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ORIGINAL ARTICLE

Reducing cost drivers in total joint arthroplasty: understanding patient readmission risk and supply cost

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ABSTRACT

Introduction: Understanding and planning for the factors that impact supply cost and unplanned readmission risk for total joint arthroplasty (TJA) patients is helpful for hospitals at financial risk under bundled payments. Readmission and operating room supply costs are two of the biggest expenses.

Methods: Logistic and linear regressions are used to measure the impacts of TJA patient attributes on readmission risk and supply costs, respectively.

Results: Patients' health market segment and the number/type of comorbidity impacts 30/90-day readmission rates. Surgeon implant preference and type of surgery impact supply costs. Discharge location and two of the five health market segments increase the odds of 30-day readmission. Arrhythmia and lymphoma are the primary comorbidities that impact the odds of readmission at 90 days.

Conclusions: Preoperatively identifying TJA patients likely to have large supply costs and higher readmission risk allows hospitals to invest in low-cost interventions to reduce risk and improve healthcare value.

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1. Introduction

Understanding the factors that impact supply cost and unplanned readmission risk for total joint arthroplasty (TJA) patients is helpful information for surgeons and hospitals operating in an "at risk" financial reimbursement model. That information can inform surgeons' decisions about what interventions to take to mitigate the risk of readmission post-discharge. Additionally, preoperative knowledge of the patient factors that increase supply costs can help physicians and hospitals manage expenses and develop cost-saving contracts with vendors. Controlling costs for joint replacement is critical for hospitals subject to the Centre for Medicare and Medicaid Services' (CMS) Comprehensive Care for Joint Replacement (CJR) payment bundle. Success in the CJR or similar bundled payment programmes requires that all stakeholders (including surgeons) understand the "actual direct costs of providing their service" (Schutzer, 2016). Under CJR, participant hospitals receive a fixed reimbursement for all expenses related to a diagnosis-related group (DRG) 469 or 470 patient from admission until discharge plus 90 days.

TJA is one of the most common surgical procedures performed in the US, but despite its popularity and effectiveness, it does come at a high cost (Barsoum et al., 2010; Bosco, Alvarado, Slover, Iorio, & Hutzler, 2014; Gioe, Sharma, Tatman, & Mehle, 2011; Healy, Rana, & Iorio, 2011). Furthermore, the cost of TJA varies widely from hospital to hospital and region to region (Comprehensive Care for Joint Replacement Model, 2016). There are several cost drivers associated with TJA: implant costs, length of stay, surgeon, and cost of rework due to a readmission (Bosco et al., 2014; Christ, Bargar, & Morris, 2000; Gioe et al., 2011; Healy et al., 2011).

TJA has gained popularity over the past few decades because it is relatively safe and effective at relieving pain and improving function (Bumpass & Nunley, 2012). Recent studies predict that the demand for TJA will grow fourfold in the next 15 years up to 4 million surgeries annually (Bosco et al., 2014; Kurtz, Ong, Lau, Mowat, & Halpern, 2007). TJA is more common in older adults and is the most common surgical procedure for patients with Medicare insurance (CMS, 2016). In 2006, Medicare costs for TJA topped $5B, a number expected to rise to $50B by 2030 (Bumpass & Nunley, 2012).

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Surgical supply costs consisting primarily of implant costs are significant cost drivers in TJA. Depending on the method used to calculate the cost of TJA, either traditional accounting or time-driven activity-based costing (TDABC), implants are one of the top three expenses (Akhavan, Ward, & Bozic, 2015; Bosco et al., 2014). The other two being hospital room and operating room (Healy et al., 2011; Rana, Iorio, & Healy, 2011). A fourth cost driver for CJR patients is readmission, which has been shown to account for 60% or more of the cost of the primary surgery (Peel et al., 2015). Prior to the CJR, Medicare reimbursed hospitals when patients were re-hospitalised unless the re-hospitalisation occurred within 24 h of discharge and for the same diagnosis as the original admission (Jencks, Williams, & Coleman, 2009). Doctors and hospitals did not focus on post-operative care, as rework was reimbursed under a fee-for-service payment model (Jencks et al., 2009). Since the CJR is a relatively new initiative, few studies have looked at the readmission costs out to 90 days post-discharge. In a recent study of primary TJA patients, the 30-day readmission rate was 5.5% and accounted for 11.2% of the post-discharge payments (Bozic, Ward, Vail, & Maze, 2013).

In a bundled payment model, hospital revenue is fixed-per-case and, therefore, reducing expenses without sacrificing quality improves health value. One of the easiest expenses that hospitals can measure and influence is the fixed costs associated with purchasing supplies in the operating room. The majority of the supplies are expendable or implant-related and are purchased at point-of-use. A second expense and one that is harder to control and carries significant financial impacts is readmission. Understanding patient risk factors that lead to high supply cost and high readmission risk can help surgeons in two ways: (1) to balance their surgical case load and (2) to predict higher cost patients for which they should invest in interventions that will reduce readmission risk.

2. New contribution

The CMS shift to value-based payment (VBP) models is part of a larger healthcare payment reform initiative authorised under the Affordable Care Act (ACA) (CMS value based programs, 2017). VBP models financially incentivise providers to deliver quality outcomes, but present a host of challenges to both hospitals and surgeons alike. In TJA, many hospitals recently transitioned from fee-for-service to bundled payment without understanding how patient risk factors, readmission costs, and supply costs were accounted for and reimbursed. This study investigates the factors that impact cost and readmission risk as a means to understand and plan for cost drivers under the CJR. The use of data analytics in healthcare is not novel, but the body of research on using electronic medical record data to improve quality of care and decrease cost in total joint replacement is. Therefore, the aim of this study is to help surgeons and hospitals understand the important patient-level factors that influence bundled payment costs in the context of readmission risk and operating room supply costs for TJA patients.

3. Literature review

One method to learn these important factors is to leverage patient data from electronic medical records (EMR) and data analytics to perform health market segmentation. Swenson, Bastian, and Nembhard (2016b) surveyed the data mining approaches to health market segmentation in order to identify opportunities to enhance personalised healthcare by identifying the latent relationships between attributes found in individual EMRs, customer surveys, and demographic data. Continuing this line of research, Swenson, Bastian, and Nembhard (2016a) applied a two-stage methodology using both unsupervised and supervised machine learning techniques to perform health market segmentation and classification of total joint replacement surgery patients. The health market segment information is useful for hospitals and clinicians to target select groups of patients, and this insight can be used to adopt specific protocols during the pre-, peri-, and post-operative phase of TJA.

There is a large body of literature on predictive modelling in health care, especially in terms of readmission risk. A recent systematic review of predictive modelling in readmission found many of the published risk prediction models have mixed results and are not generalisable across departments, specialties, and patient populations, indicating that the best model may be the one tailored to a specific patient population (Kansagara et al., 2011). Furthermore, despite advances in computer-aided statistical analysis programmes, risk prediction models that used patient-level factors were better at predicting mortality than readmission (Kansagara et al., 2011). A significant gap in readmission models could be attributed to the lack of hospital and health system factors such as number of care coordinators, number of follow up visits, effectiveness of medication reconciliation, and bed availability (Kansagara et al., 2011). Another complicating factor to understanding readmission data is the lack of information on the actual number of readmissions (Fry, Pine, Locke, & Pine, 2015). Hospitals traditionally cannot get information on patient readmission visits to other hospitals; in the case of CMS patients, that information may not come until it is too late to intervene.

Since the passing of the ACA in 2009, the CMS started to publish 30-day readmission rates for select diagnosis related groups (DRGs) which in turn encourages hospitals to focus on 30-day readmission rates. In a recent

meta-analysis studying 30-day orthopaedic readmissions, the authors found that studies that began enrolment after 2009 had lower readmission rates than ones that started before 2009 (Bernatz, Tueting, & Anderson, 2015). The study attributes some of the improvement in overall readmission rates to the Hawthorne effect, where merely drawing attention to readmissions has improved outcomes.

At the individual study level, certain risk factors have been identified with higher readmission risk. Age, hospital length of stay, discharge location, body mass index (BMI), and American Society of Anesthesiologists (ASA) score were positively associated with increased risk of 30-day readmission following orthopaedic-related surgery (Bernatz et al., 2015). Other studies found that comorbidity burden, age, and prior medical service use are useful predictors of readmission (Kansagara et al., 2011). In a total knee arthroplasty study, the authors found that a history of transient ischemic attack/cerebrovascular accident, female sex, and general anaesthesia were significant predictors of readmission (Belmont et al., 2015). Obesity has also been tied to higher readmission risk following total knee arthroplasty revision surgery (Hanly, Marvi, Whitehouse, & Crawford, 2016). In total hip arthroplasty, an increase risk of readmission has been attributed to procedure type, length of stay greater than 5 days, cardiac valvular disease, substance abuse, and diabetes with end organ complications (Schairer, Sing, Vail, & Bozic, 2014).

Although less studied than readmission, there have been several studies that investigate supply costs in the TJA operating room. These studies focus on the rising cost of implants and the reduction in margins for both primary and revision joint surgery as opposed to the patient factors that impact supply costs. The Lahey Clinic instituted cost containment methods to reduce total knee arthroplasty (TKA) expenses (Healy et al., 2011). Bosco et al. (2014) successfully managed variability in implant costs by implementing price points that were not negotiable; thus forcing implant vendors to a fixed cost (Bosco et al., 2014). Gioe et al. (2011) studied premium versus standard implants and found no significant difference in revision rates at 7–8 years. The foremost mentioned studies did not assess how patient factors influenced surgical supply costs or contributed to the variation in supply costs across similar procedures. Two other inpatient cost studies found that certain comorbidities, such as diabetes and obesity, increase inpatient hospital costs, but neither investigated which components of cost were impacted (Kremers, Visscher, Kremers, Naessens, & Lewallen, 2014; Pugely, Martin, Gao, Belatti, & Callaghan, 2014). Understanding the patient factors that increase the cost of supplies could help surgeons and hospitals to better manage the direct surgical costs of TJA.

4. Methods

4.1. Study setting and design

This study is based on a TJA patient population located at one academic hospital located in central Pennsylvania. This retroactive study looks at patients who underwent TJA between December 2013 and September 2015. The data for this study were approved under Penn State University Institutional Review Board STUDY00054. The initial data-set included all DRG 469 and 470 patients who underwent total joint replacement surgery of the knee or hip joint. Patients who had bilateral procedures were excluded. For the majority of the study period there were three primary TJA surgeons. All patients who presented for surgery between December 30 2013 and September 30 2015 were initially included. There were 248 patient records excluded due to missing or incomplete data fields. The final set included 596 patients.

This study focuses on understanding the patient-level factors that are significant in determining surgical supply costs and readmission risk, which are two critical components to understanding and managing financial risk under value-based bundled payment models. At the time of this study, the hospital was not under the CJR. Additionally, 48% of the patients were eligible for Medicare (aged 65 or older).

We employed regression modelling techniques to understand the impact of various predictors, most of which are binary or categorical variables, on supply costs and readmission. To model supply cost, a continuous variable, we used linear regression, and to model readmission, a binary response variable, we used logistic regression. Each patient has a supply cost which consists of implant and non-implant costs and includes the cost of every accountable medical consumable used in the operating room. These include implant components, drapes, and knife blades. The readmission risk model is in two parts: 30-day readmissions and 90-day readmissions.

The CJR does recognise a limited number of readmission exemptions for which it does not hold the hospital financially accountable. The readmission exemption codes are listed by the DRG of the primary discharge diagnosis for the readmission visit. Although the data we obtained did not contain the DRG for the re-hospitalisation, it did contain a description of the reason for the re-hospitalisation. For each readmitted patient, we compared the readmission description with the exemption list and found that only 14 of the 90-day readmissions would have been exempt. The 14 exemptions were for patients that returned to the hospital within 90 days for a scheduled arthroplasty on a different joint.

4.2. Data collection/variable selection

The patient data for this study came from several sources to include patient EMRs, billing records, and Surginet – the hospital data collection tool used in the operating room. The patient data-set contains over 30 attributes to include age, body mass index, length of stay, hip and knee osteoarthritis outcome score (HOOS/KOOS), smoker status, ethnicity, discharge location, and international classification of diseases version 9 (ICD-9) diagnosis codes. Dummy variables were used to represent the multiple levels of many of the attributes such as ASA score, smoking status, and discharge destination.

After data pre-processing, we calculated two primary comorbidity-based indices for use in modelling readmission risk and supply cost. A comorbidity index is a numeric score derived from the combination of documented patient comorbidities (Bjorgul, Novicoff, & Saleh, 2010). We calculated the Charlson Index and the count of Elixhauser's ICD-9 mappings to comorbidities. The Charlson Index was originally developed in 1987 to help classify comorbidity conditions that lead to mortality (Charlson, Pompei, Ales, & MacKenzie, 1987). The index uses 19 comorbidity conditions that were selected based off their association with a one-year mortality risk. Each comorbidity is weighted from one to six and the index, which ranges from 0 to 33, is the sum of the weighted comorbidities. The Charlson Index has been used to predict patient outcomes including mortality, readmission rates, and complications. For example, a Canadian study found that patients with a Charlson index of 2 or more increased both readmission and in-hospital complication risk from TKA by 2.1% (Kreder et al., 2003). A Danish study also found that high Charlson scores (>2) were strong indicators of post discharge hip replacement failure (Johnsen, 2006). Although the Charlson index demonstrated success in some studies, it does have limitations. In an Australian study, the Charlson index did not perform well as a predictor of health-related quality of life outcomes following joint replacement surgery (Harse & Holman, 2005).

The second comorbidity index is the count of the Elixhauser's ICD-9 mapping to 30 comorbidities. Similar to the Charlson Index, Elixhauser's first maps administrative patient ICD-9 codes to 30 predetermined comorbidities, then calculates the weighted index score. Instead of using the weighted index, we summed the number of positive comorbidities and used the total number of comorbidities as a patient severity index that ranges from 0 to 30. We retained the 30 binary variables from the Elixhauser's comorbidity conversion and included them as binary variables (presence of condition = 1, absence = 0). R software under the ICD-9 package was used to translate the ICD-9 codes into the Charlson score and to calculate the comorbidity count (Wasey, 2015). Paralysis, weight loss, and blood loss did not occur in any cases and were therefore dropped from models where individual comorbidities were included. Table 1 summarises the main attributes with either a count or mean depending on variable type.

Table 1. Summary of attributes considered for each model.

	Mean	Median	Min/Max	Std. Dev	
Age	63	64	22/89	11.4	
Gender	Male	Female			
	255	367			
ASA	1	2	3	4	
	13	231	371	7	
Ethnicity	Hispanic	Non-Hispanic			
	16	606			
Smoking status	Non-smoker	Smoker	Former smoker		
	339	73	210		
Procedure	Hip	Knee			
	218	404			
Length of Stay (LOS) (avg hours)	63.5				
Discharge location	Home	HHC	SNF	Rehab	Other
	477	27	32	76	10
Diagnosis related group (DRG)	469	470			
	13	609			
Readmission count	30 days	90 days			
	20	48*			
HOOS/KOOS (average)	Pain	Symptoms	Function daily life	Function sports leisure	Quality of life
	39.4	43.3	40.5	20.3	21.1
Supply cost	Mean				
	4889				
ICD-9 count	Mean	Min/Max	Std Dev		
	1.73	0/6	1.2		
Comorbidities			Total		
Congestive heart failure (CHF)			10		
Arrhythmia			75		
Valvular disease (Valvular)			18		
Pulmonary hypertension (PHTN)			11		
Peripheral vascular disease (PVD)			12		
Hypertension (HTN)			371		
Paralysis			0		
Other neurological disorder (NeuroOther)			5		
Pulmonary circulation disorder (Pulmonary)			39		
Diabetes mellitus (DM)			4		
DM w/chronic complications (DMcx)			29		
Hypothyroid			96		
Renal failure (Renal)			22		
Liver disease (Liver)			17		
Peptic ulcer disease (PUD)			3		
Human immunodeficiency virus (HIV)			2		
Lymphoma			11		
Metabolic syndrome (Mets)			1		
Solid tumour w/o metastasis (Tumour)			64		
Rheumatic disease (Rheumatic)			4		
Coagulopathy			6		
Obesity			50		
Weight loss			0		
Fluid/electrolyte disorders (FluidsLytes)			30		
Blood Loss			0		
Anaemia			89		
Alcohol			6		
Drugs			5		
Psychoses			10		
Depression			86		

*14 cases readmitted for subsequent TJA not related to index admission arthroplasty.

A correlation matrix between the aforementioned variables did show some weak correlation ($\rho < 0.40$) between several of the regressors namely ICD-9 count, Charlson score, and five of the comorbidities. To mitigate the correlation, models will either contain individual comorbidities or the comorbidity count. Also, ASA 2 and 3 are the two predominate ASA categories and therefore are highly negatively correlated ($\rho < -0.93$). ASA 3 is also weakly correlated ($\rho < 0.35$) with comorbidity count which indicates that patients with a more severe ASA (poorer fitness for surgery) score also have more chronic conditions.

Instead of using the raw patient data for HOOS/KOOS, patient age, BMI, and LOS as individual predictors, we assigned each patient to their health market segment. Market segmentation techniques applied to patient EMR data have shown that patients cluster into a small number of unique segments that share likeness between a subset of patient predictors such as age, LOS, BMI. (Swenson et al., 2016a). We applied the predictive cluster model from Swenson et al. (2016a) to our patient data-set and assigned each patient to one of six distinct clusters (i.e., health market segments). Table 2 summarises the patient clusters. The values in the tables are the means for each variable in each cluster.

4.3. Regression methods

We modelled supply cost and readmission risk using linear and binary logistic regression, respectively. Binary logistic regression is based on the fundamentals of the multiple regression model (Nelder & Wedderburn, 1972; Rush, 2001; Sheather, 2009). RStudio is used to perform all regression calculations (RStudio Team, 2015). The linear regression output from RStudio includes the coefficient estimate, which can be positive or negative, the standard error, *t*-value, and the *p*-value associated with the estimate. The output also includes the adjusted R^2 to measure the proportion of variation in the response variable explained by the predictor variables. The binary logistic regression output includes the odds ratio (OR), the standard error of the coefficient estimate, the *p*-value, and the 95% confidence interval around the OR. The marginal effect is also included in the output table. Additionally, Akaike information criterion (AIC) and McFadden's adjusted R^2 are used to evaluate the models.

5. Results

After pre-processing the data, the study included 622 patients with 42 variables. By design, not all 42 distinct (excludes dummy variables) variables were used in the same regression model to avoid correlation, especially between the 30 attributes representing the presence or absence of a comorbidity and the sum of comorbidities attribute. To further ensure consistency between both the supply cost linear regression model and the readmission risk logistic regression model, additional data modifications were required to meet the linear regression model assumptions. The initial linear regression model for predicting supply cost suffered from heteroscedasticity. After completing an outlier analysis, patients whose supply costs or ICD-9 count (variable capturing number of comorbidities or comorbidity burden) were greater than five standard deviations from the mean were removed. This reduced the size of the data-set, but ensured the model met the required assumptions. The Breusch–Pagan test supported the assumption of homoscedasticity, variance inflation factors were within tolerance indicating no significant multicollinearity, the Durbin–Watson Test was used to show non-autocorrelated errors, and plots of the residuals indicated normally distributed standardised residuals. The adjusted R^2 for the model without the outliers was 0.5176, indicating that 51% of the variation in the model is accounted for by the predictor variables.

In subsequent models, we included up to 49 regressor variables of which several are dummy variables that represent the various ASA scores, discharge destinations (Home Health Care-HHC, Skilled Nursing Facility-SNF, Rehabilitation Hospital-rehab, Other Inpatient Facility-other) and patient health market segments. Best subset selection for the linear models and the variable importance feature of the random forest model were used to identify the most significant variables. All models contained regressors that were of limited impact, but they were not consistent across models. Furthermore, the 30 comorbidities from Table 1 are well recognised in the literature. For example, in 2011, Kansagara et al. completed a system review of risk prediction models for hospital readmission and found that 24 out of 30 studies used medical comorbidities, 19 used age, 15 used gender, 7 used ethnicity, and 2 used discharge destination. Because this study is designed to explain the factors that do and do not impact supply cost and readmission rather than

Table 2. Summary of patient clusters.

Cluster	Age	BMI	LOS (hr)	Pain	Symptoms	Function (daily life)	Function (sports & leisure)	Quality of life
1	68.82	32.36	59.25	52.53	57.56	52.69	19.85	33.16
2	68.08	29.24	66.15	18.13	30.82	16.52	5.56	7.72
3	62.91	33.19	58.89	62.60	61.24	66.18	68.84	43.10
4	51.08	30.19	55.23	37.11	34.70	44.19	24.32	16.57
5	59.17	41.25	59.33	33.47	34.91	33.30	7.89	10.43
6	68.00	33.73	146.42	25.32	32.14	20.14	10.34	13.70

classify or predict the responses, we retained regressors that did not significantly impact either supply cost or readmission.

Two linear regression models (models 1 and 2) were used to model supply cost. Model 1 considered a subset of the predictor variables that included the sum of the comorbidities and model 2 considered each individual comorbidity as calculated using the Elixhauser's ICD-9 mapping to 30 comorbidities. Consistent to both models, supply cost (response) is regressed on gender, ASA score, ethnicity, smoking status, orthopaedic surgeon, procedure code, DRG, discharge destination, Charlson index, and patient cluster.

In model 1, there were numerous significant ($\alpha \leq 0.05$) variables of which some increased supply cost and others decreased it. Table 3 shows the regression output. Female gender ($92), non-smoker ($101), Medical Doctor (MD) 1 and MD2 ($901 and $395), total hip arthroplasty or THA ($392), and patients in market segment or cluster 6 ($235) all put upward pressure on the supply cost, while patients coded as DRG469 (−$449) and those in market segment 3 (−$143) decreased supply cost. Furthermore, a one point increase in Charlson index score, which is normally associated with having an increased number of comorbidities (comorbidity burden), was associated with an increase in supply costs ($45). This is contrary to the decrease in supply costs seen when moving from DRG470 (patient without major complications and comorbidities (MCC)) to DRG469 (with MCC). Although not significant at $\alpha = 0.05$, patients with ASA of 4 had a downward impact (−$471, $p = 0.055$) on supply costs. Recall, these coefficients are solely based on supply costs and not total hospitalisation or bundled payment expenses accrued during post-discharge care.

Table 3. Linear regression output for model 1.

Coefficients	Estimate	Std. error	*t* value	Pr(>|*t*|)
(Intercept)	4250.22	142.7	29.783	**<2E-16**
Female	92.29	39.54	2.334	**0.01991**
ASA2	−212.78	133.47	−1.594	0.11144
ASA3	−204.51	134.69	−1.518	0.12947
ASA4	−470.96	244.91	−1.923	0.05498
Latino	121.01	120.1	1.008	0.31407
Non-smoker	100.56	40.94	2.456	**0.01434**
Current smoker	69.31	65.58	1.057	0.29099
MD1	901.27	40.84	22.069	**< 2E-16**
MD2	395.01	54.66	7.227	**1.58E-12**
Total Hip Arthroplasty (THA)	392.38	39.71	9.88	**<2E-16**
DRG469	−448.63	164.7	−2.724	**0.00665**
Discharge HHC	50.18	94.59	0.531	0.59596
Discharge SNF	69.18	89.99	0.769	0.44234
Discharge rehab	101.85	61.48	1.657	0.09811
Discharge other	−180.84	151.55	−1.193	0.23325
# Comorbidities	−22.56	18.51	−1.219	0.22322
Charlson score	45.17	22.57	2.002	**0.04577**
Cluster 2	−91.08	56.01	−1.626	0.10445
Cluster 3	−142.8	64.47	−2.215	**0.02715**
Cluster 4	11.07	58.47	0.189	0.8499
Cluster 5	−10.13	53.88	−0.188	0.85096
Cluster 6	235.21	114.62	2.052	**0.0406**

Notes: The bold values are the statistically significant factors (statistically significant determined with a $p \leq 0.05$).

In model 2, female gender, non-smoker, surgeon MD1 and MD2, THA, and patients in cluster 6 remained significant and increased supply costs in a similar magnitude as in model 1. ASA4 patients (−$595), those discharging to inpatient rehabilitation hospitals (−$135), and those in segment 3 (−$163) were significant and decreased supply costs. Additionally, there were six individual comorbidity conditions that had a significant impact on supply cost. CHF (+$360), renal (+$257), and drug use ($782) significantly raised supply costs, whereas arrhythmia (−$125), HIV (−$1045), and fluid-slytes (−$190) decreased supply cost. The adjusted R^2 for model 2 improved to 0.5382. Table 4 shows the regression output for model 2.

To predict readmission (a binary event), we applied a binary logistic regression model to the same inputs used in the first two supply cost models. Although the input variables are the same, the beta coefficients returned are in terms of log odds. The odds ratio is derived by exponentiating the coefficient for each variable. The output is reported as the change in the odds ratio when a significant attribute increases by one holding all others at their mean. For dummy variables, the odds ratio reported is the amount the odds increase or decrease when the variable changes (i.e., male to female), whereas with continuous variables the odds ratio reflects the change in odds ratio per one-unit increase or decrease. The odds ratio can range from 0 to infinity and an odds ratio of one indicates neither an increase nor decrease in odds or risk of a readmission. Odds ratios are reported with a 95% confidence interval (CI). Since an odds ratio of 1 indicates there is neither an increase nor decrease in probability of readmission, significant attributes are only considered if the 95% CI for the odds ratio does not include 1. Models 3 and 4 capture 30-day readmission and models 5 and 6 capture 90-day readmission under both input variable options.

In model 3, female gender, THA, discharge other, the number of comorbidities, and market segment 5 are significant. Table 5 shows the regression output for model 3 to include the OR, standard error, *p*-value, 95% confidence interval, and marginal effect. The odds of a 30-day readmission are on average increased by 3.44 for females, 5.0 for hip replacement patients, and 3.13 for patients discharged to an inpatient facility other than rehabilitation. Additionally, 30-day readmission odds increase by an average of 2.2 for each comorbidity and by an average of 4.52 for patients in market segment 5. Table 5 contains the complete results of model 3 including the 95% confidence intervals and marginal effects. The AIC and McFadden's adjusted R-squared value for model 3 are 161.83 and 0.312, respectively. The results in

Table 4. Linear regression output for model 2.

Coefficients	Estimate	Std. error	*t* value	Pr(>|*t*|)
(Intercept)	4158.721	141.8098	29.326	**<2E-16**
Female	117.3564	40.5694	2.893	**0.003971**
ASA2	−153.791	132.5281	−1.16	0.246375
ASA3	−124.735	134.6469	−0.926	0.354653
ASA4	−595.047	255.7155	−2.327	**0.020329**
Latino	62.0693	119.505	0.519	0.603701
Non-smoker	144.742	41.2748	3.507	**0.000491**
Current smoker	15.9301	67.0141	0.238	0.812193
MD1	904.0303	41.4324	21.819	**< 2e-16**
MD2	427.658	55.3713	7.723	**5.42E-14**
THA	402.8949	39.8771	10.103	**< 2E-16**
DRG469	−290.308	184.299	−1.575	0.115787
Discharge HHC	34.328	95.6204	0.359	0.719731
Discharge SNF	63.4352	89.6821	0.707	0.47966
Discharge rehab	135.4856	62.4496	2.17	**0.030472**
Discharge other	−115.936	149.6541	−0.775	0.438855
CHF	359.8052	172.7928	2.082	**0.037779**
Arrhythmia	−125.196	59.8713	−2.091	**0.036981**
Valvular	−0.2156	111.9764	−0.002	0.998464
PHTN	−192.741	146.4764	−1.316	0.188775
PVD	−48.0579	136.0797	−0.353	0.724104
HTN	−45.1379	39.8851	−1.132	0.258256
NeuroOther	23.9178	205.8308	0.116	0.907536
Pulmonary	116.6937	88.5686	1.318	0.188205
DM	−277.396	270.7479	−1.025	0.306025
DMcx	56.9401	95.7854	0.594	0.552453
Hypothyroid	23.7441	52.0502	0.456	0.648444
Renal	256.9237	124.0146	2.072	**0.038759**
Liver	198.2371	143.6675	1.38	0.168201
PUD	−400.806	259.9973	−1.542	0.123753
HIV	−1045.34	397.1882	−2.632	**0.008731**
Lymphoma	−10.9103	141.3731	−0.077	0.938513
Mets	−658.525	487.1052	−1.352	0.17696
Tumour	−97.213	61.2185	−1.588	0.11287
Rheumatic	275.9431	226.4781	1.218	0.223593
Coagulopathy	135.0668	220.205	0.613	0.539887
Obesity	52.159	69.4811	0.751	0.453159
FluidsLytes	−190.382	95.4967	−1.994	**0.046691**
Anaemia	−41.3172	53.0057	−0.779	0.436029
Alcohol	41.4608	201.2687	0.206	0.836869
Drugs	782.0746	229.0146	3.415	**0.000685**
Psychoses	219.4143	162.9683	1.346	0.178742
Depression	−10.4286	55.1879	−0.189	0.85019
Charlson score	8.7871	35.3314	0.249	0.803681
Cluster 2	−90.9712	56.7029	−1.604	0.109213
Cluster 3	−162.919	64.3051	−2.534	**0.011569**
Cluster 4	−8.9098	58.0107	−0.154	0.877991
Cluster 5	−44.8049	55.447	−0.808	0.419402
Cluster 6	283.8611	118.716	2.391	**0.017135**

Notes: The bold values are the statistically significant factors (statistically significant determined with a $p \leq 0.05$).

Table 5 are based on using maximum likelihood estimators (MLE) to estimate the model parameters. Since the dependent variables, 30 and 90 day readmissions, were infrequent, a condition that can result in small-sample bias (Williams, 2016), we also evaluated the logistic models using Firth's (1993) penalised MLE (PMLE) method. The results using both methods are similar with the exception that PMLE did reduce the magnitude of the ORs and standard errors for non-significant factors. The output tables using PMLE are available in the online supplement.

Another way to look at the logit results is through a marginal effects analysis. The interpretation of the marginal effects varies depending on the type of independent variable. For binary variables, the marginal effect represents the change in the probability of the outcome (patient readmits) when a variable is increased by one (from 0 to 1). For continuous independent variables, the interpretation is more of an instantaneous rate of change in readmission status given a small change in the independent variable. The marginal effects for a given predictor are calculated based on holding all other predictors at their mean.

The results of model 4 are similar to model 3 with the exception that the market segments are not significant. Market segment 2's 95% CI on the OR does not contain 1, but the *p*-value is 0.056. Additionally, discharge with home health care and to a non-rehabilitation setting (discharge other) are significant and increase the odds of a readmission within 30 days. There were four comorbidities that were significant including arrhythmia, HTN, other neurological conditions, and lymphoma. The AIC and McFadden's adjusted *R*-squared value for model 4 are 182.23 and 0.4997, respectively. Table 6 shows the regression output for model 4.

Table 5. Logistic regression output for model 3.

Coefficients	OR	Std. error	Pr(>|*t*|)	2.50%	97.50%	Marginal effect	Std. error	*z* ratio
(Intercept)	3.21E-11	4622.301	0.996	NA	8.77E+112			
Female	3.44	0.602	**0.040**	1.09	12.0	0.0313	0.037	0.8451
ASA2	1.22E+07	4622.301	0.997	0.00	NA	0.413	0.0654	6.3105
ASA3	7.40E+06	4622.301	0.997	0.00	NA	0.4002	0.0658	6.0805
ASA4	0.2227	8233.466	1.000	2.55E-87	5.98E+85	−0.0375	NA	NA
Latino	7.00	1.310	0.137	0.282	70.9	0.0493	0.2607	0.1889
Non-smoker	1.50	0.564	0.471	0.506	4.75	0.0103	0.0283	0.3645
Current smoker	0.312	1.249	0.351	0.0131	2.55	−0.0295	0.2091	−0.141
MD1	2.62	0.635	0.130	0.789	9.95	0.0243	0.0602	0.4042
MD2	0.469	0.914	0.408	0.0664	2.61	−0.0191	0.1847	−0.1036
THA	5.00	0.579	**0.005**	1.68	16.9	0.0407	0.028	1.4559
DRG469	1.85E-08	4847.295	0.997	NA	3.71E+215	−0.4506	0.1157	−3.8956
Discharge HHC	2.65	0.946	0.303	0.323	15.3	0.0246	0.1511	0.163
Discharge SNF	7.23E-08	2633.472	0.995	NA	7.91E+58	−0.4161	0.0399	−10.4246
Discharge rehab	2.37	0.760	0.256	0.492	10.3	0.0219	0.0954	0.229
Discharge other	31.3	1.117	**0.002**	2.98	274.0	0.0872	0.2121	0.411
#Comorbidities	2.20	0.260	**0.002**	1.33	3.75	0.0199	0.0124	1.6132
Charlson score	1.22	0.259	0.436	0.716	2.00	0.0051	0.0207	0.2463
Cluster 2	1.50	0.819	0.622	0.287	7.75	0.0102	0.1334	0.0766
Cluster 3	1.05E-07	1946.071	0.993	NA	6.25E+42	−0.4066	0.0816	−4.9819
Cluster 4	2.50	0.884	0.300	0.407	14.6	0.0232	0.1469	0.1578
Cluster 5	4.52	0.741	**0.042**	1.11	21.5	0.0381	0.0868	0.4393
Cluster 6	4.73E-07	3035.104	0.996	NA	5.32E+74	−0.3685	0.1002	−3.6793

Notes: The bold values are the statistically significant factors (statistically significant determined with a $p \leq 0.05$).

Table 6. Logistic regression output for model 4.

Coefficients	OR	Std. error	Pr(>|*t*|)	2.50%	97.50%	Marginal effect	Std. error	*z* ratio
(Intercept)	1.03E-12	7093.7	0.99689	NA	2.79E+155			
Female	10.6	0.9342	**0.01159**	1.99	85.3	0.0476	2.98E+12	0
ASA2	6.36E+06	7093.7	0.99824	1.25E-190	NA	0.3159	2.69E+12	0
ASA3	1.57E+06	7093.7	0.9984	9.23E-165	NA	0.2877	1.90E+12	0
ASA4	0.00455	11,475.5	0.99963	3.01E-141	2.17E+129	−0.1088	NA	NA
Latino	21.6	1.6249	0.05844	0.569	503	0.062	3.01E+12	0
Non-smoker	2.28	0.7666	0.28304	0.538	11.5	0.0166	1.20E+12	0
Current smoker	0.0149	2.2409	0.06056	1.02E-04	0.550	−0.0848	2.01E+12	0
MD1	2.03	0.7756	0.36182	0.460	10.3	0.0143	1.36E+12	0
MD2	0.323	1.2184	0.35377	0.0235	3.15	−0.0228	1.19E+12	0
THA	10.5	0.7993	**0.00326**	2.49	61.6	0.0474	1.85E+12	0
DRG469	8.16E-07	7555.9	0.99852	NA	2.66E+189	−0.2827	8.10E+12	0
Discharge HHC	23.5	1.4372	**0.02795**	1.38	453	0.0637	4.52E+12	0
Discharge SNF	5.74E-08	3613.6	0.99632	NA	2.99E+79	−0.3363	2.83E+12	0
Discharge Rehab	1.19	1.0967	0.87331	0.117	9.53	0.0035	1.60E+12	0
Discharge Other	48.1	1.6453	**0.01855**	1.72	1250	0.0781	4.84E+12	0
CHF	2.93E-10	6305.1	0.99722	NA	9.37E+169	−0.4427	4.74E+12	0
Arrhythmia	11.3	1.0498	**0.02095**	1.32	96.8	0.0489	3.40E+12	0
Valvular	1.52	1.5822	0.79227	.0412	27.7	0.0084	1.68E+12	0
PHTN	0.0912	2.2796	0.29344	0.000310	4.43	−0.0483	4.70E+12	0
PVD	7.13E-09	7160.7	0.99791	NA	4.91E+163	−0.3783	6.13E+12	0
HTN	23.6	1.1988	**0.00837**	3.15	395	0.0638	1.79E+12	0
NeuroOther	183.0	2.0783	**0.01223**	2.76	15,000	0.105	NA	NA
Pulmonary	8.94	1.2797	0.08695	0.695	119.0	0.0442	1.14E+12	0
DM	6.73E-06	11,514.3	0.99917	NA	Inf	−0.2402	NA	NA
DMcx	4.01	1.2577	0.26986	0.313	47.9	0.028	2.42E+12	0
Hypothyroid	5.25	0.883	0.06031	0.873	30.8	0.0335	2.58E+12	0
Renal	4.23E-08	5063.5	0.99732	0.00	1.43E+95	−0.3424	1.23E+13	0
Liver	20.9	1.82	0.09512	0.534	829.0	0.0613	4.47E+12	0
PUD	1.48E-06	15,974.9	0.99933	NA	Inf	−0.2708	NA	NA
HIV	49,200	20,721.8	0.99958	7.33E-237	2.19E+242	0.2179	NA	NA
Lymphoma	23.6	1.3502	**0.0192**	1.40	361	0.0638	5.52E+12	0
Mets	2.08E-09	29,232.44	0.99945	NA	Inf	−0.4032	NA	NA
Tumour	1.76	0.9481	0.55057	0.238	11.0	0.0114	1.13E+12	0
Rheumatic	5.31E-08	10,906.1	0.99877	NA	Inf	−0.3378	NA	NA
Coagulopathy	8.81E-08	10,218.59	0.99873	NA	1.04E+252	−0.3276	NA	NA
Obesity	5.91	1.238	0.15132	0.474	68.8	0.0358	2.24E+12	0
FluidsLytes	8.03	1.2541	0.09664	0.600	96.0	0.042	2.69E+12	0
Anaemia	1.33	1.0679	0.78808	0.139	9.86	0.0058	8.25E+11	0
Alcohol	4.39E-09	10,799.08	0.99858	NA	1.25E+291	−0.3881	3.58E+12	0
Drugs	8.95E-07	12,040.09	0.99908	NA	Inf	−0.2809	NA	NA
Psychoses	1.27E-07	7643.975	0.99834	NA	8.45E+199	−0.3202	3.54E+12	0
Depression	0.107	1.6604	0.17822	0.00185	1.62	−0.0451	3.61E+12	0
Charlson score	2.07	0.5221	0.16255	0.754	6.12	0.0147	4.55E+11	0
Cluster 2	8.26	1.1071	0.05645	1.01	87.4	0.0426	2.63E+12	0
Cluster 3	9.68E-09	2438.313	0.99396	NA	3.35E+51	−0.3722	4.64E+12	0
Cluster 4	4.72	1.0824	0.1514	0.547	43.0	0.0313	1.98E+12	0
Cluster 5	6.63	1.0315	0.06675	0.968	60.3	0.0381	2.72E+12	0
Cluster 6	1.70E-07	4442.46	0.9972	NA	5.09E+119	−0.3143	2.77E+12	0

Notes: The bold values are the statistically significant factors (statistically significant determined with a $p \leq 0.05$).

In models 5 and 6, 90-day readmission is the response variable of interest. The 90-day readmission risk model will also capture 30-day readmissions. The 14 patients who readmitted within 90 days for non-index admission reasons were not treated as readmitted patients. This condition would occur for patients who schedule a second arthroplasty on an opposite joint within their 90-day recovery period. Model 5 is identical to model 3 with the exception of the response variable. In model 5, there were four significant regressors: Latino, THA, discharge other, and number of comorbidities. The confidence interval for the odds ratio for discharge other does include one. The AIC and McFadden's adjusted R-squared for model 7 are 254.14 and 0.146, respectively. The regression output for model 5 is in Table 7.

Similar to model 4, model 6 looks at 90-day readmission risk using individual comorbidities as regressors. Female gender, Latino, THA, discharge other, and the comorbidity pulmonary were significant. Also, peptic ulcer disease (PUD) was nearly significant ($p = 0.051$) as a factor that contributes to increased 90-day readmission risk. The AIC and McFadden pseudo-R-squared value are 279.16 and 0.2568, respectively. Table 8 shows the regression output.

Table 7. Logistic regression output for model 5.

Coefficients	Odds ratio	Std. error	Pr(>|t|)	2.50%	97.50%	Marginal effect	Std. error	*z* ratio
(Intercept)	1.90E-09	1806.29	0.9911	NA	1.80E+44			
Female	1.89	0.42636	0.1364	0.819	4.42	0.0287	0.0265	1.0848
ASA2	3.18E+06	1806.29	0.9934	9.91E-34	1.41E+232	0.6769	0.051	13.2848
ASA3	3.90E+06	1806.29	0.9933	3.20E-45	NA	0.6862	0.0459	14.9462
ASA4	0.456	3161.432	0.9998	1.33E-30	2.11E+29	−0.0355	NA	NA
Latino	5.78	0.88957	**0.0487**	0.761	29.0	0.0793	0.3193	0.2483
Non-smoker	0.941	0.41778	0.885	0.415	2.17	−0.0027	0.0275	−0.0993
Current smoker	0.429	0.81396	0.298	0.0623	1.77	−0.0383	0.2437	−0.1571
MD1	1.19	0.44656	0.6938	0.498	2.92	0.0079	0.032	0.2484
MD2	0.853	0.58261	0.7855	0.255	2.59	−0.0072	0.0374	−0.1919
THA	2.64	0.40955	**0.0176**	1.19	6.03	0.0439	0.0251	1.7484
DRG469	1.63E-07	1804.654	0.9931	NA	1.04E+82	−0.7067	0.1041	−6.7886
Discharge HHC	1.76	0.8394	0.5022	0.247	7.74	0.0255	0.2445	0.1041
Discharge SNF	1.74	0.87562	0.528	0.231	8.25	0.025	0.2673	0.0935
Discharge Rehab	1.97	0.55924	0.2271	0.618	5.71	0.0305	0.0927	0.3295
Discharge Other	7.72	0.94556	**0.0307**	0.937	44.0	0.0924	0.3209	0.2879
#Comorbidities	1.53	0.18597	**0.0219**	1.06	2.21	0.0193	0.0099	1.9523
Charlson score	1.02	0.206	0.9239	0.659	1.49	0.0009	0.0141	0.0631
Cluster 2	1.62	0.56525	0.3935	0.532	5.04	0.0218	0.0349	0.6242
Cluster 3	0.408	1.09668	0.4137	0.0212	2.47	−0.0405	0.3653	−0.1109
Cluster 4	2.07	0.62797	0.2462	0.586	7.18	0.0329	0.0334	0.9857
Cluster 5	1.69	0.56819	0.3581	0.548	5.28	0.0236	0.0326	0.7235
Cluster 6	2.39E-07	1231.674	0.9901	4.96E-184	1.43E+16	−0.6893	0.0566	−12.1756

Notes: The bold values are the statistically significant factors (statistically significant determined with a $p \leq 0.05$).

Table 8. Logistic regression output for model 6.

Coefficients	OR	Std. error	Pr(>|t|)	2.50%	97.50%	Marginal effect	Std. error	*z* ratio
(Intercept)	1.63E-10	4730	0.9962	NA	4.86E+137			
Female	2.78E	0.522	**0.0499**	1.02	8.05	0.0423	0.0525	0.8058
ASA2	2.11E+07	4730	0.9972	1.71E-77	Inf	0.6983	0.0707	9.8722
ASA3	1.80E+07	4730	0.9972	1.50E-88	Inf	0.6917	0.0796	8.6934
ASA4	0.117	7230	0.9998	1.05E-60	1.32E+59	−0.0889	NA	NA
Latino	9.09	0.984	**0.0248**	1.04	57.2	0.0914	0.3182	0.2872
Non-smoker	0.938	0.486	0.8947	0.364	2.48	−0.0027	0.0532	−0.05
Current smoker	0.152	1.01	0.0629	0.0155	0.889	−0.078	0.3217	−0.2426
MD1	0.949	0.495	0.9156	0.359	2.55	−0.0022	0.0471	−0.0461
MD2	0.577	0.675	0.415	0.142	2.06	−0.0228	0.0679	−0.3354
THA	3.04	0.458	**0.0152**	1.26	7.70	0.046	0.0599	0.7685
DRG469	2.22E-07	4950	0.9975	0.00	7.63E+92	−0.6343	0.2547	−2.4904
Discharge HHC	1.38	0.964	0.7371	0.156	7.80	0.0134	0.3182	0.0421
Discharge SNF	3.61	0.902	0.155	0.467	18.7	0.0531	0.2859	0.1858
Discharge rehab	1.72	0.643	0.4008	0.452	5.84	0.0224	0.1718	0.1303
Discharge other	8.90	1.10	**0.0468**	0.795	67.5	0.0905	0.332	0.2726
CHF	2.32E-09	4430	0.9964	0.00	2.26E+81	−0.823	0.1991	−4.1346
Arrhythmia	3.04	0.643	0.0844	0.782	10.2	0.046	0.1372	0.3349
Valvular	2.25	0.955	0.3955	0.261	12.6	0.0336	0.2911	0.1154
PHTN	0.659	1.48	0.7783	0.0203	9.55	−0.0173	0.4607	−0.0375
PVD	1.03E-08	4740	0.9969	0.00	2.06E+82	−0.7612	0.1003	−7.5915
HTN	1.78	0.489	0.2365	0.710	4.94	0.024	0.0552	0.4348
NeuroOther	15.2	1.50	0.0699	0.486	275	0.1126	NA	NA
Pulmonary	8.83	0.834	**0.009**	1.69	46.3	0.0902	0.1681	0.5363
DM	1.38E-07	8610	0.9985	0.00	9.27E+173	−0.654	NA	NA
DMcx	3.84	0.796	0.0909	0.739	17.7	0.0557	0.1742	0.32
Hypothyroid	0.927	0.632	0.9049	0.235	2.96	−0.0031	0.18	−0.0174
Renal	1.74E-08	3420	0.9958	0.00	2.50E+60	−0.7398	0.2977	−2.4853
Liver	5.80	1.25	0.1589	0.432	65.8	0.0728	0.3117	0.2335
PUD	20.2	1.54	**0.0514**	0.612	388	0.1244	NA	NA
HIV	1.96E+06	12,400	0.9991	0.00	4.15E+241	0.5998	NA	NA
Lymphoma	5.56	1.01	0.0885	0.621	37.9	0.0711	0.3438	0.2067
Mets	5.94E-08	17,700	0.9993	NA	Inf	−0.6889	NA	NA
Tumour	2.14	0.593	0.2004	0.617	6.54	0.0314	0.0733	0.4287
Rheumatic	3.65E-08	8360	0.9984	NA	Inf	−0.709	NA	NA
Coagulopathy	5.29E-08	7000	0.9981	NA	Inf	−0.6937	NA	NA
Obesity	2.54	0.840	0.2668	0.420	12.2	0.0386	0.1714	0.2253
FluidsLytes	1.57	0.966	0.6398	0.182	9.16	0.0187	0.3159	0.0593
Anaemia	1.99	0.577	0.2316	0.596	5.94	0.0286	0.0461	0.6204
Alcohol	4.47E-09	6700	0.9977	NA	1.02E+275	−0.7959	0.2012	−3.9557
Drugs	6.52E-08	7840	0.9983	NA	Inf	−0.685	NA	NA
Psychoses	3.87E-08	5550	0.9975	0.00	2.74E+96	−0.7065	0.2654	−2.662
Depression	1.38	0.637	0.6093	0.355	4.51	0.0135	0.1236	0.109
Charlson score	0.932	0.342	0.8362	0.447	1.77	−0.0029	0.088	−0.0333
Cluster 2	3.19	0.651	0.0747	0.906	12.0	0.0481	0.0571	0.8415
Cluster 3	0.496	1.15	0.5426	0.0243	3.46	−0.029	0.4076	−0.0711
Cluster 4	2.79	0.686	0.1348	0.715	11.0	0.0425	0.0613	0.6934
Cluster 5	1.91	0.664	0.3291	0.514	7.18	0.0268	0.0433	0.6192
Cluster 6	5.17E-08	2960	0.9955	0.00	1.91E+56	−0.6946	0.1225	−5.671

Notes: The bold values are the statistically significant factors (statistically significant determined with a $p \leq 0.05$).

6. Discussion

As one of the main costs in TJA, understanding the patient factors that impact supply costs can inform surgeon decision-making in terms of how to negotiate new contracts, how to balance patient surgical load to be financially neutral, and how to price bundled payments with non-CMS insurers. The results of model 1 show that there are numerous factors that affect supply cost including female gender, surgeon, hip surgery, Charlson comorbidity score, and patients in cluster (market segment) three. Surgeon selection is the biggest factor with one surgeon in particular increasing the cost as much as $901. This supports the literature that physician preference regarding implant use creates variability in surgical costs, and it highlights the disconnection between who pays for the implant and who selects the implant (Bosco et al., 2014; Christ et al., 2000). Procedure code is also significant in that patients having THA cost more than those having TKA. It was assumed that non-implant supply costs (drapes, knifes, etc.) were consistent across physicians and based on their surgical preferences rather than patient attributes.

Other significant factors leading to higher supply cost are non-smokers, patients who go to rehabilitation hospitals, and patients with a higher comorbidity burden. It is counter intuitive to think that non-smokers increase supply costs, especially in health care, where smoking is associated with many negative health outcomes. In these models, former smoker is the baseline. Also, in comparison to the choice of surgeon, smoking status has a much lower impact on overall supply cost. In both models 1 and 2, non-smokers had a small, but upward influence on supply costs, which could be attributed to surgeon selection of premium implants for younger patients. Premium implants can include the use of a more expensive highly crossed linked polyethylene insert and patella verse the standard polyethylene components. Although only based on one large joint registry study, Gioe et al. (2011) found no difference in revision rate for primary TKA between standard and premium implants. He did find that the average age for recipients of premium implants was younger than those of standard implants and that premium implants were more expensive (Gioe et al., 2011). These younger healthier patients would likely include non-smokers. Patients in cluster 6 (older patients with the longest average LOS) and patients discharged to a rehabilitation hospital have an increasing impact on supply costs which indicates that they may have required additional supplies or implant components resulting from a more complex procedure.

The most surprising result was that patients coded as having major complications and comorbidities (DRG469) had a downward impact on supply cost, yet patients with a greater comorbidity burden (as measured by Charlson Comorbidity Score) increased supply cost. This could be attributed to the low number of DRG469 patients in the sample or could follow from the same argument where patients with major comorbidities and complications (DRG469) have such severe medical conditions that they would not benefit from a more expensive specialty implant.

The results of model 2 were similar to model 1 except in model 2, the comorbidity count was removed. Of the 30 comorbidity conditions evaluated, 6 of them were significant. CHF, renal failure, and drug use all increased the supply costs. Drug use alone had the largest impact with a beta coefficient of $781. CHF and renal were lower averaging $360 and $257, respectively. Fluid and electrolyte disorders and arrhythmia put minor downward pressure on supply costs.

As expected, the common regressors between models 1 and 2 are consistent in magnitude and direction. In both models, the biggest impacts on supply cost are attributed to the type of procedure and the surgeon. In this study, the three surgeons each use a different vendor for primary TJA. Vendor selection drives implant costs across similar patient types. In both models, there is clearly a cost separation between surgeons (MD 1 vs. 3: $904 and MD 2 vs. 3: $428). To contain the high cost of implants, hospitals can switch to a sole source supply contract to reduce cost variation and potentially gain a volume discount. Alternatively, hospitals can renegotiate contract prices with each vendor to mitigate variation or determine a cost cap and have vendors compete on price (Bosco et al., 2014).

Contrasting the models shows that comorbidity burden or the sum of a patient's comorbidities may not be an effective way to assess supply cost. This result supports previous research that found that patient factors have little impact on supply costs (Bosco et al., 2014; Gioe et al., 2011). In model 1, comorbidity burden was not significant yet in model 2, six of the comorbidities were. This indicates that certain comorbidities impact costs more than others. This is reinforced in model 1 where the Charlson index was significant. Since the Charlson index is a weighted score, it puts more weight on specific comorbidities and only looks at a subset of the 30 used in model 2. This subset of comorbidities likely has more impact on costs. The challenge with using comorbidities as regressors is that several of them are rare events occurring in less than 1% of patients. We believe that certain comorbidities can increase the cost of implants when the comorbidity or Charlson score is a reflection of overall health such as with patients with chronic heart failure (CHF) and renal failure. We also believe that surgeons should consider all patient factors when selecting implants and acknowledge that the evidence surrounding the efficacy of using premium implants regardless of patient comorbidity is not definitive.

In addition to supply costs, readmission is a significant concern for hospitals performing TJA under the CJR. In the two 30-day readmission models, there were

several statistically significant variables. Similar to the supply cost models, gender and procedure code are significant factors to readmission. In Model 3, the factors that increased the odds ratio of 30-day readmission were female gender (OR: 3.44, 95% CI: 1.09, 12.0), hip surgery (OR: 5.0, 95% CI: 1.68, 16.9), discharge-to-other (OR: 31.3, 95% CI: 2.98, 274), number of comorbidities (OR: 2.2, 95% CI: 1.33, 3.75), and patients in cluster 5 (OR: 4.52, 95% CI: 1.11, 21.5). The distinguishing characteristic of a patient from market segment 5 (cluster 5) is their extremely high BMI (greater than 40). This is likely the contributing factor to increased 30-day readmission risk.

Model 4 results were similar to Model 3 in that gender, hip surgery, and discharge to an inpatient setting (non-rehab) were significant and increased the risk of readmission. Also, discharge to home with home health care was also significant (OR: 23.5). Cluster two and five were just over the significant factor threshold (0.05). Patients in clusters two and five are at increased odds of readmission (OR: 8.26 and OR: 6.63, respectively). There were four comorbidities that also increased the odds ratio for 30-day readmission. Arrhythmia (OR: 11.3), HTN (OR: 23.6), neuro-other (OR: 183), and lymphoma (OR: 23.6) all increased a patient's odds of 30-day readmission. As seen in both models, comorbidities did impact readmission odds.

Models 5 and 6 measured 90-day readmission. In Model 5, Latino patients (OR: 5.78), hip patients (OR: 2.64), discharge other (OR: 7.72), and number of comorbidities (OR: 1.53) were significant and increased the odds of readmission. The results of model 6 were similar to model 5 with the addition of two individual comorbidities. Pulmonary (OR: 8.83) was significant and peptic ulcer disease (PUD) nearly significant (p-value: 0.051; OR: 20.2). Compared to model 4, the number of significant individual comorbidities decreased as the length of time increased.

In summary, gender and procedure significantly impact both supply cost and readmission. Female gender and hip replacement increased supply cost and readmission risk, while comorbidity burden mainly impacts readmission risks. In measuring short-term readmission, discharge location and a few specific comorbidities increase the odds of readmission. There are fewer comorbidities that impact the odds of readmission at 90 days. Patients in market segments two and five increase the odds of 30-day readmission which is likely attributed to their long length of stay or extremely high BMI. Pulmonary and peptic ulcer diseases are the primary comorbidities that significantly increase the odds of readmission at 90 days.

The six models evaluated above underscore the importance that individual patient factors and comorbidities can have in understanding cost drivers in TJA. In evaluating the factors that impact supply cost and readmission, the role of individual comorbidities in a small study is limited by the infrequency with which they occur in the sample. They can, however, provide insight into surgeons who are debating interventions and polices as they relate to modifiable patient conditions. For instance, patients with pulmonary conditions might benefit from a specialty consult or care intervention prior to scheduling surgery, especially knowing that the patient is at a high risk for readmission. In addition to the negative impacts of readmissions on hospital revenue under bundled payments, decreasing readmission risk will improve the patient's outcome.

6.1. Limitations

This study has several limitations, some of which are noted by other authors. First, this study focused on a small sample size from one academic hospital in one region of the US. As shown by others, translating these results to other hospitals may not be effective which underscores the need for hospitals to undertake similar study using their specific patient population. A second limitation of this work is that readmission data only captures readmissions to the same hospital. Although EMRs have improved the speed with which clinicians can access a patient's current and past medical history, EMR data are not universally accessible and, therefore, the only mechanism to confirm readmission data is via insurers or asking the patient. At this time, neither option is optimal.

6.2. Concluding remarks

As CMS, the nation's largest insurer, moves from fee-for-service to value-based bundled payment models that incentivise surgeons and hospitals alike to extend care beyond discharge, the role of data analytics and economic modelling will increase. Hospitals responsible for patient costs post-discharge must take into account patient-level factors and demographics in order to understand and mitigate the potential costs associated with various types of patients. The value of understanding supply costs and readmission risk is not to limit or shield an organisation's risk and should not be used to restrict access to high-cost patients. Instead, knowing the factors that can drive-up costs (supply or readmission) can inform a hospital's decision-making regarding which interventions to apply to a patient to mitigate their risk of readmission or propensity for a high-cost implant. The CJR is not designed to penalise hospitals, rather it is designed to incentivise them to extend care beyond their borders and into a patient's home where cost-saving interventions will reduce costly and preventable readmissions.

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