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Community credit scores and community socioeconomic deprivation in association with type 2 diabetes across an urban to rural spectrum in Pennsylvania: a case–control study

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ABSTRACT

Background Area-level credit scores (the mean of credit scores for persons in a community) may be a unique indicator of community-level socioeconomic conditions associated with health outcomes. We analysed community credit scores (CCS) in association with new onset type 2 diabetes (T2D) across a geographically heterogeneous region of Pennsylvania and evaluated whether associations were independent of community socioeconomic deprivation (CSD), which is known to be related to T2D risk.

Methods In a nested case–control study, we used medical records to identify 15 888 T2D cases from diabetes diagnoses, medication orders and laboratory test results and 79 435 diabetes-free controls frequency matched on age, sex and encounter year. CCS was derived from Equifax VantageScore V.1.0 data and categorised as 'good', 'high fair', 'low fair' and 'poor'. Individuals were geocoded and assigned the CCS of their residential community. Logistic regression models adjusted for confounding variables and stratified by community type (townships (rural/suburban), boroughs (small towns) and city census tracts). Independent associations of CSD were assessed through models stratified by high/low CSD and high/low CCS.

Results Compared with individuals in communities with 'high fair' CCS, those with 'good' CCS had lower T2D odds (42%, 24% and 12% lower odds in cities, boroughs and townships, respectively). Stratified models assessing independent effects of CCS and CSD showed mainly consistent associations, indicating each community-level measure was independently associated with T2D.

Conclusion CCS may capture novel, health-salient aspects of community socioeconomic conditions, though questions remain regarding the mechanisms by which it influences T2D and how these differ from CSD.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Community socioeconomic deprivation is consistently associated with type 2 diabetes onset, likely due to its downstream influence on the built and physical environment, social environment, related health behaviours and psychological stress.

WHAT THIS STUDY ADDS

⇒ We assessed whether community credit scores, an alternative, previously unstudied measure of community socioeconomic conditions, may be associated with type 2 diabetes onset. Given their potential inter-relatedness, we also evaluated whether community credit scores and community socioeconomic deprivation had independent associations with type 2 diabetes onset.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Given the geographic disparities that exist in type 2 diabetes incidence and prevalence across the USA, research is needed to understand the community conditions that confer such risk to help target care and inform population-level interventions to prevent type 2 diabetes. This study explores the utility of community credit scores as a potential new measure of such conditions for future research.

INTRODUCTION

Affecting 11% of the US adult population, diabetes is a significant public health challenge.[1] Geographic disparities in type 2 diabetes (T2D) incidence and prevalence[2–4] have motivated epidemiologic research regarding contexts that influence T2D risk. Identifying contextual risk factors can help target care and inform interventions aimed at distal built and social constructs to prevent T2D.

Such research commonly assesses community socioeconomic conditions due to their downstream influence on other contextual

factors, including built and physical environments (eg, walkability and natural environments), social environments (eg, social cohesion, safety and healthcare access) and related health behaviours (eg, diet and physical activity).[5] Community-level disadvantage is also associated with physiological stress, a risk factor for chronic disease such as T2D.[6] Studies generally use deprivation indices that aggregate socioeconomic indicators to characterise community material deprivation.[7] Numerous studies have reported associations between area-level deprivation and T2D prevalence, incidence and control,[5] including our prior study of Pennsylvania communities.[8]

Other measures of socioeconomic conditions, such as community credit scores (CCS; individual credit scores averaged across a community), are less studied but may capture conditions uniquely related to health outcomes. As a community-level measure, CCS may represent communities' access to financial resources and economic stability.[9 10] For example, financial institutions use area-level credit scores to determine the interest rates, loans and other financial products available in certain areas. Businesses may use them to decide where to expand and which products to offer or market in specific areas. In these ways, CCS may influence communities' physical, social and economic environments, which may in turn affect disease risk.[11] CCS and community-level deprivation may therefore overlap in their contextual characterisations of communities, downstream impacts on other contextual factors and concomitant health outcomes; however, CCS may better represent communities' economic stability and vitality and may have independent associations with health outcomes.

Few studies have examined CCS as a contextual factor nor its associations with health outcomes, including T2D. One exception, conducted in Philadelphia, found that CCS was associated with lower self-reported diabetes prevalence.[9] No studies have evaluated CCS in association with health outcomes in non-urban US contexts, nor investigated whether CCS may capture novel, health-salient aspects of community socioeconomic conditions beyond traditional measures of community-level material deprivation. The primary aim of this study was to evaluate CCS in association with new onset of T2D across a geographically diverse region of Pennsylvania. We hypothesised that higher CCS is associated with lower T2D risk. Our secondary aim was to disentangle associations of CCS from community socioeconomic deprivation (CSD) in relation to T2D risk.

METHODS

Study population and design

We conducted a nested case–control study to evaluate associations of CCS and new onset T2D across a 37-county region of Pennsylvania. Using previously reported methods,[12 13] we used electronic health records (EHRs) of 1.6 million individuals with an encounter at Geisinger to identify new onset T2D from 2008 to 2016. Geisinger is an integrated health system whose primary care population is representative of the region's general population and has high residential stability.[14] Individual health data were linked via residential addresses to community features. The Geisinger Institutional Review Board approved the study and waived informed consent.

Type 2 diabetes cases and controls

New onset T2D cases (n=15 888) were identified using encounter diagnoses, diabetes medication orders and relevant laboratory test results, as previously described.[8 15] We required at least two visits to a Geisinger primary care provider prior to the diagnosis (cases) or encounter date (controls) to ensure sufficient contact with the health system to detect diabetes if the condition were present. We also required at least one encounter visit 2 years prior to T2D onset to exclude prevalent T2D cases. We frequency-matched controls (individuals who never met any diabetes criteria) to cases (5:1) with replacement on age category, sex and year of diagnosis or encounter. No controls were duplicated in the same encounter year.

Community types and features

We defined communities by incorporating Pennsylvania's minor civil divisions (townships, boroughs and cities) with cities further subdivided into census tracts. Three 'administrative community types' result, representing a continuum of lower to higher population density and land use mix:[16] rural and low-density suburban townships, boroughs (small towns of 5000–10 000 persons with a core gridded street network) and population dense city census tracts (online supplemental figure 1). This definition better reflects individuals' perceptions of community than more commonly evaluated geographies and has been validated through prior research in the region.[8 17]

Community credit scores (CCS)

We used VantageScore V.1.0 data (Equifax, Atlanta, GA) from 2012 to create CCS. VantageScore is a consumer credit-scoring system maintained by Equifax, one of three US national credit bureaus. VantageScore V.1.0 ranged from 501 to 990 and was assigned letter grades for specific ranges (A: 900–990, B: 800–899, C: 700–799, D: 600–699 and F: 501–599). Data were aggregated from census block groups and tracts to administrative community types (townships, boroughs and city census tracts), applying population-based weighting procedures.

Community socioeconomic deprivation (CSD)

CSD was measured using the sum of six z-transformed indicators: proportions unemployed, with less than a high school diploma, below poverty-level income, receiving public assistance, not in workforce and no vehicle access.[18] Data were obtained from the American Community Survey (2006–2010 and 2011–2015). CSD was time-dependent, assigned to individuals using the closest measure prior to the year of T2D onset (for controls, encounter year).

Other covariates

We used data from Geisinger's EHR to create individual-level covariates, including age, sex, race, ethnicity and per cent of time using Medical Assistance, a surrogate for family socioeconomic status.[19]

Statistical analyses

Analysis goals were twofold: (1) evaluate associations of CCS and new onset T2D; and (2) evaluate independent associations of CCS and CSD on T2D risk. Prior to modelling, we examined univariate statistics and correlations between study variables. We first modelled categorical CCS in association with new onset T2D. CCS was categorised to align with the VantageScore V.1.0 scoring system, with one modification. CCS scores ranged from 621 to 841 in the study sample, thus only 'grades' B, C and D were represented in our data. To allow for additional gradations, we split the largest group (C), yielding four categories that we labelled 'good' (≥800), 'high fair' (750–799), 'low fair' (700–749) and 'poor' (<700). Logistic regression was applied; generalised estimating equations with robust s and an exchangeable correlation structure were used to account for spatial clustering of individuals. We conducted a pooled analysis of all community types as well as analyses stratified by administrative community type due to concerns about non-positivity.[20] Analyses controlled for individual-level confounding variables, including age (years; linear, quadratic and cubic terms to allow for non-linearity), sex, race (White, Black/African American, mixed race, other (due to few individuals in other racial categories), missing), ethnicity (Hispanic vs non-Hispanic) and Medical Assistance (ever vs never).

We conducted an exploratory analysis to evaluate whether race or ethnicity modified CCS–T2D associations. We theorised that due to racial segregation and discrimination, people from minoritised groups may not experience the contextual effect of CCS in the same way as non-Hispanic White individuals, with differential impacts on risk of T2D. Due to small numbers of individuals from minoritised groups in townships and boroughs, this exploratory analysis was only feasible in city census tracts. To assess effect modification, we included an interaction between study individuals' race and ethnicity (in separate models) with CCS categories and evaluated a global test of significance of interaction terms.

To meet our second analysis goal, we evaluated independent associations of CCS and CSD on odds of T2D risk in two stratified analyses. The first set of analyses evaluated associations of CCS categories and T2D onset, stratified by low (quartiles 1 and 2) and high (quartiles 3 and 4) CSD. The second set evaluated associations of CSD quartiles and T2D onset, stratified by high ('good' and 'high fair') and low ('low fair' and 'poor') CCS.

RESULTS

The 15 888 cases of new onset T2D and 79 435 controls (65 084 unique individuals) were geocoded into 1070 communities (633 townships, 291 boroughs and 146 city census tracts). Characteristics of study individuals have been previously described.[8 15] They had a mean age of 55 years and were predominately White and non-Hispanic, reflecting the study region's racial and ethnic composition. Townships and boroughs had the least racial and ethnic diversity; approximately 98% of study individuals were White and 99% non-Hispanic in these community types. In city census tracts, 94.2% were White and 4.3% Black and 94.9% were non-Hispanic. T2D cases had higher historical use of Medical Assistance (6% vs 3% of controls), indicating lower household socioeconomic status. Cases were more likely than controls to live in a city census tract, less likely to live in a township and more likely to live in a community with lower CCS and higher CSD (table 1).

Distributions of community-level variables

There were few communities in the 'fair' or 'low poor' CCS categories, except within the highest CSD quartile in city census tracts (online supplemental figure 2). Spearman's rho correlations between (continuous) CCS and CSD, calculated at the community-level, showed a strong negative correlation within city census tracts (−0.76) and moderate negative correlations in boroughs (−0.57) and townships (−0.43) (online supplemental figure 3). Three per cent of study communities, two-thirds of which were townships, had an unexpected discordance between CCS and CSD, including 12 communities with high CCS and CSD and 16 communities with low CCS and CSD (figure 1).

Spearman's rho correlations between CCS and the proportion of the population in each community who had ever received Medical Assistance showed moderately weak negative correlations (city census tracts: −0.32; boroughs: −0.23 and townships: −0.24). Because correlations appeared to be influenced by communities containing only a few study individuals, we recalculated correlations for communities with at least five study individuals (n=750 communities). Correlations strengthened (city census tracts: −0.64; boroughs: −0.45 and townships: −0.33) (online supplemental figure 4).

Associations of CCS and new onset T2D

In adjusted models, the OR (95% CI) for an association between T2D onset and 'good' versus 'high fair' CCS was 0.85 (0.80 to 0.90), with the odds of new onset T2D for 'good' versus 'high fair' CCS 42% lower in cities, 24% lower in boroughs and 12% lower in townships (table 2). In city census tracts, point estimates indicated a trend of decreasing T2D risk from the lowest to highest CCS categories. In boroughs, there were an insufficient number of observations to evaluate the lowest CCS category. Contrary to the hypothesised direction of CCS and T2D associations, in townships, individuals in communities with 'low fair' mean credit scores had lower odds of T2D as compared with 'high fair' mean credit scores.

Table 1 Community characteristics of T2D cases and controls without T2D, frequency-matched (5:1) on age, sex and year of diagnosis or encounter date

Variable	N (%)		P value*
	Cases	Controls	
Number of individuals	15 888	79 435	n/a
Community type			<0.001
Township (n=633)	9461 (59.6)	51 131 (64.4)	
Borough (n=291)	4621 (29.1)	21 756 (27.4)	
City census tract (n=146)	1806 (11.4)	6548 (8.2)	
Community credit score (CCS)† categories			<0.001
<699 (poor)	170 (1.1)	650 (0.8)	
700–749 (low fair)	2921 (18.4)	11 834 (14.9)	
750–799 (high fair)	9480 (59.7)	46 178 (58.1)	
≥800 (good)	3317 (20.9)	20 773 (26.2)	
Community socioeconomic deprivation (CSD)† quartiles‡			<0.001
Quartile 1 (low deprivation)	3001 (18.9)	17 329 (21.8)	
Quartile 2	4300 (27.1)	23 172 (29.2)	
Quartile 3	4217 (26.5)	20 328 (25.6)	
Quartile 4 (high deprivation)	4370 (27.5)	18 606 (23.4)	

*Because controls could be in these comparisons more than once, methods were used for significance testing that accounted for this, including inverse-probability weighted regression for time-invariant characteristics, mixed-effect regression for time-varying continuous (linear), binary (logistic) and count (Poisson) characteristics and multinomial logistic regression with robust standard errors for polytomous time-varying characteristics. In the weighted analyses, weights were the number of appearances in the analysis (implemented with a data set having only one record per person).
†CCS and CSD were measured at the community level based on administrative community type (townships, boroughs and city census tracts), as described in Methods.
‡Quartile cut-offs were defined with the three time periods; the range of values for Q1, Q2, Q3 and Q4 were −18.33 to −1.82; −1.99 to 0.10; 0.01 to 2.05 and 1.89 to 12.40, respectively.
n/a, not applicable; T2D, type 2 diabetes.

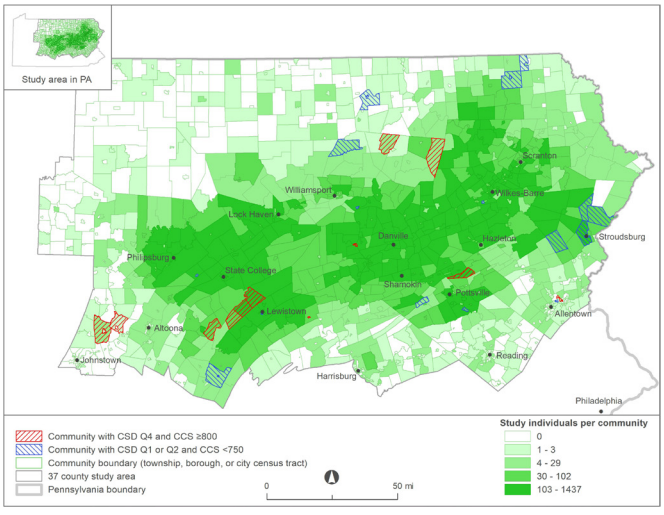

Figure 1 Map of study communities in Pennsylvania, USA, created using ArcGIS V.10.4 (ESRI, Redlands, California, USA). Red and blue cross-hatching shows communities with discordant measures of community socioeconomic deprivation (CSD) and community credit scores (CCS) (ie, communities with high deprivation and high CCS and vice versa).

As per our exploratory analysis, we found no evidence that study individuals' race or ethnicity modified CCS–T2D associations in city census tracts (global p-value of interaction terms>0.05).

Stratified analyses to evaluate independent associations of CCS and CSD with T2D odds

To determine whether CCS remained associated with T2D onset when constrained to communities with similar CSD, we evaluated CCS categories in association with T2D onset when stratified by low or high CSD. In cities, the low CSD stratum could not be evaluated due to a small number of communities in the lowest two CCS categories, and in boroughs, there were an insufficient number of communities to evaluate the lowest CCS category for both low CSD and high CSD strata. Results showed that CCS–T2D associations were attenuated in high CSD city census tracts and boroughs, strengthened in high CSD townships and remained consistent in low CSD boroughs and townships (table 3).

To determine whether CSD remained associated with T2D onset (as previously demonstrated in this study population[8]) when constrained to communities with similar CCS, we evaluated CSD quartiles in association with T2D

Table 2 Associations of CCS categories and T2D onset, combined and stratified by administrative community type, with individual (n) and community (nc) sample sizes by CCS category

	All communities OR (CI)		City census tracts OR (CI)		Boroughs OR (CI)		Townships OR (CI)	
CCS category	**Unadjusted**	**Adjusted***	**Unadjusted**	**Adjusted***	**Unadjusted**	**Adjusted***	**Unadjusted**	**Adjusted***
<700 (poor)	n=820 nc=25 **1.82** **(1.43 to 2.32)**	1.14 (0.86 to 1.52)	n=77 nc=20 **1.73** **(1.08 to 2.76)**	1.45 (0.94 to 2.24)	n=1 nc=1 –	–	n=742 nc=4 **1.20** **(1.13 to 1.27)**	0.99 (0.90 to 1.10)
700–749 (low fair)	n=14 755 nc=155 1.21 (1.14 to 1.30)	**1.09** **(1.02 to 1.16)**	n=5847 nc=84 1.10 (0.94 to 1.28)	1.03 (0.89 to 1.19)	n=6608 nc=51 1.06 (0.95 to 1.18)	1.02 (0.92 to 1.13)	n=2300 nc=20 0.93 (0.82 to 1.07)	**0.86** **(0.74 to 0.99)**
750–799 (high fair)	n=55 658 nc=677 Ref	Ref	n=2306 nc=35 Ref	Ref	n=18 141 nc=215 Ref	Ref	n=35 211 nc=427 Ref	Ref
≥800 (good)	n=24 090 nc=213 **0.82** **(0.78 to 0.87)**	**0.85** **(0.80 to 0.90)**	n=124 nc=7 **0.56** **(0.41 to 0.78)**	**0.58** **(0.42 to 0.81)**	n=1627 nc=24 **0.74** **(0.62 to 0.89)**	**0.76** **(0.63 to 0.91)**	n=22 339 nc=182 **0.85** **(0.79 to 0.91)**	**0.88** **(0.82 to 0.94)**

Bold values indicate a p-value <0.05
*Adjusted for age, age^2, age^3, sex, race, ethnicity and Medical Assistance, as described in Methods.
CCS, community credit score; T2D, type 2 diabetes.

onset when stratified by high or low CCS. Due to a small number of low CCS communities in the low CCS stratum, this stratum was not evaluated. Results within high CCS communities showed that CSD–T2D relations remained consistent in boroughs and townships and strengthened in city census tracts (table 4).

DISCUSSION

This study is among the first to evaluate area-level credit scores as a contextual factor in relation to an objective health outcome and across a heterogeneous geography representing the urban–rural spectrum. As hypothesised, higher CCS was associated with lower T2D risk, though the strength and pattern of associations differed by community type. Furthermore, CCS and CSD appeared to be independently associated with T2D in a limited set of communities, providing evidence of their unique characterisations of community socioeconomic context. However, questions remain as to how the mechanisms by which CCS influences T2D differ from that of area-level material deprivation and whether CCS reflects contextual or compositional (ie, individual-level) effects.

Non-stratified model results revealed a trend of lower T2D risk with increasing CCS. Community-stratified

Table 3 Adjusted* associations of CCS categories and T2D onset in high and low CSD strata†, stratified by administrative community type

	City census tracts OR (CI)		Boroughs OR (CI)		Townships OR (CI)	
CCS category	**Low CSD**	**High CSD**	**Low CSD**	**High CSD**	**Low CSD**	**High CSD**
<700 (poor)	–	1.38 (0.89 to 2.15)	–	–	1.27 (0.60 to 2.66)	1.01 (0.92 to 1.11)
700–749 (low fair)	–	0.98 (0.83 to 1.15)	1.10 (0.96 to 1.25)	0.98 (0.87 to 1.11)	0.85 (0.69 to 1.06)	**0.82** **(0.71 to 0.95)**
750–799 (high fair)	–	Ref	Ref	Ref	Ref	Ref
≥800 (good)	–	**0.69** **(0.52 to 0.91)**	**0.76** **(0.70 to 0.82)**	0.84 (0.54 to 1.33)	**0.89** **(0.82 to 0.96)**	**0.82** **(0.75 to 0.90)**

Bold values indicate a p-value <0.05
*Adjusted for age, age^2, age^3, sex, race, ethnicity and Medical Assistance, as described in Methods.
†The low CSD stratum combined CSD quartiles 1 and 2. The high CSD stratum combined CSD quartiles 3 and 4.
CCS, community credit score; CSD, community socioeconomic deprivation; T2D, type 2 diabetes.

Table 4 Adjusted* associations of CSD quartiles and T2D onset in all communities and high CCS strata†, stratified by administrative community type

	City census tracts (CTs) OR (CI)		Boroughs OR (CI)		Townships OR (CI)	
CSD quartiles	All city CTs	High CCS city CTs	All boroughs	High CCS boroughs	All townships	High CCS townships
Q1 (low deprivation)	**0.76 (0.58 to 0.99)**	**0.64 (0.46 to 0.89)**	0.90 (0.79 to 1.03)	0.88 (0.75 to 1.03)	0.94 (0.86 to 1.03)	0.94 (0.85 to 1.03)
Q2	**0.80 (0.66 to 0.97)**	**0.70 (0.55 to 0.88)**	0.97 (0.85 to 1.10)	0.95 (0.81 to 1.11)	0.98 (0.90 to 1.07)	0.98 (0.90 to 1.07)
Q3	**0.79 (0.68 to 0.93)**	**0.69 (0.55 to 0.87)**	0.98 (0.88 to 1.10)	0.96 (0.82 to 1.12)	0.98 (0.90 to 1.07)	0.98 (0.89 to 1.08)
Q4 (high deprivation)	Ref	Ref	Ref	Ref	Ref	Ref

Bold values indicate a p-value <0.05
*Adjusted for age, age^2, age^3, sex, race, ethnicity and Medical Assistance, as described in Methods.
†The high CCS stratum combined the highest two CCS categories ('high fair' and 'good'). The low CCS stratum combined the lowest two CCS categories ('poor' and 'low fair'), but due to a very small number of low CCS communities in CSD quartiles 1 and 2 across administrative community type, this stratum was not evaluated.
CCS, community credit score; CSD, community socioeconomic deprivation; T2D, type 2 diabetes.

models revealed idiosyncrasies in this relationship. First, consistent associations only for the highest CCS category across community types indicated that our findings were limited to the high end of the CCS distribution. Second, the strongest associations appeared in city census tracts. This is partially explained by a more even distribution of city census tracts across CCS categories, whereas few boroughs and townships were in the lowest CCS category, but could also reflect a stronger link between CCS and downstream environmental or behavioural factors that influence T2D onset. This could occur if populations with greater homogeneity in credit scores were segregated into distinct communities—a situation more likely in metropolitan areas than large rural townships. Unfortunately, we could not explore CCS variance with the available data. Third, individuals in townships with 'low fair' CCS had lower odds of T2D than those in 'high fair' townships, which was an unexpected result.

Given higher proportions of racially and ethnically minoritised groups in city census tracts, the stronger associations of CCS and T2D in this community type could potentially reflect a differential impact of CCS among these groups. It is plausible that due to residential segregation and discrimination, minoritised groups may experience the community socioeconomic context differently than majority groups, with concomitant impacts on health status, including T2D. To explore the influence of race and ethnicity on associations of CCS and T2D, we examined whether these factors modified CCS–T2D associations in city census tracts but found no supporting evidence. However, this exploratory analysis was limited by small sample sizes across the distribution of CCS categories and by the fact that—based on 2010 Census data—only half of city census tracts in our geography comprised<80% White individuals (a conservative definition of racially diverse communities[21]).

Credit score data are proprietary and thus less accessible than deprivation measures, which are commonly created with publicly available data. To justify investment in credit score data, CCS should uniquely characterise community context beyond area-level material deprivation, which is ubiquitously studied and linked to numerous health outcomes,[22] including T2D.[5 8] Through stratified models, we examined independent associations of CCS and CSD. A strong negative correlation between CCS and CSD in city census tracts and few low CCS/low CSD communities across community types constrained this analysis and demonstrated the inter-relatedness of CCS and CSD. However, CCS remained protective of T2D risk among the highest CCS communities, regardless of CSD and among high CCS communities, CSD remained associated with T2D. Furthermore, a small proportion of communities—particularly townships—had unexpectedly discordant measures for CCS and CSD (ie, both high or both low). Taken together, these findings suggest that CSD and CCS measure different community features.

CCS and CSD thus seem to each capture health-salient features that do not fully overlap. Considering the observed CCS–T2D associations primarily showed a protective effect of 'good' CCS, we conjecture CCS may be a stronger measure of community economic stability and vitality. Area-level credit scores are used by financial institutions to determine the financial resources (eg, loans and interest rates) available to an area[10] and by businesses to assess the financial potential of markets. Access to favourable loans is intrinsically tied to housing quality and the availability and quality of amenities in a community, characteristics that persist over time, as

demonstrated by studies of historic redlining.[23] CCS may therefore influence the physical environment (eg, placement of food, physical activity, tobacco and alcohol outlets; public amenities such as green space, schools and libraries) and social environment (eg, neighbourhood cohesion and safety) in ways that are similar to, but not fully overlapping with CSD. We theorise that CCS may better measure health-promoting features of communities, while CSD may better capture community-level disadvantage that adversely affects health.

Our findings revealed variation in CCS–T2D associations by CSD strata, with inconsistent patterns across community type. Associations attenuated in the most deprived city census tracts and boroughs, suggesting that the positive impact of CCS on T2D risk was offset, to some degree, by higher deprivation. The opposite was true in townships: CCS–T2D associations strengthened in townships with high CSD. One potential explanation for this inconsistency pertains to the measurement of CSD, with quartile cut-offs determined *within* community type rather than across all communities. For this reason, the most deprived townships did not have as extreme ranges of CSD as did city census tracts, for example, and so the degree of deprivation in townships may not have been sufficient to offset the positive impact of CCS. However, CIs for CCS–T2D associations encompassed the point estimates across strata, so stratum-specific differences may not be highly meaningful.

CCS–T2D associations may arise under two conditions. As a contextual measure, higher CCS would impact all individuals in a particular community, leading to lower population-level T2D risk,[24] as described above. Alternatively, as a compositional measure, the observed CCS–T2D associations could be due to individual-level effects of credit scores on T2D, as demonstrated in prior studies of chronic disease outcomes.[25 26] Such associations could arise due to a link between human capital factors (such as educational attainment, cognitive ability and self-control) with T2D, mediated through health behaviours.[26] Associations of individual credit scores and T2D could similarly occur if high credit scores reflect higher individual socioeconomic position, which is consistently associated with lower T2D risk.[11] However, we observed weak to moderate correlations between CCS and the proportion of individuals in each community with a history of using Medical Assistance, a proxy for household socioeconomic status. Similarly, a study in Philadelphia observed moderate correlations (from −0.78 to 0.49) between neighborhood-level credit scores and neighborhood-level measures of individual socioeconomic position such as income, educational attainment and median housing value,[10] and nationally, individual credit scores were only moderately correlated with household income, with wide variation in credit score distributions within income groups.[27] Deciphering whether CCS represents a contextual or compositional measure is further complicated by evidence suggesting the local credit economy underpins individual credit scores, which in turn may influence an area's overall creditworthiness.[9] For example, research found that residents of areas recovering from a local economic downturn received lower credit ratings than individuals who had the same credit history but lived in more economically robust areas.[28] Furthermore, individual credit scores have been shown to impact residential location decisions and thus the community characteristics to which individuals are exposed, such as access to quality education, proximity to amenities, crime rates and air quality.[29]

This study had limitations. CCS had a limited range in the study geography; it was skewed towards higher categories, with few communities scoring 'poor' but also no communities scoring above 'good'. This particularly limited our ability to assess associations in boroughs. Additionally, although the Geisinger primary care population is representative of the region,[14] the region itself (and therefore our study population) lacks racial and ethnic diversity, particularly in boroughs and townships. For this reason, we only controlled for race and ethnicity at the individual level and not for community-level racial and ethnic composition. The generalisability of our findings to more diverse populations remains unknown, particularly considering that Black and Hispanic individuals are less likely to have a credit score on record[30] and that credit score models penalise borrowers for using some credit types that are disproportionately used by minoritised and economically disadvantaged individuals.[31]

CONCLUSION

There is great interest in understanding community contexts that confer risk for T2D to inform policy and programmatic efforts. We observed associations of high CCS with lower T2D risk, and in a subset of mainly non-urban communities, associations were independent of CSD. Thus, in some communities, CCS may capture novel, health-promoting aspects of community socioeconomic conditions. However, future research on CCS must weigh the limitations of this data—namely, its propriety nature—and continue to explore mechanisms by which CCS influences health.

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