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The changing food environment and neighborhood prevalence of type 2 diabetes

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ABSTRACT

In this ecological study, we used longitudinal data to assess if changes in neighborhood food environments were associated with type 2 diabetes mellitus (T2DM) prevalence, controlling for a host of neighborhood characteristics and spatial error correlation. We found that the population-adjusted prevalence of fast-food and pizza restaurants, grocery stores, and full-service restaurants along with changes in their numbers from 1990 to 2010 were associated with 2015 T2DM prevalence. The results suggested that neighborhoods where fast-food restaurants have increased and neighborhoods where full-service restaurants have decreased over time may be especially important targets for educational campaigns or other public health-related T2DM interventions.

1. Introduction

Diabetes poses an increasing threat to Americans' health. The prevalence of Type 2 diabetes mellitus (T2DM) has increased from 4.5% in 1990 (American Diabetes Association, 2018) to 8.5% in 2016–17 (Xu et al., 2018), and is forecasted to increase further by 2030 (Rowley et al., 2017). This growing epidemic has led to a call for research focused on identifying population-wide strategies for preventing and managing T2DM (White, 2016). The emphasis on population-related approaches comes simultaneously with increased use of geographic information systems (GIS) to capture spatial patterns of socioeconomic and physical environmental characteristics. Integrating GIS technology into T2DM research has facilitated a more in-depth understanding of the potential health benefits of environmental features amenable to public policy interventions. Numerous studies reviewed in den Braver et al. (2018) and Dendup et al. (2018) have examined the relationship between neighborhood walkability and T2DM risk, but fewer have assessed the potential role of the local food environment. Yet, the local food environment is likely an important neighborhood-level risk factor, given that food outlets vary in offerings that can support a healthy diet and thus help prevent T2DM (Bhupathiraju & Hu, 2016).

When considering the food environment, supermarkets generally offer more healthy and unprocessed foods, such as fresh produce and whole grains, while fast-food restaurants and convenience stores offer fewer healthy food options (Sallis & Glanz, 2009). Recent longitudinal studies typically have found that neighborhood access to supermarkets and fast-food outlets have both grown over time regardless of neighborhood socio-economic status (SES) (Hobbs et al., 2021; James et al., 2017; Maguire et al., 2015; Richardson et al., 2014; Rummo et al., 2017). At the same time, some studies have reported that, despite the overall growth, fast-food outlets were relatively more prevalent in low SES neighborhoods (James et al., 2017; Maguire et al., 2015), where the risk of T2DM was also relatively high (Robbins et al., 2005). The majority of cross-sectional studies assessing the relationship of the food environment to T2DM risk reported access to more healthy retail food options was associated with lower risk of T2DM and access to less healthy retail food options was related to higher risk of T2DM (Ahern et al., 2011; Auchincloss et al., 2009; Christine et al., 2015; Cunningham et al., 2018; Gebreab et al., 2017; Wiki et al., 2021), with a minority of studies having reported no relationship (Alhasan & Eberth, 2016; Berkowitz et al., 2018; Paquet et al., 2014; Piccolo et al., 2015).

Longitudinal studies that examined changes in the food environment over time and their relationship to T2DM can provide greater insight regarding potential causality (Dendup et al., 2018), but the few longitudinal studies that have been done have produced mixed results, similar to their cross-sectional counterparts. In two cases, there was

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evidence that the loss of healthy food options was linked to increased T2DM (Mezuk et al., 2016; Zhang et al., 2017). Two other studies, however, reported no association (Feldman et al., 2020; C. Pérez-Ferrer et al., 2020). And finally, one study found no relationship between objective measures of changes in the food environment and T2DM, but reported that residents' subjective measures of declines in healthy food options within their neighborhoods was associated with higher rates of T2DM (Christine et al., 2015). Some of these longitudinal studies (1) limited or used aggregate measures of the food environment (Christine et al., 2015; Mezuk et al., 2016; Zhang et al., 2017), (2) did not control for neighborhood walkability (Mezuk et al., 2016; C. Pérez-Ferrer et al., 2020; Zhang et al., 2017), and/or (3) used definitions of neighborhoods that may have been too broad (e.g., a county) (Feldman et al., 2020). The ecological analysis conducted here aims to address these potential shortcomings.

We built on past research and developed five novel aspects in the current study. First, we examined the relationship between changes in neighborhood food environments and residents' T2DM risk using food environment data over a significantly longer time frame (i.e., 20 years) than prior studies. This is advantageous because change in the food environment happens slowly. For example, Zhang et al. (2017) reported that during a four-year period that included the 2007–09 Great Recession, only about 2% of individuals in their study lived in neighborhoods that gained one or more supermarkets and only 2–3.8% lived in neighborhoods that lost one or more supermarkets (Zhang et al., 2017). Similarly, another study assessed changes in the food environment over 40 years and found that while fast-food outlet counts doubled over that time period, there were much smaller changes in counts of supermarkets (James et al., 2017). Second, we assessed time-varying measures of five distinct aspects of the food environment – full-service restaurants, fast-food restaurants, convenience stores, grocery stores, and supermarkets – allowing us to better pinpoint aspects of the local food environment that might best be targeted for public health initiatives. Third, we controlled for a broader set of neighborhood features that have been linked to T2DM risk in other studies (e.g., air quality, green spaces, neighborhood walkability) (Beulens et al., 2021; den Braver et al., 2018; Dendup et al., 2018). These features may also be associated with the diversity of food options available in a neighborhood, allowing us to distinguish food environment associations with T2DM risk from other neighborhood characteristics. Fourth, our definition of what constitutes the geographic boundaries of the neighborhood food environment was not based on the geographic measures that are typically used when assessing neighborhood walkability. Rather, our measure was based on past research that has examined different geographic definitions of the food environment and their relationship to obesity. Finally, a recent cross-sectional study using data from New Zealand found spatial error correlation in T2DM risk across neighborhoods (Wiki et al., 2021), yet most prior research has not accounted for this. We adjusted for spatial correlation in the error term.

2. Methods

2.1. Data

Our study drew on data from the Wasatch Front region of Utah, the urban core of the state, where approximately 75% of the state population resides. The region consists of Davis, Salt Lake, Weber, and Utah counties. Diabetes statistics for these four counties are consistent with the range across the nation as the age-adjusted rates of diabetes among adults in these counties are 9.1%, 9.0%, 9.1%, and 7.3% respectively (Health Indicator Report of Diabetes Prevalence, 2022).

We utilized census tract as our unit of analysis because prior research has demonstrated that the census tract is the most appropriate geographic scale for measuring the relationship between the food environment and obesity risk along the Wasatch Front (Fan et al., 2014), a result that we argue extends to diabetes risk. There are 444 census tracts in the four counties as of the 2010 census. We eliminated five census tracts because they are dominated by institutional features that make their populations inappropriate for this study.[1] Thus, our final sample consisted of 439 census tracts comprising our neighborhoods of interest. In 2010, the average Wasatch Front census tract had 2847 residents age 18–64, and the median tract size was 2.89 km.

Data that capture neighborhood features, including food establishments, were geocoded using ArcGIS and assigned to the appropriate tracts using Federal Information Processing System (FIPS) codes. Given our focus on assessing changes in the food environment over time, we measured tract-level food establishments in 1990 and 2010. We also measured tract population in 1990 and the change in population between 1990 and 2010. All other neighborhood features were measured in 2010. T2DM prevalence rates were measured as of 2015 to allow for the possibility that it takes time for neighborhood features to influence T2DM rates. Details on variable construction and data sources follow.

T2DM Prevalence. Data on the prevalence of T2DM came from the Utah Population Database (UPDB), a unique research resource that contains longitudinal, individual-level information from demographic, genealogical, residential, and medical data sources for nearly the entire Utah population, both historic and contemporary. These data are linked together across a range of high quality statewide databases (Huntsman Cancer Institute, 2022; Smith et al., 2022). Use of these data for this study was approved by the Resource for Genetic and Epidemiologic Research, a regulatory body overseeing access to UPDB, as well as the University of Utah Institutional Review Board.

For the purposes of constructing T2DM prevalence in each of the tracts, we used the following inclusion criteria: (1) individuals were 18–64 years of age and alive in 2010; (2) they had at least one residential address in one of the four counties recorded in UPDB between 2005 and 2015. The first criterion was imposed so as to focus on working age adults. The second criterion was imposed because of our geographic focus on the urban Wasatch Front.

Type 2 diabetes diagnoses were extracted from medical records (including statewide inpatient discharge, ambulatory surgery, and emergency department records from 1996 to 2015), Utah death certificates (2010–2015), and Utah's All-Payer Claims Database (2013–2015) (APCD) using the appropriate International Classification of Disease (ICD) codes, version 9 and 10.[2] Individuals were coded as having T2DM as of 2015 if any T2DM diagnosis had been recorded in the preceding data sources from 1996 to 2015. The total number of eligible individuals who had at least one T2DM diagnosis in UPDB were calculated by census tract. The number of T2DM cases per 1000 tract residents age 18–64 was then calculated, using the decennial census 2010 counts in the denominator. [3]

To determine the census tract of residence for 2010, we obtained residential history for the entire cohort. Residential history in UPDB is derived from four possible sources: voter registrations, driver licenses, birth certificates, and medical records. Updates of residence are done based on events (e.g., renewal of a driver license, birth of a child). If an individual lived in the same census tract before and after 2010 with no report of residing in another census tract in between the two reports, the

[1] Among the five tracts that have been eliminated from the analyses, two tracts consisted of large military training facilities/bases, one consisted of the state prison, another consisted of the Salt Lake City airport (which has no residents) and the last one encompassed a large, sparsely populated mountainous region with very few residents.

[2] ICD 9 codes used to classify an individual with T2DM are 250, 250.02, 250.1, 250.12, 250.2, 250.22, 250.3, 250.32, 250.4, 250.42, 250.5, 250.52, 250.6, 250.62, 250.7, 250.72, 250.8, 250.82, 250.9, and 250.92. ICD 10 codes used to classify an individual with T2DM are E08.xx and E11.xx.

[3] Because the total population count comes from 2010, this raises the issue of potential bias in prevalence estimates in tracts that were rapidly growing after 2010 since we track T2DM through 2015. We minimize this potential bias by excluding counts of T2DM cases if their first address came after 2012.

individual was assigned the corresponding census tract. If multiple census tract addresses between 2008 and 2012 were reported, the individual was assigned the census tract reported closest to 2010. Individuals without assigned census tracts based on the above logic were removed from the T2DM rate calculation. As such, our measure of the prevalence of T2DM among residents age 18–64 was conservative.

Food Environment. Data on the tract level food environment came from Dun & Bradstreet's 1990 and 2010 files (Dun & Bradstreet, 2010). The first six digits of the 2010 primary Standard Industrial Classification (SIC) codes defined business types for 1990 and 2010. These data were then used to identify fast-food restaurants (i.e., fast food and pizza), full-service restaurants (i.e., family, ethnic, seafood, steak, and other restaurants), grocery stores (i.e. grocery markets and grocery stores not classified elsewhere), supermarkets (including independent and chain supermarkets, superstores, supercenters, and hypermarkets[4]), and convenience stores. To improve data accuracy, we followed recommendations from Jones et al. (2017) for improving classifications of SIC codes in Dun & Bradstreet data by referring to their list of national chains and correcting those that have incorrect SIC codes, removing addresses where locations are approximated (for example, at the zip code centroid), and eliminating duplicate listings (Jones et al., 2017).

Crosswalks developed by IPUMS NHGIS were used to convert all 1990 census tracts to 2010 census tract geographies (Manson et al., 2011). We then created counts of fast-food and pizza restaurants, full-service restaurants, grocery stores, supermarkets, and convenience stores in 1990 and 2010 for each tract. These counts were standardized as numbers per 10,000 tract residents.

Socio-Demographic Characteristics. Data on tract population, the median age of tract residents and racial/ethnic composition came from the 2010 census. In 2010, on average, the racial/ethnic composition of the tracts were 78.61% Non-Hispanic White, 14.28% Hispanic, 3.3% Asian Non-Hispanic, 1.2% Black Non-Hispanic. Each of the remaining racial/ethnic categories were, on average, less than 1%. As a consequence, we concluded that the best way to measure race/ethnicity effects would be to use the fraction of Hispanic residents within each tract. Hispanics compose a sizable fraction of the Wasatch Front population and nationally their T2DM rate of 12.8% is substantially higher than all other racial/ethnic groups except African Americans (Rodríguez & Campbell, 2017). To adjust for neighborhood economic status, we included the annual resident income measured in thousands of 2010 dollars per resident age 15+. Income data were taken from the 2006–2010 American Community Survey (ACS).

Walkability. We drew on the numerous studies that have linked measures of neighborhood walkability to T2DM (Fonseca et al., 2021). Three walkability measures, all measured proximate to 2010, were included as control variables. They are:

1. *Intersection Density*. Areas with higher intersection densities can make a wide variety of routes and destinations accessible to those on foot or bike and may slow traffic, thus making a neighborhood more walkable (Cervero & Kockelman, 1997). Intersection density was constructed from Topologically Integrated Geographic Encoding and Referencing (TIGER) Census data. Specifically, three-way or more intersections—excluding dangles, interstate highways, and dirt roads—were calculated for each 2010 tract (US Census Bureau, 2021) and divided by the 2010 tract area measured in kilometers.
2. *Median Housing Age.* Walkable neighborhoods are often older neighborhoods, with pedestrian-friendly design features such as sidewalks, street trees, and narrower roads. Prior research has linked housing age to obesity risk (Smith et al., 2008). In the current study, the 2010 median housing age in the tract was taken from the National Historical Geographic Information System (NHGIS) dataset (Manson et al., 2011).
3. *Active Transportation.* The percentage of workers who use active transportation—walking, bicycling, and taking public transit to work—is an indicator of land use diversity, and has been linked to lower BMI/obesity risk (Brown et al., 2013; Smith et al., 2008). The 2010 NHGIS contains counts of the number of individuals who are age 16+ and employed who (1) walk to work, (2) bicycle to work, and (3) use public transit to get to work. For the current study, we summed these counts and divided by the total number of individuals age 16+ residing in the tract who were employed.

Air Quality. Prior research has related air pollution to various health outcomes (Wang et al., 2014) and T2DM in particular (Beulens et al., 2021). We controlled for air quality in 2010 using land-use regression modeled data for PM10 as measured in micrograms per cubic meter (Center for Air Climate and Energy Solutions, 2022). PM10 estimates were developed by the Center for Air, Climate and Energy Solutions (CACES) using v1 empirical models (Kim et al., 2020).

Residential Greenness. Higher greenness or vegetation levels may influence health and T2DM risk through stress reduction, social engagement, ecosystem benefits (i.e., reducing pollution and excessive heat) and increasing physical activity (De la Fuente et al., 2021; Lin et al., 2019; Nieuwenhuijsen et al., 2017), although greenness may be higher in less densely populated areas that tend to be less walkable and have fewer food outlets (Shuvo et al., 2021). The Normalized Difference Vegetation Index (NDVI) is commonly used for greenspace assessment (Reid et al., 2018) and is used here. Our measures of greenness come from Landsat 7 satellite imagery averaged across June and July 2010 images (U.S. Geological Survey, 2022). Raster data were downloaded from Google Earth Engine (Google, 2022; Gorelick et al., 2017), and we computed the mean NDVI value for all 30 m pixels in a tract.

2.2. Analyses

To assess if changes in the food environment over time relate to T2DM prevalence, we adopted a multivariate model where the focus was on examining whether the tract-level changes in various types of food establishments between 1990 and 2010 related to 2015 T2DM prevalence, holding constant 1990 measures of the food environment, 2010 population socio-demographics, and other features of the tracts. This formulation had intuitive appeal because the 20-year time span allowed us to observe numerous changes while also assessing if historical characteristics of the neighborhood food environment (i.e., numbers of various types of establishments measured in 1990) related to T2DM prevalence.

We first estimated the multivariate model using ordinary least squares (OLS). However, T2DM prevalence is likely to show spatial patterns and therefore OLS parameter estimates associated with the geographic variables could be biased. To test this proposition, we fitted a model to account for spatial dependence in the error term (Anselin, 1988). This later estimation used a spatial weights matrix that defined neighboring tracts and specified the weight or relative influence of neighbors. The spatial weights matrix was created using the inverse distance of tract centroids based on latitude and longitude coordinates (da Silva, 2018).

Tests for possible collinearity among the independent variables in the multivariate analyses revealed no cause for concern. All empirical work was done using SAS 9.4. Estimation adjusting for spatial correlation of the equation error terms was undertaken using PROC SPATIALREG (SAS Institute Inc., 2016).

3. Results

Table 1 provides definitions and descriptive statistics for all of the variables used in the analyses. Focus first on the dependent variable,

[4] Hypermarkets carry food products along with goods historically found only in department stores.

Table 1
Definitions of tract-level variables and descriptive statistics (N = 439).

Variable	Definition	Mean/ Proportion	Standard Deviation
T2DM rate	Number of individuals age 18–64 with T2DM in 2015 per 1000 individuals	81.47	23.81
Food Environment			
Convenience stores 1990	Number of convenience stores in 1990 per 10,000 residents	1.17	3.44
Fast food and pizza 1990	Number of fast-food and pizza restaurants in 1990 per 10,000 residents	2.53	6.04
Supermarkets 1990	Number of supermarkets (including hypermarkets and superstores) in 1990 per 10,000 residents	0.38	1.25
Grocery stores 1990	Number of grocery stores in 1990 per 10,000 residents	1.60	3.51
Restaurants 1990	Number of full-service restaurants in 1990 per 10,000 residents	2.50	10.21
Change in convenience stores 1990 to 2010	Change in the number of convenience stores between 1990 and 2010 per 10,000 residents	−0.07	3.57
Change in fast food and pizza 1990 to 2010	Change in the number of fast-food establishments between 1990 and 2010 per 10,000 residents	1.22	5.84
Change in supermarkets 1990 to 2010	Change in the number of supermarkets between 1990 and 2010 per 10,000 residents	0.05	1.37
Change in grocery stores 1990 to 2010	Change in the number of grocery stores between 1990 and 2010 per 10,000 residents	−0.12	3.49
Change in restaurants 1990 to 2010	Change in the number of full-service restaurants between 1990 and 2010 per 10,000 residents	0.63	6.71
Covariates			
Population 1990	Tract population in 1990 measured in 1000s	3.02	1.57
Population change 1990 to 2010	Measured in 1000s	1.70	2.28
Median age 2010	Median age of all tract residents in 2010	29.47	4.89
Percent Hispanic 2010	Percentage of tract residents who are Hispanic in 2010	14.28	12.42
Per capita income (1000's)	Income per resident age 15+ in 2010	31.24	10.51
NDVI	Remotely sensed vegetation level in June and July 2010	0.19	0.05
Intersection density	Number of intersections per square km in 2010	33.93	20.17
Median year housing built	Median year housing was built	1978	17.58
Active transport	Sum of the percentage of tract residents age 16+ who are employed and walk to work, bike to work, or take public transit to work in 2010	6.61	7.87
Air quality	PM10 µg per cubic meter in 2010	23.60	3.18

T2DM prevalence per 1000 adults age 18–64 as of 2015. As reported for the state of Utah, the prevalence of T2DM for all adults was 85 per 1000 (95% confidence interval (CI) 81 to 89) in 2019–2020 (Health Indicator Report of Diabetes Prevalence, 2022). Given the modest time difference and age restriction placed on our data, it was not surprising that the mean was marginally lower at 81 per 1000 adults age 18–64. The tract-level map in Fig. 1 depicts T2DM prevalence, organized into quintiles, among adults age 18–64 in the four-county region, revealing considerable geographic heterogeneity especially within the northern half of the region.

In 1990, the typical tract had 2.53 fast-food and pizza establishments, 2.50 full-service restaurants, 1.60 grocery stores, 1.17 convenience stores, and 0.38 supermarkets per 10,000 residents. From 1990 to 2010, we observed 22.32% of the tracts experienced a net change in supermarkets. The corresponding figures for convenience stores, full-service restaurants, grocery stores, and fast-food and pizza restaurants were 45.79%, 51.71%, 52.85%, and 63.78%, respectively. Thus, the data reveal extensive variation in the food environment over time with the most common change being in the availability of fast food and pizza and the least common change being the opening or closing of one or more supermarkets. Maps providing visual depictions of the heterogeneous changes in various aspects of the food environment over time are included in the Supplemental Materials.

Table 1 also presents information on key neighborhood indicators. On average, the typical tract gained 1700 residents over the 20-year period. In 2010, the mean age was 29.47, 14.28% of the residents were Hispanic and the mean per capita income for residents age 15+ was \$31,238/yr. Approximately 6.6% of the residents age 16+ who were employed used some form of active transportation to go to and from work. The age of the median house in 2010 was about 32 years old (i.e., built in 1978). There were almost 34 intersections per km in the average tract, the average NDVI mean was 0.19, and modeled air quality averaged 23.60 p.m.10 µg per cubic meter per tract in 2010.

Results of the multivariate analyses with and without the correction for the possible spatial correlation of the error terms appear in Table 2.

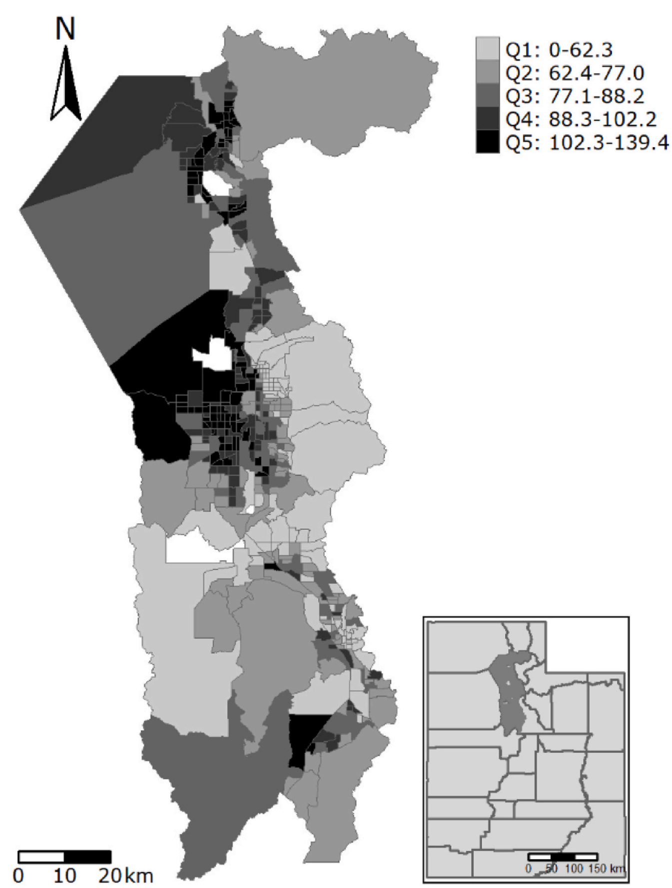

Fig. 1. Quintiles of T2DM 2015 prevalence per 1000 adults age 18–64 living in census tracts along the Wasatch Front (Utah shown in inset to identify the Wasatch Front within the state).

Table 2
Parameter estimates of T2DM prevalence per 1000 residents age 18–64[a].

Variable	Linear Model		Spatial Error Model	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	−718.97	121.03**	−667.25	119.27**
Convenience stores 1990	0.66	0.45	0.65	0.43
Fast food and pizza 1990	0.32	0.22	0.39	0.21*
Supermarkets 1990	0.72	0.77	0.58	(0.73)
Grocery stores 1990	0.81	0.35**	0.84	0.33**
Restaurants 1990	−0.31	0.16*	−0.30	0.15**
Change in convenience stores 1990 to 2010	0.11	0.38	0.22	0.36
Change in fast food and pizza 1990 to 2010	0.60	0.17**	0.61	0.16**
Change in supermarkets 1990 to 2010	0.68	0.66	0.62	0.63
Change in grocery stores 1990 to 2010	0.94	0.31**	0.92	0.29**
Change in restaurants 1990 to 2010	−0.36	0.18**	−0.28	0.17*
Population 1990	1.93	0.58*	1.99	0.55**
Population change 1990 to 2010	−1.50	0.44**	−1.56	0.42**
Median age 2010	1.21	0.25**	1.59	0.25**
Percent Hispanic 2010	0.56	0.08**	0.53	0.08**
Per capita income (1000's)	−0.73	0.11**	−0.69	0.11**
NDVI	23.45	18.29	32.03	17.76*
Intersection density	0.08	0.04**	0.10	0.04**
Median year housing built	0.38	0.06**	0.35	0.06**
Active transport	−1.17	0.11**	−1.04	0.11**
Air quality	0.75	0.36**	0.34	0.37
Lambda	–		−0.09	0.01**
Sigma^2	172.88**	11.67**	155.23	10.48**
Akaike's information criterion (AIC)	3560		3515	
Schwarz's Bayesian information criterion (SBC)	3666		3625	

*p < .10 **p < .05.
[a] Both models control for county-specific effects and a dummy variable that measures tracts dominated by student residences near a large university. The full set of estimates are available from the authors upon request.

Generally, the estimated coefficients and standard errors across the two models were quite similar with three exceptions: (1) air quality, (2) NDVI, and (3) fast food and pizza. One can think of the adjustment in the spatial error term as correcting for potentially omitted variables in the model. The fact that these three estimates change when the adjustment for spatial correlation was controlled indicates that these variables were correlated with the unadjusted error term. In the case of air quality, it was not surprising that the correlation was positive as air quality is likely to "spill over" tract borders and induce correlations. In the case of NDVI and fast-food and pizza businesses, the correlation with the error term was negative, revealing associations that were positive but statistically insignificant in the linear model become positive and significant in the spatial error model. This may be attributable to spatial concentrations of green space and/or retail clustering of fast-food outlets (Thomadsen, 2007).

The statistically significant coefficient associated with lambda in the spatial error model suggests that spatial error correlation existed. This was supported by the lower Akaike's Information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC) for the spatial error model, confirming that it was to be preferred.

The spatial error model estimates show that the population-adjusted number of fast-food establishments and grocery stores in a neighborhood in 1990 were associated with higher T2DM prevalence in 2015 while the reverse was true for the number of full-service restaurants. Moreover, the net changes in the population-adjusted numbers of these three types of food outlets over the twenty-year period were also statistically significant, suggesting that their growth over time was correlated with higher tract-level T2DM rates. Neither initial nor changing numbers of convenience stores nor supermarkets were significant. These findings were observed while controlling for an extensive set of covariates.[5]

To gain a sense of what the coefficients mean in practice, Table 3 shows the simulated marginal change in T2DM prevalence per 1000 adults age 18–64 at the mean, and in the top and bottom 5% of tracts experiencing changes in their food environment. This exercise holds constant all other covariates in the model. Table 3 reveals that the association between T2DM prevalence and changes in fast food and pizza, grocery stores, and full-service restaurants was extremely modest when evaluated at the means. However, at the extremes, the forecasted changes were substantial. For example, the tracts in the bottom 5% of the change distribution for fast-food and pizza outlets (i.e., tracts experiencing losses of such establishments) were forecasted to have almost 9 fewer individuals with T2DM per 1000 residents. In contrast, the tracts in the top 5% of the change in fast-food and pizza outlets distribution (i.e., tracts experiencing large increases in fast-food restaurants) were forecast to experience over 9 additional individuals with T2DM per 1000 residents. As another way of quantifying the association, if all tracts had had the growth in fast-food and pizza establishments that was experienced by the top 5%, then we estimated such growth would have been associated with approximately 12,000 additional T2DM cases along the Wasatch Front in 2015.

For the covariates, we observed a number of statistically significant coefficients with the expected signs. Specifically, higher population growth (i.e., more in-migration and more births, both of which signal a younger population), higher per capita income, and higher active transport usage were all associated with lower T2DM prevalence. In contrast, neighborhoods where the median housing age was younger, where the percentage of Hispanic residents was higher, and where the NDVI was higher, were all associated with higher T2DM prevalence. Only two estimated coefficients were contrary to what was predicted. We found air quality to be unrelated to T2DM after controlling for the spatially correlated error terms and we observed tracts with higher intersection density to have higher T2DM prevalence.

4. Discussion and conclusions

Our investigation provided evidence that the population-adjusted prevalence of fast-food and pizza restaurants, grocery stores, and full-service restaurants along with changes in their numbers from 1990 to 2010 were associated with 2015 T2DM prevalence. In contrast, we

Table 3
Forecasted change in T2DM tract prevalence per 1000 adults age 18–64 in 2015 due to changes in the tract food environment.

1990–2010 Change in …	Bottom 5%[a]	Mean Tract	Top 5%[b]
Fast food and pizza	−8.87	0.74	9.30
Grocery stores	−8.05	−0.11	7.19
Restaurants	4.02	−0.17	−4.46

[a] Evaluated at the mean for the tracts in the bottom 5% for the food establishment change in question, holding constant all other covariates in the model.
[b] Evaluated at the mean for the tracts in the top 5% for the food establishment change in question, holding constant all other covariates in the model.

[5] The spatial error model was also estimated controlling for selected changes in SES and neighborhood attributes over the 20-year period. The direction of the signs and statistical significance of the results, available from the authors upon request, remain the same with the exception that the statistical significance of the full-service restaurant coefficients weakens.

found no relationship between T2DM and similarly measured tract-level counts of supermarkets and convenience stores. Before discussing the implications of these results for future research, it is important to contextualize the findings. First, this was an ecological rather than a causal study. As such it illuminated associations at the neighborhood level that merit further investigation using causal modelling.

Second, our measures of the food environment were based on GIS locations of food establishments within tracts, but tract boundaries may not have necessarily represented residents' food shopping neighborhoods. In particular, our enumeration of neighborhood food establishments relies on tract boundaries, such that the use of different geographic zones of the same size could produce alternative measures with the potential to affect study inferences (known as the zoning problem). Our results may also be sensitive to the geographic scale used (Fotheringham & Wong, 1991). The optimal neighborhood scale is likely to vary depending on the relevant behavior; for instance, smaller scales may more closely approximate the relevant neighborhood for walkability and physical activity (Houston, 2014), whereas a larger scale may be optimal for the food environment as residents are more likely to drive to food establishments. The density of grocery stores and supermarkets also is generally low, such that many smaller scales (e.g., census block groups) do not have any grocers (Barnes et al., 2016). Thus, while prior research supports the tract as a meaningful scale to test longitudinal associations between the food environment and diabetes rates (Fan et al., 2014), further research is needed to test the sensitivity of results at different zones and scales.

Third, the methodology used to generate T2DM prevalence could affect the results. In this study, T2DM prevalence was measured using administrative medical records and the corresponding ICD 9 and ICD 10 codes (see Footnote 2 for specific codes). Thus, individuals were likely diagnosed as having T2DM based on HbA1c levels and/or pharmacological dispensing that are reflected in their ICD codes. Studies that rely on clinical measures of HbA1c levels alone may generate different estimates of the prevalence of T2DM. Somewhat related, our measure of T2DM did not allow us to control for T2DM prevalence in 1990 (i.e., baseline). The statewide inpatient discharge, ambulatory surgery, and emergency department records date back to 1996 and comprehensive clinic (outpatient) and pharmacological data only become available in 2013 with the availability of the All Payer Claims Database (APCD). Omission of the baseline prevalence of T2DM could bias the results if the 1990 T2DM rates were highly correlated with the 1990 measures of the food environment.

Finally, the data used came from a large urban area in the United States that has limited racial/ethnic diversity. As such, the findings may not generalize to less urbanized parts of the country or to urbanized areas that are more racially or ethnically diverse.

Our ecological findings generated several insights about the relationships between various elements of neighborhood food environments and T2DM. Specifically, some cross-sectional studies have found T2DM to be positively related to counts of fast-food restaurants and negatively related to counts of full-service restaurants (Ahern et al., 2011; Haynes-Maslow & Leone, 2017; Wiki et al., 2021). Our work expanded on that finding, suggesting that neighborhoods where the number of fast-food (full-service) restaurants have increased (decreased) over time might be especially important targets for educational campaigns or other public health-related T2DM interventions.

The consistent findings regarding fast-food and full-service restaurants also raised a question regarding the role changes in neighborhood composition may be playing in the observed relationships. There may be elements of residential selection at play with individuals choosing to reside in neighborhoods with certain types of food environments also being more/less at risk for T2DM. Future research should consider the volume and heterogeneity of population turnover in order to better separate out causation from selection forces.

The literature on T2DM and the role of neighborhood grocery stores and supermarkets is quite mixed[6] and our results add to these complex findings. We distinguish between supermarkets and grocery stores, finding the historical number of grocery stores and recent growth in the number of grocery stores to both be linked to increased prevalence of T2DM. One possible explanation for the positive finding is that while grocery stores offered a wider range of healthy foods than convenience stores, these options may have been offered at a higher price relative to supermarkets. In addition, research has shown that grocery stores offer fewer healthy options relative to supermarkets (Farley et al., 2009). Both of these factors could have incentivized some individuals to opt for less healthy foods when shopping at grocery stores.

We also found supermarket numbers and their change over time to be unrelated to T2DM. The absence of a relationship between supermarkets and T2DM may have existed because neighborhood boundaries are less relevant to the decision about traveling to a supermarket or supercenter to shop. A definitive assessment awaits research that is able to ascertain a more nuanced categorization of store types and the geographic parameters that shape grocery shopping behavior. The recent growth in online grocery shopping (Verdon, 2022; Wells, 2022) also makes it imperative that future work factor in this new food purchasing mode that may make neighborhood boundaries less relevant.

The spatial error model revealed that there are one or more geographically-linked omitted variables in the multivariate linear specification. As a consequence, it may be that prior research that did not test for spatial correlation may have biased estimates. The statistical preference for the spatial error model also raised the question of what exactly might be missing from the model specification. Candidates that merit investigation in future research include tract-level differences in (1) car ownership, (2) work commutes, and/or (3) proximity to extended family or friends, as one or more of these could create differential perceptions of what constitutes the neighborhood food environment.

Finally, given the rise in T2DM prevalence in recent years, research should focus on generating causal inferences that would inform public health recommendations about the food environment. Toward that end, our findings offered suggested directions for future work. Some prior studies linking the neighborhood food environment to T2DM have used aggregate measures of the food environment (e.g., ratio of healthy to unhealthy food establishments) or have focused on a single retail food domain (e.g., supermarkets) (Auchincloss et al., 2009; Cunningham et al., 2018; Gebreab et al., 2017; Mezuk et al., 2016; Zhang et al., 2017). While these studies often reported an association between summary measures of the food environment and T2DM, they did not provide clear guidance for public health interventions as to whether it is low levels of healthy eating options or high levels of unhealthy eating options (or both) that drive the relationship.

Other studies (Ahern et al., 2011; Haynes-Maslow & Leone, 2017; Carolina Pérez-Ferrer et al., 2020) assessed the unique associations various elements of the food environment have with T2DM. We followed

[6] For example, Ahern et al. (2011) find that the number of grocery stores (including supermarkets) has a negative association with T2DM risk. In contrast, Haynes-Maslow and Leone (2017) report that while increases in the number of neighborhood grocery stores is significantly associated with lower T2DM risk, the opposite is true for supercenters. Yet, Perez-Ferrer et al., (2020), Wiki et al. (2021) and Mezerk (2016) find no relationship between the number of neighborhood grocery stores and T2DM.

their approach, but used longitudinal data to assess how changes over time in the number of various types of food establishments relate to T2DM. This took us one step closer to identifying specific characteristics of the food environment that may be amenable to population-wide strategies for preventing and managing T2DM. Specifically, our findings suggested that neighborhoods where there has been an infusion of fast-food establishments or grocery stores and/or those neighborhoods where full-service restaurants have closed their doors in recent years may be especially at risk. From a policy standpoint, it may also be important to assess what role zoning regulations play in increasing or decreasing the risk of T2DM.

The neighborhood food environment tells only part of the story about the role that environmental features play in T2DM risk. But, it is a portion of the story that is amenable to public health interventions. As such, future research should focus on causal modelling using individual-level data. The findings of such studies could help guide the implementation of targeted population wide food-related T2DM interventions.

Ethical statement

The research reported in this manuscript was approved by the Resource for Genetic and Epidemiologic Research, a regulatory body overseeing access to Utah Population Database (UPDB), as well as the University of Utah Institutional Review Board. Funding for this study was provided by NIDDK grant 1R01DK118405-01A1. NIDDK had no involvement in the study design, data analyses, and interpretation of the findings. We also thank the Pedigree and Population Resource of Huntsman Cancer Institute, University of Utah (funded in part by the Huntsman Cancer Foundation) for its role in the ongoing collection, maintenance and support of the Utah Population Database (UPDB). We also acknowledge partial support for the UPDB through grant P30 CA2014 from the National Cancer Institute, University of Utah and from the University of Utah's program in Personalized Health and Center for Clinical and Translational Science. Research was also supported by the NCRR grant, Sharing Statewide Health Data for Genetic Research (R01 RR021746) with additional support from the Utah Department of Health and the University of Utah.

Author contributions

Cathleen D. Zick: Conceptualization, Methodology, Formal analysis, Roles/Writing - original draft, Writing - review & editing. David S. Curtis: Methodology, Software, Writing - review & editing. Huong Meeks: Data curation, Visualization. Ken R. Smith: Project administration, Data curation, Resources, Writing - review & editing. Barbara B. Brown: Resources, Writing - review & editing. Kyle Kole: Resources, Writing - review & editing. Lori Kowaleski-Jones: Funding acquisition, Project Administration, Writing - review & editing.

Declaration of competing interest

None.

Data availability

Data on T2DM come from the Utah Population Database with approval of the Resource for Genetic & Epidemiologic Research (RGE). Others who want access to these data would need to apply to RGE.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2023.101338.

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