RESEARCH BRIEF
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The Impact of Fee Schedule Updates on Physician Payments

INTRODUCTION

Physician payments are the largest category of medical expenditures for workers compensation (WC) claims, comprising approximately 40% of medical costs.[1] Most states[2] have implemented fee schedules that establish maximum reimbursement rates for physician services with three main purposes:

- Ensure adequate access to medical providers
- Contain medical costs
- Provide rules for the price of services provided, thereby reducing disputes regarding medical service reimbursements

Using a simple linear regression approach, this study investigates the effect of changes in fee schedules on physician payments. The study also examines a newly developed autoregressive model to estimate prices paid per transaction[3] for physician services in response to changes in fee schedules. The results from the autoregressive model further support the findings produced by the linear regression approach.

BACKGROUND

A fee schedule establishes the maximum allowable reimbursement (MAR) that may be paid to a service provider for a given medical service. Most WC physician[4] fee schedules apply a price ceiling for each physician service on the schedule,[5] as identified by a procedure code, such as a Current Procedural Terminology (CPT[6]) code, and in certain cases additional factors such as a modifier. Lipton et al. [1] have found that fee schedules are effective at limiting physician costs in the WC system.

Some states develop their own WC fee schedules, but most states set the MAR for each procedure code at a multiple of the amount Medicare publishes for that service. Most states that use a Medicare-based fee schedule update their fee schedule annually to remain in line with the current Medicare fee schedule. Many states with a non-Medicare fee schedule typically update their MARs annually or biannually.

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[1] In NCCI's Medical Data Call (MDC), 40% of medical payments for services provided in 2016 were paid to physicians.
[2] In this article, "state" refers to the jurisdiction.
[3] In this article, "transaction" refers to the number of units of services provided.
[4] Physician fee schedules typically apply to nurses, physician assistants, and other allied service providers. In this study, "physician" is used as a generic term to indicate all service providers subject to a state's physician fee schedule.
[5] Some fee schedules may limit reimbursements to a percentage of Usual, Customary, and Reasonable (UCR) charges instead of specific maximums expressed in dollars. Such fee schedules are not considered in this study.
[6] CPT® copyright 2018 by the American Medical Association.

In states with a physician fee schedule, the median WC price paid for physician services is always at, or very near, the fee schedule MAR [1]. Hence, changes to a state's fee schedule are expected to translate directly into changes in prices paid for physician services. Determining the impact of such fee schedule updates on medical benefit costs, and thus on WC loss costs, is one of the main functions of NCCI's legislative analysis process.

In 2013, NCCI studied the impact of physician fee schedule updates in the WC context using an impulse-response time series framework and transactional data licensed to NCCI from 31 states between the years 2000 and 2010 [2]. This study found that, in response to a fee schedule increase, overall, physician reimbursements increased by approximately 80% of the payment-weighted average increase in MARs. Fee schedule decreases resulted in a decrease in overall reimbursements of about 45% of the payment-weighted average decrease in MARs.

In addition, the research found that the magnitude of the response for physician fee schedule increases depends on the relative difference between actual prices paid and fee schedule maximums (i.e., the price departure) underlying experience prior to the change in MAR. Note that, in the 2013 study, physician payments were aggregated by state rather than procedure code, so a "fee schedule increase" was defined as a fee schedule update in which the average MAR, weighted by payments, increased. During the period of that study, there were relatively few fee schedule updates that resulted in an overall fee schedule decrease. NCCI also concluded that the impacts of fee schedule updates were realized almost entirely through changes in prices paid; fee schedule updates had no material effect on the level of utilization of physician services [2].

This new study examines the impact of fee schedule updates on costs using a more granular approach. In particular, the study examines experience in- and out-of-network, different types of physician services, and a wide range of percentage changes in MARs (including a greater share of decreases). The primary focus is a straightforward linear regression model, which compares year-to-year changes in prices against changes in MARs. This linear regression model has the advantages of intuitive interpretation and clear application to the legislative analysis context. An additional model is also explored. That model is an autoregressive log-log model of prices per transaction within a state for a given service (identified by procedure code) as a function of past prices and MAR changes.

KEY FINDINGS

- Changes to medical fee schedules for physician services affect prices paid for services that are subject to the fee schedule.
- Approximately 80% of any change in MAR for a procedure code will be realized as a change in prices paid.[7] This relationship generally holds for:
    - Both increases and decreases in MAR
    - Various types of physician services
    - Different magnitudes of changes in MAR
- Although there is some variation in the effect of MAR changes on physician payments for individual states, an estimated price response of 80% to MAR changes is a reasonable estimate for any of the states included in this study.
- Payments for services paid out-of-network are somewhat more responsive to MAR changes than payments for services paid in-network.
- Most of the impact of a MAR change on prices paid is realized within one year from the date of a fee schedule change; the carryover effect of MAR changes from the prior year is relatively minor.
- There is no discernable substitution effect on physician services in response to fee schedule changes.

[7] NCCI recognizes that this relationship might not hold if the fee schedule is set at a substantially uncompetitive level.

DATA

Fee schedules were used to calculate the MAR per transaction for each procedure code by year and state of jurisdiction. In most states, physician fee schedule updates take effect on the first calendar day of the year. However, for some states, physician fee schedules take effect on dates other than the first calendar day of the year or on multiple times per year. MARs from a physician fee schedule typically apply to all transactions with the same procedure code. However, the MAR for a given procedure code may vary based on the place of service, namely, whether the service is provided in a facility (e.g., hospital or ambulatory surgical center) or a nonfacility setting such as a physician office.

In each case where multiple MARs were in effect for a single code during a year, an average of those MARs weighted by the dollar amount of payments subject to each MAR was used. This level of aggregation provided a volume of transactions by procedure code sufficient to create a robust dataset for our analysis.

For states other than Texas, the data source used in this study is NCCI's Medical Data Call (MDC). For Texas, the data source is the DWC Medical State Reporting Public Use Data File (PUDF).[8] The MDC is a database of paid medical transactions reported by all WC carriers that write at least 1% of the market share in any one state for which NCCI is the advisory organization. Medical transactions are reported for each WC claim until the claim is closed or until 30 years from the accident date. However, lump-sum payments are not required to be reported, and self-insured data is not included.

Data subject to the following limitations was used:

- Services, other than anesthesia, provided between January 1, 2011, and December 31, 2016
- NCCI states with an enforceable physician fee schedule that was updated at least once during the study period[9]
- Payments for a procedure code within a state with less than a 300% year-to-year change in MAR or change in price paid per transaction (PPT)[10]
- Transactions that were not considered outliers during the data validation process[11]
- Transactions not subject to a payment modifier

In addition, due to the nature of typical injuries in the WC system, services associated with some procedure codes are rarely performed and year-to-year payment data for these codes may be highly volatile. To eliminate the effect of these rarely used codes, we removed payment data associated with procedure codes that had fewer than 50 transactions in a given state and year. The resulting data set consists of 65.7 million transactions representing $4.5 billion in physician payments. These transactions were aggregated into a total of 28,193 state, year, and procedure code combinations.

The transactional payment data was aggregated by procedure code, year, place of service (facility or nonfacility), and state to calculate an average price per transaction. Average price per transaction is defined as the sum of all physician payments reported with a given procedure code within state s during year t, divided by the total number of physician transactions within the same combination of state, year, place of service, and procedure code. This definition corresponds to the average MAR by state, year, place of service, and procedure code discussed above.

[8] Texas Department of Insurance, Division of Workers' Compensation, Austin, TX.

[9] AL, AR, AZ, CO, CT, DC, FL, GA, HI, ID, IL, KS, KY, MD, ME, MS, MT, NC, NE, NM, NV, OK, OR, RI, SC, SD, TN, TX, and UT.

[10] This reduces the impact of substantial one-time changes in the billing processes for a particular procedure code. These may occur, for example, when Medicare alters the coding procedures for services that are provided as an adjunct to other procedures.

[11] Outliers determined using Tukey's outlier detection rule.

DATA ANALYSIS AND UNIVARIATE REGRESSION MODEL

Understanding how prices paid for physician services in WC relate to enacted fee schedules is necessary to estimate the effect of fee schedule updates on WC costs. Exhibit 1 uses data across all states included in this study for all physician services. This exhibit shows the average price per transaction and the average price per transaction if they were to be paid at the MAR, for physician services subject to fee schedules. On average, prices paid per transaction for physician services are paid below the MAR but have a similar trajectory compared to the average price per transaction if they were paid at MAR. Therefore, as fee schedules are updated, we expect prices paid for physician services to be influenced by the new price ceilings established by the fee schedules.

AVERAGE PRICE BY YEAR

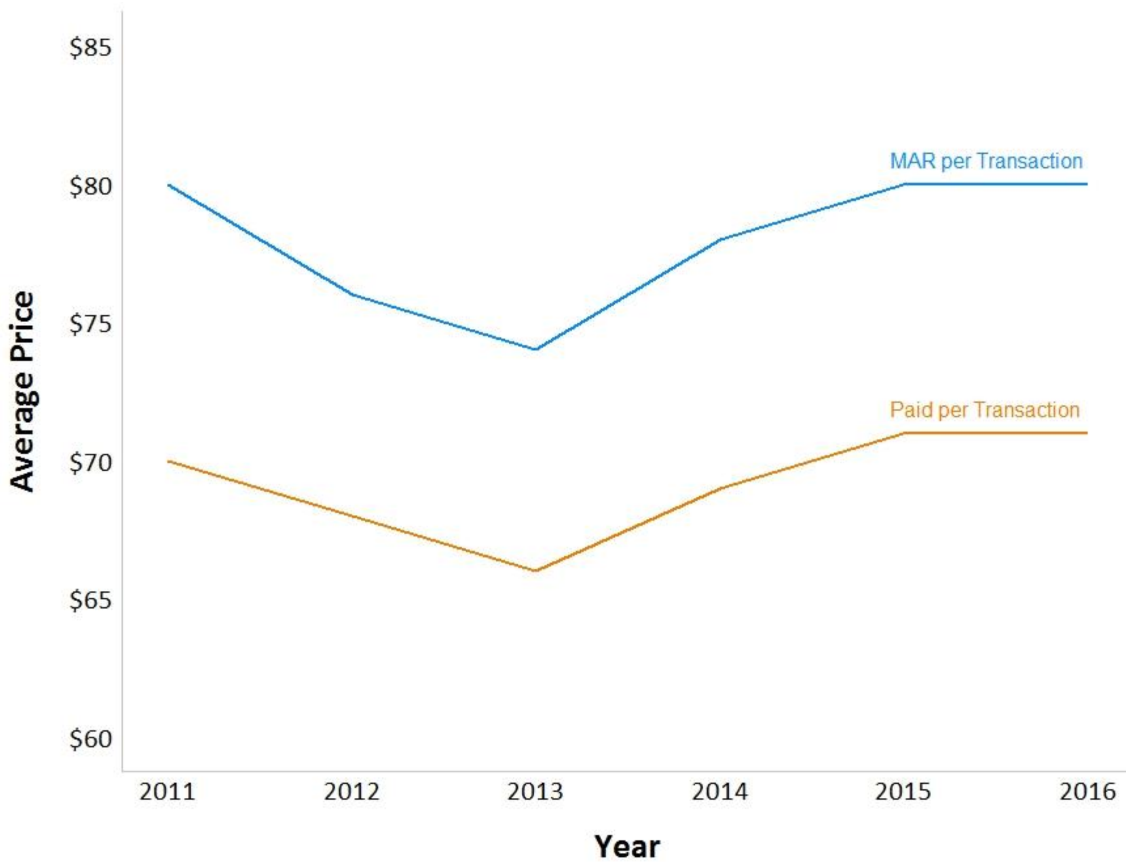

Exhibit 1

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

Exhibit 2a includes a scatterplot that displays the relationship between changes in MARs to changes in prices. Each observation (or dot) in the scatterplot is the intersection of the average percentage change in MAR and the average percentage change in price for a procedure code, state, place of service, and year combination.[12] By analyzing these observations for approximately 28,000 procedure code, state, place of service, and year combinations, we can assess the responsiveness of prices to physician fee schedule updates. Note that approximately 75% of the observations are for MAR changes between –20% and +20%. As such, we observe a cluster of observations around the origin.

CHANGE IN PRICE VS. CHANGE IN MAR

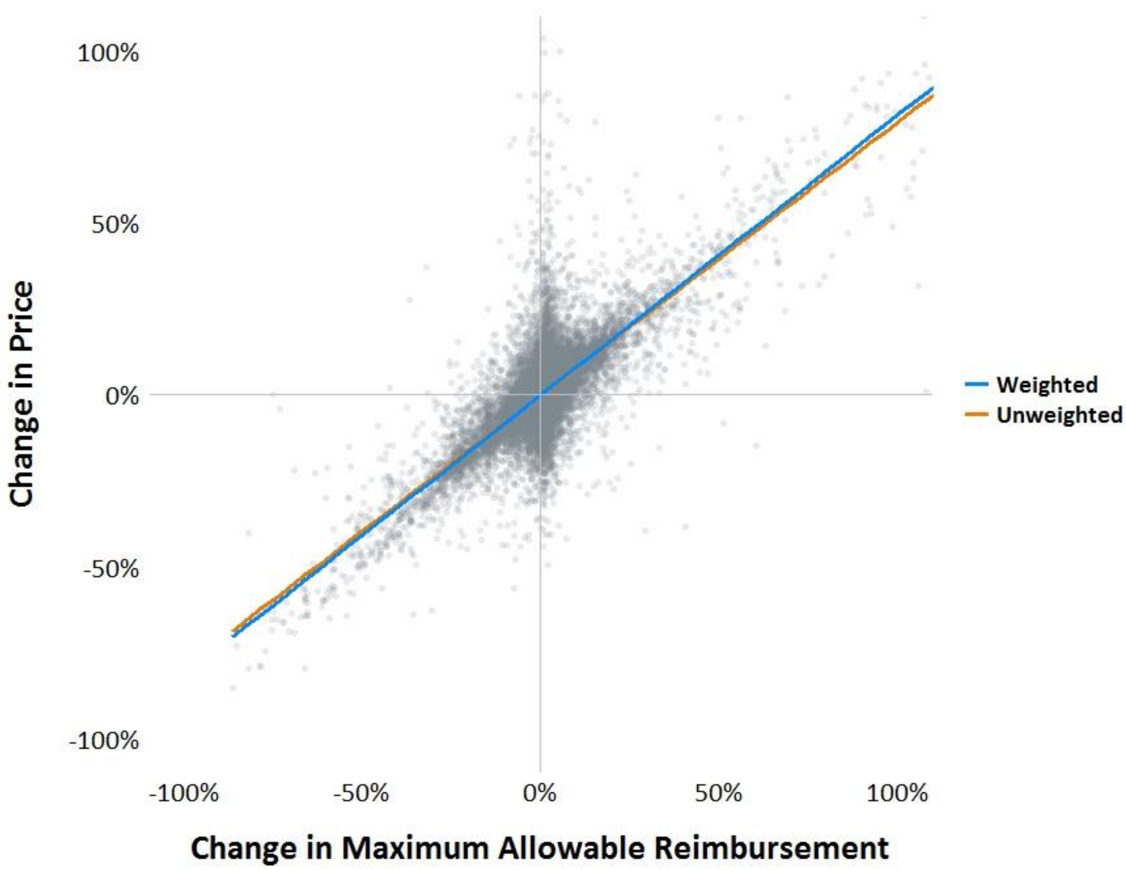

Exhibit 2a

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

Exhibit 2a also shows the two fitted univariate linear regression lines ($Y = \beta x_i + \varepsilon$) calculated from the observations, i, where the explanatory variable (or the "X") is the percentage change in MAR and the response variable (or the "Y") is the percentage change in average price paid per transaction. No intercept was included in the regression model so that the model would not associate any systematic change with no change in the MAR. Consistent with that constraint, the intercept was approximately zero when included. The weighted regression line uses payments as weights to be more influenced by frequently utilized services (and similarly to reduce the influence of infrequently utilized services). Both regression lines illustrate a strong correlation between changes in MARs and changes in prices paid for physician services.

[12] For example, for CPT 72070 in Colorado between the years 2011 and 2012, the average MAR increased 3.6% while the average price increased 2.0%. These percentages represent one observation with an x-value of 3.6% and a y-value of 2.0% on the graph.

The result of the weighted regression's coefficient of determination (R^2) implies that about 80% of the total variation in changes to prices paid for physician services is explained by changes in the MARs. The response coefficient β indicates that a 1% change in a procedure's MAR is approximately followed by a 0.8% change in the average price paid for that procedure. In other words, the price responsiveness to changes in MARs is approximately 80%.

Exhibit 2b looks at the relation of paid price changes to decreases or increases in MARs separately. Both increases and decreases in MARs appear to show a similar responsiveness in prices paid. Decreases in MARs generate a responsiveness in prices paid of 81%. Increases in MARs generate a responsiveness in prices paid of 82%. This relationship holds fairly consistently across all ranges of MAR changes as seen in Exhibit 2a and 2b. Similarly, price responsiveness to MAR changes was observed to be generally consistent for the years included in this study as seen in Exhibit 2c.[13] However, we recognize that this relationship might not hold if the fee schedule is set at a substantially uncompetitive level.

CHANGE IN PRICE VS. CHANGE IN MAR

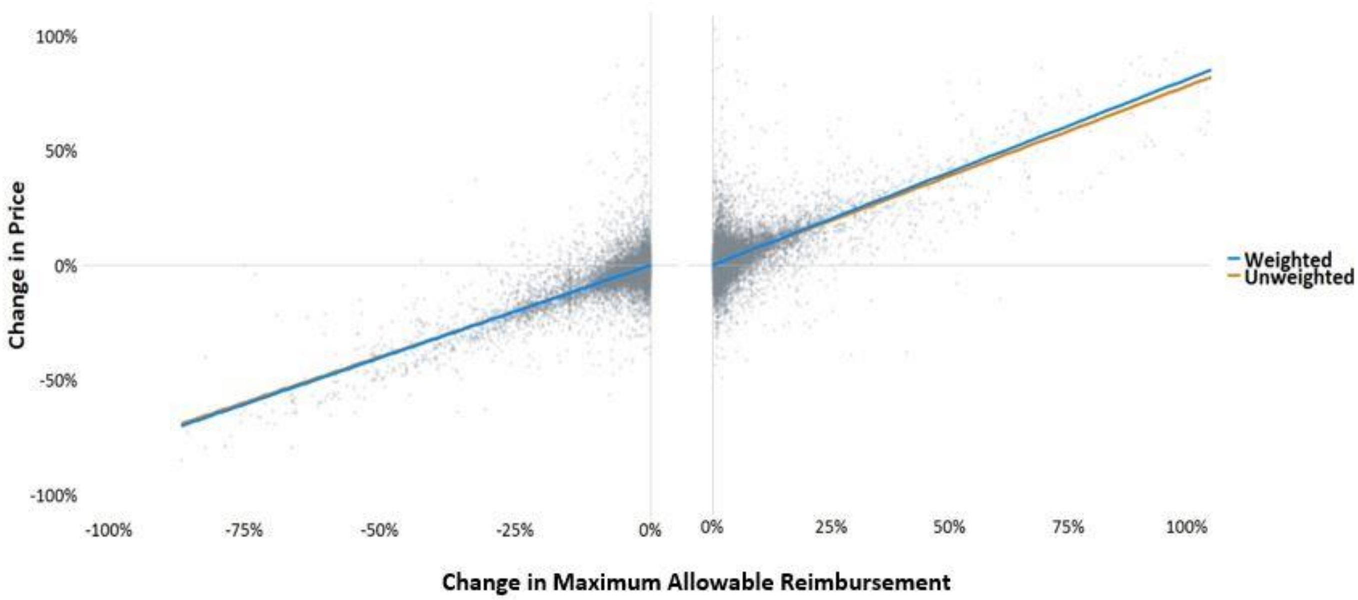

Exhibit 2b

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

[13] The response coefficients to MAR changes between 2012 and 2016 are 81%, 74%, 83%, 78%, and 87%, respectively.

CHANGE IN PRICE VS. CHANGE IN MAR

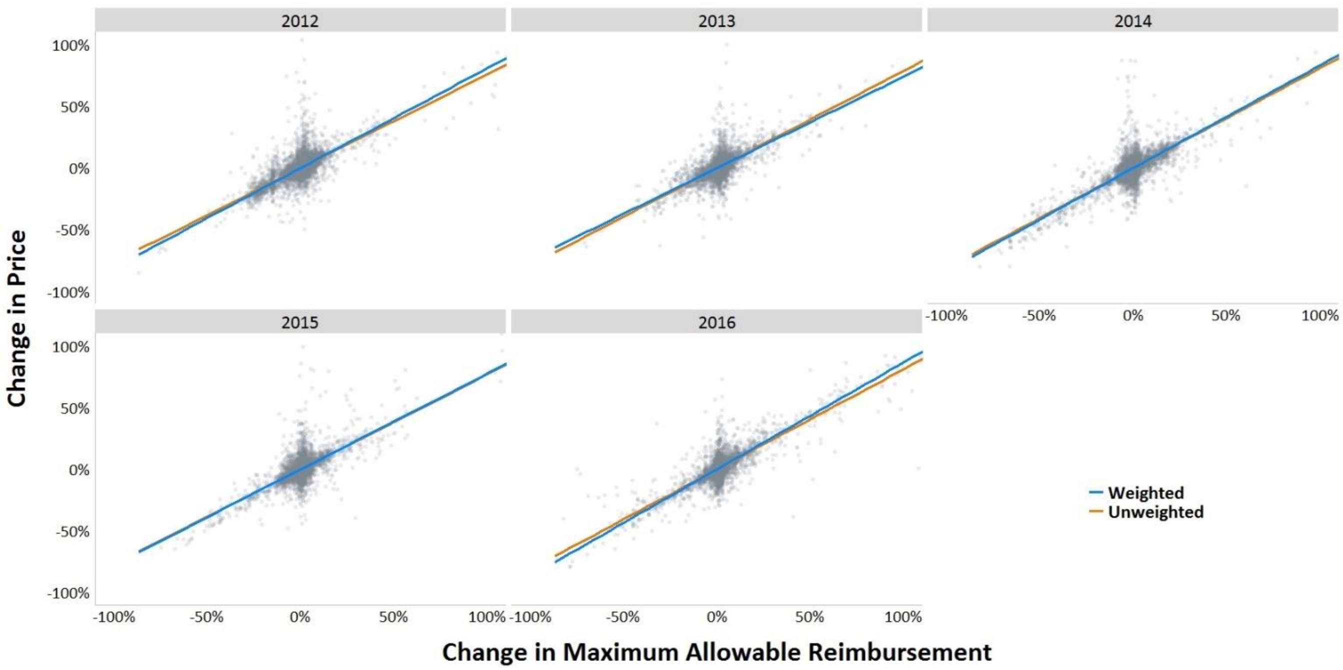

Exhibit 2c

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

Exhibit 3a plots the residuals of the regression shown in Exhibit 2a. The residual plot displays the difference between actual observations and predicted observations based on the regression's estimate. Residual plots help to analyze the goodness of fit for a regression model. For residuals plots, positive values for the residual (above the x-axis) mean that the prediction was inadequate, and negative values (below the x-axis) mean that the prediction was excessive. Values of 0 (on the x-axis) mean that the actual observation and predicted observation are equal. Residual plots also help answer two important questions:

1) Are the fitted values biased (excessive or inadequate)?
2) Are the residuals randomly dispersed?

To answer the first question, we looked for a disproportionate distribution of residuals above or below the x-axis. The exhibit shows a similar distribution between positive and negative values. Therefore, the data indicates no apparent bias in the estimated regression. To answer the second question regarding random dispersion, the residual plot shows that for small MAR changes (close to the origin), there is more variability. Recall that most of the observations were concentrated around relatively small MAR changes. Therefore, what we are seeing in the residual plot is due to the high concentration of observations that visually suggests that the dispersion of the residuals for small MAR changes is wider than for larger MAR changes.

UNIVARIATE REGRESSION RESIDUALS

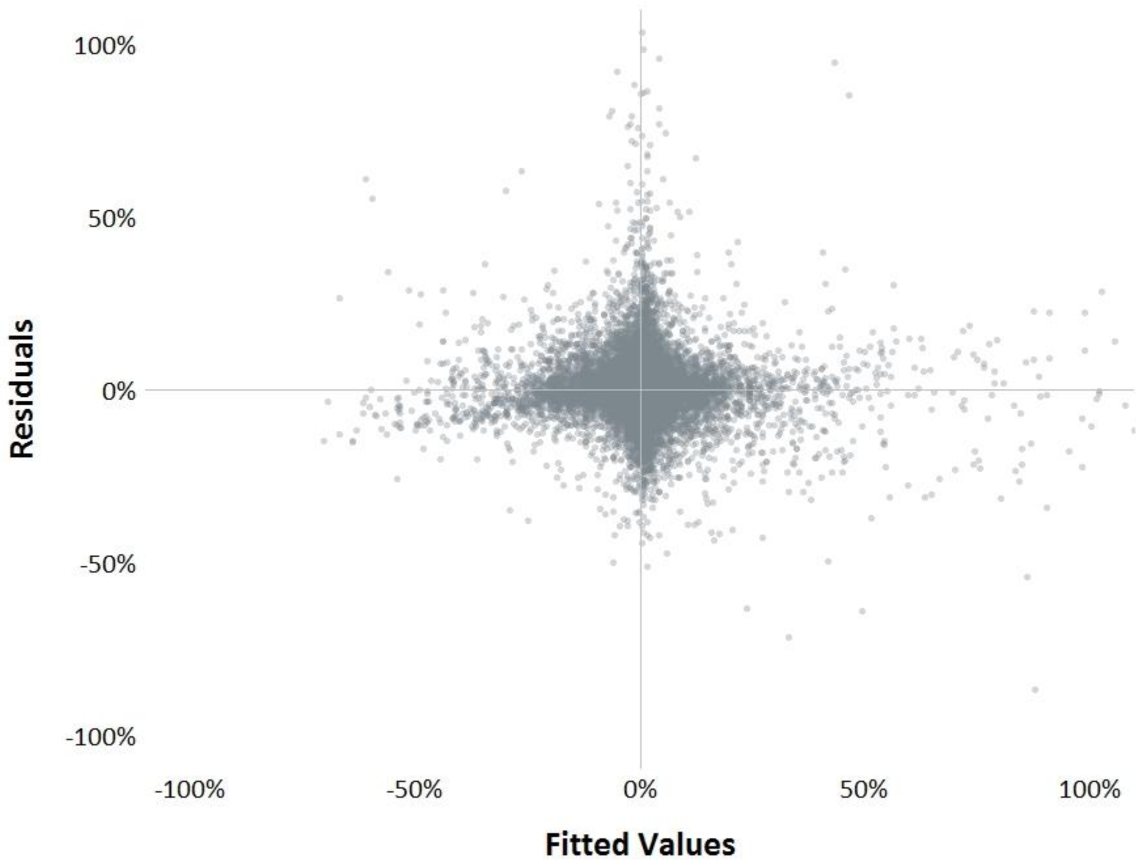

Exhibit 3a

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

The boxplots in Exhibit 3b help to analyze the dispersion of residuals for different ranges of MAR changes. These boxplots show the distribution of residuals for MAR changes between –10% and +10% compared to all other ranges. The shaded boxes indicate the 25th to 75th percentiles of the distribution, while the "whiskers" above and below the box show the broader ranges of results represented by the 95th and the 5th percentiles, respectively. A wider box indicates more spread in the observed residuals than a narrower box. Long "whiskers" indicate that there are some residuals that differ substantially from most of the observations. However, this exhibit shows that the residuals are not notably different for the different ranges of change in MARs, and the residuals are distributed around zero.

UNIVARIATE REGRESSION RESIDUALS DISTRIBUTION

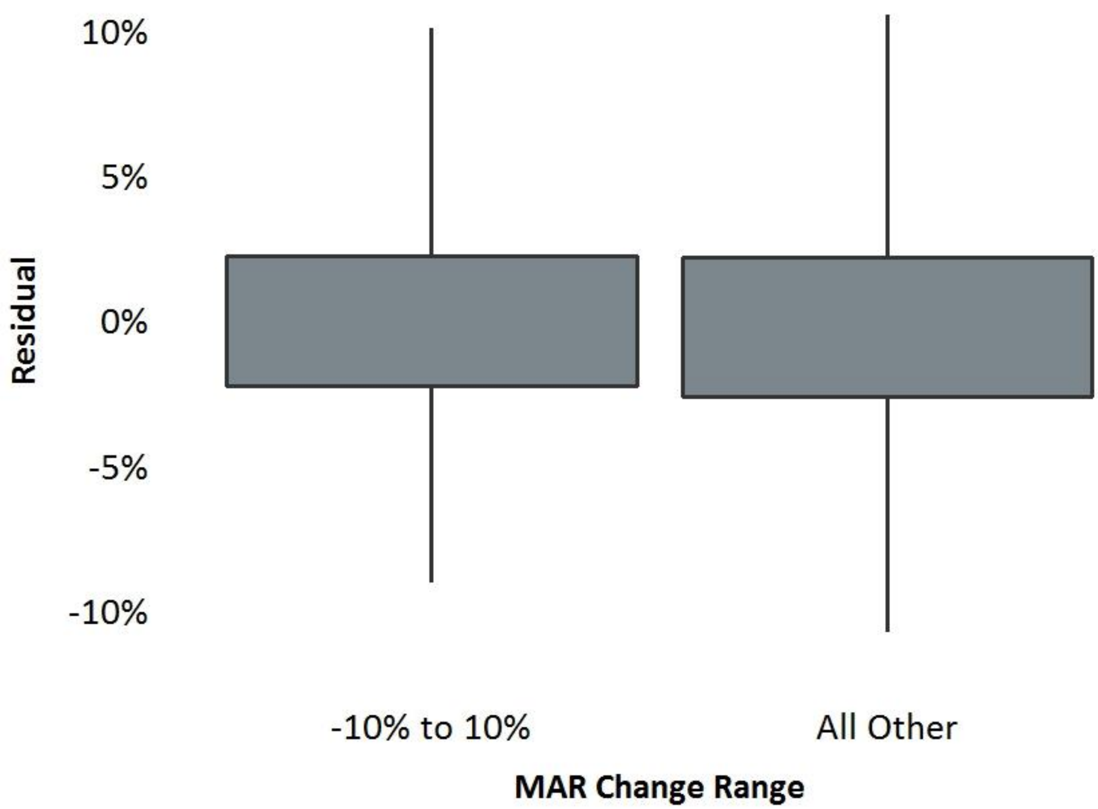

Exhibit 3b

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

Cost change is the product of changes in price and utilization.[14] Utilization is the intensity of services provided per claim. This includes:

- The number of services provided per claim
- The mix of services provided on a claim (e.g., physical therapy vs. surgery)

Changes in prices are often associated with changes in consumer and supplier behavior that we define as a change in utilization. Exhibit 4 shows the utilization responsiveness in relation to MAR changes. This exhibit tests for a potential utilization response to MAR changes in the form of a substitution effect. Substitution might be expected to cause decreased use of a procedure with a decrease in the MAR, and likewise, increased use of a procedure with an increase in the MAR. However, the exhibit implies that there is no notable utilization effect in response to MAR changes since no discernible pattern is present in the data. That is to say that the data does not seem to support a utilization effect in response to MAR changes. This finding is consistent with the prior NCCI study [2] that found no material utilization response to fee schedule changes.

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[14] In this study, a change in utilization is computed as the ratio of cost change to price change.

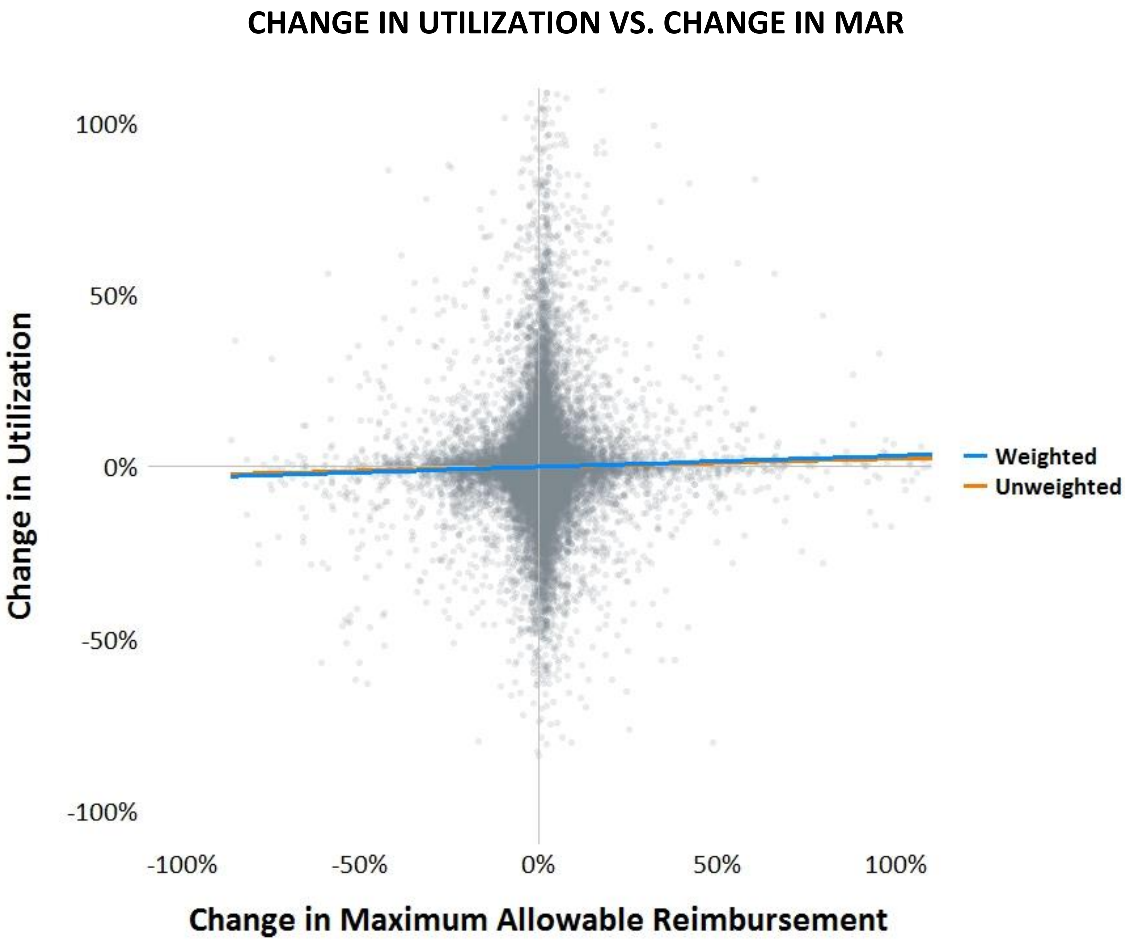

Exhibit 4

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

Physician or medical professional services are often grouped into categories such as evaluation and management, medicine, radiology, or surgery. Exhibit 5 breaks down physician services into these categories and illustrates the price responsiveness to MAR changes for the different categories of services to assess differences in price responsiveness to MAR changes. Although slight differences are present, the exhibit shows that all the categories have a response coefficient of around 80%. This implies that for different categories of services, we see a similar price responsiveness to MAR changes. The response coefficients to MAR changes range from 77% for radiology to 85% for surgery.[15]

[15] The response coefficients to MAR changes for evaluation and management, medicine, radiology, and surgery are 82%, 81%, 77%, and 85%, respectively.

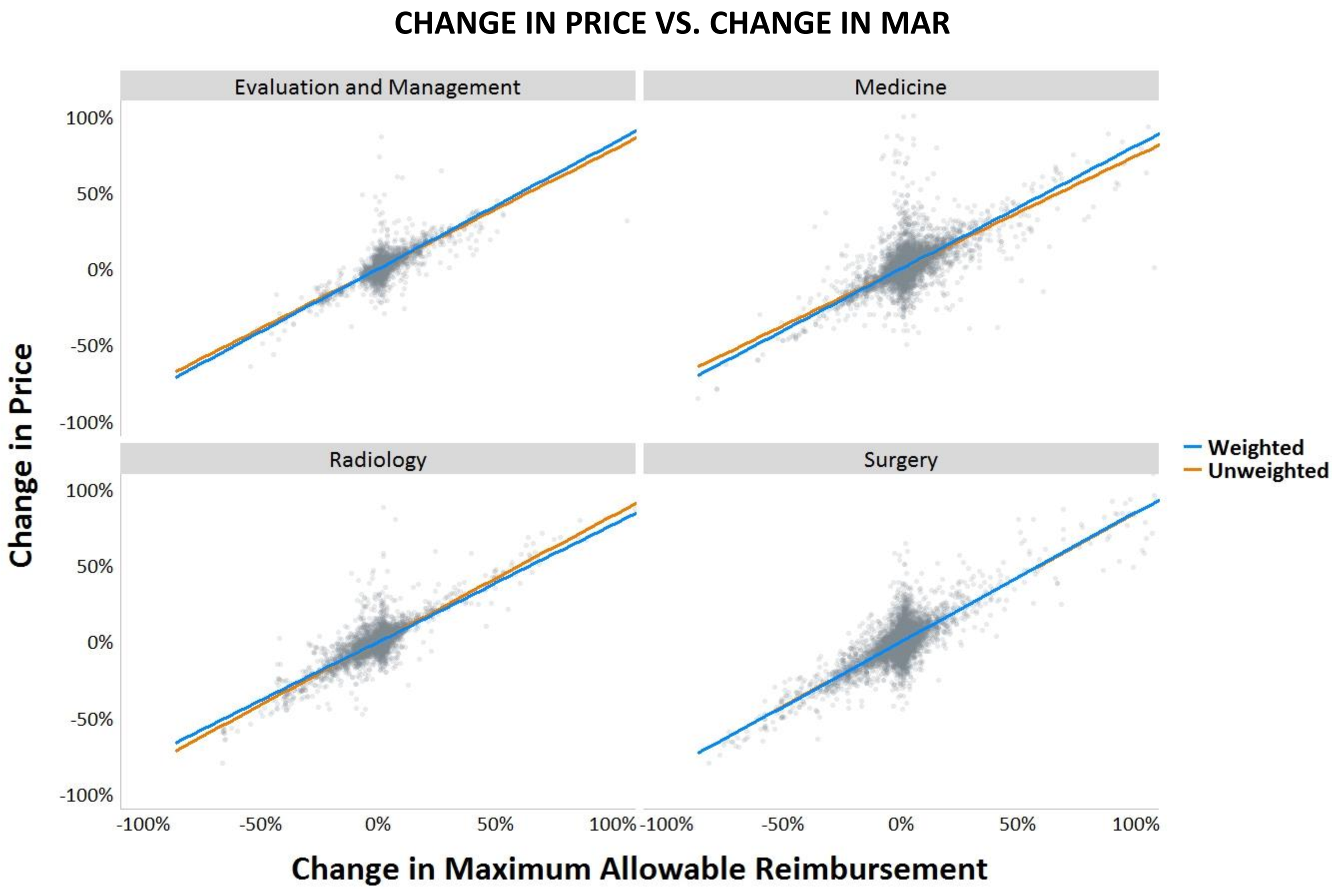

Exhibit 5

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

An additional situation considered during this study was whether transactions were paid inside or outside of a network agreement. Exhibit 6 separately shows the price responsiveness to MAR changes for transactions in-network and out-of-network. From the exhibit, we see that out-of-network services are somewhat more responsive to MAR changes at 86% compared to 79% for in-network services.

Exhibit 6

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

We also see price responsiveness to MAR changes varying by state. Exhibit 7a shows the price responsiveness to MAR changes for the states included in this study. The response coefficients to MAR changes range from 36% for DC[16] to 94% for HI are displayed in Exhibit 7b. When we look at the 95th confidence interval of the regression coefficient for each individual state in Exhibit 7b, we see wide ranges for many of the states in comparison to the all states range. However, we see that most states either include or are near the estimated price response of 80% from the all states regression model. In other words, an estimated price response of 80% to MAR changes is a reasonable estimate for any of the states included in this study.

NCCI's prior research [2] found that the magnitude of the response for physician fee schedules also depended on the relative difference between actual prices paid and fee schedule maximums (i.e., the price departure). The prior research [2] found that the larger the price departure, the lesser the state's price responsiveness was to MAR changes. By looking at the state's price departure, state differences could be accounted for. However, we find that the relationship between price responsiveness and price departure does not always hold. Several examples can be found in Exhibit 7b of pairs of states that violated such a relationship. For example, RI and MT have the same price departure but their estimated state-specific price responsiveness coefficients are 16 points apart. Similarly, GA and OK have the same price departure, but their estimated state-specific price responsiveness coefficients are 23 points apart.

[16] DC is the only jurisdiction in the study with a regression p-value outside the range to accept the predictability of the regression coefficient.

CHANGE IN PRICE VS. CHANGE IN MAR

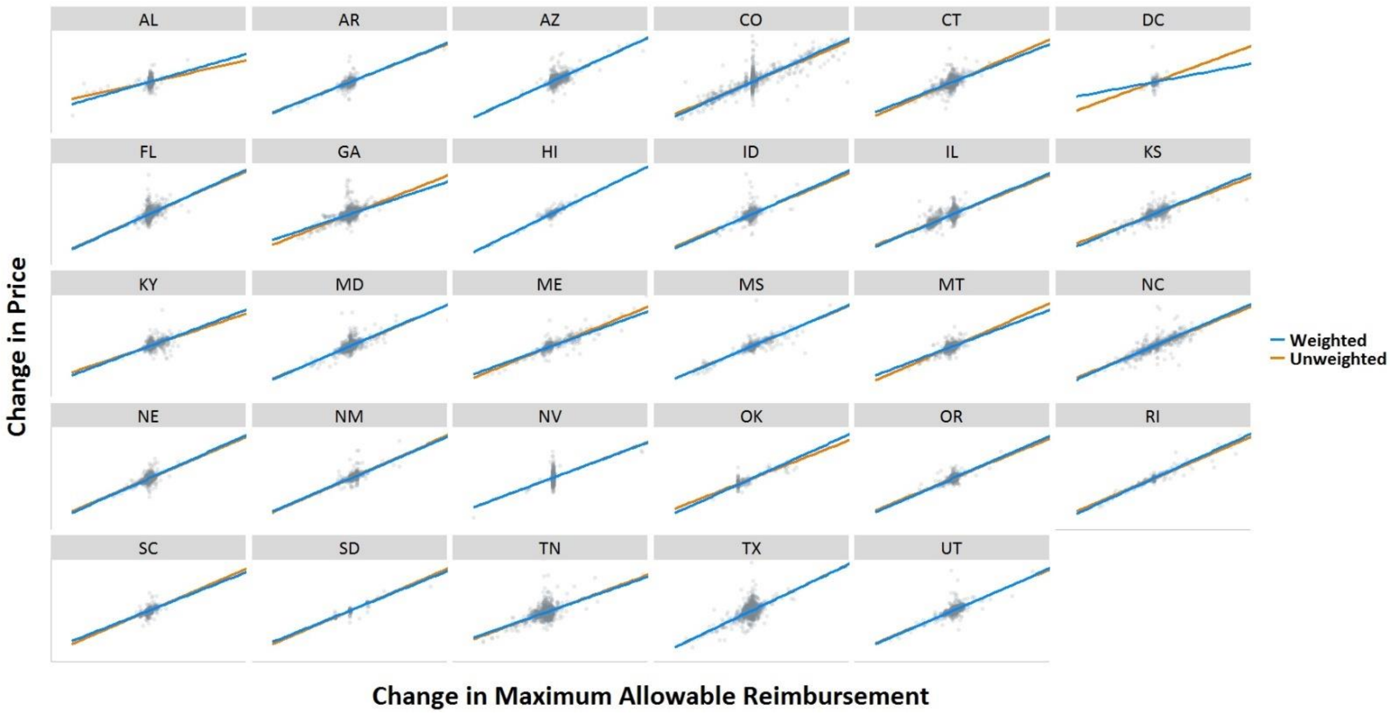

Exhibit 7a

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

			95th Confidence Interval		
State	Estimated Regression Coefficient	Pr(>|t|)	Lower Estimate	Upper Estimate	Average Price Departure
AL	55%	4.45E-05	48%	62%	–22%
AR	77%	2.20E-16	69%	84%	–12%
AZ	87%	2.20E-16	85%	90%	–15%
CO	86%	2.20E-16	84%	87%	–10%
CT	75%	2.20E-16	72%	77%	–15%
DC	36%	0.106568	–29%	101%	–10%
FL	88%	2.20E-16	84%	92%	–7%
GA	64%	2.20E-16	61%	66%	–17%
HI	94%	2.20E-16	89%	99%	–6%
ID	85%	2.20E-16	81%	90%	–11%
IL	81%	2.20E-16	80%	82%	–9%
KS	80%	2.20E-16	77%	83%	–13%
KY	72%	2.20E-16	69%	75%	–12%
MD	82%	2.20E-16	79%	85%	–8%
ME	69%	2.20E-16	66%	71%	–11%
MS	81%	2.20E-16	77%	85%	–13%
MT	72%	2.20E-16	66%	78%	–8%
NC	83%	2.20E-16	82%	85%	–11%
NE	85%	2.20E-16	81%	90%	–10%
NM	83%	2.20E-16	76%	89%	–10%
NV	71%	2.20E-16	63%	79%	–26%
OK	87%	2.20E-16	84%	89%	–17%
OR	84%	2.20E-16	79%	89%	–3%
RI	88%	2.20E-16	84%	92%	–8%
SC	76%	5.52E-15	63%	88%	–15%
SD	78%	7.32E-09	73%	83%	–10%
TN	67%	2.20E-16	65%	69%	–11%
TX	91%	2.20E-16	89%	93%	–10%
UT	83%	2.20E-16	79%	88%	–9%
All States	**81%**	**2.20E-16**	**81%**	**82%**	

Exhibit 7b

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

MULTIVARIATE LOG-LOG AUTOREGRESSIVE MODEL FORM AND ESTIMATION

Below, we specify a multivariate log-log autoregressive model to predict the average price paid per transaction (PPT) by procedure code for a given state and year. To estimate the coefficients of our model, we use an ordinary least squares (OLS) regression:

$$\log(P_{i,s,t}) = \beta_1 \log(1 + \%\Delta M_{i,s,t}) + \beta_2 \log(P_{i,s,t-1}) + \beta_3 \log(1 + \%\Delta M_{i,s,t-1}) + \beta_4 \log(P_{i,s,t-2}) + \epsilon_{i,s,t}$$

where

$P_{i,s,t}$ denotes the average PPT for procedure code i during calendar year t within state s,

$\%\Delta M_{i,s,t}$ denotes the percentage change in average MAR applying to procedure code i within state s from calendar year $t-1$ to calendar year t,

and $\epsilon_{i,s,t}$ is the random error term for each observation.

Note that log transformation of our model's variables is motivated by two observations:

1. Examining the scatterplot of the linear regression fit in Exhibit 3a suggests that the variance of the residuals may differ depending on the value of $\%\Delta M_{i,s,t}$ (i.e., the model may suffer from heteroskedasticity). Log-transformation of variables is a standard technique to reduce the presence of heteroskedasticity.
2. Log-transforming the variables also resulted in a better fit, as measured by the adjusted R^2 and p-values of the fitted coefficients. Exhibit 3a suggests that there could be a slight degree of nonlinearity in the relationship between changes in MAR and changes in price. The improved fit could be due to the log-transformation adjusting for this potential non-linearity.

MULTIVARIATE LOG-LOG AUTOREGRESSIVE RESIDUAL

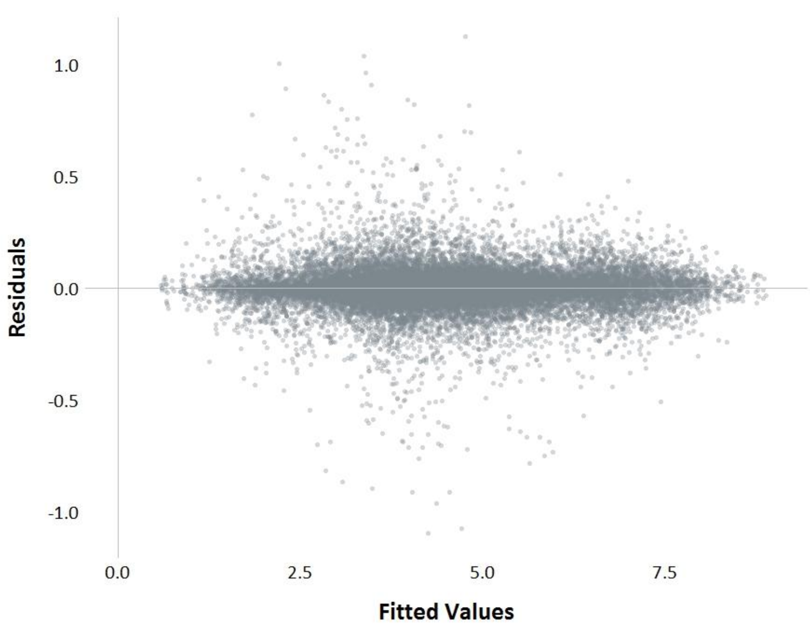

Exhibit 8

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

WC fee schedules are regulated at the state level. Even states that use Medicare as the basis for their fee schedule typically make substantial adjustments to the base Medicare fee schedule. In addition, other factors unique to each state may lead to substantial correlations among observations within each state, but not between states. Hence, observations from each state naturally form non-overlapping clusters with relatively little correlation between clusters.

Using our data, we tested the log-transformed model results for heteroskedasticity using the test developed by Breusch & Pagan [3]. As the two-tailed p-value was zero to four decimal places, we rejected the null hypothesis of homoskedasticity.

The standard errors for any OLS model must be adjusted for the presence of clustering and heteroskedasticity to avoid downward bias in the error estimates. Following Cameron and Miller [4], heteroskedasticity-consistent (HC) standard errors for our model results are derived using a cluster-robust variance-covariance estimator for one-way clustering.[17] We impose no assumption on the correlation of errors within each cluster (state).

Other than the assumptions previously described, we impose no assumptions about the error structure of our model.

MODEL RESULTS AND DISCUSSION

Exhibit 9 shows the fitted coefficients and standard errors for the autoregressive model. The first column lists the four explanatory variables identified in our autoregressive model specification, while the coefficients in the second column represent the fitted values for the associated β_is. HC cluster-robust standard errors are reported for each coefficient, consistent with the discussion above. P-values for each coefficient were determined using a two-sided t test. Additionally, Exhibit 9 reports the adjusted R^2 goodness-of-fit statistic, as well as the p-value for the F test of overall model significance.

MODEL RESULTS

Variable	Fitted Coefficient	Standard Error	p-Value
$\log(1 + \%\Delta M_{i,s,t})$	0.797	0.028	0.0000
$\log(P_{i,s,t-1})$	0.978	0.004	0.0000
$\log(1 + \%\Delta M_{i,s,t-1})$	0.049	0.011	0.0000
$\log(P_{i,s,t-2})$	0.021	0.004	0.0000

Model adj. R^2	0.9997
Model p-value[18]	0.0000

Exhibit 9

NCCI's analysis is based on Medical Data Call for services provided between 2012 and 2016

[17] Robust standard errors were estimated using the "sandwich" package in R. Zeileis lays out the theoretical framework for estimating cluster-robust HC standard errors using "sandwich" estimators in [5] and describes the practical implementation of this method as implemented in R's "sandwich" package in [6].

[18] Based on an F-statistic of 2.688$\times 10^7$ with 4 and 32,670 degrees of freedom.

Based on the adjusted R^2 statistic in Exhibit 9, the four explanatory variables in the above model collectively explain over 99.9% of the total variation in the price paid per transaction for physician services. Only a minimal proportion of the variation in PPT is explained by omitted effects included in the model's error term. The model as a whole is highly significant, with a p-value of zero (rounded to four decimal places).

An additional method of measuring goodness-of-fit is to select a subset of the data and measure the relationship between the model-estimated values against the actual values. In Exhibit 10 below, we compare the actual average and median (log-transformed) prices paid per transaction to the estimated average and median prices given particular values for the explanatory variables.[19] We see that our model performs well on this in-sample prediction, because the actual mean and median values are very close to the predicted values. The correlation between the actual and predicted in-sample values is also very high.

IN-SAMPLE PREDICTED VS. ACTUAL LOG-TRANSFORMED PRICES PER TRANSACTION

	Mean	Median
Predicted	4.4323	4.3278
Predicted Lower 95% C.I.	4.2733	4.1688
Predicted Upper 95% C.I.	4.5910	4.4870
Actual	4.4324	4.3356
Correlation between predicted and actual values	99.41%	

Exhibit 10

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2016

The above discussion has focused on how well the autoregressive model represents the 2011 to 2016 data examined in this study. However, we also wish to examine the predictive validity of the model for a data set that was not used in developing the regression model and from a different time period than the modeled data. Such a comparison between actual and predicted "out-of-sample" values may reveal variable selection bias in the development of the regression model or may indicate that patterns observed during the study period do not persist in data from outside that time period.

For our out-of-sample validation, we compare actual PPT to predicted values for transactions occurring during 2017. We see that results of the out-of-sample comparison are very similar to the analogous values from the in-sample comparison. In particular, we observe that the correlation between predicted and actual PPT remains over 99%.

[19] The sample consisted of 10,226 records from randomly selected states in years 2014 and 2016.

OUT-OF-SAMPLE PREDICTED VS. ACTUAL LOG-TRANSFORMED PRICES PER TRANSACTION

	Mean	Median
Predicted	4.4917	4.3944
Predicted Lower 95% C.I.	4.3330	4.2350
Predicted Upper 95% C.I.	4.6507	4.5534
Actual	4.4908	4.3984
Correlation between predicted and actual values	99.45%	

Exhibit 11

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2017

APPLICATION TO LEGISLATIVE ANALYSIS

An actuarial analysis of a physician fee schedule update in a state is typically a three-step process:

1. Calculate the percentage change in maximum reimbursements
2. Estimate the price level change as a result of the revised fee schedule
3. Determine the share of costs that are subject to the fee schedule

Exhibit 12 provides sample calculation from NCCI's legislative analysis process. Note that while the values in Rows (4) through (6) have been chosen for illustrative purposes, they are typical of values observed in most NCCI states.

EXAMPLE OF A PHYSICIAN FEE SCHEDULE UPDATE ON BENEFIT COSTS

(1) Weighted average change in physician MARs	+2.5%	+2.5%
(2) Price realization factor	70%	90%
(3) Impact on physician payments = (1) x (2)	+1.8%	+2.3%
(4) Share of WC medical costs attributable to physicians	40%	40%
(5) Medical share of total WC losses	58%	58%
(6) Impact on overall WC system costs = (3) x (4) x (5)	**+0.4%**	**+0.5%**

Exhibit 12

Following the results of [2], NCCI currently applies a price realization factor of approximately[20] 80% when the weighted average change in physician MARs is positive; a 50% factor is applied when the weighted average change in MARs is negative. This table shows that the estimated impact on overall costs is not particularly sensitive to the price realization

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[20] In the case of a fee schedule increase, the 80% price realization factor is adjusted for the observed price departure in that state, defined as the percentage difference between actual statewide payments to physicians and payments if all reimbursements occurred at the applicable MAR.

factor. In the above example, a 20% variation in the assumed price realization factor results in only a 0.1% difference in estimated impacts on overall system costs when the weighted average MAR changes by +2.5%.

The application of our linear regression model to the legislative analysis process is straightforward. Continuing the assumption that fee schedule updates have minimal effect on utilization, the linear regression model predicts that the year-over-year change in prices for physician services within a state will be approximately 80% of the corresponding change in MAR for each procedure code. Hence, the implied price realization factor (defined as the predicted percentage change in prices divided by the corresponding percentage change in MAR) is also 80%. The results of our linear regression model are applicable uniformly to MAR increases and decreases. We note that applying a uniform 80% price realization factor, as in the example of Exhibit 12, would result in minimal changes to the results of NCCI's current methodology in the case of fee schedule increases; however, substantially larger benefit cost impacts would be associated with fee schedule decreases.

While it may not be immediately apparent, our autoregressive model produces similar implied price realization factors to the linear regression model. To understand intuitively why this is the case, note that the fitted values for coefficients β_3 and β_4, while highly statistically significant, are quite small relative to β_1 and β_2. Thus, the terms associated with these two coefficients have minimal impact on the predicted price per transaction for the vast majority of observations. Furthermore, most MAR updates are relatively small, typically due to inflation indexing or minor updates to Medicare's relative value units. Noting that β_1 is approximately 0.8 and β_2 is approximately 1.0, for small values of $\%\Delta M_{i,s,t}$, we have the approximations:

$$\begin{aligned} P_{i,s,t} &\approx exp\big(\beta_1 \log\big(1+\%\Delta M_{i,s,t}\big) + \beta_2 \log\big(P_{i,s,t-1}\big)\big) \\ &= \big(1+\%\Delta M_{i,s,t}\big)^{\beta_1} \times P_{i,s,t-1}^{\beta_2} \approx \big(1+\beta_1 \times \%\Delta M_{i,s,t}\big) \times P_{i,s,t-1}^{\beta_2} \\ &\approx \big(1+0.8 \times \%\Delta M_{i,s,t}\big) \times P_{i,s,t-1} \Rightarrow \end{aligned}$$

$$\%\Delta P_{i,s,t} \approx 0.8 \times \%\Delta M_{i,s,t}$$

A concrete example of the above approximation may be seen in Exhibit 13, which shows the predicted price per transaction for the top three procedure codes by payment in one state.[21] Note that despite varying historical average prices per transaction and MAR changes, the implied price realization factors for the 2017 to 2018 fee schedule update tends to remain around 80% or slightly above that.

EXAMPLES OF THE IMPLIED PRICE REALIZATION FACTOR

Procedure Code	**97110**	**97530**	**99213**
(1) Year 2016 PPT	$41.98	$44.45	$90.12
(2) % Change in MAR Between 2016 and 2017	+3.2%	0.0%	+7.3%
(3) Year 2017 PPT	$42.40	$43.02	$92.46
(4) % Change in MAR Between 2017 and 2018	+2.3%	+5.5%	+2.4%
(5) Predicted Year 2018 PPT (based on (1) to (4))	$43.21	$44.90	$94.47
(6) Implied Price Realization Factor = [(5) / (3) – 1] / (4)	84%	80%	90%

Exhibit 13

NCCI's analysis is based on Medical Data Call for services provided between 2011 and 2017

[21] This state updates the WC physician fee schedule annually each January 1. The codes represent 31% of the state's physician payments in 2017.

CONCLUDING REMARKS

This study examines the effect of changes in fee schedules on physician payments and finds that in response to fee schedule changes, prices paid for physician services change by approximately 80%. The results are fairly consistent across all the various scenarios tested within each methodology examined.

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