RESEARCH BRIEF

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The Impact of Fee Schedule Updates on Hospital Outpatient Payments

INTRODUCTION

Medical advancements such as faster-acting anesthetics and less invasive procedures have allowed a growing number of surgeries to be performed in an outpatient setting. As such, hospital outpatient (HOP) payments have become a significant share of medical expenditures for workers compensation (WC) claims, comprising approximately 20% of medical costs.[1] As a cost control measure, and to ensure access to hospital services, some states[2] have implemented fee schedules that have established maximum allowable reimbursements (MARs) and rules for HOP services in WC. Updates to fee schedule MARs tend to be followed by corresponding changes in medical payments. This study further explores how HOP payments are impacted by changes in the MARs.

BACKGROUND

Fee schedule MARs act as price ceilings for the amount reimbursable to a service provider for a given WC medical service. A medical service, or group of services, is assigned an alphanumeric code. This alphanumeric code is typically called a procedure code, and it helps to identify services or a group of services for billing and reimbursement purposes.

Many states determine the MARs for these procedure codes based on rates published by the Centers for Medicare and Medicaid Services and update their fee schedules regularly to remain up to date with Medicare and to reflect inflationary effects. For states that do not base their HOP fee schedule on Medicare, the MARs are often based on state-specific rates or a percentage of charged amounts.

To analyze the impact that changes to MARs have on WC benefit costs, NCCI determines the weighted-average percentage change in MARs, where the weights are the payments. This calculation is performed by medical cost category (e.g., physicians, hospital inpatient, or HOP). The initially calculated impact on a specific medical cost category is multiplied by a price realization factor. This factor represents the relationship of how changes in MARs are expected to affect changes in prices paid. Previous NCCI research [1] indicates a price realization factor of 80% for revisions to MARs for physician services. For example, a 10% change in the MARs for physician services would translate to an approximate 8% change in payments to providers. The physician study used a linear regression model and a multivariate log-log autoregressive model to arrive at this result.

[1] In NCCI's Medical Data Call (MDC), 20% of medical payments in 2018 were for HOP services.

[2] In this article, state is defined as the state of jurisdiction that would administer the claim and whose statutes/rules apply to the claim.

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The methodology used to analyze the impacts for HOP fee schedule changes is similar to the method used for physician fee schedule changes. Like the physician study, a modeling approach was employed to determine the price realization factor to be used in calculating the impact of changes in HOP fee schedules on prices paid for such services.

KEY FINDINGS

- Changes to medical fee schedules for HOP services affect prices paid for services that are subject to the fee schedule.
- Approximately 75% of the average change in MAR for a HOP service was realized as a change in prices paid.[3]
- Although there is some variation across states, the indicated HOP price realization factor of 75% is an unbiased estimate for any jurisdiction[4] included in this study.
- The price response to fee schedule updates in a given quarter has some dependence on the price change in the prior quarter. However, this dependency is small in magnitude and generally only extends for a single quarter.

DATA AND CONSIDERATIONS

For states other than Texas, the data source used in this study is NCCI's Medical Data Call (MDC). For Texas, the data source used is the Division of Workers' Compensation (DWC) Medical State Reporting Public Use Data File.[5]

The information being used is transactional payment data for HOP services with a date of service between January 1, 2011, and December 31, 2018, which essentially corresponds to the years of available data in the MDC at the time of this research. Each reported transaction has a procedure code that represents the medical service or group of services performed, and the procedure codes have an assigned status indicator that determines how the medical service is reimbursed. State-specific MARs are assigned to each transaction, where a MAR exists, based on the state's HOP fee schedule rules.

The states included in the study were jurisdictions where NCCI is a licensed rating or advisory organization and where the states have a mandatory HOP fee schedule that was updated at least once during the time period covered by the data. We define mandatory to mean that the fee schedule meets all of the following characteristics:

- Imposes a fixed maximum on prices for procedures (e.g., not based on a percentage of charges)
- Is mandatory
- Covers out-of-state transactions or the out-of-state transactions represent a minimal share of transactions

Data from the selected states was then reviewed, and observations that were deemed to be outliers[6] or had low volume[7] were excluded. The data was then aggregated into state, service quarter, procedure code, and status indicator combinations for the model. This resulted in 10,507 combinations and $1.8 billion in HOP medical paid.

[3] NCCI recognizes that this relationship might not hold if the fee schedule is set at a level that is substantially higher or lower than standard industry price levels.
[4] Jurisdictions included in this study are AK, CO, CT, GA, ID, IL, IN, KS, ME, MT, NC, NM, NV, SC, TN, and TX
[5] Texas Department of Insurance, Division of Workers' Compensation, Austin, TX.
[6] Outliers determined using the Tukey's outlier detection rule.
[7] Procedure codes with 50 or fewer transactions.

DATA ANALYSIS AND MODELING APPROACH

Before getting into the details of our data analysis, it is important to frame the question explored—how are WC payments for HOP services impacted by changes in fee schedules? To illustrate the behavior of HOP payments in response to fee schedule updates, Exhibit 1 shows a trajectory of quarterly changes in average prices and the timing of fee schedule updates for one of the states included in our study. The mix of services is controlled to be consistent over time, thereby isolating the quarterly price-level change. Notice that average HOP prices change from quarter to quarter, but the larger changes coincide with fee schedule updates. In other words, the trajectory of price changes is impacted by the fee schedule updates. This change is what we want to measure because the impact of fee schedule updates has an effect on WC system costs.

Exhibit 1: Indexed Change in Price vs. Change in MAR

Let's begin with an explanation of how the data is organized for this research. NCCI's MDC contains transactional data for medical services provided to WC claimants, including the state of jurisdiction, date of service, the service provided, and associated reimbursement to the provider. This allows us to organize the data as shown in Exhibit 2 in order to relate quarterly changes in average payments to changes in the HOP fee schedules. We are then able to track changes in price levels by state for each HOP procedure and status indicator and compare those changes to fee schedule updates. For example, for Procedure Code 0615 in Texas, we observed some quarterly changes in prices paid between Service Quarters 2 and 4 (2Q2011 to 4Q2011). A larger change in prices paid in quarter 5 (1Q2012) corresponded to an update to the fee schedule during that same quarter. In Georgia, for Procedure Code 5114, we observed a larger change in prices paid during Service Quarter 30 (2Q2018) when compared with other quarters in which there was no change in the MAR.

Exhibit 2: Data Sample

State	Service Quarter	Code	Description	% Change in Average Price From Prior Quarter	% Change in MAR From Prior Quarter
TX	2	0615	Level 4 type A emergency department visits	–0.8%	0.0%
TX	3	0615	Level 4 type A emergency department visits	–0.3%	0.0%
TX	4	0615	Level 4 type A emergency department visits	+0.9%	0.0%
TX	5	0615	Level 4 type A emergency department visits	–1.9%	–1.3%
GA	29	5114	Level 4 musculoskeletal procedures	+2.9%	0.0%
GA	30	5114	Level 4 musculoskeletal procedures	+9.9%	+10.7%
GA	31	5114	Level 4 musculoskeletal procedures	–3.4%	0.0%

To define the specifications of our model, displayed below is a panel vector autoregression with exogenous[8] variables (PVAR(1)[9]) model of the form:

$$\%\Delta P_{i,s,t} = \gamma \times \%\Delta P_{i,s,t-1} + \beta \times \%\Delta M_{i,s,t} + \alpha + u_{i,s,t}$$

where:

- $\%\Delta P_{i,s,t}$ is the % change in price for a service *i* in state *s* between time *t–1* and *t*
- γ represents the lag effect of prior quarter price change, i.e., a measure of the "momentum" of past price changes
- β represents the price realization factor
- $\%\Delta M_{i,s,t}$ is the % change in MAR for a service *i* in state *s* between time *t–1* and *t*, and is assumed to be an exogenous variable
- α represents the healthcare cost trend occurring apart from the change in MAR, assumed to be constant over time and by state
- $u_{i,s,t}$ is the error term; our model assumes that the errors are independent of the model variables, with independent, identical, normal distributions

Four considerations drove our modeling choice:

- Potentially autocorrelated observations over time
- Large number of relatively short time series (a panel)
- Variable of interest (change in the MAR) is exogenous
- Emphasis on simplicity and interpretability of results

For each of these considerations, a PVAR is a natural modeling choice because it addresses each of the above considerations.

In summary, this model is designed to measure the responsiveness of price changes to fee schedule updates, while considering past price changes and general healthcare cost trends occurring apart from the change in HOP fee schedules. During the exploratory phase of this study, the following additional control variables were considered but were determined to have a small effect on the responsiveness of price changes to HOP fee schedule updates:

- State of jurisdiction
- Surgical vs. nonsurgical services
- Emergency vs. nonemergency services
- Overall fee schedule generosity relative to Medicare

[8] In this study, HOP fee schedule updates are assumed to occur through an exogenous process. A variable is exogenous if it is correlated with the dependent variable in the model but none of the other model variables exert any influence on it.
[9] Vector autoregression (VAR) is a stochastic process model used to capture the linear interdependencies among multiple time series. PVAR(n) models are a class of models that can create VAR models for a panel of time series, where n represents the number of lags of the dependent variable.

The results of the model are shown in Exhibit 3.

Exhibit 3: Model Results

Coefficient	Variable	Fitted Coefficient Value	Standard Error
γ	$\%\Delta P_{i,s,t-1}$	–0.1058	0.0187***
β	$\%\Delta M_{i,s,t}$	0.7501	0.0326***
α	$constant$	0.0013	0.0006***

*** Statistically significant at the 1% confidence level

To illustrate what the model accomplishes, let us consider a hypothetical example in which a procedure in state X increased in price by 2% last quarter and the MAR increased 5% in this quarter. The model is:

$$\%\Delta P_{i,s,t} = \gamma \times \%\Delta P_{i,s,t-1} + \beta \times \%\Delta M_{i,s,t} + \alpha + u_{i,s,t}$$

Based on our model, the change in price for this quarter is expected to be:

$$+\mathbf{3.7}\% \;(= -0.1058 \times \mathbf{2}\% + 0.7501 \times \mathbf{5}\% + 0.0013 + 0)$$

What the result of the model tells us is that the price responsiveness for HOP services in response to HOP fee schedule updates is about 75% (β= 0.7501). Furthermore, the model tells us that price changes in the prior quarter have an approximate –11% (γ = –0.1058) impact on price changes. Finally, the healthcare cost trend occurring apart from the change in MAR is about 0.2% ($\alpha = 0.0013$). Looking at the standard errors of each of the fitted coefficients in Exhibit 3, we see that each is statistically significant at the 1% confidence level.

MODEL DIAGNOSTICS

After reviewing the fitted coefficients and determining that they are statistically significant, we move to analyze the distribution of residuals. A residual plot displays the difference between actual observations and predicted observations based on the model. Residual plots help to analyze the goodness-of-fit for a model and help determine if the fitted values are biased (over or under predicting). To determine possible bias, we look for a disproportionate distribution of residuals above or below the horizontal line or x-axis. For plots of residuals, 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 zero (on the x-axis) mean that the actual observation and predicted observation are equal. An unbiased model would have a similar distribution between positive and negative values. We analyze residuals in the following ways:

- **Exhibit 4a—By state of jurisdiction:** Does the model perform equally well by jurisdiction?
- **Exhibit 4b—Across time:** Does the model perform equally well across time? Changing levels of hospital market power, changing types of medical services, or changes to the structure of Medicare's reimbursement could all cause model performance to degrade over time.
- **Exhibit 4c—By Service Quarter:** Is there seasonality in the residuals? The use of a quarterly data aggregation but only a one-quarter lag suggests that there is potential for seasonality.
- **Exhibit 4d—By payment volume:** Does the model perform equally well for procedures of different payment volume? Does it become biased as the volume of payments gets larger or smaller?

For each of the above questions, bias can be detected by observing whether the residuals are evenly scattered around zero across the analyzed variables. As Exhibits 4a through 4d below indicate, there appears to be no evidence of such bias in the residuals. Much of the variation in the dispersion of residuals across states is a function of the volume of observations. For example, in Exhibit 4a, we see IL having the widest dispersion of residuals. That is highly because IL is a high-volume jurisdiction with a mandatory HOP fee schedule in effect during the entire timeframe of this study. In contrast, in GA we see a tighter dispersion of residuals. Although GA is a high-volume state the mandatory HOP fee schedule was enacted in May 2014.

Exhibit 4a: Residuals by State

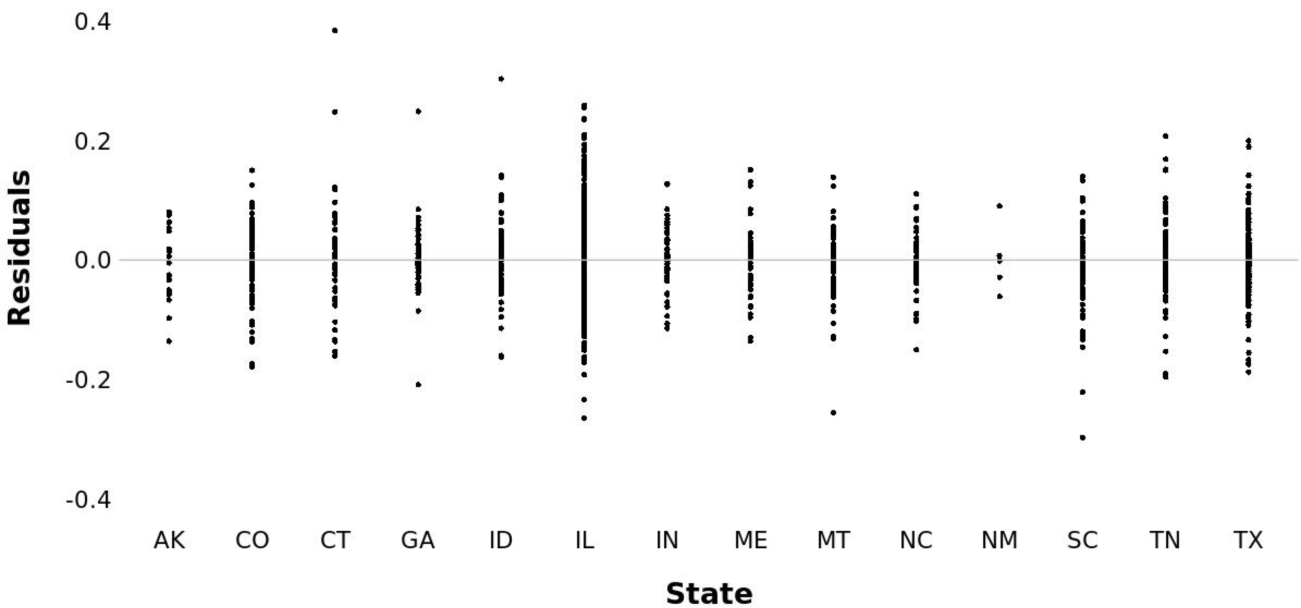


Exhibit 4b: Residuals Over Time (by Quarter of Service)

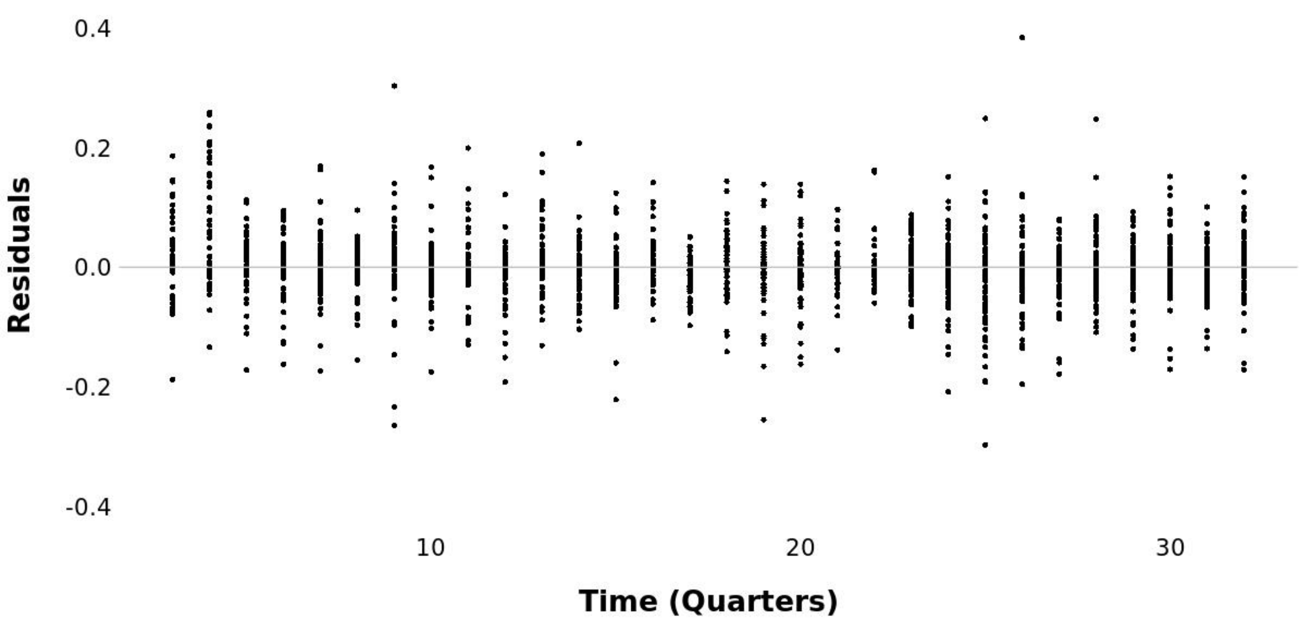


Exhibit 4c: Residuals by Quarter

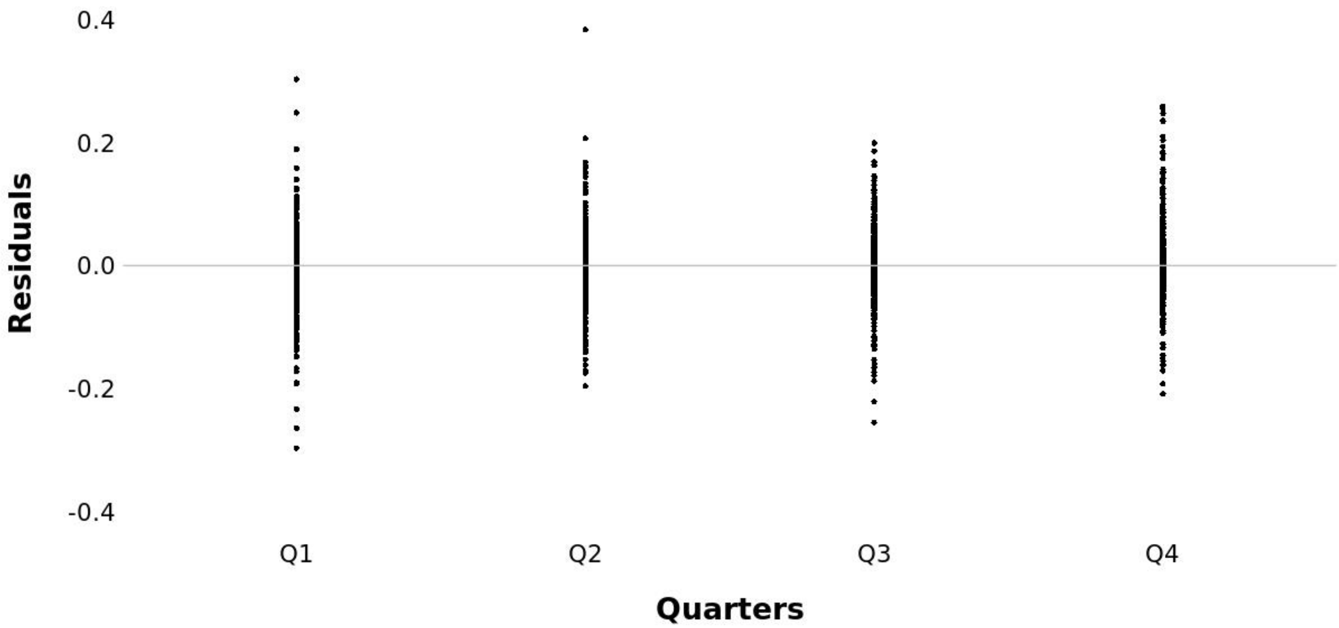
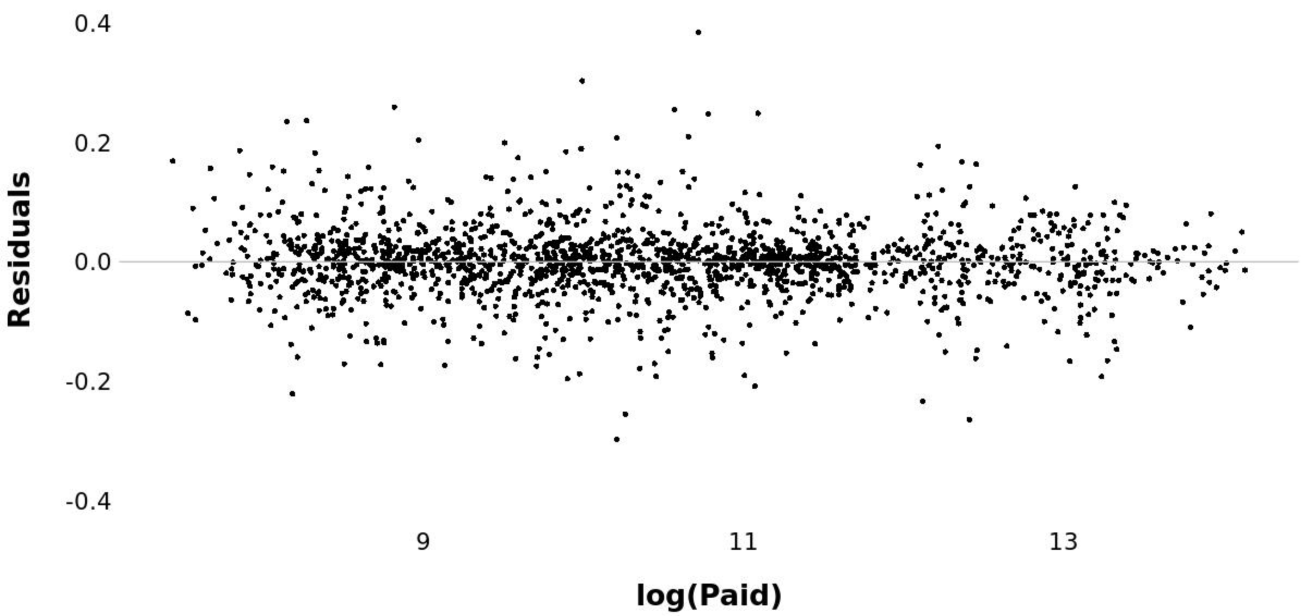


Exhibit 4d: Residuals by Payment Volume



In addition to analyzing residuals, it is important to test the performance of the model by using data that was not used in the "training" of the model (i.e., the "holdout" dataset). Model creation used approximately 80% of the data in the study dataset. To further test model performance, the remaining 20% of the data was used as a holdout sample to test the model. There were two types of tests performed:

- Comparison of model performance against simpler alternatives
- Analysis of goodness-of-fit and residual plots

In comparing the model against simpler alternatives, we looked at the mean squared error of each of these models. When comparing models using this metric, the lower the mean squared error the better the performance of the model. The models and corresponding mean squared errors are displayed in Exhibit 5. The exhibit shows that the selected model notably outperforms the simpler models by having the lowest mean square error.

Exhibit 5: Holdout Sample Testing—Model Comparison

Model Includes:	Mean Squared Error
Inflation Only	0.80%
Inflation and Lag	0.79%
Inflation, Lag, and MAR Changes (Selected model)	0.41%

Another test of model effectiveness using the holdout sample is to analyze the relationship between predicted and actual price values. Exhibit 6 displays a scatterplot that demonstrates the relationship between predicted and actual price values. Each observation in the scatterplot is the intersection of the predicted price index value and actual price index value for a procedure code, state, and service quarter. The linearity of these observations suggests that the model's predicted prices are close to the actual values. In testing this relationship, we look at the regression line of this scatter plot and find it to be close to unity (at 0.99), thus indicating a near perfect correlation between the predicted and actual price index values.

Exhibit 6: Holdout Sample Testing—Actual vs. Predicted

CONCLUDING REMARKS

This study examines the effect of changes in fee schedules on HOP payments and finds that in response to fee schedule changes, prices paid for HOP services changed by approximately 75%. Furthermore, price responsiveness to fee schedule updates in a given quarter has some dependence on the price change in the prior quarter. However, this dependency is small in magnitude and generally only extends to a single quarter.

ACKNOWLEDGMENT

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