RESEARCH BRIEF

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DO DRUG FEE SCHEDULES BASED ON AWP HAVE AN EFFECT ON PRICES PAID FOR DRUGS IN WORKERS COMPENSATION?

Abstract. Using a high-frequency cross-sectional transaction dataset (Medical Data Call) and an econometric model, this study quantifies the impact of Average Wholesale Price-based prescription drug fee schedules on workers compensation (WC) drug costs. Partial effects of explanatory variables and the cost impact of a change in drug fee schedules across fee schedule regimes (low-, medium-, high-, and no- fee schedule) are estimated. Controlling for observed characteristics of drugs dispensed (e.g., whether a drug is dispensed within a network or not, whether a drug is a brand name drug or a generic drug, and whether a drug is dispensed by a physician or not), our model results show that average prices paid for WC drugs in low-fee schedule states are significantly lower than prices paid for WC drugs in states without a fee schedule, and average prices paid for WC drugs in high-fee schedule states are significantly higher than prices paid for WC drugs in states without a fee schedule. However, the average difference in price paid per unit for WC drugs between medium-fee schedule states and no-fee schedule states is statistically insignificant.

Keywords: workers compensation; fee schedule; prescription drugs; medical cost

INTRODUCTION

Faced with rapidly growing prescription drug expenditures, regulation of prescription drug prices has become a focus of legislative activity in workers compensation (WC). The projected prescription drug share of total medical costs for Accident Year 2014 is 17% (Lipton and Colón, 2016).

Most states have prescription drug fee schedules that limit the prices that must be paid to service providers, absent some specific agreements between providers and payers (e.g., WC insurers and self-insureds). Typically, prescription drug fee schedules are based on the Average Wholesale Price (AWP). The AWP is generally set by the drug manufacturer and does not necessarily reflect the actual average market wholesale price paid by most drug purchasers, such as pharmacy chains (Gencarelli, 2002). For most states with prescription drug fee schedules, the maximum amount reimbursable (MAR)[1] to a prescription drug vendor is in general specified as a multiplier times AWP times the quantity of drugs dispensed, plus a dispensing fee. Multipliers, dispensing fees, and therefore the MAR allowed may vary between and within states according to characteristics of the drug transactions (e.g., brand name vs. generic drugs, pharmacy vs. physician dispensing). AWP multipliers (i.e., the multiple to the AWP) range from 80% to 140%, and dispensing fees generally go from $0 to $12. Even though dispensing fees vary and contribute to the MAR, the multiplier is the major determinant of the MAR (Moore et al., 2015).

Following Moore et al. (2015), we categorize jurisdictions (hereafter, states) into four prescription drug fee schedule regimes (see Table 1). The AWP multiplier used for this categorization is the multiplier for pharmacy-dispensed generic prescription drugs during the period from 2011 to 2013.

[1] This term is also known as maximum allowable reimbursement. It is defined as "a fee schedule established within a jurisdiction by rule, regulation, or statute, which limits the maximum amount to be reimbursed for the Rx provided" (Moore et al., 2015), where Rx denotes prescription drug.

State WC fee schedules for prescription drugs have been in place for several years. Previous empirical research on prescription drug fee schedules has been limited to descriptive and univariate analyses. For instance, Moore et al. (2015), using Medical Data Call for prescriptions provided between Service Years 2011 and 2013, found that mix-adjusted average prices[2] paid for WC drugs (capsules and tablets) in low-fee-schedule states were $1.63 per unit, $1.73 per unit in medium-fee-schedule states, $1.78 per unit in high-fee-schedule states, and $1.73 per unit in states without a fee schedule. These authors also looked at other variables, such as WC networks and the type of drug, and found that each of these factors play a role in explaining WC prescription drug costs when considered individually.

Our research estimates an econometric model that quantifies the impact of AWP-based prescription drug fee schedules on the price paid for WC drugs, controlling explicitly for observed characteristics of the drugs dispensed (e.g., whether the drug is dispensed within a network or not; whether the drug is a brand-name drug or a generic drug) that simultaneously affect actual prices paid. Using this model, we perform a legislative analysis to estimate percentage changes in the predicted total paid amount (the cost impact of a change in fee schedules) across the four prescription drug fee schedule regimes defined in Table 1.

Table 1. Prescription Drug Fee Schedule Regimes and States

Fee Schedule Regime	Description	States Included in This Study
No	States with no fee schedule in place	DC, IA, ID, IL, IN, MD, ME, MO, NC, NE, NH, NJ, SD, UT, VA, and WV
Low	States with an AWP multiplier < 100%	AZ, KS, MI, MT, NM, NY, OK, and OR
Medium	States with an AWP multiplier = 100%	AR, CO, CT, FL, GA, KY, MN, MS, NV, SC,TN, VT, and WI
High	States with an AWP multiplier > 100%	AK, AL, HI, LA, and RI

Notes: MA is not included in this study because its drug fee schedule is based on factors other than AWP. None of the states included in this study had a closed formulary in place during the period used for this study. Closed formularies have an effect on prices paid for WC drugs (Lipton and Colón, 2016).

KEY FINDINGS

- From the model results, after controlling for characteristics of drug dispensed:
  - Fee schedules in:
    - Low-fee-schedule states significantly reduce prices paid for drugs in WC relative to no-fee schedule states
    - Medium-fee-schedule states do not have a significant impact on prices paid for drugs in WC compared to states without a fee schedule
    - High-fee-schedule states significantly increase prices paid for drugs in WC relative to no fee schedule states, when the drug is not dispensed in a network
  - AWP is the most significant determinant of prices paid per unit for WC drugs
- From the legislative analysis, if a state with a:
  - High-fee or no-fee schedule were to move to a low-fee schedule, the estimated cost impact would be a 9% decrease in the state's prescription drug costs, while changing regimes from a low-fee schedule to a high- or no-fee- schedule regime is estimated to result in a 10% increase in prescription drug costs
  - No-fee schedule for prescription drugs were to adopt a high-fee schedule, then we estimate that prescription drug costs would increase by 1%
  - High-fee schedule for prescription drugs were to eliminate its fee schedule entirely, then we estimate that there would be no effect on prescription drug costs

[2] Prices adjusted for mix of prescription drugs and mix of network transactions.

DATA

The data for this study is NCCI's Medical Data Call (MDC), which consists of medical transactions. Carriers are not required to report transactions for services provided more than 30 years after the date of injury.

We use data for:

- The 42 states listed in Table 1
- Services provided between January 1, 2011 and December 31, 2013, and reported to the insurer by March 31, 2014
- Prescriptions for drugs provided as capsules and tablets
- Prescriptions for which the paid amount is greater than or equal to $1

Claims, and all associated transactions, are assigned to their state of jurisdiction, which is not necessarily the state where the prescription was filled.

We did not include transactions for drugs coded as repackaged drugs because these drugs might be subject to cost drivers that differ from cost drivers of most drugs in WC.

Our dataset consists of 14,039,234 transactions. The model is estimated using a random sample of 9,827,464 of these transactions to make computations more manageable. The sample selection method for extracting this random sample is a simple random sampling procedure, which is conducted without replacement and allows each transaction to have an equal probability of selection.

AWP is a published Rx price reported by commercial publishers of drug pricing data, such as First Databank, Red Book, or Medi-Span. AWP in this study is NCCI's estimate of the AWP based on drug pricing data published by First Databank.

MODEL

Specification of the Model

We specify a multivariate linear regression model to quantify the effect of AWP-based prescription drug fee schedules on the price paid per unit for drugs in WC. Note that below we use bold notation to indicate vector or matrices and nonbold to indicate scalars.

We assume that each observation,[3] which is a member of one non-overlapping cluster,[4] is generated by the following underlying process

$$\begin{aligned} y_{ig} &= \beta_0 + \beta_1 x_{ig1} + \beta_2 x_{ig2} + \ldots + \beta_k x_{igk} + \varepsilon_{ig} \qquad g = 1,\ldots,G \quad i = 1,\ldots,n_g \\ &= \mathbf{x}_{ig}'\boldsymbol{\beta} + \varepsilon_{ig} \end{aligned} \tag{1}$$

where:

y_{ig} denotes the price paid per unit (the dependent variable) for transaction i in state g

$\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_k)$ is the $((k+1)\times 1)$ parameter vector: β_0 is the intercept and $\beta_1, \beta_2, \ldots, \beta_k$ are unknown slope parameters

$\mathbf{x}_{ig} = (1, x_{ig1}, x_{ig2}, \ldots, x_{igk})$ contains the observed explanatory[5] variables. The superscript " ' " denotes transpose

[3] Each observation is a transaction, which is a single "billing line" for a medical service.
[4] A cluster in this study is meant to be a state.
[5] This term is used interchangeably with regressors, covariates, factors, independent variables, or predictor variables.

ε_{ig} is the unobservable random error (disturbance) term for transaction i in state g

$k+1$ denotes the number of parameters, including the intercept

We impose the following moment assumption about the probability distribution of ε_{ig} in (1)

$E\left[\varepsilon_{ig} \mid \mathbf{x}_{ig}\right] = 0$ — The mean value of the error term is zero for any given value of $\mathbf{x}_{ig}$ within its state g

We also control for clustering by assuming that the errors in our model are *independent across states,* but those errors for transactions belonging to the same state may be correlated, with general heteroskedasticity and correlation. Thus, for $i \neq j$ in the joint distribution of $\left(\varepsilon_{ig}\varepsilon_{jg'}\right)$ conditional on **x**, the covariance is zero

$E\left[\varepsilon_{ig}\varepsilon_{jg'} \mid \mathbf{x}_{ig}, \mathbf{x}_{jg'}\right] = 0$ if $g \neq g'$

In other words, our model relaxes the independent and identically distributed classical assumption in favor of a more realistic error structure, which allows for arbitrary correlation between errors within states of any form.[6]

Using our data, the Breusch-Pagan test (relaxing the normality assumption), the White general test for heteroskedasticity, and a special form of the White test that is more conserving on the degrees of freedom proposed by Wooldridge (2013) reject the null hypothesis of homoscedasticity. The resulting two-tailed p-value of zero in each of these tests rejects the null hypothesis convincingly, suggesting strong evidence that the errors are heteroskedastic. Moreover, adjusted standard errors for clustering and robust to heteroskedasticity (i.e., cluster-robust standard errors) are on average two times larger than standard unadjusted standard errors.

Since the regression model errors are not actually homoscedastic and are suspected to be correlated within states but independent across states, standard errors in this study are derived using a cluster-robust variance-covariance estimator for one-way clustering (see Estimation of Standard Errors below).

Beyond the assumptions discussed above, we impose no assumptions concerning the distribution of ε_{ig}. Thus, model (1) is fully determined once the coefficients of the parameters are known, even though the form of the probability distribution of the disturbances is unknown.

Equation (1) can be rewritten as

$$\mathbf{y}_g = \mathbf{x}_g\boldsymbol{\beta} + \boldsymbol{\varepsilon}_g,\ E\left(\boldsymbol{\varepsilon}_g \mid \mathbf{x}_g\right) = \mathbf{0},\ \boldsymbol{\Omega}_g = V\left(\boldsymbol{\varepsilon}_g \mid \mathbf{x}_g\right) = E\left(\boldsymbol{\varepsilon}_g\boldsymbol{\varepsilon}_g' \mid \mathbf{x}_g\right) \quad (2)$$

by grouping transactions for each state g, and $\mathbf{y} = \mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ by further stacking $\mathbf{y}_g$, $\mathbf{x}_g$, and $\boldsymbol{\varepsilon}_g$ over all states. The components $\mathbf{y}$, $\mathbf{x}$, $\boldsymbol{\beta}$, and $\boldsymbol{\varepsilon}$ contain the same data elements as in (1), but now $\mathbf{y}$ is an n-dimensional column vector, $\mathbf{x}$ is an $\left(n \times \left(k+1\right)\right)$ matrix with $rank\left(\mathbf{x}\right) = k+1 < n$, $\boldsymbol{\varepsilon}$ is an n-dimensional column vector, and $n = \sum_{g=1}^{G} n_g$. In (2), $\boldsymbol{\Omega}_g$ denotes the cluster error variance matrix for state g, which under $\mathbf{y} = \mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ is represented by a bloc-diagonal matrix $\boldsymbol{\Omega}$ with the cluster error variance matrices on the main diagonal.

[6] Bertrand, Duflo, and Mullainathan (2004) emphasize the need to control for clustering within states in order to achieve valid statistical inference.

ESTIMATION OF THE MODEL

To estimate our model, we use a Weighted Least Squares (WLS) estimator to control for differences in the mix of prescription drugs. The WLS estimator is given by

$$\hat{\boldsymbol{\beta}}_W = \left(\mathbf{x}'\mathbf{W}\mathbf{x}\right)^{-1}\mathbf{x}'\mathbf{W}\mathbf{y} = \left(\sum_{g=1}^{G}\mathbf{x}_g'\mathbf{W}\mathbf{x}_g\right)^{-1}\sum_{g=1}^{G}\mathbf{x}_g'\mathbf{W}\mathbf{y}_g \tag{3}$$

where $\hat{\boldsymbol{\beta}}_W$ is a $((k+1)\times 1)$ column vector of WLS coefficients and $\mathbf{W}$ is a diagonal matrix of dimension $(n\times n)$ whose main diagonal elements are positive weights. Weights in this study are estimated for each National Drug Code (NDC) drug as follows

$$ew_{i,i} = \frac{\sum_{j:NDC_j=NDC_i} paidamt_j}{\sum_j paidamt_j}, ew_{i,j} = 0, i \neq j \tag{4}$$

where $ew_{i,i}$ denotes the estimated expenditure (paid amount) weight for the NDC drug in transaction i, and $paidamt_j$ is the total paid amount for transaction j. In **W**, the estimated weights do not need to sum to 1. We also estimate weights for the same NDC drugs based on units.

ESTIMATION OF STANDARD ERRORS

As indicated above and given error independence across states, the standard errors for each coefficient are derived using the $(k+1)\times(k+1)$ one-way cluster-robust variance-covariance estimator of $\hat{\boldsymbol{\beta}}_W$

$$\hat{V}\left(\hat{\boldsymbol{\beta}}_w \mid \mathbf{x}\right) = q\cdot\left(\mathbf{x}'\mathbf{W}\mathbf{x}\right)^{-1}\hat{\boldsymbol{\Omega}}\left(\mathbf{x}'\mathbf{W}\mathbf{x}\right)^{-1} \tag{5}$$

where:

- $q = \frac{n-1}{n-(k+1)}\cdot\frac{G}{G-1}$ is a finite-cluster correction constant for one-way clustering to reduce downward bias[7]
- $\hat{\boldsymbol{\Omega}} = \sum_{g=1}^{G}\mathbf{x}_g'\mathbf{W}_g\hat{\boldsymbol{\varepsilon}}_g\hat{\boldsymbol{\varepsilon}}_g'\mathbf{W}_g'\mathbf{x}_g$ is a consistent cluster-robust estimator of $\boldsymbol{\Omega}$
- $\hat{\boldsymbol{\varepsilon}}_g = \mathbf{y}_g - \mathbf{x}_g\hat{\boldsymbol{\beta}}_W$ is the vector of WLS residuals for state g

- G is the number of states
- $\mathbf{x}$ and $\mathbf{W}$ are as defined previously

This estimator is consistent in the presence of any correlation pattern within clusters (states) and is robust to both the arbitrary correlation of disturbances within states and to arbitrary heteroskedasticity. Failure to control for the within-

[7] $q = \frac{n-1}{n-k}\cdot\frac{G}{G-1} \approx \frac{G}{G-1}$ as n goes to infinity.

cluster error correlation makes both the conventional and the heteroskedastic-robust estimates of the variance-covariance matrix invalid, leading to possibly misleadingly small standard errors and spurious findings of significance of the parameters in our model (Moulton, 1990; Cameron and Miller, 2014).

Equation (5) does not require specification for $\boldsymbol{\Omega}_g$ since unlike other methods, the cluster-robust variance-covariance estimator permits quite general forms of $\boldsymbol{\Omega}_g$ (Cameron et al., 2012). Indeed, equation (5) places no restriction on heteroskedasticity and correlation within a state as the $V(\varepsilon_{ig})$ and $Cov[\varepsilon_{ig}, \varepsilon_{jg}]$ are unrestricted. Equation (5) also maintains the form of the heteroskedasticity-robust estimator of the variance covariance matrix for Ordinary Least Squares introduced by White (1980) for cross-section data, known as the Huber-White-Eicker sandwich estimator.

Variables Used

Table 2 defines the variables included in equation (1), along with descriptive statistics.

Table 2. Variables Used in the Model and Descriptive Statistics

Variable Name	Description	Unconditional Mean	Std. Dev.
Dependent Variable			
paidamtunit	Paid amount ($/unit) for a drug transaction divided by the number of units	2.14	3.93
Explanatory Variables			
*nofs**	= 1 if the transaction occurs in a no-fee schedule state; 0 otherwise	0.24	0.43
lowfs	= 1 if the transaction occurs in a low-fee schedule state; 0 otherwise	0.35	0.48
mediumfs	= 1 if the transaction occurs in a medium-fee schedule state; 0 otherwise	0.34	0.48
highfs	= 1 if the transaction occurs in a high-fee schedule state; 0 otherwise	0.07	0.25
phydisp	= 1 if the drug is dispensed by a physician; 0 otherwise	0.05	0.22
*pharmdisp**	= 1 if the drug is dispensed by a pharmacy; 0 otherwise	0.95	0.22
otherdisp	= 1 if the drug is dispensed by others**; 0 otherwise	0.0009	0.03
network	= 1 if the transaction occurs in-network***; 0 otherwise	0.75	0.43
brand	= 1 if the transaction is for a brand name drug and the drug is only available with a brand name; 0 otherwise	0.10	0.30
brand.g	= 1 if the transaction is for a brand-name drug, but the drug is also available as generic; 0 otherwise	0.09	0.29
*generic**	= 1 if the transaction is for a generic drug and the drug is only available as generic; 0 otherwise	0.06	0.23
generic.b	= 1 if the transaction is for a generic drug, but the drug is also available with a brand name; 0 otherwise	0.75	0.43
AWP	Average Wholesale Price ($/unit) for a drug transaction	2.36	4.44
		Conditional Mean**	**Std. Dev.**
lowfs × AWP		2.46	4.55
mediumfs × AWP		2.28	4.30
highfs × AWP		2.37	4.15
phydisp × AWP		1.53	2.98
otherdisp × AWP		2.78	4.62
network × AWP		2.39	4.34
brand × AWP		6.99	8.29
brand.g × AWP		6.34	5.76
generic.b × AWP		1.39	2.60
network × lowfs × AWP		2.46	4.30
network × mediumfs × AWP		2.33	4.27
network × highfs × AWP		2.39	4.15

Notes: * Base group subsumed into the intercept in the model, i.e., the group against which comparisons are made; ** For example, hospitals and home nursing facilities; *** Health Maintenance Organizations or Preferred Provider Organizations; **** Mean values conditioned on having values different than zero for the variable interacting with AWP; Std. Dev. denotes standard deviation; The term "unit" is defined as being all drugs sold in the form of tablets or capsules; descriptive statistics are computed based on the random sample of 9,827,464 transactions.

For the transactions used in the study, Table 2 shows that:

- 69% are in low and medium prescription drug fee schedule regimes
- 24% are in states with no prescription drug fee schedule
- 7% fall into the high prescription drug fee schedule regime
- 95% are dispensed by pharmacies
- 75% occur in-network
- 75% are for generic name drugs that are also available as a brand name

The price paid per unit, *paidamtunit*, is $2.14 on average, with a minimum of $0.00177 and a maximum of about $445. The mean price paid per unit is slightly smaller than the mean AWP per unit, but the AWP exhibits a little bit more variation than the price paid per unit. Also, but not shown in Table 2, 55% of the transactions have a price paid per unit less than or equal to $1, and the middle 50%of all transactions lies between 44 cents (25th percentile) and $2.58 (75th percentile).

Table 3 shows that across all fee schedule regimes, 90% of drug transactions have a price paid per unit less than $6. While low-fee schedule states have lower mean and median prices paid per unit than states in the other three fee schedule regimes, the distribution of prices paid per unit in the low-fee schedule regime is distinguished by the heaviest right-hand tail; the skewness statistic for the low-fee schedule is the largest among all fee schedule regimes. Using three statistical distribution-free tests (the Kolmogorov-Smirnov test, the Wilcoxon-Mann-Whitney rank-sum test, and the Epps-Singleton test [Epps and Singleton, 1986]) we reject the null hypothesis, H_0, that the underlying univariate prices paid per unit distributions are equal for the fee schedule regimes. The null hypothesis of equality of distribution functions is rejected at the 0.01 level, confirming significant differences among prices paid per unit distributions for the fee schedule regimes under study.

Table 3. Paid Amount Distribution by Fee Schedule Regime

	PAID AMOUNT ($ per unit) Percentiles										
Fee Schedule Regime	**Min**	**0.25**	**0.50**	**0.75**	**0.90**	**0.99**	**Max**	**Mean**	**S.D.**	**sk**	***n***
No	.00177	0.46	0.86	2.50	5.41	19.92	217.30	2.19	4.11	9.60	2,352,267
Low	.00234	0.40	0.77	2.62	5.35	17.63	444.97	2.09	3.90	18.08	3,428,572
Medium	.00398	0.46	0.90	2.48	5.10	19.47	319.79	2.13	3.85	10.48	3,389,709
High	.00620	0.47	0.94	2.93	5.69	18.99	318.26	2.27	3.86	9.83	656,916
Total											**9,827,464**

Notes: S.D. denotes standard deviation, *sk* denotes skewness, percentile 0.50 is the median, and *n* indicates the size of the data sample.

RESULTS AND DISCUSSION

Model Results

Table 4, column 1 lists the variables described in Table 2, as well as multiplicative interaction terms. Interaction terms are variables in which the *partial effect*[8] of the dependent variable, with respect to an explanatory variable, depends on the magnitude of at least yet another explanatory variable. Column 2 reports parameter estimates with cluster-robust standard errors in parentheses for the model specified with expenditure weights; and column 3 does the same for the model specified with unit weights. Table 4 also reports the adjusted R-squared[9] goodness-of-fit statistic, as well as the estimated standard error of the regression $\hat{\sigma}$, and the p-value[10] for the F test for overall significance of the model.

Model Performance

Based on the adjusted R-squared statistic in Table 4, the explanatory variables from either weighting specification for our regression model explain collectively about 95% of the total variation in the price paid per unit for drugs in WC. This indicates that our econometric model provides a good fit to the data. Note that the included regressors in equation (1) explain a little bit more when using unit weights than when using expenditure weights, but the difference is not material. Only 5% of the price paid per unit variations is left unexplained by unobserved factors included in the regression's error term. The model using unit weights has a smaller standard deviation of the unobservables, namely $\hat{\sigma}$ = 0.44, than the model using expenditure weights for which $\hat{\sigma}$ = 0.76. In either case, approximately 95% of the fitted (predicted) values of the paid amount per unit are within a range of $2\hat{\sigma}$ of the actual value of paid amount per unit.[11] The high explanatory power of our model, as per the adjusted R-squared statistic, suggests that our estimates of the partial effects of explanatory variables effectively account for observed variations in the price paid per unit of prescription drugs.

The econometric model as a whole, using either expenditure or unit weights, is highly significant. The resulting p-value of zero (to four decimal places) in Table 4 rejects very convincingly the null hypothesis at the 1% significance level that the whole set of explanatory variables has no effect on the price paid per unit. Hence, we conclude that the explanatory variables included in our model help explain some variation in the price paid per unit for drugs in WC.

By comparing the actual mean prices paid per unit to an estimate of the expected value of the price paid per unit given particular values for the explanatory variables (i.e., the mean of the in-sample predicted values), we see that in general, our model performs well in predicting the price paid per unit (see Table 5). Even though there are some differences between the mean of the in-sample predicted values and the actual mean observed in the data using either type of weights, these differences are not material, especially when using expenditure weights. Slightly more revealing are the comparisons of the median values, which are larger compared to the mean values due to the skewness in the actual prices paid per unit (see Table 3). On the other hand, while the confidence intervals for the predictions for the mean are quite similar (2.2173-2.0710 =0.1463 for expenditure weights and 2.1598-2.0202=0.1396 for unit weights), the interval is slightly tighter for unit weights than for expenditure weights. Overall, the results reported in Table 5 show that the in-sample predictions from our model estimated using WLS adequately explain prices paid per unit for drugs in WC.

Table 6, which reports out-of-sample predictions using a separate data sample with 4,211,770 transactions, shows that the model is statistically useful for predicting prices paid per unit for drugs in WC. Note that the difference between actual and predicted mean and medians are very similar for in-sample and out-of-sample, which is further evidence of the robustness of the model.

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[8] "The effect of an explanatory variable on the dependent variable, holding other factors in the regression model fixed" (Wooldridge, 2013).

[9] A non-monotonic statistic in the number of regressors and an improvement of the R-squared statistic.

[10] $p-value = P(\mathrm{F} > F)$ where F denotes an F random variable with $(q, n-k-1)$ degrees of freedom, F is the actual value of the test statistic, q is the number of exclusion restrictions to test, n is number of observations, and k denotes the number of regressors (one of which is the constant).

[11] Using unweighted regression, the in-sample $\hat{\sigma}$ = 0.84.

Table 4. Model Results Using Expenditure and Unit Weights (n = 9,827,464 Transactions)

	Expenditure Weights	Unit Weights
Variable Name	**Coefficient**	**Coefficient**
[1]	[2]	[3]
lowfs	-0.044*	-0.037*
	(0.023)	(0.019)
mediumfs	-0.011	0.007
	(0.019)	(0.015)
highfs	-0.022	0.003
	(0.017)	(0.014)
phydisp	0.081***	0.051*
	(0.023)	(0.027)
otherdisp	-0.147**	-0.022
	(0.058)	(0.030)
network	-0.048**	-0.042***
	(0.023)	(0.013)
brand	-0.094***	-0.129***
	(0.012)	(0.016)
brand.g	-0.069***	-0.202***
	(0.017)	(0.031)
generic.b	0.049***	-0.0007
	(0.013)	(0.009)
AWP	0.762***	0.692***
	(0.021)	(0.022)
lowfs × *AWP*	-0.062*	-0.061*
	(0.033)	(0.032)
mediumfs × *AWP*	0.001	-0.005
	(0.016)	(0.017)
highfs × *AWP*	0.057**	0.054**
	(0.021)	(0.025)
phydisp × *AWP*	0.028***	0.054***
	(0.007)	(0.010)
otherdisp × *AWP*	0.075	0.049
	(0.081)	(0.094)
network × *AWP*	-0.012	-0.014
	(0.013)	(0.015)
brand × *AWP*	0.168***	0.247***
	(0.016)	(0.015)
brand.g × *AWP*	0.154***	0.244***
	(0.014)	(0.015)
generic.b × *AWP*	-0.014	0.046***
	(0.011)	(0.007)
network × *lowfs* × *AWP*	-0.0004	-0.005
	(0.025)	(0.025)
network × *mediumfs* × *AWP*	-0.0098	-0.007
	(0.015)	(0.017)
network × *highfs* × *AWP*	-0.055***	-0.056**
	(0.019)	(0.022)
intercept	0.258***	0.245***
	(0.029)	(0.021)
$Adj.R^2$	0.9520	0.9564
♂	0.76	0.44
p-value	0.0000	0.0000

Notes: The variables *nofs*, *pharmdisp*, and *generic* are used as the base group in the model; reported standard errors in parenthesis are asymptotic one-way cluster-robust standard errors; *, **, and *** denote statistical significance at the 99%, 95%, and 90% confidence levels, respectively, using a two-sided Wald test.

Table 5. In-Sample Predictions and 95% Confidence Limits for Prices Paid for Drugs by Type of Weight

Type of Weight: Expenditure

	PAID AMOUNT ($/unit)					
	LL	**Mean**	**UL**	**LL**	**Median**	**UL**
Actual		2.1403			0.8541	
Predicted	2.0710	2.1441	2.2173	0.8406	0.8728	0.9092
Absolute difference		0.0038			0.0187	
Pearson correlation	0.9766					
Spearman's rank correlation	0.9026					

Type of Weight: Unit

	PAID AMOUNT ($/unit)					
	LL	**Mean**	**UL**	**LL**	**Median**	**UL**
Actual		2.1403			0.8541	
Predicted	2.0202	2.0903	2.1598	0.7874	0.8095	0.8427
Absolute difference		0.0500			0.0446	
Pearson correlation	0.9763					
Spearman's rank correlation	0.9030					

Notes: The correlation coefficients denote the correlation between predicted and actual prices paid per unit; LL and UL denote the lower and upper confidence limits, respectively. These limits of the predicted mean and predicted median values of prices paid per unit are computed given $\hat{y} \pm t_{1-\alpha/2,n-k} \times \sqrt{\hat{v}_p}$ where $\hat{y}$ denotes the predicted price paid per unit, t is two-tailed t value for a 95% confidence interval, $\alpha = 0.05$ is the significance level (in decimal form), and $\sqrt{\hat{v}_p}$ is the square root of the estimated prediction variance (i.e., the standard error of the linear prediction) (see Baum, 2006).

Table 6. Out-of-Sample Predictions and 95% Confidence Limits for Prices Paid for Drugs by Type of Weight

Type of Weight: Expenditure

	PAID AMOUNT ($/unit)					
	LL	**Mean**	**UL**	**LL**	**Median**	**UL**
Actual		2.1405			0.8547	
Predicted	2.0736	2.1450	2.2164	0.8423	0.8711	0.9062
Absolute difference		0.0045			0.0164	
Pearson correlation	0.9759					
Spearman's rank correlation	0.9029					

Type of Weight: Unit

	PAID AMOUNT ($/unit)					
	LL	**Mean**	**UL**	**LL**	**Median**	**UL**
Actual		2.1405			0.8547	
Predicted	2.0217	2.0909	2.1602	0.7885	0.8101	0.8422
Absolute difference		0.0496			0.0446	
Pearson correlation	0.9756					
Spearman's rank correlation	0.9032					

Interpretation of the Coefficients

Before interpreting the coefficients of the model, it is worth mentioning that we have chosen explicitly the categories *nofs*, *pharmdisp*, and *generic* to be the base group against which comparisons are made. These groups are subsumed into the overall intercept of our econometric model, as well as out-of-network, in order to avoid the so-called perfect multicollinearity.[12]

The empirical results for the model using expenditure weights and the model using unit weights are qualitatively similar, as shown in Table 4, columns 2 and 3.

- AWP

The estimation results indicate that AWP is by far the most significant determinant of the price paid per unit for drugs in WC. Its *t* statistic (0.762/0.021=36.29 when using expenditure weights, and 0.692/0.022=31.45 when using unit weights) is the largest among all the *t*-values for the variables included in the model. In addition, AWP is highly significant at the 0.01 level of type I error and positively related to the price paid per unit. *Ceteris paribus*, a $1 increase in AWP leads to an increase in the price paid per unit of about 69 cents, on average, based on unit weights. When using expenditure weights, the partial effect of AWP per unit on the conditional mean of the paid amount per unit increases to 76 cents.

- Fee Schedule Regime Variables

Table 4 also shows that:

- Average prices paid for WC drugs in low-fee-schedule states are significantly lower than prices paid for WC drugs in states without a fee schedule.

  Both the coefficient of *lowfs* and *lowfs* × *AWP* are negatively related to the price paid per unit and statistically different from zero at the 0.1 level.

- The average difference in price paid per unit for WC drugs between medium-fee-schedule states and no-fee schedule states is statistically insignificant.

  The coefficient of *mediumfs* and *mediumfs* × *AWP* are both insignificantly different from zero.

- Average prices paid for WC drugs in high-fee-schedule states are significantly higher than prices paid for WC drugs in states without a fee schedule, when the drug is not dispensed in a network. When drugs are dispensed in a network in a no-fee-schedule state, there is an offset effect from the *network* × *highfs* × *AWP* coefficient that reduces the impact of the high-fee-schedule.

  The coefficient for *highfs* itself is insignificant and very close to zero. However, *highfs* × *AWP* is statistically significant at 0.05 level and positively related to the price paid per unit. Based on the joint hypothesis test, we reject the null hypothesis, at conventional levels when using either type of weight, that both explanatory variables *highfs* and *highfs* × *AWP* have no effect on the price paid per unit.

[12] This problem is also known as *dummy variable trap* and occurs when an explanatory variable is an exact linear combination of other explanatory variables. In this case, if, for example, a dummy variable is included for the categories low, medium, high, and no-fee-schedule regimes a linear dependency will exist between the dummies and the intercept. Thus, the unknown parameters β cannot be estimated uniquely. Consequently, one of the dummy variables (indicators) has to be chosen as the base group.

Figure 1 illustrates how the mean paid amount per unit in low-fee-schedule states compared to no-fee-schedule states changes given different values of AWP, using both unit weights and expenditure weights. Based on these results, the model suggests that in low-fee-schedule states, as AWP increases, the absolute discount relative to no-fee-schedule states also increases, on average. For example, given an AWP of $2.36 (the mean AWP in our data; see Table 2) and using expenditure weights, WC drugs in low-fee schedules relative to no-fee schedule-states cost about 19 cents less, on average. When AWP is $7.94, using the same type of weight, the absolute discount increases to 54 cents in low-fee- schedule states relative to no-fee-schedule states.

The mean difference in price paid per unit for WC drugs in high-fee schedule states relative to no-fee schedule states, holding other factors fixed and given an AWP of $2.36, increases to 11 cents when using expenditure weights and to 13 cents more when using unit weights. This positive effect increases as AWP increases, when using either type of weight (see Appendix A).

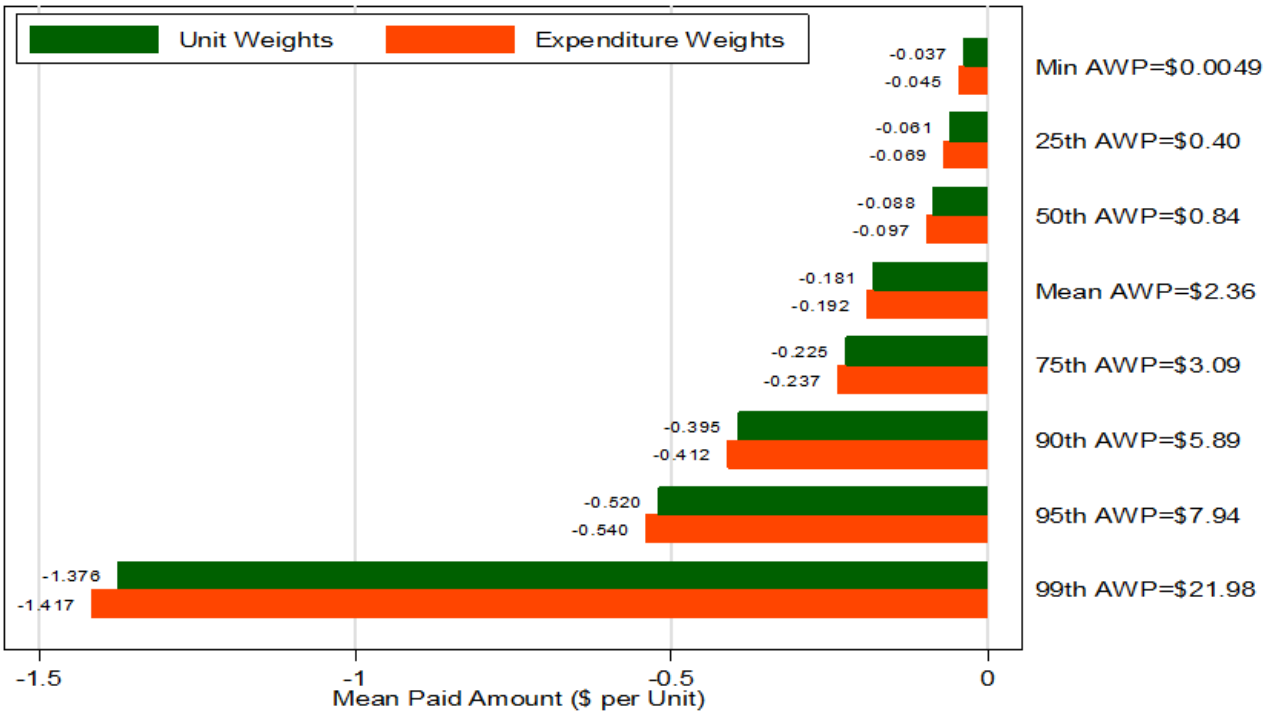

Figure1. Mean Price Paid per Unit for WC Drugs in Low-Fee-Schedule States Relative to No-Fee-Schedule States Given Different Values of AWP

- Other Variables

According to Table 4, the *network* variable has a significant and negative effect on the price paid per unit for drugs in WC.[13] Therefore, the price paid per unit for drugs in-network compared to out-of-network, given an AWP of $2.36 per unit, is

[13] Based on the joint hypothesis test with two exclusion restrictions $H_0 : \beta_{network} = 0, \beta_{network \times AWP} = 0$, where the alternative hypothesis is that at least one of parameters $\beta_{network}$ or $\beta_{network \times AWP}$ is different from zero, the explanatory variables *network* and *network* × *AWP* are jointly significant. The p-value of 0.0126 and 0.0779 using unit and expenditure weights, respectively, reject the null hypothesis in either case.

about 8 cents less, on average (*ceteris paribus*) when using either type of weight. This negative differential effect between prices paid per unit for WC drugs in-network and out-of-network becomes larger as AWP increases. The average difference between prices paid per unit for drugs in and out-of-network is small. This is probably because 75% of the prescriptions are in-network and the in-network prices probably affect the out-of-network prices.

Prices paid for brand-name drugs are significantly higher than prices paid for generic drugs; the coefficient of the individual term *brand* and the coefficient associated to the interaction of *brand* and AWP are both statistically significant different from zero at 0.01 level.

Lastly, by looking at the three-way interaction terms in which low-, medium-, and high-fee schedules are interacted with AWP and network (see Table 4), we see that the relationship between the price paid per unit and *lowfs* or *mediumfs* is not conditioned on the values of AWP and network, while the relationship between states with a high-fee schedule and the price paid for drugs in WC does depend upon both the magnitude of AWP per unit and whether the drug is dispensed in a network.

LEGISLATIVE ANALYSIS

As mentioned in the Introduction, prescription drugs have been a focal point of interest in the WC arena for several years now. Regulators and legislative bodies have responded to market conditions in various ways, often by instituting or changing provisions regarding prescription drug fee schedules, which currently are in effect in practically half of the US jurisdictions.

The objective of this section is to estimate an overall percentage change in state prescription drug costs if a state moves from one of the fee schedule regimes (low-, medium-, high-, and no-fee schedule) to another.

In pursuit of this objective, we use the regression model based on expenditure weights (see Table 4, column 2) and the methodology described in Appendix B.

Table 7 summarizes the results of this analysis and shows that if:

- A state with a high-fee schedule were to move to a low-fee schedule, the estimated cost impact is a 9% decrease in prescription drug costs
- A state with a low-fee schedule were to move to a high-fee schedule or to a regime with a no-fee schedule, the estimated cost impact is a 10% increase in prescription drug costs
- A state with a no-fee schedule were to adopt a high-fee schedule for prescription drugs, then we estimate that prescription drug costs would increase by 1%
- A state with a high-fee schedule for prescription drugs were to eliminate its fee schedule entirely, then we estimate that there would be no effect on prescription drug costs

Table 7. Percentage Changes in Predicted Total Paid Amount (rounded to zero decimals)

	To			
From	**High FS**	**No FS**	**Medium FS**	**Low FS**
High FS	--	0	-1	-9
No FS	+1	--	-1	-9
Medium FS	+1	+1	--	-8
Low FS	+10	+10	+8	--

Note: FS denotes fee schedule.

Table 7 also shows that for a state with no fee schedule, the estimated cost impact of implementing a high-fee schedule—a 1% increase in prescription drug costs—is greater than the cost impact of implementing a medium-fee schedule—a 1% decrease in prescription drug costs—and far greater than the 9% savings if a low-fee schedule is adopted.

In order to examine how robust these results are, we estimate cost impacts at the state level. In particular, we estimate cost impacts for individual states with a high-fee schedule when changing to a low-fee schedule regime. Individual state impacts ranged from -8.6% to -9.8%, with a group estimated saving for all states with a high fee schedule of 9.2%. Estimated cost impacts are also consistent across service years. For example, for the group of states with high-fee schedules, taken as a whole, the estimated impacts of changing to a low-fee-schedule regime by service year range from -9.0% to -9.3%.

For illustrative purposes we show how to estimate the impact on total costs for a high-fee-schedule state changing to a low-fee schedule (see Table 8). This can be generalized to the other fee schedule regimes using the corresponding estimated cost impacts from Table 7.

Table 8. Total System Cost Impact of Moving From a High-Fee Schedule to a Low-Fee Schedule

Description	Impact
(1) Rx Cost Impact (from Table 7)	-9%
(2) Rx Costs as a Percentage of Medical Costs	12%
(3) Impact on Medical Costs = (1) x (2)	-1.1%
(4) Medical Costs as a Percentage of Total Costs	60%
(5) **Total System Cost Impact** = (3) x (4)	-0.7%

Notes: Percentage values in (2) and (4) are hypothetical representative values based on a multistate average; Rx denotes prescription drug.

NCCI studies by Schmid and Lord (2013) and Lipton et al. (2014) show that resulting impacts from fee schedule changes depend on several factors other than the imposed fee schedule provisions, including prior price departure from the maximums previously in place, prices for the services in the market place at large, and geographic factors. Consequently, when evaluating the cost impact of a specific change to a prescription drug fee schedule, factors to be considered include current prices paid, the effectiveness of current fee schedule provisions, and other related rules impacting prices and utilization of prescription drugs in WC and in the state in general.

CONCLUSION

This study presents an econometric model that looks at the effect of AWP-based prescription drug fee schedules on WC drug costs. We find that among the explanatory variables included in our model, AWP is by far the most significant determinant of the price paid per unit for drugs in WC. Further, average prices paid for WC drugs in low-fee-schedule states are significantly lower than prices paid for WC drugs in states without a fee schedule, and average prices paid for WC drugs in high-fee-schedule states are significantly higher than prices paid for WC drugs in states without a fee schedule. However, the average difference in price paid per unit for WC drugs between medium-fee schedule states and no-fee-schedule states is statistically insignificant.

Pharmacy benefit managers (PBMs) and pharmacy networks play a role in restraining prices paid for WC prescription drugs. PBMs regularly negotiate lower prices than the AWP. The presence of PBMs might help explain the lack of significant

average price differences between states with medium-fee schedules and states without fee schedules. PBMs might also help explain why average price differences between low-fee-schedule states and medium-fee-schedule states, and those between high-fee-schedule states and medium-fee-schedule states, are not as large as the nominal differences in the respective AWP multipliers.

Finally, if a state with a high- or no-fee schedule were to move to a low-fee schedule, the estimated cost impact would be a 9% decrease in prescription drug costs. Conversely, changing regimes from a low-fee schedule to a high- or no-fee schedule regime is estimated to result in a 10% increase in prescription drug costs. If a state with a no-fee schedule for prescription drugs was to adopt a high-fee schedule, then we estimate that prescription drug costs would increase by 1%. On the other hand, if a state with a high-fee schedule for prescription drugs eliminated its fee schedule entirely, then we estimate that there would be no effect on prescription drug costs.

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APPENDIX A

	Mean Price Paid per Unit for WC drugs			
	lowfs relative to nofs		highfs relative to nofs	
AWP	***uw***	***ew***	***uw***	***ew***
0.0049	-0.037	-0.044	0.003	-0.022
0.84	-0.088	-0.096	0.048	0.026
2.36	-0.181	-0.190	0.130	0.113
21.98	-1.378	-1.407	1.190	1.231
100	-6.137	-6.244	5.403	5.678

Notes: **lowfs** is low-fee schedule, **nofs** is no-fee schedule, and **highfs** is high-fee schedule; **uw** and **ew** denote unit weight and expenditure weight, respectively; AWP is measured in dollars per unit.

APPENDIX B

To calculate the overall percentage changes reported in Table 7, we proceed as follows. Using the regression coefficients from Table 4, column 2:

1. Calculate predicted value estimates of the price paid per unit (the dependent variable in our model) for each transaction *i* using the entire data set (n = 14,039,234 transactions; Service Years 2011–2013). These predicted values were calculated separately in each fee schedule regime (high, medium, low, no):

$PPA_{high,i} = \mathbf{x}_i\hat{\boldsymbol{\beta}}_{\mathbf{w}}$ where highfs=1, mediumfs=0, and lowfs=0

$PPA_{medium,i} = \mathbf{x}_i\hat{\boldsymbol{\beta}}_{\mathbf{w}}$ where highfs=0, mediumfs=1, and lowfs=0

$PPA_{low,i} = \mathbf{x}_i\hat{\boldsymbol{\beta}}_{\mathbf{w}}$ where highfs=0, mediumfs=0, and lowfs=1

$PPA_{no,i} = \mathbf{x}_i\hat{\boldsymbol{\beta}}_{\mathbf{w}}$ where highfs=0, mediumfs=0, and lowfs=0

2. Compute the predicted total paid amount for each fee schedule group at each transaction *i*, using the previous predicted values and the actual number of units involved in that transaction *i*:

$PTPA_{r,i} = PPA_{r,i} \times units_i$, i=1,…,n, r = high, medium, low, no

3. Add the predicted total paid amounts at the state level *s* at each fee schedule regime *r*:

$PTPA_{s,r} = \sum_{i=1}^{n} PTPA_{r,i}$, s=1,…,42

4. Cumulate state-level predicted paid amounts over the fee schedule regime:

$PTPA_r = \sum PTPA_{s,r}$

5. Calculate the cost impact of a change in fee schedules (see Table 7) in moving from one fee schedule regime *r* to another fee schedule regime *t* (*r* and *t* each indicate a different fee schedule regime, either low-, medium-, high-, or no-fee schedule):

$$\%\Delta\ PTPA_r = 100\left(\frac{PTPA_t - PTPA_r}{PTPA_r}\right),\ r \neq t$$