Estimating the Effect of Dental Insurance on the Use of Dental Services When True Coverage is Unobserved*

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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 – as well as 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 would rise between 2%-9% if everyone were to become insured. These results are consistent with the dental care utilization rate increasing from 75% to around 80%, but they are inconsistent with the idea that universal coverage might lead to near universal utilization.

Keywords: dental insurance, dental care, treatment effect, selection, classification errors, partial identification

JEL classification numbers: I13, I18, C14

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I. Introduction

While 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 dental care (IOM and NRC, 2011). Yet many Americans suffer from serious oral health related problems. Nearly half of persons aged 65-74 perceive their dental health as poor, and one in four are classified as having severe periodontal disease (U.S. 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 United States as a “silent epidemic” and highlights the potential role dental insurance – or the lack thereof – plays in understanding this 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). In particular, many fewer adults have dental insurance than have medical insurance (about 2.5 times more have medical insurance) and, since 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 United States.

Using a potential outcomes framework designed to accommodate missing counterfactuals and data errors, we examine how the prevalence of dental care would change if dental insurance coverage were to be extended to the uninsured. 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 and aversion to risk are arguably correlated with both dental care and dental insurance. As a result, the data alone cannot reveal what the utilization rate

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\(^1\) See, e.g., 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 & Medicaid Services, 2010).
would be if all people were to be covered. While 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).³

Second, a misclassification problem arises because dental insurance coverage is likely to be misreported by some respondents. While direct evidence on the magnitude of this problem is limited, there is a large literature documenting the misclassification of health insurance coverage.⁴ Duncan and Hill’s (1985) validation study of responses from workers at a large manufacturing firm provides direct evidence on misreporting: five-percent of respondents at this firm provided erroneous reports of dental coverage whereas only one percent of respondents misreported insurance coverage. For the general population, recent studies suggest significantly larger misreporting rates of general health insurance coverage (e.g., DeNaves-Walt et al. 2005). Arguably, these 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 literature on dental insurance and care, compromise a researcher’s ability to make reliable inferences about the status quo and further confound 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 (Millimet, 2010). As a result, these measurement problems may constitute an important barrier to identifying the role of dental insurance in health care.

We examine the impact of dental insurance on the use of dental care services in light of both the

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³ Several papers attempt to address the selection problem using parametric instrumental variable models (e.g., Cooper, Manski and Pepper, forthcoming; and Selden and Hudson, 2006). 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. Manning et al. (1985) find that data from the RAND experiment reveal that reducing coinsurance rates leads 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 United States (see U.S. Congress, Office of Technology Assessment, 1993).

⁴ See Section 2 for further discussion.
selection and misclassification problems. To do so, we apply the partial identification methods in Kreider and Hill’s (2009; henceforth referred to as KH) evaluation of universal health insurance.\footnote{Gerfin and Schellhorn (2006) also apply partial identification methods to evaluate the impact of health insurance deductibles on the probability of visiting a doctor.} \footnote{We also draw on the related partial identification literature in Manski (1995 and 1997), Manski and Pepper (2000 and 2009); Pepper (2000), Kreider and Pepper (2007); Molinari (2008 and 2010), and Kreider, Pepper, Gundersen, and Jolliffe (2012). Cooper et al.’s (forthcoming) analysis of the effect of dental insurance on dental care applies basic partial identification methods to address the selection problem.} Using data from the 2006 wave of the Health and Retirement Survey (HRS), we focus our analysis on older adults (age 50 and over), a subpopulation that is especially vulnerable to oral disease and often lacks dental insurance (especially retirees) (DHHS, 2000; IOM and NRC, 2011). We estimate two basic parameters for this population: 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.\footnote{The literature evaluating the demand for care has also estimated two part models that first evaluate the probability of receiving any dental care and then consider the amount or type of care (Sintonen and Linnosmaa, 2000). This prior research, however, does not address the measurement error problems considered in this paper. In future work, the models applied in this paper might be generalized to account for heterogeneity in the types of dental care and insurance plans.}

After describing the data in Section II, Section III 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 (Reisine, 1988; Gooch and Berkey 1987; Mueller and Monheit, 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 settings 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 more policy relevant questions, Section IV 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 the selection and classification error problems. To do so, we combine 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 are able to bound the causal impact of universal coverage without relying on more controversial assumptions involving functional forms and independence conditions.

Section V 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 75.2% to around 80%, but they are inconsistent with the idea that universal coverage would lead to near universal utilization.
II. Health and Retirement Study

To evaluate the impact of dental insurance coverage on utilization, we use data from 2006 wave of the Health and Retirement Study (HRS). The HRS, administered by the Institute for Social Research (ISR) 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 United States. Every two years, individuals older than 50 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 and restrict the sample to only those who have teeth (20% dropped due to this restriction). The final sample includes 12,746 older adults.

Dental care is measured using a binary indicator of whether the individual reports receiving care during the two year period preceding the 2006 HRS interview. We also observe whether the respondent received care in the time 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 III below, these latter two measures are used to aid in “verifying” the accuracy of self-reports of dental insurance coverage. We assume these measures of dental care are measured accurately. Based on the 2006 survey, just over three-quarters of the population (0.752) received care within the two year period prior to the 2006 survey.

Dental insurance coverage is identified in one of two ways: either (1) the respondent reported seeing a dentist during the two-year period preceding the survey and having expenses at least partially covered by insurance, or (2) 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. Based on this classification, 46.1% of the population reports having dental insurance coverage.

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8 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).
Some of these self-reported measures on dental insurance status, however, are thought to be misclassified. There is a large literature documenting the misclassification of health insurance status. Significant misreporting has been documented in the Current Population Survey (CPS), the Survey of Income and Program Participation (SIPP), the Behavioral Risk Factor Surveillance System (BRFSS) survey, the Medical Expenditure Panel Survey (MEPS), and other surveys (Davern et al. 2007; Card et al. 2004; Hill, 2007; Nelson et al. 2000). 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. Other evidence, however, reveals concerning amounts of misreporting on coverage status. Hill (1997), for example, finds that false negative reports in the MEPS – i.e., covered persons reporting no coverage – may be substantial, and the Census Bureau issues caveats about the accuracy of insurance coverage estimates from the CPS (DeNaves-Walt et al. 2005). Finally, as noted above, Duncan and Hill (1985) find that 5% of respondents from a large manufacturing firm provide erroneous reports about dental coverage. While 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.

Table 1 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.
III. 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 IV, 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 \( Y = 1 \) 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. Let \( H = 1 \) denote that the respondent received dental care in the last year, with \( H = 0 \) otherwise. Then, the utilization gap between the insured and uninsured can be written as:

\[
\Delta = E(H|I^* = 1) - E(H|I^* = 0) = P(H = 1|I^* = 1) - P(H = 1|I^* = 0),
\]

where true insurance status, \( I^* \), may be unobserved. Thus, the utilization gap \( \Delta \) is not identified since we observe \( E(H|I) \) but not \( E(H|I^*) \).

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

\[
P(H = 1|I^* = 1) = P(H = 1, I^* = 1)/P(I^* = 1).
\]

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

\[
\theta_1^+ \equiv P(H = 1, I = 1, Z^* = 0) \quad \text{and} \quad \theta_1^- \equiv P(H = 1, I = 0, Z^* = 0)
\]

denote the fraction of false positive and false negative classifications of dental insurance coverage, respectively, for respondents receiving dental care. Similarly, let \( \theta_0^+ \equiv P(H = 0, I = 1, Z^* = 0) \) and \( \theta_0^- \equiv P(H = 0, I = 0, Z^* = 0) \) denote the analogous fractions for respondents not receiving dental care. Then, it follows that
\[ P(H = 1|I^* = 1) = (p_{11} + \theta_{1^-} - \theta_{1^+})/[p_1 + (\theta_{1^-} + \theta_{0^-}) - (\theta_{1^+} + \theta_{0^+})] \]  

where \( p_{11} = P(H = 1, I = 1) \) 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 health 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, \( \theta \). We start by maintaining the following basic assumption:

(A1) **Upper Bound Error Rate:**

\[ a. \text{Among the unverified: } P(\bar{Z}^* = 1 | Y = 0) \geq v \in [0.5,1] \]
\[ b. \text{Among the verified: } P(\bar{Z}^* = 1 | Y = 1) = 1 \]

where \( v \) 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 (\( Y = 0 \)) and verified (\( Y = 1 \)) respondents, respectively. The literature evaluating the utilization gap has maintained the 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 coverage. Of the 12,746 respondents in our sample, 4,775 report receiving care that is at least partly covered by insurance, 1,094 respondents did not see a dentist but reported that they would expect costs to be covered by insurance, and the remaining 6,877 did not report having dental insurance. Thus, under this verification model 4,775 respondents – 37% – are assumed to provide accurate reports of coverage. Assumption (A1a) applies to the reports of the remaining 7,871 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:** \( P(I = 1|I^*, H) = P(I = 1|I^*) \) 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 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 \( \Delta \) is bounded below by the reported utilization gap, \( P(H = 1|I = 1) - P(H = 1|I = 0) \). 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.

While 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 health care utilization:
(A4) \textit{Nonincreasing Errors}: \quad P(I = 1|I^* = 0, H = 1) \leq P(I = 1|I^* = 0, H = 0), \quad \text{and} \quad
P(I = 0|I^* = 1, H = 1) \leq P(I = 0|I^* = 1, H = 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 the inequalities are replaced with equalities.

\textit{a. empirical results}

Figures 1A-1C present the estimated bounds on the utilization gap, \( \Delta \), 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-Manski (2004) confidence intervals that cover the true value of \( \Delta \) with 95\% probability. So, for example, the results found under \( v = 0.95 \) applies if the direct evidence on misreporting provided the Duncan and Hill (1985) analysis of workers at one large manufacturing firm holds for the full population.

When \( v = 1 \), \( \Delta \) 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 \( \Delta \) 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). While this negative result persists under the orthogonal errors (A2) and nonincreasing error (A4) models, \( \Delta \) is always estimated to exceed zero under the nondifferential errors (A3) model. As noted above, the estimated lower bound under (A3) equals the reported utilization gap (Bollinger, 1996).
Figures 1B and 1C 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 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% are likely to use dental care than the uninsured.

IV. Utilization under Universal Health Insurance

We now examine how the fraction of the population using dental services might change if dental insurance coverage were extended to the uninsured. Let $H(I^* = 1)$ 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, $P[H(I^* = 1) = 1]$, to the status quo utilization rate, $P(H =1)$. The identification problem is that the utilization outcome under universal insurance, $P[H(I^* = 1) = 1]$, is only observed for respondents who are verified to be insured ($I^* = 1$ and $Y =1$). We do not observe $H(I^* = 1)$ if $I^* = 0$ since in that case this quantity represents an unknown counterfactual outcome. Nor is this quantity observed in the presence of classification errors since we do not know the value of $I^*$.

If dental insurance status were randomly assigned, then the utilization rate among the insured,
\[ P(H = 1 | I^* = 1) \], 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 \( P[H(I^* = 1) = 1] \) is not identified even if reported insurance status is always accurate.

A. MTR and MTS 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.

The monotone treatment response assumption (MTR), 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:

\[ (A5) \quad \text{Monotone Treatment Response: } H(I^* = 1) \geq H(I^* = 0). \]

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

Under the monotone treatment selection (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:

\[ (A6) \quad \text{Monotone Treatment Selection: } P[H(I^* = j) = 1 | I^* = 1] \geq P[H(I^* = j) = 1 | I^* = 0] \text{ for } j = 0, 1. \]
The MTS assumption relaxes the commonly imposed “exogenous treatment selection” (ETS) assumption (see Manski and Pepper 2000, p. 1001). Rather than random assignment, we would expect those who consider themselves likely to use dental services to tend to self-select themselves into obtaining insurance. In imposing the MTS assumption across the population as a whole, we allow for the possibility that this tendency is reversed within some subpopulations. Proposition 3 in KH provides bounds on the latent utilization probability $P[H(I^* = 1) = 1]$ under the joint MTR and MTS assumptions.

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, while Figures 2B and 2C 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 to 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 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 \( v = 0.95 \) narrow from \([0.379, 1.00]\) to \([0.429, 0.922]\), a 21 percent 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, while 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.

B. 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. While 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, \( H(I^*) \), 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 monotone instrumental variable (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 increases with income adjusted for family composition. A large body of empirical research supports the idea of a negative gradient between reported income and health care utilization in general (e.g., Deaton, 2002) and dental health care
utilization in particular (e.g., Manski et al., 2010). To formalize this idea, let \( w \) be the monotone instrumental variable such that

\[
\begin{align*}
\begin{array}{c}
\begin{align*}
\quad u_1 < u < u_2 \Rightarrow \\

\quad P[H(I^* = 1) = 1 | w = u_1] \leq P[H(I^* = 1) = 1 | w = u] \leq P[H(I^* = 1) = 1 | w = u_2].
\end{align*}
\end{array}
\end{align*}
\]

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 and 2009). Although the conditional expectations in (4) are not identified, they can be bounded using the methods described above. 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:

\[
\sup_{u_1 \leq u \leq u_2} LB(u) \leq P[H(I^* = 1) = 1 | w = u] \leq \inf_{u_1 \leq u \leq u_2} UB(u).
\]

Bounds on the unconditional utilization rate under universal coverage, \( P[H(I^* = 1) = 1] \) are then obtained using the law of total probability.\(^9\)

Estimates of these bounds and confidence intervals around the true value \( P[H(I^* = 1) = 1] \) under this MIV assumption are presented in Table 2, which reveals the bounds under the strongest verification model and the joint MTS-MTR assumption. In this model, the dental care utilization rate under universal insurance, \( P[H(I^* = 1) = 1] \), 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

\(^9\) 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. Since this MIV estimator is consistent but biased in finite samples (see Manski and Pepper, 2000 and 2009), we employ Kreider and Pepper’s (2007) modified MIV estimator that accounts for the finite sample bias using a nonparametric bootstrap correction method.
MIV assumption also reduces the estimated upper bound. When $\nu = 0.95$ 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 $\nu = 0.75$). 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%.

V. 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, 2001). 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 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 75.2% to around 80%, but they are inconsistent with the idea that universal coverage might lead to (near) universal utilization.
References


Cooper, Philip F., Richard J. Manski and John V. Pepper. forthcoming. “The Effect of Dental Insurance on Dental Care Use and Selection Bias,” *Medical Care*.


Table 1: Means by Reported Dental Insurance Status

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full Sample</th>
<th>Reportedly Insured ($I=1$)</th>
<th>Reportedly Uninsured ($I=0$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of income to the poverty line</td>
<td>6.77 (0.30)</td>
<td>7.05 (0.12)</td>
<td>6.47 (0.57)</td>
</tr>
<tr>
<td>Dental Insurance (2004-06)</td>
<td>0.513 (0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used Dental Care (2004-06)</td>
<td>0.752 (0.004)</td>
<td>0.836 (0.005)</td>
<td>0.664 (0.006)</td>
</tr>
<tr>
<td>Used Dental Care (2002-04)</td>
<td>0.756 (0.004)</td>
<td>0.825 (0.005)</td>
<td>0.684 (0.006)</td>
</tr>
<tr>
<td>Spouse Used Dental Care (2004-06)</td>
<td>0.751 (0.005)</td>
<td>0.827 (0.006)</td>
<td>0.662 (0.007)</td>
</tr>
<tr>
<td>Sample Size</td>
<td>12,746</td>
<td>5,869</td>
<td>6,877</td>
</tr>
</tbody>
</table>

Notes: Sample estimates are weighted using the survey respondent weights. Standard errors are in parentheses.
Δ = P(U=1 | I\ast = 1) - P(U=1 | I\ast = 0):

<table>
<thead>
<tr>
<th>v_0</th>
<th>Arbitrary Errors</th>
<th>Orthogonal</th>
<th>Nondifferential</th>
<th>Nonincreasing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172] p.e. †</td>
</tr>
<tr>
<td></td>
<td>[0.153, 0.190]</td>
<td>[0.153, 0.190]</td>
<td>[0.153, 0.190]</td>
<td>[0.153, 0.190] CI ‡</td>
</tr>
<tr>
<td>0.95</td>
<td>[0.021, 0.324]</td>
<td>[0.072, 0.268]</td>
<td>[0.172, 0.191]</td>
<td>[0.022, 0.323] p.e.</td>
</tr>
<tr>
<td></td>
<td>[0.007, 0.337]</td>
<td>[0.058, 0.282]</td>
<td>[0.155, 0.206]</td>
<td>[0.008, 0.336] CI</td>
</tr>
<tr>
<td>0.90</td>
<td>[-0.137, 0.446]</td>
<td>[-0.030, 0.366]</td>
<td>[0.172, 0.215]</td>
<td>[-0.133, 0.443] p.e.</td>
</tr>
<tr>
<td></td>
<td>[-0.151, 0.456]</td>
<td>[-0.044, 0.379]</td>
<td>[0.155, 0.232]</td>
<td>[-0.148, 0.453] CI</td>
</tr>
<tr>
<td>0.75</td>
<td>[-0.420, 0.689]</td>
<td>[-0.337, 0.520]</td>
<td>[0.172, 0.351]</td>
<td>[-0.413, 0.601] p.e.</td>
</tr>
<tr>
<td></td>
<td>[-0.429, 0.717]</td>
<td>[-0.353, 0.540]</td>
<td>[0.155, 0.379]</td>
<td>[-0.424, 0.620] CI</td>
</tr>
</tbody>
</table>

NOTES: Orthogonal errors imposes \(P(I=1 | I\ast = 0) = P(I = 1 | I\ast = 1)\), nondifferential errors imposes \(P(I = 1 | I')\) = \(P(I = 1 | U, I)\), and nonincreasing error rates imposes \(P(I = 1 | I' = 0, U_i) \leq P(I = 1 | I' = 0, U_i)\) and \(P(I = 0 | I = 1, U_i) \leq P(I = 0 | I = 1, U_i)\) for \(U_i \geq U_i\) where \(U = \) use of 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
$\Delta = P(U=1|I^*=1) - P(U=1|I^*=0)$:

<table>
<thead>
<tr>
<th>$v_0$</th>
<th>Arbitrary Errors</th>
<th>Orthogonal</th>
<th>Nondifferential</th>
<th>Nonincreasing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172] p.e.</td>
</tr>
<tr>
<td></td>
<td>[0.153, 0.190]</td>
<td>[0.153, 0.190]</td>
<td>[0.153, 0.190]</td>
<td>[0.153, 0.190] CI</td>
</tr>
<tr>
<td>0.95</td>
<td>[0.086, 0.258]</td>
<td>[0.169, 0.227]</td>
<td>[0.172, 0.181]</td>
<td>[0.087, 0.256] p.e.</td>
</tr>
<tr>
<td></td>
<td>[0.072, 0.271]</td>
<td>[0.156, 0.240]</td>
<td>[0.156, 0.195]</td>
<td>[0.073, 0.269] CI</td>
</tr>
<tr>
<td>0.90</td>
<td>[-0.001, 0.346]</td>
<td>[0.167, 0.281]</td>
<td>[0.172, 0.194]</td>
<td>[0.001, 0.344] p.e.</td>
</tr>
<tr>
<td></td>
<td>[-0.015, 0.359]</td>
<td>[0.153, 0.294]</td>
<td>[0.156, 0.209]</td>
<td>[-0.014, 0.357] CI</td>
</tr>
<tr>
<td>0.75</td>
<td>[-0.286, 0.483]</td>
<td>[0.156, 0.448]</td>
<td>[0.172, 0.242]</td>
<td>[-0.286, 0.475] p.e.</td>
</tr>
<tr>
<td></td>
<td>[-0.304, 0.493]</td>
<td>[0.140, 0.462]</td>
<td>[0.156, 0.260]</td>
<td>[-0.304, 0.485] CI</td>
</tr>
</tbody>
</table>
Figure 1C. Gap Between the Insured and Uninsured in the Probability of Using Dental Services:

(iii) Verified if Saw Dentist in Previous Two Waves or Spouse Saw in Previous Wave

\[ \Delta = P(U=1|I^*=1) - P(U=1|I^*=0) : \]

<table>
<thead>
<tr>
<th>( \nu_0 )</th>
<th>Arbitrary Errors</th>
<th>Orthogonal</th>
<th>Nondifferential</th>
<th>Nonincreasing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.172, 0.172] CI</td>
</tr>
<tr>
<td>0.95</td>
<td>[0.152, 0.191]</td>
<td>[0.171, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.154, 0.189] p.e.</td>
</tr>
<tr>
<td>0.90</td>
<td>[0.133, 0.210]</td>
<td>[0.171, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.135, 0.208] p.e.</td>
</tr>
<tr>
<td>0.75</td>
<td>[0.075, 0.269]</td>
<td>[0.169, 0.172]</td>
<td>[0.172, 0.172]</td>
<td>[0.076, 0.268] p.e.</td>
</tr>
</tbody>
</table>

Arbitrary errors: Error rates do not increase with utilization
Orthogonal errors
Nondifferential errors
Nonincreasing errors

up to half of the unverified insurance classifications may be inaccurate

\[ 0.172 \]
**Figure 2A. Bounds on the Fraction of the Population that Would Have Used Dental Services Under Universal Dental Insurance Coverage:**

(i) No Verification

<table>
<thead>
<tr>
<th>Fraction Using Any Services</th>
<th>UB with MTR and MTS, arbitrary or nonincreasing errors</th>
<th>UB under arbitrary errors, no MTR or MTS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Status Quo**

- UB, orthogonal errors
- UB, nondifferential errors

**LB under MTR+MTS, any error patterns**

**LB under arbitrary errors, no MTR or MTS**

**No Monotonicity Assumptions**

<table>
<thead>
<tr>
<th>v₀</th>
<th>Arbitrary Errors</th>
<th>Arbitrary Errors</th>
<th>Orthogonal Errors</th>
<th>Nondifferential Errors</th>
<th>Nonincreasing Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[0.429, 0.916]</td>
<td>[0.752, 0.836]</td>
<td>[0.752, 0.836]</td>
<td>[0.752, 0.836]</td>
<td>[0.752, 0.836]</td>
</tr>
<tr>
<td></td>
<td>[0.421, 0.920]</td>
<td>[0.746, 0.844]</td>
<td>[0.746, 0.844]</td>
<td>[0.746, 0.844]</td>
<td>[0.746, 0.844]</td>
</tr>
<tr>
<td>0.95</td>
<td>[0.379, 1.000]</td>
<td>[0.752, 0.926]</td>
<td>[0.752, 0.883]</td>
<td>[0.752, 0.853]</td>
<td>[0.752, 0.926]</td>
</tr>
<tr>
<td></td>
<td>[0.370, 1.000]</td>
<td>[0.745, 0.936]</td>
<td>[0.745, 0.892]</td>
<td>[0.745, 0.862]</td>
<td>[0.745, 0.935]</td>
</tr>
<tr>
<td>0.90</td>
<td>[0.329, 1.000]</td>
<td>[0.752, 1.000]</td>
<td>[0.752, 0.930]</td>
<td>[0.752, 0.876]</td>
<td>[0.752, 1.000]</td>
</tr>
<tr>
<td></td>
<td>[0.320, 1.000]</td>
<td>[0.745, 1.000]</td>
<td>[0.745, 0.939]</td>
<td>[0.745, 0.887]</td>
<td>[0.745, 1.000]</td>
</tr>
<tr>
<td>0.75</td>
<td>[0.179, 1.000]</td>
<td>[0.752, 1.000]</td>
<td>[0.752, 1.000]</td>
<td>[0.752, 1.000]</td>
<td>[0.752, 1.000]</td>
</tr>
<tr>
<td></td>
<td>[0.170, 1.000]</td>
<td>[0.745, 1.000]</td>
<td>[0.745, 1.000]</td>
<td>[0.745, 1.000]</td>
<td>[0.745, 1.000]</td>
</tr>
</tbody>
</table>

**UB, orthogonal errors**

**UB, nondifferential errors**

**UB with MTR and MTS, arbitrary or nonincreasing errors**

**UB under arbitrary errors, no MTR or MTS**

**LB under MTR+MTS, any error patterns**

**LB under arbitrary errors, no MTR or MTS**

**Fraction Using Any Services**

- LB under MTR+MTS, any error patterns
- LB under arbitrary errors, no MTR or MTS
- UB, orthogonal errors
- UB, nondifferential errors
- UB with MTR and MTS, arbitrary or nonincreasing errors
- UB under arbitrary errors, no MTR or MTS
Figure 2B. Bounds on the Fraction of the Population that Would Have Used Dental Services Under Universal Dental Insurance Coverage:

(ii) Verified if Saw Dentist and Reported Coverage

<table>
<thead>
<tr>
<th>No Monotonicity Assumptions</th>
<th>MTR+MTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arbitrary Errors</td>
<td></td>
</tr>
<tr>
<td>$v_0 = 1$</td>
<td>[0.429, 0.916]</td>
</tr>
<tr>
<td></td>
<td>[0.421, 0.920]</td>
</tr>
<tr>
<td>$v_0 = 0.95$</td>
<td>[0.429, 0.973]</td>
</tr>
<tr>
<td></td>
<td>[0.421, 0.977]</td>
</tr>
<tr>
<td>$v_0 = 0.90$</td>
<td>[0.429, 1.000]</td>
</tr>
<tr>
<td></td>
<td>[0.421, 1.000]</td>
</tr>
<tr>
<td>$v_0 = 0.75$</td>
<td>[0.429, 1.000]</td>
</tr>
<tr>
<td></td>
<td>[0.421, 1.000]</td>
</tr>
</tbody>
</table>
Figure 2C. Bounds on the Fraction of the Population that Would Have Used Dental Services Under Universal Dental Insurance Coverage:

(iii) Verified if Saw Dentist in Previous Two Waves or Spouse Saw in Previous Wave
Table 2. Bounds on the Fraction of the Population that Would Have Used Dental Services Under Universal Dental Insurance Coverage:

(iii) MIV, Verified if Saw Dentist in Previous Two Waves or Spouse Saw in Previous Wave

<table>
<thead>
<tr>
<th></th>
<th>MIV+MTR+MTS</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Arbitrary</td>
<td>Orthogonal</td>
<td>Nondifferential</td>
<td>Nonincreasing</td>
</tr>
<tr>
<td>Errors</td>
<td>Errors</td>
<td>Errors</td>
<td>Errors</td>
<td>Errors</td>
</tr>
<tr>
<td>$v_0 = 1$</td>
<td>[0.764, 0.809]</td>
<td>[0.764, 0.809]</td>
<td>[0.764, 0.809]</td>
<td>[0.764, 0.809]</td>
</tr>
<tr>
<td></td>
<td>[0.743, 0.860]</td>
<td>[0.743, 0.860]</td>
<td>[0.743, 0.860]</td>
<td>[0.743, 0.860]</td>
</tr>
<tr>
<td></td>
<td>[0.016, -0.035]</td>
<td>[0.016, -0.035]</td>
<td>[0.016, -0.035]</td>
<td>[0.016, -0.035]</td>
</tr>
<tr>
<td>$v_0 = 0.95$</td>
<td>[0.764, 0.822]</td>
<td>[0.764, 0.812]</td>
<td>[0.764, 0.809]</td>
<td>[0.764, 0.821]</td>
</tr>
<tr>
<td></td>
<td>[0.743, 0.874]</td>
<td>[0.743, 0.863]</td>
<td>[0.743, 0.860]</td>
<td>[0.743, 0.872]</td>
</tr>
<tr>
<td></td>
<td>[0.016, -0.036]</td>
<td>[0.016, -0.036]</td>
<td>[0.016, -0.035]</td>
<td>[0.016, -0.035]</td>
</tr>
<tr>
<td>$v_0 = 0.90$</td>
<td>[0.764, 0.837]</td>
<td>[0.764, 0.816]</td>
<td>[0.764, 0.809]</td>
<td>[0.764, 0.836]</td>
</tr>
<tr>
<td></td>
<td>[0.743, 0.889]</td>
<td>[0.743, 0.868]</td>
<td>[0.743, 0.860]</td>
<td>[0.743, 0.888]</td>
</tr>
<tr>
<td></td>
<td>[0.016, -0.038]</td>
<td>[0.016, -0.036]</td>
<td>[0.016, -0.035]</td>
<td>[0.016, -0.038]</td>
</tr>
<tr>
<td>$v_0 = 0.75$</td>
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<td>[0.764, 0.831]</td>
<td>[0.764, 0.809]</td>
<td>[0.764, 0.884]</td>
</tr>
<tr>
<td></td>
<td>[0.743, 0.938]</td>
<td>[0.743, 0.883]</td>
<td>[0.743, 0.860]</td>
<td>[0.743, 0.936]</td>
</tr>
<tr>
<td></td>
<td>[0.016, -0.047]</td>
<td>[0.016, -0.039]</td>
<td>[0.016, -0.035]</td>
<td>[0.016, -0.046]</td>
</tr>
</tbody>
</table>

Notes:
†Point estimates (p.e.) and ‡95% Imbens-Manski confidence intervals (CI) using 1,000 pseudosamples
*Estimated finite sample bias used to correct estimates.