RESEARCH BRIEF

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Impairment Ratings in Workers Compensation: Gaining Insights From Claim Demographics

INTRODUCTION

Permanent partial disability injuries account for approximately 50% of all workers compensation costs, with impairment ratings playing a key role in most states. Consequently, changes in impairment ratings can have a significant impact on workers compensation costs. For instance, a 1% change in the average impairment rating could result in an approximate $2,500[1] change in permanent partial disability costs, or about an 8% change in indemnity benefits for a permanent partial claim.

Given frequent updates to the *American Medical Association Guides to the Evaluation of Permanent Impairment (AMA Guides)* and advancement in medical treatment, it is essential to understand how different claim characteristics can influence these ratings. This research focuses on analyzing impairment ratings, incorporating a diverse range of claim characteristics. The primary goal of this study is to provide insights into factors related to impairment ratings and analyze state differences using a regression model. The html version of this article also provides the ability to drill down on state-specific results and download the statistics used for each of the charts.

KEY INSIGHTS

- Across states included in the study,[2] the average whole-body[3] impairment rating is 6.5%, and the average time to maximum medical improvement (MMI) for claims identified as permanent partial is 363 days
- After accounting for key factors such as medical condition, surgery count, age, and time-to-MMI in a controlled model:
  - The average impairment rating varies by state, ranging from about 4% to approximately 11%
  - Claims involving surgery have, on average, impairment ratings that are 2 points higher than those without surgery (7.2% vs. 5%)
  - Claims with time-to-MMI under 90 days average a 4.4% impairment rating, while those taking over two years average 9.1%
  - Average impairment ratings for the most common medical conditions vary from about 3% for hand/wrist synovitis to approximately 10% for lumbar spine degeneration

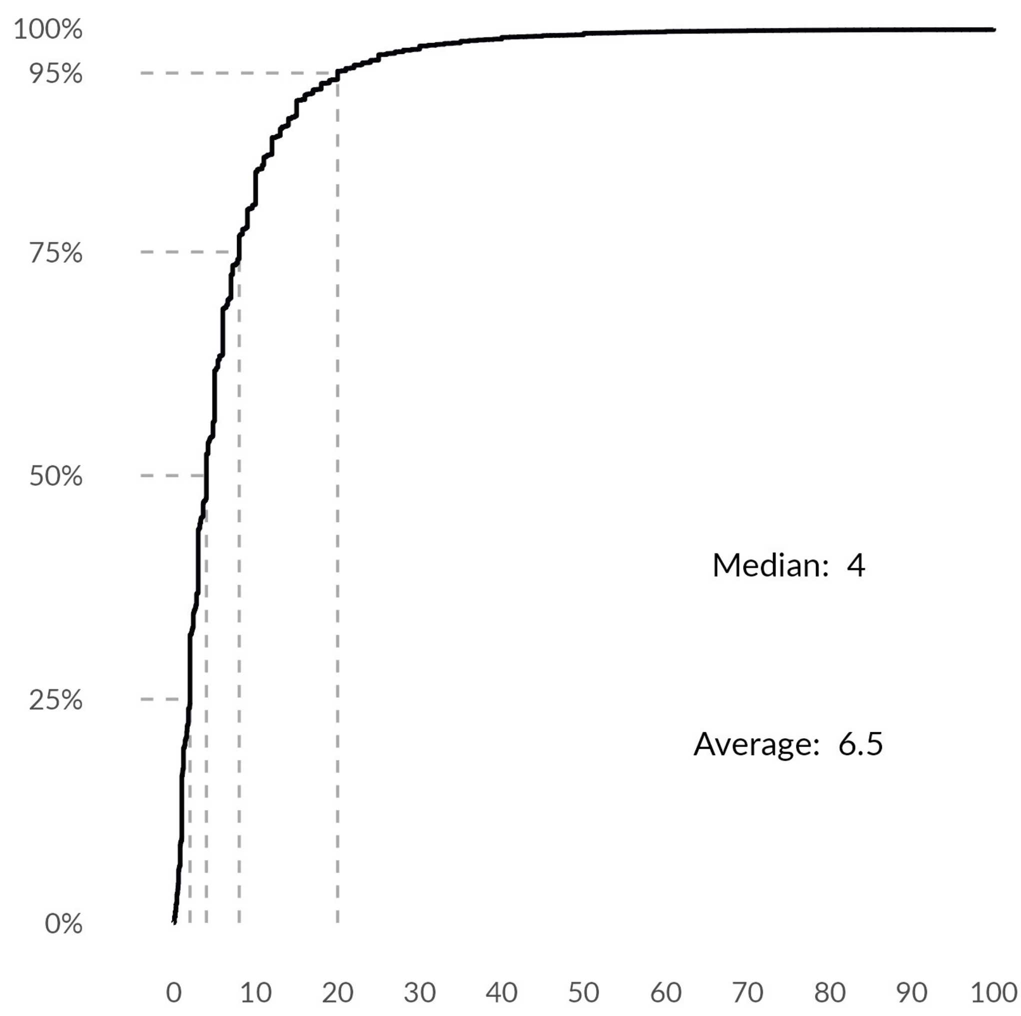
[1] Based on a sampling of states.
[2] Includes data from the following jurisdictions: AK, AL, AR, AZ, CO, CT, DC, FL, GA, HI, IA, ID, IL, IN, KS, KY, MD, MO, MS, MT, NC, NE, NH, NM, NV, OK, OR, SC, SD, TN, UT, VA, VT, and WV.
[3] In NCCI's Indemnity Data Call, impairment ratings may be reported for either individual body parts or on a whole-body basis. For consistency, all part of body ratings in this study are converted to their whole-body equivalent.

DATA ANALYSIS AND SUMMARY STATISTICS

Impairment ratings can range from 0% to 100% depending on various factors assessed during a medical provider's evaluation. For the states included in this study, the average whole-body impairment rating is 6.5%. Exhibit 1 illustrates the overall distribution of these ratings by showing the percentage of claims (y-axis) with a whole-body impairment rating (x-axis) at or below a certain value.

From Exhibit 1, we get that 50% of claims have an impairment rating of 4% or less. The steep slope of the graph indicates that most claims have a whole-body impairment rating in the single digits. In fact, 95% of claims have an impairment rating of 20% or less. Across study states, the median impairment ranges between 2% and 9%.

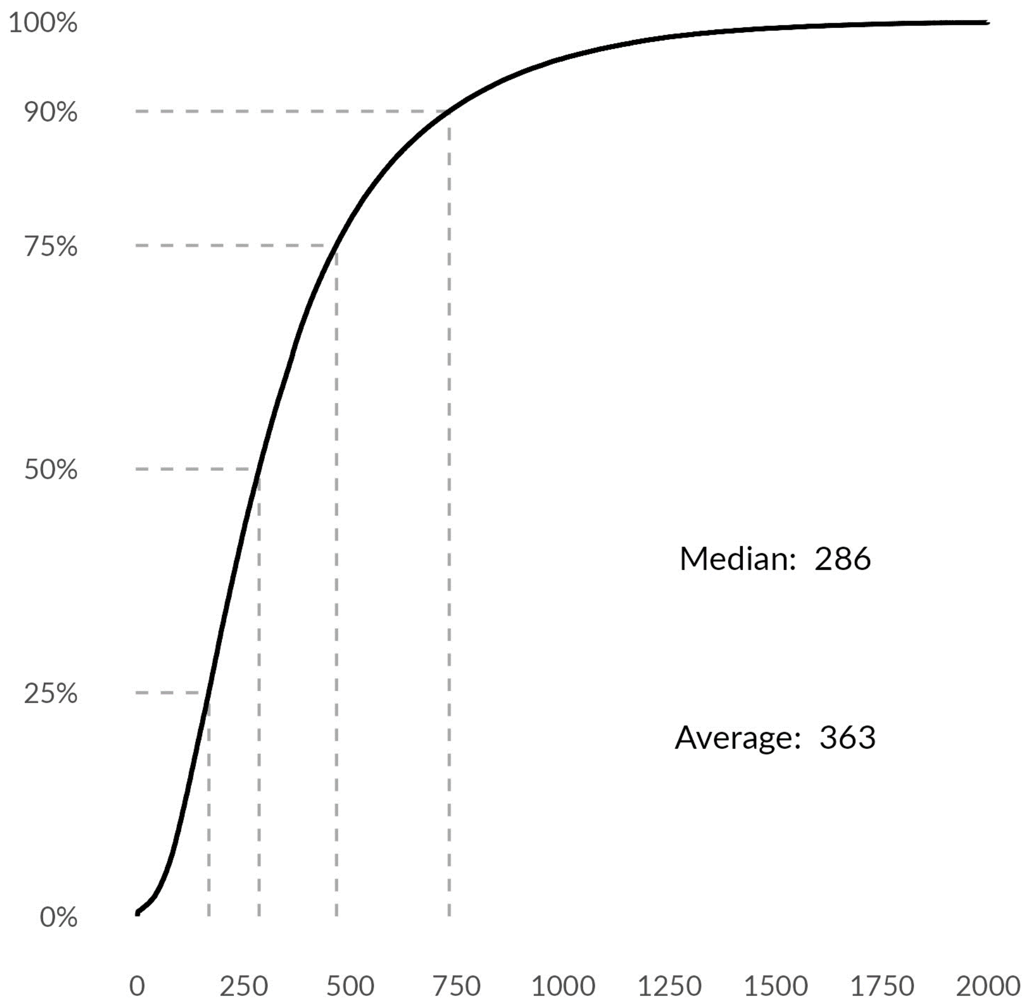
Exhibit 1: Cumulative Density of Impairment



Achieving maximum medical improvement (MMI) marks a pivotal milestone in the recovery journey, especially for cases involving potential permanent disability. The recovery period is critical because it precedes the determination of impairment ratings and is contingent upon various factors specific to each claim, such as the nature of the medical condition or any complications that may arise.

In Exhibit 2, the distribution of time taken from injury to reach MMI across all claims underscores the variability in recovery periods. This time frame spans from a few days to well beyond a year, with an average duration of 363 days. Notably, 90% of cases achieve MMI within two years post-injury, highlighting the general timeline within which most claims stabilize medically. Across study states, the median time-to-MMI ranges between 189 and 644 days.

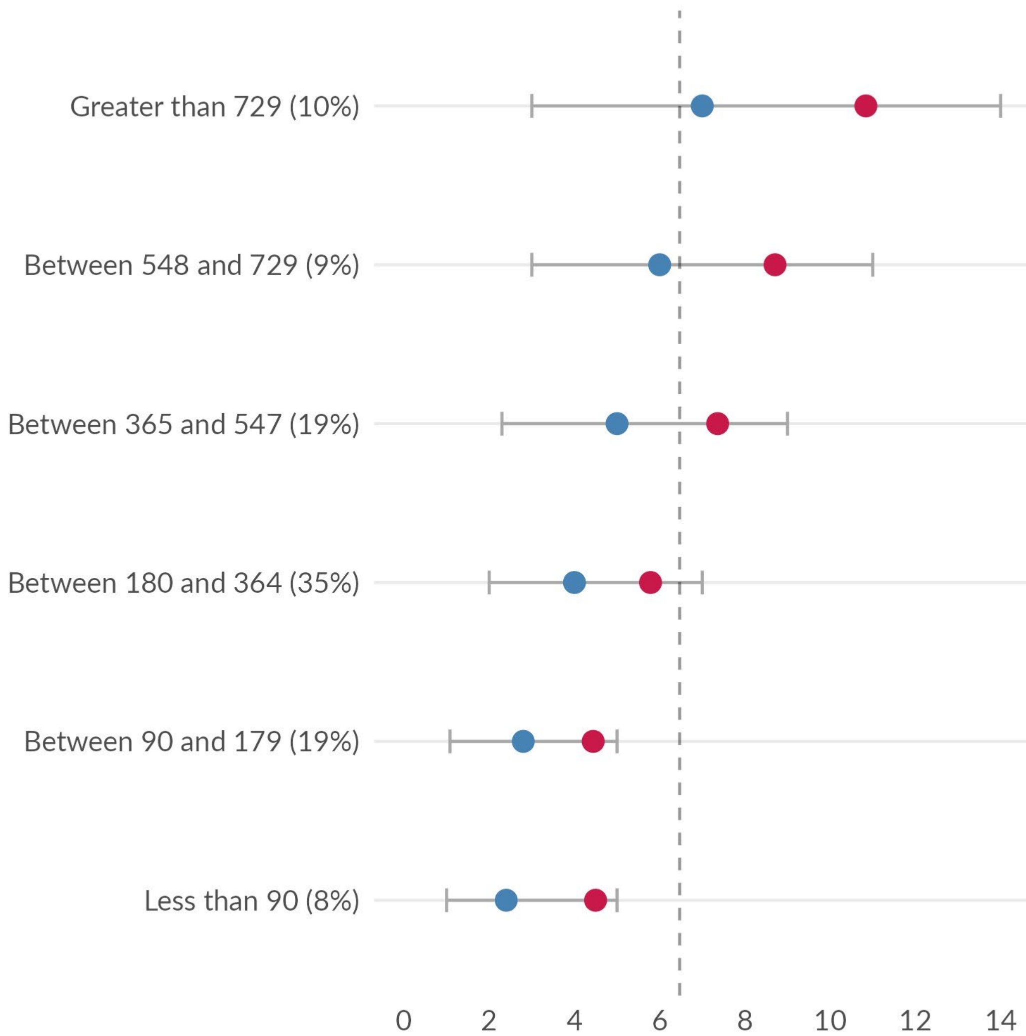
Exhibit 2: Cumulative Density of Time-to-MMI



The time-to-MMI is expected to correlate with the extent of anticipated impairment. Notably, a longer time-to-MMI tends to correspond to higher levels of impairment.

Exhibit 3 presents the averages, the medians, and the range (between the 25th and 75th percentiles) of impairment levels categorized by time-to-MMI. In this exhibit, the overall average impairment is indicated by a dashed line, allowing above-average categories to be identified by average values to the right of the line. Additionally, the proportion of claims for each group is shown in parentheses next to the group description. The exhibit reveals that claims reaching MMI in less than six months result in an average impairment of approximately 5%, whereas claims taking more than two years typically result in an average impairment of about 11%.

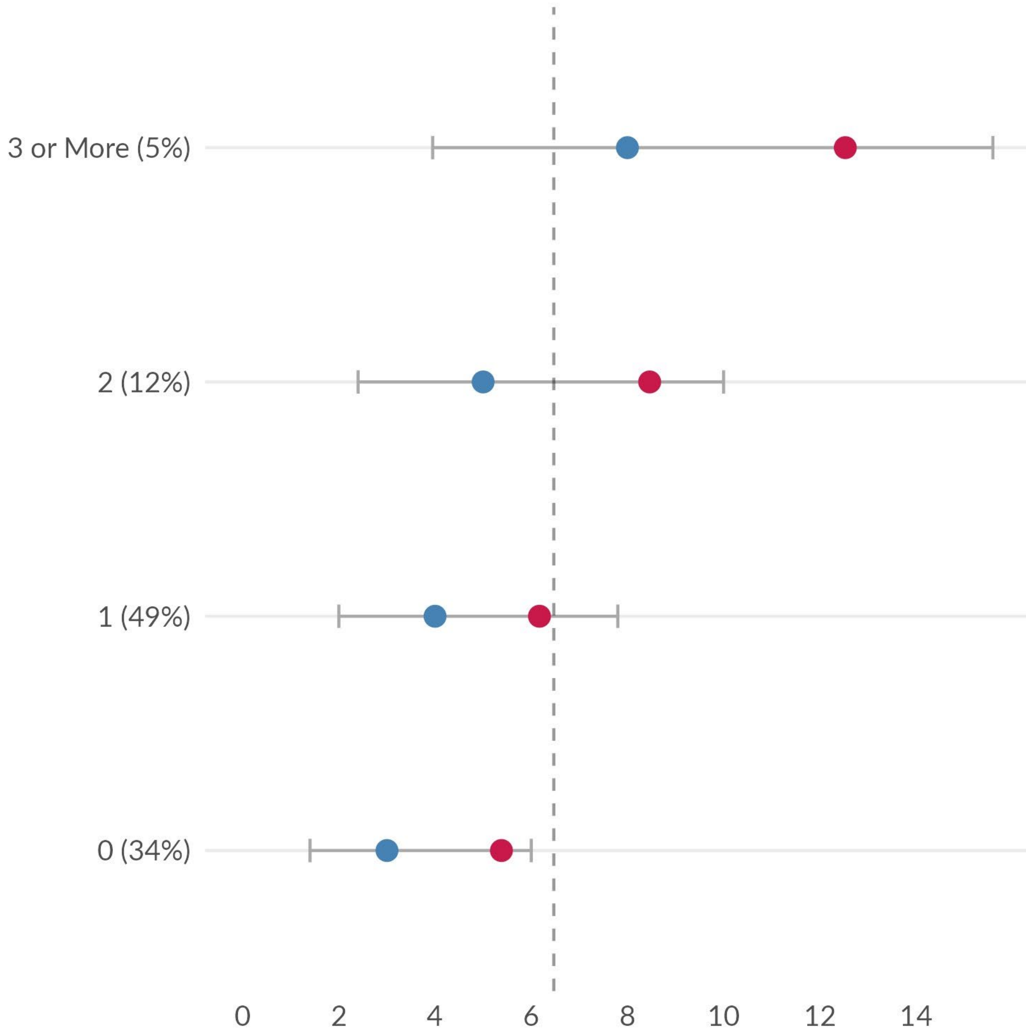
Exhibit 3: Average and Median Impairment by Time-to-MMI Group With 25th to 75th Percentile Range



Another factor expected to relate to the impairment rating is whether an injured worker received surgical treatment. To analyze this relationship, we compare the impairment levels between claimants who did not undergo any surgical procedures[4] and those who had at least one. Exhibit 4 illustrates the impairment levels for claims involving 0, 1, 2, and 3 or more surgical procedures. Claims involving more than two surgical procedures exhibit above-average impairment ratings. Claims involving two or more surgeries likely indicate multiple injuries and/or potential post-surgery complications requiring further operations.

[4] In this study, a service is classified as "surgical" if it falls within the surgical category as defined by the AMA. A service is further classified as "major surgery" if it is not an injection and has a global follow-up period of 90 days, as defined by the Centers for Medicare & Medicaid Services, or the procedure involves spine/spinal cord neurostimulators.

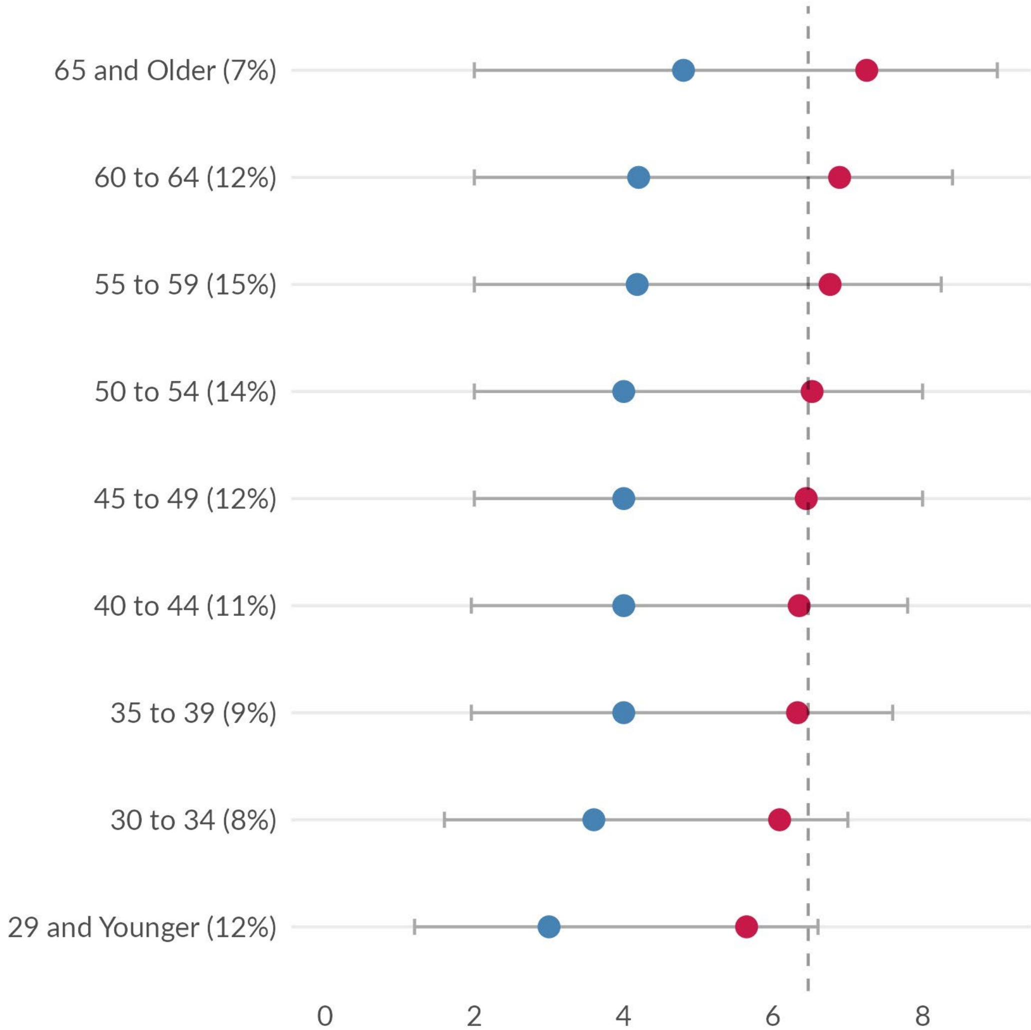
Exhibit 4: Average and Median Impairment by Surgery Group With 25th to 75th Percentile Range



The worker's age at the time of injury is another factor that might influence the level of impairment rating. A healthy 25-year-old is generally anticipated to recover from a fracture more swiftly and experience fewer post-injury complications than an injured worker nearing retirement age. Exhibit 5 compares impairment levels across different age groups.

Although the average impairment rating increases with age, the rate of increase is moderate. The exhibit shows that claimants 29 and younger have an average impairment of approximately 6%, whereas claimants older than 65 have an average impairment of about 7%. Between each adjacent age group, the marginal average increase in impairment is less than half a percentage point.

Exhibit 5: Average and Median Impairment by Age Group With 25th to 75th Percentile Range

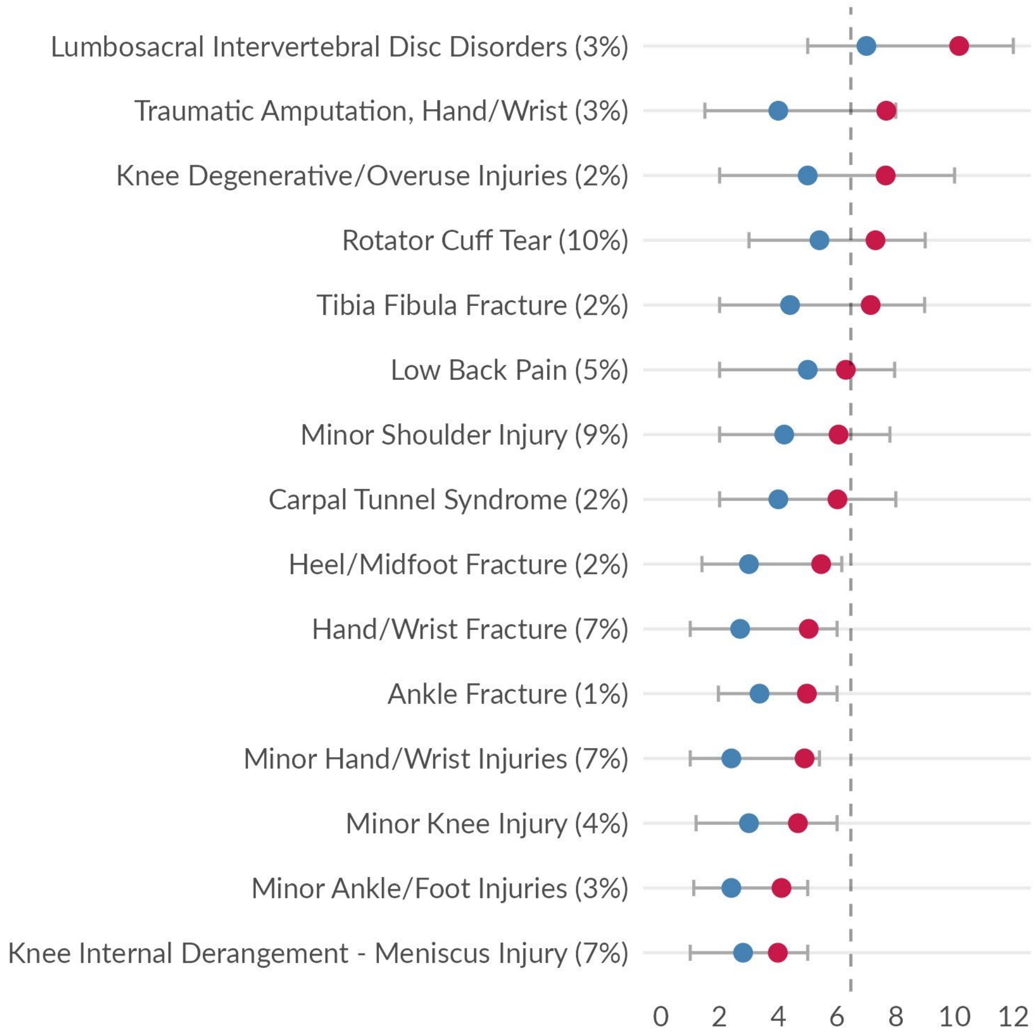


Medical condition or diagnosis is important in determining impairment ratings by medical providers. One would expect a finger amputation to result in a higher average impairment than a fractured finger. Medical providers often rely on guidelines that are established for specific medical conditions.

By using the primary medical condition associated with all medical transactions for each individual claim, we establish a single medical condition for each claim in our study. This approach allows us to compare differences in impairment levels among the most common medical conditions in workers compensation, as shown in Exhibit 6.

Among the conditions with the highest average impairment, we observe back-related injuries of disc disorders. In contrast, conditions related to lower extremities, such as meniscus injuries and minor ankle injuries, exhibit lower impairment levels.

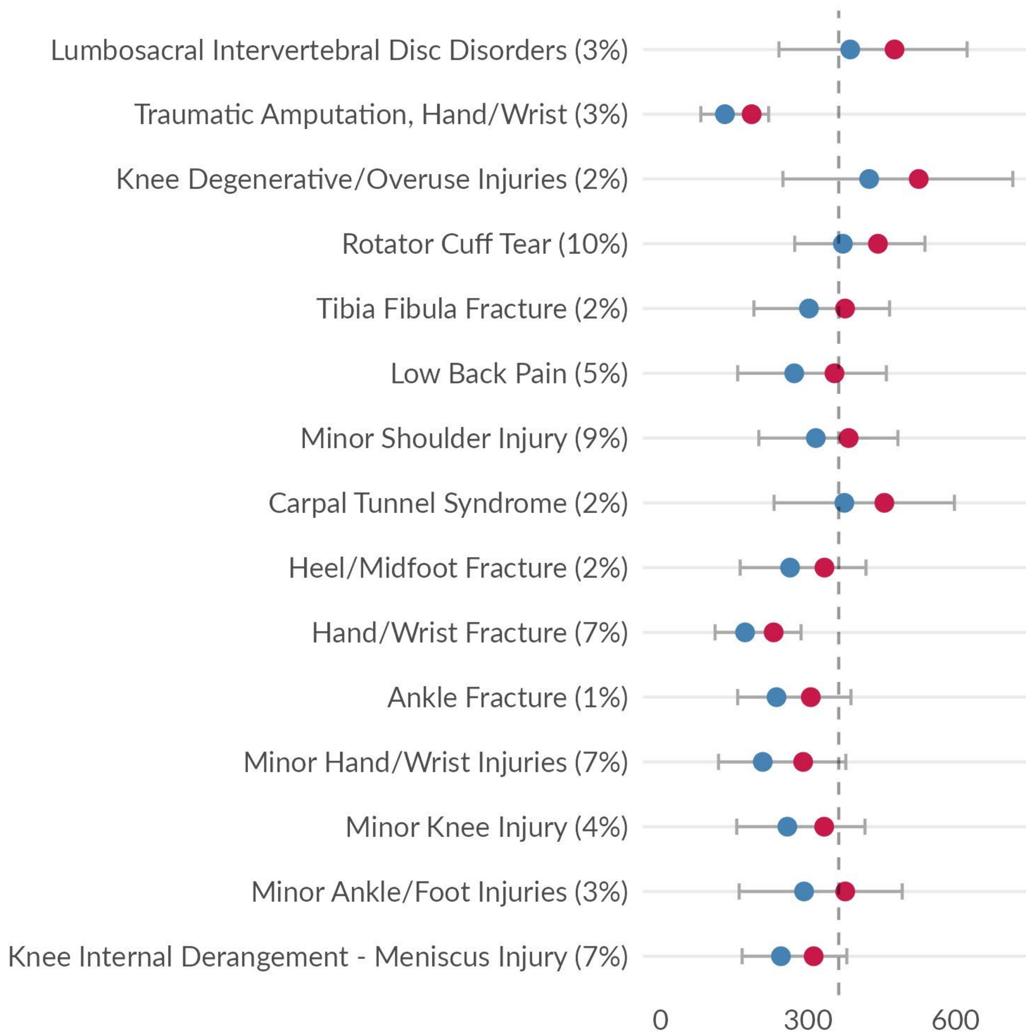
Exhibit 6: Average and Median Impairment by Medical Condition With 25th to 75th Percentile Range



As shown in Exhibit 3, the level of impairment correlates with the length of time to reach maximum medical improvement (MMI). However, when comparing the time-to-MMI for the top medical conditions, some conditions exhibit above-average impairment ratings but below-average time-to-MMI, and vice versa. Exhibit 7 presents the time-to-MMI statistics for the top medical conditions, maintaining the order of average impairment from the previous exhibit.

Generally, medical conditions with above-average impairment ratings also have an average time-to-MMI that is above average. However, there are exceptions to this pattern. For example, hand amputations tend to have above-average impairment ratings, but the average time-to-MMI for these cases is among the lowest for common medical conditions. Conversely, carpal tunnel syndrome has a below-average impairment rating, but the average time-to-MMI is above average.

Exhibit 7: Average and Median Time-to-MMI (days) by Medical Condition With 25th to 75th Percentile Range



Analyzing state differences in average impairment is a primary objective of this research. To fairly compare states, we must first account for underlying differences in claim characteristics that relate to impairment ratings. For example, concluding that state X has higher average impairments than state Y might be misleading if state X has more severe claims. Therefore, we must consider state-specific factors that relate to impairment ratings.

Exhibit 8 presents information on these factors by state, as discussed in previous sections.[5] For each factor, we examine the share of claims in each state with characteristics associated with above-average impairment ratings, such as claims with a time-to-MMI of 365 days or more. This analysis reveals significant variation between states for each of these factors. To account for these differences simultaneously, we will employ a modeling approach, which will be discussed in the next section.

[5] Given the available data, this study focuses on these factors, acknowledging that other unaccounted variables may significantly influence state differences.

Exhibit 8: State Shares of Categories With Characteristics Leading to Higher-Than-Average Impairment

MODELING STATE RELATIVITIES FOR IMPAIRMENT RATINGS

Variable Selection

We explored numerous factors in our data that we believed could correlate with impairment ratings. Variable selection was determined both qualitatively and quantitatively. For example, while body system is associated with differences in impairment ratings, it is also highly correlated with medical condition. Therefore, we excluded this variable from the model. Additional information on variable selection is included in the Appendix.

Model Specification

To estimate state differences in impairment ratings, we used a linear regression model. Specifically, the model estimates average impairment ratings for each state while adjusting for the following covariates: the number of major surgeries, age, medical condition, and time-to-MMI.

$$impairment\ rating_i = \beta_0 + \beta_1 \times State_i + \beta_2 \times surgery\ count_i + \beta_3 \times age_i + \beta_4 \times medical\ condition_i + \beta_5 \times time\ to\ MMI_i + \epsilon_i$$

where:

- $impairment\ rating_i$ is the impairment rating for the *i*-th observation, or claim *i*
- $State_i$ is the jurisdiction state reported on claim *i*
- $surgery\ count_i$ is the number of major surgeries on claim *i*
- age_i is the age of the claimant on claim *i*
- $medical\ condition_i$ is the primary medical condition associated with all medical transactions for claim *i*
- $time\ to\ MMI_i$ is the time-to-MMI (maximum medical improvement) on claim *i*
- β_0 is the intercept
- $\beta_1,\ \beta_2,\ \beta_3,\ \beta_4,$ and β_5 are the coefficients to be estimated that are associated with the dummy variables representing the categorical variables
- ϵ_i is the error or residual term for the *i*-th observation

Under a normal linear regression model, we assume that errors are homoscedastic and normally distributed:

$$\epsilon_i \sim N(0, \sigma^2)$$

However, we violate the assumption of homoscedasticity (errors do not demonstrate constant variance), thus biasing the standard error estimates. Therefore, the standard errors were adjusted to be heteroscedasticity-robust. After fitting this model, we computed robust standard errors using the Huber-White method to account for potential heteroscedasticity.

Estimated Marginal Means

After fitting the model, we calculated each state's estimated marginal mean (EMM) from the model and divided each state's EMM by the average across states. The EMM represents the modeled state estimate for impairment rating after averaging over all combinations of the covariates. We decided that this summary approach would allow for easier interpretation, compared to state estimates at reference levels for surgery count, age, time-to-MMI, and medical condition.

For more information on the model specification, variable selection, and model diagnostics, see the Appendix.

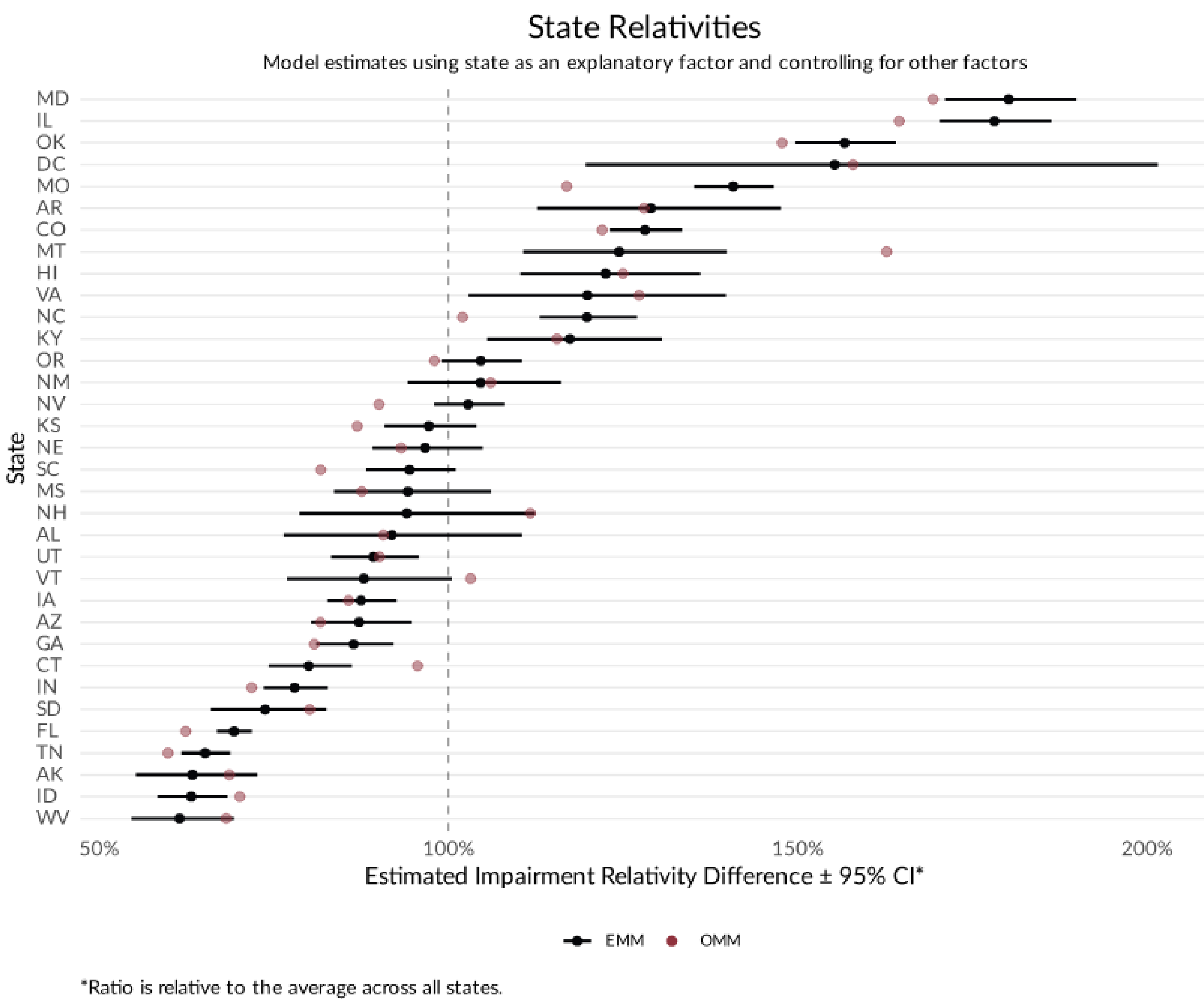
State Results

Exhibit 9 illustrates the modeled estimates of impairment ratings for each state, relative to the overall average. These estimates are adjusted for the age of a claimant, the surgery count on the claim, the medical condition, and the time-to-MMI. The black point intervals represent the modeled point estimate and 95% confidence interval for each state's EMM relativity in impairment ratings. The red dots represent the ordinary marginal mean (OMM) relativity for each state. The estimated impairment rating varies considerably by state, ranging from 3.8% to 11%.

Generally, states with high ordinary marginal means also have high estimated marginal means. However, some states can experience a substantial shift in the estimate after adjustment for covariates. For example, Montana had a particularly high amount of severe medical conditions, which inflate the OMM. After accounting for the variance attributable to medical condition (and other covariates), Montana's modeled estimate (EMM) is shifted closer toward the overall average (to the left).

This example highlights the utility of using a model to provide state estimates of impairment ratings; it enables us to fairly compare state differences after accounting for factors that also influence impairment ratings. Additionally, this information allows us to consider the level of uncertainty in the comparisons by referencing the confidence intervals.

Exhibit 9: State Relativities in Impairment Rating After Adjusting for Differences in Surgery Count, Age, Medical Condition, and Time-to-MMI

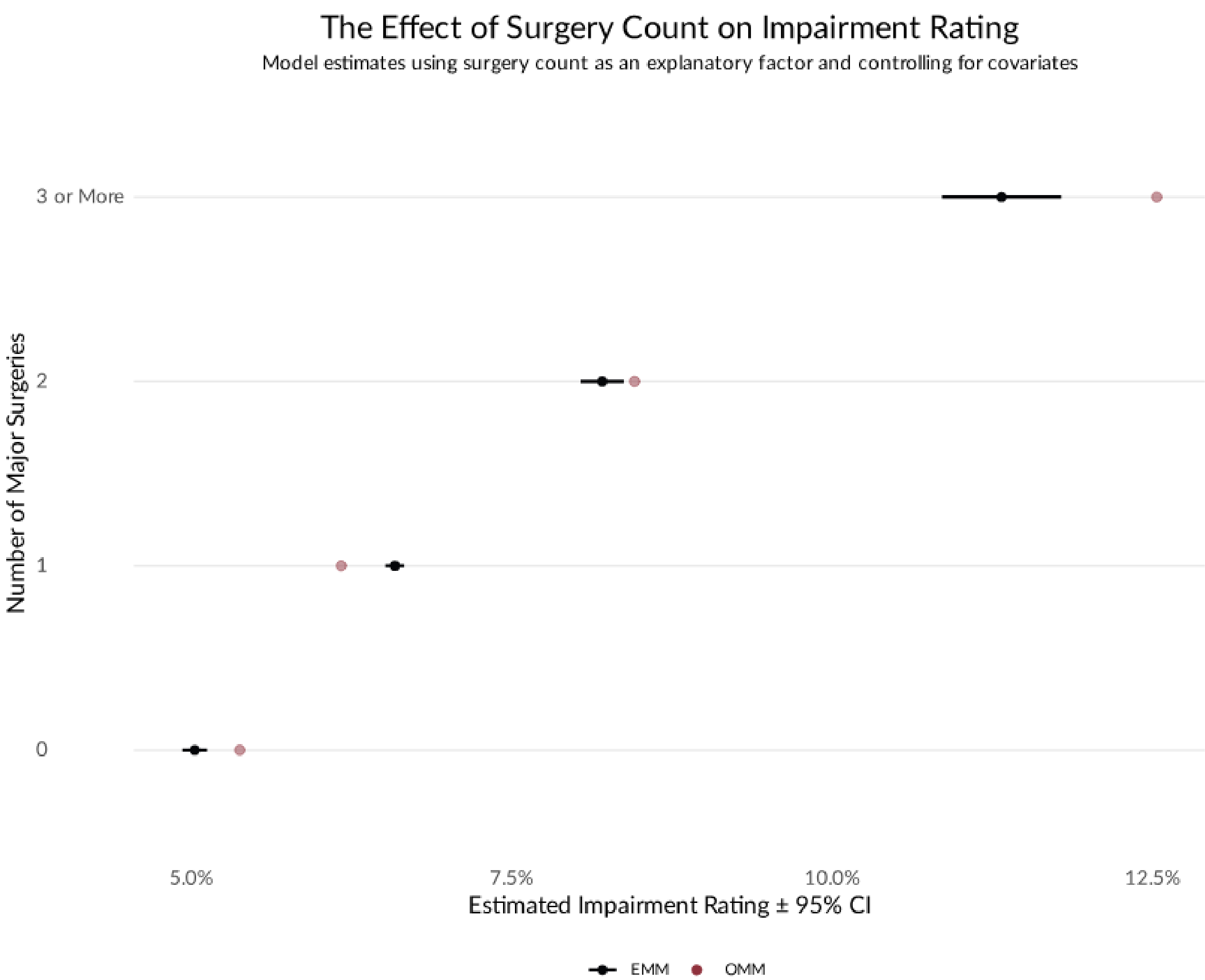


Surgery Results

Exhibit 10 illustrates the modeled estimates of impairment ratings for each level of major surgery count. These estimates are adjusted for state differences, as well as for variation attributable to the age of a claimant, the medical condition, and the time-to-MMI. Said differently, we obtained estimates for each level of surgery count after group-mean centering the data across the other factors in the model (state, age, medical condition, and time-to-MMI). The model's estimates demonstrate a clear trend of increasing average impairment ratings with higher surgery counts:

- Nonsurgical claims have an average impairment of 5%
- Claims with a single surgery average 1.6 points higher than those without surgery (6.6% vs. 5%)
- Claims with two surgeries average 3.2 points higher than those without surgery (8.2% vs. 5%)
- Claims with three or more surgeries average 6.3 points higher than those without surgery (11.3% vs. 5%)

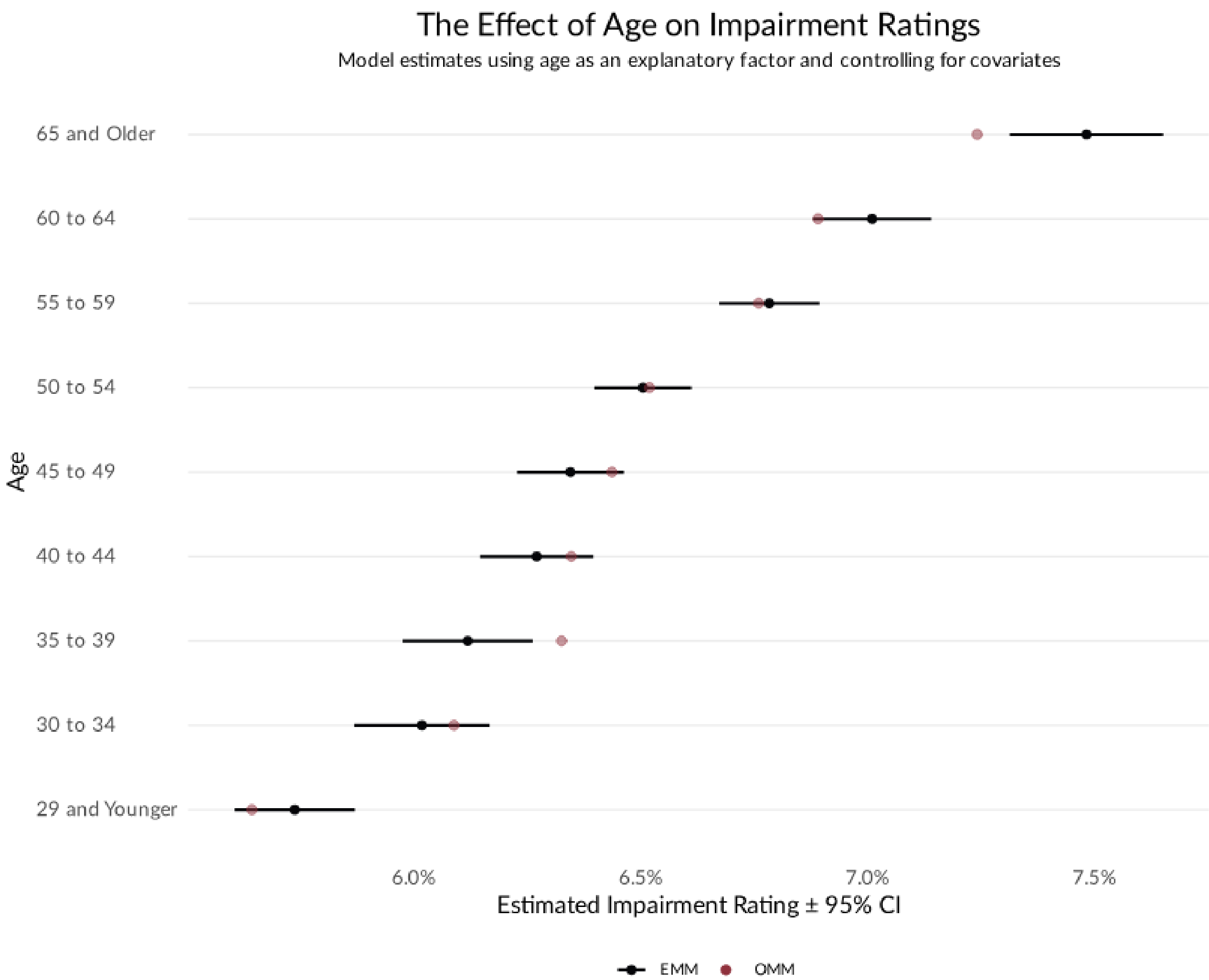
Exhibit 10: Impairment Rating Estimates After Adjusting for State and Differences in Age, Medical Condition, and Time-to-MMI



Age at Injury Results

Exhibit 11 illustrates the modeled estimates of impairment ratings for each age group. These estimates are adjusted for state, surgery count on the claim, medical condition, and time-to-MMI. While estimated average impairment ratings increase with age, the effect size is rather modest with a total range of about 2 points across all groups (i.e., from 5.7% in the youngest age group to 7.5% in the oldest age group).

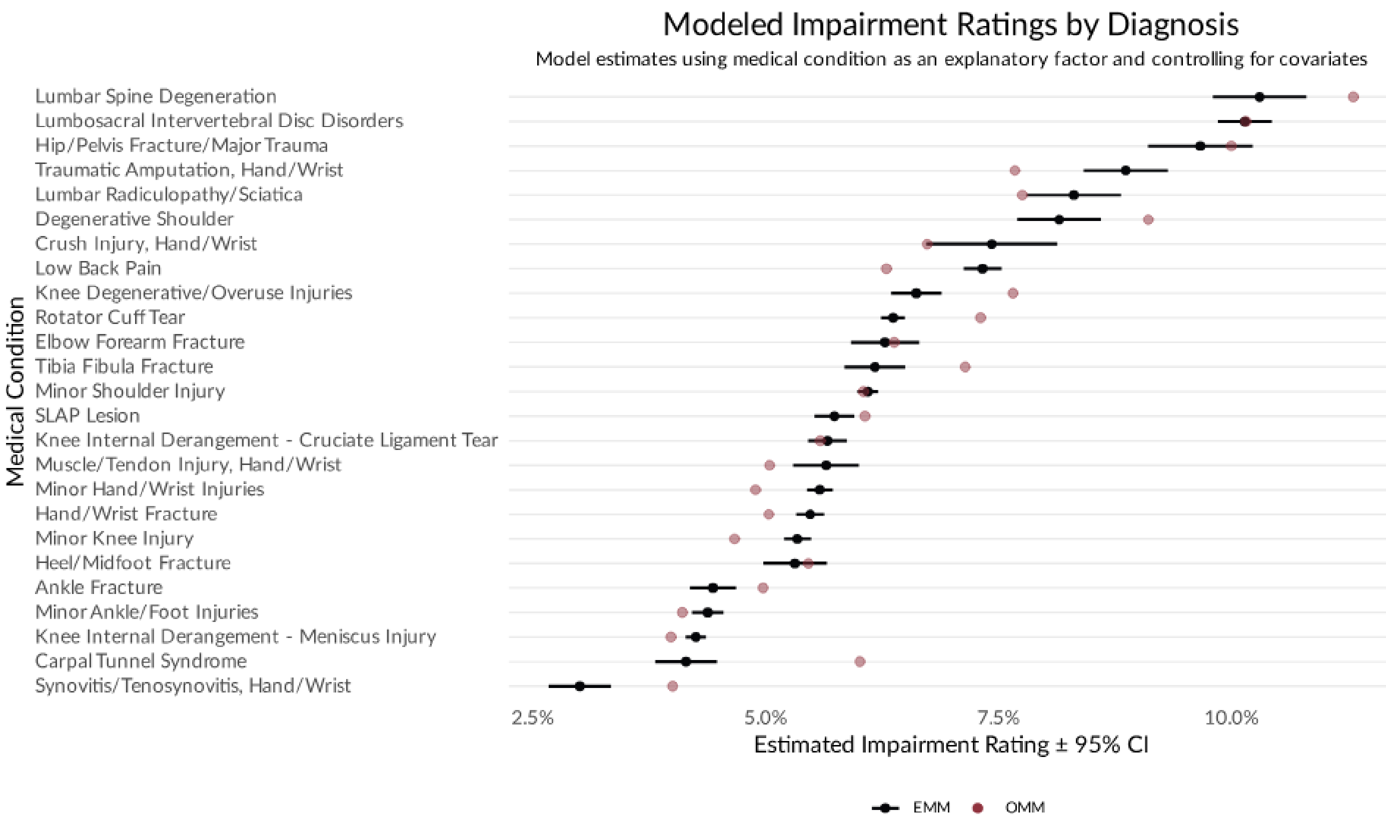
Exhibit 11: Impairment Rating Estimates for Each Age Group After Adjusting for State and Differences in Surgery Count, Medical Condition, and Time-to-MMI



Medical Condition Results

Exhibit 12 illustrates the modeled estimates of impairment ratings for the 25 most common medical conditions. These estimates are adjusted for state, surgery count on the claim, age of the claimant, and time-to-MMI. Among the most common medical conditions, impairment ratings range from 3% for hand/wrist synovitis to 10.3% for lumbar spine degeneration.

Exhibit 12: Impairment Rating Estimates for the Top 25 Most Common Medical Conditions After Adjusting for State and Differences in Surgery Count, Age, and Time-to-MMI



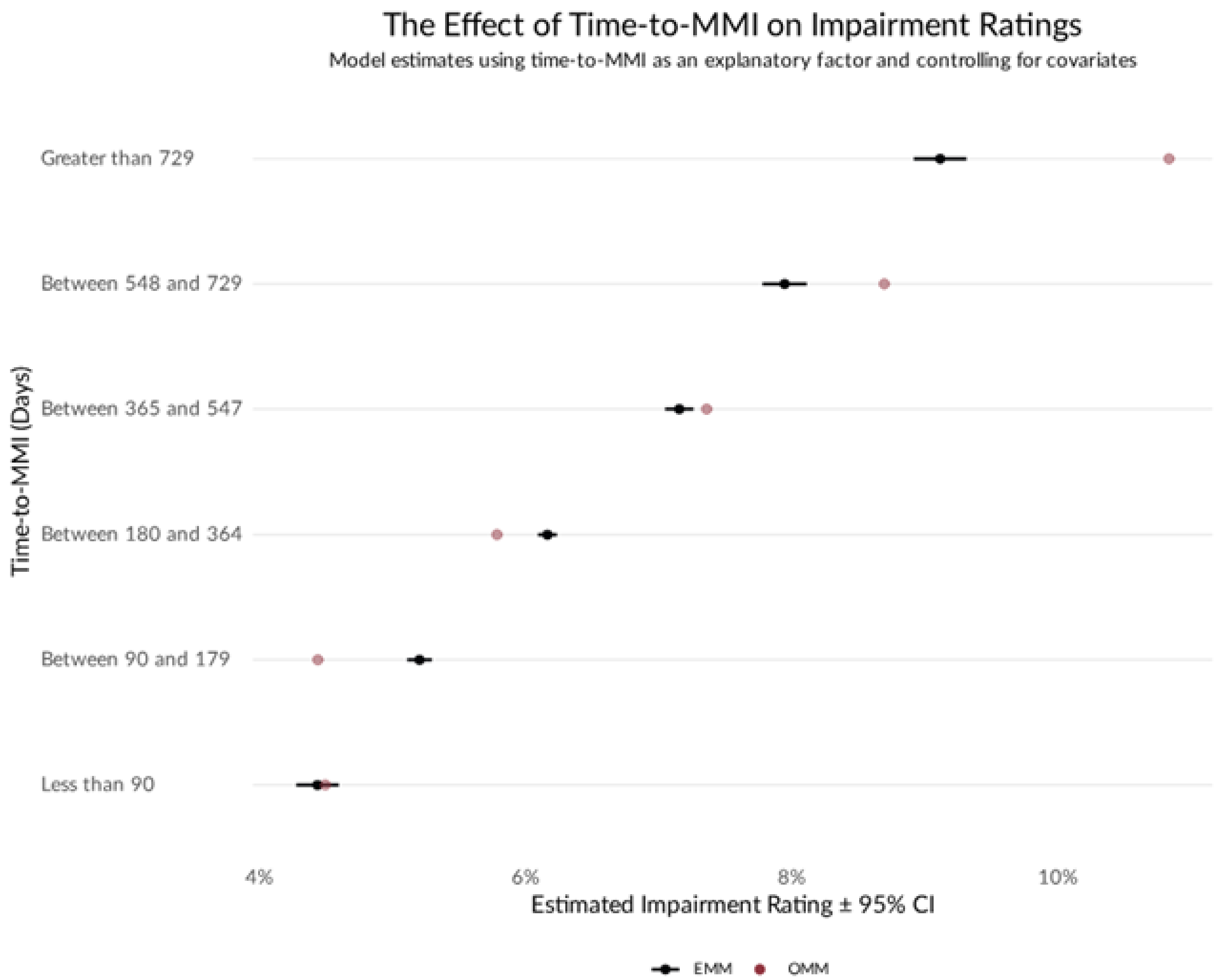
Time-to-MMI Results

Exhibit 13 illustrates the modeled estimates of impairment ratings for claims with time-to-MMI in the following bins:

- Less than 90 days
- Between 90 and 179 days
- Between 180 and 364 days
- Between 365 and 547 days
- Between 548 and 729 days
- Greater than 729 days

These estimates are adjusted for state, surgery count on the claim, age of the claimant, and medical condition. Impairment ratings for claims with time-to-MMI under 90 days average 4.4%, compared to claims requiring over two years to reach MMI which have, on average, a 9.1% impairment rating.

Exhibit 13: Differences in Impairment Rating by Time-to-MMI After Adjusting for State and Differences in Surgery Count, Age, and Medical Condition



CONCLUDING REMARKS

Our analysis has explored several key factors influencing impairment ratings in workers compensation claims. We observed that the time to maximum medical improvement (MMI) correlates with the level of impairment, with longer time-to-MMI generally resulting in meaningful higher impairment ratings. Surgical interventions also play a significant role, with more surgical procedures typically leading to higher impairments.

Age at the time of injury emerged as another influencing factor, with impairment ratings moderately increasing with age. The primary medical condition or diagnosis is crucial in assessing differences in impairment ratings. Additionally, we highlighted the importance of considering state-specific factors when comparing impairment ratings across states, emphasizing the need for a nuanced approach to account for these differences.

By analyzing these factors comprehensively, we aim to provide a clearer understanding of the determinants of impairment ratings and insights into claim costs.

APPENDIX: DATA USED, MODEL, AND VARIABLE SELECTIONS

Data Used

In this research, NCCI's Indemnity Data Call was used as the primary source for impairment ratings, while both the Indemnity Data Call and Medical Data Call were utilized for claim characteristics. The study includes claims with accident years between 2017 and 2022, valued as of September 30, 2023. It includes data from the following jurisdictions: AK, AL, AR, AZ, CO, CT, DC, FL, GA, HI, IA, ID, IL, IN, KS, KY, MD, MO, MS, MT, NC, NE, NH, NM, NV, OK, OR, SC, SD, TN, UT, VA, VT, and WV. Note that claims closed or settled before April 1, 2020, are not captured by the Indemnity Data Call.

Variable Selection

We expected impairment ratings to also be influenced by other factors in the dataset. We grouped these potential confounding, mediating, and/or moderating factors into the following broadly defined groups:

- **Factors related to laws and regulations:** attorney involvement, *AMA Guide* edition, physician choice, and loss settlement
- **Factors related to the injury:** type of injury, body part, severity of the injury, and cause of injury
- **Factors related to recovery**: age, surgery, physical therapy, and time-to-MMI

The research team compiled a list of all variables expected to affect the relationship between state and impairment ratings. Generally, we followed recommendations provided by Gelman and Hill (2006)[6] for inclusion and exclusion decisions. We then experimented with various model specifications and documented goodness-of-fit. After discussions with the research team and some experimentation, we decided to *exclude* the following factors:

- ***AMA Guide* edition** was excluded because no state in this sample changed editions. Thus, this variable would completely overlap with State.
- **Attorney involvement** shares a strong association with impairment ratings. However, we decided that a state estimate that was *inclusive* of this variable, rather than *exclusive* of it, was more representative of each state's unique characteristics.
- **Physician choice** and **loss settlement** had negligible associations with impairment ratings. Leaving these variables out of the model simplified things.
- **Physical therapy (PT)** demonstrates an association with impairment ratings, but in an unexpected direction: PT is associated with *higher* ratings. A deeper look into this relationship reveals that the direction of this effect depends on the medical condition and surgery count. Rather than modeling this complicated relationship, we left this variable out of the model.
- **Body system** is highly correlated with medical condition.

Statistical Modeling

Statistical inference is an organized approach to yield estimates and confidence intervals about a prediction or parameter of interest. It allows us to learn from imperfect data. When attempting to understand a system with complex interactions, it is ideal to try and understand those influences simultaneously. In this study, we sought to estimate state relativities in impairment ratings, after adjusting for meaningful covariates like age, time to maximum medical improvement (MMI), medical condition, and surgeries.

Assumptions of a Linear Regression Model

Aside from the assumption of **Homoscedasticity**, we were able to meet the assumptions of a multiple linear regression model. I will briefly describe how we addressed each of the model assumptions:

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[6] Andrew Gelman and Jennifer Hill, Data Analysis Using Regression and Multilevel/Hierarchical Models, Cambridge University Press, New York, 2006.

1. **Normality**—Model residuals *should* be normally distributed.
   - Conveniently, this assumption isn't *too* important. Ordinary least squares estimates tend to have sampling distributions close to normal even if the error term is far from normal.
2. **Linearity**—The residuals *should* have mean zero for every value of the fitted values and of the predictors.
   - This is trivially met due to use of categorical variables.
3. **Homoscedasticity**—The residuals *should* have equal variance for every value of the fitted values and of the predictors.
   - We *will* need to consider this assumption further.
4. **Independence**—The errors *should* be independent of each other.
   - We have no reason to assume otherwise.
5. **Multicollinearity**—A significant amount of the information contained in one predictor *should* not be contained in the other predictors.
   - We did not violate this assumption. Typically, variance inflation factor (VIF) is used to assess multicollinearity. For this model, we calculated the adjusted generalized standard error inflation factor (aGSIF). Fox and Monette (1992)[7] recommend using the aGSIF for categorical predictors with more than 2 levels because it adjusts for the number of levels allowing comparability with the other predictors.

Robust Standard Errors

Under a normal linear regression model, we assume that errors are homoscedastic and normally distributed:

$$\epsilon_i \sim N(0, \sigma^2)$$

However, we violate the assumption of homoscedasticity, thus biasing the standard error estimates. Therefore, the standard errors were adjusted to be heteroscedasticity-robust.

After fitting this model, we computed robust standard errors using the Huber-White method to account for potential heteroscedasticity.

The Huber-White correction adjusts the covariance matrix of the coefficient estimates ($Var(\hat{\beta})$) as follows:

$$Var(\hat{\beta})_{Huber-White} = (X'X)^{-1}X'\hat{H}X(X'X)^{-1}$$

where:

- X is the matrix of independent variables (including the intercept column)
- X' is the transpose of X
- $\hat{H}$ is the Huber-White sandwich estimator of the covariance matrix of the residuals ϵ_i

The Huber-White estimator $\hat{H}$ is defined as:

$$\hat{H} = \frac{1}{n}\sum_{i=1}^{n} h_i\, x_i x_i'$$

[7] John Fox and Georges Monette, "Generalized Collinearity Diagnostics," Journal of the American Statistical Association, Vol. 87, No. 417, March 1992, pp. 178–183, www.doi.org/10.1080/01621459.1992.10475190.

where:

- n is the number of observations
- h_i is a weight function based on ϵ_i
- x_i is the vector of regressors for the *i*-th observation, or claim *i*

To calculate the robust standard error around each coefficient estimate, we use the diagonal elements of $Var(\hat{\beta})_{Huber-White}$:

$$SE(\hat{\beta}_j) = \sqrt{Var(\hat{\beta})_{Huber-White_{jj}}}$$

where:

$Var(\hat{\beta})_{Huber-White_{jj}}$ denotes the *j*-th diagonal element of $Var(\hat{\beta})_{Huber-White}$

This correction ensures that the estimated standard errors of this model's coefficients (β_0, β_1, β_2, β_3, β_4, and β_5) are robust to account for the violation of the assumption of homoscedasticity in a typical linear regression model.

In this study, we used a Huber's weight function that is a piecewise function that assigns a weight of 1 to residuals below a threshold *k* and then decreases linearly with the magnitude of the residuals beyond that threshold. A default value of the value *k* = 1.345 was used.

Note: *A threshold of k = 1.345 is thought to be efficient in minimizing the mean squared error of the robust estimator under normality assumptions, particularly in cases where the distribution of errors may deviate from normality but still exhibit some moderate degree of heteroscedasticity or outliers.*

Estimated Marginal Means

The fundamental difference between (a) a descriptive average of the data or ordinary marginal means (OMMs) of data and (b) modeled estimates or estimated marginal means (EMMs) is:

- OMMs summarize the data
- EMMs summarize a model

OMMs can be rendered unreliable if the data is unbalanced and/or contains spurious interactions.

As an alternative, EMMs represent the average value of the response variable (in this case, impairment) for each level of explanatory variable (i.e., State).

EMMs represent an estimate of the mean impairment if all groups had the same sample size and/or the same mean value on a covariate/factor. To obtain an estimated marginal mean:

1. Construct a *grid* with all combinations of categorical variables
2. Calculate adjusted predictions for each cell in that grid
3. Take the weighted average of those adjusted predictions across one dimension of the grid to obtain the marginal means

This approach was also used for each covariate in the model (i.e., surgery count, age, medical condition, and time-to-MMI).

Confidence Intervals

The confidence interval (given a level of significance) around an EMM is calculated as follows:

$$CI_{EMM_j} = EMM_j \pm z_{\alpha_{adjusted}} * SE_{EMM_j}$$

where:

- EMM_j is the EMM for State j
- z is the critical value for the standard normal distribution
- $\alpha_{adjusted}$ is the adjusted significance level
- SE_{EMM_j} is the standard error estimate around each EMM for State j, including the Huber-White adjustment

Ratio to Grand Mean

Each state's EMM was transformed to a ratio relative to the grand mean (i.e., a state relativity) as follows:

$$State\ relativity = \frac{EMM_{State_i}}{geomean_{EMM_{State}}}$$

where:

- EMM_{State_i} is the estimated marginal mean for a given state
- $geomean_{EMM_{State}}$ is the geometric mean of all state EMM for impairment rating:

$$geomean_{EMM_{State}} = \sqrt[n]{EMM_{State_1} \cdot EMM_{State_2} \cdot \ldots \cdot EMM_{State_n}}$$

Software Packages

Statistical analyses were conducted in **R** (R Development Core Team, 2007), and figures were produced using the **ggplot2** package (2016). Estimated marginal means were calculated using the **emmeans** package (2024).