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The Seasonal Variability of Surgical Site Infections in Knee and Hip Arthroplasty

Chris A. Anthony, MD[1,5], **Ryan A. Peterson, MS**[2,5], **Daniel K. Sewell, PhD**[2], **Linnea A. Polgreen, PhD**[3], **Jacob E. Simmering, PhD**[5], **John J. Callaghan, MD**[1], and **Philip M. Polgreen, MD**[4,5]

[1]The Department of Orthopaedic Surgery and Rehabilitation, University of Iowa Hospitals and Clinics, 200 Hawkins Drive, 01008 JPP, Iowa City, IA 52242, USA

[2]The Department of Biostatistics, University of Iowa, 135 N. Riverside Drive, Iowa City, IA 52242, USA

[3]The Department of Pharmacy Practice and Science, University of Iowa, 115 S. Grand Ave., Iowa City, IA 52242, USA

[4]Departments of Internal Medicine and Epidemiology, University of Iowa Hospitals and Clinics, 200 Hawkins Drive, Iowa City, IA 52242, USA

[5]Signal Center, University of Iowa Hospitals and Clinics

Abstract

Background—Surgical site infections (SSI) after total knee (TKA) and total hip (THA) arthroplasty are devastating to patients and costly to healthcare systems. Prior single center and regional reports describe a seasonal incidence of SSIs following TKAs and THAs. The purpose of this study was to investigate the seasonality of TKA and THA SSIs at a national level.

Methods—All data were extracted from the National Readmission Database (NRD) for 2013 and 2014. Patients were included if they had undergone TKA or THA. We modeled the odds of having a primary diagnosis of SSI as a function of discharge date by month, payer status, hospital size and various patient comorbidities. SSI status was defined as patients who were readmitted to the hospital with a primary diagnosis of SSI within 30 days of their arthroplasty procedure.

Results—There were 760,283 procedures (TKA: 424,104, THA: 336,179) in our sample. Our models indicate that SSI risk was highest for patients discharged from their surgery in June and lowest for December discharges (controlling for other risk factors). For TKA the odds of a 30-day readmission for SSI were 30.5% higher at the peak compared to the nadir time (95% CI: [20%–42%]). For THA, the seasonal increase in SSI was 19% (95% CI: [9%–30%]). Compared to Medicare, patients with Medicaid as the primary payer had 49% higher odds of 30-day SSI after TKA (95% CI: [32%–68%]). Patients who paid with private insurance experienced a 32%

Corresponding author: Chris A. Anthony MD (Chris-Anthony@uiowa.edu).

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decrease in the odds of 30-day SSI after TKA (95% CI: [27%–37%]) compared to those with Medicare insurance, and this effect was also strong for THA (a 38% decrease, 95% CI: [32%–43%]).

Discussion—The risk of SSIs following TKA and THA are seasonal peaking in summer months. Payer status was also a significant risk factor for SSIs. Future work should focus on the potential for diverting the highest risk patients to lower risk months when performing elective TKA and THA as a strategy for preventing SSIs.

INTRODUCTION

Surgical site infections (SSIs) are a major cause of morbidity and mortality. [1–4] In addition, SSIs generate longer lengths of stay, [3, 5] hospital readmissions, [3, 6, 7] and substantially increased healthcare costs. [1, 2, 5, 7] Although SSI rates are relatively lower for elective orthopedic procedures [8–11] than emergent procedures, they are important to prevent given the large number of total hip (THA) and knee arthroplasties (TKA) performed each year. [12, 13] Additionally, the number of joint arthroplasties are expected to continue to increase along with the costs for treating arthroplasty-associated SSIs. [14]

Several patient-level risk factors for SSIs have been described including diabetes [15, 16], obesity [17], increasing age, [16, 18] poor nutrition, [19] smoking, [16, 20] and colonization with *Staphylococcus aureus*. [21] Because some of these risk factors are modifiable prior to surgery, elective orthopedic procedures present a unique opportunity for designing interventions to prevent SSIs. However, the design of such interventions is dependent on an understanding of SSI risk factors. We recently reported that SSIs were not only seasonal but also dependent on local weather patterns; specifically, the risk for SSIs increased during warmer months in a dose dependent fashion. [22] However, we were unable to determine the seasonality of SSIs after specific orthopedic procedures. Other reports have demonstrated that the incidence of SSIs increased during summer months for patients undergoing spine surgery [23, 24] and total joint arthroplasty [25] as well as other surgical procedures. [26] However, these results were mostly single center or regional investigations.

The primary objective of this study was to determine if the incidence of SSIs following TKA and THA is seasonal in a large, population-based cohort after adjusting for other possible risk factors.

METHODS

Data Extraction

This study was deemed exempt by our institutional review board. All data were extracted from the National Readmission Database (NRD), which is a newer addition to a family of databases developed for the Healthcare Cost and Utilization Project (HCUP) by the Agency for Healthcare Research and Quality (AHRQ). Available for the years 2013 and 2014, the NRD offers unique patient identifiers that allow us to link patients across visits. The NRD contains data from 22 geographically dispersed states, accounting for 51.2 percent of the U.S. resident population and 49.3 percent of all U.S. hospitalizations. However, these data

do not have any geographical information, and thus cannot be used for regional, state, or hospital specific analysis.

We identified every adult hospitalization from January 2013 to December of 2014 (2-year period) for which the primary procedure code was either TKA or THA. Then, for each of these discharges, we looked at the subsequent 30 days to see if patients were readmitted within that time with a primary diagnosis of postoperative surgical site infection (SSI). To identify patients who underwent TKA or THA, we used HCUP's Clinical Classification Software (CCS) codes 152 and 153, respectively. To identify cases with a SSI, we used the International Classification of Diseases, 9th Revision, Clinical Modification ICD-9-CM codes 686.8, 686.9, 711.00, 711.05, 711.08, 711.09, 711.40, 711.45, 711.48, 711.49, 711.90, 711.95, 711.98, 711.99, 730.00, 730.05, 730.08 – 730.10, 730.15, 730.18, 730.19, 730.20, 730.25, 730.28, 730.29, 730.90, 730.95, 730.98, 730.99, 996.60, 996.66, 996.67, 996.69, 998.51, 998.59, and 998.6, in addition to patients listed as undergoing the ICD-9-CM procedures 84.56, 86.01, 86.04, 86.22, and 86.28. [27] We applied discharge weights provided by HCUP to aggregate to national readmission rates and to account for yearly changes in the sampling design.

Statistical Analysis

We used logistic regression to estimate the odds of being readmitted for a SSI within 30 days using three models: a model for TKAs only, a model for THAs only, and a pooled model. We consider the following patient-level covariates: Age (grouped by decade), sex, length-of-stay (with a log transformation to account for high skew), Elixhauser Comorbidity Index (a series of 29 indicators), the number of diagnoses on the record (NDX), the number of procedures on the record (NPR), and patient location (Urban/Rural). Patient location was dichotomized using the categories provided by HCUP, with urban defined as metropolitan statistical areas with population greater than or equal to 50,000. We also considered the following hospital-level covariates: size (small, medium, large, as provided by HCUP), and teaching/metropolitan status (rural, urban-teaching, urban-nonteaching). TKA and THA discharges containing missing covariate data were imputed using univariate medians, or subsumed into an "other" category for primary payer status.

To gauge a seasonal effect, we used sine and cosine terms on discharge month in the regression equation. A nonlinear transformation of these two estimated regression coefficients allows us to calculate and make inferences about the "average amplitude of seasonality" over the course of the study period after controlling for the other covariates in the model (see *Statistical Methods* in appendix for details).

Since the NRD does not track patients across years, estimates for 30-day readmission for patients discharged in the month of December will be underestimated: many of these patients will not be readmitted until after January 1, and thus they are censored. To account for the decrease in odds of an SSI due to this censoring, we include a dummy variable for December in the regression equation.

Finally, we investigated whether the pattern of seasonality differed for specific at-risk populations. Specifically, we focused on patients with diabetes, patients with obesity, and

patients with at least one comorbidity. We tested whether the sine and cosine terms in the regression equation for the pooled model interacted with dummy variables denoting group membership; if these interaction coefficients were significantly different from zero (via likelihood ratio tests), we concluded that the patterns of seasonality were statistically different. For all analyses, we used R 3.3.3.

RESULTS

There were 760,283 procedures (TKA: 424,104, THA: 336,179) in our sample. When the AHRQ weights were applied, this reflected 1,757,553 procedures. The missingness in the covariate data was sparse (n = 1,792 missing), so the univariate median imputation had negligible impact. Due to this imputation, no procedures or SSIs in our dataset were excluded from our analysis.

Baseline characteristics and summary information for THA, TKA, and the pooled groups are available in Table 1. Fifty-eight percent of the patients were 65 or older and 59% were female. Eighty-five percent of patients had at least one comorbidity. The five most common comorbidities were hypertension (63.3%), obesity (20.9%), diabetes (16.6%), hypothyroidism (15.2%) and chronic lung disease (14.8%). We observed 4,478 (weighted: 9,991) readmissions due to SSI within 30 days for a weighted rate of 0.6%.

The results from our logistic regression models are presented in Table 2. Though age group was included in the final model, it was not determined to be a statistically significant risk factor for SSI in any model. Primary payer, an indicator of socioeconomic status, was statistically significant: compared to Medicare, patients with Medicaid as the primary payer have 49% higher odds of 30-day SSI after TKA (95% CI: [32%–68%]), though this effect was less strong for patients with THA. On the other hand, patients who paid with private insurance experienced a 32% decrease in the odds of 30-day SSI after TKA (95% CI: [27%–37%]), and this effect was strong for THA (a 38% decrease, 95% CI: [32%–43%]). Diabetes, hypertension, and obesity were all strong and significant risk factors, though the odds ratios were all higher for the odds of SSI after THA. Hospital size was a consistently significant risk factor for SSI. Women experienced significantly lower odds of SSI readmission for both THA and TKA.

The seasonality results from our logistic regression models are presented in Table 3, and further visualized in Figure 1. Seasonality was present in each model, and took a similar shape with SSI readmissions peaking in the summer months and bottoming out in the winter. For TKA, and controlling for all other covariates, the odds of a 30-day readmission for SSI are 30.5% higher at the peak time (June) than for the nadir time (December) (95% CI: [20%–42%]). For THA, this increase is 19% (95% CI: [9%–30%]) with an estimated peak in July and estimated nadir in January. For the pooled model, this increase was 24% (95% CI: [16%–31%]), peaking in June and bottoming out in December. We found no evidence to suggest that these patterns of seasonality differed significantly if patients had obesity ($p = 0.80$), diabetes ($p = 0.14$), or if the patient had at least one comorbidity ($p = 0.74$). This pattern of seasonality is consistent across these patient groups.

DISCUSSION

Our results demonstrate that the incidence of SSIs among patients undergoing TKA and THA is clearly seasonal with SSIs peaking in the summer. We observed the highest risk among cases in June with the lowest in December. In addition, after adjusting for observable risk factors, we found that patients on Medicaid had 49% higher odds of 30-day SSI after TKA than patients on Medicare. Other independent risk factors included diagnoses of diabetes, hypertension and obesity. TKA and THAs performed at larger hospitals also had higher odds of SSI.

Our seasonal results confirm other smaller single-center and regional studies. For example, work at a single institution found an increased risk of SSI in August and other summer months in patients undergoing TKA and THA procedures. [25] Reports have also demonstrated increased SSIs in summer months in those undergoing elective spine surgeries. [23, 24] In addition, surgeries following open fractures have also demonstrated seasonality in the US. [28] We have also previously reported a seasonal pattern in the incidence of hospital admissions for SSIs using data from the National Inpatient Sample, but because admissions were not linked over time we could not link SSIs to previous specific surgeries. [22] The reason for the seasonality of SSIs is currently unclear. Many infections are seasonal with some infections peaking in winter months [29–32] and some during summer months. [33–37] In many cases, weather is thought to be a driver of the seasonality for many different infectious diseases. [32] Interestingly, the incidence of cellulitis is also seasonal, [37] and we have shown in other work that the seasonality of SSI and cellulitis can be largely explained by warmer weather. [22, 38] Given that skin colonization is a risk factor for SSIs, weather patterns may influence SSIs because elevated levels of bacteria have been found in certain anatomic locations in climates with higher temperature and humidity compared to climates that are cooler and drier. [39] We recommend surgeons consider seasonal risk of SSI when planning elective TKA and THA. Future work should estimate the possible impact of diverting surgical interventions for higher risk patients to lower risk months. It may be possible to lower risk by delaying elective procedures such as TKA and THA to less risky months of the year. Healthcare systems should account for the seasonal effects of SSI in TKA and THA when performing quality assessment and cost accounting.

The “July effect”, wherein the arrival of new trainees reduces the quality of care has been suggested to be a cause of the seasonal incidence of SSIs. However, we previously found no difference in the seasonality of SSIs associated with a broad range of surgical procedures with regard to institutions’ teaching status. [22] Other studies have reported similar results: SSIs peaked during the summer months for spine surgeries at a regional collection of non-teaching hospitals, [23] and other work demonstrated a seasonal effect in non-teaching hospitals across a range of surgical procedures. [26] In total, these results strongly suggest that the seasonality of SSI is not driven by surgical trainees.

Consistent with prior literature, we found that patients with the diagnosis of diabetes, hypertension and obesity were all at higher risk for SSIs following both TKAs and THAs. We also found that patients with Medicaid as a primary payer had a 49% higher odds of an SSI within 30 days of a TKA than patients with Medicare insurance. Prior authors have

described the relationship between Medicaid payer status and increased complications after joint arthroplasty procedures. [40] The higher level of risk that we identify is most likely a marker for other comorbidities, social or socio-economic factors not measured by the variables we considered in our model. Further work with more granular data should attempt to determine what factors are driving the higher levels of risk for patients with Medicaid as their primary insurance.

There are several limitations with our work. First, we used administrative data and our findings are dependent on appropriate documentation and coding of complications after TKA and THA. Additionally, NRD data does not allow us to perform chart review and our data do not include microbiology results or antibiotic administration data. The NRD dataset is currently limited to two years and a more extensive and prolonged period to assess the seasonality of SSI following elective orthopedic infections is warranted. Finally, we limited our postoperative follow up period for SSIs to 30 rather than 90 days because visits are not linked across calendar years. Certainly, longer follow-up and assessment would likely reveal a greater number of SSIs after TKA and THA.

Despite our limitations, we demonstrate clear seasonality of SSI following TKAs and THAs with a peak in June and a nadir in December. Given our findings, more work is needed to explore seasonality as a risk factor for SSIs especially for elective orthopedic procedures. If the month arthroplasty procedures are performed is a risk factor for SSIs, it may be possible to lower risk by delaying the elective procedure. Thus, future work should estimate the possible impact of diverting higher risk patients to lower risk months.

References

1. Sandy-Hodgetts K, et al. Surgical wound dehiscence in an Australian community nursing service: time and cost to healing. J Wound Care. 2016; 25(7):377–83. [PubMed: 27410391]
2. de Lissovoy G, et al. Surgical site infection: incidence and impact on hospital utilization and treatment costs. Am J Infect Control. 2009; 37(5):387–97. [PubMed: 19398246]
3. Kirkland KB, et al. The impact of surgical-site infections in the 1990s: attributable mortality, excess length of hospitalization, and extra costs. Infect Control Hosp Epidemiol. 1999; 20(11):725–30. [PubMed: 10580621]
4. Astagneau P, et al. Morbidity and mortality associated with surgical site infections: results from the 1997–1999 INCISO surveillance. J Hosp Infect. 2001; 48(4):267–74. [PubMed: 11461127]
5. Leaper DJ, et al. Surgical site infection - a European perspective of incidence and economic burden. Int Wound J. 2004; 1(4):247–73. [PubMed: 16722874]
6. Ramkumar PN, et al. Causes and Rates of Unplanned Readmissions After Elective Primary Total Joint Arthroplasty: A Systematic Review and Meta-Analysis. Am J Orthop (Belle Mead NJ). 2015; 44(9):397–405. [PubMed: 26372748]
7. Whitehouse JD, et al. 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. Infect Control Hosp Epidemiol. 2002; 23(4):183–9. [PubMed: 12002232]
8. Kurtz SM, et al. Infection burden for hip and knee arthroplasty in the United States. J Arthroplasty. 2008; 23(7):984–91. [PubMed: 18534466]
9. Kurtz SM, et al. Prosthetic joint infection risk after TKA in the Medicare population. Clin Orthop Relat Res. 2010; 468(1):52–6. [PubMed: 19669386]
10. Namba RS, Inacio MC, Paxton EW. Risk factors associated with surgical site infection in 30,491 primary total hip replacements. J Bone Joint Surg Br. 2012; 94(10):1330–8. [PubMed: 23015556]

11. Ong KL, et al. Prosthetic joint infection risk after total hip arthroplasty in the Medicare population. J Arthroplasty. 2009; 24(6 Suppl):105–9. [PubMed: 19493644]
12. Wolford, M., Palso, K., Bercovitz, A. National Center for Health Statistics Data Brief. 2015. Hospitalization for Total Hip Replacement Among Inpatients Aged 45 and Over: United States, 2000–2010; p. 186
13. Williams SN, Wolford ML, Bercovitz A. Hospitalization for Total Knee Replacement Among Inpatients Aged 45 and Over: United States, 2000–2010. National Center for Health Statistics Data Brief. 2015:210.
14. Kurtz SM, et al. Economic burden of periprosthetic joint infection in the United States. J Arthroplasty. 2012; 27(8 Suppl):61–5.e1. [PubMed: 22554729]
15. Lilienfeld DE, et al. Obesity and diabetes as risk factors for postoperative wound infections after cardiac surgery. Am J Infect Control. 1988; 16(1):3–6. [PubMed: 3369746]
16. Harrop JS, et al. Contributing factors to surgical site infections. Journal of the American Academy of Orthopaedic Surgeons. 2012; 20(2):94–101. [PubMed: 22302447]
17. Nystrom PO, et al. Incisional infection after colorectal surgery in obese patients. Acta Chir Scand. 1987; 153(3):225–7. [PubMed: 3604524]
18. Mishriki SF, Law DJ, Jeffery PJ. Factors affecting the incidence of postoperative wound infection. J Hosp Infect. 1990; 16(3):223–30. [PubMed: 1979572]
19. Casey J, et al. Correlation of immune and nutritional status with wound complications in patients undergoing vascular operations. Surgery. 1983; 93(6):822–7. [PubMed: 6857500]
20. Beitsch P, Balch C. Operative morbidity and risk factor assessment in melanoma patients undergoing inguinal lymph node dissection. Am J Surg. 1992; 164(5):462–5. discussion 465–6. [PubMed: 1443370]
21. Kalmeijer MD, et al. Nasal carriage of Staphylococcus aureus: Is a major risk factor for surgical-site infections in orthopedic surgery. Infection Control & Hospital Epidemiology. 2000; 21(5): 319–323. [PubMed: 10823564]
22. Anthony CA, et al. The Seasonal Variability in Surgical Site Infections and the Association With Warmer Weather: A Population-Based Investigation. Infect Control Hosp Epidemiol. 2017; 38(7): 809–816. [PubMed: 28506327]
23. Durkin MJ, et al. Postoperative infection in spine surgery: does the month matter? J Neurosurg Spine. 2015; 23(1):128–34. [PubMed: 25860519]
24. Gruskay J, et al. The seasonality of postoperative infection in spine surgery. J Neurosurg Spine. 2013; 18(1):57–62. [PubMed: 23121653]
25. Kane P, et al. Seasonality of infection rates after total joint arthroplasty. Orthopedics. 2014; 37(2):e182–6. [PubMed: 24679206]
26. Durkin MJ, et al. Seasonal Variation of Common Surgical Site Infections: Does Season Matter? Infect Control Hosp Epidemiol. 2015; 36(9):1011–6. [PubMed: 26008876]
27. Calderwood MS, et al. Use of Medicare diagnosis and procedure codes to improve detection of surgical site infections following hip arthroplasty, knee arthroplasty, and vascular surgery. Infect Control Hosp Epidemiol. 2012; 33(1):40–9. [PubMed: 22173521]
28. Sagi HC, et al. Institutional and Seasonal Variations in the Incidence and Causative Organisms for Posttraumatic Infection following Open Fractures. J Orthop Trauma. 2017; 31(2):78–84. [PubMed: 27755339]
29. Polgreen PM, et al. A time-series analysis of clostridium difficile and its seasonal association with influenza. Infect Control Hosp Epidemiol. 2010; 31(4):382–7. [PubMed: 20175682]
30. Reil M, et al. Seasonality of Clostridium difficile infections in Southern Germany. Epidemiol Infect. 2012; 140(10):1787–93. [PubMed: 22152928]
31. Brown KA, et al. The co-seasonality of pneumonia and influenza with Clostridium difficile infection in the United States, 1993–2008. Am J Epidemiol. 2013; 178(1):118–25. [PubMed: 23660799]
32. Fisman DN. Seasonality of infectious diseases. Annu Rev Public Health. 2007; 28:127–143. [PubMed: 17222079]

33. Anderson JE. Seasonality of symptomatic bacterial urinary infections in women. J Epidemiol Community Health. 1983; 37(4):286–90. [PubMed: 6655418]
34. 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(3):e91105. [PubMed: 24599500]
35. Al-Hasan MN, et al. Seasonal variation in Escherichia coli bloodstream infection: a population-based study. Clin Microbiol Infect. 2009; 15(10):947–50. [PubMed: 19845704]
36. Simmering JE, et al. The Increase in Hospitalizations for Urinary Tract Infections and the Associated Costs in the United States, 1998–2011. Open Forum Infectious Diseases. 2017; 4(4):ofw281. [PubMed: 28480273]
37. Peterson RA, et al. Increasing Incidence, Cost, and Seasonality in Patients Hospitalized for Cellulitis. Open Forum Infectious Diseases. 2017; 4(4):ofx008. [PubMed: 28480281]
38. Peterson, RA., et al. Clinical Infectious Diseases. 2017. Warmer Weather as a Risk Factor for Cellulitis: A Population-based Investigation.
39. McBride ME, Duncan WC, Knox JM. The environment and the microbial ecology of human skin. Appl Environ Microbiol. 1977; 33(3):603–8. [PubMed: 16345214]
40. Browne JA, Novicoff WM, D'Apuzzo MR. Medicaid payer status is associated with in-hospital morbidity and resource utilization following primary total joint arthroplasty. J Bone Joint Surg Am. 2014 Nov 5.96(21):e180. [PubMed: 25378513]

Appendix. Statistical Methods

Let Y_{it} refer to the event that patient i gets readmitted 30 days after being discharged in month t. Also, let $\boldsymbol{x}_i$ refer to a vector of covariates unrelated to the month of discharge, e.g. sex. The model can be expressed as:

$$\text{logit}(Y_{it}) = \boldsymbol{x}_i^T \boldsymbol{\beta} + \beta_1 \sin(2\pi t/12) + \beta_2 \cos(2\pi t/12)$$

Then, the seasonal amplitude (SA) can be estimated by the following nonlinear transformation of (β_1, β_2):

$$SA = g(\beta_1, \beta_2) = \sqrt{\beta_1^2 + \beta_2^2}$$

Further, using the Delta method, we can approximate the variance of SA. Note that Δg refers to the vector of partial derivatives of g with respect to the seasonal coefficients, and Σ refers to the covariance between these coefficients.

$$\begin{pmatrix} \widehat{\beta_1} \\ \widehat{\beta_2} \end{pmatrix} \sim N\left(\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}, \Sigma \right),$$

$$g(\widehat{\beta_1}, \widehat{\beta_2}) \sim N(g(\beta_1, \beta_2), \Delta g^T \Sigma \Delta g),$$

$$\sqrt{\widehat{\beta_1}^2 + \widehat{\beta_2}^2} \sim N\left(\sqrt{\beta_1^2 + \beta_2^2}, \Delta g^T \Sigma \Delta g \,|_{\widehat{\beta_1}, \widehat{\beta_2}} \right),$$

where $\hat{\beta}_1$and $\hat{\beta}_2$ are the maximum likelihood estimates of β_1 and β_2. Taking the partial derivatives, we find that

$$\Delta g = \begin{pmatrix} \beta_1(\beta_1^2 + \beta_2^2)^{-0.5} \\ \beta_2(\beta_1^2 + \beta_2^2)^{-0.5} \end{pmatrix}$$

Therefore, an approximate 95% confidence interval for the seasonal amplitude can be calculated via the following:

$$\sqrt{\widehat{\beta_1}^2 + \widehat{\beta_2}^2} \pm 1.96 \Delta g^T \Sigma \Delta g \,|_{\widehat{\beta_1}, \widehat{\beta_2}}$$

This appendix takes “amplitude” in the trigonometric sense, i.e. the deviation from the inflection point. To further transform this statistic (and confidence interval) to provide the interpretation used in this paper (the odds in the peak month compared to the nadir month), one must simply multiply these estimates by 2.

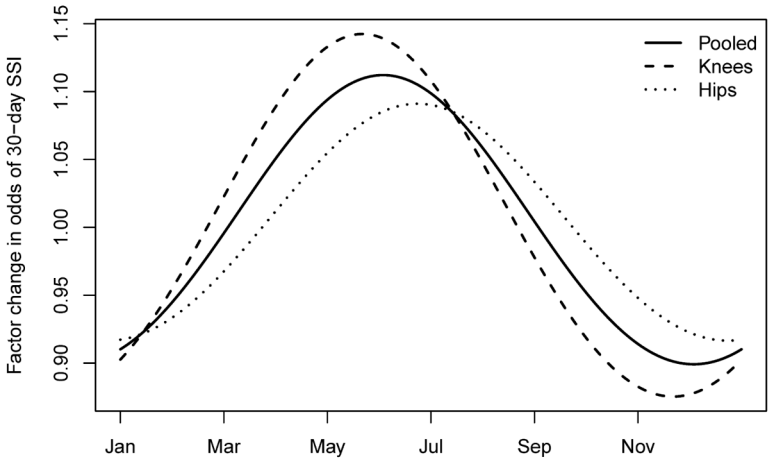

Figure 1.

Seasonal variation (factor change) in the odds of 30-d SSI readmission, controlling for covariates listed in Table 2.

Table 1

Summary of Important Variables by Procedure Type (Sample Sizes Are Weighted).

	TKA	THA	Total
Age group	**n (%)**	**n (%)**	**n (%)**
< 18	1,007 (0.1%)	602 (0.1%)	1,608 (0.1%)
[18, 30)	1,789 (0.2%)	3,557 (0.5%)	5,346 (0.3%)
[30, 40)	5,331 (0.5%)	11,439 (1.5%)	16,770 (1%)
[40, 50)	42,956 (4.4%)	47,170 (6.1%)	90,126 (5.1%)
[50, 60)	211,002 (21.5%)	160,148 (20.7%)	371,150 (21.1%)
[60, 70)	368,878 (37.5%)	228,983 (29.6%)	597,861 (34%)
[70, 80)	271,806 (27.7%)	184,599 (23.8%)	456,405 (26%)
80+	80,065 (8.1%)	138,221 (17.8%)	218,286 (12.4%)
Primary payer			
Medicare	543,346 (55.3%)	441,704 (57%)	985,050 (56%)
Medicaid	32,947 (3.4%)	27,216 (3.5%)	60,163 (3.4%)
Private insurance	362,355 (36.9%)	277,955 (35.9%)	640,310 (36.4%)
Self-Pay	4,114 (0.4%)	5,198 (0.7%)	9,311 (0.5%)
No charge	826 (0.1%)	975 (0.1%)	1,801 (0.1%)
Other	38,136 (3.9%)	20,945 (2.7%)	59,081 (3.4%)
Missing	1,110 (0.1%)	726 (0.1%)	1,836 (0.1%)
Hospital Size			
Small	223,937 (22.8%)	168,641 (21.8%)	392,578 (22.3%)
Medium	267,909 (27.3%)	206,103 (26.6%)	474,012 (27%)
Big	490,989 (50%)	399,975 (51.6%)	890,964 (50.7%)
Hospital location			
Metropolitan non-teaching	356,884 (36.3%)	258,582 (33.4%)	615,466 (35%)
Metropolitan teaching	516,758 (52.6%)	442,220 (57.1%)	958,978 (54.6%)
Non-metropolitan	109,192 (11.1%)	73,918 (9.5%)	183,110 (10.4%)
Female indicator	602,796 (61.3%)	436,676 (56.4%)	1,039,472 (59.1%)
Hypertension flag	650,621 (66.2%)	462,779 (59.7%)	1,113,399 (63.3%)
Obesity flag	246,156 (25%)	121,734 (15.7%)	367,890 (20.9%)
Diabetes flag	188,553 (19.2%)	102,792 (13.3%)	291,345 (16.6%)
30-d SSI readmission	5,217 (0.5%)	4,773 (0.6%)	9,991 (0.6%)
Continuous variables	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**
Length of stay	3.004 (1.93)	3.35 (2.884)	3.157 (2.405)
Number of diagnoses	7.761 (4.322)	8.175 (4.842)	7.943 (4.564)
Number of procedures	1.106 (0.429)	1.56 (0.721)	1.306 (0.621)

SD, standard deviation.

Table 2

Logistic Regression Results for All 3 Models.

	Odds Ratio (95% CI)		
Age group	**TKA**	**THA**	**Pooled**
< 18	(Baseline)	(Baseline)	(Baseline)
[18, 30)	0.114 (0.02–0.63)	1.412 (0.36–5.6)	0.628 (0.29–1.36)
[30, 40)	1.121 (0.5–2.53)	1.303 (0.34–4.94)	0.895 (0.45–1.77)
[40, 50)	1.076 (0.5–2.32)	1.489 (0.4–5.56)	0.956 (0.49–1.85)
[50, 60)	0.977 (0.46–2.1)	1.35 (0.36–5.02)	0.876 (0.45–1.69)
[60, 70)	0.771 (0.36–1.66)	1.119 (0.3–4.17)	0.713 (0.37–1.38)
[70, 80)	0.69 (0.32–1.49)	0.838 (0.22–3.12)	0.594 (0.31–1.15)
80+	0.633 (0.29–1.37)	0.841 (0.23–3.14)	0.579 (0.3–1.12)
Primary payer			
Medicare	(Baseline)	(Baseline)	(Baseline)
Medicaid	1.489 (1.32–1.68)	1.083 (0.94–1.24)	1.282 (1.17–1.4)
Private insurance	0.679 (0.63–0.73)	0.625 (0.57–0.68)	0.655 (0.62–0.69)
Self-pay	1.009 (0.69–1.47)	1.082 (0.8–1.47)	1.067 (0.84–1.35)
No charge	0.613 (0.21–1.76)	3.384 (2.31–4.95)	2.255 (1.58–3.21)
Other	0.961 (0.84–1.1)	0.599 (0.49–0.73)	0.825 (0.74–0.92)
Hospital size			
Small	(Baseline)	(Baseline)	(Baseline)
Medium	1.119 (1.03–1.21)	1.267 (1.16–1.38)	1.194 (1.13–1.27)
Big	1.144 (1.06–1.23)	1.165 (1.08–1.26)	1.16 (1.1–1.22)
Hospital status			
Metropolitan non-teaching	(Baseline)	(Baseline)	(Baseline)
Metropolitan teaching	0.904 (0.85–0.96)	0.9 (0.85–0.96)	0.902 (0.86–0.94)
Non-metropolitan	0.977 (0.87–1.1)	1.036 (0.92–1.17)	0.995 (0.92–1.08)
Elixhauser index[a]			
Diabetes	1.122 (1.05–1.2)	1.336 (1.24–1.44)	1.207 (1.15–1.27)
Hypertension	1.189 (1.11–1.27)	1.263 (1.18–1.35)	1.223 (1.17–1.28)
Obesity	1.182 (1.11–1.26)	1.577 (1.47–1.69)	1.324 (1.26–1.39)
Dichotomous indicators			
THA indicator (vs TKA)	-	-	1.161 (1.11–1.21)
Rural (vs urban)	0.868 (0.8–0.94)	0.971 (0.89–1.06)	0.923 (0.87–0.98)
December discharge	0.634 (0.55–0.72)	0.419 (0.36–0.49)	0.53 (0.48–0.59)
Female	0.559 (0.53–0.59)	0.785 (0.74–0.83)	0.653 (0.63–0.68)
Continuous covariates			
Seasonal sine term[b]	0.877 (0.84–0.91)	0.922 (0.88–0.96)	0.899 (0.87–0.93)
Seasonal cosine term[b]	1.023 (0.98–1.06)	0.968 (0.93–1.01)	0.996 (0.97–1.02)
Log(length of stay + 0.5)	0.927 (0.86–1)	1.173 (1.09–1.26)	1.079 (1.02–1.14)
Number of diagnoses	1.006 (1–1.01)	1.015 (1.01–1.02)	1.011 (1.01–1.02)
Number of procedures	1.182 (1.13–1.23)	0.952 (0.91–0.99)	1.034 (1–1.07)

[a] All 29 elixhauser comorbidities are included, but only 3 are listed in this table.

[b] Further information about the sine and cosing terms is given in the Appendix.

Table 3

Transformed Logistic Regression Results for Seasonality, Controlling for All the Covariates Listed in Table 2.

	Nadir Peak, Odds Ratio (95% CI)	Estimated Nadir Month	Estimated Peak Month
TKA	1.305 (1.201–1.418)	December	June
THA	1.19 (1.091–1.298)	January	July
Pooled	1.237 (1.164–1.314)	December	June