Physician Code Creep: Evidence in Medicaid Billing?

Eric E. Seiber

Clemson University, Department of Public Health Sciences
523 Edwards Hall, Clemson, SC 29634-0745 USA
seiber@clemson.edu, Tel: 864-656-6206, Fax: 864-656-6227

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Abstract:

This study estimates a fixed effects ordered logit model physician office visit billing using claims data from South Carolina Medicaid and the South Carolina State Employees Health Plan. The results find code creep increasing expenditures on physician office visits at a rate of 2.1% annually for both programs, with no significant difference in the rate between the two programs. The models also indicate that physician billing patterns differ between the two programs, with the Medicaid claims averaging 1.9% less per visit than comparable State Health Plan claims.

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Many studies refer to code creep as a contributing factor to improper billing, but policy makers have few estimates of its magnitude to use for guidance. Despite the lack of studies estimating code creep and improper billing, the Deficit Reduction Act (DEFRA) of 2005 progressively increases funding for the Medicaid Integrity Program, reaching its maximum of $75 million in 2009. With few studies to guide policy, Medicaid agencies have little guidance on whether code creep is a problem they should target with the assistance of DEFRA 2005. This paper estimates an upper bound for code creep in physician office billing for the state Medicaid program in South Carolina.

A formal definition of code creep is elusive, but Seinwald and Dummit (1989) summarized code creep as “changes in hospital record keeping practices to increase case mix and reimbursement”. Code creep is also often referred to as “upcoding” and, in hospital billing, “DRG creep”. Finally, not all temporal variation in coding falls under code creep. Changes over time in billing can also be attributable to true changes in case mix (sicker patients), improvements in coding (provider education), and changes instituted by the payer (program reforms) (Carter et al. 1990).

The code creep literature has focused primarily on hospital billing of diagnosis related groups or DRGs, especially following Medicare’s switch to the prospective payment system (PPS) in the 1980s. Results for these early studies proved mixed. Multiple studies did find evidence for DRG creep in during the implementation of PPS (Steinwald and Dummit 1989, Chulis 1991, and Hsia et al. 1988) with the estimates falling below 3%. Subsequent studies found no evidence of code creep that could not be attributed to true case mix changes and improved coding practices (Hsia et al. 1992, Carter et al. 1990).

After the papers assessing the billing impact of the switch to PPS, academic interest in code creep became sporadic. Unlike the mixed results examining PPS, later studies produced repeated evidence indicating that code creep exists. Survey data have indicated that 44% of health care managers have received pressure from their senior managers to promote coding optimization, but 33% reported that their coding behavior varies depending on the payer (Lorence and Richards 2002, Lorence and Spink 2002). Other authors have examined specific diagnoses that provide strong incentives to code a higher complexity in that diagnosis family. Silverman and Skinner (2003) found extensive code creep for pneumonia across all hospitals, but the largest increase appeared in for-profit hospitals, hospitals converting to for-profit status, and hospitals where physicians have an equity stake. Similarly, Psaty et al. (1999) examined charts for patients diagnosed with heart failure and could find no documentation in 38% of the charts to support higher reimbursement diagnoses. Lastly, code creep has not been limited to U.S. hospitals, with German studies attributing 1% of all inpatient payments to code creep (Lungen and Lauterbach 2000).

Few studies examine physician billing for office visits in the United States. Two studies in Canada have found that code creep is not limited to hospitals and also occurs in Canadian physician offices (Nassiri and Rochaix 2006 and Chan et al. 1998). Evidence of code creep for physician office billing in the United States remains indirect. Wynia et al. (2000) surveyed physicians and found that 39% of physicians reported manipulating reimbursement rules, with 54% indicating that they were manipulating their billing more frequently in 1998 than they did in 1993. Interestingly, fear of prosecution did not affect the billing decisions of physicians admitting to manipulating reimbursement rules. Lastly, Cromwell et al. (2006) indicated that code creep was one explanation for the physicians in their study dedicating between 9% and 32% less actual time for a visit than the visit times associated with the Medicare fee schedule.

This study expands on previous work in three ways. First, this study will be the first to examine code creep in Medicaid. Excluding those using survey methods, all code creep studies in the United States have examined Medicare data. Second, it will be the first to examine billing for the same providers across two payers by comparing physicians' Medicaid billing to their own billing in the South Carolina State Employees Health Plan (SHP). Lastly, this study will be the first to estimate the magnitude of code creep for physician office billing. Specifically, this study tests (1) whether physicians bill office visits at equal levels of complexity across the two state programs, (2) whether the billing behavior displays unexplained changes over time, and (3) estimates the a rate of increase for physician billing.

Methodology:

In state fee-for-service programs, physician prices are routinely set by a fixed price schedule or through negotiations with the payer. Although prices are fixed, physicians still have the power to choose the level of complexity or billing code for the visit. If probability of detection is low, profit maximizing physicians can be expected to choose higher reimbursement codes or up-code on the margin.

Table 1 and Table 2 present an overview of the physician's choice set when assigning a code to an office visit. When billing the visit for an established patient (a patient seen previously), the provider must choose from one of the five billing codes listed in Table 1. The American Medical Association (AMA 2004) establishes definitions for the codes, and an extensive literature explains and analyzes each in detail (Hill 2001, King, Sharp, and Lipsky 2001). For visits dominated by counseling or coordination of care, a physician may use the length of the visit assigned to the billing code. Otherwise, the provider bases the code assignment on the complexity of the visit (documenting the problem's history, examinations of the problem, and the complexity of the medical decision making). Established visits are most frequently billed by complexity, and in these cases, the visit must meet or exceed the criteria for two of the three complexity categories (history, examination, and medical complexity) listed in Table 1. Lastly, payers reimburse providers for each visit based on the reported complexity and the administratively set rates attached to that billing code.

Table 2 lists the median reimbursement rates for physician office visits in the South Carolina Medicaid and South Carolina State Employees Health Plan (SHP) programs. Over the three years in the study, reimbursement rates for the established patient visits remained flat for both plans. Reimbursement for the most common Medicaid code, 99213, started at $36 in 2001 and ended at $35 in 2003 ($44 and $47 for SHP). For the less common New Patient and Consultation codes, reimbursement rates remained flat in State Health Plan, but Medicaid did grant a substantial increase in 2003.

Faced with flat reimbursement rates, this paper examines the question of whether reimbursement rates influence providers' coding of complexity of office visits. This sequencing of rates influencing complexity contrasts with the accepted view that prices are exogenous for physicians (that providers accept prices as given). If a physician considered the probability of detection low, a substantial incentive exists for the provider to "upcode" or report visits of higher complexity. Although rates for individual codes remained unchanged over the study period, a provider could obtain a 50%-60% increase in their reimbursement for a visit by assigning a code one level higher than the true code for the visit.

Data:

This study utilizes 2001–2003 health care claims from the South Carolina Medicaid program and SC State Employee Health Plan to estimate a fixed effects ordered logit model of physician office visit billing. The analysis excludes visits at sites other than a physician office. Limited information on providers outside of South Carolina required the elimination of claims from any provider with an address outside of South Carolina. Physicians providing fewer than 150 total fee-for-service visits to Medicaid and SHP patients over the three year period were dropped from the data. Due to the very large number of remaining claims, a random sample was drawn of 500 providers and for each provider, 800 Medicaid visits and 800 State Health Plan visits (1,600 visits total). The sample retained all Medicaid or State Health Plan claims for physicians that provided fewer than 800 visits in that program. This sampling procedure produced a final dataset of 204,945 office visits for the 500 providers.

Provider identification proved difficult in some cases. Although every physician is assigned a unique provider identification number, many group practices file all claims under a single group identification number. Since groups share billing resources and behaviors, the model analyzes billing behavior at the group level. The federal tax identification number filed with each claim allowed the linking of providers (or groups for multi-physician practices) across programs. Not all providers participated in both programs, and some physicians filed claims under separate tax identification numbers for each program. The analysis controls for these physicians who do not participate in both programs or who could not be linked across programs.

Model Specification

The model combines three classes of office visits into a single Visit Complexity variable. Routine office visits fall under New Patient Visits (codes 99201-99205), Established Patient Visits (codes 99211-99215), or Consultations (codes 99241-99245), with each group broken into five codes representing lowest through highest complexity. The study considers five potential outcomes:

Y_1 = Codes 99201, 99211, or 99241
Y_2 = Codes 99202, 99212, or 99242
Y_3 = Codes 99203, 99213, or 99243
Y_4 = Codes 99204, 99214, or 99244
Y_5 = Codes 99205, 99215, or 99245.

With the ranked nature of the dependent variable, an ordered probit can estimate the probability of choosing outcome Y_j,

$$\Pr(Y_j = i) = \Pr(k_{i-1} < \Sigma_j ß_j X_j + u < k_i) \quad (1)$$

where the probability that the estimated linear function of the independent variables plus a normally distributed random error lies between the estimated cut-points, k_i (Zavoina and McKelvey 1975, Greene 2003).

In equation (1), X_j represents a matrix of independent variables indicating patient demographics and provider characteristics. Although claims data provides a rich source of information of provider behavior, potential independent variables are limited to the fields common to the claims forms for both programs. Given this limitation, the model includes patient age, gender, marital status, and urban residence to control for patient demographics. A dummy variable identifies providers who can be matched on both lists of participating physicians to control for providers not participating in both programs and those that use separate federal tax id numbers when billing Medicaid and SHP.

Since sicker patients will also produce higher billing codes, the model includes controls for the fifteen most expensive conditions and the patient's number of diagnoses that year. The claims data uses ICD-9 codes to classify diagnoses, so the Clinical Classifications Software developed by the Agency for Healthcare Research and Quality was used to collapse the over 12,000 potential diagnosis codes into 260 clinically meaningful categories (Elixhauser, Steiner, and Palmer 2006). From these 260 categories, the model includes dummy variables for the fifteen most expensive medical conditions: heart disease, pulmonary conditions, mental disorders, cancer, hypertension, trauma, Cerebrovascular disease, arthritis, diabetes, back problems, skin disorders, pneumonia, infectious disease, Endocrine, and kidney. (Druss et al. 2002, Thorpe, Florence, and Joski 2004). Lastly, the model includes dummy variables indicating the number of separate conditions reported for that patient in the year of the claim.

An array of program and year dummy variables tests the Code Creep and differential billing hypotheses. A Medicaid dummy flags all claims to Medicaid and tests whether physicians as a whole bill Medicaid differently than the State Health Plan.

Interactions between the Medicaid dummy and two year dummies test whether the Medicaid versus SHP relationship changes over time. Finally, dummies for 2002 and 2003 test whether physicians are billing increasingly higher codes every year. Table 3 presents the variable means and distribution of the dependent variable.

Results:

The summary statistics in Table 3 indicate that physicians bill both Medicaid and the State Health plan both in a similar manner, despite serving very different demographic groups. In both programs, physicians code half of their visits (49% for Medicaid and 50% for SHP) at complexity Level Three. The lowest and highest complexities are both uncommon, with only 6% billed at Level One and 3% at Level Five. The remaining visits fall almost equally across the remaining two categories with 24% billed at Level Two and 18% at Level Four. Between the two programs, lower complexity visits were marginally more common in Medicaid while SHP displayed more Level 4 and Level 5 visits.

For the independent variables, Medicaid patients tend to be younger and less likely to be married, but females make two-thirds of the visits in both programs and another two-thirds of visits are made by individuals living in urban areas. Providers that cannot be matched across both datasets are more likely to appear in the State Health Plan, with 97% of visits in Medicaid being made by physicians on both lists compared to 85% in the State Health Plan. Finally, the case-mix controls varied widely by the sample drawn and should not be used to infer prevalence of these conditions in the Medicaid and SHP populations.

Table 4 presents two sets of estimates for the Ordered Logit model with provider fixed effects. The first column presents the estimates from a model excluding the case-mix variables, and the model in the second column includes the case-mix variables. Comparing the estimates from the two models reveals the contribution of a sicker population to billing of higher complexity visits. The provider fixed effects control for time-invariant physician characteristics, including specialty and physician practice patterns.

In both models, visit complexity increased with time (p=0.000). Including the case-mix controls produced only modest reductions in the coefficients for the year dummies. Medicaid visits were billed at lower complexities in both models (p=0.000). The positive coefficients for the Medicaid*Year dummies indicate that the difference between Medicaid and State Health Plan billing decreased over the three year period, but the decline was not statistically significant. For the sample used in Table 4, providers participating in both programs billed higher complexity visits, but this result proved sample dependent. All other estimates were robust across repeated samples.

The Ordered Logit estimates in Table 4 indicate that office visit complexities billed to Medicaid and the State Health Plan did increase over the three year period after controlling for case-mix and time-invariant physician characteristics, but they reveal little about the magnitude of the increase. Table 5 presents the average predicted probabilities for each complexity, illustrating the effect of code creep on physician billing. For each visit in the data, the model predicts the probability of the physician assigning each complexity level. The simulated values in Table 5 represent the averages for these probabilities for each complexity level. Only the values for the simulated variable change, with all other variables in the model retaining their original values.

Table 5 simulates two scenarios. In the first scenario, all visits are billed under the prevailing billing patterns in 2001, 2002, and 2003. In the second scenario, all visits are billed under the billing patterns representative of the State Health Plan and then with Medicaid billing patterns. Again, all other variables in the model retain their original values. The table lists each scenario, first, based on the model excluding the case-mix control variables, and second, with the case-mix variables.

The scenarios in Table 5 show the complexity of the average visit gradually increasing over the study period. Over the three years, Level 1 and Level 2 visits become progressively less frequent, with Level 1 visits declining from 5.9% of visits to 4.6% and Level 2 visits decreasing from 25.6% to 22.1%. In contrast, visits coded at Levels 3-5 each become more common, with Level 3 visits increasing from 49.9% to 50.7%, Level 4 accelerating from 15.9% to 19.1%, and Level 5 visits increasing from 2.6% to 3.4% of all visits. Including the case-mix variables produces no appreciable difference on the predicted complexity, with the frequencies changing no more than one-tenth of a percent.

The significant difference between Medicaid and State Health Plan billing manifests in the simulations, but the case-mix variables can account for some of the observed differences between the two programs. With the billing patterns typical of the State Health Plan, 50.6% of all visits are coded at Level 3, compared to 49.9% in Medicaid. Adding in the case-mix controls narrows these differences across all coding options, with Level 3 State Health Plan visits slipping to 50.5% and Medicaid increasing to 50.1%. Similarly, Level 4 visits start higher in State Health Plan, at 18.4% and

Medicaid at 16.3%, but this difference declines to 18.0% and 16.6% after including the case-mix controls.

The last columns in Table 5 indicate that, after controlling for case-mix and physician characteristics, code creep increased the cost of the average visit by 2.1% annually over the study period. The average costs in the last column collapse the billing distributions into a single number and are calculated by multiplying the percent of visits at each complexity by the 2003 Medicaid reimbursement rate for Established Patient Office Visits from Table 2. These Medicaid rates were used for both Medicaid and State Health Plan visits and New Patients, Established Patients and Consultation visits. With this conversion, the average visit in 2001 costs $35.85, increasing by 2.0% to $36.56 in 2002, and another 2.4% in 2003, ending at $37.44. Including the case-mix controls changes the cost of the average visit cost by no more than four cents. Based on these average visits, the case-mix controls reduce the code creep estimated from 2.2% annually to 2.1% per year. Finally, comparing all Medicaid to all State Health Plan visits reveals that physicians bill the average Medicaid visit $0.69 or 1.9% lower than the average State Health Plan visit. This difference is a third smaller than the $1.05 spread between the average Medicaid and State Health Plan visit when the case-mix controls are excluded.

Discussion:

The Ordered Logit estimates and their associated simulations indicate that code creep increased the cost of physician visits by 2.1% annually over the study period. Although the existence of code creep should be a concern for Medicaid agencies, only an estimate of the total cost of the issue can indicate whether code creep would prove a worthwhile program integrity target. In 2003, South Carolina Medicaid spent $73 million on physician office visits. Excluding increases in utilization, Medicaid can expect code creep to inflate physician office expenditures by 2.1% per year or $1.5 million in 2004 and a total of $8.0 million over 2004-2008. With South Carolina accounting for only 1.38% of all Medicaid spending, code creep is projected to inflate national Medicaid expenditures on physician office visits by $111 million in 2004 and $578 million for 2004-2008. It should be noted that these figures only consider physician office visits and exclude hospital based expenditures. Additional research will be necessary to determine if billing by South Carolina physicians is representative of other states and to determine how code creep in physician office visits compares to other physician and hospital billing.

The key limitation to this study also highlights a difficulty program integrity offices face in addressing code creep. As Carter et al. (1990) highlighted, changes in billing can be attributed to true changes in case mix (sicker patients), improvements in coding (provider education), changes instituted by the payer (program reforms), and code creep. Medicaid did not implement any program reforms during the study period, and the model includes case-mix variables to control for sicker patients. However, distinguishing code creep from legitimate improvements in coding attributable to provider education would require documentation audits of medical charts. Therefore, the 2.1% annual increase attributed to code creep in this paper should be considered an upper bound since it was not possible to distinguish code creep from legitimate improvements in coding. This limitation carries the additional implication that the only viable method to address code creep remains random audits of medical charts, despite their unpopularity with physicians.

Conclusions:

This study found significant code creep in both South Carolina Medicaid and the South Carolina State Employees Health Plan. No difference in code creep was observed across the two programs, with code creep increasing expenditures on physician office visits at a rate of 2.1% annually. The models also indicate that physician billing patterns differ between the two programs, with the Medicaid claims averaging 1.9% less per visit than comparable State Health Plan claims. Controlling for case-mix produced little change in the code creep estimates, but did account for a third of the difference between Medicaid and State Health Plan billing.

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Table 1: Physician Evaluation and Management (E/M) Service Codes for Established Patients

Code	Time (Min)	Problem History	Problem Examination	Decision Making Complexity
99211	5	None	None	None
99212	10	Problem focused	Problem focused	Straight-forward
99213	15	Expanded, problem focused	Expanded, problem focused	Low
99214	25	Detailed	Detailed	Moderate
99215	40	Comprehensive	Comprehensive	High

Table 2: Median Reimbursement for Physician E/M Service Codes, 2001 - 2003

	SC Medicaid			SC State Health Plan		
	2001	**2002**	**2003**	**2001**	**2002**	**2003**
New Patient Office Visit						
99201	$30	$30	$30	$46	$33	$33
99202	$30	$30	$44	$59	$57	$57
99203	$30	$30	$64	$82	$84	$84
99204	$50	$50	$91	$119	$123	$123
99205	$100	$112	$116	$149	$156	$156
Established Patient Office Visit						
99211	$6	$6	$14	$26	$18	$18
99212	$26	$22	$26	$35	$33	$33
99213	$36	$33	$35	$44	$47	$47
99214	$56	$51	$55	$68	$73	$73
99215	$83	$76	$81	$114	$109	$109
Consultation (for other provider)						
99241	$30	$30	$38	$60	$46	$46
99242	$30	$30	$63	$80	$82	$82
99243	$30	$30	$81	$115	$109	$109
99244	$50	$50	$114	$150	$155	$155
99245	$50	$50	$148	$190	$203	$203

Table 3: Variable Means - Full Sample and by Program

Variable	All Claims Mean	(n=204,945) Std. Dev.	SC Medicaid Mean	(n=93,915) Std. Dev.	SC SHP Mean	(n=111,030) Std. Dev.
Visit Complexity						
1	5.5%		6.8%		4.4%	
2	24.2%		24.6%		23.9%	
3	49.7%		49.0%		50.2%	
4	17.6%		16.8%		18.2%	
5	3.1%		2.8%		3.3%	
Year 2002	0.330	0.470	0.313	0.464	0.344	0.475
Year 2003	0.387	0.487	0.430	0.495	0.350	0.477
Medicaid	0.458	0.498	1.000	0.000	0.000	0.000
Medicaid 2002	0.143	0.350	0.313	0.464	0.000	0.000
Medicaid 2003	0.197	0.398	0.430	0.495	0.000	0.000
On Both Lists	0.906	0.292	0.973	0.161	0.849	0.359
Age 18-40	0.247	0.431	0.332	0.471	0.175	0.380
Age 41-50	0.148	0.355	0.118	0.322	0.173	0.378
Age 51-64	0.225	0.417	0.139	0.346	0.298	0.457
Age >= 65	0.156	0.363	0.061	0.240	0.235	0.424
Female	0.676	0.468	0.685	0.464	0.669	0.471
Married	0.410	0.492	0.151	0.358	0.630	0.483
Urban	0.658	0.474	0.645	0.479	0.669	0.471
Number of diagnosis						
= 4-6	0.130	0.336	0.248	0.432	0.030	0.170
= 7-9	0.100	0.301	0.175	0.380	0.038	0.190
>= 10	0.629	0.483	0.288	0.453	0.917	0.276
Heart disease	0.316	0.465	0.102	0.303	0.497	0.500
Cancer	0.243	0.429	0.056	0.230	0.401	0.490
Trauma	0.338	0.473	0.136	0.343	0.509	0.500
Mental disorders	0.197	0.398	0.115	0.319	0.268	0.443
Pulmonary conditions	0.497	0.500	0.256	0.436	0.700	0.458
Diabetes	0.257	0.437	0.089	0.285	0.399	0.490
Hypertension	0.461	0.498	0.164	0.370	0.712	0.453
Cerebrovascular disease	0.053	0.223	0.011	0.105	0.088	0.283
Arthritis	0.332	0.471	0.127	0.333	0.506	0.500
Pneumonia	0.052	0.222	0.017	0.128	0.082	0.274
Kidney	0.089	0.285	0.034	0.181	0.135	0.342
Endocrine	0.268	0.443	0.097	0.296	0.413	0.492
Skin disorders	0.397	0.489	0.132	0.338	0.621	0.485
Back problems	0.330	0.470	0.126	0.332	0.502	0.500
Infectious disease	0.299	0.458	0.137	0.344	0.436	0.496

Table 4: Fixed Effects Ordered Logit Estimates of Visit Complexity

Variable	Coef.	Standard Error		Coef.	Standard Error	
Year 2002	0.107	0.031	***	0.098	0.031	***
Year 2003	0.245	0.043	***	0.230	0.043	***
Medicaid	-0.254	0.055	***	-0.183	0.065	***
Medicaid 2002	0.037	0.045		0.037	0.045	
Medicaid 2003	0.075	0.058		0.080	0.057	
On Both Lists	1.148	0.031	***	1.047	0.042	***
Age 18-40				0.137	0.041	***
Age 41-50				0.310	0.044	***
Age 51-64				0.352	0.046	***
Age >= 65				0.300	0.056	***
Female				0.037	0.015	**
Married				0.045	0.017	***
Urban				-0.070	0.028	**
Number of diagnosis = 4-6				-0.106	0.025	***
Number of diagnosis = 7-9				-0.119	0.036	***
Number of diagnosis >= 10				-0.286	0.052	***
Heart disease				0.025	0.015	
Cancer				-0.052	0.018	***
Trauma				-0.053	0.014	***
Mental disorders				0.079	0.015	***
Pulmonary conditions				0.066	0.017	***
Diabetes				0.073	0.019	***
Hypertension				0.088	0.019	***
Cerebrovascular disease				0.039	0.024	
Arthritis				0.022	0.015	
Pneumonia				0.026	0.023	
Kidney				0.018	0.025	
Endocrine				0.034	0.015	**
Skin disorders				-0.029	0.017	*
Back problems				0.043	0.018	**
Infectious disease				-0.046	0.014	***
Number of Observations:		204,645			203,835	

*** P<0.01
** P<0.05
* P<0. 10

Table 5: Predicted Visit Complexity

Without Case-Mix Variables	Level 1	2	3	4	5	Cost of Average Visit	Percent Change
Year = 2001	5.9%	25.6%	49.9%	15.9%	2.6%	$35.85	
Year = 2002	5.3%	24.0%	50.4%	17.3%	3.0%	$36.56	2.0%
Year = 2003	4.6%	22.1%	50.7%	19.1%	3.4%	$37.44	2.4%
Medicaid = 0	4.9%	23.0%	50.6%	18.4%	3.2%	$37.07	
Medicaid = 1	5.8%	25.3%	49.9%	16.3%	2.7%	$36.02	97.2%

With Case-Mix Variables	Level 1	2	3	4	5	Cost of Average Visit	Percent Change
Year = 2001	5.9%	25.5%	50.0%	16.0%	2.7%	$35.89	
Year = 2002	5.3%	24.0%	50.4%	17.3%	3.0%	$36.55	1.9%
Year = 2003	4.6%	22.1%	50.8%	19.1%	3.4%	$37.43	2.4%
Medicaid = 0	5.0%	23.3%	50.5%	18.0%	3.1%	$36.90	
Medicaid = 1	5.6%	24.8%	50.1%	16.6%	2.8%	$36.21	98.1%

*Based on 2003 Medicaid reimbursement rates