Economic Research Initiative on the Uninsured
Working Paper Series

Partially Identifying Treatment Effects with an Application to Covering the Uninsured

Brent Kreider
Department of Economics
Iowa State University
bkreider@iastate.edu

Steven C. Hill
Center for Financing, Access and Cost Trends
Agency for Healthcare Research and Quality
SHill@AHRQ.gov

ERIU Working Paper 30
http://www.umich.edu/~eriu/pdf/wp30.pdf

Economic Research Initiative on the Uninsured
University of Michigan
555 South Forest Street, 3rd Floor
Ann Arbor, MI 49104-2531

April, 2006

1 Introduction

Numerous academic studies have investigated relationships between health insurance status and a wide variety of outcomes such as health care utilization, health status, labor supply, and participation in public assistance programs. In more than 70 articles surveyed by Gruber and Madrian (2004), Levy and Meltzer (2004), and Buchmueller *et al.* (2005), nearly all parameters of interest are identified using a variety of parametric approaches.[1]

We develop the first nonparametric framework for studying the potential impact of universal health insurance on the nation's use of medical services. Within this framework, we study relationships between insurance status and use of services (expenditures and number of provider visits) in an environment of uncertainty about both counterfactual utilization outcomes and status quo insurance status. Our empirical work exploits detailed data in the 1996 Medical Expenditure Panel Survey (MEPS). To aid in identification, we construct health insurance validation data for a non-random portion of the sample based on insurance cards, policy booklets, and follow-back interviews with employers and insurance companies.

Motivated by limitations inherent in self-reported insurance data, our analysis extends the non-parametric literature on partially identified probability distributions in several dimensions. First, we provide sharp bounds on the conditional mean of a continuous or discrete random variable (in our case health care utilization) for the case that a binary conditioning variable (insurance status) is subject to arbitrary endogenous classification error. In this environment, insurance reporting errors may be arbitrarily related to true insurance status and health care use. Second, we formally assess how statistical identification of a treatment effect decays with the degree of uncertainty about the status quo. Our approach extends the nonparametric treatment effect literature for the case that some treatments are unobserved (especially Molinari, 2005).[2] Third, we relax the nondifferential independence assumption – evaluated by Bollinger (1996) and Bound *et al.* (2001) – embedded in the classical errors-in-variables model. As an alternative, we evaluate the identifying power of a weaker monotonicity assumption that misreporting of insurance status does not rise with the

[1] An exception is the study by Olson (1998) who uses semiparametric techniques to estimate the relationship between women's labor hours and the availability of health insurance through a spouse.

[2] To isolate identification problems associated with partially unobserved insurance status as a conditioning variable or treatment, we assume that other variables in the analysis are measured without error.

level of utilization. Given the difficulty in identifying plausible instruments in our application, we consider what can be identified in the absence of instruments.[3]

Evidence from validation studies, which compare survey data with administrative data or follow-back interviews with insurers or employers, suggests that surveys of health insurance contain classification errors. Error rates vary across surveys and may arise in part from difficulty recalling duration of coverage and difficulty reporting the status of other family members. Using matched surveys of employers and their employees, for example, Berger *et al.* (1998) find that 21% of the workers and their employers disagree about whether the worker was eligible for insurance. Their study appears to represent the only prior analysis of potentially mismeasured insurance status in an econometric framework. Assuming exogenous measurement error in a classical errors-in-variables setting (accounting for the binary nature of the mismeasured variable), they find that even non-systematic reporting error seriously biases their estimated effect of insurance eligibility on wage growth.

In the only study to examine all sources of insurance, Nelson *et al.* (2000) conducted in-person interviews with 351 reportedly insured adults using the Behavioral Risk Factor Surveillance System (BRFSS) survey and interviews with insurers. They do not find evidence of large-scale misreporting of current insurance status itself, but they find large inconsistencies in reported source of coverage and duration of coverage.[4] In other studies, estimated error rates vary across surveys for both Medicaid and private insurance. Card *et al.* (2004) and Klerman *et al.* (2005), respectively, find significant error rates for reporting Medicaid in the CPS and the Survey of Income and Program Participation (SIPP). In some surveys, underreporting Medicaid may be largely offset by overreporting other sources of coverage (Call *et al.* 2001; Davidson 2005). Studies find a narrower range of errors in reporting private insurance (Berger *et al.* 1998; Davern *et al.* 2005; Nelson *et al.* 2000).

In all validation studies, the level of misreporting in cases that could not be verified is unknown and may be higher than among those who cooperated with the study. Nelson *et al.* (2000), for example, excluded adults who did not complete permission forms to contact insurers.[5] Furthermore,

[3] Using methods in Lewbel (2004), the treatment effects could be point-identified in certain cases if we had instruments that affect insurance status but not classification error or the average treatment effect. For related work on potentially endogenous classification errors in a linear regression framework, see Frazis and Loewenstein (2003).

[4] For example, when an insurer said an adult was insured for a year or less, the adult's report agreed only 40% of the time.

[5] Card *et al.*'s (2004) study of the SIPP and Klerman et al.'s (2005) study of the CPS exclude respondents who did not provided Social Security numbers, which were used to match to MediCal administrative data. A Census Bureau

a major limitation of this research is difficulty validating lack of insurance.

The presence of reporting errors compromise a researcher's ability to make reliable inferences about the status quo, and they further confound identification of counterfactual outcomes associated with policies that would alter the distribution of insurance coverage within the population, such as national health insurance.[6] The Census Bureau now issues caveats about the accuracy of insurance estimates from the CPS (DeNaves-Walt *et al.* 2005). Highlighting surprising degrees of insurance classification error in many popular national surveys - along with dramatic inconsistencies in responses when experimental follow-up insurance questions have been posed - Czajka and Lewis (1999) write:

> "Until we can make progress in separating the measurement error from the reality of uninsurance, our policy solutions will continue to be inefficient, and our ability to measure our successes will continue to be limited."

Our analysis does not presume the existence of large-scale insurance classification error in any particular dataset. In fact, we find no evidence of large-scale error in the MEPS. Instead, we formalize important identification problems associated with even small degrees of potential error. The next section discusses the MEPS data and our health insurance verification strategy. Section 3 formalizes the statistical identification problem associated with estimating the gap in service use between the insured and uninsured under existing policies when insurance status is subject to arbitrary patterns of classification error. We derive bounds on the unknown utilization gap under alternative assumptions about the nature and degree of reporting errors. We weaken the strict nondifferential independence assumption embodied in the classical errors-in-variables framework to allow for the possibility that using health services may inform a patient of her true insurance status.

Section 4 investigates what can be learned about the impact of national health insurance on the use of health services. We show how common monotonicity assumptions, such as monotone treatment response (MTR) and monotone treatment selection (MTS), can be combined to substantially reduce uncertainty about the size of the policy effect. Under an additional monotone instrumental

study found that in 2000, 30 percent of MediCal enrollment records lacked valid Social Security Numbers (Killion 2005). Hence, estimates based on surveys matched to MediCal records may not be representative of the MediCal population.

[6] The extent to which universal coverage would increase use of services and expenditures has been estimated in a variety of parametric studies (Institute of Medicine 2003). Estimates of incremental spending range from $34 to $69 billion per year depending on the statistical assumptions and choice of comparison groups.

variable assumption that exploits information on age and health status combined with a natural monotone restriction on the pattern of classification errors, we can provide tight bounds on the impact of universal coverage without relying on some of the more controversial assumptions involving functional forms and independence. Section 5 concludes.

2 The Medical Expenditure Panel Survey

The data come from the 1996 Medical Expenditure Panel Survey (MEPS), a nationally representative household survey conducted by the U.S. Agency for Healthcare Research and Quality. In the MEPS Household Component (MEPS HC), each family (reporting unit) was interviewed five times over two and a half years to obtain annual data reflecting a two year reference period (Cohen 1997). This paper focuses on the nonelderly population because almost all adults become eligible for Medicare at age 65. The sample contains 18,851 individuals.

We study insurance and service use in July 1996. We focus on July because the 1996 MEPS has a follow-back survey of employers, unions, and insurance companies which reported insurance information as of July 1, 1996. We use 1996 data because that is the only year for which respondents to the follow-back survey reported on the employees' and policyholders' insurance status rather than whether the establishment offered insurance.[7] Studying insurance and service use in one month also reduces the likelihood of confounding the dynamics of insurance status with misreported insurance status because employment-related insurance typically covers an entire month.

2.1 Insurance Status Reported in the Household Component

The MEPS HC asks about insurance from a comprehensive list of all possible sources of insurance. In the first interview, conducted between March and August 1996, MEPS HC asked the family respondent about insurance held at any time since January 1st. Because employment-related insurance is the most prevalent source of insurance, the family respondent was asked about all jobs held by coresiding family members since January 1st, jobs family members had retired from, and the last job held. The family respondent was asked whether the employee had insurance from each job. Then the family respondent was asked whether anyone had:

- Medicare
- Medicaid

[7] These data are available at the AHRQ Data Center.

- Champus/Champva
- For those who did not report Medicaid, any other type of health insurance through any state or local government agency which provided hospital and physician benefits
- Health benefits from other state programs or other public programs providing coverage for health care services[8]
- Other sources of private insurance, such as from a group or association, insurance company, previous employer, or union.

For each source of insurance, MEPS HC asked which family members were covered and when.[9]

In the second interview, conducted between August and December 1996, MEPS HC asked questions based on jobs and insurance reported to be held at the time of the first interview to determine whether previously reported insurance was still held or when it ended. MEPS also asked about new jobs and insurance from those jobs, public insurance acquired since the first interview, and insurance acquired from other sources since the first interview. The recall period is not especially long, typically four to seven months. Responses to the questions from the first and second interview were used to construct indicators of insurance coverage at any time during July 1996 and uninsurance, the residual category. Family respondents reported 80.7% of the nonelderly population were insured in July 1996 and 19.3% were uninsured (Table 1).

2.2 Service Use and Expenditures

In each interview, the MEPS asks about health care services used by all coresiding family members since the last interview. The MEPS also obtains permission to interview a sample of the medical providers identified in the Household Component surveys to supplement household-reported health care expenditure and source of payment information. We create measures of service use and expenditures in July 1996: number of provider visits for ambulatory medical care (a medical provider visit, hospital outpatient visit, or emergency room visit), an indicator for whether the sample person had a hospital stay or ambulatory services, and expenditures for hospital stays and ambulatory

[8] A very small number of individuals are reportedly covered through Aid to Families with Dependent Children (AFDC) or Supplemental Security Income (SSI), and these are counted as Medicaid. Other sources, such as the Veterans Administration and the Indian Health Services, are not included in measures of hospital/physician insurance.

[9] State-specific program names are used in the questions. Single-service and dread disease plans are not included in measures of hospital/physician insurance. Insurance status is not imputed to families with missing data, which are rare.

services. Twenty-one percent of the (weighted) sample used medical care in that month.[10] Persons who the family respondent said were insured in July were nearly 80% more likely to have used medical care (22.5% of the insured versus 12.7% of the uninsured, Table 1). The mean number of provider visits is also much greater for the reportedly insured, as are mean expenditures.

2.3 Verification Data

We use detailed data to identify sample members for whom there is evidence corroborating their insurance status. The 1996 MEPS includes three sources that can be used to confirm health insurance reported by families: (1) the HC interviewers ask respondents to show insurance cards, (2) the HC interviewers ask respondents to provide policy booklets, and (3) separate interviews were conducted with family members' employers and insurance companies. Respondents for the family, employers, or insurance companies could err in reporting a person's insurance status; none provides a gold standard of information. Nonetheless, we use confirmations of insurance status to formally verify the insurance status of some sample members. This approach represents a compromise between taking reported insurance status at face value for all sample members and discarding valuable family respondents' reports about insurance status.

We label sample members as verified insured if an insurance card was shown at the time of the interview, a policy booklet was given to the interviewer, or if an employer or insurance company confirmed that the person was covered by insurance. We assume that a report that a sample member is uninsured is accurate as long as there is no contradictory information from any family member's employers and all employers provided data. The person's insurance status was not verified (but not assumed to be incorrect) if there were insufficient verification data or if employers or insurance companies contradicted the family respondent. Details are provided in a detailed data appendix available upon request.

As shown in Table 1, we find that 80.2% of the reportedly insured were confirmed as insured by a card, policy booklet, or an establishment. For the few cases in which a respondent produced an insurance card but the establishment reported that the person was uninsured, we treat these cases as verified insured based on the physical evidence of insurance. Among the reportedly uninsured,

[10] In the MEPS, outpatient prescription medications, medical supplies, and durable medical equipment are not linked to specific months; these expenditures are excluded.

11.7% are verified (Table 1). This relatively low number reflects the lack of an employed family member in some uninsured families and the lack of response by some employers. Recall that uninsurance is verified under this strategy only if all of the family's employers responded and confirmed that they did not provide insurance to the sample member. Overall, 67.0% of the sample was verified.

3 The Identification Problem

To evaluate the impact of inaccurate insurance classifications, we introduce notation that distinguishes between classified insurance status and actual insurance status. In this section, we focus on identification issues at the population level; when presenting empirical estimates, we also consider the uncertainty created by sampling variability. Let $I^* = 1$ indicate that a person is truly insured, with $I^* = 0$ otherwise. We observe the self-reported counterpart I. A latent variable Z^* indicates whether a report is accurate. If I and I^* coincide, then $Z^* = 1$; otherwise, $Z^* = 0$. Let $Y = 1$ indicate that I is verified to be accurate (i.e., Z^* is known to equal 1). If $Y = 0$, then Z^* may be either 1 or 0.[11] In no case is the value of Z^* assumed to be 0.[12]

Let U denote the amount of health care services consumed during the reference period. Typically, the amount of care is measured as health expenditures or number of provider visits. Policymakers are also interested in the proportion of the population that uses any medical care, in which case U can be treated as a binary variable. In this section, we investigate what can be learned about the utilization gap between the insured and uninsured,

$$\Delta = E(U|I^* = 1) - E(U|I^* = 0), \tag{1}$$

when true insurance status, I^*, is unobserved for part of the sample.[13] In Section 4, we focus on the impact of universal coverage.

The utilization gap Δ is not identified since we observe $E(U|I)$ but not $E(U|I^*)$. Our objective is to provide worst-case bounds on Δ. To partially identify $E(U|I^*)$, we will first derive bounds on the

[11] In their analysis of testing for environmental pollutants, Dominitz and Sherman (2004) were the first to formalize the idea of distinguishing between "verified" and "unverified" observations in the data.

[12] That is, we conservatively allow for the possibility that the MEPS insurance classification is accurate even if the classification is not confirmed by a card, booklet, employer, or insurance company.

[13] Our notation leaves implicit any other covariates of interest. We focus on bounding the utilization gap for the nonelderly population as a whole, but it is straightforward to condition on subpopulations of interest. Note that we are not estimating a regression, and there are no regression orthogonality conditions to be satisfied.

fraction of the population that consumes no more than a particular amount of care conditional on unobserved insurance status, $P(U \leq t|I^*)$. We can then provide bounds on $E(U|I^*)$ by integrating over these worst-case probabilities.

Using Bayes' rule, we can write

$$P(U \leq t|I^* = 1) = \frac{P(U \leq t, I^* = 1)}{P(I^* = 1)}. \tag{2}$$

Neither the numerator nor the denominator are identified, but assumptions on the pattern of classification errors can place restrictions on relationships between the unobserved quantities. Let $\theta_t^+ \equiv P(U \leq t, I = 1, Z^* = 0)$ and $\theta_t^- \equiv P(U \leq t, I = 0, Z^* = 0)$ denote the fraction of false positive and false negative insurance classifications, respectively, among those whose medical consumption did not exceed t. Let $\theta_t'^+ \equiv P(U > t, I = 1, Z^* = 0)$ and $\theta_t'^- \equiv P(U > t, I = 0, Z^* = 0)$ denote the analogous fractions among those whose use of care exceeded t. We can then decompose the numerator and denominator in (2) into identified and unidentified quantities:

$$P(U \leq t|I^* = 1) = \frac{P(U \leq t, I = 1) + \theta_t^- - \theta_t^+}{P(I = 1) + \left(\theta_t^- + \theta_t'^-\right) - \left(\theta_t^+ + \theta_t'^+\right)} \tag{3}$$

where $P(U \leq t, I = 1)$ and $P(I = 1)$ are identified by the data. In the numerator, $\theta_t^- - \theta_t^+$ reflects the unobserved excess of false negative vs. false positive insurance classifications among those whose use of services did not exceed t. In the denominator, $\left(\theta_t^- + \theta_t'^-\right) - \left(\theta_t^+ + \theta_t'^+\right)$ reflects the unobserved excess of false positive vs. false negative insurance classifications within the entire population. Utilization among the uninsured, $P(U \leq t|I^* = 0)$, can be decomposed in a similar fashion.

We now assess what can be learned about Δ under various sets of assumptions. First, we derive "arbitrary error" bounds that impose no structure on the distribution of false positives and false negatives. We next examine the identifying power of two common independence assumptions. Because these independence assumptions may not be plausible in our application, we introduce weaker variants of these assumptions.

3.1 Arbitrary error bounds

Following Horowitz and Manski (1995) and the literature on robust statistics (e.g., Huber 1981), we can study how identification of an unknown parameter varies with the confidence in the data.

Consider a lower bound on the fraction of accurate classifications among unverified cases:

$$P(Z^* = 1|Y = 0) \geq v. \tag{4}$$

If $v = 1$, then Δ is point-identified. We evaluate patterns of identification decay as v departs from 1. Molinari's (2005) treatment effect analysis (discussed in Section 4) implicitly sets $v = 0$. Since we do not observe I^* when $Z^* = 0$, the data alone cannot logically reveal a particular value of v. Nevertheless, we consider candidate values for v based on Hill's (2006) detailed exploration of the accuracy of self-reported insurance status in the MEPS. Based on evidence regarding rates of inconsistencies between self-reports and validation information (e.g., from employers and insurance companies), we focus on two values of v: 0.74 and 0.95. The larger value relies on an assumption that a presumed upper bound error rate among those reporting private insurance can be extrapolated to the population reporting public insurance. It also links error rates among reportedly uninsured individuals with at least one employed family member to those uninsured with no employed family member. The smaller value, 0.74, requires less extrapolation. Details are provided in the appendix below. If the researcher is unwilling to assume anything about the unverified responses, then identification can be studied for the case that v is set to 0. At any rate, we can assess the sensitivity of conclusions to the degree of confidence in the data.

We begin by logically determining the lowest feasible value of $P(U \leq t|I^* = 1)$. Differentiating the right hand side of (3), we find that this quantity is increasing in $\theta_t'^{+}$, the unobserved fraction of individuals with $U > t$ misclassified as being insured, and in θ_t^{-}, the unobserved fraction of individuals with $U \leq t$ misclassified as being uninsured. As a worst-case possibility for the lower bound, we must therefore set $\theta_t'^{+} = \theta_t^{-} = 0$ to obtain:

$$P(U \leq t|I^* = 1) \geq \frac{P(U \leq t, I = 1) - \theta_t^{+}}{P(I = 1) - \theta_t^{+} + \theta_t'^{-}}. \tag{5}$$

While θ_t^{+} and $\theta_t'^{-}$ are unobserved, their ranges are restricted. The unobserved fraction that was falsely classified as insured, $\theta_t^{+} = P(U \leq t, I = 1, Z^* = 0)$, cannot exceed the observed fraction that was classified as insured with unknown insured status. Nor can this fraction exceed the total allowed fraction of misclassified cases, $\phi(v) \equiv (1 - v)P(Y = 0)$. Similarly, the unobserved fraction of individuals that was falsely classified as being uninsured, $\theta_t'^{-} = P(U > t, I = 0, Z^* = 0)$, cannot exceed the observed fraction that was classified as being uninsured with unknown insured status;

nor can it exceed the total fraction of misclassified cases:

$$\begin{aligned} 0 &\leq \theta_t^+ \leq \min\{\phi(v), P(U \leq t, I = 1, Y = 0)\} \equiv \overline{\theta_t^+} \\ 0 &\leq \theta_t'^- \leq \min\{\phi(v), P(U > t, I = 0, Y = 0)\} \equiv \overline{\theta_t'^-}. \end{aligned}$$

To find the lower bound of $P(U \leq t|I^* = 1)$, we must find the minimum feasible value for the right-hand side (5). Therefore, for any candidate value of θ_t^+, we need $\theta_t'^-$ to attain its maximum allowed value conditional on θ_t^+:

$$\theta_t'^- = \min\left\{\phi(v) - \theta_t^+, \overline{\theta_t'^-}\right\} = \min\left\{\phi(v) - \theta_t^+, P(U > t, I = 0, Y = 0)\right\}.$$

The objective then becomes one of minimizing

$$\frac{P(U \leq t, I = 1) - \theta_t^+}{P(I = 1) - \theta_t^+ + \min\left\{\phi(v) - \theta_t^+, P(U > t, I = 0, Y = 0)\right\}} \tag{6}$$

over feasible values of θ_t^+.

Define $\theta_t^{+o} \equiv \phi(v) - P(U > t, I = 0, Y = 0)$, the critical value of θ_t^+ which makes the two arguments in the min function equal. First consider values of $\theta_t^+ \leq \theta_t^{+o}$. For such values, the derivative of (6) with respect to θ_t^+ is negative; therefore, we can exclude as potential candidates any values of θ_t^+ less than $\theta_{t\min}^+ \equiv \max\left\{0, \min\left\{\overline{\theta_t^+}, \theta_t^{+o}\right\}\right\}$. For $\theta_t^+ > \theta_t^{+o}$, the derivative has the same sign as

$$\delta_t^L \equiv P(U \leq t, I = 1) - P(U > t, I = 1) - \phi(v). \tag{7}$$

When this quantity is negative, we must raise θ_t^+ to its maximum feasible value, $\overline{\theta_t^+}$; otherwise, we set θ_t^+ equal to $\theta_{t\min}^+$.

Similar logic provides an upper bound on $P(U \leq 1|I^* = 1)$. After defining $\delta_t^H \equiv P(U > t, I = 1) - P(U \leq t, I = 1) - \phi(v)$, the preceding results establish the following proposition:

Proposition 1: *Let $P(Z^* = 1|Y = 0) \geq v$, and suppose that nothing is known about the pattern of false positive and false negative reporting errors. Then the mean utilization rate among the truly insured is bounded sharply as follows:*

$$\int U dF_H \leq E(U|I^* = 1) \leq \int U dF_L$$

using the distribution functions

$$F_L(t) = \frac{P(U \leq t, I = 1) - \alpha_t^+}{P(I = 1) - \alpha_t^+ + \min\left\{\phi(v) - \alpha_t^+, P(U > t, I = 0, Y = 0)\right\}}$$

$$F_H(t) = \frac{P(U \le t, I=1) + \alpha_t^-}{P(I=1) + \alpha_t^- - \min\left\{\phi(v) - \alpha_t^-, P(U > t, I=1, Y=0)\right\}}.$$

and values

$$\alpha_t^+ = \begin{cases} \min\left\{\phi(v), P(U \le t, I=1, Y=0)\right\} & \text{if } \delta_t^L < 0 \\ \max\left\{0, \min\left\{P(U \le t, I=1, Y=0), \phi(v) - P(U > t, I=0, Y=0)\right\}\right\} & \text{otherwise} \end{cases}$$

$$\alpha_t^- = \begin{cases} \min\left\{\phi(v), P(U \le t, I=0, Y=0)\right\} & \text{if } \delta_t^H \ge 0 \\ \max\left\{0, \min\left\{P(U \le t, I=0, Y=0), \phi(v) - P(U > t, I=1, Y=0)\right\}\right\} & \text{otherwise.} \end{cases}$$

Analogous bounds for the utilization rate among the uninsured, $E(U|I^* = 0)$, are obtained by replacing $I = 1$ with $I = 0$ and vice versa. Notice that increasing v narrows the bounds over some ranges of v but not others, and the rate of identification decay can be highly nonlinear as v declines. Kreider and Pepper's (2005) Proposition 2 bounds apply as a special case when the outcome U is binary and $v = 0$.[14]

We next turn to our first set of empirical results. We compute a lower bound on the utilization gap, Δ, by subtracting the upper bound on $E(U|I^* = 0)$ from the lower bound on $E(U|I^* = 1)$. Similarly, we compute an upper bound by subtracting the lower bound on $E(U|I^* = 0)$ from the upper bound on $E(U|I^* = 1)$.

3.2 Arbitrary error results

Figures 1(a)-(c) trace out estimated bounds on the utilization gap, Δ, as a function of v for any use of services, number of provider visits, and expenditures, respectively. Following much of the classification error literature, we focus on cases in which at least half the unverified classifications are assumed to be accurate.[15] The widest sets of bounds in the figures correspond to the Proposition 1 bounds. For all sets of bounds, the figures depict the 5th percentile lower bound and 95th percentile upper bound.[16]

When $v = 1$, Δ is point-identified as the self-reported gap, $P(U = 1|I = 1) - P(U = 1|I = 0) = 0.098$. Accounting for sampling variability, the gap lies within $[0.086, 0.110]$. The point estimates

[14] They study how labor force participation varies with disability status given a lack of knowledge of any particular respondent's true disability status. Our Proposition 1 extends their methodology by considering continuous outcomes and by assessing identification for values of v greater than 0 within unverified classifications. Their analysis does not impose our assumption that all verified cases are accurate.

[15] That is, the data are more informative than their converse (see, e.g., Bollinger (1996), and Frazis and Loewenstein (2003)).

[16] We account for sampling variability using balanced repeated replication methods that account for the complex survey design (Wolter, 1985).

for the gap in average number of provider visits and expenditures are 0.19 and \$77, respectively, with ranges $[0.15, 0.23]$ and $[\$49, \$102]$ after accounting for sampling variability. The wider bounds on expenditures reflect greater variability in expenditures.

Taken at face value (reflecting the values in Table 1), the data indicate that the insured consumed substantially more health services than the uninsured. In the absence of additional assumptions, however, we see in the figures that identification of Δ decays rapidly as v departs from 1. The lower bounds on Δ are particularly sensitive to the value of v. Indeed, classification error rates as low as 1 to 2% are sufficient to create uncertainty about whether expenditures and provider visits are truly higher among the insured than among the uninsured (Figures 1b, c).[17]

Without stronger assumptions on the distribution of classification errors, we cannot be confident that the insured consume more health services than the uninsured unless virtually all classifications are known to be accurate. This represents an important negative result: being almost fully confident in the accuracy of the data is not enough, by itself, to be informative about even the sign of the utilization gap between the insured and uninsured.

3.3 Independence assumptions

The parameter bounds thus far have allowed for arbitrary patterns of insurance classification errors, including the possibility that reporting errors are endogenously related to true insurance status or the health care utilization outcome. In contrast, most economic research presumes that measurement error is exogenous to the extent that it exists at all. In this section, we make transparent the identifying power of two common (nonnested) independence assumptions that tighten the Proposition 1 bounds. Then we introduce a weaker alternative assumption that is more plausible in our context.

First, a researcher might consider a "contaminated sampling" assumption that insurance clas-

[17] The discrete changes in slopes at some values of v are most easily understood by considering the binary case in Figure 1a. As a worst case lower bound on $P(U = 1|I = 1)$, we must make the unknown false positive quantity $a = P(U = 1, X = 1, Z = 0)$ among health care users as large as possible and then make the unknown false negative quantity $b = P(U = 0, X = 0, Z = 0)$ among non-users as large as possible conditional on a. For sufficiently low values of v, nothing prevents a from being as large as $P(U = 1, X = 1, Y = 0)$, the observed fraction of health care users who report health insurance coverage without verification, and nothing prevents b from being as large as $P(U = 0, X = 0, Y = 0)$, the observed fraction of non-users who report being uninsured without verification. Once v exceeds 0.49, the allowed total degree of misclassification is small enough that b must begin declining with v. Then once v exceeds 0.89, a must also start declining with v. Similar patterns apply to the other sets of bounds.

sification errors arise independently of true insurance status:[18]

$$P(I^* = 1|Z^*) = P(I^* = 1). \tag{8}$$

This assumption may be relatively innocuous compared with the set of homogeneity and exogeneity assumptions imposed in standard parametric frameworks. Still, stories can be told in which this assumption may be violated. Reporting errors may not be orthogonal to true insurance status if, for example, better educated respondents are both more likely to be insured and more likely to accurately answer survey questions. Similarly, Card *et al.* (2004) provide evidence that errors in reporting Medicaid coverage vary with family income, which is also a key aspect of Medicaid eligibility.

Alternatively, or in combination with (8), a researcher might place restrictions on the relationship between insurance classification errors and the use of health services. In the popular classical measurement error framework, reported insurance status does not depend on the level of health care utilization conditional on true insurance status:

$$P(I = 1|I^*, U) = P(I = 1|I^*) \text{ for } I^* = 0, 1. \tag{9}$$

Aigner (1973) and Bollinger (1996) study this type of "nondifferential" classification error for the case of a binary conditioning variable. When the independence assumption (9) holds, Bollinger's Theorem 1 can be used to show that Δ is bounded below by the reported utilization gap $E(U|I = 1) - E(U|I = 0)$ (> 0) as long as the extent of insurance classification errors is not too severe.[19] Reflecting well-known attenuation bias associated with random measurement error, the magnitude of the reported utilization gap represents a downward-biased estimate of the magnitude of the true utilization gap.[20] Berger *et al.* (1998) impose the nondifferential errors assumption in the only previous econometric analysis that allows for misreported insurance status.

Bound *et al.* (2001, p. 3725) note, however, that in general the nondifferential measurement error assumption is strong and often implausible. In our context, the nondifferential assumption

[18] The sampling process is referred to as "corrupt" when nothing is known about the pattern of reporting errors, as assumed in Proposition 1.

[19] Specifically, the true utilization gap can be no larger than the reported gap as long as the false positive rate plus the false negative rate is less than one: $P(I = 1|I^* = 0) + P(I = 0|I^* = 1) < 1$.

[20] The observed correlation between use of services and reported insurance, $\mathrm{Cov}(U, I)$, is positive. If this correlation were instead negative, then Δ would be bounded above by $E(U|I = 1) - E(U|I = 0)$.

is most likely to be violated if using health care informs respondents about their true insurance status. For example, a health care provider may enroll a patient in Medicaid. More generally, a regular user of health services (or a high expenditure user) is more likely to know her insurance status than an infrequent user of services.

We propose a weaker alternative assumption on the pattern of reporting errors. Relaxing the nondifferential assumption in (9), we suppose that the probability of misreporting insurance status does not rise with the level of health care utilization:

$$P(I = 1|I^* = 0, U_1) \leq P(I = 1|I^* = 0, U_0) \tag{10}$$

$$P(I = 0|I^* = 1, U_1) \leq P(I = 0|I^* = 1, U_0)$$

for $U_1 \geq U_0$. The nondifferential assumption represents a special case. In the next section, we illustrate how the identifying power of this monotone "nonincreasing error rate" assumption compares with the standard nondifferential errors assumption. We also separately evaluate the sensitivity of the bounds to departures from the exact equality in (9).

3.4 Results under independence and partial independence

The dashed lines in Figures 1(a-c) trace out the estimated bounds under the contaminated sampling assumption in (8).[21] Compared with the case of arbitrary errors, we find that the critical value of v that identifies $\Delta > 0$ declines from about 0.95 to about 0.82 for any use of services, from about 0.98 to about 0.91 for number of visits, and from nearly 1 to about 0.79 for expenditures. At $v = 0.95$, the width of the bounds decreases by 41% to $[0.067, 0.175]$ for any use of services (Table 2). Similarly, the bounds narrow 66% to $[0.08, 0.25]$ for number of visits and narrow 56% to $[\$38, \$102]$ for expenditures.

Under nondifferential errors, the lower bound on Δ is given by the self-reported value of Δ across all values of v. Therefore, the insured are identified to use more health services than the uninsured regardless of the extent of reporting error. These bounds are presented as shaded identification regions in the figures, with special case values of v provided in the right-hand column of Table 2. Even if half of the unverified classifications may be misreported ($v = 0.5$), Δ is constrained to

[21] We numerically computed bounds under the various independence assumptions by searching over logically allowed combinations of false positives and false negatives $\{\theta_t^-, \theta_t'^-, \theta_t^+, \theta_t'^+\}$.

lie within the 11-point range $[0.098, 0.207]$ for any use of services. As the degree of misreporting rises, the fractions of false positive and false negative reports must rise jointly, thus constraining the increase in uncertainty about the use of service probabilities. For $v = 0.95$, this uncertainty narrows to the one-point range $[0.098, 0.105]$; the gap in the number of visits lies within $[0.19, 0.22]$ while the gap in expenditures lies within $[\$77, \$78]$.

As discussed above, strict nondifferential independence may not be plausible in the context of insurance reporting errors. As seen in Figures 1(a)-(c) and the last column of Table 2, the bounds on Δ expand when replacing strict independence with the assumption in (10) that error rates do not increase with the level of utilization. The bounds remain quite informative compared with case of arbitrary error patterns. Compared with that case, the critical value of v that identifies $\Delta > 0$ declines from 0.95 to 0.80 for any use of services, from 0.98 to 0.93 for number of visits, and from nearly 1 to 0.75 for expenditures. At $v = 0.95$, the bounds on Δ for the use of services are less than one-fifth as wide as the bounds under arbitrary errors, and we can tightly bound Δ to lie within the narrow 3 point range [0.081, 0.112]. Mean number of visits and expenditures are bounded to lie within $[0.15, 0.23]$ and $[\$71, \$83]$, respectively.

We also investigate the sensitivity of the bounds to departures from the strict equality in (9). In particular, we generalize the standard nondifferential error assumption as follows:

$$|P(I = 1|I^*, U) - P(I = 1|I^*)| \leq \kappa \tag{11}$$

for some $\kappa \in [0, 1]$. Strict nondifferential independence holds when $\kappa = 0$, while the case of arbitrary errors follows when $\kappa = 1$. The nondifferential bounds naturally widen for larger values of κ. Appendix Table 1A illustrates the sensitivity of the bounds for various values of κ. For expenditures, we continue to identify Δ as being positive – for any value of v – unless reported insurance status, conditional on true insurance status, differs more than 12 percentage points (i.e., unless $\kappa > 0.12$) across different values of utilization. The analogous critical values for provider visits and any use of services are 0.07 and 0.08, respectively. For $v = 0.95$, we continue to identify Δ as being positive if $\kappa < 0.35$ for any use, $\kappa < 0.30$ for visits, and $\kappa < 0.40$ for expenditures. Thus, this "partial nondifferential independence" assumption can provide strong identification power even when strict independence is substantially relaxed.

4 Utilization under Universal Health Insurance

We now turn to inferences about health care utilization under a hypothetical policy of universal health insurance. Let $U(I^* = 1)$ denote the amount of health services an individual would have used in July 1996 if insured. This outcome is observed in the data only for sample members who are verified to be currently insured; it is unobserved for those verified to be uninsured and for those whose insurance status is not verified. We wish to learn the population's expected utilization if everyone were insured, $E[U(I^* = 1)]$. If current insurance status were randomly assigned, then the utilization among the currently insured, $E(U|I^* = 1)$, would represent the best prediction of the utilization rate under universal coverage. Since I^* is not observed for all individuals, we could instead bound $E(U|I^* = 1)$ using the methods derived in the previous sections.

Of course, the observed distribution of health insurance coverage in the population is not randomly assigned. Instead, insurance status is affected by characteristics potentially related to the use of medical resources. For example, families that expect to use health services may be more likely to acquire health insurance. In that case, an observed positive association between insurance coverage and utilization reflects not only the effect of insurance on use of services but also the effect of anticipated service use on insurance status. More generally, insurance status may depend on individual and family characteristics that also determine health care use.

In the absence of random assignment or other assumptions, the quantity $E[U(I^* = 1)]$ is not identified even if all insurance classifications are known to be accurate. Unlike identification of the conditional utilization rate $E(U|I^* = 1)$, identification of the "treatment" outcome $E[U(I^* = 1)]$ requires knowledge about the counterfactual utilization rate of the uninsured had they instead been insured. Uncertainty about the accuracy of insurance classifications, the focus of the current paper, further complicates identification of counterfactuals.

To bound the impact of universal coverage on utilization, we begin by using the law of total probability to decompose the projected utilization rate under universal coverage into verified and unverified current insurance status:

$$E[U(I^* = 1)] = E[U(I^* = 1)|Y = 1]P(Y = 1) + E[U(I^* = 1)|Y = 0]P(Y = 0). \qquad (12)$$

The data identify $P(Y = 1)$ and $P(Y = 0)$ but neither utilization term. The first term involving verified insurance status can be written as

$$E[U(I^*=1)|Y=1] = E(U|I^*=1,Y=1)P_{11} + E[U(I^*=1)|I^*=0,Y=1](1-P_{11}) \qquad (13)$$

where $P_{11} \equiv P(I^*=1|Y=1)$ denotes the status quo insured rate among verified cases. All of the terms in (13) are observed except for the counterfactual expected utilization among those uninsured under the status quo, $E[U(I^*=1)|I^*=0,Y=1]$. Without additional assumptions, this quantity may lie anywhere within the support of U, $[0, \sup U]$.

Returning to (12) and decomposing the third term involving the unverified cases obtains:

$$E[U(I^*=1)|Y=0] = E(U|I^*=1,Y=0)P_{10} + E[U(I^*=1)|I^*=0,Y=0](1-P_{10}) \qquad (14)$$

where $P_{10} \equiv P(I^*=1|Y=0)$ is the status quo insured rate among unverified cases. None of the quantities in (14) are identified. We do not know P_{10}, and we cannot match health care use outcomes to insurance status when insurance status is unknown.

Implicitly assuming that $v=0$, Molinari (2005) shows that we can learn something about the first term, $E(U|I^*=1,Y=0)$, if the researcher has outside information restricting the range of P_{10} (denoted p in her framework).[22] In her innovative analysis, she estimates the treatment effect of drug use on employment when drug use is unobserved for part of the sample. As shown below, we extend her analysis in two dimensions when $v>0$. First, an assumption on v translates into internally-generated restrictions on P_{10} as a function of v. The identifying power of this information depends on the joint distribution of the outcome variable, the self-reported conditioning variable, and the individual's validation status. Second, an assumption on v allows us to restrict the expected utilization rate among the unverifiably truly uninsured, $E(U|I^*=0,Y=0)$, which in turn allows us to tighten Molinari's bounds on the expected utilization rate among the unverifiably truly insured, $E(U|I^*=1,Y=0)$. In the figures that follow, Molinari's framework can be used to provide sharp bounds at the points $v=0$ and $v=1$. Our extension allows us to fill in identification patterns for values of v between 0 and 1.

We proceed by writing the insured rate among unverified cases as a function of $P(I=1|Y=0)$, false positive, and false negative classification rates:

$$P_{10} = P(I=1|Y=0) + P(I=0,Z^*=0|Y=0) - P(I=1,Z^*=0|Y=0).$$

[22]In Molinari's framework, $Y=0$ (our notation) denotes survey nonresponse instead of lack of verification. Molinari (2004) presents a general treatment of the identification problem for a variety of measurement issues.

Allowing the unidentified terms to vary over their feasible ranges implies $P_{10} \in [\underline{P}_{10}, \overline{P}_{10}]$ where

$$\begin{aligned} \underline{P}_{10} &\equiv P(I=1|Y=0) - \min\{1-v, P(I=1|Y=0)\} \\ \overline{P}_{10} &\equiv P(I=1|Y=0) + \min\{1-v, P(I=0|Y=0)\}. \end{aligned} \tag{15}$$

When $v = 0$, P_{10} is trivially bounded within $[0,1]$; at the other extreme when $v = 1$, $P_{10} = P(I = 1|Y = 0)$.

This knowledge about the range of P_{10} places restrictions on the utilization patterns of the subpopulation of unverified cases. We know that the distribution of utilization outcomes among unverified cases is a weighted average of the utilization levels among unverified insured and uninsured cases:

$$P(U \le t|Y=0) = P(U \le t|I^*=1, Y=0)P_{10} + P(U \le t|I^*=0, Y=0)(1-P_{10}). \tag{16}$$

For a particular value of P_{10}, solving for the expected utilization rate among the unverified currently insured obtains

$$P(U \le t|I^*=1, Y=0) = \frac{P(U \le t|Y=0) - P(U \le t|I^*=0, Y=0)(1-P_{10})}{P_{10}}. \tag{17}$$

The quantity $P(U \le t|I^* = 0, Y = 0)$ in the right-hand-side is nontrivially bounded if and only if $v > 0$. In that case, we can use the methods developed in Section 3.1 to obtain

$$\begin{aligned} \Omega_1(t,v) \equiv \; & \frac{P(U \le t, I=0, Y=0) - \alpha_t^-}{P(I=0,Y=0) - \alpha_t^- + \min\left\{\phi(v) - \alpha_t^-, P(U > t, I=1, Y=0)\right\}} \\ & \le P(U \le t|I^*=0, Y=0) \le \\ \Omega_2(t,v) \equiv \; & \frac{P(U \le t, I=0, Y=0) + \alpha_t^+}{P(I=0,Y=0) + \alpha_t^+ - \min\left\{\phi(v) - \alpha_t^+, P(U > t, I=0, Y=0)\right\}} \end{aligned} \tag{18}$$

where α_t^- and α_t^+ were defined in Proposition 1 and we redefine $\delta_t^L \equiv P(U \le t, I = 0, Y = 0) - P(U > t, I = 0, Y = 0) + \phi(v)$ and $\delta_t^H \equiv P(U > t, I = 0, Y = 0) - P(U \le t, I = 0, Y = 0) + \phi(v)$.

Varying $P(U \le t|I^* = 0, Y = 0)$ within the feasible range $[\Omega_1(t), \Omega_2(t)]$ in (17) reveals that $P(U \le t|I^* = 1, Y = 0)$ must lie within the range $[G_L(t,v), G_H(t,v)]$ given by[23]

$$\begin{aligned} G_L(t,v) &\equiv \max\left\{0, \frac{P(U \le t|Y=0) - (1-P_{10})\Omega_2(t,v)}{P_{10}}\right\} \\ G_H(t,v) &\equiv \min\left\{\frac{P(U \le t|Y=0) - (1-P_{10})\Omega_1(t,v)}{P_{10}}, \sup U\right\}. \end{aligned}$$

[23] Note that $v > 0$ also directly places restrictions on $E(U|I = 1, Y = 0)$. However, we can show that the direct restrictions on this quantity represent a subset of the restrictions imposed on it indirectly via the restrictions on $E(U|I = 0, Y = 0)$.

Then we can bound expected health care utilization among the unverifiably truly insured as follows:

$$\int U dG_H \leq E(U|I^* = 1, Y = 0) \leq \int U dG_L. \tag{19}$$

Applying this result to the first term in (14) and varying $E[U(I^* = 1)|I^* = 0, Y = j]$ within $[0, \sup U]$ for $j = 0, 1$ in (13) and (14) yields the following sharp bounds on the population's use of health services under universal health insurance:[24]

Proposition 2. *Given $P(Z^* = 1|Y = 0) \geq v$ and a known value $P_{10} \in \left[\underline{P}_{10}(v), \overline{P}_{10}(v)\right]$, the population's health care utilization rate under mandatory universal insurance coverage is bounded sharply as follows:*

$$\begin{aligned} E(U|I = 1, Y = 1)P(I = 1, Y = 1) + P_{10}P(Y = 0) \int U dG_H \\ \leq E\left[U(I^* = 1)\right] \leq \end{aligned} \tag{20}$$

$$\begin{aligned} E(U|I &= 1, Y = 1)P(I = 1, Y = 1) + P_{10}P(Y = 0) \int U dG_L \\ &+ \left[P(I = 0, Y = 1) + (1 - P_{10})P(Y = 0)\right] \sup U. \end{aligned}$$

If P_{10} is unknown, the lower and upper bounds in (20) are replaced by the infimum and supremum, respectively, of these bounds over values of $P_{10} \in \left[\underline{P}_{10}, \overline{P}_{10}\right]$.

Molinari's (2005) Proposition 1 is similar except that her probability distributions L_p and U_p (in place of G_L and G_H) implicitly assume that $v = 0$ such that nothing is known about the reliability of unverified classifications. For that special case, the bounds in (20) collapse to Molinari's bounds after setting $\Omega_1(t) = 0$ and $\Omega_2(t) = 1$ in (18) and $\left[\underline{P}_{10}, \overline{P}_{10}\right] = [0, 1]$. Molinari allows for the possibility that the researcher has outside information restricting P_{10} to a range narrower than $[0, 1]$ (including the possibility that P_{10} is known). In that case, something can be learned about $E[U(I^* = 1)|Y = 0]$ even though $\Omega_1(t) = 0$ and $\Omega_2(t) = 1$. Her bounds are as tight as possible given her imposed assumptions, but the proposition above allows us to assess how identification decays with the degree of uncertainty about the reliability of the data.

For the binary utilization case, $\sup U$ in Proposition 2 is naturally set equal to 1. Yet there is no natural limit to the number of provider visits or dollars spent on medical services. Unless

[24] This analysis does not account for potential increases in gross prices for health care resulting from universal coverage. Since such price increases would not increase utilization, these upper bounds on $E(U|I = 1)$ should still apply. We also assume that insurance coverage to the uninsured would be representative of the current mix of public and private coverage available to the insured.

a researcher is nevertheless willing to set an upper bound on U, it must be recognized that an informative upper bound on $E\left[U(I^*=1)\right]$ cannot be logically identified under the weak conditions specified in Proposition 2. For our Proposition 2 empirical results, we set $\sup U$ equal to 1.69 for number of visits and to $655 for expenditures reflecting mean values among individuals who (1) perceived themselves to be in poor health at the time of the first interview and (2) were verified to be insured. These values reflect the 93rd percentile for visits and the 98th percentile for expenditures. We do not require any assumptions on $\sup U$ for the Proposition 3 bounds or monotone instrumental variable (MIV) bounds which follow.

4.1 Monotonicity assumptions

The preceding bounds can be narrowed substantially under common monotonicity assumptions on treatment response and treatment selection. The monotone treatment response assumption (MTR) specifies that an individual's utilization is at least as high in the insured state as in the uninsured state:

$$U_i(I^*=1) \geq U_i(I^*=0). \tag{21}$$

Under monotone treatment selection (MTS), expected utilization under either "treatment" (insured or uninsured) would be at least as high among those currently insured as among those currently uninsured:[25]

$$E[U(I^*=j)|I^*=1] \geq E[U(I^*=j)|I^*=0] \text{ for } j=0,1. \tag{22}$$

The validity of this assumption depends on the process by which individuals have selected themselves into insured and uninsured status. This assumption is consistent with evidence from Miller *et al.* (2004) who find that while the uninsured tend to be less healthy than the privately insured, they tend to be healthier than those publicly insured (e.g., through Medicaid). The uninsured may also have unobserved characteristics, such as attitudes toward care, that make them less likely to seek care. To the extent that the uninsured are less health conscious, they may seek less preventive care and wait longer before deciding to seek treatment for an ailment. In general, those who are currently insured may have a greater propensity to use care than those who are currently unin-

[25] In the July 1996 MEPS sample, the probability of using services among those classified as being insured was 0.23 compared with 0.13 among the uninsured, and mean expenditures were $114 among the reportedly insured compared with $36 among the reportedly uninsured (Table 1).

sured. Using data from the SIPP to estimate a parametric structural model of health care use and insurance coverage, Li and Trivedi (2004) find that a significant part of the observed lower health care use among the uninsured can be attributed to self-selection instead of the lack of insurance.[26]

When both MTR and MTS hold, we can use a result in Manski and Pepper (2000, Corollary 2.2) to obtain

$$E(U) \leq E\left[U(I^* = 1)\right] \leq E(U|I^* = 1).$$

The lower bound on the population's use of services under universal coverage rises to $E(U)$, the status quo national utilization rate in the absence of universal coverage. The upper bound falls to the status quo utilization rate among those currently insured. This result combined with the upper bound on $E(U|I^* = 1)$ derived in Proposition 1 leads to the following proposition:

Proposition 3. *Suppose that the MTR and MTS assumptions hold across the population and* $P(Z^* = 1|Y = 0) \geq v$. *Then the expected use of services under insurance coverage is bounded above by* $\int U dF_L$ *where*

$$F_L(t) = \frac{P(U \leq t, I = 1) - \alpha_t^+}{P(I = 1) - \alpha_t^+ + \min\left\{\phi(v) - \alpha_t^+, P(U > t, I = 0, Y = 0)\right\}},$$

$$\alpha_t^+ = \begin{cases} \min\left\{\phi(v), P(U \leq t, I = 1, Y = 0)\right\} & \text{if } \delta_t^L < 0 \\ \max\left\{0, \min\left\{P(U \leq t, I = 1, Y = 0), \phi(v) - P(U > t, I = 0, Y = 0)\right\}\right\} & \text{otherwise} \end{cases}$$

and $\delta_t^L \equiv P(U \leq t, I = 1) - P(U > t, I = 1) - \phi(v)$.

In the empirical work that follows, we also consider the additional identifying power of the independence and nonincreasing errors assumptions considered in Section 3.3.

4.2 Universal Coverage Results

Empirical results are presented in Table 3 and the bottom frames of Figures 2(a-c). Each set of bounds for $E\left[U(I^* = 1)\right]$ is calculated with the insured rate among unverified classifications, P_{10}, allowed to lie anywhere within its logically consistent range $\left[\underline{P}_{10}, \overline{P}_{10}\right]$.

The status quo fraction of the (nonelderly) population using health services in a month is 0.206. For $v = 1$ (no classification error) and no monotonicity assumptions, we estimate that the fraction of the population using health services could fall by up to 2 percentage points to 0.182 or rise by

[26] Of course, their finding relies in part on the types of parametric assumptions we are trying to avoid.

up to 17 percentage points to 0.374. This projected range, given by $[-12\%, +82\%]$ in percentage terms, represents the well-known classical effect of a mandatory policy given uncertainty about counterfactuals (e.g., Manski, 1995). For mean number of visits and expenditures, the projected ranges are $[-27\%, +54\%]$ and $[-23\%, +105\%]$, respectively. These results are presented in Table 3, Column (1).

As seen in Column (2), these ranges narrow dramatically under MTR and MTS. With $v = 1$, the fraction using any services would rise by no more than 2 percentage points, a 9% increase. The mean number of visits would rise by no more than four-tenths of a visit (a 10% increase), while per capita expenditures would rise by no more than \$15, a 15% increase. The lower bounds rise to the status quo utilization rates.

Table 3 and Figures 2a-c also allow us to observe patterns of identification decay as v departs from 1. Without monotonicity assumptions, the upper bound on the fraction using any health services under universal coverage rises from 0.374 when $v = 1$ (82% above the status quo) to 0.407 when $v = 0.95$ (98% above the status quo). When MTR and MTS are imposed, the upper bound rises from 0.225 when $v = 1$ (9% above the status quo) to 0.240 when $v = 0.95$ (17% above the status quo). The patterns are similar for provider visits and expenditures. For example, the upper bound on mean provider visits when MTR and MTS are imposed rises from 0.45 when $v = 1$ (10% above the status quo) to 0.49 when $v = 0.95$ (20% above the status quo). The upper bound on mean expenditures rises from \$114 (15% above the status quo) when $v = 1$ to \$123 (24% above the status quo) when $v = 0.95$.

These bounds can be narrowed further under stronger assumptions about the nature of reporting errors. Columns (3) and (4) present bounds on $E\left[U(I^* = 1)\right]$ under contaminated sampling and nondifferential errors, respectively. As v declines from 1 to 0.95 under contaminated sampling, the upper bound for mean visits barely rises from 0.45 to only 0.46. The change under nondifferential errors is similar. For expenditures, the upper bound barely rises from \$114 to \$118 under contaminated sampling and remains nearly unchanged under nondifferential errors. For the fraction using any services, the contaminated sampling assumption has substantially more identifying power for smaller values of v; the upper bound is nearly flat for $v < 0.9$. The nondifferential assumption has more immediate identifying power as v departs from 1.

As in Section 3.5, we can examine the sensitivity of these results to departures from strict independence. We first consider the assumption that error rates do not increase with utilization (equation (10)). Suppose that MTR and MTS hold. Then as long as v is not much less than 0.75, the upper bound on $E\left[U(I^*=1)\right]$ under nonincreasing error rates (for all three measures of utilization) is closer to the upper bound under nondifferential errors than to the upper bound under arbitrary errors (see Figures 2a-c). For $v=0.95$, for example, Column (5) of Table 3 shows that the upper bound rises only four-tenths of a percentage point from 0.226 under nondifferential errors to 0.230 under nonincreasing error rates.

Second, we examine the effects of varying κ in Equation (11) while assuming MTR and MTS hold. Appendix Table 2A presents bounds on $E\left[U(I^*=1)\right]$ under partial independence across different values of κ. Recall that $\kappa=0$ corresponds to the case of strict independence while $\kappa=1$ corresponds to the case of no independence. As κ varies between 0 and 0.20 at $v=0.95$, the upper bound on the number of visits under universal coverage ranges from 0.45 and 0.49. Expenditures range from \$114 to \$118.

4.3 Monotone Instrumental Variables

We next use monotone instrumental variables (MIV) techniques developed by Manski and Pepper (2000) and extended by Kreider and Pepper (2005) to assess how the bounds can be narrowed when combined with monotonicity assumptions linking utilization outcomes and observed covariates such as age or health status. Consider, for example, age and use of health services. The incidence of many health conditions rises with age, and many health conditions are persistent once developed. These tendencies suggest that the utilization rate among adults under universal coverage would be nondecreasing in age.

Formally, consider the utilization rate at some age, age_0, above some threshold, age'. We set age' equal to 30 years of age. The MIV restriction implies the following inequality restriction:

$$\begin{aligned} age\prime \quad &\leq \quad age_1 \leq age_0 \leq age_2 \\ &\Longrightarrow \quad E\left[U\left(I^*=1\right)|age_1)\right] \leq E\left[U\left(I^*=1\right)|age_0)\right] \leq E\left[U\left(I^*=1\right)|age_2)\right]. \end{aligned} \tag{23}$$

The conditional probabilities in Equation (23) are not identified, but they can be bounded using the methods described above. Let $LB(age)$ and $UB(age)$ be the known lower and upper bounds, respectively, given the available information on $E(U|I^*, age)$; in computing these bounds, we assume that MTR and MTS continue to hold. Then using Manski and Pepper (2000, Proposition 1), we have

$$\sup_{age_1 \in [age',\, age_0]} LB(age_1) \leq E\left[U\left(I^* = 1\right)|age_0)\right] \leq \inf_{age_2 \geq age_0} UB(age_2). \tag{24}$$

The MIV bound on expected utilization under universal coverage is obtained using the law of total probability:

$$\begin{aligned} &\sum_{age_0 \epsilon U} P(age = age_0)\{\sup_{age_1 \in [age',\, age_0]} LB(age_1)\} \\ &\leq E\left[U\left(I^* = 1\right)\right] \leq \\ &\sum_{age_0 \epsilon U} P(age = age_0)\{\inf_{age_2 \geq age_0} UB(age_2)\}. \end{aligned} \tag{25}$$

Thus, to find the MIV bounds on the utilization rate, one takes the appropriate weighted average of the lower and upper bounds across the different values of the instrument. We treat age and general health status as MIVs. We divide the population into 18 age groups: 0-30, 31-32, 32-34, ..., 63-64. Within each age group, we assume that use of services under universal coverage would be nondecreasing in worse health across the following categories: poor/fair, good, very good, and excellent.

This MIV estimator is consistent but biased in finite samples. To account for this bias, we employ Kreider and Pepper's (2005) modified MIV estimator that directly estimates and adjusts for finite-sample bias using Efron and Tibshirani's (1993a) nonparametric bootstrap correction method. Let T_n be a consistent analog estimator of some unknown parameter θ such that the bias of this estimator is $b_n = E(T_n) - \theta$. Using the bootstrap distribution of T_n, one can estimate this bias as $\widehat{b} = E^*(T_n) - T_n$, where $E^*(\cdot)$ is the expectation operator with respect to the bootstrap distribution. A bootstrap bias-corrected estimator then follows as $T_n^c = T_n - \widehat{b} = 2T_n - E^*(T_n)$. In our setting, the finite bias is simulated from the bootstrap distributions of the estimated Proposition 3 bounds calculated for each MIV group.[27]

[27] See Kreider and Pepper (2005) for estimation details. Monte-carlo simulations have shown the approach to effectively correct for the finite sample bias in a variety of different settings and to be asymptotically efficient at higher orders. See, for example, Parr (1983), Efron and Tibshirani (1993), Hahn et al. (2002), and Ramalho (2005).

4.4 MIV Results

MIV results are presented in Table 3, Columns (6) and (7). We assess the identifying power of the MIV assumption by comparing these columns with Columns (2) and (5) for the case of arbitrary errors and nonincreasing error rates, respectively. In Column (2), identification is achieved through verification and monotonicity assumptions alone. For $v = 0.95$ in that case, we estimated that the fraction of the nonelderly population using health services would rise no more than 17% above the status quo to 0.240. Under the additional MIV assumption in Column (6), we estimate that this fraction would rise no more than 12% to 0.231. For $v = 0.74$, the upper bound improves from 0.266 to 0.246. Improvements in the upper bounds for mean number of visits and expenditures are similar. Under the MIV assumption, the upper bound on the number of visits improves from 0.49 to 0.47 for $v = 0.95$ and from 0.54 to 0.50 for $v = 0.74$. The upper bound on expenditures improves from \$123 to \$118 for $v = 0.95$ and from \$134 to \$123 for $v = 0.74$.

Combining MIV with the assumption of nonincreasing error rates, we find that the fraction using services in a month would rise by no more than 1.8 percentage points to 0.224 when $v = 0.95$ and by no more than 2.5 percentage points to 0.231 when $v = 0.74$ (Table 3, Column (7)). Note the improvements over the bounds without MIV in Column (5): 0.230 when $v = 0.95$ and 0.252 when $v = 0.74$. The mean number of provider visits would rise no more than four-tenths of a visit to 0.45 when $v = 0.95$ and no more than half a visit to 0.46 when $v = 0.74$. Expenditures would rise no more than 15% to \$114 when $v = 0.95$ and no more than 17% to \$116 when $v = 0.74$.

5 Conclusion

Policymakers have long been interested in identifying the consequences of uninsurance for access to health care and the potential impacts of universal coverage (e.g., Institute of Medicine 2003). Identification of policy outcomes, however, is confounded by both the presence of unobserved counterfactuals and the potential unreliability of self-reported insurance status. To account for these two distinct types of uncertainty, we developed a nonparametric framework that extends the literature on partially identified probability distributions and treatment effects. Using the new analytical results, we can provide tight bounds on the impact of universal health insurance on provider visits and medical expenditures. As part of the paper's contribution, we showed how to partially identify the conditional mean of a random variable for the case that a binary conditioning variable – in our case health insurance – is subject to arbitrary endogenous measurement error.

Our conservative statistical approach provides informative bounds without imposing parametric distributional assumptions. We began by corroborating self-reported insurance status for a nonrandom portion of the MEPS sample using outside information from insurance cards and follow-back interviews with employers, insurance companies, and medical providers. We remained agnostic about true insurance status for the remainder of the sample and illustrated how a variety of verification, monotonicity, and independence assumptions can be combined to shrink identification regions. We also weakened the strict nondifferential independence assumption embodied in the classical errors-in-variables framework to allow for the possibility that using health services may inform a patient of her true insurance status.

In July 1996, about 21% of the nonelderly population used inpatient or ambulatory medical services. Under relatively weak nonparametric assumptions, we estimate that this proportion would rise no more than 1.8 percentage points if everyone had insurance. We further estimate that per capita monthly provider visits across the nonelderly population would rise by no more than four-tenths of a visit (a 9% change), with mean expenditures per month rising by no more than 15%. These results rely on evidence from our constructed validation sample that no more than 5 percent of unverified insurance classifications (representing 2 percent of the total sample) are likely to be misreported.

In parametric studies, Miller *et al.* (2004) and Hadley and Holahan (2003) estimate that providing coverage to the uninsured would increase annual expenditures between $10\% - 17\%$ depending on their specific assumptions. Their models assume no measurement error, and self-selection into insured status is allowed only through a set of observed characteristics. Depending on assumptions about the nature of selection and the potential degree of insurance reporting error, we find a wide range of potential outcomes. Yet as long as reporting errors in the MEPS are relatively few and do not increase with the level of utilization, our upper bounds are fairly tight and comparable to estimates in the parametric studies.

Buchmueller et al. (2005) review studies of the effects of insurance on the amount of service use. Parametric studies find that insurance increases visits among the uninsured $16\% - 106\%$, which corresponds to increases among all nonelderly of $3\% - 20\%$. The highest estimates exceed our upper bound, but they come from studies comparing people without insurance the entire year to those with private insurance for an entire year. Those results can be expected to be higher due to the generosity of employment-related benefits compared with the mix of public and private insurance considered in our study.

Without assumptions on the specific pattern of insurance classification errors, we find that a very small degree of classification error is sufficient to generate uncertainty about the sign – let alone the magnitude - of the status quo gap in use of services between the insured and uninsured under current policies. This represents an important negative result: a high degree of confidence in the accuracy of the data is not enough, by itself, to be confident about conclusions drawn from the data. Conclusions about differing health care patterns across the insured and uninsured, for example, appear to be critically dependent on researchers' auxiliary identifying assumptions.

The methods developed in this paper can be applied to a wide range of topics that involve identification of conditional expectations or treatment effects given uncertainty about the accuracy of the conditioning variable. Our framework, for example, offers an alternative approach to Blau and Gilleskie's (2001) parametric analysis of the impact of employer-provided retiree health insurance on retirement outcomes. In the Health and Retirement Study data used in their study, about 13 percent of the respondents nearing retirement age said they were unsure about whether they had retiree insurance – thus forming a natural subpopulation of respondents to be characterized as providing unreliable treatment information. The methods in this paper could be used to bound the effects of retiree insurance on employment, informing policymakers about the potential consequences of allowing retirees younger than 65 to purchase Medicare coverage. More generally, we expect this developing line of research to improve researchers' understanding of the consequences of nonclassical measurement error for inferences, which should in turn yield more informed policy analyses.

References

[1] Aigner, D.J. (1973). "Regression with a Binary Independent Variable Subject to Errors of Observation." *Journal of Econometrics*, 2, 49-59.

[2] Berger M., D. Black and F. Scott. (1998). "How Well Do We Measure Employer-Provided Health Insurance Coverage?" *Contemporary Economic Policy*, 16: 356-367.

[3] Blau, D. and D. Gilleskie. (2001). "Retiree Health Insurance and Labor Force Behavior of Older Men in the 1990s." *Review of Economics and Statistics*, 83(1): 64-80.

[4] Bollinger, C. (1996). "Bounding Mean Regressions When A Binary Variable is Mismeasured." *Journal of Econometrics*, 73(2): 387-99.

[5] Bound, J. and R. Burkhauser. (1999). "Economic Analysis of Transfer Programs Targeted on People with Disabilities." In Orley Ashenfelter and David Card (Eds.), Handbook of Labor Economics, Vol. 3C. Amsterdam: Elsevier Science: 3417-3528.

[6] Bound, J., C. Brown, and N. Mathiowetz. (2001). "Measurement Error in Survey Data." In J. Heckman and E. Leamer (Eds.), Handbook of Econometrics, 5, Ch. 59: 3705-3843.

[7] Buchmueller, T.C., K. Grumbach, R. Kronick and J.G. Kahn. (2005). "The Effect of Health Insurance on Medical Care Utilization and Implications for Insurance Expansion: A Review of the Literature." *Medical Care Research and Review*, 62(1): 3-30.

[8] Call, K.T., G. Davidson, A.S. Sommers, R. Feldman, P. Farseth, and T. Rockwood. (2001). "Uncovering the Missing Medicaid Cases and Assessing their Bias for Estimates of the Uninsured." *Inquiry*, 38(4): 396-408.

[9] Card, D., A.K.G. Hildreth, and L.D. Shore-Sheppard. (2004). "The Measurement of Medicaid Coverage in the SIPP: Evidence From a Comparison of Matched Records." *Journal of Business & Economic Statistics* 22(4): 410-420.

[10] Cohen, J. (1997). "Design and Methods of the Medical Expenditure Panel Survey Household Component." MEPS Methodology Report no. 1, AHCPR Pub. no. 97-0026. Rockville, MD AHCPR 1997.

[11] Czajka, J. and K. Lewis. (1999). "Using Universal Survey Data to Analyze Children's Health Insurance Coverage: An Assessment of Issues." Washington, DC: Mathematica Policy Research, Inc., http://aspe.os.dhhs.gov/health/reports/Survey%20Data.htm.

[12] Davern, M., K.T. Call, J. Zeigenfuss, G. Davidson, and L. Blewett. (2005). "Validating Health Insurance Survey Coverage Estimates: A Comparison Between Self-Reported Coverage and Administrative Data Records" School of Public Health, University of Minnesota, mimeo.

[13] Davidson, G. (2005). "Early Results from the Pennsylvania Medicaid Undercount Experiment." Presentation at the SHADAC Spring Workshop: Survey and Administrative Data Sources of the Medicaid Undercount, Washington DC.

[14] DeNaves-Walt, C., B.C. Proctor, and C. Hill Lee. (2005). Income, Poverty, and Health Insurance Coverage in the United States, 2004. U.S. Census Bureau, Current Population Reports P60-229. U.S. Government Printing Office, Washington DC.

[15] Dominitz, J., and R. Sherman. (2004). "Sharp Bounds Under Contaminated or Corrupted Sampling With Verification, With an Application to Environmental Pollutant Data," *Journal of Agricultural, Biological and Environmental Statistics*, 9(3): 319-338.

[16] Efron, Bradley and Robert J. Tibshirani. (1993). An Introduction to the Bootstrap. Chapman and Hall. New York: NY.

[17] Frazis, H. and M. Loewenstein. (2003). "Estimating Linear Regressions with Mismeasured, Possibly Endogenous, Binary Explanatory Variables," *Journal of Econometrics*, 117: 151-178.

[18] Gruber, J., and B.C. Madrian. (2004). "Health Insurance, Labor Supply, and Job Mobility: A Critical Review of the Literature." In Health Policy and the Uninsured, C.G. McLaughlin (ed.), Washington DC: Urban Institute.

[19] Hadley, J., and J. Holahan. (2003/2004). "Is Health Care Spending Higher under Medicaid or Private Insurance?" *Inquiry* 40(4): 323-42.

[20] Hadley, J., and J. Holahan. (2003). "Covering the Uninsured: How Much Would It Cost?" *Health Affairs* Supplemental Web Exclusives W3: 250-265.

[21] Hahn, J., G. Kuersteiner, and W. Newey. (2002). "Higher Order Properties of the Bootstrap and Jackknife Bias Corrected Maximum Likelihood Estimators," MIT Working Paper.

[22] Hill, Steven C. (2006). "The Accuracy of Reported Insurance Status in the MEPS," Center for Financing, Access and Cost Trends, Agency for Healthcare Research and Quality.

[23] Horowitz, J., and C. Manski. (1995). "Identification and Robustness With Contaminated and Corrupted Data." *Econometrica* 63(2): 281-02.

[24] Huber, P. (1981), *Robust Statistics*. New York: Wiley.

[25] Institute of Medicine. (2003). Hidden Costs, Lost Value: Uninsurance in America. Washington, DC: National Academy Press.

[26] Killan, R.A. (2005). "Calendar Year (CY) 2000 MSIS: Research on SSN Verification Rates." U.S. Census Bureau, Planning, Research and Evaluation Division Administrative Records Research Memorandum Series #2005-0001.

[27] Klerman, J.A., J.S. Ringel, and B. Roth. (2005). "Under-Reporting of Medicaid and Welfare in the Current Population Survey." Santa Monica: RAND Working Paper WR-169-3.

[28] Kreider, B. and J. Pepper. (2005). "Disability and Employment: Reevaluating the Evidence in Light of Reporting Errors," Working Paper, Iowa State University.

[29] Levy, H. and D. Meltzer. (2004). "What Do We Really Know About Whether Health Insurance Affects Health?" In Health Policy and the Uninsured, C.G. McLaughlin (ed.), Washington DC: Urban Institute.

[30] Lewbel, A. (2004). "Estimation of Average Treatment Effects With Misclassification." Working Paper, Boston College.

[31] Li, C., and P. Trivedi. (2004). "Disparities in Medical Care Utilization, Insurance Coverage, and Adverse Selection." Working Paper.

[32] Manski, C. (1995). Identification Problems in the Social Sciences. Cambridge, MA: Harvard University Press.

[33] Manski, C. and J. Pepper (2000). "Monotone Instrumental Variables: With an Application to the Returns to Schooling." *Econometrica*, 68(4): 997-1010.

[34] Miller, G.E., J. Banthin, and J. Moeller. (2004). "Covering the Uninsured: Estimates of the Impact on Total Health Expenditures for 2002." AHRQ Working Paper 04007. Rockville, MD: Agency for Healthcare Research and Quality.

[35] Molinari, F. (2005). "Missing Treatments," mimeo, Department of Economics, Cornell University.

[36] __________ (2004). "Partial Identification of Probability Distributions with Misclassified Data." mimeo, Department of Economics, Cornell University.

[37] Nelson, D.E., B.L. Thompson, N.J. Davenport, and L.J. Penaloza. (2000). "What People Really Know about Their Health Insurance: A Comparison of Information Obtained from Individuals and Their Health Insurers." *American Journal of Public Health* 90(6): 94-8.

[38] Olson, C. (1998). "A Comparison of Parametric and Semiparametric Estimates of the Effect of Spousal Health Insurance Coverage on Weekly Hours Worked by Wives." *Journal of Applied Econometrics*, 13, 543-565.

[39] Parr, William C. (1983). "A Note on the Jackknife, the Bootstrap and the Delta Method Estimators of Bias and Variance," Biometrika, 70(3): 719-22.

[40] Ramalho, Joaquim J.S. (2005). "Small Sample Bias of Alternative Estimation Methods for Moment Condition Models: Monte Carlo Evidence for Covariance Structures," *Studies in Nonlinear Dynamics & Econometrics*: Vol. 9: No. 1, Article 3.

[41] Wolter, K. M. (1985). Introduction to Variance Estimation. New York: Springer-Verlag.

Appendix: Proposed values of v

Given our particular verification strategy discussed in Section 2.3, let $D = 1$ indicate that sufficient documentation exists to *potentially* verify insurance status. Let $A = 1 \subset D = 1$ represent the subset of cases for which there is sufficient information to potentially contradict reported insurance status. If an individual produces an insurance card, for example, then this person is included in the $D = 1$ set; without additional validation evidence, however, this case is not included in the $A = 1$ subset because we do not take the failure to produce an insurance card as contradictory information. Let $B = 1 \subset A = 1$ denote the subset for which all validation data is consistent with reported insurance status, and let $B = 0 \subset A = 1$ denote cases where a contradiction exists. For the reportedly insured, define $A = 1$ as the subset of individuals reportedly covered by private insurance from a nonfederal employer (with more than one employee) for whom all of the family's employers/insurance companies were interviewed. For the reportedly uninsured, define $A = 1$ as the subset of individuals for which the family's employers were interviewed. For these samples, we estimate $\theta^+ \leq 0.014$ and $\theta^- \leq 0.075$.[28] Treating these estimates as upper bounds on the fractions of false positives and false negatives for the unverified ($Y = 0$) sample, we obtain $v = 0.95$.[29] Under these assumptions, less than two percent of the entire sample may be misclassified.

This approach for identifying $v = 0.95$ implicitly assumes that the false positive rate among those reporting private insurance can be generalized to the population reporting public insurance. It also assumes that the false negative rate among those with at least one employed family member can be generalized to the population with no employed family member. Suppose instead that (1) we know nothing about the false positive rate among unverified cases reporting public insurance, and (2) we know nothing about the false negative rate among unverified cases in which no family member is employed. In this more conservative setting that allows for complete misreporting within these groups, we obtain the value $v = 0.74$. Under these assumptions, less than 9 percent of the entire sample may be misclassified.

[28] See Hill (2006) for details.

[29] Specifically, the fraction of inaccurate reports among $Y = 0$ cases can be written as $P(Z = 0|Y = 0) = \sum_{j=0}^{1}\sum_{k=0}^{1} P(Z = 0|Y = 0, X = j, D = 1, A = k)P(X = j, D = 1, A = k|Y = 0) + \sum_{j=0}^{1} P(Z = 0|Y = 0, X = 1, D = 0)P(X = j, D = 0|Y = 0)$. For cases in which we have comprehensive validation data, $A = 1$, yet we cannot verify insurance status, $Y = 0$, we allow for the possibility that all reports are misclassified: $P(Z = 0|Y = 0, X = j, D = 1, A = 1) \leq 1$ for $j = 0, 1$. For subsamples of unverified cases in which we did not find contradictions (i.e., $D = 0$ or $\{D = 1$ and $A = 0\}$), suppose that the false positive and false negative rates do not exceed error rates for their corresponding $A = 1$ subsamples: $P(Z = 0|Y = 0, X = j, D = 1, A = 0)$, $P(Z = 0|Y = 0, X = j, D = 0) \leq P(B = 0|X = j, A = 1)$ for $j = 0, 1$ where $P(B = 0|X = 1, A = 1) = 0.015$ and $P(B = 0|X = 0, A = 1) = 0.071$. Based on these results, we obtain the following calculation: $v = 1 - P(D = 1, A = 1|Y = 0) - P(B = 0|X = 1, A = 1)[P(X = 1, D = 1, A = 0|Y = 0) + P(X = 1, D = 0|Y = 0)] - P(B = 0|X = 0, A = 1)P(X = 0, D = 0|Y = 0) = 0.95$.

Table 1

Reported Insurance Status, Service Use, Expenditures, and Verification of Insurance Status: Nonelderly in July, 1996

	Insurance Status Reported by Family		
	Insured	Uninsured	Overall
Percent of Sample	80.7	19.3	100.0
Mean Ambulatory Provider Visits	0.45	0.26*	0.41
Percent Using Hospital or Ambulatory Services	22.5	12.7*	20.6
Mean Expenditures for Hospital and Ambulatory Services	$114	$36*	$99
Percent Verified by Insurance Cards, Policy Booklets, Employers, or Insurance Companies	80.2	11.7*	67.0
Number of Observations	14,772	4,079	18,851

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996. Ambulatory provider visits include medical provider office visits, hospital outpatient visits, and emergency room visits.

* Statistically different from insured at the 0.01 level, two-tailed test.

Table 2

Bounds on the Monthly Utilization Gap Between the Insured and Uninsured, U.S. Nonelderly Population

Lower Bound on the Proportion of Unverified (Y=0) Cases Reported Accurately (v)	Assuming the Following Patterns of Insurance Classification Errors:			
	(1) Arbitrary Errors [a]	(2) Contaminated Sampling [b]	(3) Nondifferential Errors [c]	(4) Nonincreasing in Utilization [d]
	I. Probability of Using Any Hospital or Ambulatory Services			
1	[0.098, 0.098] †	[0.098, 0.098]	[0.098, 0.098]	[0.098, 0.098]
	[0.086 0.110] ‡	[0.086 0.110]	[0.086 0.110]	[0.086 0.110]
0.95	[0.013, 0.195]	[0.067, 0.175]	[0.098, 0.105]	[0.081, 0.112]
	[0.000 0.209]	[0.057 0.182]	[0.086 0.118]	[0.069 0.124]
0.74	[-0.141, 0.252]	[-0.077, 0.225]	[0.098, 0.174]	[-0.026, 0.167]
	[-0.159 0.259]	[-0.090 0.232]	[0.086 0.193]	[-0.048 0.193]
0.50	[-0.510, 0.281]	[-0.417, 0.225]	[0.098, 0.207]	[-0.317, 0.222]
	[-0.556 0.288]	[-0.457 0.232]	[0.086 0.219]	[-0.379 0.234]
	II. Mean Number of Visits			
1	[0.19, 0.19]	[0.19, 0.19]	[0.19, 0.19]	[0.19, 0.19]
	[0.15 0.23]	[0.15 0.23]	[0.15 0.23]	[0.15 0.23]
0.95	[-0.07, 0.43]	[0.08, 0.25]	[0.19, 0.22]	[0.15, 0.23]
	[-0.12 0.46]	[0.04 0.29]	[0.15 0.26]	[0.11 0.27]
0.74	[-0.40, 0.52]	[-0.25, 0.29]	[0.19, 0.35]	[-0.06 0.38]
	[-0.48 0.54]	[-0.30 0.32]	[0.14 0.38]	[-0.12 0.42]
0.50	[-1.75, 0.58]	[-1.25, 0.29]	[0.19, 0.38]	[-0.93, 0.45]
	[-2.18 0.61]	[-1.54 0.32]	[0.13 0.42]	[-1.21 0.48]
	III. Mean Hospital and Ambulatory Expenditures ($)			
1	[77, 77]	[77, 77]	[77, 77]	[77, 77]
	[49 102]	[49 102]	[48 102]	[48 102]
0.95	[-31, 115]	[37, 102]	[77, 78]	[71, 83]
	[-73 136]	[16 126]	[48 104]	[41 109]
0.74	[-115, 129]	[-22, 106]	[77, 88]	[35, 104]
	[-181 151]	[-40 129]	[48 115]	[0 127]
0.50	[-601, 145]	[-260, 103]	[77, 90]	[-146, 120]
	[-932 169]	[-350 128]	[48 117]	[-276 142]

NOTES: [a] No restrictions; [b] imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$; [c] imposes $P(I=1|I^*) = P(I=1|I^*,U)$; [d] imposes $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ for $U_1 \geq U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; Z^* = 1 if $I^* = I$. Insurance status is verified for 67% of the sample.

† Point estimates of the population bounds.

‡ 5^{th} and 95^{th} percentile bounds estimated with balanced repeated replication.

Table 3

Bounds on the Monthly Utilization Rate Under Universal Insurance Coverage: U.S. Nonelderly Population, July 1996

Lower Bound on the Proportion of Unverified (Y=0) Cases Reported Accurately (v)	(1) Arbitrary Errors, No Monotonicity Assumptions	Assuming Monotone Treatment Response (MTR) and Monotone Treatment Selection (MTS)					
		With No Monotone Instrumental Variables (MIV) and the Following Patterns of Insurance Classification Errors:				With Age and Health MIV and Insurance Classification Errors:	
		(2) Arbitrary Errors	(3) Contaminated Sampling	(4) Nondifferential Errors	(5) Nonincreasing in Utilization	(6) Arbitrary Errors	(7) Nonincreasing in Utilization
I. Fraction Using Any Using Any Hospital or Ambulatory Services (status quo = 0.206)							
1	[0.182, 0.374] [†] [0.176 0.382] [‡]	[0.206, 0.225] [0.200 0.231]	[0.206, 0.225] [0.200 0.231]	[0.206, 0.225] [0.200 0.231]	[0.206, 0.225] [0.200 0.231]	[0.206, 0.220] [0.200 0.227]	[0.206, 0.220] [0.200 0.227]
0.95	[0.165, 0.407] [0.159 0.415]	[0.206, 0.240] [0.200 0.247]	[0.206, 0.238] [0.200 0.242]	[0.206, 0.226] [0.200 0.232]	[0.206, 0.230] [0.200 0.236]	[0.206, 0.231] [0.200 0.237]	[0.206, 0.224] [0.200 0.230]
0.74	[0.153, 0.481] [0.147 0.491]	[0.206, 0.266] [0.200 0.272]	[0.206, 0.245] [0.200 0.251]	[0.206, 0.236] [0.200 0.243]	[0.206, 0.252] [0.200 0.258]	[0.206, 0.246] [0.200, 0.252]	[0.206, 0.231] [0.200, 0.238]
0.50	[0.153, 0.505] [0.147 0.513]	[0.206, 0.291] [0.200 0.297]	[0.206, 0.245] [0.200 0.251]	[0.206, 0.249] [0.200 0.257]	[0.206, 0.267] [0.200 0.274]	[0.206, 0.253] [0.200 0.260]	[0.206, 0.233] [0.200 0.242]
II. Mean Number of Visits (status quo = 0.41)							
1	[0.30, 0.63] [0.29 0.65]	[0.41, 0.45] [0.39 0.47]	[0.41, 0.45] [0.39 0.47]	[0.41, 0.45] [0.39 0.47]	[0.41, 0.45] [0.39 0.47]	[0.41, 0.44] [0.39 0.47]	[0.41, 0.44] [0.39 0.47]
0.95	[0.30, 0.67] [0.29 0.69]	[0.41, 0.49] [0.39 0.51]	[0.41, 0.46] [0.39 0.47]	[0.41, 0.45] [0.39 0.47]	[0.41, 0.46] [0.39 0.48]	[0.41, 0.47] [0.39 0.50]	[0.41, 0.45] [0.39 0.47]
0.74	[0.30, 0.80] [0.29 0.82]	[0.41, 0.54] [0.39 0.56]	[0.41, 0.46] [0.39 0.48]	[0.41, 0.48] [0.39 0.49]	[0.41, 0.50] [0.39 0.52]	[0.41, 0.50] [0.39 0.53]	[0.41, 0.46] [0.39 0.49]
0.50	[0.30, 0.90] [0.29 0.92]	[0.41, 0.60] [0.39 0.62]	[0.41, 0.46] [0.39 0.48]	[0.41, 0.51] [0.39 0.53]	[0.41, 0.55] [0.39 0.57]	[0.41, 0.53] [0.39 0.56]	[0.41, 0.48] [0.39 0.51]

Lower Bound on the Proportion of Unverified (Y=0) Cases Reported Accurately (v)	(1) Arbitrary Errors, No Monotonicity Assumptions	Assuming Monotone Treatment Response (MTR) and Monotone Treatment Selection (MTS)					
		With No Monotone Instrumental Variables (MIV) and the Following Patterns of Insurance Classification Errors:				With Age and Health MIV and Insurance Classification Errors:	
		(2) Arbitrary Errors	(3) Contaminated Sampling	(4) Nondifferential Errors	(5) Nonincreasing in Utilization	(6) Arbitrary Errors	(7) Nonincreasing in Utilization
		III. Mean Hospital and Ambulatory Expenditures (status quo = $99)					
1	[76, 203]	[99, 114]	[99, 114]	[99, 114]	[99, 114]	[99, 112]	[99, 112]
	[59 218]	[79 133]	[79 133]	[79 133]	[79 133]	[79 132]	[79 132]
0.95	[76, 220]	[99, 123]	[99, 118]	[99, 114]	[99, 116]	[99, 118]	[99, 114]
	[59 236]	[79 142]	[79 136]	[79 133]	[79 134]	[79 136]	[79 133]
0.74	[76, 274]	[99, 134]	[99, 118]	[99, 115]	[99, 125]	[99, 123]	[99, 116]
	[59 290]	[79 156]	[79 136]	[79 134]	[79 144]	[79 146]	[79 137]
0.50	[76, 307]	[99, 149]	[99, 118]	[99, 118]	[99, 136]	[99, 131]	[99, 120]
	[59 323]	[79 173]	[79 136]	[79 139]	[79 156]	[79 153]	[79 141]

NOTES: Monotone treatment response: an uninsured individual's use would not decline if she became insured; monotone treatment selection: under universal coverage, the currently insured would use at least as much services as the currently uninsured. Contaminated sampling imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,U)$, and nonincreasing error rates imposes $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ for $U_1 \geq U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; $Z^* = 1$ if $I^* = I$. Monotone instrumental variables estimates assume use and expenditures are nondecreasing in age among those older than 30 and nondecreasing in perceived worse health status.

†Point estimates of the population bounds

‡ 5th and 95th percentile bounds estimated with balanced repeated replication

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Appendix Table 1A

"Partial Nondifferential Independence" Bounds on the Monthly Utilization Gap Between the Insured and Uninsured

Lower Bound on the Proportion of Unverified (Y=0) Cases Reported Accurately (v)	Degree of Deviance from Strict Nondifferential Independence (κ) [a]					
	Strict Independence ($\kappa = 0$)	$\kappa = 0.05$	$\kappa = 0.10$	$\kappa = 0.15$	$\kappa = 0.20$	Arbitrary Errors ($\kappa = 1$)
	I. Probability of Using Any Hospital or Ambulatory Services					
1	[0.098, 0.098] [†] [0.086 0.110] [‡]	[0.098, 0.098] [0.086 0.110]	[0.098, 0.098] [0.086 0.110]	[0.098, 0.098] [0.086 0.110]	[0.098, 0.098] [0.086 0.110]	[0.098, 0.098] [0.086 0.110]
0.95	[0.098, 0.105] [0.086 0.118]	[0.077, 0.158] [0.064 0.172]	[0.072, 0.192] [0.057 0.205]	[0.063, 0.192] [0.051 0.205]	[0.055, 0.192] [0.042 0.205]	[0.013, 0.195] [0.000 0.209]
0.74	[0.098, 0.174] [0.086 0.193]	[0.056, 0.215] [0.040 0.224]	[-0.011, 0.242] [-0.035 0.250]	[-0.046, 0.245] [-0.067 0.251]	[-0.056, 0.245] [-0.077 0.251]	[-0.141, 0.252] [-0.159 0.259]
0.50	[0.098, 0.207] [0.086 0.219]	[0.056, 0.241] [0.041 0.255]	[-0.037, 0.269] [-0.123 0.276]	[-0.303, 0.271] [-0.359 0.278]	[-0.432, 0.271] [-0.473 0.281]	[-0.510, 0.281] [-0.556 0.288]
	II. Mean Number of Visits					
1	[0.19, 0.19] [0.15 0.23]	[0.19, 0.19] [0.15 0.23]	[0.19, 0.19] [0.15 0.23]	[0.19, 0.19] [0.15 0.23]	[0.19, 0.19] [0.15 0.23]	[0.19, 0.19] [0.15 0.23]
0.95	[0.19, 0.22] [0.15 0.26]	[0.15, 0.33] [0.11 0.37]	[0.14, 0.39] [0.10 0.41]	[0.13, 0.39] [0.08 0.42]	[0.11, 0.39] [0.06 0.42]	[-0.07, 0.43] [-0.12 0.46]
0.74	[0.19, 0.35] [0.14 0.38]	[0.10, 0.42] [0.04 0.45]	[-0.05, 0.45] [-0.12 0.47]	[-0.09, 0.45] [-0.17 0.48]	[-0.12, 0.46] [-0.20 0.49]	[-0.40, 0.52] [-0.48 0.54]
0.50	[0.19, 0.38] [0.13 0.42]	[0.07, 0.47] [-0.06 0.50]	[-0.12, 0.50] [-0.35 0.53]	[-0.56, 0.50] [-0.79 0.53]	[-1.16, 0.51] [-1.47 0.54]	[-1.75, 0.58] [-2.18 0.61]

Lower Bound on the Proportion of Unverified (Y=0) Cases Reported Accurately (v)	Degree of Deviance from Strict Nondifferential Independence (κ) [a]					
	Strict Independence (κ = 0)	κ = 0.05	κ = 0.10	κ = 0.15	κ = 0.20	Arbitrary Errors (κ = 1)
	III. Mean Hospital and Ambulatory Expenditures					
1	[77, 77] [48 103]	[77, 77] [48 103]	[77, 77] [48 103]	[77, 77] [48 103]	[77, 77] [48 103]	[77, 77] [49 102]
0.95	[77, 78] [48 104]	[71, 91] [41 118]	[71, 96] [41 124]	[70, 96] [40 124]	[68, 96] [38 124]	[-31, 115] [-73 136]
0.74	[77, 88] [48 115]	[61, 94] [30 123]	[36, 99] [-1 127]	[33, 101] [-4 129]	[31, 104] [-7 131]	[-115, 129] [-181 151]
0.50	[77, 90] [48 117]	[61, 102] [30 128]	[31, 106] [-12 132]	[-66, 108] [-149 134]	[-179, 109] [-338 136]	[-601, 145] [-932 169]

[a] $|\, P(I=1|I^*,U)-P(I=1|I^*)| < \kappa$, where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status.
[†] Point estimates of the population bounds
[‡] 5^{th} and 95^{th} percentile bounds estimated with balanced repeated replication

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Appendix Table 2A

"Partial Nondifferential Independence" Bounds on Monthly Utilization Rate Under Universal Insurance Coverage Assuming Monotone Treatment Response (MTR) and Monotone Treatment Selection (MTS)

Lower Bound on the Proportion of Unverified (Y=0) Cases Reported Accurately (v)	Degree of Deviance from Strict Nondifferential Independence (κ)					
	Strict Independence (κ = 0)	κ = 0.05	κ = 0.10	κ = 0.15	κ = 0.20	Arbitrary Errors (κ = 1)
	I. Fraction Using Any Using Any Hospital or Ambulatory Services (status quo = 0.206)					
1	[0.206, 0.225] [b]	[0.206, 0.225]	[0.206, 0.225]	[0.206, 0.225]	[0.206, 0.225]	[0.206, 0.225]
	[0.200 0.231] [c]	[0.200 0.231]	[0.200 0.231]	[0.200 0.231]	[0.200 0.231]	[0.200 0.231]
0.95	[0.206, 0.226]	[0.206, 0.236]	[0.206, 0.240]	[0.206, 0.240]	[0.206, 0.240]	[0.206, 0.240]
	[0.200 0.232]	[0.200 0.242]	[0.200 0.246]	[0.200 0.246]	[0.200 0.246]	[0.200 0.247]
0.74	[0.206, 0.236]	[0.206, 0.250]	[0.206, 0.263]	[0.206, 0.264]	[0.206, 0.264]	[0.206, 0.266]
	[0.200 0.243]	[0.200 0.257]	[0.200 0.269]	[0.200 0.271]	[0.200 0.271]	[0.200 0.272]
0.50	[0.206, 0.249]	[0.206, 0.270]	[0.206, 0.287]	[0.206, 0.289]	[0.206, 0.289]	[0.206, 0.291]
	[0.200 0.257]	[0.200 0.278]	[0.200 0.294]	[0.200 0.295]	[0.200 0.295]	[0.200 0.297]
	II. Mean Number of Visits (status quo = 0.41)					
1	[0.41, 0.45]	[0.41, 0.45]	[0.41, 0.45]	[0.41, 0.45]	[0.41, 0.45]	[0.41, 0.45]
	[0.39 0.47]	[0.39 0.47]	[0.39 0.47]	[0.39 0.47]	[0.39 0.47]	[0.39 0.47]
0.95	[0.41, 0.45]	[0.41, 0.47]	[0.41, 0.49]	[0.41, 0.49]	[0.41, 0.49]	[0.41, 0.49]
	[0.39 0.47]	[0.39 0.49]	[0.39 0.50]	[0.39 0.50]	[0.39 0.51]	[0.39 0.51]
0.74	[0.41, 0.48]	[0.41, 0.51]	[0.41, 0.52]	[0.41, 0.52]	[0.41, 0.52]	[0.41, 0.54]
	[0.39 0.49]	[0.39 0.53]	[0.39 0.54]	[0.39 0.54]	[0.39 0.55]	[0.39 0.56]
0.50	[0.41, 0.51]	[0.41, 0.55]	[0.41, 0.57]	[0.41, 0.58]	[0.41, 0.58]	[0.41, 0.60]
	[0.39 0.53]	[0.39 0.57]	[0.39 0.59]	[0.39 0.60]	[0.39 0.60]	[0.39 0.62]

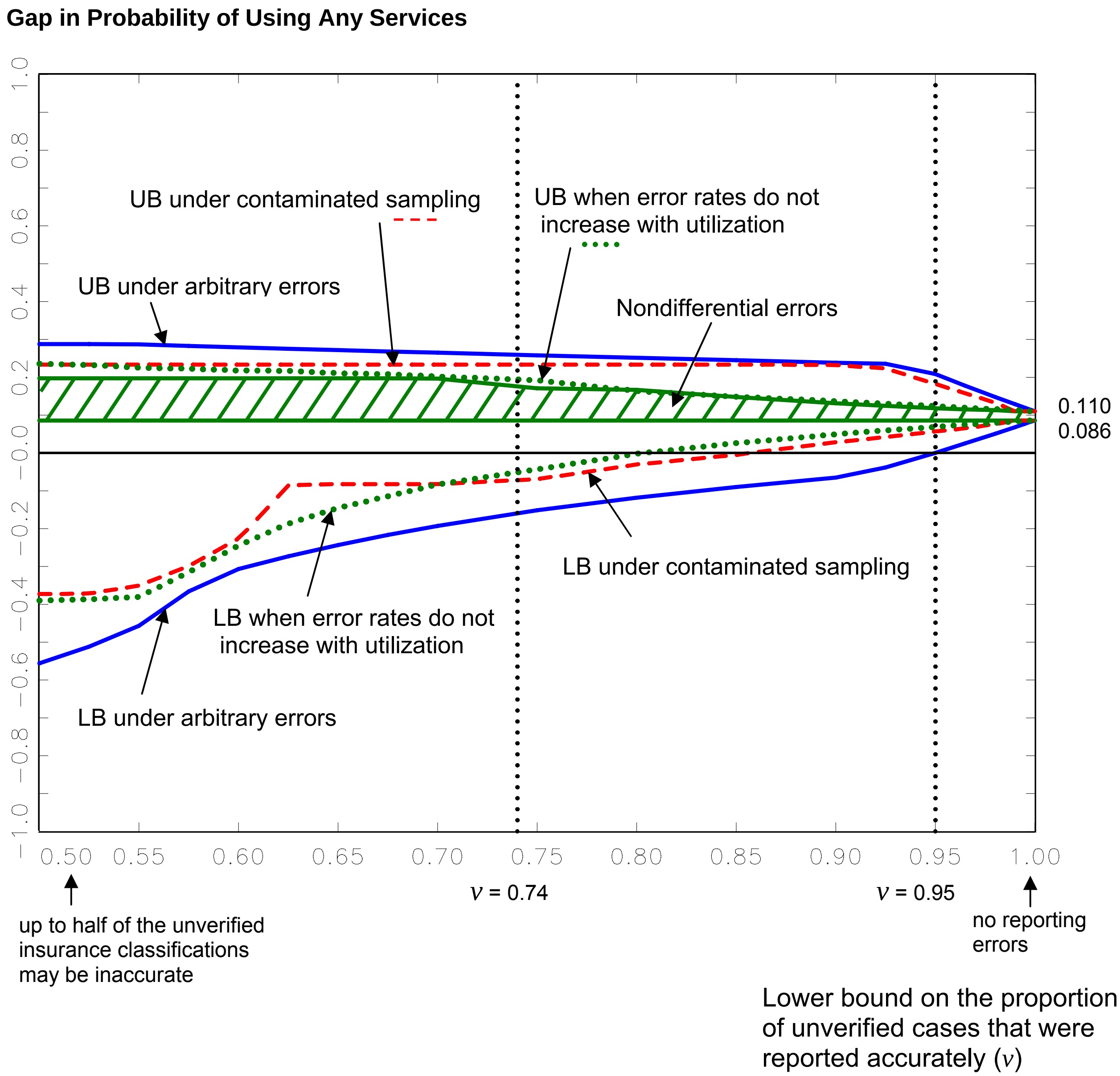
Lower Bound on the Proportion of Unverified (Y=0) Cases Reported Accurately (v)	Degree of Deviance from Strict Nondifferential Independence (κ)					
	Strict Independence (κ = 0)	κ = 0.05	κ = 0.10	κ = 0.15	κ = 0.20	Arbitrary Errors (κ = 1)
	III. Mean Hospital and Ambulatory Expenditures (status quo = $99)					
1	[99, 114]	[99, 114]	[99, 114]	[99, 114]	[99, 114]	[99, 114]
	[79 133]	[79 133]	[79 133]	[79 133]	[79 133]	[79 133]
0.95	[99, 114]	[99, 117]	[99, 118]	[99, 118]	[99, 118]	[99, 123]
	[79 133]	[79 135]	[79 137]	[79 137]	[79 137]	[79 142]
0.74	[99, 115]	[99, 119]	[99, 121]	[99, 122]	[99, 123]	[99, 134]
	[79 134]	[79 137]	[79 140]	[79 142]	[79, 143]	[79 156]
0.50	[99, 118]	[99, 127]	[99, 130]	[99, 130]	[99, 131]	[99, 149]
	[79 139]	[79 145]	[79 148]	[79 148]	[79 149]	[79 173]

[a] | $P(I=1|I^*,U)-P(I=1|I^*)$| < κ, where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status.
[b] Point estimates of the population bounds
[c] 5th and 95th percentile bounds estimated with balanced repeated replication

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Figure 1a

Bounds on the Gap Between the Nonelderly Insured and Uninsured in their Probability of Using Any Hospital or Ambulatory Services in July 1996

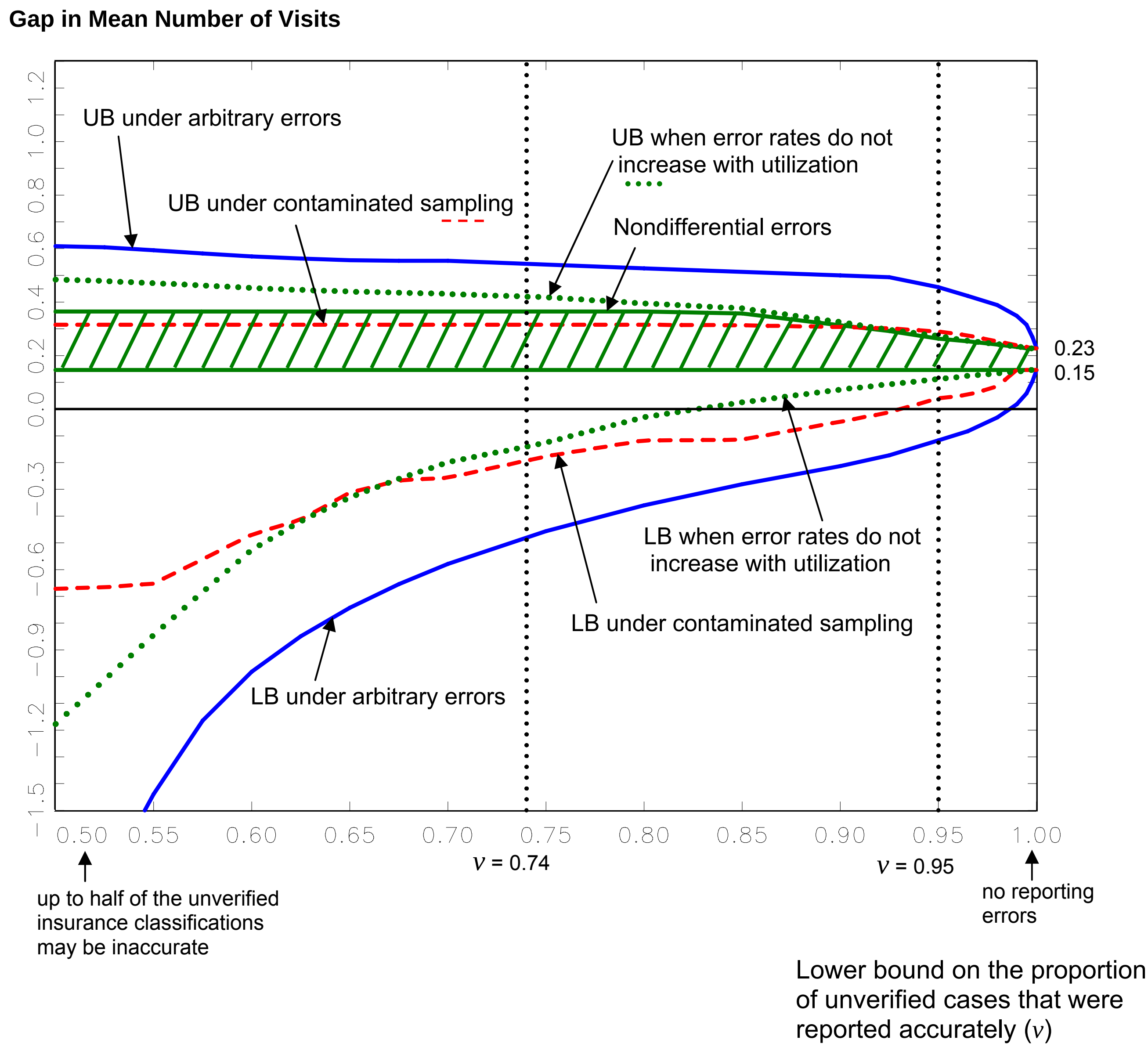


NOTES: LB = 5th percentile lower bound. UB = 95th percentile upper bound. Contaminated sampling imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,U)$, and nonincreasing error rates imposes $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ for $U_1 \geq U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; $Z^* = 1$ if $I^* = I$. Vertical dotted lines reflect proposed values of v motivated in the text. Insurance status is verified for 67% of the sample.

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Figure 1b

Bounds on the Gap Between the Nonelderly Insured and Uninsured
in their Mean Number of Provider Visits in July 1996

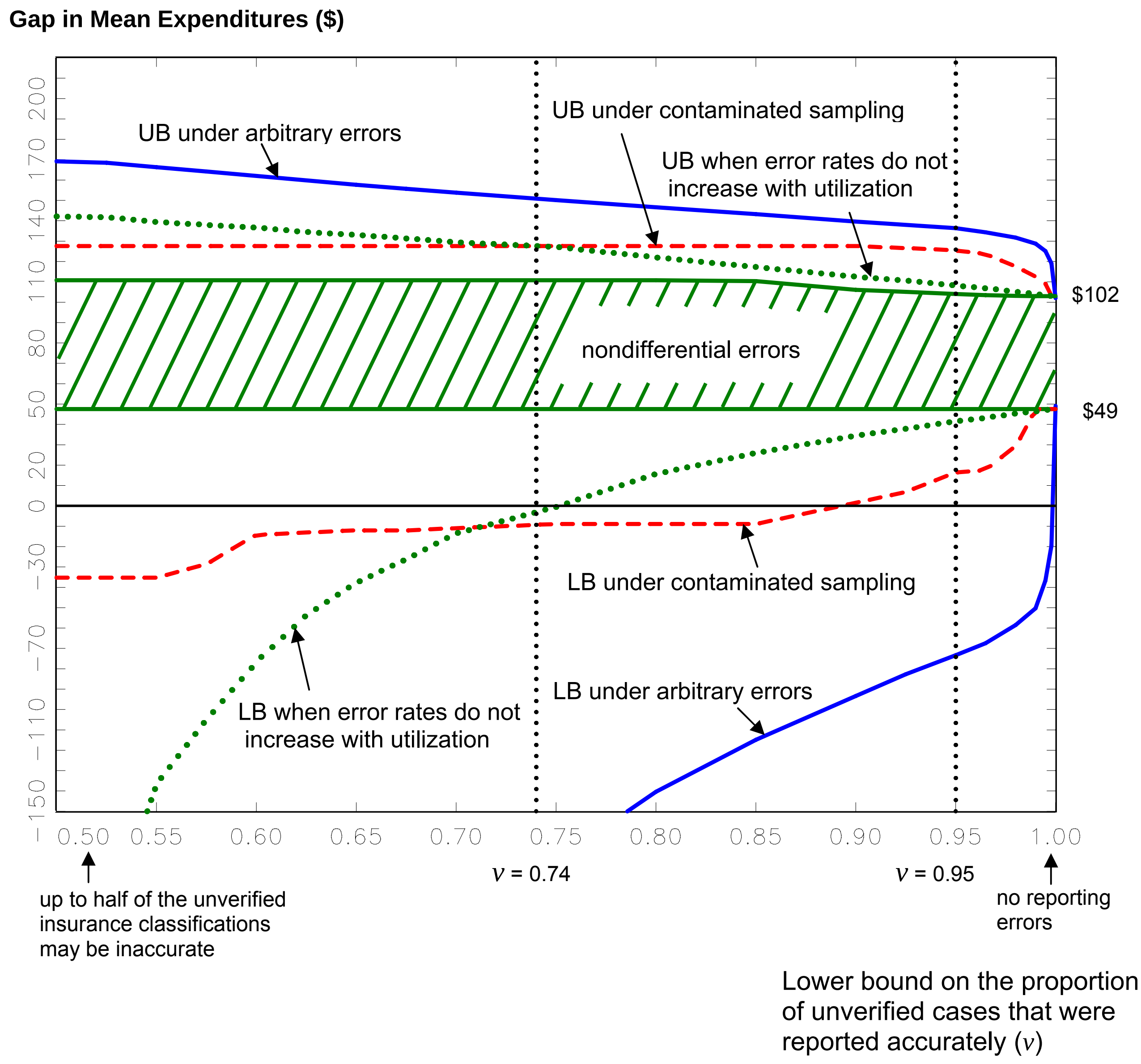


NOTES: LB = 5th percentile lower bound. UB = 95th percentile upper bound. Contaminated sampling imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,U)$, and nonincreasing error rates imposes $P(I=1|I^*=0,U_1) \le P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \le P(I=1|I^*=0,U_0)$ for $U_1 \ge U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; $Z^* = 1$ if $I^* = I$. Vertical dotted lines reflect proposed values of v motivated in the text. Insurance status is verified for 67% of the sample.

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Figure 1c

Bounds on the Gap Between the Nonelderly Insured and Uninsured
in their Hospital and Ambulatory Expenditures in July 1996

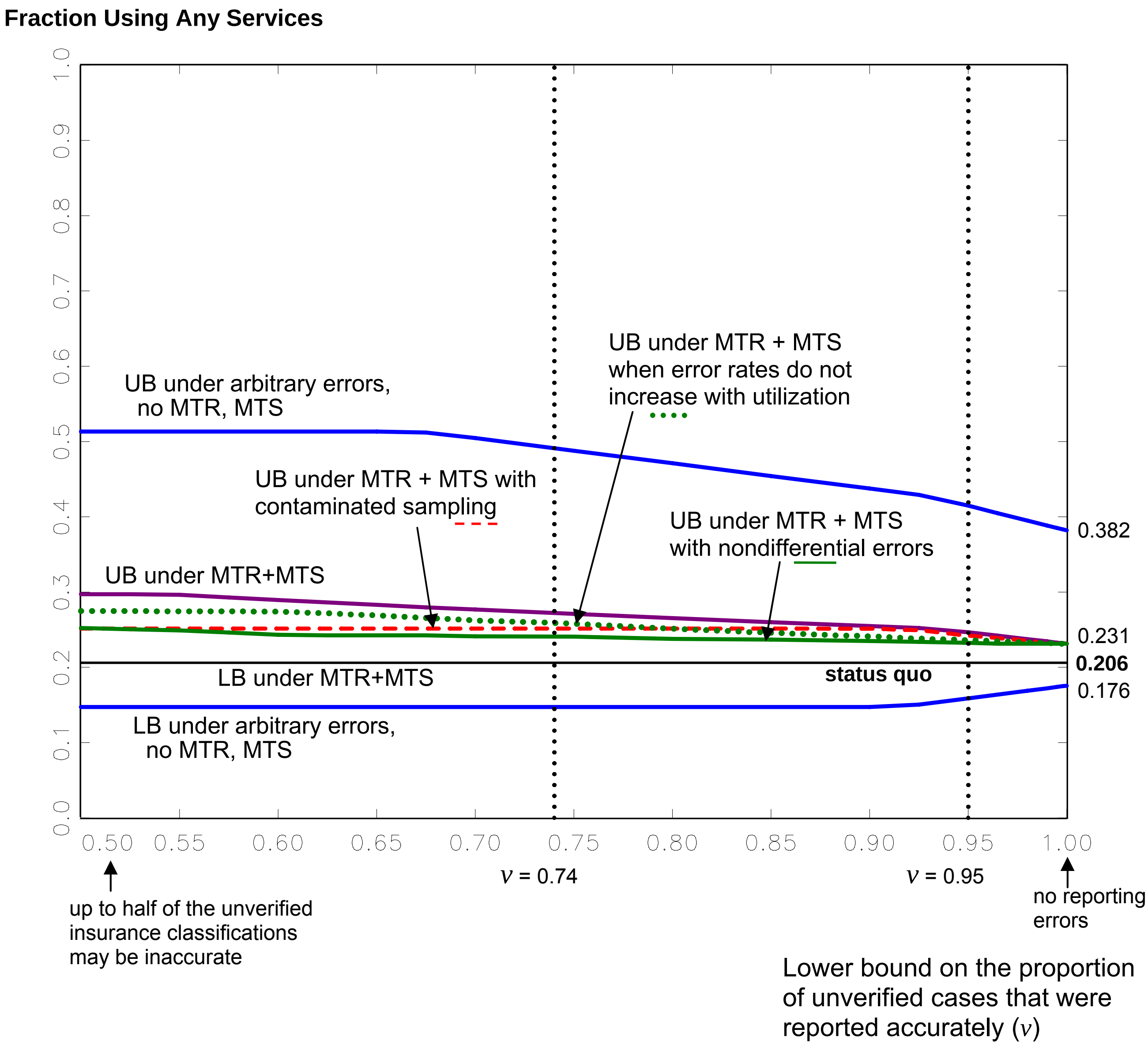


NOTES: LB = 5th percentile lower bound. UB = 95th percentile upper bound. Contaminated sampling imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,U)$, and nonincreasing error rates imposes $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ for $U_1 \geq U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; Z^* = 1 if $I^* = I$. Vertical dotted lines reflect proposed values of v motivated in the text. Insurance status is verified for 67% of the sample.

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Figure 2a

Bounds on the Fraction of the Nonelderly Population that Would Have Used Any Hospital or Ambulatory Services in July 1996 under Universal Insurance Coverage

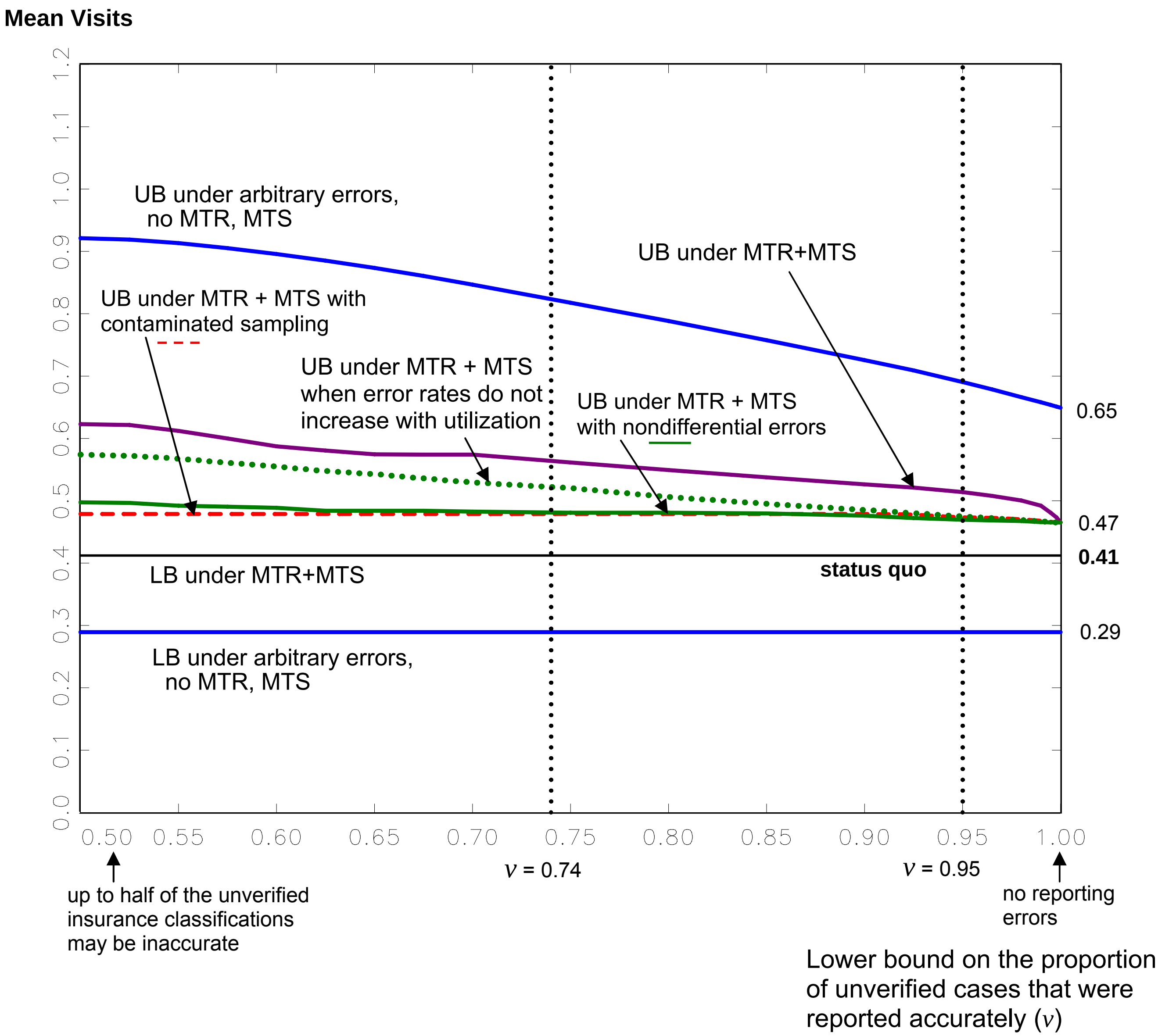


NOTES: LB = 5th percentile lower bound. UB = 95th percentile upper bound. MTR = monotone treatment response: an uninsured individual's use would not decline if she became insured. MTS = monotone treatment selection: under universal coverage, the currently insured would use at least as much services as the currently uninsured. Contaminated sampling imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,U)$, and nonincreasing error rates imposes $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ for $U_1 \geq U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; $Z^* = 1$ if $I^* = I$. Vertical dotted lines reflect proposed values of v motivated in the text. Insurance status is verified for 67% of the sample.

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Figure 2b

Bounds on the Nonelderly Population's Mean Number of Provider Visits
in July 1996 under Universal Insurance Coverage

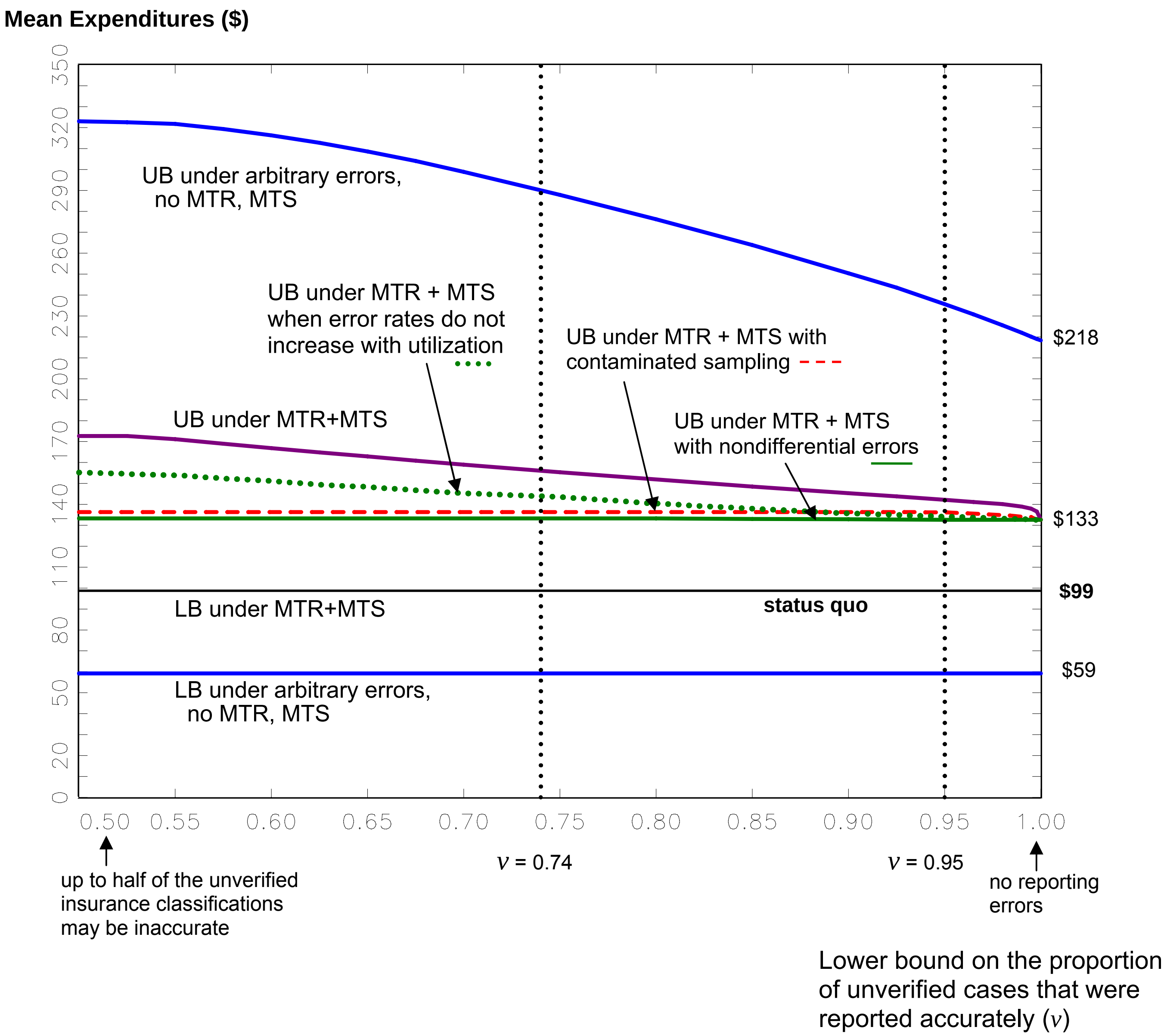


NOTES: LB = 5th percentile lower bound. UB = 95th percentile upper bound. MTR = monotone treatment response: an uninsured individual's use would not decline if she became insured. MTS = monotone treatment selection: under universal coverage, the currently insured would use at least as much services as the currently uninsured. Contaminated sampling imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,U)$, and nonincreasing error rates imposes $P(I=1|I^*=0,U_1) \le P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \le P(I=1|I^*=0,U_0)$ for $U_1 \ge U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; $Z^* = 1$ if $I^* = I$. Vertical dotted lines reflect proposed values of v motivated in the text. Insurance status is verified for 67% of the sample.

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.

Figure 2c

Bounds on the Nonelderly Population's Mean Hospital and Ambulatory Expenditures in July 1996 under Universal Insurance Coverage



NOTES: LB = 5th percentile lower bound. UB = 95th percentile upper bound. MTR = monotone treatment response: an uninsured individual's use would not decline if she became insured. MTS = monotone treatment selection: under universal coverage, the currently insured would use at least as much services as the currently uninsured. Contaminated sampling imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,U)$, and nonincreasing error rates imposes $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ and $P(I=1|I^*=0,U_1) \leq P(I=1|I^*=0,U_0)$ for $U_1 \geq U_0$ where U = use, visits, or expenditures; I^* = true insurance status; I = reported insurance status; $Z^* = 1$ if $I^* = I$. Vertical dotted lines reflect proposed values of v motivated in the text. Insurance status is verified for 67% of the sample.

DATA: Medical Expenditure Panel Survey Household Component and linked Insurance Component, 1996. Sample members age 0 to 64 as of July, 1996.