The effects of social determinants of health on diagnosed diabetes in the United States

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ABSTRACT

Diabetes is one of the highest mortalities globally, and there are no treatment options that can permanently cure it. Nowadays, the number of diabetes patients is increasing dramatically, which requires people to take appropriate preventive measures to avoid the prevalence of this disease. This paper presented 9 social determinants of health (SDOHs) related to diabetes. Using relevant data collected from 3,142 counties in the United States on the CDC website, the final dataset was formed with a sample size 3,141. There were applying GLM and GWR two models to explore the association between 9 SDOHs and diabetes mellitus. The results showed that high overall socioeconomic status, overall SVIs and living in urban increased the risk of diabetes, while food insecurity, access to exercise opportunities and no health insurance had little effects on diabetes globally. Among them, the overall SVIs and access to exercise opportunities had various degrees of impact in different U.S. counties.

CCS CONCEPTS

• Computing methodologies; **• Modeling and simulation**; **• Model development and analysis**; **• Model verification and validation**;

KEYWORDS

Diabetes, Social determinants of health (SDOHs), Generalized linear model (GLM), County, Geographically Weighted Regression (GWR)

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1 INTRODUCTION

Diabetes mellitus is a metabolic syndrome in which blood sugar rises due to a relative lack of insulin. The mortality rate ranks in the top 10 of global disease mortality rates. In the past few decades, the number of patients diagnosed diabetes has increased dramatically worldwide. According to data released by the International Diabetes Federation (IDF) in 2021, 537 million adults (ages 18-99) in the world were diagnosed with diabetes, resulting in 6.7 million deaths, and the number of cases is predicted to continue to increase over the next decade [1]. The risk factors of diabetes include age, ethnicity, family medical history, obesity, unhealthy lifestyle, the influence of other diseases and some social factors, among which the dynamic interaction makes diabetes prevalent in individuals. If not treated early, diabetes may cause cardiovascular disease or blurred vision, these kinds of complications.

Now, there extensive researches are available for the prevention and management of diabetes. For example, compared to women, men diagnosed diabetes appeared high risk when they were young and had low body mass index (BMI), but women's risk increased dramatically after menopause [2]. By analyzing the dataset with the Random Forest Algorithm, researchers provided end users with a universally available, user-friendly tool to detect the risk of diabetes according to evaluable symptoms such as sudden weight loss, muscle stiffness and visual blurring [3]. According to estimates from the Centers for Disease Control and Prevention (CDC), 11.3% of the U.S. population, or 37.3 million people, had diabetes [4]. In county-level estimates of diagnosed diabetes, the southeastern United States had a high concentration of diabetes patients, covering Kentucky, Georgia, and 15 other states [4]. The diabetes cluster presented a different social profile of risk factors than the other regions of the United States, including a higher prevalence of physical inactivity, lower levels of health care, lower household income, and a lower percentage of the population with a college degree [4]. As a result, studies have explored the impact of socioeconomic factors on diabetes. Among teens enrolled with type 2 diabetes at the Pediatric Diabetes Alliance clinic, 70 percent had parents with no more than a high school education, and 43 percent had a household economic income of less than $25,000 [5]. From the Nashville Study on Stress and Health, researchers using ordinary least squares regression analysis illustrated that income and education were inversely associated with glycated hemoglobin (Hba1c, to test for diabetes.) in undiagnosed participants [6]; A prospective Dutch Lifeline cohort study showed that people who had a lower level of education and an income of up to € 1,000 per month had a high risk of being diagnosed with type 2 diabetes [7]. These socioeconomic factors are influenced by social determinants of health.

The CDC stipulates social determinants of health (SDOH) as the environment where people are born, age, work, living and the health care system [8]. Analyzing SDOH data that can promote or hinder health, such as education levels, language and literacy skills, employment, income, and access to safe housing, nutritious food, health care, and physical activity, can help to improve people's health on a local condition [8]. Existing paradigms for the prevention and management of diabetes have broadly targeted traditional diabetes risk factors, but the role of SDOH in outcomes is often

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overlooked. There is limited evidence of an association between ordinary SDOH (e.g., income, education) and diabetes. However, most of these studies used traditional global regression models, assuming that the regression parameters are independent of the spatial location of the sample. In addition, there were few studies on other SDOHs, and many reviews only lightly covered the results of the effects of SDOHs on diabetes, and did not explicitly study their impact on the results.

Thus, the objective of this paper was to use Generalized Linear Model (GLM) to explore the association between diabetes and broader SDOHs. Considering the spatial heterogeneity or non-stationarity of the real geographical world, this paper also used Geographically Weighted Regression (GWR)to establish a local regression model based on the detailed data.

2 METHODS

2.1 Data Acquisition

The 2018 dataset of 3,142 counties in United States was obtained from CDC website. The dataset contains 51 states' names, 3142 counties' names, the county-fip, the population of each county, diagnosed diabetes percentage and 9 SDOHs.

The diagnosed diabetes percentage as a dependent variable was estimated by the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (BRFSS) and the U.S. Census Bureau through monthly ongoing telephone surveys of adults ($ages > 18$), on a continental basis [9].

County data for 3,142 counties in the United States was estimated using an indirect model of one of the Bayesian multi-layer modelling techniques. The approach of the model used a statistical model for small area estimation, which was to estimate a county from BRFSS data collected by other counties [10]. Aiming at the incidence of newly diagnosed diabetes, a county-level binomial regression model with random impacts of population variables was established [10]. County prevalence was measured based on the power prior log weights (PLOW) technique [10]. Unique PLOW advantages include 1) using single-year BRFSS data rather than combining years; 2) inclusion of historical data that can be used for power priors or defined information priors; 3) Integrate adjusted sample weights to account for BRFSS's complex survey design; 4) more timely estimates with more minor variance [10].

This paper used 9 SDOHs as explanatory variables overall socioeconomic status, overall social vulnerability index (SVI), households without Internet service, severe housing cost burden, food insecurity, access to exercise opportunities, commute >60 minutes, no health insurance, urban or rural. Urban or rural are classified by National Center for Health Statistics (NCHS). Overall socioeconomic status and overall SVIs are derived from CDC/ATSDR created and maintained by the Geospatial Research, Analysis and Services Project (GRASP). Social vulnerability is defined the potential negative effects of external pressures on human health, including poor economy, inconvenient transportation, serious housing burden, etc. The remaining 6 were estimated according to the American Community Survey (ACS) by surveying people living in housing units (HU) and dormitories (GQ), respondents were identified as: 1) Household with no internet service: no subscribe to any type of computer and Internet. 2) Severe housing cost burden: 50% or more of household income is spent on housing. 3) Food insecure: unable to acquire a guaranteed source of food in the past year. 4) No Health Insurance: don't have medical insurance. 5) With Access to Exercise Opportunities: have sufficient access to parks or recreational facilities for physical activity. 6) Commute ≥ 60 minutes: commute time is 60 minutes or more.

2.2 Statistics analysis

I applied two methods to study the problem: Ordinary Least Squares Regression (OLS) and Geographically Weighted Regression (GWR). OLS is applied to fit linear models. It can find the minimum sum of squares of the result of the actual value minus the model estimate, and measure the coefficient of the independent variable. The OLS displays as follows:

$$Y = \beta_0 \ + \beta_i * i + \varepsilon$$

where Y is the diagnosed diabetes percentage, β_0 refers the intercept of the model, X_i is each 9 SDOHs, β_i refers to the correlation coefficient for each SDOH, and ϵ refers to a random error term. However, based on the preliminary analysis of the real dataset discussed in this paper, the residual of the linear model does not perfectly obey the normal distribution and equal variance. Therefore, an extension of OLS is used for resolve the problem. The Generalized Linear Model (GLM) with gaussian family and identity canonical link will be implemented in the following research.

Notably, GLM can't demonstrate the spatial heterogeneity between the explained variables and their explanatory variables in geographic world. Therefore, I used GWR in this study to estimate the relationship between diagnosed diabetes and SDOHs in 2018. The use of GWR for disease research (e.g., COVID-19) has been described in recent publications [11]. By using the GWR method and establishing a local regression model, the spatial change of the research object at a particular scale and related interfering or promoting factors can be explored, reflecting the spatial impact of the relationship between the explanatory variable and the explained variable. Bandwidth is an important parameter affecting the coverage of kernel function in GWR. There are generally two methods for finding bandwidth automatically: minimizes cross-validation (CV) functions and minimizes Akaike information criteria (AIC).

In conclusion, I applied two models to research regional differences in rates of diagnosed diabetes and SDOHs. I compiled and executed the GLM and GWR models through R. For GWR models, in order to evaluate relevant spatial structure features, I chose CV to get the optimal bandwidth. In the GLM model, the coefficient and P-value will be discussed in the results. In the GWR model, the coefficient will be discussed. The coefficient represents the extent to which each unit change of the explanatory variable influences the average change of the explained variable. The P-value is a confident indicator of the result. P-value < 0.01 is a significant association, meaning the possibility that the discrepancy between the samples is due to sampling error is less than 0.01.

3 RESULTS

The initial dataset contained data for 3,142 counties in United States. After cleaning and processing the dataset, I filled in the missing values with the average and added the latitude and longitude of

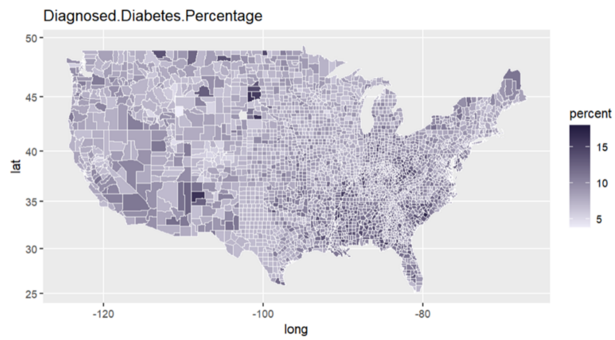

Figure 1: Spatial distribution of diagnosed diabetes in U.S. counties (per 100 people).

each county. The final dataset was formed with a sample size of 3,141 counties.

Table 1 provides a description of the dataset. More than half of the counties were diagnosed diabetes percentage between 7% and 10% (64.5%), households without Internet service between 15% and 25% (66.5%), severe housing cost burden between 6% and 12% (63.9%), food insecurity between 10% and 16% (60.4%), access to exercise opportunities between 40% and 80% (58.7%), commute >60 minutes less than 10% (73.1%), no health insurance between 5% and 15% (70.5%), defined urban (57.5%). Almost half of the counties had overall socioeconomic status and overall SVIs between 0.25% and 0.75% (50%).

Figure 1 shows the spatial distribution of diagnosed diabetes percentage (dependent variable, Y) in the study area. The darker the color, the greater the percentage of diagnosed diabetes. The southeast of the United States had dark concentrations (10%-15%), while a few scattered areas in the West had darker colors (10%-15%). Other regions were lighter (about 5%).

As discussed in the method section, the GLM was applied to analyze the global relationship between 9 SDOHs and diagnosed diabetes percentage. Table 2 shows the GLM results. According to the results, 6 variables were very confident that the 6 estimates were statistically significant They were overall socioeconomic status, overall SVIs, food insecurity, access to exercise opportunities, no health insurance and urban or rural ($P < 0.01$).

Among them, overall socioeconomic status, overall SVIs, food insecurity and urban or rural played positive roles ($\beta > 0$). The overall socioeconomic status ($\beta = 0.898, P = 0.0158$) was confident that it had an outstanding influence on diagnosed diabetes percentage, which increased with the increase of overall socioeconomic status. The coefficient of overall SVI ($\beta = 1.9742, P = 1.18E - 15$) was estimated with high confidence, and as it went up, the diagnosed diabetes percentage went up significantly. Urban or rural ($\beta = 0.7887, P < 2E - 16$) positive effect on diagnosed diabetes percentage also was obvious, and the reliability of coefficient estimation was very high. Food insecurity ($\beta = 0.0523, P = 4.15E - 05$) was highly confident that it had little or no positive effect on diagnosed diabetes percentage.

The access to exercise opportunities and no health insurance played negative roles ($\beta < 0$). Access to exercise opportunities ($\beta = -0.0047$, $P = 0.00125$) was confident that it had a slight influence on diagnosed diabetes percentage, which decreased or kept with the increase of access to exercise opportunities. Also, as no health insurance ($\beta = -0.0516$, $P = 9.57E - 16$) rose, there was a very high confidence that Y decreased slightly or did not respond.

Household with no internet service also played a positive role ($\beta > 0$), and severe housing cost burden and commute > 60 min also played negative roles ($\beta < 0$). However, their P-values were bigger than 0.01, or even bigger than 0.05. Therefore, their coefficient estimates were unreliable and unconfident, and there was no apparent relationship with diagnosed diabetes percentage.

Considering the spatial effects of explained variables and explanatory variables in geographical phenomena, GWR was used to determine whether there were differences in coefficient sizes within the study area. I found that among the 6 variables selected above ($P < 0.01$), the coefficients of 3 variables were different in different regions. They were overall SVIs, no health insurance and access to exercise opportunities. Figure 2, Figure 3, Figure 4, show GWR model results. The darker the color, the larger the coefficient.

The coefficient of overall SVIs showed significant regional differences. The eastern United States was significantly darker than the western United States, with the southeast being the darkest overall and the southwest the lightest overall. Diagnosed diabetes percentage in all regions increased as overall SVIs increased ($\beta > 0$), but the southeast increased more significantly ($\beta > 10$), and the

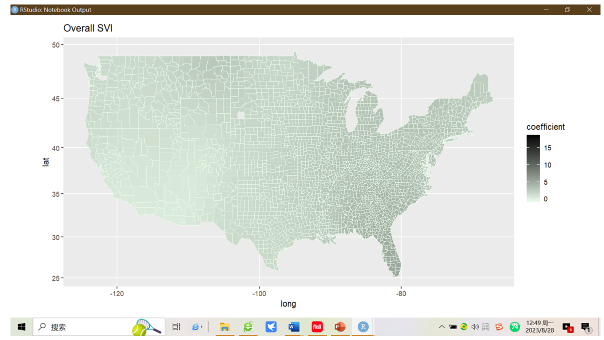

Figure 2: The size of the SVI coefficients by county in U.S.

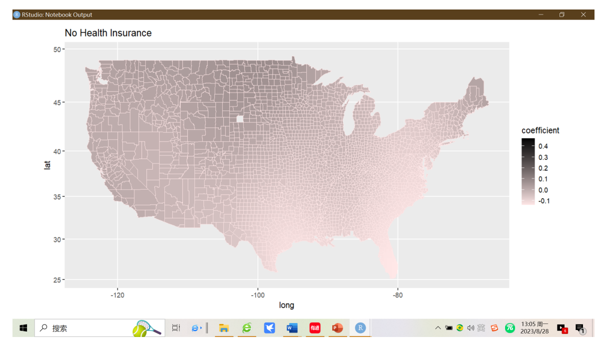

Figure 3: The size of the no health insurance coefficients by county in U.S.

Table 1: Statistical description of selected features in the study

Characteristics	N	Min	1st Qu.	Median	Mean	3st Qu.	Max	std	percentage	NA rate
Diagnosed Diabetes (%)	3141	3.8	7.3	8.4	8.721	9.7	17.9	1.7946		0
<7	429								0.137	
7-10	2027								0.645	
≥10	685								0.218	
Overall Socioeconomic Status (%)	3140	0	0.2502	0.5	0.5001	0.7501	1	0.2888		0.0032
<0.25	784								0.25	
0.25-0.75	1570								0.5	
≥0.75	786								0.25	
Overall SVI (%)	3140	0	0.2497	0.5001	0.5001	0.7501	1	0.2888		0.0032
<0.25	786								0.25	
0.25-0.75	1568								0.5	
≥0.75	786								0.25	
Household with No Internet Service (%)	3141	2.5	14.8	19.5	20.56	25.2	59.6	8.2545		0
<15	234								0.074	
15-25	2089								0.665	
≥25	818								0.260	
Severe Housing Cost Burden (%)	3137	0.7775	8.3814	10.2365	10.6804	12.5714	30.3417	3.5204		0.0013
<6	206								0.066	
6-12	2004								0.639	
≥12	927								0.296	
Food Insecurity (%)	3141	2.9	10.5	12.9	13.1	15.6	29.4	3.7176		0
<10	642								0.204	
10-16	1897								0.604	
≥16	602								0.192	
Access to Exercise Opportunities (%)	3061	0.03939	39.5121	56.6315	55.215	72.635	100	23.769		0.025
<40	777								0.254	
40-80	1797								0.587	
≥80	487								0.159	
Commute >60 min (%)	3136	0.2	4.5	6.8	8.093	10.3	38.7	5.0424		0.0016
<10	2293								0.731	
≥10	843								0.269	
No Health Insurance (%)	3140	0.7	5.8	8.7	9.639	12.1	46.3	5.1036		0.0032
<5	495								0.158	
5-15	2215								0.705	
≥15	430								0.137	
Urban or Rural										
Urban	1807								0.575	
Rural	1334								0.425	

Table 2: The result of GLM.

Characteristics	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	6.9	0.1878	36.734	<2E-16	***
Overall Socioeconomic Status (%)	0.898	0.2839	3.163	0.00158	**
Overall SVI (%)	1.9742	0.2453	8.048	1.18E-15	***
Household with No Internet Service (%)	0.0046	0.0054	0.86	0.38998	
Severe Housing Cost Burden (%)	-0.0057	0.0091	-0.631	0.52806	
Food Insecurity (%)	0.0532	0.013	4.105	4.15E-05	***
Access to Exercise Opportunities (%)	-0.0047	0.0015	-3.23	0.00125	**
Commute >60 min (%)	-0.0055	0.0056	-0.971	0.3316	
No Health Insurance (%)	-0.0516	0.0064	8.074	9.57E-16	***
Urban or Rural	0.7887	0.0636	12.394	<2E-16	***

Note: p < 0.001 '***', p < 0.01 '**'

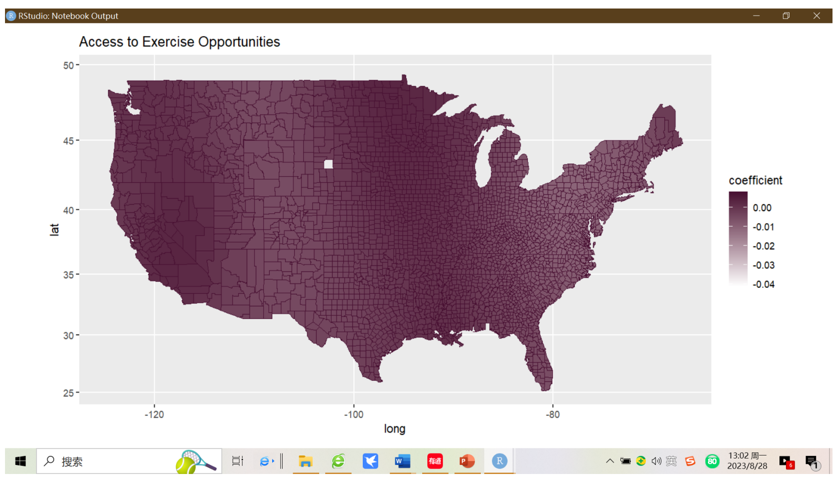

Figure 4: The size of the access to exercise opportunities coefficients by county in U.S.

southwest increased slightly ($\beta < 5$). Growth in the north was in the middle ($5 < \beta < 10$).

No health insurance coefficients also varied widely by county. With longitude -100 as the dividing line, the color of the western region on the right was darker, and the color of the eastern region on the left was lighter, of which the color of the southeast was the lightest. In the western region, no health insurance had positive effects on diagnosed diabetes percentage ($\beta > 0.1$), while in the northeastern region, the positive effects were relatively weak ($0 < \beta < 0.1$). But in 632 counties in the Southeast, diagnosed diabetes percentage decreased as no health insurance increased ($\beta < 0$).

The coefficient of access to exercise opportunities showed more minor regional difference than the other two. From the eastern to the western United States, the color of access to exercise opportunities coefficient showed a trend of first getting lighter, second darker and then lighter. Between longitudes -80 to -100 and longitudes less than -115, there were 2255 counties where the coefficients were positive. As access to exercise opportunities increased, diagnosed diabetes percentage also increased ($\beta > 0$). The remaining 886 counties' access to exercise opportunities had negative effects, located between longitudes -100 to -115 and longitudes more than -80 ($\beta < 0$).

The P-value of overall socioeconomic status, food insecurity and urban or rural were also less than 0.01, but visualizing their 3,141 counties' coefficient estimates on the map showed no significant color difference. Therefore, their effects on diagnosed diabetes percentage did not change with spatial position.

4 DISCUSSION

In order to fill the previous research gap, 2 different types of methods, GLM and GWR, were used to measure the relationship between a diagnosis of diabetes and broader SDOHs, and to compare the variation in variable coefficients in different regions of the United States. The results indicated that 6 variables were found to be confident, 4 had a positive effect and 2 had a negative effect. In particular, among which 2 variables coefficients had significant regional differences and 1 had weaker differences.

According to the GLM model, our results showed overall socioeconomic status, overall SVIs, food insecurity, urban or rural had positive functions in diagnosing diabetes. It supports the hypothesis that residents living in vulnerable neighbourhoods in urban with higher rates of poverty may face a higher risk of being diagnosed with diabetes. Although food insecurity played a positive role in the diagnosis of diabetes, the estimated coefficient was minimal, almost close to 0, so it could be considered that there was hardly a relationship between food insecurity and diabetes. These claims were consistent with previous researches [12-14]. Surprisingly, the coefficient for socioeconomic status was estimated to be positive, too. This finding contradicts claim that high socioeconomic status reduced the risk of being diagnosed with diabetes [15]. Therefore, after the literature review, there were articles indicating that Latinos of lower socioeconomic status in the United States experienced fewer harmful health consequences than non-Latinos, suggesting that income wasn't a decisive factor in avoiding unhealthy eating behaviours [16]. Furthermore, the social economic status is usually evaluated objectively, and there is a lack of subjective evaluation [17]. For example, objectively evaluate people with very low socioeconomic status, still they disagree with themselves, and there is no tremendous psychological pressure or other stress that may have prompted them to be diagnosed with diabetes.

The GLM model also showed access to exercise opportunities and no health insurance played negative roles. The coefficient estimates for both were small, close to 0, so they could be considered irrelevant to the diagnosed diabetes. This contradicts studies indicating that exercise and health insurance decreased the risk of diagnosed diabetes [18, 19]. However, although studies showed that exercise was beneficial for reducing the risk of being diagnosed with diabetes, they have focused on aerobic exercise and resistance exercise [20]. What this paper study is whether there is sufficient access to parks or recreational facilities for physical activity, people do not necessarily exercise and achieve the corresponding intensity. This may have contributed to the difference in results. Finally, the slight negative or no correlation between no health insurance and diagnosed diabetes cannot be explained. It is possible that and the number of people without health insurance may have changed over time, which is one of the shortcomings of the cross-sectional data.

In the GWR model, the result of overall SVI suggested that people in United States living in poor, vulnerable communities had a higher risk of being diagnosed with diabetes in the Southeast than in the West. This could be explained by previous research. The incidence of diabetes was higher among blacks than whites [21], and black people who live mainly in the southern United States have higher SVI. In addition, the southern United States has a higher risk of cardiovascular disease than other regions because of higher SVI [22], and cardiovascular disease is one of the diabetes complications.

GWR model also suggested that people living in the West and Mideast United States who have more access to exercise had a higher risk of being diagnosed with diabetes or no influence, while those living in the Midwest and East had a lower risk of being diagnosed with diabetes with more access to exercise. There is a research analysis that identified three types of exercise: team sports, fitness sports, and sports that require facilities. Whites were found to disproportionately exercise in facilities, and Mexican Americans tended to prefer team sports [23]. Most Mexican Americans live in the western state of California, and up to 93.6% of whites live in Maine in the northeastern corner of the country. As previously discussed in GLM results, aerobic exercise and resistance exercise were more likely to reduce the risk of diabetes diagnosis, both of which are biased towards fitness activities and facility exercises. Access to exercise opportunities studied in this paper was to provide venues for these two kinds of exercises. Thus, it could be explained that in the whiter Northeast, providing more opportunities for exercise reduced the risk of being diagnosed with diabetes, while it had no obvious effect in the west.

I acknowledge the limitations of the study. First, this dataset was based on cross-sectional data for 2018 and did not reflect long-term trends for each factor. Moreover, most of the data in this dataset was collected through surveys. Generally, the survey designer has designed the range of answers in advance, which may cause the answers of respondents limited and miss some detailed or deep information. Thus, researchers cannot obtain the rich information from the answers for complex questions. Finally, the regional variation in the GWR results in the coefficient estimates of no health insurance couldn't be explained.

5 CONCLUSION

My study supports the hypothesis that different SDOHs had different effects on the diagnosis of diabetes. In global, high overall socioeconomic status, overall SVIs and living in urban increased the risk of diabetes, while food insecurity, access to exercise opportunities and no health insurance had little effect on diabetes. Among them, the overall SVI and access to exercise opportunities had different degrees of impact in different counties of the United States. It could be reasonably explained.

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