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Research Article

Entrepreneurial Environment and the Prevalence of Diabetes in U.S. Counities

Troy C. Blanchard,[1] Jing Li,[2] Carson Mencken,[2] and Charles M. Tolbert[2]

[1] *Department of Sociology, Louisiana State University, 126 Stubbs Hall, Baton Rouge, LA 70803, USA*
[2] *Department of Sociology, Baylor University, 97326 One Bear Place, Waco, TX 76798, USA*

Correspondence should be addressed to Troy C. Blanchard, troy@lsu.edu

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Objective. To examine whether the presence of an entrepreneurial culture in a community is associated with county-level diabetes prevalence in the U.S. after accounting for high level of spatial clustering of prevalence rates observed in prior research. *Methods.* We perform a county-level spatial regression analysis of CDC diabetes prevalence rates. We measure entrepreneurial culture as the number of businesses with 0 to 4 employees per 1,000 residents. *Results.* The level of entrepreneurial culture in a community is associated with lower rates of diabetes. Our findings show that the key measure of entrepreneurial culture has expected effects on county diabetes rates. However, we show that failure to control for spatial error dependence in previous research leads to an overestimation of the effects of entrepreneurial culture on diabetes prevalence. *Conclusion.* Policies aimed at curbing diabetes prevalence should utilize the business community as a key agent of social change. Researchers should also utilize spatial regression techniques when analyzing county-level diabetes prevalence rates, because of high level of spatial clustering of rates.

1. Introduction

An emerging line of research on county-level variation in morbidity and mortality points to the importance of structural aspects of the county that are features of *the social and cultural environment* of the community.Facilitated by the development of county-level estimates of diabetes prevalence by the Centers for Disease Control [1], health researchers studying the health of U.S. communities have been provided the capacity to understand county-level variation in diabetes prevalence.The study of diabetes prevalence for U.S. counties is valuable to public policy practitioners because many federal programs are administered at the county level.

Recent research on the role of the cultural environment in diabetes prevalence by Blanchard et al. [2] suggests that a community's level of entrepreneurial culture is a key explanatory factor for variation in diabetes prevalence.An important aspect of the entrepreneurial culture is the capacity for a community to solve local problems without external assistance. The presence of an entrepreneurial culture implies that a community possesses a higher level of collective efficacy, or the capacity and willingness of community members to take responsibility for solving local problems [3–5]. Because business owners are both economically and socially tied to the community, local entrepreneurs have an economic interest in maintaining the quality of life for local residents [6].

Blanchard et al. [2] propose three pathways through which collective efficacy may influence health outcomes. First, communities with a higher level of collective efficacy have a greater capacity to procure health infrastructure, such as hospitals and clinics, and to recruit health professionals. Prior research suggests that this investment in the local health care system is directly associated with improved population health [7, 8].

Second, a high level of collective efficacy also facilitates investments in the local environment. Environmental factors, such as educational programming, environmental safety, affordable housing, and recreational facilities, have been linked to improved health outcomes [8]. Research demonstrates that community health programming educates local residents about their health status and informs residents about avoiding or managing chronic illnesses, such as diabetes [9]. Moreover, Cohen et al. [10] find a strong link between collective efficacy and the quality of the built environment in terms of the safety and walkability of the community.

Third, a final mechanism through which collective efficacy impacts health outcomes are the social control of health related behaviors. Collective efficacy provides a foundation for community members to share and enforce public health related norms, such as smoking, poor diet, and exercise. For example, Cohen et al. [10] argue that collective efficacy reduces levels of stress by enhancing networks of social support, increasing the level of guardianship of adults over health-related behavior of children, and a great level of involvement in sports related activities.

A key shortcoming of findings regarding entrepreneurial culture by Blanchard et al. [2] is that the authors do not account for findings by Barker et al. [11] who identify and describe a contiguous "diabetes belt" among U.S. counties. The authors identify a cluster of counties with a high prevalence of diabetes diagnosis in Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Texas, Virginia, and West Virginia. More importantly, the authors find that the difference in risk of diabetes is significantly greater in the "diabetes belt" after adjusting for demographic and socioeconomic differences. Barker and colleagues [11] find that counties in the "diabetes belt" have population characteristics that differ in important ways from other U.S. counties. The most profound difference observed between "diabetes belt" counties and the remainder of the U.S. was the larger percentage of non-Hispanic blacks. These finding lends support to the notion of unhealthy places noted in prior studies (e.g., see Cossman et al. [12]).

In this paper, we integrate research by Blanchard et al. [2] and Barker et al. [11] to test the entrepreneurial culture hypothesis using a spatial regression framework that accounts for observed levels of spatial clustering of county-level diabetes prevalence. We begin our analysis by performing an exploratory spatial data analysis of county-level diabetes prevalence. We then assess two spatial regression model specifications to identify the appropriate form of spatial dependence. Our models address two questions. First, how spatially dependent is county-level diabetes prevalence after accounting for key predictors identified in prior studies? Second, do the findings regarding entrepreneurial culture hold after accounting for spatial dependence?

2. Data and Methods

In the analysis that follows, we test the hypothesis that the level of entrepreneurial culture within a community is associated with a lower prevalence of diabetes. Our analysis is based on data from the 2000 Census of Population and Housing, Summary Files 3, the 2002 County Business Patterns, the 2002 Nonemployer Statistics, the 2007 Centers for Disease Control Obesity and Diabetes Estimates, and the National Center for Health Statistics Compressed Mortality records from 1994 to 1998. The units of analysis for our study are 3,060 counties in the contiguous USA In the event that a county contained an independent city, data for the independent city and county were combined to a single-county unit. The dependent variable in our analysis is the county-level diabetes prevalence rate, an estimate from the 2007 Centers for Disease Control Obesity and Diabetes Estimates.

Our independent variables come from a variety of sources. We measure entrepreneurial culture using data from the 2002 County Business Patterns and the 2002 Nonemployer Statistics. We classify small businesses as the number of business establishments with zero to four employees. Entrepreneurial culture is measured as the number of small businesses per 1,000 people.

We also control for a variety of covariates of diabetes prevalence, such as health insurance coverage, per capita income, income inequality, minority concentration, health infrastructure, metropolitan status, as well as population characteristics. Measured in thousand dollars, per capita income variable is derived from the 2000 Census of Population and Housing by using total income per person. We measure income inequality using the Gini coefficient of inequality based on household income form the 2000 Census. Measures of the percentage of non-Hispanic Black population and the percentage of Hispanic population are included to account for spatial disparities in diabetes prevalence [11].

The local health infrastructure is operationalized as the number of physicians per 1,000 residents in 2002. Because the availability of health-care facilities and professionals varies substantially across rural and urban localities [13], we use a dummy variable to indicate metropolitan status by using the classification in the 2003 Urban Influence Codes (ERS2003: http://www.ers.usda.gov/data/urbaninfluencecodes/2003/). To take population size and age into consideration, we also include the natural logarithm of the county population size and the percentage of the population that are 65 years and older as control variables. Following Blanchard et al. [2], we account for possible endogeneity in our analyses and include the 1994–1998 age-adjusted mortality rate in the models. Adding the time-lagged measure of mortality provides a more robust test of our model because of possible reverse causation. For example, unhealthier populations may be less economically productive than those that are healthy. Descriptive statistics for the variables in the analysis are reported in Table 1.

To investigate the effect of our independent variables on the county-level diabetes prevalence rate, we initially estimate a standard, multivariate, linear ordinary least squares (OLS) regression model. However, due to the intrinsic heterogeneity of rates across varying populations at risk created by the presence of a "diabetes belt," we then check the OLS residuals and perform an exploratory spatial data analysis (ESDA) for spatial dependence. If so indicated, spatial models (i.e., spatial lag and spatial error models) are applied to accommodate spatial autocorrelation, which may lead to artificially low-standard errors in the classical OLS regressions [14].

Table 1: Descriptive statistics.

Variable	Mean	S.D.
Diabetes prevalence rate, 2007 (in percentage)	9.65	2.01
Number of businesses with 0–4 employees per 1,000 people	76.05	23.28
Percent of population uninsured	17.74	7.32
Income inequality (gini coefficient)	42.41	3.48
Per capita income (in thousand dollars)	17.45	3.88
Percent of population nonhispanic black	8.60	14.39
Percent of population hispanic	6.14	12.13
Number of physicians per 1,000 people	1.51	3.20
Population size, natural log	10.25	1.40
Percent of population age 65 and older (2000)	14.82	4.10
Age adjusted mortality rate, 1994–1998	922.61	128.14
County part of metropolitan area (1 = Yes, 0 = No)	0.34	0.48

$N = 3,060$.

3. Results

In our analyses, we proposed that the presence of a strong entrepreneurial culture, measured as the number of small businesses with zero to four employees, would be associated with communities with lower rates of diabetes. We find support for this argument in our classical OLS results (Panel 1 of Table 2). The concentration of small businesses is strongly associated with lower percentages of population diagnosed with diabetes. However, both the diagnostics on OLS residuals and ESDA reveal a very strong spatial autocorrelation. The Moran's *I* statistic, a measure of global spatial dependence, is 0.72, suggesting significant clustering in space of similar diabetes prevalence rates. (The diagnostics on OLS residuals and other ESDA results are available upon request.) Therefore, we employed spatial models to formally account for this lack of independence. (The first order queen contiguity weights matrix was applied for the final spatial models. The exploratory analysis using the first order rook contiguity weights shows similar results.)

Once again, the results show that counties with a vibrant small-business sector have a lower prevalence of diabetes (Panels 2 and 3 in Table 2). Although the absolute value of the coefficient of the small businesses becomes smaller in these models, indicating that the effect was partially reflected in spatial dependence, it remains in the expected direction and is still highly significant. These findings provide robust support for our hypothesis that the importance of small-business sector goes beyond job growth; it has significant implications on physical healthiness of the local communities such as diabetes prevention. We obtain this finding after accounting for spatial dependence in addition to the control variables in the model. Moreover, our results hold after adjusting for the lagged age-adjusted mortality rate from 1994 to 1998.

With only one exception, our control variables generally conform to findings from previous studies. As expected, the percent of the population uninsured is associated with a higher level of diabetes, while increases in per capita income are associated with a lower level of diabetes. Counties with a large presence of physicians per 1,000 people enjoy less diabetes. Consistent with prior studies, we find that the percentage of Hispanic population is negatively associated with diabetes rates, and the percentage of non-Hispanic Black population is positively associated with diabetes rates [15]. The only inconsistent finding is that in the spatial error model income inequality, as measured by the Gini coefficient, is associated with lower rates of diabetes. Though not common finding, a couple of other studies also show similar results [2, 16].

The spatial parameters are highly significant for both models, confirming the presence of strong spatial autocorrelation. Compared with the classical OLS regression, both the spatial lag and the spatial error regressions provide an improved model fit with increased Log Likelihood (LL), decreased Akaike Information Criterion (AIC). and Schwarz Criterion (SC, the bottom panel in Table 2). These model fit statistics also show that the spatial error model performs slightly better than the spatial lag model. Importantly, robust lag and error statistics (Lagrange Multiplier tests; Anselin [17]) indicate a preference for spatial error dependence (236.32 versus 284.72). Moreover, the spatial lag model does not follow the expected ordering of three classic specification tests that compare the OLS with the alternative spatial model: Wald > Log Likelihood Ratio > Lagrange Multiplier, while the spatial error model does. Overall, the diagnostics suggest a clear preference for the spatial error model than for the spatial lag model, but we show both models to test whether either specification might improve the performance of our key independent variable—small businesses, as well as control variables. It turns out the effect of small businesses on the prevalence rate of diabetes is 1.5 times larger in the spatial error model than in the spatial lag model, but both are smaller than the OLS effect, as predicted. The percent of population uninsured changed to the expected direction in both spatial models, while income inequality changed sign unexpectedly in the spatial error model. Overall, most effects are smaller in the spatial models than in the OLS regression, as expected.

4. Discussion

In this study we assess a structural explanation of county-level variation in diabetes prevalence. Our findings provide strong support for the entrepreneurial culture argument after accounting for spatial clustering of prevalence rates in the "diabetes belt" identified by Barker et al. [11]. An entrepreneurial culture provides for greater levels of interaction and trust among community members, which fosters collective efficacy. Higher levels of collective efficacy have a greater capacity to procure health infrastructure, such as hospitals and clinics, as well as recruit health professionals. Communities with large stocks of collective efficacy also can provide a healthier social environment through educational programming, environmental safety, affordable housing, and recreational facilities. Collective efficacy provides a foundation for community members to share and enforce

Table 2: Classic OLS, spatial lag model, and spatial error model of the county-level diabetes prevalence rate (2007).

	Classic OLS		Spatial lag		Spatial error	
	b	s.e.	*b*	s.e.	*b*	s.e.
Number of small businesses per 1,000 people	−0.0129***	0.0013	−0.0063***	0.0011	−0.0094***	0.0012
Percent of population uninsured	−0.0096+	0.0058	0.0109*	0.0046	0.0312***	0.0057
Income inequality (gini coefficient)	0.0983***	0.0092	0.0103	0.0074	−0.0191*	0.0081
Per capita income (in thousand dollars)	−0.0585***	0.0103	−0.0155+	0.0082	−0.0263**	0.0093
Percent of population nonhispanic black	0.0434***	0.0021	0.0249***	0.0018	0.0417***	0.0027
Percent of population hispanic	−0.0215***	0.0027	−0.0093***	0.0021	−0.0248***	0.0034
Number of physicians per 1,000 people	−0.0236**	0.0073	−0.0174**	0.0057	−0.0102*	0.0051
Population size, natural log	−0.0834***	0.0242	−0.0346+	0.0191	−0.0876***	0.0211
Percent of population age 65 and older (2000)	0.1157***	0.0069	0.1090***	0.0055	0.1502***	0.0063
Age adjusted mortality rate, 1994−1998	0.0052***	0.0002	0.0035***	0.0002	0.0024***	0.0002
County part of metropolitan area	0.2428***	0.0617	0.0919+	0.0486	0.0365	0.0470
Spatial parameter			0.5596***	0.0145	0.7779***	0.0136
Intercept	1.7286***	0.4573	−0.2735	0.3696	7.2912***	0.4097
R-square	0.6302		0.7708		0.8049	
Log likelihood	−4955.88		−4327.05		−4211.06	
Akaike info criterion (AIC)	9935.77		8680.09		8446.12	
Schwarz criterion (SC)	10008.10		8758.43		8518.43	
Wald			1482.25		3249.42	
Likelihood ratio (LR)			1257.67		1489.64	
Lagrange multiplier (LM)			1429.44 (236.32)		1477.84 (284.72)	

Two-tailed tests: $^{***}P < .001$; $^{**}P < .01$; $^{*}P < .05$; $^{+}P < 0.1$.
$N = 3,060$.
Numbers in the parentheses are robust LM values.

public health related norms. Combined, these factors provide a social environment that fosters a low prevalence of diabetes.

An important implication of our analysis is that researchers examining county-level variation in diabetes prevalence should account for spatial clustering. Within a multivariate regression framework, our analyses uncovered significant spatial clustering after accounting for demographic and socioeconomic controls. Although Barker et al. [11] noted key population differences between "diabetes belt" and other counties, our models indicate that there is significant unobserved heterogeneity that drives the spatial clustering of diabetes prevalence. In other words, unmeasured factors, such as culture, may be generating spatial dependence in prevalence rates. Researchers seeking to analyze county-level prevalence rates of diabetes using a multivariate regression framework should be careful to utilize a spatial regression technique that captures unobserved heterogeneity. We suspect that prevalence rates of similar diseases, such as obesity, follow a similar pattern.

Overall, our analysis further underscores the importance of local small businesses for communities. Small business owners hold a unique community position where economic investment in the local economy intersects with the quality of life and well-being of residents.

Given their stake in the community, policymakers should seek to integrate small businesses into community health efforts. For example, local small business owners may interface with nearby farms to include locally grown food in restaurants and grocery stores. Given the high level of social capital possessed by small business owners, these individuals may provide support to laws that improve health outcomes, such as antismoking legislation.

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