HEALTH ECONOMICS LETTER

THE RELATIONSHIP BETWEEN PERIODONTAL INTERVENTIONS AND HEALTHCARE COSTS AND UTILIZATION. EVIDENCE FROM AN INTEGRATED DENTAL, MEDICAL, AND PHARMACY COMMERCIAL CLAIMS DATABASE

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ABSTRACT

Periodontal disease has been linked to poor glycemic control among individuals with type 2 diabetes. Using integrated dental, medical, and pharmacy commercial claims from Truven MarketScan® Research Databases, we implement inverse probability weighting and doubly robust methods to estimate a relationship between a periodontal intervention and healthcare costs and utilization. Among individuals newly diagnosed with type 2 diabetes, we find that a periodontal intervention is associated with lower total healthcare costs (−$1799), lower total medical costs excluding pharmacy costs (−$1577), and lower total type 2 diabetes-related healthcare costs (−$408). © 2016 The Authors. *Health Economics* Published by John Wiley & Sons Ltd.

1. INTRODUCTION

A bidirectional relationship has been established between type 2 diabetes and periodontitis, otherwise known as periodontal disease (Taylor *et al*., 1996; Chee *et al*., 2013). However, the evidence is mixed as to whether periodontal interventions in individuals with type 2 diabetes lead to improvements in glycemic control and other health outcomes (Simpson *et al*., 2015; Engebretson and Kocher, 2013). These studies sought to determine whether periodontal interventions for individuals with type 2 diabetes result in reduced inflammatory markers in the body. Reduced inflammation could lead to fewer diabetes-related complications, which would lower the probability of hospitalizations and emergency room visits and subsequently reduce total healthcare costs. We evaluate whether a periodontal intervention in the 2 years after initial diagnosis of type 2 diabetes is associated with lower healthcare costs and utilization in years 3 and 4. We also perform a subgroup analysis among individuals who start prescription drug treatment for type 2 diabetes after initial diagnosis. Our objective here is to determine whether a periodontal intervention is associated with lower healthcare costs among individuals who are managing their type 2 diabetes with prescription drug treatment.

2. STUDY DATA AND METHODS

2.1. Data source

We use integrated medical, pharmacy, and dental claims from Truven Health MarketScan® Research Databases. For more information, please see Appendix A1 in the Supporting Information.

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2.2. Study sample and sample selection

In this study, we selected adults aged 18 through 64 who were newly diagnosed for type 2 diabetes anytime from January 1, 2006 to December 31, 2007. An individual has to have one inpatient or two outpatient medical claims for type 2 diabetes with a corresponding ICD-9 code (American Medical Association, 2003). For individuals without an inpatient type 2 diabetes medical claim, we required two outpatient type 2 diabetes medical claims to reduce the chance of false positives. Individuals have to be continuously enrolled in a medical plan for 12 months prior to and 48 months after the initial medical claim for type 2 diabetes. Figure 1 outlines the sample selection criterion, and Figure 2 shows the longitudinal design of the study. After incorporating these restrictions, 15,002 individuals were included in the analysis. We also stratified our sample into two subgroups: initiators of diabetes medication (7367 individuals) and non-initiators of diabetes medication (7635 individuals) in the first 2 years after diagnosis. We assessed the impact of a periodontal intervention on healthcare outcomes in these two subgroups.

2.3. Treatment and control groups

We grouped individuals into treatment and control groups. Over the 2-year period after diagnosis, patients were categorized as periodontal therapy users if they had any periodontal therapy visit. We used Codes on Dental Procedures and Nomenclature (CDT) (American Dental Association, 2014) D4000 through D4999 to enumerate periodontal therapy visits. Individuals with type 2 diabetes who had no periodontal therapy visits in the 2 years after initial diagnosis were placed in the control group. We classify 2310 individuals as users of periodontal therapy.

2.4. Outcomes

We analyzed the impact of a periodontal intervention on total all-cause healthcare costs (sum of total inpatient medical costs, outpatient medical costs, and prescription drug costs), total all-cause medical costs (sum of total inpatient and outpatient medical costs), and total type 2 diabetes-related healthcare costs. The claims associated with type 2 diabetes-related medical costs have a corresponding type 2 diabetes ICD-9 diagnosis code, while the claims associated with diabetes-related prescription drug costs are paired with a diabetes prescription. We generated two binary variables capturing the incidence of a hospitalization and emergency room visit and a count variable measuring total outpatient physician visits. All cost and utilization outcomes were measured over years 3 and 4 after the initial type 2 diabetes medical claim.

2.5. Confounders

In evaluating potential confounders, we assessed factors that might influence a patient newly diagnosed with type 2 diabetes to have a periodontal intervention. Factors such as age, gender, area of residence (census region or rural inhabitant), prior medical or dental care utilization, the comorbid medical conditions a patient presents, and accumulated healthcare costs prior to diagnosis could impact a patient's likelihood to seek a periodontal intervention and their overall health. These factors are included in the model. Patient comorbidity is measured by a Charlson score (Charlson *et al*., 1987), an index value capturing the number of chronic medical conditions a person has. We calculated the Charlson index using ICD-9 diagnosis codes over 12-month periods in the year prior to and the 2 years after the initial type 2 diabetes medical claim. These three index values were then averaged to generate an average Charlson comorbidity score for each individual.

2.6. Methodology

We estimate the average treatment effect (ATE) (Rubin, 1974) of a periodontal intervention on healthcare costs and utilization. Each subject in our study has potential outcomes (Y_1, Y_0), where Y_1 is the outcome the subject would have if he received a periodontal intervention and Y_0 is the outcome the subject would have if he did not
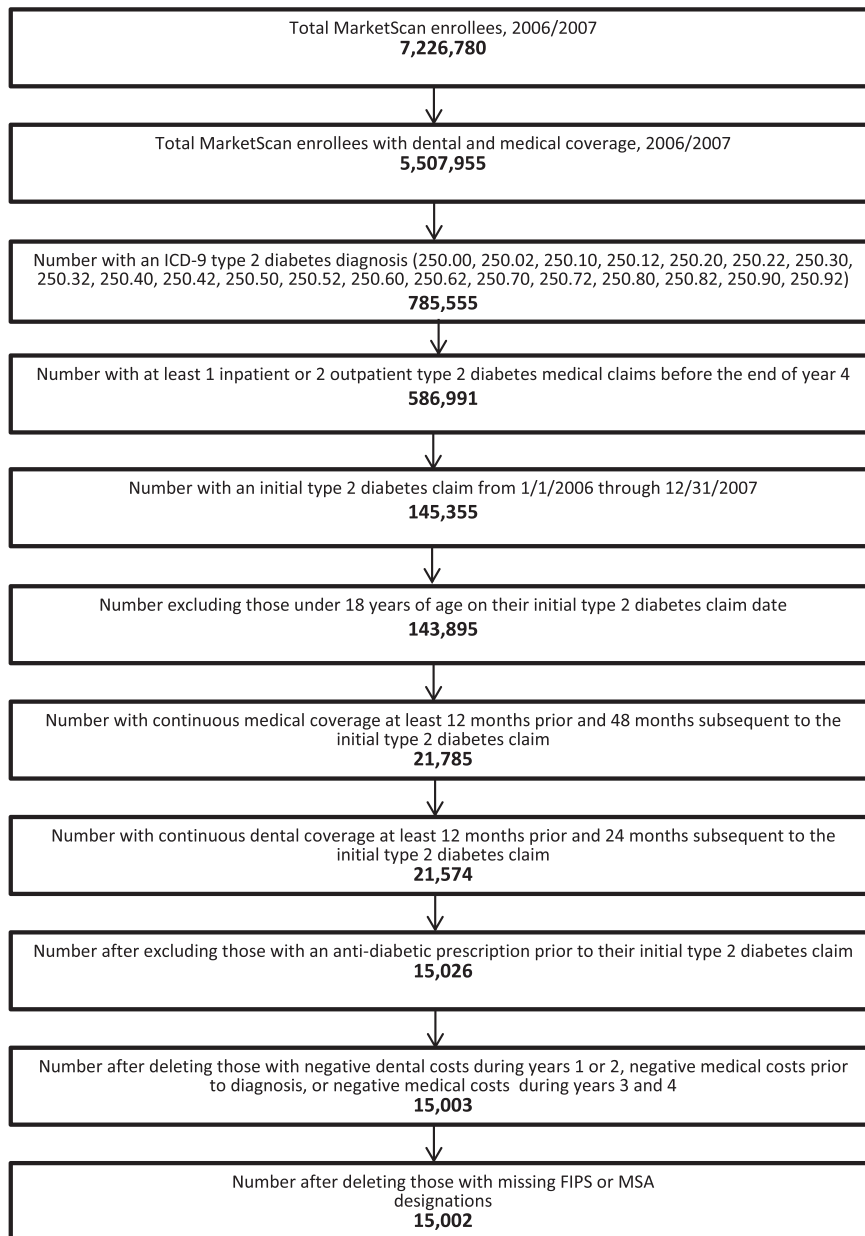
Figure 1. Study flow. Sample selection criterion for individuals with type 2 diabetes

receive an intervention. We do not observe (Y_1, Y_0) for all subjects in our study but instead only observe Y, which is defined as

$$Y = (1 - w)*Y_0 + w*Y_1 \tag{1}$$

where w *is* the intervention indicator. Given the vector of observed covariates, **X**, which have been previously specified in Section 2.4, we assume ignorability of treatment otherwise known as 'selection on observables' (Rosenbaum and Rubin, 1983). By ignorability, we assume that conditional on **X**, w and (Y_1, Y_0) are
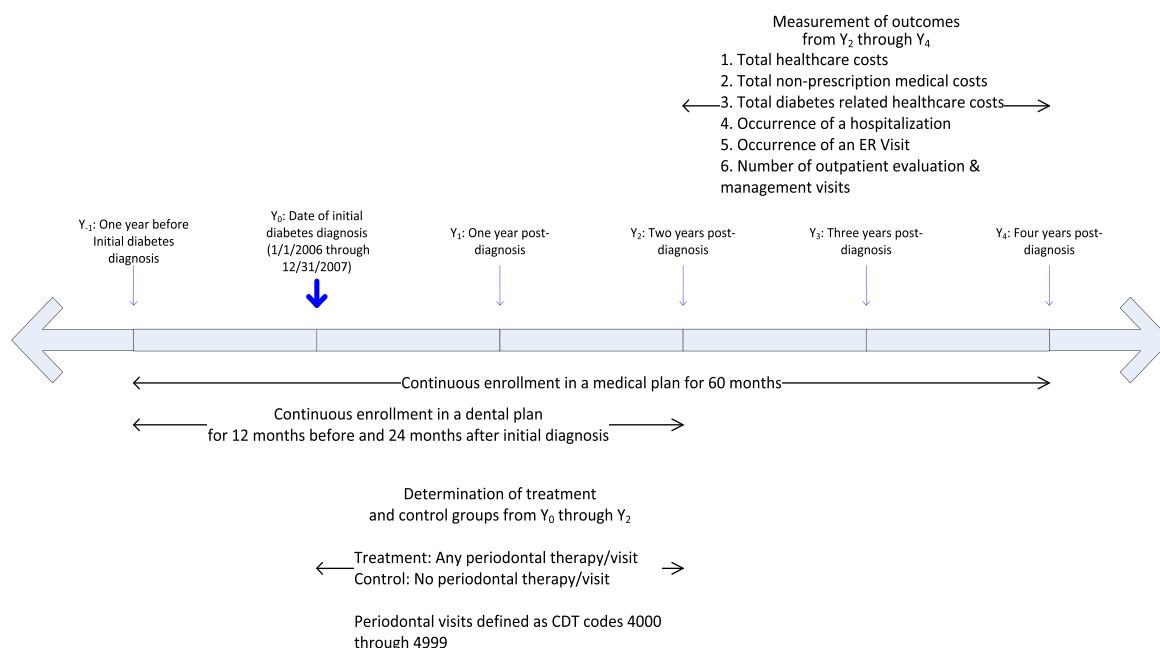
Figure 2. Study timeline. Determination of treatment and control groups along with outcome measures. [Colour figure can be viewed at wileyonlinelibrary.com]

independent. We make the strong assumption that unobservable factors do not confound the relationship between a periodontal intervention and healthcare outcomes. We also assume overlap, $0 < p$ (w = 1|$\mathbf{X}$) < 1, in the distribution of the propensity score in the treatment and control groups. Given these assumptions, we estimate an ATE.

$$
\begin{aligned}
\text{ATE} \quad &= E(Y_1) - E(Y_0) \\
&= E\{ E(Y \,|w \,=\, 1, \mathbf{X}) \,-\, E(Y \,|w \,=\, 0, \mathbf{X}) \} = E[m_1(\mathbf{X}) - \, m_0(\mathbf{X})]
\end{aligned}
\tag{2}
$$

For each observation, $m_1(\mathbf{X})$ and $m_0(\mathbf{X})$ are estimates of the potential outcomes (Y_1, Y_0). We average the differences in these estimates across the entire sample in order to estimate an ATE. After using a logit model to estimate the propensity score, $\hat{p}(\mathbf{X}_i)$,

$$
\hat{p}(\mathbf{X}_i) = \frac{\exp(\mathbf{X}_i \hat{\beta})}{(1 + \exp(\mathbf{X}_i \hat{\beta}))}
$$

we estimate ATEs of a periodontal intervention on years 3 and 4 costs and utilization using inverse-probability weighting and doubly robust (DR) methods (Wooldridge, 2007). The estimated propensity score is used in the inverse weights used to compute the ATEs (Appendix A2 in the Supporting Information). In order to account for the fact that costs and number of physician visits are nonnegative responses with continuous and discrete properties respectively, we use an exponential mean function with the Poisson quasi-log likelihood (QLL) weighted by the inverse of the propensity score to estimate a DR estimator (Robins and Rotnitzky, 1995; Robins, Rotnitzky, and Zhao, 1995; van der Laan and Robins, 2003; Wooldridge, 2007). Without having to make strong distributional assumptions, as long as either the propensity score model or the conditional mean outcome model is correctly specified, double robustness holds, and the ATE is consistently estimated. The DR property holds when estimating a Poisson QLL for nonnegative outcome responses and a logistic function with the Bernoulli QLL for a binary outcome response (Wooldridge, 2007). We used a Bernoulli QLL when estimating the DR ATE of a periodontal intervention on binary outcome variables. Standardized differences on the reweighted sample are calculated to assess balance in

observed covariates across the treatment and control groups. For comparison, we also estimate average treatment effects on the treated (ATET). For more information on ATETs, please see Appendix A2 in the Supporting Information.

2.7. Limitations

There are a number of limitations in this study. First, because diagnostic coding is not used in dentistry, we cannot identify periodontal disease status. Ideally, we would select patients with type 2 diabetes and periodontitis and split them into treatment and control groups depending on whether they received a periodontal intervention. Unfortunately, we can only identify whether a person newly diagnosed with type 2 diabetes had a periodontal visit, which is identified using CDT codes. As a result, we expect that some portion of newly diagnosed individuals with type 2 diabetes not receiving a periodontal intervention actually do not have periodontal disease. Among this subgroup, there is likely no medical cost savings associated with a periodontal intervention. Hence, we believe that our estimates of medical costs savings associated with periodontal interventions are biased downward because of this limitation.

Second, we cannot observe other possible confounders, such as a patient's motivation to seek care or ability to self-manage their health. We also do not have access to variables measuring household income or race/ethnicity, factors that could influence one's ability to seek a periodontal intervention and subsequent healthcare outcomes. We proxy for possible unobserved confounders by including pre-diagnosis healthcare costs and medical and dental care use in our models. Despite the inclusion of these factors in our models, we cannot rule out unobservable confounding.

Although we attempt to control for confounding bias using propensity score methods, we may not be able to mitigate the impact of selection bias on our treatment effect estimates (Haneuse, 2013). Our sample falls from 143,895 individuals to 21,785 when we impose a continuous insurance enrollment restriction. However, in order to identify individuals who are newly diagnosed for type 2 diabetes, we need to make sure that no individual had a drug or medical claim for the disease in the year prior to diagnosis. In order to assess the long-term impact of a periodontal intervention on healthcare costs and utilization, we also require that an individual be enrolled in a healthcare plan. Because of the nature of the association between type 2 diabetes and periodontitis, a sufficient follow-up period is necessary in order to pick up any effect of a periodontal intervention on healthcare outcomes. Unfortunately, our continuous enrollment criteria may induce sample selection bias in our study and compromise external validity. We also do not have variables in our claims data that would allow us to determine the potential factors that would cause an enrollee to drop out of a healthcare plan and allow for us to build a selection model. For example, an individual's employment status may determine whether someone is enrolled in a healthcare plan. As acknowledged by Haneuse (2013), resolving selection bias using claims data is an 'open methodologic problem'.

Furthermore, we restricted our sample to only individuals newly diagnosed with diabetes in order to minimize patient heterogeneity between the treatment and control groups. Patients with established diabetes and higher HbA1c levels may be more likely to self-select into periodontal treatment. Ideally, we would have individuals in the treatment and control groups with roughly the same HbA1c levels. Unfortunately, we do not have access to lab records in our claims data. Hence, diabetes disease progression and HbA1c levels are potential unobserved confounders in our models.

3. RESULTS

In Appendix Table I in the Supporting Information, we calculate descriptive statistics. Standardized differences on the un-weighted data indicate some imbalance in the potential confounders. The treatment group is older, more urban, less concentrated in the south, and more likely to have a dental visit prior to initial diabetes diagnosis. After the data are re-weighted based on the estimated propensity score, the standardized differences in the

confounders across the treatment and control groups declined significantly. This indicates good balance between the two groups (Appendix Table II in the Supporting Information). The distribution of the propensity score for the treatment and control groups also suggests good overlap (Appendix Figure 1 in the Supporting Information).

Table I shows the DR ATE estimates of a periodontal intervention on costs and utilization. Individuals newly diagnosed with type 2 diabetes who have undergone a periodontal intervention have total healthcare costs that are \$1799 lower on average over years 3 and 4 compared with those who have not had a periodontal intervention. Total medical costs are \$1577 less on average for the treatment group. Total diabetes-related healthcare costs are \$408 lower on average for the treatment group. There are not statistically significant differences in total outpatient physician visits, probability of a hospitalization, or the occurrence of an emergency room visit between the treatment and control groups. For visual comparison of all ATE estimates, please see Appendix Figures 2–7 in the Supporting Information. DR ATETs estimates measuring the relationship between a periodontal intervention and healthcare costs and utilization were very similar to DR ATE estimates (Table II).

3.1. Subgroup analysis

In Appendix Table III in the Supporting Information, we estimate the DR ATE of a periodontal intervention among individuals who did not receive any diabetes-related medication in years 1 and 2 after initial diagnosis. Users of periodontal therapy have total healthcare costs that are \$2042 lower on average over years 3 and 4. Total medical costs are \$1609 lower on average. Type 2 diabetes-related healthcare costs are \$411 lower on average. A periodontal intervention does not have a statistically significant association with emergency room usage or the number of outpatient physician visits. The un-weighted logit regression estimate suggests that a periodontal intervention is associated with a 2.1 percentage point lower probability of a hospitalization (odds ratio: 0.829; 95% CI [0.684, 1.00]).

A periodontal intervention does not have a statistically significant association with healthcare costs or utilization among individuals who initiated drug treatment (Appendix Table IV in the Supporting Information). The DR ATETs estimates were very similar to DR ATE estimates (Appendix Tables V and VI in the Supporting Information).

4. SUMMARY

We found a statistically significant association between a periodontal intervention and lower healthcare costs. However, this association is only noted among individuals who did not initiate diabetes prescription drug therapy after diagnosis. Among individuals who have initiated diabetes prescription drug therapy, a periodontal intervention appears to have no impact on costs. This may be a sign of a heterogeneous treatment effect. For example, a periodontal intervention may provide little incremental benefit when type 2 diabetes is being managed through prescription drug treatment. Or, there could be unobservable confounding factors. For example, prescription drug treatment could be a marker for disease severity. Patients with higher HbA1C levels may be more likely to be on a prescription drug regimen. As stated previously, we do not have access to patient lab records in our data. As for patients who did not initiate prescription drug treatment after diagnosis, we hypothesize that their HbA1c levels are sufficiently controlled that their physicians do not deem drug treatment necessary. Hence, there may be a modest benefit from a periodontal intervention in this subgroup.

After factoring in the cost of periodontal therapy in the first 2 years after diagnosis (\$471) and subsequent total healthcare cost savings in years 3 and 4 among users of a periodontal intervention (\$1799), net savings are \$1328 over 2 years. If one only accounts for total type 2 diabetes-related healthcare cost savings in years 3 and 4 (\$408), there is a small net cost of \$63 associated with a periodontal intervention. Compared with the simple difference estimates, our DR ATE estimates were similar. This may suggest that observable factors do not significantly confound the estimates. However, we were unable to fully capture factors, such as patient motivation, that potentially confound the relationship between a periodontal intervention and healthcare outcomes.

Table I. Cost and utilization outcomes

Outcome	Simple difference	Un-weighted regression adjustment (Poisson)	Un-weighted regression adjustment (Gamma)	Un-weighted regression adjustment (Logit)	IPW estimate	Doubly robust[a]
Total healthcare cost	−1485.55** (677.60)	−1744.27*** (665.08)	−1477.59* (785.86)	NA	−1726.01** (702.16)	− 1798.71*** (674.38)
Total medical cost	−1422.99** (624.67)	−1541.36** (632.05)	−1229.39 (752.85)	NA	−1525.29*** (648.54)	−1576.71** (634.57)
Total type 2 diabetes healthcare cost	−449.31*** (183.44)	−411.85** (188.46)	−335.76* (192.52)	NA	−401.66*** (188.49)	−407.87** (199.65)
Any hospitalization	−0.017** (0.008)	NA	NA	−0.013* (0.008)	−0.012 (0.008)	−0.012 (0.009)
Any emergency room visit	−0.026*** (0.010)	NA	NA	−0.012 (0.010)	−0.011 (0.011)	−0.011 (0.011)
Total outpatient physician visits	0.023 (0.227)	−0.179 (0.209)	NA	NA	−0.111 (0.232)	−0.142 (0.205)
Number of observations	15,002					
Periodontal treatment group observed	2310					
Periodontal control group observed	12,692					

ATE estimates. All type 2 diabetes individuals.
Standard errors are in parentheses. Cost and utilization outcomes measured in years 3 and 4 after initial diabetes diagnosis. Ordinary least squares used to estimate simple differences. Robust standard errors used in simple difference, pooled Poisson, pooled Gamma, and inverse-probability weighting (IPW) estimation. Truven MarketScan® Research Databases.
[a]Bootstrapped standard errors using 400 replications.
*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table II. Cost and utilization outcomes

Outcome	ATET[a]
Total healthcare cost	−1829.50*** (676.38)
Total medical cost	−1580.87** (640.80)
Total type 2 diabetes healthcare cost	−439.22** (193.66)
Any hospitalization	−0.012 (0.008)
Any emergency room visit	−0.013 (0.010)
Total outpatient physician visits	−0.242 (0.209)

Average treatment effect on the treated (ATET) doubly robust estimates. All individuals with type 2 diabetes
Standard errors are in parentheses. Cost and utilization outcomes measured in years 3 and 4 after initial diabetes diagnosis. Truven MarketScan® Research Databases.
[a]Bootstrapped standard errors using 400 replications.
*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

DISCLOSURE STATEMENT

There are no further disclosures or disclaimers.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's web site.