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THE EFFECT OF DENTAL INSURANCE ON THE USE OF DENTAL CARE FOR OLDER ADULTS: A PARTIAL IDENTIFICATION ANALYSIS

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ABSTRACT

We evaluate the impact of dental insurance on the use of dental services using a potential outcomes identification framework designed to handle uncertainty created by unknown counterfactuals—that is, the endogenous selection problem—and uncertainty about the reliability of self-reported insurance status. Using data from the health and retirement study, we estimate that utilization rates of adults older than 50 years would increase from 75% to around 80% under universal dental coverage.

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KEY WORDS: dental insurance; dental care; treatment effect; selection; classification errors; partial identification

1. INTRODUCTION

Although there is a large literature evaluating the impact of health insurance on a wide variety of health related outcomes,[1] very little attention has been paid to the role of dental insurance in the use of dental care (IOM and NRC, 2011). Yet many Americans suffer from serious oral health related problems. Nearly half of persons aged 65–74 years perceive their dental health as poor, and one in four are classified as having severe periodontal disease (US Department of Health and Human Services (DHHS), 2000). A report of the surgeon general (DHHS, 2000) goes so far as to characterize oral disease in the USA as a 'silent epidemic', and a recent report by the National Academy of Sciences notes that 'little has changed in the intervening years' (IOM and NRC, 2011, p. 21). Both the surgeon general and the National Academy of Sciences reports highlight the potential role dental insurance—or the lack thereof—plays in understanding this epidemic. In particular, many fewer adults have dental insurance than have medical insurance (about 2.5 times more have medical insurance), and because dental insurance is not provided through Medicare, coverage is often lost when individuals retire.[2] Thus, a clear and credible evaluation of the role of dental insurance on dental care is a critical step in understanding this epidemic and for understanding how insurance impacts general health and well-being in the USA.

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[1]See, for example, the surveys by Gruber and Madrian (2004), Levy and Meltzer (2004), and Buchmueller *et al.* (2005).
[2]A relatively large proportion of dental care expenses are paid out of pocket—just over 40% in 2010—whereas only 9% of physician and clinical services were paid out of pocket (Centers for Medicare and Medicaid Services, 2010).

Using data from the 2006 wave of the Health and Retirement Survey (HRS), we examine how dental care utilization rates of adults older than 50 years would change under universal dental insurance coverage. Previous studies have found that dental insurance increases utilization. For example, focusing on youth and working aged adults, Mueller and Monheit (1988) conclude that dental insurance increases utilization from 0.47 to about 0.55, a nearly 17% increase. A recent evaluation from Meyerhoefer *et al.* (2014) finds that coverage increases the annual utilization rate by between 11% and 19%. Our analysis makes several notable contributions to this literature. At the most basic level, we provide one of the few recent evaluations of this important question; much of the literature is nearly three decades old and uses data from the 1970s or earlier.[3] More importantly, in contrast to the existing literature which evaluates the impact of insurance on infants, youth, or working aged adults, we focus attention on older adults (age 50 years and older), a subpopulation that is especially vulnerable to oral disease and often lacks dental insurance (especially retirees) (DHHS, 2000; IOM and NRC, 2011).

Finally, we use an innovative partial identification approach to address key identification problems that, for the most part, have been ignored in the literature. Drawing inferences on the effect of insurance on utilization is complicated by two fundamental identification problems. First, a selection problem arises because the decision to seek dental care and the decision to obtain dental insurance (or, more broadly, the circumstances under which individuals become insured) may be driven by similar unobserved factors. For example, expectations about future dental care needs, aversion to risk, and latent healthfulness are arguably correlated with both dental care utilization and dental insurance. Persons with greater needs or preferences for care may also be more likely to be insured (Meyerhoefer *et al.*, 2014). As a result, the data alone cannot reveal what the utilization rate would be if more people were to be covered. Although known to confound inferences about the impact of dental coverage on dental care, the empirical literature has largely ignored this selection problem (IOM and NRC, 2011, Chapter 5; Sintonen and Linnosmaa, 2000).[4] In general, researchers have not been able to identify credible instrumental variables that are related to coverage but otherwise unrelated to utilization.

Second, a misclassification problem arises because dental insurance coverage is likely to be misreported by some respondents. Duncan and Hill's (1985) validation study of responses from workers at a large manufacturing firm provides direct evidence on misreporting: whereas only 1% of respondents at this firm misreported health insurance coverage, 5% of respondents provided erroneous reports of dental coverage. Although direct evidence of dental coverage misreporting in the general population is limited, there is a large literature documenting the misclassification of health insurance coverage.[5] Arguably, such measurement problems are magnified when considering dental insurance coverage, which is sometimes a component of a larger insurance package provided by employers, and government-run insurance programs such as Medicaid and Medicare provide only limited coverage. The presence of reporting errors, which have been ignored in the existing dental health literature, compromises a researcher's ability to make reliable inferences about the status quo and further confounds identification of counterfactual outcomes associated with policies such as universal insurance (Kreider and Hill, 2009). Even infrequent response errors can have dramatic consequences for identifying causal relationships between treatments and outcomes (Kreider, 2010; Millimet, 2011). As a result, these measurement problems may constitute an important barrier to identifying the role of dental insurance in health care.

[3]See, for example, Manning and Phelps (1979), Hay *et al.* (1982), Gooch and Berkey (1987), Mueller and Monheit (1988), Reisine (1988), and Manning *et al.* (1987). Sintonen and Linnosmaa (2000) provide a review of this earlier literature. More recent studies include Meyerhoefer *et al.* (2014) and Munkin and Trivedi (2008).

[4]Exceptions include Munkin and Trivedi (2008), who address the selection problem using parametric instrumental variable models (also see Cooper *et al.*, 2012) and Meyerhoefer *et al.* (2014) who use panel data methods. These observational studies conclude that the selection problem leads to a notable upward bias. In addition, The RAND Health Insurance Experiment in the mid-1970s applied a randomized design to evaluate the impact of insurance coverage on health care costs and utilization. On the basis of these data, Manning *et al*. (1987) find that lower coinsurance rates lead to increased dental care utilization. This experiment, however, did not focus on older adults, did not apply to persons without insurance, and may be outdated given the dramatic changes to the health care system in the USA (U.S. Congress, Office of Technology Assessment, 1993).

[5]See Section 2 for further discussion.

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To address these two identification problems, we apply the partial identification methods in Kreider and Hill's (2009; henceforth referred to as KH) evaluation of universal health insurance.[6,7] We focus on the relatively basic question of whether insurance effects utilization, a first-order concern which is directly relevant for assessing the traditional dentist recommendation for biannual dental checkups (Patel *et al*., 2010).[8] We estimate two basic parameters for the population of older adults: the true utilization gap between those with and without insurance and the causal impact on utilization rates of providing universal dental coverage to the full population.[9]

After describing the data in Section 2, Section 3 formalizes the problems associated with evaluating the gap in dental care use between the insured and uninsured. A number of studies have found coverage to be associated with higher rates of dental care utilization (Gooch and Berkey, 1987; Mueller and Monheit, 1988; Reisine, 1988; Manski *et al*., 2002; Manski and Brown, 2007), but these studies do not address the problem that insurance status may be misclassified. Addressing the problem of classification errors in a binary regressor is known to be difficult. The classical measurement error model does not apply in our setting because reporting errors in a binary variable are mean reverting, the propensity to misreport might depend on true insurance status, and errors may be systematic in a particular direction. Instead, following KH, we bound the unknown true utilization gap under alternative assumptions about the nature and degree of reporting errors on dental insurance coverage.

We begin by allowing for arbitrary patterns of classification error under weak restrictions on the total degree of misreporting combined with 'verification' assumptions that members of certain observed subgroups accurately report. This setting allows for the possibility that reporting errors are endogenously related to the true insurance status and dental care utilization. We then explore the identifying power of independence assumptions relating classification errors and outcomes including, for example, the nondifferential error model evaluated by Bollinger (1996) and Bound *et al*. (2001). In that model, insurance reporting errors arise independently of utilization outcomes after conditioning on true insurance status. Relaxing this assumption, we also consider the case that individuals who used dental services in the last year are (weakly) less likely to make mistakes in reporting their insurance status.

Moving beyond the descriptive utilization gap to a more policy relevant question, Section 4 investigates what can be learned about the impact of universal dental insurance coverage on the use of dental care. In this section, we simultaneously address both identification problems by combining the classification error model assumptions with three common monotonicity assumptions in the treatment effects literature. We first apply the monotone treatment response (MTR) restriction (Manski, 1997) that having dental insurance would not decrease the likelihood of using dental care. We combine this assumption with the monotone treatment selection (MTS) restriction (Manski and Pepper, 2000) that the latent utilization probability is weakly larger for those who have obtained insurance. These assumptions rule out the possibility that being insured reduces the likelihood that a person uses dental services or that those who obtained coverage systematically had less proclivity to use dental services. We then apply a monotone instrumental variable (MIV) restriction that the latent use of dental care utilization weakly increases with family income. Given these assumptions, we bound the causal impact of universal coverage without relying on more controversial assumptions involving functional forms and independence conditions.

[6]Gerfin and Schellhorn (2006) also apply partial identification methods to evaluate the impact of health insurance deductibles on the probability of visiting a doctor.
[7]We also draw on the related partial identification literature in Manski (1995, 1997), Manski and Pepper (2000, 2009); Pepper (2000), Kreider and Pepper (2007); Molinari (2008, 2010), and Kreider *et al.* (2012). The (2012) analysis, by Cooper *et al*., of the effect of dental insurance on dental care applies basic partial identification methods to address the selection problem.
[8]Although the literature evaluating the demand for care has estimated two part models that jointly evaluate the probability of receiving any dental care and then consider the amount or type of care (Sintonen and Linnosmaa, 2000), this research does not address the selection and classification error problems.
[9]Future research might apply these partial identification methods to address intramarginal questions about dental health, including the impact of insurance on the intensity of use (e.g., expenditures or number of visits) and moral hazard.

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Section 5 draws conclusions. We find that universal dental insurance coverage would increase dental care utilization from the status quo rate of 0.752 by at least 2% and as much as 9%. These results are consistent with the utilization rate increasing from 75% to around 80%.

2. HEALTH AND RETIREMENT STUDY

To evaluate the impact of dental insurance coverage on utilization, we use data from the 2006 wave of the HRS. The HRS, administered by the Institute for Social Research at the University of Michigan and sponsored by the National Institute on Aging, is a longitudinal household survey useful for the study of aging, retirement, and health among older populations in the USA.[10] Every 2 years, individuals older than 50 years and their spouses are surveyed by the HRS; approximately 20,000 interviews are completed in each survey wave. Each respondent is asked a large battery of questions including information about demographics, income and assets, physical and mental health, dental care utilization, and dental care insurance coverage. We observe whether the respondent has lost his or her teeth. For our main analysis, we restrict the sample to only those who have teeth (20% dropped because of this restriction), in which case the final sample includes 12,746 older adults. In Section 4.3, we consider the impact of insurance on the edentulous using data on the 3,041 respondents without teeth.

Dental care is measured using a binary indicator of whether the individual reports receiving care during the 2-year period preceding the 2006 HRS interview. We also observe whether the respondent received care in the period covered by the 2004 wave of the HRS and whether the respondent's spouse received care in the 2006 wave of the survey. As described in Section 3, these latter two measures are used to aid in 'verifying' the accuracy of self-reports of dental insurance coverage. We assume that these measures of dental care are measured accurately. On the basis of the 2006 survey, just over three-quarters of the population (0.752) received care within the 2-year period prior to the 2006 survey.

Dental insurance coverage is identified in one of two ways: either (i) the respondent reported seeing a dentist during the 2-year period preceding the survey and having expenses at least partially covered by insurance or (ii) the respondent did not see a dentist but reported that he or she would expect some of the costs to be covered by insurance. We classify the remainder of the sample as uninsured for dental services. On the basis of this classification, 51.3% of the population reports having dental insurance coverage.

Some of these self-reported measures of dental insurance status, however, are thought to contain classification errors. There is a large literature documenting the misclassification of health insurance status. Significant misreporting has been documented in the Current Population Survey, the Survey of Income and Program Participation, the Behavioral Risk Factor Surveillance System survey, the Medical Expenditure Panel Survey, and other surveys (Nelson *et al*., 2000; Card *et al*., 2004; Hill, 2007; Davern *et al*., 2007a). Some evidence on misreporting pertains to reports on the type of coverage (e.g., private versus public) instead of coverage status itself. Nelson *et al*. (2000), for example, finds evidence of substantial misreporting on the source of coverage but more modest error rates (about 3%) on coverage status (see also Davern *et al.*, 2008). Other evidence, however, reveals concerning amounts of misreporting on coverage status. Hill (2007), for example, finds that false negative reports in the Medical Expenditure Panel Survey—that is, covered persons reporting no coverage—may be substantial (see also Davern *et al*., 2007b). Finally, as previously noted, Duncan and Hill (1985) find that 5% of respondents from a large manufacturing firm provide erroneous reports about dental coverage. Although we are not aware of more recent studies that provide direct evidence on misreporting of dental insurance coverage, the risk of measurement problems are heightened in this application: dental coverage is often a relatively small component of a larger insurance package provided by employers, and coverage is not included in Medicare.

[10]We use the RAND HRS Data, Version H, produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration, Santa Monica, CA (February 2008).

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Table I displays means and standard errors for the variables used in this study. The estimates in this table (and elsewhere in the paper) are weighted to account for the survey design used in the HRS: just over half the sample reports having dental insurance. Consistent with previous work on this topic, the use of dental care is much more prevalent for those reporting to be insured. In particular, 83.6% of respondents reporting to be insured received dental care, whereas only 66.4% of respondents reporting to be uninsured received dental care. Thus, the estimated utilization gap in the absence of misreporting is about 17 percentage points.

3. IDENTIFYING UTILIZATION DIFFERENCES BETWEEN THE INSURED AND UNINSURED

We first study what can be learned about the utilization gap—that is, the difference in dental care utilization rates between the insured and uninsured—when true insurance status may be unknown. In Section 4, we extend the analysis to assess what can be learned about the causal impact of universal dental insurance coverage on the use of dental services. Let $I^*=1$ indicate that a person is truly insured, with $I^*=0$ otherwise. Instead of observing I^*, we observe the self-reported indicator of coverage, I. A latent variable Z^* indicates whether a report is accurate. If I and I^* coincide, then $Z^*=1$; otherwise, $Z^*=0$. Let $V=1$ indicate that I is verified to be accurate (i.e., Z^* is known to equal 1). If $V=0$, then Z^* may be either 1 or 0. Let $D=1$ denote that the respondent received dental care in the last year, with $D=0$ otherwise. Then, the utilization gap between the insured and uninsured can be written as

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

where true insurance status, I^*, may be unobserved. Thus, the utilization gap Δ is not identified because we observe $E(D|I)$ but not $E(D|I^*)$.

To formalize this identification problem, consider the first term in Equation 1, which can be written as

$$P(D = 1|I^* = 1) = P(D = 1, I^* = 1)/P(I^* = 1). \tag{2}$$

Neither the numerator nor the denominator is identified. To see this identification problem, it is useful to decompose the conditional probability into observed and unobserved quantities. Let

$$\theta_1^+ \equiv P(D = 1, I = 1, Z^* = 0) \text{ and}$$
$$\theta_1^- \equiv P(D = 1, I = 0, Z^* = 0)$$

denote the fraction of false positive and false negative classifications of dental insurance coverage, respectively, for respondents receiving dental care. Similarly, let $\theta_0^+ \equiv P(D = 0, I = 1, Z^* = 0)$ and $\theta_0^- \equiv P(D = 0, I = 0, Z^* = 0)$ denote the analogous fractions for respondents not receiving dental care. Then, it follows that

$$P\left(D = 1\middle|I^* = 1\right) = \left(p_{11} + \theta_1^- - \theta_1^+\right)/\left[p_1 + \left(\theta_1^- + \theta_0^-\right) - \left(\theta_1^+ + \theta_0^+\right)\right] \tag{3}$$

Table I. Means by reported dental insurance status

Variable	Full sample	Reportedly insured ($I=1$)	Reportedly uninsured ($I=0$)
Ratio of income to the poverty line	6.77 (0.30)	7.05 (0.12)	6.47 (0.57)
Dental insurance (2004–2006)	0.513 (0.004)		
Used dental care (2004–2006)	0.752 (0.004)	0.836 (0.005)	0.664 (0.006)
Used dental care (2002–2004)	0.756 (0.004)	0.825 (0.005)	0.684 (0.006)
Spouse used dental care (2004–2006)	0.751 (0.005)	0.827 (0.006)	0.662 (0.007)
Sample size	12,746	5,869	6,877

Sample estimates are weighted using the survey respondent weights. Standard errors in parentheses.

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where $p_{11} = P(D = 1, I = 1)$ and $p_1 = P(I = 1)$ are identified by the data. In the numerator, $\theta_1^- - \theta_1^+$ reflects the unobserved excess of false negative versus false positive classifications among those who received dental care. In the denominator, $\theta_1^- + \theta_0^- - \theta_1^+ - \theta_0^+$ reflects the unobserved excess of false negative versus false positive classifications within the entire population. Dental care among the uninsured can be decomposed in a similar fashion.

To draw inferences on the utilization gap, assumptions on the pattern and degree of classification errors are used to place meaningful restrictions on the unobserved quantities, θ. We start by maintaining the following basic assumption:

(A1) *Upper bound error rate:*
a. Among the unverified: $P(Z^* = 1|V = 0) \geq \upsilon \in [0.5, 1]$
b. Among the verified: $P(Z^* = 1|V = 1) = 1$

where υ is a known or conjectured lower bound on the degree of accurate reporting. Assumptions (A1a) and (A1b) bound the degree of accurate reporting among unverified ($V = 0$) and verified ($V = 1$) respondents, respectively. The previous literature has maintained the implicit assumption of fully accurate reporting, in which case v is implicitly assumed to equal 1. In the current analysis, this accurate reporting assumption is maintained for verified respondents but not for the unverified. Instead, we assess the sensitivity of inferences to classification errors among unverified reports by varying v between 0.5 and 1. Restricting attention to values of v larger than 0.5 presumes only that the self-reports of insurance status contain more information about the truth than random guessing.

Proposition 1 in KH provides analytic bounds on the true utilization gap under Assumption A1. These bounds allow for arbitrary patterns of insurance classification errors among unverified cases, including the possibility that reporting errors are endogenously related to true insurance status and the use of dental services.

Given the lack of research on the misclassification of dental insurance in self-reported surveys, we have no direct information on which respondents provide an accurate report. Thus, rather than presenting a single model of misclassification, we instead assess how identification varies with the strength of assumptions on misreporting patterns. A natural starting point is to consider the case where there is no prior information revealing respondents who provide accurate reports. In this case, all responses are unverified, and Assumption (A1a) applies to the full sample.

To verify responses, we use information on whether the respondent recently received dental care. Arguably, respondents who have received dental care are likely to know about their dental insurance coverage. We apply two nested verification models. First, we assume that respondents who report seeing a dentist and having expenses at least partially covered by insurance provide accurate reports of dental insurance. Of the 12,746 respondents in our sample, 4775 report receiving care that is at least partly covered by insurance, 1094 respondents did not see a dentist but reported that they would expect costs to be covered by insurance, and the remaining 6877 did not report having dental insurance. Thus, under this verification model 4775 respondents—37%—are assumed to provide accurate reports of coverage. Assumption (A1a) applies to the reports of the remaining 7871 unverified cases. Second, we strengthen this verification assumption by presuming accurate responses among those who either report receiving care in the previous two waves of the HRS (i.e., the 2006 or 2004 wave) or report that their spouse received care in the 2006 wave. Under this more restrictive model, we verify the self-reports of dental insurance for 11,914 respondents. That is, 93.5% are assumed to provide accurate reports of insurance coverage. The remaining 832 unverified respondents (i.e., 6.5% of the sample) may misreport subject to the constraint in Assumption (A1a).

To further tighten inferences on the utilization gap, we consider restrictions on the patterns of errors. We first consider two independence assumptions:

(A2) *Orthogonal errors*: $P(I^* = 1|Z^*) = P(I^* = 1)$ and
(A3) *Nondifferential errors*: $P(I = 1|I^*, D) = P(I = 1|I^*)$ for $I^* = 1, 0$.

Assumption (A2) formalizes an independence assumption that insurance classification errors occur independently of true insurance status. That is, the propensity to misreport insurance status does not depend on whether

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the respondent is truly insured or not. This assumption is obviously weaker than the usual implicit assumption of no reporting errors. Still, the assumption will be violated, for example, if better educated respondents are both more likely to be insured and more likely to accurately answer survey questions (KH).

Assumption (A3) places restrictions on the relationship between insurance classification errors and the use of health services. Conditional on true insurance status, reporting errors are assumed to be unrelated to the respondent's use of dental services. Aigner (1973) and Bollinger (1996) study this type of 'nondifferential' classification error for the case of a binary conditioning variable. When (A3) holds, Bollinger's Theorem 1 (for $v > 0.5$) shows that Δ is bounded below by the reported utilization gap, $P(D=1|I=1) - P(D=1|I=0)$. 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 may be violated if using dental care informs respondents about their true insurance status. In fact, our verification assumptions are predicated on the idea that using dental services resolves uncertainty about insurance status.

Although the nondifferential errors assumption is quite strong, the assumption can be weakened considerably. Instead of assuming independence between insurance misreporting and the use of services, Assumption (A4) merely rules out patterns of errors in which the probability of misreporting insurance status rises with the level of dental health care utilization:

(A4) *Nonincreasing errors*: $P(I=1|I^*=0, D=1) \leq P(I=1|I^*=0, D=0)$, and
$P(I=0|I^*=1, D=1) \leq P(I=0|I^*=1, D=0)$.

It seems plausible that, on average, respondents who recently used dental services are at least as likely as their non-using counterparts to accurately report their insurance status. The nondifferential assumption (A3) represents a special case in which these inequalities are replaced with equalities.

3.1. Empirical results

Figure 1A–C presents the estimated bounds on the utilization gap, Δ, with panel A displaying the bounds under the assumption that none of the self-reports of insurance status are verified to be accurate. These bounds account only for identification uncertainty and abstract away from the additional layer of uncertainty associated with sampling variability. The accompanying table presents the estimated bounds for the selected values $v = \{0.75, 0.90, 0.95, 1.00\}$ and also provides Imbens and Manski (2004) confidence intervals that cover the true value of Δ with 95% probability. So, for example, the results found under $v = 0.95$ apply if the direct evidence on misreporting provided in Duncan and Hill's (1985) analysis of workers at one large manufacturing firm holds for the full population.

When $v = 1$, Δ is point-identified as the self-reported gap obtained from taking the data at face value. In this case, the utilization gap is estimated to be $0.836 - 0.664 = 0.172$. Under arbitrary errors, identification of the utilization gap deteriorates rapidly as v departs from 1. When $v = 0.95$, for example, the utilization gap in dental care may lie anywhere between 0.021 and 0.324, and when $v = 0.90$ (or smaller), the sign of Δ is no longer identified to be positive. This represents an important negative result: even small amounts of classification errors may lead to ambiguity about inferences on the sign of the utilization gap between the insured and uninsured (KH). Although this negative result persists under the orthogonal errors (A2) and nonincreasing error (A4) models, Δ is always estimated to exceed zero under the nondifferential errors (A3) model. As previously noted, the estimated lower bound under (A3) equals the reported utilization gap (Bollinger, 1996).

Figures 1B and C incorporate the two nested verification models. Under the weaker verification assumption, Figure 1B displays results for the case that insurance responses can be treated as accurate among respondents who report having dental care expenses partially covered by insurance. Under the stronger verification assumption, Figure 1C displays results under the assumption that insurance responses can be treated as accurate among those who received care in either of the previous two waves of the HRS (i.e., the 2006 or 2004 wave) or their spouse received care in the 2006 wave. In this latter case, the utilization gap is estimated to be positive unless nearly half the 6.5% of unverified respondents may misreport. Moreover, the gap is point-identified to equal the self-reported rate of 0.172 in the nondifferential errors models for all displayed values of v, and it is nearly

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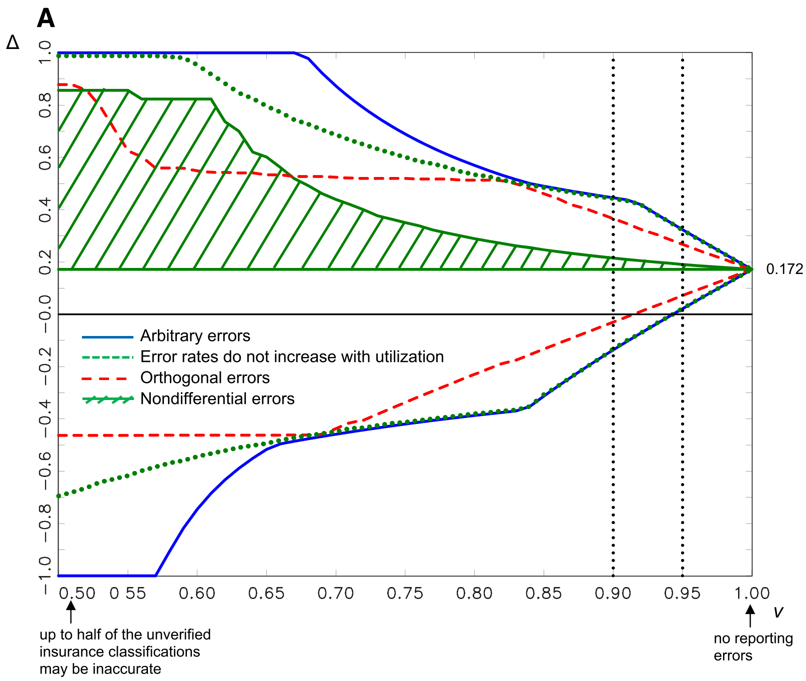

$\Delta = P(D=1|I^*=1) - P(D=1|I^*=0)$:

	Arbitrary Errors	Orthogonal	Nondifferential	Nonincreasing	
v=1	[0.172, 0.172]	[0.172, 0.172]	[0.172, 0.172]	[0.172, 0.172]	p.e. †
	[0.153 0.190]	[0.153 0.190]	[0.153 0.190]	[0.153 0.190]	CI ‡
v=0.95	[0.021, 0.324]	[0.072, 0.268]	[0.172, 0.191]	[0.022, 0.323]	p.e.
	[0.007 0.337]	[0.058 0.282]	[0.155 0.206]	[0.008 0.336]	CI
v=0.90	[-0.137, 0.446]	[-0.030, 0.366]	[0.172, 0.215]	[-0.133, 0.443]	p.e.
	[-0.151 0.456]	[-0.044 0.379]	[0.155 0.232]	[-0.148 0.453]	CI
v=0.75	[-0.420, 0.689]	[-0.337, 0.520]	[0.172, 0.351]	[-0.413, 0.601]	p.e.
	[-0.429 0.717]	[-0.353 0.540]	[0.155 0.379]	[-0.424 0.620]	CI

NOTES: Orthogonal errors imposes $P(I^*=1|Z^*=0)=P(I^*=1|Z^*=1)$, nondifferential errors imposes $P(I=1|I^*) = P(I=1|I^*,D)$, and nonincreasing error rates imposes $P(I=1|I^*=0,D_1) \leq P(I=1|I^*=0,D_0)$ and $P(I=0|I^*=1,D_1) \leq P(I=0|I^*=1,D_0)$ for $D_1 \geq D_0$ where D = use of dental services, I^* = true insurance status, I = reported insurance status, and Z^* = 1 if and only if $I^* = I$.

†Point estimates (p.e.) and ‡95% Imbens-Manski confidence intervals (CI) using 1,000 pseudosamples

Figure 1. Gap between the insured and uninsured in the probability of using dental services: (A) no verification; (B) insurance status verified if saw dentist and reported coverage; and (C) verified if saw dentist in previous two waves or spouse saw in previous wave

point-identified under the orthogonal errors model. Thus, under these verification restrictions, the utilization gap is found to be positive and, under traditional measurement error models, close to the reported gap of 0.172. So, even if we allow for some misclassification, the estimates from these models imply that the insured are at least 8% and at most 27% more likely to use dental care than the uninsured.

4. UTILIZATION UNDER UNIVERSAL HEALTH INSURANCE

We now examine how the fraction of the population using dental services might change if dental insurance coverage were to be extended to the uninsured. Our primary analysis focuses on the full sample of adults with

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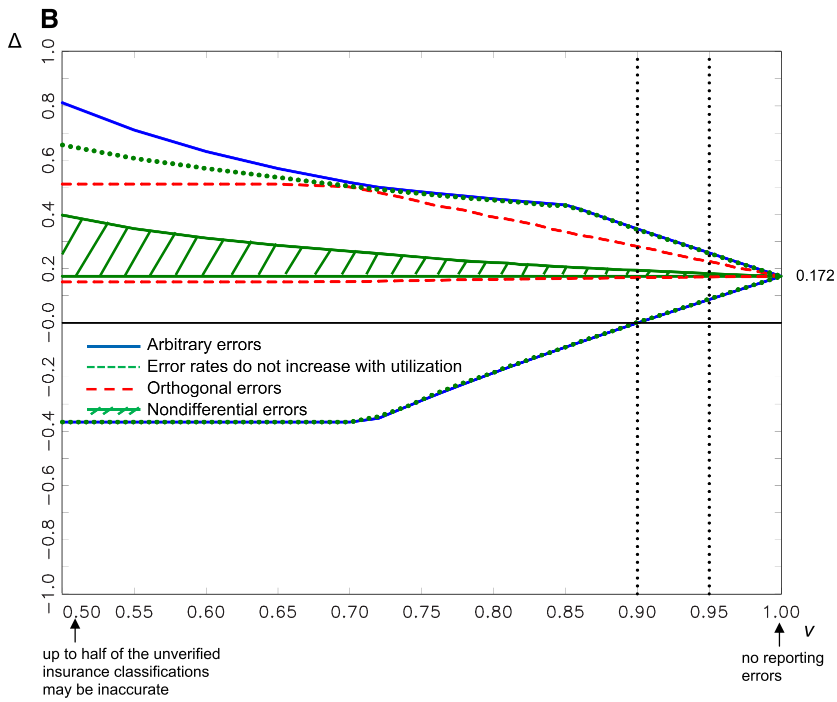


$\Delta = P(D=1|I^{*}=1) - P(D=1|I^{*}=0)$:

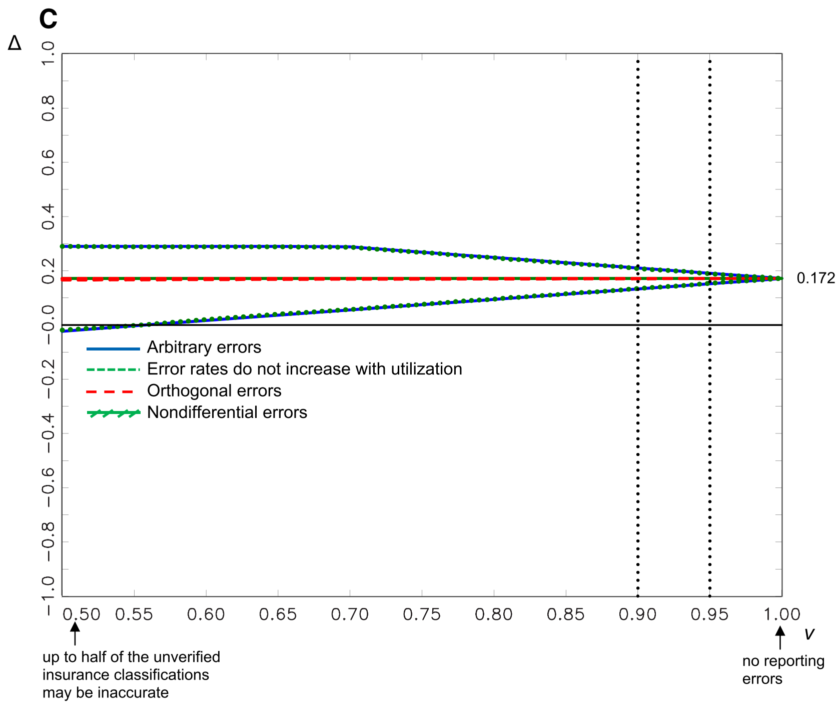
	Arbitrary Errors	Orthogonal	Nondifferential	Nonincreasing	
$v=1$	[0.172, 0.172]	[0.172, 0.172]	[0.172, 0.172]	[0.172, 0.172]	p.e.
	[0.153 0.190]	[0.153 0.190]	[0.153 0.190]	[0.153 0.190]	CI
$v=0.95$	[0.086, 0.258]	[0.169, 0.227]	[0.172, 0.181]	[0.087, 0.256]	p.e.
	[0.072 0.271]	[0.156 0.240]	[0.156 0.195]	[0.073 0.269]	CI
$v=0.90$	[-0.001, 0.346]	[0.167, 0.281]	[0.172, 0.194]	[0.001, 0.344]	p.e.
	[-0.015 0.359]	[0.153 0.294]	[0.156 0.209]	[-0.014 0.357]	CI
$v=0.75$	[-0.286, 0.483]	[0.156, 0.448]	[0.172, 0.242]	[-0.286, 0.475]	p.e.
	[-0.304 0.493]	[0.140 0.462]	[0.156 0.260]	[-0.304 0.485]	CI

Figure 1. (Continued)

teeth. In Section 4.3, we provide separate estimates for the subsamples of adult without teeth and adults over 64 years of age.

Let $D(I^*=1)$ indicate whether the individual would have used dental services if insured. Our objective is to compare the utilization probability if everyone were to be insured, $P[D(I^*=1)=1]$ to the status quo utilization rate, $P(D=1)$. The identification problem is that the utilization outcome under universal insurance, $P[D(I^*=1)=1]$, is observed only for respondents who are verified to be insured ($I^*=1$ and $V=1$). We do not observe $D(I^*=1)$ if $I^*=0$ because in that case, this quantity represents an unknown counterfactual outcome. Nor is this quantity observed in the presence of classification errors because we do not know the value of I^*.

Our notation leaves implicit any other covariates of interest. In a usual regression framework, the inclusion of additional observed covariates is motivated as a means of controlling for other factors that may influence utilization outcomes; omitting relevant explanatory variables may lead to biased estimates. In contrast, there are no regression orthogonality conditions to be satisfied in our approach. Instead, conditioning on covariates serves only to define subpopulations of interest, and our problem is well-defined regardless of how the



$\Delta = P(D=1|I^*=1) - P(D=1|I^*=0)$:

	Arbitrary Errors	Orthogonal	Nondifferential	Nonincreasing	
v=1	[0.172, 0.172]	[0.172, 0.172]	[0.172, 0.172]	[0.172, 0.172]	p.e.
	[0.153 0.190]	[0.153 0.190]	[0.153 0.190]	[0.153 0.190]	CI
v=0.95	[0.152, 0.191]	[0.171, 0.172]	[0.172, 0.172]	[0.154, 0.189]	p.e.
	[0.137 0.206]	[0.153 0.190]	[0.153 0.190]	[0.139 0.205]	CI
v=0.90	[0.133, 0.210]	[0.171, 0.172]	[0.172, 0.172]	[0.135, 0.208]	p.e.
	[0.118 0.226]	[0.153 0.190]	[0.153 0.190]	[0.120 0.224]	CI
v=0.75	[0.075, 0.269]	[0.169, 0.172]	[0.172, 0.172]	[0.076, 0.268]	p.e.
	[0.061 0.285]	[0.153 0.190]	[0.153 0.190]	[0.061 0.284]	CI

Figure 1. (Continued)

subpopulations are specified (Pepper, 2000). Our models condition on age and whether the respondent has teeth. In Section 4.3, we evaluate other subpopulations of respondents.

If dental insurance status were randomly assigned, then the utilization rate among the insured, $P(D=1|I^*=1)$, would identify the utilization rate under universal coverage. As discussed earlier, however, dental insurance coverage is not randomly assigned. Instead, insurance status is affected by characteristics potentially related to the use of dental care. Thus, the quantity $P[D(I^*=1)=1]$ is not identified even if reported insurance status is always accurate.

4.1. Monotone treatment response and monotone treatment selection assumptions

A natural starting point is to consider what can be inferred about the potential utilization probability if no assumptions are imposed to address the selection problem. To do so, we apply Proposition 2 in KH. We then consider two common monotonicity assumptions—one for treatment response and one for treatment selection.

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The MTR assumption, introduced by Manski (1997) (see also Pepper, 2000), specifies that an individual's likelihood of using dental services is at least as high in the insured state as in the uninsured state:

(A5) *MTR:* $D(I^* = 1) \geq D(I^* = 0)$.

Given moral hazard, we would expect some individuals to increase their use of dental care services upon becoming insured; at any rate, their use of services presumably would not decline.[11] Under this MTR assumption, the utilization probability under universal insurance is restricted to be no less than the status quo probability of 0.752.

Under the MTS assumption introduced in Manski and Pepper (2000), the probability of using dental care services under either 'treatment' (insured or uninsured) would be at least as high among the currently insured as among the currently uninsured:

(A6) *MTS*: $P[D(I^* = j) = 1 | I^* = 1] \geq P[D(I^* = j) = 1 | I^* = 0]$ *for* $j = 0, 1$.

Proposition 3 in KH provides bounds on the latent utilization probability $P[D(I^* = 1) = 1]$ under the joint MTR and MTS assumptions.

The MTS assumption relaxes the commonly imposed 'exogenous treatment selection' assumption (Manski and Pepper, 2000, p. 1001). Using traditional parametric models, Munkin and Trivedi (2008) and Meyerhoefer *et al*. (2014) find strong support for this selection model. Those who are likely to use dental services either because of *need* or *preferences* also tend to self-select themselves into obtaining insurance.[12] For example, a traditional adverse selection model implies that persons in need of dental care are likely to purchase dental insurance, whereas a preference-based model implies that persons who are risk adverse or who are healthful may be insured and receive dental care.

In the status quo, where some people have dental insurance and others do not, the dental care utilization rate is estimated to be 0.752. We are interested in comparing this status quo rate to the fraction of the population that would receive care under a policy of universal dental insurance coverage. We first consider what can be learned about the utilization rate under the weakest modeling assumptions—that is, allowing for arbitrary patterns of insurance classification errors while imposing no restrictions on the selection process. Estimates of these bounds, along with 95% confidence intervals, are presented in Figure 2 and column 1 of the associated tables. Figure 2A displays the bounds under the assumption that no self-reports of insurance status are verified to be accurate, whereas Figure 2B and C incorporate the nested verification models.

Under the standard assumption that insurance status is reported accurately, $v = 1$, the dental care utilization rate if everyone were to become insured is estimated to lie in the range [0.429, 0.916]. Thus, the data cannot reveal whether universal coverage increases or decreases utilization compared with the status quo rate, 0.752. Utilization rates might fall to the lower bound of 0.429 or rise to the upper bound of 0.916. Clearly, in the absence of additional restrictions to address the selection problem, we learn very little about the impact of universal dental insurance coverage. Moreover, as the accurate reporting rate v departs from 1, the estimated bounds become even wider.

The ambiguity associated with the dental care utilization rate under universal coverage can be substantially reduced, however, by applying credible restrictions. Consider, for example, the results illustrated in Figure 2C,

[11]This leads to an MTR restriction that insurance weakly increases the demand for care, a property that holds even without moral hazard. A basic economic model of dental care utilization is provided by Meyerhoefer *et al.* (2014). See also Manning and Phelps (1979) and Sintonen and Linnosmaa (2000).

[12]Observed features of economic well-being and health, including self-reported measures of health, education, employment, and earnings, are all positively correlated with both dental insurance and dental care utilization (Manski *et al.*, 2010a). Although these observed associations may suggest that an adverse selection model is not applicable to all groups of respondents (persons with insurance have better, not worse, self-reported measures of health), it does not invalidate the MTS assumption. In particular, the MTS assumption holds if adverse selection applies to some respondents and preference-based selection applies to others. Moreover, in imposing the MTS assumption across the population as a whole, we allow for the possibility that this tendency is reversed within some subpopulations.

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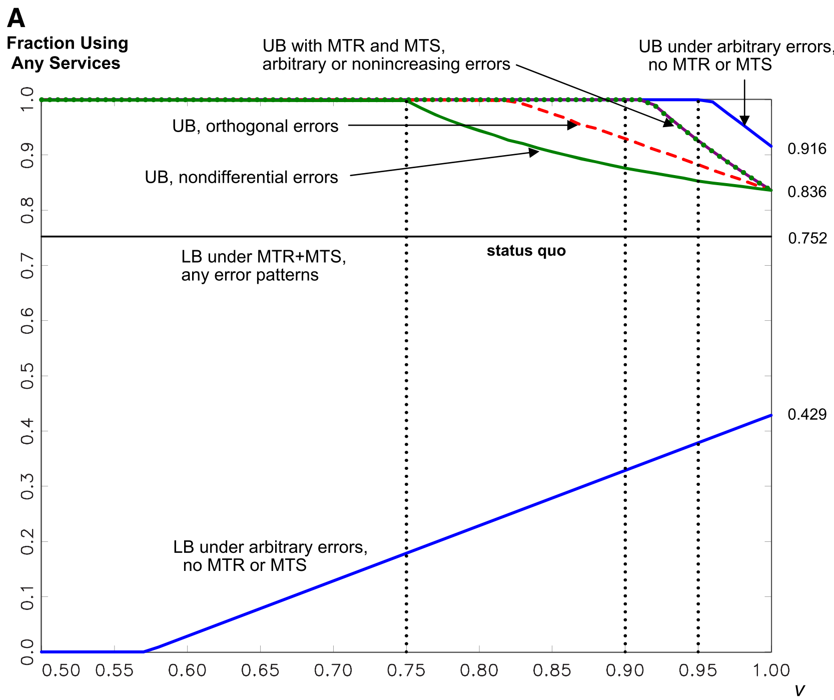

	No Monotonicity Assumptions	MTR+MTS				
	Arbitrary Errors	Arbitrary Errors	Orthogonal Errors	Nondifferential Errors	Nonincreasing Errors	
v=1	[0.429, 0.916]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.836]	p.e.
	[0.421 0.920]	[0.746 0.844]	[0.746 0.844]	[0.746 0.844]	[0.746 0.844]	CI
v=0.95	[0.379, 1.000]	[0.752, 0.926]	[0.752, 0.883]	[0.752, 0.853]	[0.752, 0.926]	p.e.
	[0.370 1.000]	[0.745 0.936]	[0.745 0.892]	[0.745 0.862]	[0.745 0.935]	CI
v=0.90	[0.329, 1.000]	[0.752, 1.000]	[0.752, 0.930]	[0.752, 0.876]	[0.752, 1.000]	p.e.
	[0.320 1.000]	[0.745 1.000]	[0.745 0.939]	[0.745 0.887]	[0.745 1.000]	CI
v=0.75	[0.179, 1.000]	[0.752, 1.000]	[0.752, 1.000]	[0.752, 1.000]	[0.752, 1.000]	p.e.
	[0.170 1.000]	[0.745 1.000]	[0.745 1.000]	[0.745 1.000]	[0.745 1.000]	CI

Figure 2. Bounds on the fraction of the population that would have used dental services under universal dental insurance coverage: (A) no verification; (B) verified if saw dentist and reported coverage; and (C) verified if saw dentist in previous two waves or spouse saw in previous wave

where respondents are verified to provide accurate reports of dental insurance if they or their spouse received dental care. Under this verification model, the estimated bounds when $\upsilon = 0.95$ narrow from [0.379, 1.00] to [0.429, 0.922], a 21% reduction in the width of the bounds. Adding the MTR and MTS assumptions to address the selection problem further reduces the ambiguity associated with universal coverage; the lower bound increases to the observed status quo utilization rate of 0.752, whereas the upper bound falls to 0.847. Thus, under this model, we estimate that universal coverage would increase the dental care utilization rate by no more than 0.095 (from 0.752 to 0.847), a 13% increase. This finding appears to be fairly robust. The lower bound is constant across all measurement error models, and the upper bound estimates vary only slightly (at the second decimal place) across the different error models.

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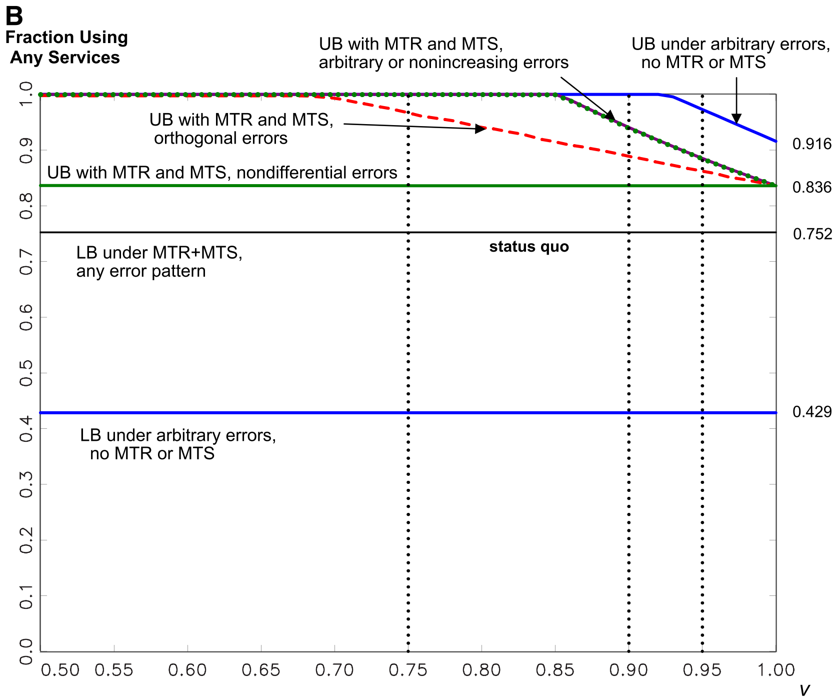

	No Monotonicity Assumptions	MTR+MTS				
	Arbitrary Errors	Arbitrary Errors	Orthogonal Errors	Nondifferential Errors	Nonincreasing Errors	
v=1	[0.429, 0.916]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.836]	p.e.
	[0.421 0.920]	[0.746 0.844]	[0.746 0.844]	[0.746 0.844]	[0.746 0.844]	CI
v=0.95	[0.429, 0.973]	[0.752, 0.885]	[0.752, 0.863]	[0.752, 0.836]	[0.752, 0.884]	p.e.
	[0.421 0.977]	[0.746 0.894]	[0.746 0.871]	[0.746 0.844]	[0.746 0.893]	CI
v=0.90	[0.429, 1.000]	[0.752, 0.941]	[0.752, 0.889]	[0.752, 0.836]	[0.752, 0.939]	p.e.
	[0.421 1.000]	[0.746 0.950]	[0.746 0.897]	[0.746 0.844]	[0.746 0.949]	CI
v=0.75	[0.429, 1.000]	[0.752, 1.000]	[0.752, 0.968]	[0.752, 0.836]	[0.752, 1.000]	p.e.
	[0.421 1.000]	[0.746 1.000]	[0.746 0.978]	[0.746 0.844]	[0.746 1.000]	CI

Figure 2. (Continued)

4.2. Monotone instrumental variables

Researchers often address selection and misclassification problems using an instrumental variable assumption that certain observed covariates are mean independent of the latent outcome of interest. Although this instrumental variable assumption is known to have identifying power (Manski, 1995), in practice, finding credible instruments can be difficult. Observed variables that are correlated with dental insurance coverage are also thought to be related to the latent dental care indicator, $D(I^*)$, as well. As a result, we have not found an instrumental variable for this application that plausibly satisfies the mean independence restriction.

Instead, however, the weaker MIV restriction that certain observed covariates are known to be monotonically related to the latent response variable can be credibly applied in this setting. In particular, we consider the relatively innocuous assumption that the latent utilization probability under universal coverage weakly

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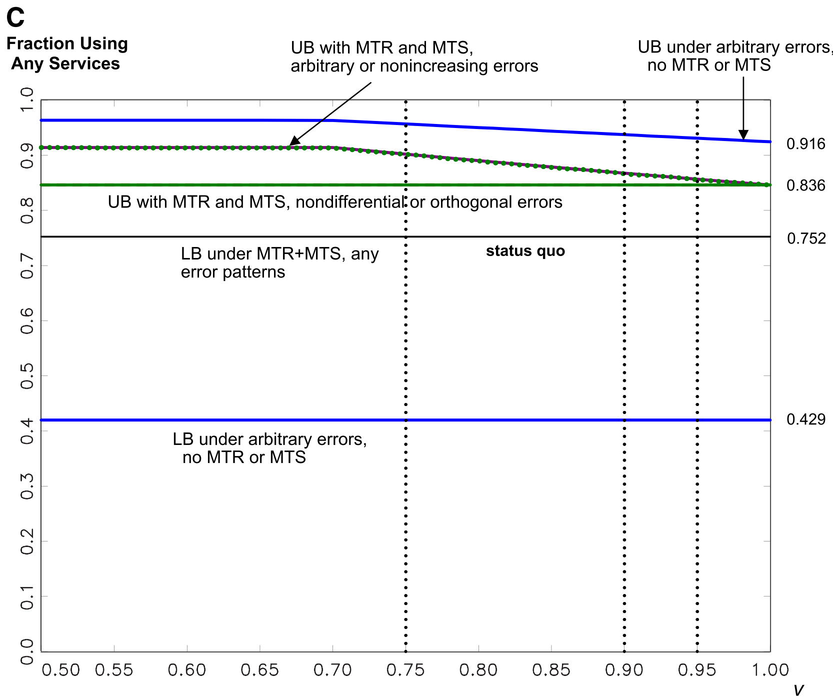

	No Monotonicity Assumptions	MTR+MTS				
	Arbitrary Errors	Arbitrary Errors	Orthogonal Errors	Nondifferential Errors	Nonincreasing Errors	
v=1	[0.429, 0.916]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.836]	p.e.
	[0.421 0.920]	[0.746 0.844]	[0.746 0.844]	[0.746 0.844]	[0.746 0.844]	CI
v=0.95	[0.429, 0.922]	[0.752, 0.847]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.846]	p.e.
	[0.421 0.927]	[0.745 0.856]	[0.745 0.845]	[0.745 0.845]	[0.745 0.855]	CI
v=0.90	[0.429, 0.929]	[0.752, 0.857]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.856]	p.e.
	[0.421 0.934]	[0.745 0.867]	[0.745 0.845]	[0.745 0.845]	[0.745 0.865]	CI
v=0.75	[0.429, 0.948]	[0.752, 0.892]	[0.752, 0.836]	[0.752, 0.836]	[0.752, 0.891]	p.e.
	[0.421 0.953]	[0.745 0.901]	[0.745 0.845]	[0.745 0.845]	[0.745 0.901]	CI

Figure 2. (Continued)

increases with income adjusted for family composition. A large body of empirical research supports the idea of a negative gradient between reported income and dental health care utilization (e.g., Manski *et al*., 2010b). To formalize this idea, let w be the MIV such that

$$u_1 < u < u_2 \Rightarrow P[D(I^* = 1) = 1 | w = u_1] \leq P[D(I^* = 1) = 1 | w = u] \leq P[D(\mathrm{I}^* = 1) = 1 | w = u_2]. \quad (4)$$

This mean monotonicity condition relaxes the mean independence assumption in which the inequalities across the expectations in 4 would be replaced with equalities (Manski and Pepper, 2000, 2009). Although the conditional expectations in 4 are not identified, they can be bounded using the methods described in the previous text. Let $LB(u)$ and $UB(u)$ be the known lower and upper bounds evaluated at $w = u$, respectively, given the available information. Then, the MIV assumption formalized in Manski and Pepper (2000, Proposition 1) implies:

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Table II. Bounds on the fraction of the population that would have used dental services under universal dental insurance coverage

	MIV + MTR + MTS				
	Arbitrary errors	Orthogonal errors	Nondifferential errors	Nonincreasing errors	
$v = 1$	[0.764, 0.809]	[0.764, 0.809]	[0.764, 0.809]	[0.764, 0.809]	p.e.[†]
	[0.743, 0.860]	[0.743, 0.860]	[0.743, 0.860]	[0.743, 0.860]	CI [‡]
	[0.016, −0.035]	[0.016, −0.035]	[0.016, −0.035]	[0.016, −0.035]	Bias*
$v = 0.95$	[0.764, 0.822]	[0.764, 0.812]	[0.764, 0.809]	[0.764, 0.821]	p.e.
	[0.743, 0.874]	[0.743, 0.863]	[0.743, 0.860]	[0.743, 0.872]	CI
	[0.016, −0.036]	[0.016, −0.036]	[0.016, −0.035]	[0.016, −0.036]	Bias
$v = 0.90$	[0.764, 0.837]	[0.764, 0.816]	[0.764, 0.809]	[0.764, 0.836]	p.e.
	[0.743, 0.889]	[0.743, 0.868]	[0.743, 0.860]	[0.743, 0.888]	CI
	[0.016, −0.038]	[0.016, −0.036]	[0.016, −0.035]	[0.016, −0.038]	Bias
$v = 0.75$	[0.764, 0.885]	[0.764, 0.831]	[0.764, 0.809]	[0.764, 0.884]	p.e.
	[0.743, 0.938]	[0.743, 0.883]	[0.743, 0.860]	[0.743, 0.936]	CI
	[0.016, −0.047]	[0.016, −0.039]	[0.016, −0.035]	[0.016, −0.046]	Bias

Note: verified if saw dentist in previous two waves or spouse saw in previous wave.
[†]Point estimates (p.e.). [‡]95% Imbens-Manski confidence intervals (CI) using 1000 pseudosamples. *Estimated finite sample bias used to correct estimates.

$$\sup_{u_1 \le u} LB(u_1) \le P[D(I^* = 1) = 1 | w = u] \le \inf_{u_2 \ge u} UB(u_2).$$

Bounds on the unconditional utilization rate under universal coverage, $P[D(I^* = 1) = 1]$ are then obtained using the law of total probability.[13]

Estimates of these bounds and confidence intervals around the true value $P[D(I^* = 1) = 1]$ under this MIV assumption are presented in Table II, which reveals the bounds under the strongest verification model and the joint MTS-MTR assumption. The MTS assumption applies at each value of the instrument, w. In this model, the dental care utilization rate under universal insurance, $P[D(I^* = 1) = 1]$, is estimated to exceed the status quo rate of 0.752 by at least 0.012 (a 1.6% increase), although this lower bound result is not statistically significant at the 5% significance level. The MIV assumption also reduces the estimated upper bound. When $v = 0.95$ and reporting errors can be arbitrary, for example, the upper bound on the utilization rate under universal coverage falls from 0.847 to 0.822. Depending on the measurement error model, the upper bound varies from 0.809 (under the nondifferential errors model) to 0.885 (under the arbitrary errors model where $v = 0.75$). Despite the sensitivity of the upper bound estimates, the overall results are fairly consistent. Relative to the status quo utilization rate of 0.752, we estimate that universal coverage would increase the dental care utilization rate by at least 0.012, or 2%, and no more than about 0.08, or 10%.

These results are consistent with, but somewhat smaller, than analogous results found in the literature using parametric models to evaluate the impact of insurance on younger populations. As previously noted, Mueller and Monheit (1988) conclude that dental insurance increases utilization from 0.47 to about 0.55, a nearly 17% increase, and Meyerhoefer *et al.* (2014) find that coverage increases the probability of preventive care by about 19% (from a base of 0.41). Thus, our results suggest that although older adults are more likely to use dental care, utilization decisions may be somewhat less sensitive to dental insurance.

[13]Following the approach developed in Kreider and Pepper (2007), we estimate these MIV bounds by first dividing the sample into equally sized groups (more than 200 observations per cell) delineated by an increasing ratio of income to the poverty line. Then, to find the MIV bounds on the rates of dental care utilization, we take the average of the plug-in estimators (weighted to account for the survey design) of lower and upper bounds across the different income groups observed in the data. Because this MIV estimator is consistent but biased in finite samples (Manski and Pepper, 2000, 2009), we employ Kreider and Pepper's (2007) modified MIV estimator that accounts for the finite sample bias using a nonparametric bootstrap correction method.

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Table III. Bounds on the fraction of the population that would have used dental services under universal dental insurance coverage

	MIV + MTR + MTS				
	Arbitrary errors	Orthogonal errors	Nondifferential errors	Nonincreasing errors	
	A. Aged 51 years and older, no teeth ($N = 3041$)				
$v = 1$	[0.207, 0.250]	[0.207, 0.250]	[0.207, 0.250]	[0.207, 0.250]	p.e.
	[0.162, 0.321]	[0.162, 0.321]	[0.162, 0.321]	[0.162, 0.321]	CI
	[0.015, −0.022]	[0.015, −0.022]	[0.015, −0.022]	[0.015, −0.022]	Bias
$v = 0.95$	[0.207, 0.273]	[0.207, 0.260]	[0.207, 0.250]	[0.207, 0.273]	p.e.
	[0.162, 0.352]	[0.162, 0.334]	[0.162, 0.321]	[0.162, 0.351]	CI
	[0.015, −0.025]	[0.015, −0.024]	[0.015, −0.022]	[0.015, −0.025]	Bias
$v = 0.90$	[0.207, 0.299]	[0.207, 0.270]	[0.207, 0.250]	[0.207, 0.298]	p.e.
	[0.162, 0.386]	[0.162, 0.349]	[0.162, 0.321]	[0.162, 0.385]	CI
	[0.015, −0.028]	[0.015, −0.025]	[0.015, −0.022]	[0.015, −0.028]	Bias
$v = 0.75$	[0.207, 0.408]	[0.207, 0.308]	[0.207, 0.250]	[0.207, 0.406]	p.e.
	[0.162, 0.530]	[0.162, 0.406]	[0.162, 0.321]	[0.162, 0.527]	CI
	[0.015, −0.048]	[0.015, −0.030]	[0.015, −0.022]	[0.015, −0.047]	Bias
	B. Aged 65 years and older, teeth ($N = 7653$)				
$v = 1$	[0.749, 0.763]	[0.749, 0.763]	[0.749, 0.763]	[0.749, 0.763]	p.e.
	[0.723, 0.822]	[0.723, 0.822]	[0.723, 0.822]	[0.723, 0.822]	CI
	[0.015, −0.025]	[0.015, −0.025]	[0.015, −0.025]	[0.015, −0.025]	Bias
$v = 0.95$	[0.749, 0.781]	[0.749, 0.771]	[0.749, 0.763]	[0.749, 0.781]	p.e.
	[0.723, 0.842]	[0.723, 0.830]	[0.723, 0.822]	[0.723, 0.841]	CI
	[0.015, −0.027]	[0.015, −0.026]	[0.015, −0.025]	[0.015, −0.026]	Bias
$v = 0.90$	[0.749, 0.802]	[0.749, 0.780]	[0.749, 0.763]	[0.749, 0.801]	p.e.
	[0.723, 0.864]	[0.723, 0.840]	[0.723, 0.822]	[0.723, 0.863]	CI
	[0.015, −0.029]	[0.015, −0.027]	[0.015, −0.025]	[0.015, −0.029]	Bias
$v = 0.75$	[0.749, 0.842]	[0.749, 0.796]	[0.749, 0.763]	[0.749, 0.841]	p.e.
	[0.723, 0.912]	[0.723, 0.860]	[0.723, 0.822]	[0.723, 0.910]	CI
	[0.015, −0.027]	[0.015, −0.025]	[0.015, −0.025]	[0.015, −0.027]	Bias
	C. Aged 65 years and older, no teeth ($N = 2456$)				
$v = 1$	[0.173, 0.216]	[0.173, 0.216]	[0.173, 0.216]	[0.173, 0.216]	p.e.
	[0.132, 0.293]	[0.132, 0.293]	[0.132, 0.293]	[0.132, 0.293]	CI
	[0.015, −0.021]	[0.015, −0.021]	[0.015, −0.021]	[0.015, −0.021]	Bias
$v = 0.95$	[0.173, 0.241]	[0.173, 0.228]	[0.173, 0.216]	[0.173, 0.241]	p.e.
	[0.132, 0.329]	[0.132, 0.311]	[0.132, 0.293]	[0.132, 0.329]	CI
	[0.015, −0.024]	[0.015, −0.022]	[0.015, −0.021]	[0.015, −0.024]	Bias
$v = 0.90$	[0.173, 0.276]	[0.173, 0.245]	[0.173, 0.216]	[0.173, 0.276]	p.e.
	[0.132, 0.377]	[0.132, 0.335]	[0.132, 0.293]	[0.132, 0.376]	CI
	[0.015, −0.028]	[0.015, −0.024]	[0.015, −0.021]	[0.015, −0.028]	Bias
$v = 0.75$	[0.173, 0.453]	[0.173, 0.332]	[0.173, 0.216]	[0.173, 0.450]	p.e.
	[0.132, 0.606]	[0.132, 0.456]	[0.132, 0.293]	[0.132, 0.602]	CI
	[0.015, −0.059]	[0.015, −0.036]	[0.015, −0.021]	[0.015, −0.058]	Bias
	D. Aged 65 years and older, with or without teeth ($N = 10,109$)				
$v = 1$	[0.622, 0.657]	[0.622, 0.657]	[0.622, 0.657]	[0.622, 0.657]	p.e.
	[0.596, 0.715]	[0.596, 0.715]	[0.596, 0.715]	[0.596, 0.715]	CI
	[0.018, −0.035]	[0.018, −0.035]	[0.018, −0.035]	[0.018, −0.035]	Bias
$v = 0.95$	[0.622, 0.682]	[0.622, 0.667]	[0.622, 0.657]	[0.622, 0.682]	p.e.
	[0.596, 0.742]	[0.596, 0.726]	[0.596, 0.715]	[0.596, 0.742]	CI
	[0.018, −0.036]	[0.018, −0.035]	[0.018, −0.035]	[0.018, −0.036]	Bias
$v = 0.90$	[0.622, 0.710]	[0.622, 0.679]	[0.622, 0.657]	[0.622, 0.709]	p.e.
	[0.596, 0.774]	[0.596, 0.739]	[0.596, 0.715]	[0.596, 0.773]	CI
	[0.018, −0.038]	[0.018, −0.036]	[0.018, −0.035]	[0.018, −0.038]	Bias
$v = 0.75$	[0.622, 0.831]	[0.622, 0.733]	[0.622, 0.657]	[0.622, 0.831]	p.e.
	[0.596, 0.904]	[0.596, 0.799]	[0.596, 0.715]	[0.596, 0.905]	CI
	[0.018, −0.058]	[0.018, −0.043]	[0.018, −0.035]	[0.018, −0.059]	Bias

Note: verified if saw dentist in previous two waves or spouse saw in previous wave.

4.3. Subgroups analysis

Thus far, our analysis has focused on evaluating the average effect of insurance for the full population of adults with teeth. In this section, we report estimates under the MTR-MTS-MIV model for two subpopulations: toothless adults and persons aged 65 years or older. Edentulous individuals are likely to have important but very different dental care needs than the general population and thus are treated separately. Likewise, the oldest individuals in the sample—those 65 years and older—may have more acute dental health problems and face different dental insurance coverage options than those under 65 years old.

Table III displays the results for these subpopulations. For toothless adults (panel A), the estimated lower bound under universal insurance, $P[D(I^*=1)=1]$, equals the status quo utilization rate of 0.207. Thus, we cannot rule out the possibility that insurance has no impact on the dental care utilization rate for toothless adults over 51 years of age. At the same time, the upper bound estimates imply that insurance may have a substantial effect. For example, if $v=0.90$, the estimated upper bound varies from 0.250 (under the nondifferential errors model) to 0.299 (under the arbitrary errors model).

For adults age 65 years or older with teeth (panel B), the status quo utilization rate is estimated to equal 0.744. Under universal insurance, we estimate the utilization rate, $P[D(I^*=1)=1]$, to exceed the status quo rate by at least 0.005, although this lower bound result is not statistically significant at the 5% significance level. The upper bound estimates vary from 0.763 (under the nondifferential errors model) to 0.842 (under the arbitrary errors model where $v=0.75$). Despite the sensitivity of the upper bound estimates, the overall results are fairly consistent. Relative to the status quo utilization rate of 0.744, we estimate that universal coverage may have a very limited impact on the dental care utilization rate but may also increase this rate by as much as 0.098, or 13%. For comparison purposes, the last two panels provide analogous estimates for adults aged 65 years and older with no teeth (panel C) and for all adults 65 years and older (panel D). Patterns are similar to those previously described.

5. CONCLUSION

Oral health is thought to be an integral part of general health and well-being, yet most adults display signs of dental diseases, and nearly one-fourth of the elderly have severe periodontal disease (DHHS, 2000). Many Americans do not maintain oral health, even though it can often be achieved with minimal care. In this paper, we examine how universal dental care insurance would impact the utilization of dental care. Identifying the impact of universal coverage is confounded by both the unobservability of counterfactuals and the potential unreliability of self-reported insurance status. To account for these two distinct types of uncertainty, we apply a nonparametric framework from KH (2009) that allows us to partially identify probability distributions and treatment effects.

Using this approach, we provide tight bounds on the impact of universal health insurance on dental care utilization. The resulting estimates imply that extending coverage to the uninsured would increase the utilization rate by at least 2% under universal coverage and as much as about 10%. These results are consistent with the dental care utilization rate increasing from 75% to around 80%.

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