How Does Medicaid-Managed Care Impact Reporting of Medicaid Status?

Michael R. Plotzke, Jacob Alex Klerman, and Michael Davern

Objective. To resolve a conflict in the literature on whether Medicaid-Managed Care (MMC) impacts the Medicaid Undercount.

Data Sources/Study Setting. California county-level data (1995–1997) on MMC penetration, public use data from the Current Population Survey (CPS) (1995–1997), and restricted CPS data matched to administrative records on Medicaid enrollment (2001–2002).

Study Design. We explore the robustness of previous results from the literature first using aggregate data and alternative models. We then examine CPS data linked to Medicaid enrollment data to estimate models of Medicaid reporting errors related to MMC.

Data Collection/Extraction Methods. The Census Bureau linked administrative data on Medicaid enrollment to the CPS. Other data used were public use.

Principal Findings. We find similar results to a previous study using aggregate data that suggest that MMC worsens reporting of Medicaid enrollment. However, using alternative methods we find those results are not statistically significant and can have opposite signs. Our linked CPS microdata analysis suggests that MMC improves reporting. The article concludes with implications of these results for policy makers.

Conclusion. It is unlikely that increased MMC penetration explains the increased Medicaid Undercount.

Key Words. Medicaid Undercount, Current Population Survey (CPS), Medicaid-Managed Care

General population surveys typically have lower counts of the number of Medicaid enrollees than enrollment counts derived from administrative data. This discrepancy has been called the “Medicaid Undercount” (Klerman, Ringel, and Roth 2005; Call et al. 2008; Davern et al. 2008). Davern et al. (2009) estimated that for 2000 and 2001, the Medicaid enrollment counts implied by the Current Population Survey (CPS) were roughly 32 percent below the corresponding administrative data from the Medicaid Statistical Information System (MSIS). In addition, the magnitude of the Medicaid

Undercount appears to be growing over time (Lewis, Ellwood, and Czajka 1998; Klerman, Ringel, and Roth 2005; Wheaton 2007; State Health Access Data Assistance Center 2008b). To evaluate the recently passed health reform legislation, it will be crucial to have accurate measures of the uninsured.

Davern et al. (2009) showed that the Medicaid Undercount was related to two issues: first, how the administrative data are tabulated; and second, survey measurement error, with the larger portion of the undercount due to the latter. Earlier studies show that misreporting is related to the length of time enrolled, enrollment at the time of the survey interview, utilization of health care, and proxy reporting (Call et al. 2008; Davern et al. 2008; State Health Access Data Assistance Center 2008a). The State Health Access Data Assistance Center (2008a) also discusses additional causes of the undercount.

However, one potential cause of the undercount remains in dispute. Chattopadhyay and Bindman (2006) find that enrollment in Medicaid Managed Care (MMC) worsens reporting, while Call et al. (2008) find that it improves reporting. Specifically, Chattopadhyay and Bindman posit that many MMC enrollees perceive they have private health insurance through their MMC provider rather than Medicaid. They argue that this perception depresses Medicaid responses in the CPS, and because MMC has steadily replaced fee for service as the primary delivery system in Medicaid (Kaye 2005), the increase in MMC might explain the increase in the undercount. Consistent with this line of reasoning, Chattopadhyay and Bindman's econometric estimate—based on county-level regressions of MMC on the Medicaid Undercount for California—implies that much of the recent increase in Medicaid underreporting is due to increased enrollment in MMC. They conclude that improving the CPS's ability to identify MMC enrollees would mitigate the Medicaid Undercount and make the health insurance component of the CPS a better tool for policy makers. That would be beneficial because the undercount is a measurement problem that would affect the evaluation of any legislation expanding public coverage to the uninsured.

Call et al. (2008) use a different approach to assess the impact of MMC on survey measurement error. They field three special-purpose surveys that ask known Medicaid (and sometimes other public program) enrollees a standard health insurance question series to see how well they answered the survey

Address correspondence to Michael R. Plotzke, Ph.D., Abt Associates Inc., 55 Wheeler Street, Cambridge, MA 02138-1168; e-mail: mplotzke@wustl.edu. Jacob Alex Klerman, M.A., is with Abt Associates Inc., Cambridge, MA. Michael Davern, Ph.D., is with the NORC, University of Chicago, Chicago, IL.

items. In two states, California and Florida, they compared MMC enrollees with non-MMC enrollees. Their analysis suggests that MMC enrollees were *better* reporters of their Medicaid status than non-MMC enrollees. Based in part on qualitative interviews with Medicaid administrators, they explain that enrolling into a MMC program involves more time and contact with the MMC organization than the process of enrolling in fee-for-service Medicaid, and this extra contact makes MMC enrollees *more aware* they are enrolled in Medicaid. These results suggest that improving the CPS by collecting more detail on MMC would not decrease the Medicaid Undercount.

This article attempts to resolve the conflicting findings of these authors (Chattopadhyay and Bindman 2006; Call et al. 2008). In the next section, we reexamine Chattopadhyay and Bindman's (2006) model using several complementary analyses. Mimicking Chattopadhyay and Bindman's basic approach—that is, analyzing cross-county data from California for the period they examined—allows us to test the robustness of their specification using several model enhancements and additional data. Turning from their aggregate analysis, we explore the individual-level relationship between MMC enrollment and Medicaid underreporting using a version of the CPS linked to Medicaid administrative enrollment data (Davern et al. 2009). The final section of this article summarizes the results and discusses their implications for the Medicaid Undercount and future research.

METHODS AND RESULTS

Analysis of California County-Level Data

We first analyze models similar to those of Chattopadhyay and Bindman (2006). Given their understanding of the response process for the Medicaid question for those with MMC, all else being equal, regions with a higher MMC penetration should have a larger Medicaid Undercount. In addition, MMC penetration that increases over time would increase the Medicaid Undercount.

To formally test whether higher MMC enrollment leads to a larger Medicaid Undercount, Chattopadhyay and Bindman estimate the following equation using California county-level aggregates:

$$\begin{aligned} \text{Medicaid Undercount}_{it} &= 100 \times (1 - \text{CPS estimate}_{it} / \text{MMEF count}_{it}) \\ &= \beta_0 + \beta_1 \text{MCP}_{it} + \beta_2 \text{year} + \varepsilon_{it} \end{aligned} \quad (1)$$

where subscript i indexes counties and subscript t indexes year. The dependent variable is one minus the ratio of the survey estimate of total Medicaid

enrollment in a county to the administrative data estimate of total Medicaid enrollment in that county. The independent variables include a constant, Medicaid Managed Care Penetration (MMCP), and a linear time trend. MMCP is equal to the number of MMC enrollees divided by all Medicaid enrollees for a given county as reported in California administrative data. The final term, ε , is a regression residual, implicitly assumed orthogonal to the included regressors. We return to whether that orthogonality assumption is plausible below. Chattopadhyay and Bindman estimate equation (1) using weighted least squares (WLS), where the weights equal the estimated population of each county from the CPS. Chattopadhyay and Bindman used data from 1995 to 1999.

To estimate equation (1), we used Medicaid enrollment information from the California Medicaid Monthly Enrollment Files (MMEF) (California Department of Health Care Services 2008) and the Medi-Cal (i.e., the Medicaid program in California) Annual Statistical Reports (California Department of Health Care Services 1997a, b, 1998). Appendix SA2 details how we used these data in the analysis.

For survey counts of county-level Medicaid enrollment and overall population, Chattopadhyay and Bindman use the *CPS Annual Social and Economic Supplement*. We note that CPS California samples are small (roughly between 4,000 and 6,000 households). While in net there is a large Medicaid *Undercount*, small samples in any given county induce a Medicaid *Overcount* in some county-year combinations. Because smaller counties are somewhat more likely to have a Medicaid Overcount, the approach of Chattopadhyay and Bindman to use WLS should help account for this. Appendix Table SA1 compares the data we collected to the data reported by Chattopadhyay and Bindman. The Medicaid and MMC enrollment numbers we found are generally consistent with Chattopadhyay and Bindman. Some differences arise because we use a different source of data than Chattopadhyay and Bindman from 1995 to 1997. However, our estimates of the Medicaid Undercount from 1995 to 1999 and MMCP from 1998 to 1999 are similar to the estimates of Chattopadhyay and Bindman. Our estimates of MMCP from 1995 to 1997 are slightly lower.

The left panel of Figure 1 shows a scatterplot of Medicaid Undercount rates by county and MMC penetration rates. As predicted by Chattopadhyay and Bindman's theory, the scatterplot in Figure 1 and the corresponding simple regression line show a positive correlation between the MMC penetration rate and the Medicaid Undercount.

Turning to the results of the multivariate model, row A of Table 1 copies Chattopadhyay and Bindman's published results. Row B displays our attempt to reproduce their findings.

Figure 1: Scatterplot of Percent Medicaid Undercount and MMC Penetration Rate

Note. Regression line comes from simple regression of Percent Medicaid Undercount on MMC Penetration Rate.

It appears that Chattopadhyay and Bindman treat the county-level aggregate observations as independent; however, some serial correlation within counties over time seems almost certain (Bertrand, Duflo, and Mullainathan 2004). To adjust for possible serial correlation, row B of Table 1 and all subsequent tables and models report estimates clustered by county (as per the suggestion of Bertrand, Duflo, and Mullainathan 2004). Correcting for clustering only adjusts the standard errors for the simple WLS regressions. The point estimates are unchanged. However, for this application it substantially increases the standard errors, such that the point estimate for the variable of interest is no longer statistically significant.

Rows C, D, and E of Table 1 replace the restrictive linear time trend specification with a full set of year dummy variables (i.e., a full difference-of-different specification; Meyer 1995). Row C uses the Chattopadhyay and Bindman time period; row D uses a more recent time period (2000–2007); and row E pools the data across both periods (1995–2007). These regressions have

Table 1: The Association between Medi-Cal Managed Care Penetration and the Medicaid Undercount (OLS)

<i>Years of Data</i>	<i>Description of Model</i>	<i>Medi-Cal Managed Care Penetration</i>	<i>Year</i>	<i>Constant</i>	<i>Observations</i>	<i>R²</i>
1995–1999	(A) Chattopadhyay and Bindman's original results	0.40*** [0.140]	– 2.71 [2.430]	23.92*** [6.780]		
1995–1999	(B) All California counties	0.35** [0.170]	– 0.04 [0.033]	79.62 [65.530]	125	0.04
1995–1999	(C) All California counties [†]	0.35 [0.282]	—	0.23** [0.0811]	125	0.05
2000–2007	(D) All California counties [†]	0.58** [0.234]	—	– 0.03 [0.181]	223	0.14
1995–2007	(E) All California counties [†]	0.49** [0.233]	—	0.21*** [0.07]	348	0.11
2001, 2003, 2005, 2007	(F) All California counties [†] (CHIS)	0.40 [0.275]	—	0.10 [0.21]	106	0.09
2000–2007	(G) All U.S. states [†]	0.02 [0.060]	—	0.42*** [0.037]	357	0.01

Notes. Robust standard errors in brackets; regressions were weighted by the sample size of each county in the CPS. Boldface type indicates coefficients/standard errors that were statistically significant at the 10% level.

* $p < .1$; ** $p < .05$; *** $p < .01$.

[†]Model includes unreported year dummies.

CPS, Current Population Survey.

a coefficient on the MMCP variable that is similar in magnitude to the results of Chattopadhyay and Bindman (0.35, 0.58, and 0.49; versus 0.40), but the coefficient on the 1995–1999 time period is not significantly different from zero. For the later time period (2000–2007), the effect is significant and the magnitude of the coefficient has increased.

Finally, we reestimated the models using the much larger California Health Interview Survey (40,000–50,000 households every 2 years versus the CPS's 4,000–6,000 California households per year). The results from row F of Table 1 show that using this data produces similar point estimates to those of Chattopadhyay and Bindman, but the MMC Penetration variable is not significant.

Analysis of State-Level Data

As a further robustness check, we reestimated equation (1) using national data with states as the unit of observation (versus counties as the unit of

observation). If the theory is correct, the hypothesized relationship should be present in national data. Furthermore, national data have the added benefit of larger sample sizes (the smallest states have samples larger than all but the largest California counties) and a CPS sample explicitly designed to produce efficient state-level estimates.

For state-level MMC penetration rates, we use estimates from the Centers for Medicare and Medicaid Services (CMS) (2008) estimates. These annual enrollment reports provide state-level enrollment counts in MMC and in Medicaid. Enrollment is reported annually as of December 31 from 2000 to 2006. One disadvantage of this national data is that it does not overlap with the time period that Chattopadhyay and Bindman examined. However, Table 1 suggests that for California county data, the estimated impact is larger during the 2000s, so the time period should not be a concern.

The right panel of Figure 1 presents a scatterplot of Medicaid Undercount rates and MMC penetration rates by state. The U.S. state scatterplot shows a flat regression line between the penetration rates and the level of the Medicaid Undercount. Correspondingly, row G of Table 1 shows our analysis of the national data using equation (1). Compared with the findings using California data, the regression coefficient on the penetration rate variable in the aggregate state-level model is still positive, but much smaller in magnitude, and not statistically different from zero (and clearly different from the original Chattopadhyay and Bindman point estimates).

Fixed-Effects Analysis

To further test the robustness of Chattopadhyay and Bindman's model, we consider a specification using fixed effects:

$$\text{Medicaid Undercount}_{it} = \beta_0 + \beta_1 \text{MCP}_{it} + \beta \text{YEAR_DUMMIES} + \alpha_i + e_{it} \quad (2)$$

Equation (2) is identical to equation (1) except for the inclusion of a fixed-effect term α_i that represents each geographic unit (either county or state) and year dummies instead of a linear time trend. The purpose of the fixed effect is to control for any unobservable characteristics at either the county or state level that do not change over time and are correlated with both the MMC penetration rate and the Medicaid Undercount. Not controlling for these characteristics would bias the estimate of the coefficients. For example, within certain counties, health departments may offer more support in enrolling in MMC and also, because of their effort, make enrollees more aware they are

Table 2: The Association between Medi-Cal Managed Care Penetration and the Medicaid Undercount for California's Counties (Fixed Effects)

	<i>Medi-Cal Managed Care Penetration</i>	<i>Observations</i>	<i>R²</i>
County fixed effects—all California counties (1995–1999)	0.33 [0.326]	125	0.07
County fixed effects—all California counties (2000–2007)	0.16 [0.804]	223	0.12
County fixed effects—all California counties (1995–2007)	0.05 [0.218]	348	0.12
County fixed effects—all California counties (CHIS) (2001, 2003, 2005, 2007)	0.38 [2.788]	106	0.20
State fixed effects—all U.S. states (2000–2006)	–0.02 [0.039]	357	0.01

Note. Robust standard errors are in brackets.

enrolled in Medicaid. Or, the reverse could happen, where the health department offers more support in enrolling in MMC and advertises their program in a way that makes it unclear the enrollee has Medicaid. Either outcome would bias the results of the model if not properly controlled for, but in either case the fixed-effects model would account for the problem if the actions of the health department were time invariant.

Note that equations (1) and (2) are estimating the same parameter. If unobserved variables are not an issue, the point estimates should be identical. They are not (see Table 2 versus Table 1). Most of the point estimates with fixed effects (i.e., Table 2) are similar to the corresponding estimates in Table 1, but none of them approach statistical significance. Again, our robustness checks suggest that the Chattopadhyay and Bindman result is not robust.

Expanded Analysis Using CPS/MSIS Linked Data

The previous results use aggregate data and are open to the ecological inference fallacy (Robinson 1950). That is, hypotheses about individual behavior that are confirmed by comparing group-level data may not hold up using individual-level data. In this section, we use a special CPS data match to conduct an individual-level analysis. In the standard CPS public use file, we know neither true Medicaid status nor MMC status. However, for CPS survey years 2001 and 2002 (corresponding to health insurance coverage in calendar years 2000 and 2001, respectively), the SNACC project merged individual-level CPS data onto individual-level administrative data on Medicaid

enrollment and MMC enrollment using the CMS MSIS data (State Health Access Data Assistance Center 2008a). Davern et al. (2008) discuss the CPS/MSIS linked data file, its construction, and its characteristics in more detail.

Using both national and California-only samples, we find results consistent with earlier individual-level analyses (e.g., Call et al. 2008), but opposite of the result of Chattopadhyay and Bindman. That is, a slightly higher proportion of MMC beneficiaries correctly report Medicaid enrollment compared with non-MMC beneficiaries. Of the MMC beneficiaries in the United States, 58.8 percent correctly report Medicaid enrollment in the CPS compared with only 54.1 percent of non-MMC beneficiaries. In California, the discrepancy is even larger, with 63.3 percent of MMC beneficiaries correctly reporting Medicaid enrollment in the CPS compared with only 42.9 percent of non-MMC beneficiaries.

Table 3 reports the results of individual-level logit regressions. The dependent variable indicates whether the respondent incorrectly reported their Medicaid status on the CPS. We estimate the model on the sample of respondents who have Medicaid. We estimate four models: two for the national data and two for the California data. For each set, the first model includes MMC status (from the MSIS), but no other controls; the second model includes controls for reporting other insurance in the CPS besides Medicaid, race/ethnicity, age groups, income groups relative to the poverty line, and receipt of Temporary Assistance for Needy Families or Supplemental Security Income, where all of these controls are as reported in the CPS. We picked demographic variables based on earlier research that examined what was associated with incorrect Medicaid reporting (Call et al. 2008). The model is not intended to be causal. We are simply looking for associations and control for variables associated with geography (and managed care penetration) and reporting errors.

Specifically, Table 3 reports the logistic regression coefficients associated with each variable from the logit model. To better explain our results, we will discuss them in terms of predicted probabilities. We calculate predicted probabilities for those with MMC and those without MMC using the average characteristics of the entire sample (shown in Table 3) and computing the logistic function for each group, that is, $\exp(\beta_0 + x\beta)/(1 + \exp(\beta_0 + x\beta))$ such that x represents the average value of the variables. As with the simple cross-tabs, each model suggests that MMC enrollees are better reporters of Medicaid status. In the nation as a whole with no controls (i.e., model A), individuals enrolled in MMC and those not enrolled in MMC have a predicted probability of incorrectly reporting of 41.24 percent and 45.87 percent,

Table 3: The Association between Medicaid Managed Care Enrollment and the Incorrect Medicaid Reporting Status on CPS among Medicaid Enrollees (CPS/MSIS Linked Data)

Variable	All of United States			California		
	Model A	Model B	Mean Values	Model C	Model E	Mean Values
Constant	− 0.17 [0.036]***	− 0.16 [0.071]**		0.29 [0.189]	0.28 [0.274]	
Enrolled in managed care	− 0.19 [0.038]***	− 0.14 [0.047]**	0.64	− 0.83 [0.182]***	− 0.47 [0.228]**	0.93
Received other insurance		1.48 [0.039]***	0.42		1.30 [0.155]***	0.36
Black		0.28 [0.049]***	0.29		0.24 [0.228]	0.10
Hispanic		0.36 [0.055]***	0.20		0.16 [0.181]	0.49
Age 0–18		0.14 [0.054]**	0.34		0.17 [0.155]	0.33
Age 19–34		− 0.06 [0.039]	0.29		0.00 [0.128]	0.29
100% of FPL or less		− 0.55 [0.054]***	0.48		− 0.42 [0.161]*	0.40
101–200% of FPL		− 0.38 [0.056]***	0.32		− 0.42 [0.166]	0.38
Receipt of TANF or SSI		− 3.41 [0.082]***	0.25		− 3.53 [0.197]***	0.33
Child dummy (elderly excluded)		− 0.14 [0.0366]***	0.54		− 0.16 [0.131]	0.53
Adult female dummy (elderly excluded)		0.54 [0.038]***	0.28		0.49 [0.102]***	0.24
Adult male dummy (elderly excluded)		0.36 [0.044]***	0.11		0.31 [0.123]**	0.12
Observations	45,044	45,044		3,904	3,904	

Notes. The dependent variable equals 1 if respondent reports on the CPS that they did not have Medicaid and 0 otherwise. Robust standard errors in brackets. Boldface type indicates coefficients/standard errors that were statistically significant at the 10% level.

*** $p < .01$; ** $p < .05$; * $p < .1$.

CPS, Current Population Survey; MSIS, Medicaid Statistical Information System.

respectively. Therefore, MMC enrollees are less likely to report Medicaid status incorrectly by 4.63 percentage points compared with non-MMC enrollees. This is opposite of the inference from Chattopadhyay and Bindman's California-only, county-level, aggregate analysis. For just the respondents in

California (model C), the probability of incorrectly reporting Medicaid status decreased by 20.4 percentage points for those with MMC compared with those without MMC. When including controls for respondent characteristics, model B shows that for the entire United States, those enrolled in MMC decreased their probability of incorrectly reporting Medicaid by 3.22 percentage points. For just the California respondents (model D), those enrolled in MMC decreased their probability of incorrectly reporting Medicaid by 11.59 percentage points.

Again, these findings are counter to Chattopadhyay and Bindman's California-only, county-level, aggregate analysis. Our findings show that Medicaid beneficiaries enrolled in MMC are *better* reporters of Medicaid status in the CPS compared with Medicaid beneficiaries not enrolled in MMC. These findings also show that for the California respondents, the effect of being an MMC enrollee on reporting Medicaid status accurately is much larger compared with the effect for the entire United States.

DISCUSSION

The level of the Medicaid Undercount (i.e., one minus the ratio between survey estimates of Medicaid enrollment and administrative estimates of Medicaid enrollment) is large and increasing over time. As shown in Appendix SA2, we find the Medicaid Undercount has increased from 30 percent in 1995 to 41 percent in 2007. Chattopadhyay and Bindman (2006) attempted to explain this phenomenon using panel data aggregated by California counties showing that MMC penetration rates were correlated with the Medicaid Undercount. They hypothesize that enrollees in MMC are more likely to think they have private insurance because their MMC provider typically offers private insurance in addition to MMC. Therefore, counties with higher levels of MMC enrollment should also have higher levels of Medicaid Undercount.

Our analysis suggests that Chattopadhyay and Bindman's findings are not robust. Correcting their panel data estimates for serial correlation by clustering substantially increases the standard errors of the estimates, such that few of the estimates are different from zero at conventional significance levels. We do find a statistically significant effect similar in magnitude to Chattopadhyay and Bindman when using a longer time series (1995–2007), with year dummies (not a linear time trend) and compute the standard errors to allow for serial correlation. However, models with fixed effects have similar point estimates, but the estimates are statistically insignificant. With national data, the point estimate is essentially zero. Finally, contrary to Chattopadhyay

and Bindman, analyses of individual-level CPS data matched to CMS administrative data suggests that those with MMC are more likely to report Medicaid. We conclude that there is no robust evidence that MMC causes more Medicaid underreporting.

If increased MMC enrollment is not the cause of the growing Medicaid Undercount, what else could explain the growth? It is possible that as public programs such as Medicaid and SCHIP expanded into higher income brackets, there may have been more misreporting among those with higher income (perhaps from a stigma associated with enrollment in a public program). Analysis has shown that people with higher incomes are worse reporters of their Medicaid status than people with lower incomes (Call et al. 2008; Davern et al. 2008; State Health Access Data Assistance Center 2008a). As higher income people began to enroll in the program, it is possible the survey counts of enrollment decreased relative to administrative data.

Survey data are the only way to measure the number of uninsured Americans and thereby to assess the success of health insurance reforms. The Medicaid Undercount is therefore a serious problem. Our findings suggest that the increased role of MMC has not contributed to the increased Medicaid Undercount. If anything, increased MMC enrollment may have kept the Medicaid Undercount from being larger.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Appendix SA2: Data Description.

Table SA1: Comparison of Medicaid Population (Aggregating Information from all California Counties)

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