MDGuidelines' Medical Cost and Treatment Utilization Tool

Introduction

Health care costs and treatment utilization have high variability, do not produce better health outcomes, and threaten the solvency of private and public insurers.[1–3] Without the ability to measure spending and treatment utilization, there is limited ability to improve savings and patient outcomes. To address this dynamic, MDGuidelines offers Medical Cost and Treatment Utilization Tool, which provides users with the following capabilities:

- Predict medical costs for a disability case
- Medical cost benchmarking
- Treatment and diagnosis statistics
- Service-specific cost estimates

The medical cost estimates will be especially useful for Actuaries, Utilization Review Nurses, and Nurse Case Managers; the treatment utilization estimates will be useful for Physicians, Utilization Review Nurses, and Nurse Case Managers.

Methods

Conditions Covered

Using millions of disability claims and billions of medical transactions, we provide medical cost and treatment utilization statistics for 15,000 unique medical diagnoses (ICD-10-CMs) from more than 200 medical topics.

Tool Inputs

The model uses the following inputs to produce the statistics generated in the Medical Cost and Treatment Utilization Tool:

- Reason for Disability. MDGuidelines' topics were used for the reason for disability. These topics have diagnostic medical codes attached to them.
- Principal Procedure. The user may select the most significant procedure in the patient's claim (see definition).
- Age. The patient's age at the date of injury or disability.
- Inpatient Stay. This determines whether the patient had an inpatient stay as part of their treatment, as defined by being admitted to an inpatient unit of a hospital.
- Inpatient/Outpatient. Claims may be identified as being for inpatient or outpatient treatment.
- Reason for Inpatient Stay. If an inpatient stay occurred, the user can select the reason for inpatient stay.
- Zip Code. The postal code of where the majority of treatment is performed.

- Program Type. The claim may be for an occupational injury covered by Workers' Compensation or for a non-occupational injury covered by a Short-Term Disability program.
- Comorbidities. Up to five comorbidities may be entered using Quan et. al's comorbidity mappings.[4]

Geographic Cost Estimates

The geographic variation in medical costs and treatment utilization is known, but the underlying reasons for these differences remain mysterious.[3] Therefore, our tools accounts and cannot "control" statistically with variables within our dataset including age and industry. The effect of geographic variability in medical costs was addressed by using Medicare's Geographic Practice Cost Index (GPCI), which is mapped to zip code by the Department of Labor.[5] The GPCI provides payment indices for work performed, practice expense, and malpractice by geographic location. While the GPCI is typically multiplied to the corresponding relative value units (RVUs) of a procedure, a weighted average of the GPCI per zip code was used and multiplied so that the medical cost was associated with the disability claim. The weighted average used the distribution of work (52.5%), practice expense (43.7%), and malpractice (3.9%) percentages reported by the Government Accountability Office.[6]

Non-Occupational Claims

Non-occupational cost and treatment statistics were estimated using two of IBM Watson's MarketScan databases: Commercial Claims and Encounters (CCAE), and Health and Productivity Management (HPM). Short-term disability claims with medical insurance eligibility during, and at least 180 days after the return to work (RTW) date, were included in this analysis. The HPM databases' primary diagnosis was used for the claim's reason for disability. All procedures, prescriptions, and diagnoses noted between 7 days prior to disability and 180 days after the disability end date were collected from the CCAE database. In the CCAE database, procedures have an associated diagnosis; therefore, only procedures that were related to the reason for disability were included. We used the single-level category from Healthcare Cost and Utilization Project's multi-level Clinical Classification Software (CCS) to link procedures to the reason for disability.[7] In the CCAE database, prescriptions are not linked to a diagnosis; therefore, we linked new prescriptions dated within 2 days of the date of diagnosis in outpatient and inpatient claims. All prescriptions up to 180 days after disability in the therapeutic class of the prescriptions matched to the date of diagnosis were then collected.

Workers' Compensation Claims

Workers' Compensation (WC) cost and treatment statistics were estimated using state-specific WC cost estimates combined with claim level WC data from California's Workers Compensation Information System (WCIS). California's WC data includes records between 2007 and 2016 from medium to large firms required to report to the Department of Industrial Relations. The primary reason for disability was determined by matching the nature of injury (e.g., "strain or sprain") and body part injured (e.g., "low back") fields provided by WCIS with the medical codes in the medical claim data. An algorithm was used to match the medical code description to the information noted in the first report of injury by WCIS and weight the frequency in which the medical code appeared in the claim. In addition to collecting medical costs at the billing level, we included lump sum medical payments in the total outpatient and prescription costs according to the empirical (observed) distribution.

To make state-specific estimates of medical costs, we searched the literature for information on cost differences across states. With limited available research, the main references included: 1) Workers Compensation Research Institute's (WCRI) 19th Edition of the CompScope™ Benchmark Reports;[8] 2) Oregon's Department of Consumer and Business Services (ODCBS) Worker's Compensation Premium Rate Ranking for Calendar Year 2016;[9] 3) WC average costs calculated using the IBM Watson HPM database by state; and 4) the National Academy of Social Insurance (NASI)'s 2016 report on *Workers' Compensation: Benefits, Costs, and Coverage*.[10] The WCRI CompScope™ Benchmark Reports present the average medical costs on all paid claims at 36 months' average maturity for 18 states. The ODCBS rate is reported as a state's cost of workers compensation claims per $100 of payroll in all 50 states. NASI's report provided the total benefits paid per $100 of covered payroll by state and percent of benefits attributed to medical payments by state. We combined NASI's benefits paid with the percent of attributed to medical to make a state specific medical benefits paid per $100 of covered payroll.

When we compared WCRI's average costs per claim to the premium rate of ODCBS, we found moderate correlation (Spearman's rho = 0.47, p-value = 0.05). Higher correlation was observed between IBM's average WC costs and WCRI's average medical costs (Spearman's rho = 0.65, p-value = 0.004), whereas lower correlation was observed between IBM's average WC costs and ODCBS rates (Spearman's rho = 0.35, p-value = 0.02). NASI's medical benefits per $100 of covered payroll had a high correlation with WCRI's average medical costs (Spearman's rho = 0.62, p-value = 0.007).

Given WCRI's estimates are widely used in the Workers' Compensation field, and NASI's rates were correlated with WCRI estimates and available for all 50 states, we used NASI's rates to estimate medical costs by state. These estimates were combined with zip code specific Geographic Practice Cost Indices to account for the variation in medical costs by geographic location within a state.[11]

Procedure and Prescription Groupings

For both non-occupational and occupational claims, procedures were coded using Current Procedural Terminology (CPT®) and/or Healthcare Common Procedure Coding System (HCPCS). Prescriptions were coded using the National Drug Code (NDC). CPT codes were grouped using treatment/diagnosis groupings developed for MDGuidelines' Diagnosis and Related Treatment (DART) module. For CPT codes not covered by DART and HCPCS codes, we used SNOMED CT groupings derived from Observational Health Data Science and Informatics' ATHENA standardized vocabularies.[12] SNOMED CT is one of a suite of designated standards for use in U.S. Federal Government systems for the electronic exchange of clinical health information, and is also a required standard in interoperability specifications of the U.S. Healthcare Information Technology Standards Panel. NDCs were grouped using the drug classes in MDGuidelines' Formulary or the therapeutic class defined by IBM Micromedex Red Book.

After combining all costs from the treatment group within a disability episode together, the principal treatments were identified by finding the most expensive procedure within a disability episode, and where that treatment was the most expensive procedure in at least 5% of the cases for that diagnosis group. Anesthesia procedures were not considered principal treatments, as they are typically part of a surgical procedure.

Inpatient Costs and Length of Stay

We used the 2016 National Inpatient Sample (NIS) database developed by the Healthcare Cost and Utilization Project (HCUP) to estimate inpatient cost and length of stay. The 2016 NIS provides all-payer data (including persons covered by Medicare, Medicaid, private insurance, and the uninsured) on approximately 7 million inpatient stays from about 4,500 hospitals; this approximates a 20% stratified sample of discharges from U.S. community hospitals. The 2016 NIS was the latest data obtainable by HCUP in the year 2018.

Hospitalization statistics are presented by Diagnosis Related Groups (DRGs). DRGs were established by the Centers for Medicare and Medicaid Services as a patient classification scheme to account for the severity of illness, prognosis, treatment difficulty, need for intervention, and resource intensity. Since NIS data captures only charge data, we used their charge-to-cost ratio to produce cost estimates per DRG. To produce national estimates, we weighted the cost and length of stay (LOS) predictive models using the *survey* package in R.[13] Only DRGs present in 5% of the cases in the diagnosis group are included in the tool.

Comorbidities

Comorbid diagnoses noted in the STD/WC claim were grouped using the Comorbidity Grouper developed by Quan et al.[14] For each diagnosis, the top five most frequent comorbidities were identified and used as inputs in the medical cost and treatment models.

Outpatient and Prescription Treatment Statistics

Outpatient statistics include frequency of the outpatient service, time to outpatient service, and a distribution of the number of times an individual received the outpatient service. Prescription statistics include frequency of filling the prescription class, time to filling the prescription class, and the total number of days' supply for that prescription class. Given the low number of claims with reported days' supply in our WC data set, these values are only derived using the non-occupational injury dataset. Outpatient and prescription treatment statistics do not utilize geographic location.

Predicting Costs and Treatment Variability Metrics

Outpatient costs, prescription costs, and treatment statistics were predicted using generalized linear models with explanatory variables selected using the Least Absolute Shrinkage and Selection (lasso) algorithm[15] implemented using the *glmnet* function in R. [16] We used 5-fold cross validation to protect against overfitting each model. Medical costs, treatment counts, and duration were log transformed and fit with a linear regression kernel within lasso, whereas frequency was predicted using a logistic regression kernel.

Cumulative Medical Costs versus Disability Duration Figure

The Medical Cost and Treatment Utilization tool provides a figure that presents the cumulative medical costs by disability duration. Disability duration represents calendar days from the start of disability to returning at full duty. The cumulative medical costs are modeled using disability durations, and are useful for benchmarking claim medical costs when the disability duration is known. It should be noted that total medical costs includes costs related to the disability for up to 180 days after the claimant returns to work to account for individuals who continue to receive treatment for their injury after they return to work.

Variability around Predicted Values

The variability of cost and treatment statistics was assessed using the standard deviation of the residuals (σ), which is the difference between the predicted (Y) and observed values.

Outcomes	Lower estimate equation	Predicted estimate equation	Upper estimate equation
Binomial (Frequency)	100*exp(Y- σ)/(1+exp(Y- σ))	100*exp(Y)/(1+exp(Y))	100*exp(Y+ σ)/(1+exp(Y+ σ))
Log normal	exp(Y- σ)	exp(Y)	exp(Y+ σ)

Cost Profile Builder

The Cost Profile Builder allows the user to create a unique cost profile by entering specific procedures, drugs, and inpatient stays related to a patient claim. The Cost Profile Builder does not depend on the inputs used to generate claim costs or treatment statistics. Instead, it is a summary of the 25th percentile, 50th percentile (median), and 75th percentile of costs associated with a treatment. The procedure and drug summary statistics were calculated by distinct CPT and NDC codes using the CCAE database, not restricted to patients with a disability, where statistics were only calculated if the treatment had at least associated 100 payments. For the DRG codes, we used the NIS database and calculated nationwide estimates using the supplied survey weights.

Accuracy

In-Sample Accuracy

When specifying a principal procedure/treatment, the total cost models captured approximately 19% of the variability, as measured by the R^2 between the predicted and observed costs. The average mean squared error was 1.7. The maximum amount of variability captured was 64%. The reasons for variability in our models include the variability in the care costs, the limited number of variables provided for the models, and limiting the models to either logistic or log-linear models. Variability in medical costs is well known, and we also found significant variability between research study findings, making comparisons of our results to those in the literature difficult.

Out-of-Sample Accuracy

Predicted costs were compared to IBM Watson's Workers' Compensation medical costs. Although the total amount of medical expenses for WC claims is available in IBM's HPM database, we do not have access to information at the medical billing level that corresponds to the type of procedures or prescriptions. Because we did not use this data in building our models, this is a true validation dataset to compare our predicted costs to an external data source. IBM's WC data includes diagnosis, age, and geographic location, but no other variables present in our predictive models, requiring this analysis to assume that IBM's WC population had similar characteristics as our population including the types of procedures performed for the specific diagnosis. For our population, we predicted the medical costs for WC claims by diagnosis not specifying a specific principal treatment, but averaging the costs across all principal treatments performed. Then for both IBM and our sample, we took the median medical costs per diagnosis for those conditions with at least 1000 records. Our WC claim predictions tended to be higher than IBM's WC costs in the lower range of estimates and lower than IBM's WC costs in the higher range of estimates (Figure 1). Nonetheless, the correlation is strong (Spearman's rho = 0.89) and provides confidence in the accuracy of the model results.

Next, we compared state estimates to those reported by WCRI in their Benchmark Scope Reports.[8] WCRI reports that the 2015/2018 average medical payment per claim for all paid claims at 36 months' average maturity by state. Therefore, to compare, we calculated the average predicted medical costs across all diagnoses (not knowing the exact case mix in WCRI's reports) and applied our state medical price index factor to the estimate. In the 18 states WCRI provides estimates for, our estimates correlations was good (Spearman's rho = 0.62); however, claims in several states (Louisiana, New Jersey, and Illinois) were approximately $2,000 higher in WCRI's estimates (Figure 1). Continued testing with external estimates should help resolve these issues in the future.

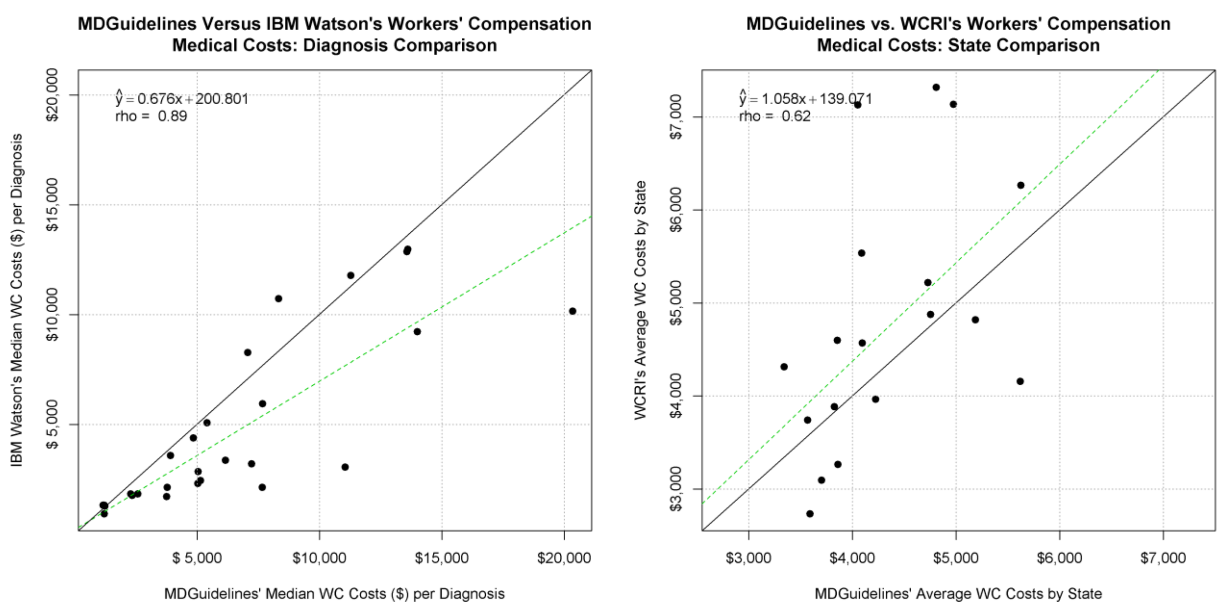

Figure 1. Comparison of MDGuidelines predicted medical costs to IBM Watson's Medical Costs grouped by diagnosis (left plot) and WCRI's 2015/2018 Average medical payment per claim for all paid claims at 36 months average maturity grouped by state (right plot). The green line is the linear fit from a robust linear regression and the black line is the identity.

Finally, we compared our results to estimates found in the literature. When looking at "all diagnoses," our results are generally in line with external estimates (Table 1). For example, our estimates are within $1,000 when comparing to estimates compiled by WCRI, WCIRB, and Pumkam et al. (2013). When we compared our estimates using specific chronic diagnoses like low back pain, our results were in line with three of the four studies (Table 2). For example, Shraim et al. (2015) reported a median medical cost for low back pain of $3,786,[17] which is approximately $500 higher than our estimate. Our estimates for disabilities with surgeries are also in alignment with the research (Table 3), likely due to our models being able to use the principal procedure variable to get a more accurate estimate.

Table 1. Comparison of MDGuidelines' medical cost estimates for "all diagnoses" to external estimates

Medical episode/procedure	MDGuidelines' Estimate	External Estimate	Reference to External Estimate
All diagnoses	\$5,433 (WC median) \$5,281 (WC mean)	\$4,631	WCRI's 18-state median of average medical costs. 2014/2017 all paid claims at 36 months average maturity. U.S.
All diagnoses	\$5,433 (WC median) \$5,281 (WC mean)	\$5,018	WCIRB's average medical costs in 2014 with 30 months of maturity.[18] California, U.S.
All diagnoses	\$5,433 (WC median) \$5,281 (WC mean)	\$10,896	WC estimates from White et al. (2012). Michigan, U.S. 2006 to 2011. Average costs. [19]
All diagnoses	\$5,433 (WC median) \$5,281 (WC mean)	\$3,841	Average costs for 418 claims reported at The Erickson Living Experience. Results presented by Shiner and Thorne at AOHC 2019.[20] U.S.
All diagnoses	\$5,433 (WC median) \$5,281 (WC mean)	\$2,718 (workers with persistent disabilities) \$1,797 (workers without persistent disabilities)	Expenditure per occupational injury. U.S. national estimate from MEPs data. 2004 – 2011. Shi et al. (2015)[21]
All diagnoses	\$2,292 (STD median) \$3,184 (STD mean)	With persistent disabilities: \$4,234 With temporary disabilities: \$1,612 No disabilities: \$748	Data from Medical Expenditure Panel Survey panel 12 (2007 to 2008). U.S. Pumkam et al. (2013). Median annual expenditures, self-reported.[22]
All diagnoses	\$5,281 (WC mean)	\$5,566 (mean)	WorkSafeBC average medical expenditure for 2017. British Columbia, Canada.[23] Converted from Canadian dollars using 1 CAD = 0.76 USD.
All diagnoses	\$5,281 (WC mean)	\$3,498 (mean)	Average compensated WC claims in 2012/2013. Australia.[24] Converted from Australian dollars using 1 AUD = 0.70 USD:

Table 2. Comparison of MDGuidelines' medical cost estimates to external estimates. Chronic conditions. MDGuidelines estimates are a weighted average of all STD or WC claims with and without inpatient stays.

Medical episode/procedure	MDGuidelines' Estimate	External Estimate	Reference to External Estimate
Low back pain	$3,252 (WC median) $3,522 (WC mean)	$3,786 (median) $8,296 (mean)	Low back pain WC claims from 49 U.S. states, Shraim et al. (2015).[17]
Low back pain	$3,252 (WC median)	$770 (median)	Low back pain WC claims from Utah. U.S. Owens et al. (2019).[25]
Low back pain	$3,252 (WC median) $3,522 (WC mean)	$12,188 (mean)	Low back WC claims from Webster et al. (2007). 2002 to 2003, U.S. nationwide sample.[26]
Major depressive disorder	$1,233 (STD median) $1,708 (STD mean)	$1,730 (mean)	Gauthier et al. (2017) reported per-patient-per-year mean medical costs associated with MDD-related pharmacy costs and mental health related mental costs following first-line antidepressant treatment for patients with major depressive disorder. U.S. Non-disability related claims from 2003 to 2014.[27]
Major depressive disorder	$1,233 (STD median) $1,708 (STD mean)	$487 (adjusted mean)	Mental health and addiction costs per person per year. Nationally weighted and covariate adjusted. Chiu et al. (2017). Canadian, general population in 2002.[28]

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Table 3. Comparison of MDGuidelines' average medical cost estimates to external estimates. Surgeries. MDGuideline estimates use STD program type, age = 45, no inpatient stay, and zip code = 80033.

Medical episode/procedure	MDGuidelines' Estimate	External Estimate	Reference to External Estimate
Cataract surgery	$4,878 (no comorbidities) $5,060 (with hypertension)	$3,600 to $6,000	https://www.allaboutvision.com/conditions/cataract-surgery-cost.htm. Accessed 5/14/2019.
Cataract surgery	$4,878 (no comorbidities) $5,060 (with hypertension)	$8,808	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs. Accessed May 2019. Inpatient/Outpatient care combined.
Knee arthroscopy	$5,747 (no comorbidities) $5,648 (with depression)	$9,775	Fair Health Consumer Episode of Care. Using zip code of 80033, in-network costs. Accessed May 2019. Inpatient/Outpatient care combined.
Achilles tendon rupture	$5,010 (no comorbidities) $9,542 (with hypertension)	Surgical: €5007 or $5,6585 Non-surgical: €2890 or $3,224	Direct costs of surgical vs. non-surgical treatment of Achilles rupture by Westin et al. (2018).[29] Sweden. Euro conversion made May 22, 2019.
Achilles tendon rupture	$5,010 (no comorbidities) $9,542 (with hypertension)	$3,145	Initial surgical cost of surgical repair from a Markov cost-utility analysis.[30]
Carpal tunnel release	$5,308 (no comorbidities) $10,046 (with depression)	$4,000 to $12,000	https://www.mycarpaltunnel.com/carpal-tunnel-surgery/cost.shtml. Accessed 5/14/2019.

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References

1. Zaidel CS, Ethiraj RK, Berenji M, Gaspar FW. Health Care Expenditures and Length of Disability Across Medical Conditions. *J Occup Environ Med*. 2018;60(7):631-636. doi:10.1097/JOM.0000000000001308
2. Berwick DM, Hackbarth AD. Eliminating waste in US health care. *Jama*. 2012;307(14):1513-1516. doi:10.1001/jama.2012.362
3. Institute of Medicine. Variation in Health Care Spending Assessing Geographic Variation. 2013;(July). http://nationalacademies.org/hmd/~/media/Files/Report Files/2013/Geographic-Variation2/geovariation_rb.pdf.
4. Quan H, Li B, Couris CM, et al. Updating and validating the charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. *Am J Epidemiol*. 2011;173(6):676-682. doi:10.1093/aje/kwq433
5. Department of Labor. Geographic Practice Cost Index by Zip Code. https://www.dol.gov/owcp/regs/feeschedule/fee/feeOct1518/download.htm. Published 2018. Accessed February 1, 2019.
6. United States Government Accountability Office. *Geographic Adjustment Indices Are Valid in Design, but Data and Methods Need Refinement. GAO-05-119*.; 2005.
7. Agency for Healthcare Research and Quality. Clinical Classifications Software. Healthcare Cost and Utilization Project. http://www.ahrq.gov/data/hcup/. Published 2016. Accessed August 2, 2017.
8. Belton SE, Yang R (Rui), Telles CA, Radeva E, Savych B, Monnin-Browder W. *CompScope™ Medical Benchmarks*.; 2018. www.wcrinet.org/reports/compscope-medical-benchmarks-19th-edition.
9. Central Services Division Information Technology and Research Section. *Oregon Workers' Compensation Premium Rate Ranking Calendar Year 2016*.; 2106. www.oregon.gov/DCBS/reports/Documents/general/prem-rpt/16-2083.pdf.
10. McLaren C, Baldwin M, Boden L. *Workers ' Compensation: Benefits, Coverage, and Costs (2016 Data)*. National Academy of Social Insurance; 2018. https://www.nasi.org/sites/default/files/WorkersComp2016_FINAL.pdf.
11. Office of Workers' Compensation Programs. Geographic Practice Cost Index Values. *Accessed Febr 1, 2019*. 2018. https://www.dol.gov/owcp/regs/feeschedule/fee/feeOct1518/download.htm.
12. Observational Health Data Sciences and Informatics. ATHENA Standardized Vocabularies. Accessed. http://athena.ohdsi.org. Accessed July 11, 2018.
13. Lumley T. Survey: Analysis of Complex Survey samples. *CRAN*. 2019.
14. Quan H, Sundararajan V, Halfon P, et al. Coding algorithms for defining comorbidities in ICD-9-CM and ICD-10 administrative data. *Med Care*. 2005;43(11):1130-1139. doi:10.1097/01.mlr.0000182534.19832.83
15. Tibshirani R. Regression Shrinkage and Selection via the Lasso. *J R Stat Soc*. 1996;58(1):267-288.

16. Friedman J, Hastie T, Tibshirani R. Regularization Paths for Generalized Linear Models via Coordinate Descent. *J Stat Softw*. 2010;33(1):1-22. http://www.jstatsoft.org/v33/i01/.

17. Shraim M, Cifuentes M, Willetts JL, Marucci-Wellman HR, Pransky G. Length of disability and medical costs in low back pain: Do state workers' compensation policies make a difference? *J Occup Environ Med*. 2015;57(12):1275-1283. doi:10.1097/JOM.0000000000000593

18. Workers' Compensation Insurance Rating Bureau of California. Interactive Policy Year Stats- 2018 Edition. 2018. https://www.wcirb.com/content/interactive-policy-year-stats. Accessed July 1, 2019.

19. White J a, Tao X, Talreja M, Tower J, Bernacki E. The effect of opioid use on workers' compensation claim cost in the State of Michigan. *J Occup Environ Med*. 2012;54(8):948-953. doi:10.1097/JOM.0b013e318252249b

20. Shiner J, Thorne C. Successful Application of Evidence-Based Workers' Compensation Best Practices: The Erickson Living Experience. In: *American Occupational Health Conference*. Anaheim, CA; 2019.

21. Shi J, Wheeler KK, Lu B, Bishai DM, Stallones L, Xiang H. Medical expenditures associated with nonfatal occupational injuries among U.S. workers reporting persistent disabilities. *Disabil Health J*. 2015;8(3):397-406. doi:10.1016/j.dhjo.2014.10.004

22. Pumkam C, Probst JC, Bennett KJ, Hardin J, Xirasagar S. Health care expenditures among working-age adults with physical disabilities: Variations by disability spans. *Disabil Health J*. 2013;6(4):287-296. doi:10.1016/j.dhjo.2013.03.002

23. WorkSafeBC. Statistics 2017. 2017. https://www.worksafebc.com/en/resources/about-us/annual-report-statistics/2017-stats?lang=en. Accessed July 7, 2019.

24. Safe Work Australia. *The Cost of Work-Related Injury and Illness for Australian Employers, Workers and the Community: 2012-13*.; 2015. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:THE+COST+OF+WORK-RELATED+INJURY+AND+ILLNESS+FOR+AUSTRALIAN+EMPLOYERS+,+WORKERS+AND+THE+COMMUNITY+:+2008-09#0.

25. Owens JD, Hegmann KT, Thiese MS, Phillips AL. Impacts of Adherence to Evidence-Based Medicine Guidelines for the Management of Acute Low Back Pain on Costs of Worker's Compensation Claims. *J Occup Environ Med*. 2019;61(6):1. doi:10.1097/jom.0000000000001593

26. Webster BS, Verma SK, Gatchel RJ. Relationship Between Early Opioid Prescribing for Acute Occupational Low Back Pain and Disability Duration, Medical Costs, Subsequent Surgery and Late Opioid Use. *Spine (Phila Pa 1976)*. 2007;32(19):2127-2132. doi:10.1097/BRS.0b013e318145a731

27. Gauthier G, Guérin A, Zhdanava M, et al. Treatment patterns, healthcare resource utilization, and costs following first-line antidepressant treatment in major depressive disorder: a retrospective US claims database analysis. *BMC Psychiatry*. 2017;17(1):222. doi:10.1186/s12888-017-1385-0

28. Chiu M, Lebenbaum M, Cheng J, De Oliveira C, Kurdyak P. The direct healthcare costs associated with psychological distress and major depression: A population-based cohort study in Ontario, Canada. *PLoS One*. 2017;12(9):1-13. doi:10.1371/journal.pone.0184268

29. Westin O, Svensson M, Nilsson Helander K, et al. Cost-effectiveness analysis of surgical versus

non-surgical management of acute Achilles tendon ruptures. *Knee Surgery, Sport Traumatol Arthrosc*. 2018;26(10):3074-3082. doi:10.1007/s00167-018-4953-z

30. Ellis S, Koltsov J, Nwachukwu B, Marinescu A, Gribbin C. Cost-Effectiveness of Operative Versus Nonoperative Management of Acute Achilles Tendon Ruptures. *Foot Ankle Orthop*. 2017;2(3):2473011417S0001. doi:10.1177/2473011417s000164