

Georgia State University
ScholarWorks @ Georgia State University

Public Health Theses

School of Public Health

Summer 2018

AN INVESTIGATION OF CHANGES IN DIABETES TRENDS AFTER THE AFFORDABLE CARE ACT

Blair Christensen

Follow this and additional works at: https://scholarworks.gsu.edu/iph_theses

Recommended Citation

Christensen, Blair, "AN INVESTIGATION OF CHANGES IN DIABETES TRENDS AFTER THE AFFORDABLE CARE ACT."
Thesis, Georgia State University, 2018.
https://scholarworks.gsu.edu/iph_theses/610

This Thesis is brought to you for free and open access by the School of Public Health at ScholarWorks @ Georgia State University. It has been accepted for inclusion in Public Health Theses by an authorized administrator of ScholarWorks @ Georgia State University. For more information, please contact scholarworks@gsu.edu.

ABSTRACT

AN INVESTIGATION OF CHANGES IN DIABETES TRENDS AFTER THE AFFORDABLE CARE ACT

By

BLAIR CHRISTENSEN

4/15/18

INTRODUCTION: Diabetes Mellitus (DM) is one of the fastest growing and most costly chronic diseases in the United States. DM is severely underdiagnosed, resulting in increased complications, costs, and mortality. Primary goals of the Affordable Care Act (ACA) were to increase health insurance coverage and access to care, and to improve chronic disease outcomes. However, the effects of the legislation have not been widely studied, particularly the relationship between proper diabetes diagnosis and a variety of health related factors.

AIM: Determine the relationship between DM prevalence and under-diagnosis, to healthcare utilization, usual source of care, insurance, type of insurance, and population characteristics have changed since the implementation of the ACA.

METHODS: Data collected between 2005 and 2016 in the National Health and Nutrition Examination Survey were used for this work. The Andersen behavioral health model was used as a theoretical framework and selection of study variables. Descriptive statistics and advanced statistical modeling techniques were applied. Distinct multilevel models were used to model the logit of the probability of DM and the logit of the probability of a proper DM diagnosis each as a function of study variables with an indicator of pre- or post-ACA included as a fixed effect. Marginal models are multilevel models that apply population averaged estimates for parameters. Marginal models were specified to account for clustering by time, and generalized estimating equations used to estimate model parameters. The quasi-likelihood under the null (QIC) statistic was estimated for model comparisons. The SAS Software System was used for data analysis and the level of significance set at .05.

RESULTS: The sample consisted of 31,225 participants, with half pre-ACA (n=15,612) and half post-ACA. Females comprised 51.64% of the study sample with 43.50% White, 25.82% Hispanic, and 20.65% Black and a mean (standard deviation) age of 49.3 (17.9) years. About 11.45% of those in the Pre ACA period had a diagnosis of DM, while 13.5% of those in the Post ACA period had a diagnosis of DM. The percentage of uninsured was 23.95% in the Pre ACA

period and 20.69% in the Post ACA time period. The prevalence of undiagnosed DM patients was 26.7% before the ACA, and 21.3% after. A multilevel model with DM status as the dependent outcome showed that sex (females vs males: OR=0.83, 95%CI=0.78,0.89,p=.02), USC (yes vs no: OR=1.28, 95%CI=1.03,1.59, p=.03), health insurance (yes vs no: OR=1.21, 95%CI=1.17,1.26, p=.02), and education level(college graduate vs less than high school: OR=0.79, 95%CI=0.64,0.97, p=.05, high school graduate vs less than high school: OR=0.97, 95%CI=0.93,1.03, p=.05) were significantly associated with presence of DM. Participants were more likely to have their DM properly diagnosed after the ACA: in the final multivariable multilevel model, only ACA time period had a significant effect on correct DM diagnosis (OR=1.51, 95%CI=1.24,1.85, p=.04).

CONCLUSIONS: Although prevalence of DM has increased in recent years, under-diagnosis is less of an issue after the ACA. In the multivariable model comparing DM status (having the disease) to selected covariates, sex, health insurance, education, and USC were related to DM status. The ACA time period had no significant relationship with DM status in the multivariable model. However, in the multivariable model for correctly diagnosed DM, ACA time period was the only independent variable that had a significant association with correct DM diagnosis.

AN INVESTIGATION OF CHANGES IN DIABETES TRENDS AFTER THE AFFORDABLE
CARE ACT

by

BLAIR CHRISTENSEN

B.S.E.S., UNIVERSITY OF GEORGIA

A Thesis Submitted to the Graduate Faculty
of Georgia State University in Partial Fulfillment

of the

Requirements for the Degree

MASTER OF PUBLIC HEALTH

ATLANTA, GEORGIA

30303

APPROVAL PAGE

AN INVESTIGATION OF CHANGES IN DIABETES TRENDS AFTER THE AFFORDABLE
CARE ACT

by

BLAIR CHRISTENSEN

Approved:

Matthew Hayat

Committee Chair

Ashli Owen-Smith

Committee Member

April 17th 2018

Date

Author's Statement Page

In presenting this thesis as a partial fulfillment of the requirements for an advanced degree from Georgia State University, I agree that the Library of the University shall make it available for inspection and circulation in accordance with its regulations governing materials of this type. I agree that permission to quote from, to copy from, or to publish this thesis may be granted by the author or, in his/her absence, by the professor under whose direction it was written, or in his/her absence, by the Associate Dean, School of Public Health. Such quoting, copying, or publishing must be solely for scholarly purposes and will not involve potential financial gain. It is understood that any copying from or publication of this dissertation which involves potential financial gain will not be allowed without written permission of the author.

____Blair Christensen_____

Signature of Author

TABLE OF CONTENTS

LIST OF TABLES.....	vii
INTRODUCTION.....	1
1.1 Background.....	1
1.2 Research Questions.....	2
REVIEW OF THE LITERATURE.....	2
2.1 Epidemiology of DM	2
2.2 Health Behaviors and Outcomes	4
2.3 Factors Associated with DM Outcomes.....	5
2.4 Impact of the ACA.....	7
2.5 Gaps in the Literature.....	8
METHODS AND PROCEDURES.....	9
3.1 Data Source.....	9
3.2 Study Population.....	10
3.3 Study Sample.....	10
3.4 Dependent Variables.....	11
3.5 Independent Variables.....	11
3.6 Statistical Analysis.....	11
RESULTS.....	13
4.1 Descriptive Statistics for DM.....	13
4.2 Associations with DM.....	15
4.3 Descriptive Statistics for DM Diagnosis.....	17
4.4 Associations with DM Diagnosis.....	18
DISCUSSION AND CONCLUSION.....	19

5.1 Discussion.....	19
5.2 Methodological Limitations.....	22
5.3 Statistical Limitations.....	24
5.4 Conclusions.....	24
REFERENCES.....	26

List of Tables

Table 4.1 Descriptive statistics of socio-demographic factors, health behavior, and DM study variables.

Table 4.2 Multilevel marginal model regression coefficient estimates (p-values) for DM status with selected covariates (n=31,225).

Table 4.3 Model comparisons across correlation structures

Table 4.4 Final multivariable multilevel model of DM status with selected covariates

Table 4.5 Descriptive statistics of study variables by DM diagnosis before and after the ACA

Table 4.6 Table 4.6: Final multivariable multilevel marginal model of an indicator of properly diagnosed DM with selected covariates (n=3394).

Introduction

Diabetes Mellitus (DM) is one of the fastest growing and most impactful chronic diseases in the United States and encompasses several different diseases, all characterized by issues in proper insulin manufacture and utilization and resulting high blood glucose levels[1] [2].

Chronic diseases have fast been replacing infectious diseases as the primary public health issues of interest in developed countries. Those afflicted suffer from not only diminished life expectancies but also a decrease in quality of life, and a high burden of expenses and time that must be devoted to managing the disease. When a healthcare system is ill-equipped to handle the regular maintenance and upkeep of the disease, it is reflected in poor self-care, complications, and worsened outcomes, not to mention an increased financial burden at both the individual and the system-level.

DM is also severely underdiagnosed. Nearly a quarter of those with DM have not been diagnosed by a doctor[1]. An unknown or late-stage DM diagnosis results in a lack of self-care and awareness, manifesting in increased complications, costs, and mortality[3]. Someone who has DM but has not been formally diagnosed by a doctor is known as a “missed patient”.

One of the primary goals of the Affordable Care Act (ACA) was to increase the prevalence of health insurance and access to care, and to improve chronic disease outcomes. The rationale behind this is that broadened insurance coverage in the population and improved ease of access should lead to an increase in utilization, which prior research dictates should improve healthcare outcomes. Since the legislation is still relatively new and untested, there is no definitive answer as to whether DM-related outcomes have improved.

The National Health and Nutrition Examination Survey (NHANES) contains information on socio-demographic, behavioral, and laboratory values, and is designed to be representative of the entire US population[4]. NHANES provides an ideal data source for an adapted Andersen model examining health behaviors and DM outcomes as they relate to the ACA. This adapted model can be used as a starting point for multivariate analysis and the eventual construction of a multilevel model taking the clustering by survey cycle into account.

This study will address not only how DM outcomes might have changed following the implementation of the ACA but also how the relationship between insurance status (type and presence or absence of), utilization, and Usual Source of Care(USC) with DM outcomes may have changed along with the shift in the regulatory and policy environment. It will also determine if there has been a shift in patterns of diagnosis since the passage of the ACA. Previous studies (detailed below) have usually examined only one of these factors' relationship to a health outcome, rather than how they might interact to result in an outcome. For DM, disease status is also usually only assessed by clinical diagnosis, which becomes problematic in underserved populations that do not utilize healthcare services- a diagnosis is not the best reflection of actual disease status in these instances. In this study, a HbA1c blood test is used to determine if an individual has DM. By employing a multi-level modeling approach to study time periods before and after the passage of the ACA, the disregard for the clustering of the data found in many prior studies will be remedied.

Disentangling the relationship between policy, healthcare behaviors, and DM outcomes is important for several reasons. Better understanding the impact of healthcare reform on chronic disease outcomes could help to improve and shape future legislation. An idea of the true relationship between complicated sets of healthcare behaviors and causes can also guide

healthcare recommendations and improve outcomes for diabetics. Understanding these relationships for DM could also help to inform decisions about other chronic diseases.

The questions this study seeks to answer are:

- I. Controlling for demographic characteristics, has the association between insurance status and DM changed since the passage of the ACA?
- II. Controlling for demographic characteristics, has the association between healthcare utilization and DM changed since the passage of the ACA?
- III. Controlling for demographic characteristics, has the association between having a USC and DM changed since the passage of the ACA?
- IV. What demographic characteristics are associated with being a “missed patient” and have the associations changed since the passage of the ACA?
- V. Has the prevalence of “missed patients” changed since the passage of the ACA?

Literature Review

Epidemiology of DM

DM encompasses several different diseases, all characterized by issues in proper insulin manufacture and utilization and resulting high blood glucose levels[1]. Type 2 DM is the most common form and can be defined as an acquired intolerance to insulin due to dietary and lifestyle factors. The prevalence of DM has been increasing and is projected to continue increasing[2]. DM has become a public health crisis, with 30.3 million diabetics in the US, nearly a quarter of which (23.8%) are estimated to be undiagnosed[5]. The low diagnosis rates are thought to be consequence of the fact that many diabetics do not enter the healthcare system until they begin suffering from complications from their disease[1]. Type 2 DM is diagnosed

using the HbA1c test, with results greater than or equal to 6.5% indicating controlled DM and values above 8% indicating uncontrolled DM[6]. The HbA1c is considered the gold standard in diagnosing DM[1]. DM patients spent more than twice as much on medical expenditures and non-diabetics[7]. Diabetics have a high burden of maintenance costs, which include regular doctor visits, medication, education programs, specialized diets, and other assorted items[8]. In addition to the maintenance costs associated with DM, the potential of comorbidities and complications from mismanagement and the natural progression of the disease also impose a massive burden on the public health system[8-10]. Uncontrolled DM can lead to foot ulcers and amputations, eye deterioration, kidney disease, cardiovascular disease, mobility issues, high cholesterol, and an overall reduction in both quality of life and overall life span[1]. The estimated cost from DM in 2012 was \$245B, not including the undiagnosed burden and unpaid care[7].

Health Behaviors and Outcomes

Andersen's Behavioral Model of Health Utilization was first proposed in the early 1970's as a way to study and predict individual usage of health services. [11] The next update to the model included external and environmental factors, along with incorporating user satisfaction with services [12]. The current iteration of the model includes four primary spheres of influence, all of which connect and create a kind of feedback loop: Environment, Population Characteristics, Health Behavior, and Outcomes.[13, 14] This construction allows for the examination of the relationship between complicated sets of healthcare behaviors, demographic characteristics, policy and healthcare system changes, and outcomes, both quantitative and qualitative. The Andersen model is generally accepted as the best framework when analyzing complex and nuanced healthcare concepts, like utilization and access to care [15-17].

Environmental factors can include regulatory environment and policy changes in the health care system and time could be incorporated as a variable. Population characteristics are divided into three distinct sections: Predisposing (including Demographic and Social attributes), Enabling (including Financial and Accessibility factors) and Need. Need-based characteristics are rooted more in perception of need than in actual physical need, including perceived health status and previous diagnosis of a disease[13]. Using Andersen's model allows for a better understanding of health behavior and utilization and the inclusion of the necessary characteristics and external factors to fully describe the relationship.

Factors Associated with DM-outcomes

It has been long established that health outcomes and behavior exhibit distinct racial and cultural disparities. Minorities, smokers, those of lower Socioeconomic Status(SES) and those with less education are more likely to have DM[18]. DM development and outcomes, along with management of care, are also associated with socioeconomic factors and behaviors[19]. Perception of health status and denial about health problems is a common reason why health services might not be fully utilized or chronic disease care left unmanaged[20]. There are racial and socioeconomic class differences in DM screening diagnosis accuracy[21]. Increased utilization of health services, medication adherence and disease management were shown to be associated with the perception of personal health status [22]. An official diagnosis of DM did not seem to influence health behaviors or perception of health status[22]. A 2009 study found that a significant proportion of Diabetics (around 10%) had no health insurance coverage, usually due to high premium costs[23].

Health Services Utilization is a multifaceted and difficult to quantify concept. It can be defined as “the measure of the population's use of the health care services available to them,”

and can be an indicator of “how efficiently a health care system produces health in a population”[24]. Utilization is a behavior pattern determined by demographic characteristics, like ethnicity, and external environmental factors, like policy, the effect of which can be measured in discrete outcomes. Utilization has been associated with increased mortality in high risk groups[25], but this association is not causal and, in general, utilization is associated with improved preventative care and health behaviors[26]. Insurance coverage increases the likelihood of utilizing care[27].

Usual Source of Care(USC) is defined as “a particular doctor’s office, clinic, health center, or other place one goes to if one is sick or needs advice about health.”[28] The effects of having a USC have been a source of debate in the literature for some time now. One theory is that a USC is determined by utilization and only indirectly affects doctor visit frequency, while the other is that the lack of a USC serves as a barrier to access, directly minimizing the amount of doctor visits and utilization[29]. It has been established that not having a USC can limit continuous utilization of services. This is particularly important for DM care, which requires consistent monitoring and attention[30, 31]. Having a USC also serves as a proxy for access to the overall healthcare system and is associated with improved outcomes and preventative care[30, 32]. A USC was found to be a better predictor of access to care than whether or not a patient was insured[33].

Insurance coverage alone does not ensure utilization of care[34-38]. A 2012 study found that a USC was more important than health insurance coverage in determining utilization and outcomes; children with both a USC and insurance had better outcomes than those with only insurance. Having only a USC was more beneficial than only having insurance[34]. While

insurance does not ensure access, being insured has been found to be associated with a higher quality of care and improved access[39].

Type of insurance has also been shown to effect health outcomes and perceptions. Less physicians accept new patients with public insurance than private, and certain physicians do not accept any public insurance coverage[40, 41]. Medicaid users report feeling more stigmatized and have worse access and health outcomes than those with private insurance [42]. Private health insurance coverage has also been found to be correlated with higher incomes and previous health status, and public insurance programs tend to decline in per capita resources and quality of care over time[43].

Having DM is associated with physician quality and type of insurance plan, and DM patients with self-stigma issues had worsened outcomes. [44-46] Poor glycemic control and outcomes in DM patients were associated with cost and lack of insurance, isolation, and difficulty accessing care[47]. A lack of access and lack of insurance were found to be associated with a delay or complete failure to have DM diagnosed, known as being a “missed patient”. [48]

Impact of the ACA

The passage of the Patient Protection and Affordable Care Act (ACA) was supposed to provide renewed focus on lowering barriers to access and expanded, affordable insurance coverage. While research has been done on the effects of the legislation, many studies are contradictory, small, or focused more in the realm of health economics[49-52]. The ACA certainly increased insurance coverage, with the lowest ever amounts of uninsured Americans. It is estimated that the number of those without coverage was reduced by around 20 million due to

the passage of the ACA, and the effects were present in the entire population, regardless of age, race, gender, or level of education[53]. Studies conducted after the implementation of the ACA have found improved access to care and higher percentages of insured, compared to before the legislation was passed[26]. In Medicaid expansion states, DM outcomes were greatly improved and hospitalizations were minimized. [54] Diabetic adults without insurance utilize care less and have less access to care. The increased access and coverage provided by the ACA has increased the utilization of healthcare services among diabetics, possibly leading to better overall health conditions and lower incidence of DM complications.[55]

In those newly insured due to the ACA, having a USC was more common, preventative visits, glucose testing and utilization of services increased, and there was a marked improvement in self-reported health status[56]. Socioeconomic status is linked to utilization, and health status must be considered when analyzing utilization across different socioeconomic classes[57, 58]. In the past, major policy initiatives and shifts in the regulatory environment have been shown to influence utilization[59].

Gaps in the Literature

There has been no research comparing the relationship between utilization, access, insurance and blood glucose level outcomes before and after the implementation of the Affordable Care Act. This study will address not only how DM outcomes might have changed following the implementation of the ACA but also how the relationship between insurance status (type and presence or absence of), utilization, and access with DM outcomes may have changed along with the shift in the regulatory and policy environment. Among studies that have examined one of these factors relationship to DM outcomes, none have used a multilevel modeling approach or examined a wide array of NHANES data. Failing to take the clustering of the data

into account in this way results in biased parameter estimates and ultimately leads to incorrect conclusions.

There has also been little research on missed patients, and nothing assessing their prevalence comparing regulatory environment. Studying underdiagnosis is fundamentally difficult, because the true disease status must be determined for those without a diagnosis, usually through a blood test. This is much more invasive and resource-intensive than simply filling out a questionnaire with disease status. Most previous studies have not analyzed DM status as a function of a HbA1c test. The problem of under-diagnosis is remedied, as the results of this test are not dependent on having been previously diagnosed with the disease. Previous studies examining more than one cycle of NHANES have also often neglected to take the clustering of data by year into account.

Methods

Data source

The National Health and Nutrition Examination Survey (NHANES) is completed in continuous 2-year cycles by the Centers for Disease Control and was created to examine the nutritional and health status of all non-institutionalized adults and children in the United States. The survey sample contains around 5000 people each year from 15 United States counties and is designed to be nationally representative. NHANES oversamples Blacks, Hispanics, and those older than 60 years of age, and the examination portion is more extensive in older participants. The interview portion gathers information on socioeconomic, dietary, demographic, and health questions. This interview is conducted in the participants home, in a variety of different languages. There is also an examination portion, where medical, dental, and physical aspects are

measured; laboratory tests are also included. This portion of the survey takes place through participant visits to mobile clinics that travel with NHANES [1]. One unique aspect of the survey is that it collects biological samples along with questionnaire and demographic data. An HbA1c is included in the laboratory data, and has been shown as a useful and accurate indicator of DM status and previously undiagnosed DM, particularly in a single-visit setting[60]. This provides a unique opportunity when studying DM outcomes- the usual under-diagnosis is a negligible factor and does not need to be considered. NHANES also includes information on demographics, use of health services, insurance coverage and type, and USC (USC). Socio-demographic characteristics and general healthcare questions were utilized from the NHANES questionnaires. Three two-year cycles (2005-2006, 2007-2008, and 2009-2010) represented the time period before the ACA, and three cycles (2011-2012, 2013-2014, and 2015-2016) for after the ACA.

Study population

The study population captured by NHANES are United States residents of all ages who are not institutionalized, living in nursing homes, living abroad, or in the armed forces.

Study sample

To create the sample, the entire United States (including Alaska and Hawaii) is divided into 15 groups, and a single county is selected from each group. Then around 20 smaller subdivisions are selected from each county. Roughly 30 households are selected from each subdivision, and all household members are interviewed. A random algorithm then selects a random number of the participants in each household[4]. Only individuals who had participated in the relevant questionnaires and had a measurement for the response variable were included in the analysis. Individual observations for some questions could still be missing. Only respondents

age 20 or above were included in the final dataset. Table 4.1 includes the measurements for the study sample by pre- and post-ACA.

Dependent Variables

The traditional HbA1c test findings were used to create the dependent variable. The continuous measured value represented the percentage of glycated hemoglobin present in the blood. For the analysis, the outcome was created by dichotomizing HbA1c test with a cutoff of 6.5% or above indicating DM[1]. Only those with non-missing values for the outcome variable were selected for the sample(n=31225). “Missed Patient” status was determined by creating a new variable from only those above the 6.5% cutoff and whether they had previously received a DM diagnosis from a doctor.

Independent Variables

Utilization and access were operationalized in this study as the amount of doctor visits in the last 12 months and whether an individual had a USC, defined as “a routine place to go for healthcare or when you are sick”. Frequency of doctor visits was an ordinal variable with the categories: 0 visits, 1 visit, 2-3 visits, 4-9 visits, 10-12 visits, and 13 or more visits. General health condition was recoded into a three-category variable: Poor/Fair, Average, and Good/Excellent. Insurance status and DM diagnosis were binary variables. Insurance type was recoded into Private, Medicare, Medicaid/Medigap, Other, and None. Education was recoded into a three-category variable, less-than High school, High school graduate, and College graduate or above. Income was assessed using the income to poverty level ratio. Race/Ethnicity was broken into 4 categories: Hispanic, White, Black, and other.

Statistical Analysis

The SAS Software System was used for all the statistical analyses. The level of significance was set at .05. Although NHANES is a complex multistage weighted survey, previous studies have shown that the difference in error that comes from discounting them may be potentially insignificant and possibly may not greatly alter inferences made [61]. The methods for including survey weights in a multilevel modeling scheme are also complex. The SAS Software System multilevel modeling procedures do not allow for simultaneously fitting multilevel models and accounting for complex sampling weights. Since a primary interest was in accounting for the clustering within survey year to apply multilevel models, these were used and survey weights not accounted for in analyses presented here. The caveats and possible repercussions of this choice are included in the discussion.

In repeated measures or clustered longitudinal data, the assumption of independence of observations necessary for many modeling techniques (Logistic Regression, ANOVA) is violated[62]. In this dataset, there are two levels of variables. The first level is individual measurements and the second level is the survey year. Ignoring the clustering of observations leads to biased estimation and incorrect standard errors. Multilevel modeling techniques account for clustering or grouping of data. Marginal models are a semi-parametric method that averages the random effects of the second-level variable to provide a population-averaged coefficient, rather than individual-level estimates. This approach allows meaningful conclusions to be drawn. Marginal models use Generalized Estimating Equations(GEE) to estimate parameters [63]. A Marginal Mixed model was constructed for each Bivariate comparison and for the selected multivariable model.

Variables were selected for inclusion in the final model using a combination of a data-driven and a theory driven approach. A theoretical relationship between the outcome, health

behavior, population characteristics and environment was assessed by creating a modified Andersen Behavioral model of Healthcare Utilization. This model was used to select variables to be tested for inclusion in the model from the NHANES dataset. Eight possible models were identified from the constructed behavior model and tested. Quasi likelihood under the Independence Model Criterion(QIC) was then used to select the correlation structure and the variables for inclusion in the final model[64]. Although GEE is robust to misclassification of the correlation structure, testing for correct structure is efficient and desirable. The structures compared in this work were Independence, Compound Symmetry, and First-order Autoregressive (a steady and equivalent heterogeneity of variance). Type of insurance was assessed only with a bivariate model since health insurance status was already considered in the model and to avoid multicollinearity issues. Bivariate comparison models are also included for all variables, which allows full examination of how associations are affected by the adjustments in the final model.

For the analysis of missed patients, a subset of the data with only DM patients was created(n=3394). Descriptive frequencies were tabulated, stratified by missed patient status and before or after ACA time-period. Adjusted and crude by-characteristic Odds Ratio point estimates and 95% Confidence Intervals were calculated and p-values reported for a final multivariable model.

Results

Descriptive Statistics for DM

Table 4.1 includes the descriptive statistics of socio-demographic, health behavior, and DM in persons 20 years and older in NHANES 2005-2010 (before time period or Pre ACA) and NHANES 2011-2016(after time period or Post ACA). The overall study sample consisted of

31,225 participants, with half pre-ACA (n=15,612) and half post-ACA. Females comprised 51.64% of the study sample with 43.50% White, 25.82% Hispanic, and 20.65% Black and a mean (standard deviation) age of 49.3 (17.9) years. About 11.45% of those in the Pre ACA period had a diagnosis of DM, while 13.5% of those in the post ACA period had a diagnosis of DM. In the Pre and Post ACA periods respectively, 1.91% and 2.56% had missing values for DM diagnosis. The percentage of uninsured decreased from 23.95% in the Pre ACA period to 20.69% in the Post ACA time period. Overall, less than a tenth of a percent had a missing value for insurance. In the overall sample, 25.91% had less than a high school education, 51.52% had a high school diploma, and 22.48% were college graduates or higher. Only a tenth of a percent were missing education level. Levels of Utilization were constant across both time periods. Overall, 16.52% had no doctors visits in the last year, 17.59% had 1 doctors visit in the last year, 27.07% had 2-3 visits, 25.02% had 4-9 visits, 6.44% had 10-12 visits, and 7.27% had 13 or more visits. Less than a tenth of a percent of respondents had a missing value for utilization. Pre ACA 10.53% had DM, while Post ACA 12.16% had DM. Pre ACA, 7.83% had Medicaid or Medigap, 18.01% had Medicare, 23.96% had no insurance, 38.8% had private insurance, and 11.16% had some other form of insurance. In the Pre ACA period, 0.22% had a missing value for insurance type. Post ACA, 11.43% had Medicaid or Medigap, 15.22% had Medicare, 20.75% had no insurance, 37.80% had private insurance, and 14.3% had some other form of insurance. In the post ACA period, 0.55% had missing values for insurance type. USC was constant across the time periods, with 84.68% having a USC Pre ACA and 83.72% having a USC Post ACA. There were no responses missing for USC. Health condition also remained constant from Pre to Post ACA, with 39.37% reporting poor/fair health, 36.41% reporting average health, and 24.22% reporting good/excellent health. Overall, less than a tenth of a percent of responses were missing

for health condition, with 0.06% missing from Pre ACA and 0.09% missing from Post ACA. The distribution across sexes remained constant across the time periods, with slightly more females than males (51.64% and 48.36%, respectively). The distribution of ethnicities across the two time periods were slightly different, and there were no missing responses for ethnicity. Pre ACA, 19.32% of respondents were black, 27.13% Hispanic, 48.94% White, and 4.61% Other. Post ACA, 21.98% of respondents were Black, 24.52% Hispanic, 38.06% White, and 15.44% Other. Pre ACA, 18.27% of respondents were below the poverty line, with 8.46% missing a response, while Post ACA 20.62% were, with 9.32% missing a response. The mean age in years Pre ACA was 49.50 and 49.13 Post ACA.

Associations with Diabetes

Time-period(Pre or Post ACA), age, sex, utilization, USC, health condition, insurance, education, ethnicity, and income were selected for inclusion in the final multivariable multilevel model (Table 4.2), and an independent correlation structure was chosen, with QIC=16773.27(Table 4.3).

The final multivariable multilevel model of DM status (table 4.4) showed that the time-period after the ACA was unrelated to DM in both the bivariate (OR=1.77, 95%CI=0.99,1.4,p=.07) and the adjusted model (OR=1.90, 95%CI=1.1,1.33,p=.09). Those with health insurance were significantly more likely to have DM in the unadjusted analysis (OR=1.51, 95%CI=1.44,1.58,p<.0001). Once adjusting for covariates, those with DM were also significantly more likely to have health insurance (OR=1.21, 95%CI=1.17,1.26, p =.02). Those with Medicaid/Medigap (OR=2.17, 95%CI=1.86,2.53,p<.0001), Medicare (OR=2.79, 95%CI=2.64,2.96,p<.0001), and Other (OR=1.5, 95%CI=1.31,1.7,p<.0001) types of insurance were more likely to have DM, compared to those with a private insurance plan. Income above

the poverty level was not related to DM outcomes in the adjusted model (OR=0.97, 95%CI=0.86,1.1,p=.28) but was found to be significant in a simple bivariate analysis (OR=0.76, 95%CI=0.65,0.89,p=.0007). Those with a high school education had lower odds of having DM (OR=0.60, 95%CI=0.58,0.68,p<.0001), and this result remained significant in the adjusted model (OR=0.97, 95%CI=0.93,1.03,p=.05). College graduates consistently had significantly lower odds of having DM in both the multivariable (OR=0.79, 95%CI=0.64,0.97,p=.05) and bivariate (OR=0.39, 95%CI=0.36,0.42, p<.0001) model. Compared to Whites in a bivariate model, Blacks (OR=1.88, 95%CI=1.63,2.16,p<.0001), Hispanics (OR=1.72, 95%CI=1.52,1.97,p<.0001), and those of Other ethnicity (OR=1.35, 95%CI=1.18,1.56,p<.0001) had higher odds of having DM. Compared to Whites in the multivariable model, Blacks (OR=1.88, 95%CI=1.68,2.12,p=.11), Hispanics (OR=1.99, 95%CI=1.75,1.2.26,p=.11), and those of Other ethnicity (OR=1.85, 95%CI=1.66,2.05,p=.11) did not have significantly higher odds of having DM.

Compared to no visits, having one doctor visit in the past year was not associated with increased odds of having DM in both the bivariate (OR=1.03, 95%CI=0.99,1.07) and the multivariable (OR=1.03, 95%CI=0.93,1.14,p=.31) model. In the bivariate model, having DM was correlated with increased doctor visits, ranging from 2-3 visits (OR=1.77, 95%CI=1.55,2.03,p<.0001), 4-9 visits (OR=3.34, 95%CI=3.23,3.44, p<.0001), 10-12 visits (OR=3.99, 95%CI=3.83,4.15, p<.0001) and 13 or more visits (OR=3.28, 95%CI=2.93,3.67, p<.0001). In the multivariable model, having DM was correlated with increased doctor visits, ranging from 2-3 visits (OR=1.40, 95%CI=1.26,1.55, p<.0001), 4-9 visits (OR=2.06, 95%CI=1.88,2.27, p<.0001), 10-12 visits (OR=2.12, 95%CI=1.96,2.29, p<.0001) and 13 or more visits (OR=1.83, 95%CI=1.61,2.08, p<.0001). Compared to males, females had lower odds of having DM in both the bivariate (OR=0.83, 95%CI=0.78,0.89, p<.0001) and multivariable

(OR=0.72, 95%CI=0.67,0.76, p=.02) models. Average health condition was associated with decreased odds of having DM, compared to those of poor health condition in both the bivariate (OR=2.79, 95%CI=2.51,3.11) and multivariable (OR=2.45, 95%CI=2.22,2.71) models. Those who considered themselves in good or excellent condition had very low odds of having DM, compared to those in poor health condition in both the bivariate (OR=6.52, 95%CI=5.68,7.48) and multivariable (OR=4.82, 95%CI=4.26,5.45) models.

Descriptive Statistics for DM Diagnosis

Table 4.5 includes descriptive statistics of the study variables by DM diagnosis before and after the ACA. The prevalence of undiagnosed DM patients was less (21.32%) than before the ACA (26.73%). In the Pre ACA period, 75.91% of diagnosed patients were insured, compared to 81.03% in the Post ACA period. Of diagnosed patients in the Pre ACA period, 43.2% had less than a high education, 45.8% had a high school education, and 10.8% had a college education or higher. The distribution of education among properly diagnosed patients post ACA changed slightly, with 33.7%, 49.8%, and 16.8%, respectively. Post ACA, utilization increased overall, with 96.5% of those with properly diagnosed DM had at least 1 doctors visit, compared to 96.2% Pre ACA. 82.3% of Medicaid/Medigap patients were properly diagnosed after the ACA, compared to only 80.1% before. 75.6% of those on Medicare were properly diagnosed before the ACA, compared to 84.8% after the ACA. Before the ACA, 76.6% of those with a USC were properly diagnosed, compared to 80.8% Post ACA. Before the ACA, only 71.5% percent of males had properly diagnosed DM, compared to 80.9% Post ACA. 77.2% of Blacks, 78.2% of Hispanics, 84.34% of Whites, and 71.3% of other ethnicity had properly diagnosed DM after the ACA, compared to 74.5%, 71.0%, 74.3%, and 73.3% Pre ACA,

respectively. Post ACA, 78.0% of those below the poverty line had properly diagnosed DM, compared to 73.8% before.

Associations with undiagnosed DM

Table 4.6 contains the final multivariable multilevel model of an indicator of properly diagnosed DM with selected covariates. Utilization of at least one doctors visit was significantly related to proper DM diagnosis in a bivariate model($p < .0001$), but this effect became insignificant in the multivariable model (for 1 visit, $OR=2.19$, $95\%CI=1.63,2.94$, $p=.31$). In a bivariate model, USC was related to proper DM diagnosis($OR=4.6$, $95\%CI=3.5,6.05$, $p < .0001$), but in a multivariable model USC was not associated with correct DM diagnosis($OR=1.64$, $95\%CI=1.09,2.48$, $p = .07$). In a bivariate model, insurance was not significantly associated with correct DM diagnosis ($OR=1.92,95\%CI=0.97,1.26$, $p=.06$), and the association remained insignificant in a multivariable model ($OR=2.76$, $95\%CI=2.3,3.81$, $p=.34$). In a bivariate model, Medicaid/Medigap ($OR=1.52$, $95\%CI=1.14,2.02$), Medicare ($OR=1.37$, $95\%CI=1.17,1.60$), No Insurance ($OR=0.65$, $95\%CI=0.53,0.79$) and other forms of insurance ($OR=1.44$, $95\%CI=1.25,1.65$) were significantly associated with having correctly diagnosed DM, compared to those on private insurance($p < .0001$). In the multivariable model, no particular type of insurance is associated with having correctly diagnosed DM($p=.69$). In a bivariate model, good/excellent health condition ($OR=2.9$, $95\%CI=2.4,3.5$) and average health condition ($OR=1.6$, $95\%CI=1.37,1.85$) were associated with correct DM diagnosis, compared to those in poor health condition($p < .0001$). However, in a multivariable model, this relationship did not hold, and good/excellent health condition ($OR=2.42$, $95\%CI=1.88,3.11$) and average health condition ($OR=1.38$, $95\%CI=1.11,1.71$) were not found to be associated to correct DM diagnosis, compared to poor health condition($p=.06$).

We failed to find an association between income and missed patient status. There was no significant association in a bivariate model (OR=1.02, p=.82) and income was not included in the multivariable model. In a bivariate model, education was not found to be associated with properly diagnosed DM (OR=1.11, 95%CI=0.97,1.26, p=.06). In a bivariate model, sex was not significant (OR=0.96, 0.71,1.17, p=.69). In a bivariate model, Black (OR=0.84, 95%CI=0.67,1.06), Hispanic (OR=0.79, 95%CI=0.61,1.02), and Other ethnicity (OR=0.68, 95%CI=0.47,0.97) were significantly related to correctly diagnosed DM, compared to those of White ethnicity (p=.05). However, in a multivariable model, no other ethnicity was associated with correctly diagnosed DM, when compared to those of White ethnicity (p-value=.41).

Individuals were more likely to have their DM properly diagnosed after the ACA, as opposed to before. In a bivariate model, the period after the ACA was significantly associated (OR=1.34, 95%CI=1.10,1.64, p=.003) with proper DM diagnosis. In a multivariable model adjusted for Time Period, Utilization, USC, Health Condition, Insurance, Ethnicity, and Insurance Type, only time period was related to correctly diagnosed DM. Those in the period after the ACA were more likely (OR=1.51, 95%CI=1.24,1.85, p=.04) to have properly diagnosed DM, when compared to those in the time period before the ACA was passed.

Discussion

Controlling for demographic characteristics, the association between insurance status and DM has not changed since the passage of the ACA. Those with insurance were still much more likely to have DM. A possible explanation for this finding is that many of the uninsured are young or in good health and do not feel pressure to purchase health insurance. DM prevalence also increases with age. In this sample, those with insurance are, on average, 11 years older than those without. Using only the NHANES dataset, it is not possible to determine the effect of

insurance on the development of DM. A longitudinal study that follows individuals over time could determine whether those who have insurance are less likely to develop DM in the future. There have not been any studies of this type conducted in the period after the ACA.

The association between healthcare utilization and DM have not changed since the passage of the ACA. While a single yearly doctor's visit was not significantly associated with having DM, it did significantly decrease the odds of being a missed patient. While this association has not been studied in among those who are undiagnosed with diabetes, a failure to receive annual Primary Care visits has been found to be associated with poorer outcomes and increased hospitalizations due to DM[65]. Although utilization above 2 visits was associated with an increased chance of having DM, this is expected due to more frequent doctor's visits by diabetics. Diabetics, particularly those with a formal diagnosis, tend to have a much higher frequency of physician visits than those without DM[66]. Controlling for previous diagnosis might be a way to further explore this relationship. Future studies analyzing utilization should consider if subjects have a DM diagnosis.

Having a USC and level of health services utilization do seem to be linked. Those with a USC generally had much higher utilization rates. However, it is still unclear if there is a causal pathway between USC and utilization. Like previous studies suggested, having a USC was more strongly related to having properly diagnosed diabetes than having health insurance [31, 34]. This could be due to the fact that many who are insured have high copays and do not visit the doctor enough to establish a USC. This would explain the lower diagnosis rates.

A higher percentage of subjects had some form of health insurance after the ACA, compared to before. This implies that the legislation may have actually led to increased healthcare coverage, as it was intended to. Those without health insurance were much more

likely to be a missed patient, compared to those with any type of health insurance. If the trend of expanded healthcare coverage in the population continues, the prevalence of missed patients should continue to decrease.

Those without insurance were less likely to go to the doctor or have a USC. We did not find evidence to support some earlier studies. Earlier studies found those that a USC alone improved access and outcomes, but the effect on DM diagnosis rates due to a USC was negligible [31]. The link between these factors and being a missed patient had not been previously studied. Although insurance, USC, and utilization all independently influenced missed patient status, none were found to be significant in an adjusted model.

Before the ACA, those on Medicaid/Medigap were less likely to be missed patients than those with private health insurance. After the ACA, there was no perceptible increase in likelihood of having DM properly diagnosed. This contradicts the idea and previous evidence that Medicaid expansion lead to better care and more healthcare attention paid to vulnerable populations[67]. The failure of Medicaid expansion in some states and changes in funding could be responsible for this effect[68]. Although the geographical data collected by NHANES is restricted, study of the differences in missed patients and DM outcomes between Expansion and Non-Expansion states or different state-level policies could be informative. This would allow for a more specific assessment of policies.

While we did not find any significant effects due to income other than in the bivariate model for DM, prior studies have found lower income to be associated with a greater probability of developing DM[18]. This could be because the binary indicator for income did not contain enough information to capture these differences or that there truly is no effect, particularly when other characteristics are accounted for.

There were significant disparities and differences in outcomes between races. Compared to whites, ethnic minorities were more likely to qualify as a missed patient after the passage of the ACA. While ethnic minority changes in missed patient status after the ACA has not been studied, a 2016 study found that access for minorities had increased overall[69]. There is no research concerning Diabetes outcomes for ethnic and racial minorities in the period after the ACA. Future studies should place an increased focus on outcomes for minorities. Poorer outcomes for minorities are a common finding in this study, and targeted interventions are needed.

While this sample does not show a significant difference in DM prevalence between the two time-periods, other estimates show that the overall prevalence of DM increased after the ACA[1]. Chronic diseases have long latent periods, and it is not realistic to expect any noticeable decrease or change in DM occurrence over such a short time period. The increased prevalence of DM should not be taken as an indicator that the ACA has been ineffective or has somehow contributed to DM cases.

Controlling for all other relevant factors, ACA time-period was the only significant effect, meaning that the time After the ACA was the only factor related to a patient receiving a correct DM diagnosis. After the passage of the ACA, patients had lower odds of being a missed patient than before the ACA, signifying that the ACA may have had a positive effect on awareness of DM and willingness of physicians to screen for DM, even if the prevalence is increasing. This effect has not been studied before and is an important piece of evidence in determining if the ACA has generated a tangible change in DM diagnosis.

Methodological Limitations

While some research exists concerning other biological measures, there have been no studies concerning the validity of the HbA1c results from NHANES[70]. Past studies have found that certain biological markers, particularly caloric data, measured by NHANES do not have good predictive validity[70]. However, since HbA1c is considered the gold standard for a single-visit diagnosis of diabetes and past studies have found that DM can be accurately diagnosed from HbA1c data, it is reasonable to assume those measurements can be used to predict the presence or absence of DM. However, the validity of the NHANES HbA1c values are another matter entirely. A 2003 study found that data collected by the survey on blood lead levels suffered from widespread methodological errors and failed to approximate the actual population distribution levels of lead[71]. While there have been changes in the survey methodology since that time, there has been no research on how those changes may have led to better validity.

Generalizing findings from analyses of NHANES biomarker data is common in the literature, but needs further study to ensure that it is valid to do so[72]. NHANES also does not select participants from nursing homes, the armed forces, prisons, or those living abroad[4]. As these groups make up a significant proportion of the population and ignoring them could lead to a lack of generalizability.

There are also possible measurement issues. While HbA1c values should not be subject to bias, not all survey participants are tested and there may be significant differences between those tested and those who are not. The methods behind which subjects are tested and why are not made clear by the survey, and there is no ‘refused to participate’ or ‘not selected to participate’ categories in the laboratory data. NHANES does not provide any information or documentation on which participants are selected for blood testing. The particular wording of the survey questions could also lead to systematic bias, particularly if wording leads the participant

to believe that one response is more desirable than the other, and the self-reported nature of the diagnosis questions and much of the healthcare behavior data could be subject to widespread inaccuracy. Primary issues in the questionnaire for this study include recall bias and unacceptability of a given response. [73] Whether or not a patient has been diagnosed with DM is not verified and based only on the response to a single question.

Statistical Limitations

Using retrospective data makes it difficult to establish causality. Future studies could use propensity scores and matching to determine causality, rather than just an association.

Prospective studies could also establish causality.

A limitation of the GEE method is that all missing values must be assumed to be missing completely at random(MCAR). Since there was a low frequency of missing data, and the missing values seemed to be evenly distributed and unassociated with any single category, the results should not have been significantly affected. Survey weights were not accounted for. Although some studies have found that discounting survey weights does not have inferential consequences, it still would have been preferable to include them.

Conclusions

Since the trends in DM are unlikely to change without massive, societal-level changes, focusing on strategies to prevent missed patients seems like a realistic policy focus. Identifying populations at risk of being missed patients and focusing efforts and programs in their direction will lead to earlier diagnosis and less complications and costs from the disease. Utilization, USC, and Insurance would be the best focuses for an intervention, as these are factors that can be influenced, unlike demographics. Physicians should be aware of factors that predispose a patient to having undiagnosed DM (non-white ethnicity, lower level of education, older age, being

uninsured, lack of a USC) and take steps to see if undiagnosed DM could be possible. Patients should be more regularly screened for DM. Increasing insurance coverage and encouraging regular doctor visits could seriously decrease the amount of undiagnosed cases of DM and the associated burden of care.

References

1. CDC, *National Diabetes Statistics Report*. 2017, Centers for Disease Control.
2. Menke, A., et al., *Prevalence of and trends in diabetes among adults in the united states, 1988-2012*. JAMA, 2015. **314**(10): p. 1021-1029.
3. *Standards of Medical Care in Diabetes—2007*. Diabetes Care, 2007. **30**(suppl 1): p. S4-S41.
4. CDC. *Questionnaires, Datasets, and Related Documentation*. 2018; Available from: <https://wwwn.cdc.gov/nchs/nhanes/Default.aspx>.
5. Guariguata, L., et al., *Global estimates of diabetes prevalence for 2013 and projections for 2035*. Diabetes Research and Clinical Practice. **103**(2): p. 137-149.
6. Lee, H., et al., *Optimal hemoglobin A1_C Cutoff Value for Diagnosing type 2 diabetes mellitus in Korean adults*. Diabetes Research and Clinical Practice. **99**(2): p. 231-236.
7. American Diabetes, A., *Economic Costs of Diabetes in the U.S. in 2012*. Diabetes Care, 2013. **36**(4): p. 1033-1046.
8. Zhang, Y., et al., *The Economic Costs of Undiagnosed Diabetes*. Population Health Management, 2009. **12**(2): p. 95-101.
9. Pappas, G., et al., *Potentially avoidable hospitalizations: inequalities in rates between US socioeconomic groups*. American Journal of Public Health, 1997. **87**(5): p. 811-816.
10. Dall, T.M., et al., *The Economic Burden of Elevated Blood Glucose Levels in 2012: Diagnosed and Undiagnosed Diabetes, Gestational Diabetes Mellitus, and Prediabetes*. Diabetes Care, 2014. **37**(12): p. 3172-3179.
11. Anderson, J.G., *Health Services Utilization: Framework and Review*. Health Services Research, 1973. **8**(3): p. 184-199.
12. Andersen, R.M., et al., *Exploring dimensions of access to medical care*. Health Services Research, 1983. **18**(1): p. 49-74.
13. Andersen, R.M., T.H. Rice, and G.F. Kominski, *Improving Access to Care*, in *Changing the US Healthcare System: Key Issues in Health Services Policy and Management* 2014, John Wiley & Sons, Inc.: San Francisco, CA. p. 33-64.
14. Andersen, R.M., *Revisiting the Behavioral Model and Access to Medical Care: Does it Matter?* Journal of Health and Social Behavior, 1995. **36**(1): p. 1-10.
15. Moeller, J.F., H. Chen, and R.J. Manski, *Is Preventive Dental Care a Good Investment for the Medicare Population? A Preliminary Analysis*. American journal of public health, 2010. **100**(11): p. 2262-2269.
16. Heider, D., et al., *Health care costs in the elderly in Germany: an analysis applying Andersen's behavioral model of health care utilization*. BMC Health Services Research, 2014. **14**: p. 71-71.
17. Babitsch, B., D. Gohl, and T. von Lengerke, *Re-revisiting Andersen's Behavioral Model of Health Services Use: a systematic review of studies from 1998–2011*. GMS Psycho-Social-Medicine, 2012. **9**: p. Doc11.
18. Wu, Y., et al., *Risk Factors Contributing to Type 2 Diabetes and Recent Advances in the Treatment and Prevention*. International Journal of Medical Sciences, 2014. **11**(11): p. 1185-1200.
19. Egede, L.E., *Race, Ethnicity, Culture, and Disparities in Health care*. Journal of General Internal Medicine, 2006. **21**(6): p. 667-669.

20. Gazmararian, J.A., D.C. Ziemer, and C. Barnes, *Perception of Barriers to Self-care Management Among Diabetic Patients*. The Diabetes Educator, 2009. **35**(5): p. 778-788.
21. Olson, D.E., et al., *Screening for Diabetes and Pre-Diabetes With Proposed A1C-Based Diagnostic Criteria*. Diabetes Care, 2010. **33**(10): p. 2184-2189.
22. Balkrishnan, R., et al., *Predictors of medication adherence and associated health care costs in an older population with type 2 diabetes mellitus: A longitudinal cohort study*. Clinical Therapeutics, 2003. **25**(11): p. 2958-2971.
23. Stark Casagrande, S. and C.C. Cowie, *Health Insurance Coverage Among People With and Without Diabetes in the U.S. Adult Population*. Diabetes Care, 2012. **35**(11): p. 2243-2249.
24. *Health Care Utilization*, in *Concept Dictionary and Glossary*. 2008, Manitoba Centre for Health Policy, University of Manitoba.
25. Bell, J., et al., *Factors associated with high-utilization in a safety net setting*. BMC Health Services Research, 2017. **17**(1): p. 273-273.
26. Simon, K., A. Soni, and J. Cawley, *The Impact of Health Insurance on Preventive Care and Health Behaviors: Evidence from the First Two Years of the ACA Medicaid Expansions*. Journal Of Policy Analysis And Management: [The Journal Of The Association For Public Policy Analysis And Management], 2017. **36**(2): p. 390-417.
27. Chomi, E.N., et al., *Health care seeking behaviour and utilisation in a multiple health insurance system: does insurance affiliation matter?* International Journal For Equity In Health, 2014. **13**: p. 25-25.
28. Viera, A.J., D.E. Pathman, and J.M. Garrett, *Adults' Lack of a Usual Source of Care: A Matter of Preference?* Annals of Family Medicine, 2006. **4**(4): p. 359-365.
29. Kuder, J.M. and G.S. Levitz, *Visits to the physician: an evaluation of the usual-source effect*. Health Services Research, 1985. **20**(5): p. 579-596.
30. Xu, K.T., *Usual Source of Care in Preventive Service Use: A Regular Doctor versus a Regular Site*. Health Services Research, 2002. **37**(6): p. 1509-1529.
31. DeVoe, J.E., C.J. Tillotson, and L.S. Wallace, *Usual source of care as a health insurance substitute for U.S. adults with diabetes?* Diabetes Care, 2009. **32**(6): p. 983-989.
32. Laiteerapong, N., et al., *Health care utilization and receipt of preventive care for patients seen at federally funded health centers compared to other sites of primary care*. Health Services Research, 2014. **49**(5): p. 1498-1518.
33. Sox, C.M., et al., *Insurance or a Regular Physician: Which is the Most Powerful Predictor of Health Care?* American Journal of Public Health, 1998. **88**(3): p. 364-370.
34. DeVoe, J.E., et al., *Is health insurance enough? A usual source of care may be more important to ensure a child receives preventive health counseling*. Maternal And Child Health Journal, 2012. **16**(2): p. 306-315.
35. Patel, N., S. Bae, and K.P. Singh, *Association between utilization of preventive services and health insurance status: findings from the 2008 Behavioral Risk Factor Surveillance System*. Ethnicity & Disease, 2010. **20**(2): p. 142-147.
36. Fox, J.B. and F.E. Shaw, *Receipt of Selected Clinical Preventive Services by Adults — United States, 2011-2012*. MMWR. Morbidity And Mortality Weekly Report, 2015. **64**(27): p. 738-742.
37. Fox, J.B. and F.E. Shaw, *Relationship of income and health care coverage to receipt of recommended clinical preventive services by adults - United States, 2011-2012*. MMWR. Morbidity And Mortality Weekly Report, 2014. **63**(31): p. 666-670.

38. DeVoe, J.E., et al., *Receipt of preventive care among adults: insurance status and usual source of care*. American Journal Of Public Health, 2003. **93**(5): p. 786-791.
39. Nguyen, K.H. and B.D. Sommers, *Access and Quality of Care by Insurance Type for Low-Income Adults Before the Affordable Care Act*. American Journal of Public Health, 2016. **106**(8): p. 1409-1415.
40. Gindi, R.M., W.K. Kirzinger, and R.A. Cohen, *Health Insurance Coverage and Adverse Experiences With Physician Availability: United States, 2012*, in *NCHS Data Brief*. 2013.
41. Cossman, R.E., et al., *Access to Primary Care Physicians Differs by Health Insurance Coverage in Mississippi*. Southern Medical Journal, 2014. **107**(2): p. 87-90.
42. Allen, H., et al., *The role of stigma in access to health care for the poor*. The Milbank Quarterly, 2014. **92**(2): p. 289-318.
43. Pardo, C. and W. Schott, *Public versus Private: Evidence on Health Insurance Selection*. International Journal of Health Care Finance and Economics, 2012. **12**(1): p. 39-61.
44. Amundson, G.M., et al., *Diabetes care quality: insurance, health plan, and physician group contributions*. The American Journal Of Managed Care, 2009. **15**(9): p. 585-592.
45. Kato, A., et al., *Psychological and behavioural patterns of stigma among patients with type 2 diabetes: a cross-sectional study*. BMJ Open, 2017. **7**(3): p. e013425-e013425.
46. Nelson, K.M., et al., *The Association between Health Insurance Coverage and Diabetes Care; Data from the 2000 Behavioral Risk Factor Surveillance System*. Health Services Research, 2005. **40**(2): p. 361-372.
47. McBrien, K.A., et al., *Barriers to care in patients with diabetes and poor glycemic control-A cross-sectional survey*. Plos One, 2017. **12**(5): p. e0176135-e0176135.
48. Zhang, X., et al., *The Missed Patient With Diabetes: How access to health care affects the detection of diabetes*. Diabetes Care, 2008. **31**(9): p. 1748-1753.
49. Faul, A.C., P.A. Yankeelov, and L.R. McCord, *Inequitable access to health services for older adults with diabetes: potential solutions on a state level*. Journal Of Aging & Social Policy, 2015. **27**(1): p. 63-86.
50. Phillips, R.L., et al., *Usual Source Of Care: An Important Source Of Variation In Health Care Spending*. Health Affairs, 2009. **28**(2): p. 567-577.
51. Béland, D., P. Rocco, and A. Waddan, *Obamacare and the Politics of Universal Health Insurance Coverage in the United States*. Social Policy & Administration, 2016. **50**(4): p. 428-451.
52. Walker, R.J., et al., *Independent effects of socioeconomic and psychological social determinants of health on self-care and outcomes in Type 2 diabetes*. General Hospital Psychiatry, 2014. **36**(6): p. 662-668.
53. Garrett, B. and A. Gangopadhaya, *Who Gained Health Insurance Coverage Under the ACA, and Where Do They Live?*, in *ACA Implementation- Monitoring and Tracking*. 2016, Robert Wood Johnson Foundation, Urban Institute.
54. Freedman, S., et al., *Changes in inpatient payer-mix and hospitalizations following Medicaid expansion: Evidence from all-capture hospital discharge data*. PLoS ONE, 2017. **12**(9): p. e0183616.
55. Brown, D.S. and T.D. McBride, *Impact of the Affordable Care Act on Access to Care for US Adults With Diabetes, 2011–2012*. Preventing Chronic Disease, 2015. **12**: p. E64.
56. Sommers, B.D., et al., *Three-Year Impacts Of The Affordable Care Act: Improved Medical Care And Health Among Low-Income Adults*. Health Affairs, 2017. **36**(6): p. 1119-1128.

57. Saeed, B., II, et al., *Impact of socioeconomic status and medical conditions on health and healthcare utilization among aging Ghanaians*. BMC Public Health, 2015. **15**(1): p. 1-9.
58. Agerholm, J., et al., *Socioeconomic differences in healthcare utilization, with and without adjustment for need: An example from Stockholm, Sweden*. Scandinavian Journal of Public Health, 2013. **41**(3): p. 318-325.
59. .
60. Silverman, R.A., et al., *Hemoglobin A(1c) as a Screen for Previously Undiagnosed Prediabetes and Diabetes in an Acute-Care Setting*. Diabetes Care, 2011. **34**(9): p. 1908-1912.
61. Carle, A.C., *Fitting multilevel models in complex survey data with design weights: Recommendations*. BMC Medical Research Methodology, 2009. **9**: p. 49-49.
62. McCulloch, C.E., *Repeated Measures ANOVA, R.I.P.? CHANCE*, 2005. **18**(3): p. 29-33.
63. Azuero, A., et al., *An Application of Longitudinal Analysis with Skewed Outcomes*. Nursing research, 2010. **59**(4): p. 301-307.
64. Pan, W., *Akaike's Information Criterion in Generalized Estimating Equations*. Biometrics, 2001. **57**(1): p. 120-125.
65. Nuti, L.A., et al., *No-shows to primary care appointments: subsequent acute care utilization among diabetic patients*. BMC Health Services Research, 2012. **12**: p. 304-304.
66. ADA, *Standards of Medical Care for Patients With Diabetes Mellitus*. Diabetes Care, 2003. **26**(suppl 1): p. s33.
67. Sohn, H. and S. Timmermans, *Social Effects of Health Care Reform: Medicaid Expansion under the Affordable Care Act and changes in Volunteering*. Socius : sociological research for a dynamic world, 2017. **3**: p. 10.1177/2378023117700903.
68. Myerson, R. and N. Laiteerapong, *The Affordable Care Act and Diabetes Diagnosis and Care: Exploring the Potential Impacts*. Current diabetes reports, 2016. **16**(4): p. 27-27.
69. Chen, J., et al., *Racial and Ethnic Disparities in Health Care Access and Utilization Under the Affordable Care Act*. Medical Care, 2016. **54**(2): p. 140-146.
70. Archer, E., G.A. Hand, and S.N. Blair, *Validity of U.S. Nutritional Surveillance: National Health and Nutrition Examination Survey Caloric Energy Intake Data, 1971–2010*. PLoS ONE, 2013. **8**(10): p. e76632.
71. Stone, B.M. and C.R. Reynolds, *Can the National Health and Nutrition Examination Survey III (NHANES III) data help resolve the controversy over low blood lead levels and neuropsychological development in children?* Archives of Clinical Neuropsychology, 2003. **18**(3): p. 219-244.
72. Sobus, J.R., et al., *Uses of NHANES Biomarker Data for Chemical Risk Assessment: Trends, Challenges, and Opportunities*. Environmental Health Perspectives, 2015. **123**(10): p. 919-927.
73. Choi, B.C.K. and A.W.P. Pak, *A Catalog of Biases in Questionnaires*. Preventing Chronic Disease, 2005. **2**(1): p. A13.

Table 4.1: Descriptive statistics of socio-demographic, health behavior, and DM study variables.

		PRE ACA	POST ACA	TOTAL
		Count (%)	Count (%)	Count (%)
Variable		15612(50.00%)	15613(50.00%)	31225(100%)
Diagnosis				
	No	13513(20.08%)	13105(83.94%)	26618(85.25%)
	Yes	1801(11.54%)	2109(13.50%)	3910(12.52%)
	Missing	298(1.91%)	399(2.56%)	697(2.23%)
Insured				
	No	3740(23.95%)	3231(20.69%)	6971(22.33%)
	Yes	11861(75.97%)	12363(79.18%)	24224(77.59%)
	Missing	11(0.07%)	19(0.12%)	30(0.09%)
Education				
	Less than High School	4541(29.09%)	3548(22.72%)	8089(25.91%)
	High School Grad	7963(51.01%)	8123(52.03%)	16086(51.52%)
	College Graduate	3086(19.77%)	3932(25.18%)	7018(22.48%)
	Missing	22(0.14%)	10(0.06%)	32(0.10%)
Utilization				
	0	2590(16.58%)	2567(16.44%)	5157(16.52%)
	1	2697(17.28%)	2795(17.90%)	5492(17.59%)
	2-3	4075(26.10%)	4379(28.05%)	8454(27.07%)
	4-9	3922(25.12%)	3890(24.92%)	7812(25.02%)
	10-12	1096(7.02%)	916(5.87%)	2012(6.44%)
	>13	1220(7.81%)	1050(6.73%)	2270(7.27%)
	Missing	12(0.08%)	16(0.10%)	28(0.09%)
Diabetes				
	No	13968(89.47%)	13714(87.84%)	27682(88.65%)
	Yes	1644(10.53%)	1899(12.16%)	3543(11.35%)
Insurance Type				
	Medicaid/Medigap	1223(7.83%)	1784(11.43%)	3007(9.63%)
	Medicare	2812(18.01%)	2376(15.22%)	5188(16.61%)
	None	3742(23.96%)	3239(20.75%)	6981(22.36%)
	Other	1743(11.16%)	2232(14.30%)	3975(12.73%)
	Private	6058(38.80%)	5902(37.80%)	11960(38.30%)
	Missing	34(0.22%)	80(0.51%)	114(0.37%)
Usual Source of Care				
	No	2391(15.32%)	2542(16.28%)	4933(15.80%)
	Yes	13221(84.68%)	13071(83.72%)	26292(84.02%)
	Missing	0	0	0
Health Condition				
	Poor/Fair	6267(40.14%)	6018(38.54%)	12885(39.37%)
	Average	5521(35.36%)	5839(37.40%)	11360(36.41%)
	Good/Excellent	3815(24.45%)	3742(23.96%)	7557(24.22%)

Sex	Missing	9(0.06%)	14(0.09%)	23(0.07%)
	Female	8057(51.61%)	8068(51.67%)	16125(51.64%)
	Male	7555(48.39%)	7545(48.33%)	15100(48.36%)
Ethnicity	Missing	0	0	0
	Black	3017(19.32%)	3432(21.98%)	6449(20.65%)
	Hispanic	4235(27.13%)	3828(24.52%)	8063(25.82%)
	White	7641(48.94%)	5942(38.06%)	13583(43.50%)
	Other	719(4.61%)	2411(15.44%)	3130(10.02%)
	Missing	0	0	0
Income	Below Poverty Line	2852(18.27%)	3219(20.62%)	6071(19.44%)
	Above Poverty Line	11439(73.27%)	10939(70.06%)	22378(71.67%)
	Missing	1321(8.46%)	1455(9.32%)	2776(8.89%)
Age		Mean (SD)	Mean (SD)	Mean (SD)
		49.5 (18.2)	49.1 (17.7)	49.3 (17.9)

**Missing values included those who responded 'Don't Know' or 'Refuse to Answer'*

Definitions: ACA- Affordable Care Act, SD- Standard Deviation, DM- Diabetes Mellitus

Table 4.2: Multilevel marginal model regression coefficient estimates (p-values) for DM status with selected covariates (n=31,225)⁺.

Variable	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>	<i>Model 5</i>	<i>Model 6</i>	<i>Model 7</i>	<i>Model 8</i>
Fixed intercept	-4.39 (.01)	-4.47 (.01)	-4.41 (.01)	-5.10 (.002)	-5.21 (.002)	-4.96 (.001)	-4.94 (.01)	-4.99 (.003)
Affordable Care Act								
After v. Before	0.02(.01)	0.22(.01)	0.22(.01)	0.21(.002)	0.22(.002)	0.23(.001)	0.15(.01)	0.17(.003)
Age								
(in years)	0.04(<.0001)	0.04(<.0001)	0.04(<.0001)	0.03(<.0001)	0.04(<.0001)	0.04(<.0001)	0.04(<.0001)	0.04(<.0001)
Sex(p-value)								
Female v. Male	-0.17(<.0001)	-0.25(<.0001)	-0.25(<.0001)	-0.27(<.0001)	-0.28(<.0001)	-0.29(<.0001)	-0.31(<.0001)	-0.33(<.0001)
Utilization(p-value)								
1 visit v. no visits		-0.08(<.0001)	-0.11(<.0001)	-0.02(<.0001)	0.01(<.0001)	0.02(<.0001)	0.02(<.0001)	0.03(<.0001)
2-3 Visits v. no visits		0.26(<.0001)	0.22(<.0001)	0.23(<.0001)	0.26(<.0001)	0.28(<.0001)	0.30(<.0001)	0.34(<.0001)
4-9 Visits v. no visits		0.74(<.0001)	0.70(<.0001)	0.55(<.0001)	0.60(<.0001)	0.62(<.0001)	0.68(<.0001)	0.72(<.0001)
10-12 Visits v. no visits		0.92(<.0001)	0.88(<.0001)	0.58(<.0001)	0.63(<.0001)	0.65(<.0001)	0.72(<.0001)	0.75(<.0001)
>13 Visits v. no visits		0.77(<.0001)	0.73(<.0001)	0.36(<.0001)	0.42(<.0001)	0.45(<.0001)	0.56(<.0001)	0.61(<.0001)
Usual Source of Care								
No v Yes			-0.01(.29)	-0.20(.01)	-0.25(.004)	-0.26(.003)	-0.25(.004)	-0.25(.03)
Health condition								
Good/Excellent v. Poor/Fair				1.17(<.0001)	1.60(<.0001)	1.50(<.0001)	1.39(<.0001)	1.42(<.0001)
Average v. Poor/Fair				0.94(<.0001)	0.93(<.0001)	0.88(<.0001)	0.81(<.0001)	0.83(<.0001)
Insurance								
No v. Yes					0.17(<.0001)	0.13(.001)	0.09(.01)	0.14(<.0001)
Education								
High School v. Less than High School						-0.12(<.0001)	-0.006(.05)	-0.02(.07)
College Graduate v. Less than High School						-0.36(<.0001)	-0.23(.05)	-0.23(.07)
Ethnicity								

Black v Other							0.05(<.0001)	0.07(<.0001)
Hispanic v Other							-0.02(<.0001)	0.019(<.0001)
White v Other							-0.68(<.0001)	-0.61(<.0001)
<hr/>								
Income								
Above Poverty Line v. Below								-0.03(.62)
QIC	20416.35	20074.16	20075.70	19036.59	19010.63	18957.36	18690.69	16774.19

*Based on QIC, model 8 was selected

Smaller QIC values indicate a better fitting model

*Definitions: QIC- Quasi-Information Criterion, ACA- *Affordable Care Act*, CI- *Confidence Interval*, OR- *Odds Ratio*,

DM- *Diabetes Mellitus*

Table 4.3: Model comparisons across correlation structures*.

Variable	<i>Independence</i>	<i>First-order Autoregressive</i>	<i>Compound Symmetry</i>
	Estimate(p-value)	Estimate(p-value)	Estimate(p-value)
Intercept	-4.99(<.0001)	-3.04(<.0001)	-4.99(<.0001)
Affordable Care Act After v. Before	0.17(.003)	0.23(.05)	0.17(.003)
Age (in years)	0.04(<.0001)	0.02(<.0001)	0.04(<.0001)
Sex Female v. Male	-0.33(<.0001)	-0.23(<.0001)	-0.34(<.0001)
Utilization			
1 visit v. no visits	0.03(.53)	0.03(.15)	0.03(.54)
2-3 Visits v. no visits	0.33(<.0001)	.21(<.0001)	0.33(<.0001)
4-9 Visits v. no visits	0.72(<.0001)	0.49(<.0001)	0.72(<.0001)
10-12 Visits v. no visits	0.75(<.0001)	0.53(<.0001)	0.75(<.0001)
>13 Visits v. no visits	0.60(<.0001)	0.42(<.0001)	0.60(<.0001)
Usual Source of Care No v Yes	-0.24(.03)	-0.14(.002)	-0.25(.03)
Health condition			
Good/Excellent v. Poor/Fair	1.41(<.0001)	0.93(<.0001)	1.41(<.0001)
Average v. Poor/Fair	0.83(<.0001)	0.47(<.0001)	0.83(<.0001)
Insurance No v. Yes	0.14(<.0001)	0.06(<.0001)	0.14(<.0001)
Education			
High School v. Less than High School	-0.02(.38)	-0.04(.01)	-0.02(.38)
College Graduate v. Less than High School	-0.23(.03)	-0.17(.001)	-0.23(.03)
Ethnicity			
Black v Other	0.07(.31)	0.06(.16)	0.08(.30)
Hispanic v Other	0.02(.71)	0.004(.89)	0.02(.68)
White v Other	-0.61(<.0001)	-0.41(<.0001)	-0.61(<.0001)
Income Above Poverty Line v. Below	-0.03(.62)	-0.03(.50)	-0.03(.63)
QIC μ	16773.27	19399.92	16773.28

*Based on QIC μ , an Independent correlation structure was chosen for the final model

Smaller QIC values indicate a better fitting model

Definitions: QIC- Quasi-Information Criterion, ACA- Affordable Care Act, USC- Usual Source of Care, DM- Diabetes Mellitus

Table 4.4: Final multivariable multilevel marginal model for the association between DM status with selected covariates (n=31225).

Variable	Bivariate		Multivariable	
	Unadjusted OR(95%CI)	p-value	Adjusted OR (95%CI)	p-value
ACA		.07		.09
	After	1.77(0.99,1.40)	1.90(1.06,1.33)	
	Before	Reference	Reference	
Sex		<.0001		.02
	Female	0.83(0.78,0.89)	0.72(0.67,0.76)	
	Male	Reference	Reference	
Utilization		<.0001		.31
	No Visits	Reference	Reference	
	1 Visit	1.03(0.99,1.07)	1.03(0.93,1.14)	
	2-3 Visits	1.77(1.55,2.03)	1.40(1.26,1.55)	
	4-9 Visits	3.34 (3.23,3.44)	2.06(1.88,2.27)	
	10-12 Visits	3.99 (3.83,4.15)	2.12(1.96,2.29)	
	>13 Visits	3.28(2.93,3.67)	1.83(1.61,2.08)	
Usual Source of Care		<.0001		.03
	No	Reference	Reference	
	Yes	2.37(2.07,2.73)	1.28(1.03,1.59)	
Health condition		<.0001		.05
	Good/Excellent	6.52(5.68,7.48)	4.82(4.26,5.45)	
	Average	2.79(2.51,3.11)	2.45(2.22,2.71)	
	Poor/Fair	Reference	Reference	
Insurance		<.0001		.02
	No	Reference	Reference	
	Yes	1.51(1.44,1.58)	1.21(1.17,1.26)	
Education		<.0001		.05
	College Graduate	0.39(0.36,0.42)	0.79(0.64,0.97)	
	High School Graduate	0.60(0.58,0.68)	0.97(0.93,1.03)	
	Less than High School	Reference	Reference	
Ethnicity		<.0001		.11
	Black	1.88(1.63,2.16)	1.88(1.68,2.12)	
	Hispanic	1.72(1.52,1.97)	1.99(1.75,2.26)	
	Other	1.35(1.18,1.56)	1.85(1.66,2.05)	
	White	Reference	Reference	
Income		.0007		.28
	Above Poverty Line	0.76(0.65,0.89)	0.97(0.86,1.10)	
	Below Poverty Line	Reference	Reference	
Insurance Type		<.0001		
	Medicaid/Medigap	2.17(1.86,2.53)		
	Medicare	2.79(2.64,2.96)		
	None	1.05(0.96,1.14)		
	Other	1.50(1.31,1.70)		
	Private	Reference		

A Marginal Model with Generalized Estimating Equations was used to account for clustering within year; probability of Diabetes is modeled

‡Wald χ^2 test, at $\alpha=0.05$

Missing Data: Diagnosis (N=697), Insurance (N=30), Education (N=32), Utilization (N=28), Diabetes (N=0), Insurance Type (N=114), USC (N=0), Health Condition (N=23), Sex (N=0), Ethnicity (N=0), Income (N=2776), Age (N=0)

Definitions: ACA- Affordable Care Act, CI- Confidence Interval, OR- Odds Ratio, DM- Diabetes Mellitus

Table 4.5: Descriptive statistics of study variables by DM diagnosis before and after the ACA (n=3394).

		PRE ACA n= 1579		POST ACA n= 1815	
		Diagnosed		Diagnosed	
Variable		Yes 1157(73.27%)	No 422(26.73%)	Yes 1428(78.68%)	No 387(21.32%)
Insured	No	184(64.79%)	100(35.21%)	183(65.83%)	95(34.17%)
	Yes	973(75.91%)	321(24.81%)	1243(81.03%)	291(18.97%)
Education	Less than High School	500(74.18%)	174(25.82%)	481(78.59%)	131(21.41%)
	High School	530(72.11%)	205(27.89%)	704(78.57%)	192(21.43%)
	College Graduate	125(74.50%)	43(25.60%)	240(79.21%)	63(20.79%)
Utilization	0	41(31.78%)	88(68.22%)	54(36.00%)	96(64.00%)
	1	60(45.45%)	72(54.55%)	104(61.18%)	66(38.82%)
	2-3	258(73.30%)	94(26.70%)	350(81.59%)	79(14.45%)
	4-9	469(80.72%)	112(19.28%)	592(85.55%)	100(12.90%)
	10-12	160(82.05%)	35(17.95%)	162(87.10%)	24(12.90%)
	>13	167(88.83%)	21(11.17%)	164(88.17%)	22(11.83%)
Insurance Type	Medicaid/Medigap	151(80.32%)	37(19.68%)	232(82.27%)	50(17.73%)
	Medicare	384(75.59%)	124(24.41%)	397(84.47%)	73(15.53%)
	None	184(64.79%)	100(35.21%)	184(65.71%)	96(34.29%)
	Other	297(70.88%)	122(29.12%)	388(77.29%)	114(22.71%)
	Private	140(80.00%)	35(20.00%)	223(81.09%)	52(18.91%)
Usual Source of Care	No	46(35.94%)	82(64.06%)	72(54.94%)	64(47.06%)
	Yes	1111(76.57%)	340(23.43%)	1356(80.76%)	323(19.24%)
Health Condition	Poor/Fair	153(61.20%)	97(38.80%)	165(63.71%)	94(36.29%)
	Average	366(68.67%)	167(31.33%)	513(75.78%)	164(24.22%)
	Good/Excellent	637(80.13%)	158(19.87%)	749(85.31%)	129(14.69%)
Sex	Female	574(75.23%)	189(24.77%)	656(76.28%)	204(23.72%)
	Male	583(71.45%)	233(28.55%)	772(80.84%)	183(19.16%)
Ethnicity	Black	316(74.53%)	108(25.47%)	376(77.21%)	111(22.79%)
	Hispanic	359(71.09%)	146(29.91%)	437(78.18%)	122(21.82%)
	Other	55(73.33%)	20(26.67%)	184(71.32%)	74(28.68%)
	White	427(74.26%)	148(25.74%)	431(84.34%)	80(15.66%)
Income	Above Poverty Line	786(72.58%)	297(27.42%)	909(78.84%)	244(21.16%)
	Below Poverty Line	239(73.77%)	85(26.23%)	364(77.94%)	103(22.06%)

Missing Data: Insurance(n=4), Insurance Type(n=10), Education (N=6), Utilization (N=4), Usual Source of Care (N=0), Health Condition (N=2), Sex (N=0), Ethnicity (N=0), Income (N=367)

Table 4.6: Final multivariable multilevel marginal model of an indicator of properly diagnosed DM with selected covariates (n=3394).

Variable	Bivariate		Multivariable	
	Unadjusted OR(95% CI)	p-value [‡]	Adjusted OR (95% CI)	p-value [‡]
ACA		.003		.04
After	1.34 (1.10,1.64)		1.51(1.24,1.85)	
Before	Reference		Reference	
Sex		.69		
Female	0.96 (0.71,1.17)			
Male	Reference			
Utilization		<.0001		.31
No Visits	Reference		Reference	
1 Visit	2.30(1.82,2.90)		2.19(1.63,2.94)	
2-3 Visits	1.77(1.55,2.03)		5.99(4.82,7.47)	
4-9 Visits	9.69(8.30,11.32)		8.16(7.03,9.47)	
10-12 Visits	10.57(8.69,12.86)		8.31(7.06,9.79)	
>13 Visits	14.90(10.91,20.37)		10.72(8.55,13.45)	
Usual Source of Care		<.0001		.07
No	Reference		Reference	
Yes	4.60(3.50,6.05)		1.64(1.09,2.48)	
Health condition		<.0001		.06
Good/Excellent	2.90(2.40,3.50)		2.42(1.88,3.11)	
Average	1.60(1.37,1.85)		1.38(1.11,1.71)	
Poor/Fair	Reference		Reference	
Insurance		<.0001		.34
No	Reference		Reference	
Yes	1.92(1.59,2.33)		2.76(2.30,3.81)	
Education		.06		
College Graduate	1.11(0.97,1.26)			
High School Graduate	1.03(0.87,1.14)			
Less than High School	Reference			
Ethnicity		.05		.41
Black	0.84(0.67,1.06)		0.78(0.60,1.00)	
Hispanic	0.79(0.61,1.02)		0.89(0.64,1.25)	
Other	0.68(0.47,0.97)		0.75(0.55,1.03)	
White	Reference		Reference	
Income		.82		
Above Poverty Line	1.02(0.84,1.25)			
Below Poverty Line	Reference			
Insurance Type		<.0001		.69
Medicaid/Medigap	1.52(1.14,2.02)		0.85(0.63,1.16)	
Medicare	1.37(1.17,1.60)		0.99(0.82,1.21)	
None	0.65(0.53,0.79)		0.39(0.32,0.48)	
Other	1.44(1.25,1.65)		1.02(0.93,1.14)	
Private	Reference		Reference	

A Marginal Model with Generalized Estimating Equations was used to account for clustering within year; probability modeled was whether diabetic subjects had a proper diabetes diagnosis

[†]Wald χ^2 test, at $\alpha=0.05$

Missing Data: Insurance(n=4), Insurance Type(n=10), Education (n=6), Utilization (n=4), Usual Source of Care (n=0), Health Condition (n=2), Sex (n=0), Ethnicity (n=0), Income (n=367)

Definitions: ACA- Affordable Care Act, CI- Confidence Interval, OR- Odds Ratio, DM- Diabetes Mellitus
