3.05)
December	1.13 (1.11, 1.15)	[50, 60)	2.758 (2.71, 2.81)
		[60, 70)	2.270 (2.22, 2.32)
Average Temperature		[70, 80)	1.664 (1.63, 1.70)
<40	Baseline	80+	0.896 (0.88, 0.92)
[40, 45)	1.02 (1.00, 1.035)		
[45, 50)	1.04 (1.02, 1.06)	**Region**	
[50, 55)	1.03 (1.01, 1.06)	Northeast	Baseline
[55, 60)	1.08 (1.05, 1.10)	Midwest	1.12 (1.10, 1.15)
[60, 65)	1.07 (1.04, 1.10)	South	1.16 (1.14, 1.17)
[65, 70)	1.11 (1.08, 1.15)	West	1.73 (1.64, 1.81)
[70, 75)	1.09 (1.05, 1.13)		
[75, 80)	1.12 (1.08, 1.17)	**Gender**	
[80, 85)	1.13 (1.08, 1.19)	Male	Baseline
[85, 90)	1.23 (1.15, 1.32)	Female	0.91 (0.90, 0.91)
90+	1.29 (1.20, 1.39)		
		Continuous Variables	
Comorbidities *		Time Trend (years)	1.02 (1.02, 1.02)
None	Baseline	Length of Stay	1.02 (1.02, 1.02)
DM	1.27 (1.26, 1.28)	Latitude (scaled)	1.10 (1.10, 1.11)
Obese	1.38 (1.36, 1.40)	Longitude (scaled)	1.18 (1.16, 1.21)

*All 29 Elixhauser comorbidities are included in the model as indicator variables, but only those for DM and Obese are presented here