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Published in:
European Journal of Public Health

DOI:
10.1093/eurpub/ckz085

The European Journal of Public Health, Vol. 30, No. 1, 189–194

doi:10.1093/eurpub/ckz085 Advance Access published on 21 May 2019

Regional variation in type 2 diabetes: evidence from 137 820 adults on the role of neighbourhood body mass index

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Background: Body mass index (BMI) is a key covariate in the study of type 2 diabetes, but can also be theorized as a contextual effect. The purpose of this study was to explore the extent to which variation in individual risk factors and neighbourhood BMI explain the variation in type 2 diabetes prevalence across neighbourhoods and municipalities. **Methods:** Cross-sectional data were collected from 137 820 adults aged ≥18 years from 3296 neighbourhoods in 296 municipalities in the Northern Netherlands. The odds of type 2 diabetes was assessed using a multilevel model. Median odds ratios were calculated and choropleth maps were created to visually assess neighbourhood variation in type 2 diabetes prevalence. **Results:** The overall prevalence of type 2 diabetes was 4%, ranging from 0 to ≥10 and 0–7% across neighbourhoods and municipalities, respectively. Of the regional variation, 67.0 and 71.6% is explained through variation of individual risk factors at the neighbourhood and municipality level, respectively. Analysis on the smallest spatial scale, i.e. the neighbourhood, best captured the regional variance. Statistically significant interaction between individual and neighbourhood BMI was found (OR = 1.06; 95% CI = 1.03–1.08, *P* for interaction < 0.001), adjusted for the individual risk profile. **Conclusion:** The results suggest a more cautious interpretation of neighbourhood effects in type 2 diabetes is warranted, and reveals the need for further investigation into risk-prone groups to guide the design of community-level interventions to halt the rise in type 2 diabetes prevalence.

Introduction

Type 2 diabetes, fuelled by the obesity epidemic, has emerged as a major health problem worldwide by affecting 422 million adults,[1] and continuing to be an important cause of mortality and health-system costs.[2] The prevalence of type 2 diabetes varies regionally, with <6% in northwestern Europe, to >20% in Polynesia and Micronesia.[2] Although differences in type 2 diabetes prevalence between nations are well known, variation also exists within countries.[3,4] It is relevant to understand the underlying factors that drive regional variation in type 2 diabetes prevalence especially within countries.

Individual-level demographic factors are considered key covariates in the study of human health and well-being. Previous studies found regional differences in type 2 diabetes to be partially explained by corresponding variance in individual risk factors, such as age, sex and body mass index (BMI) and material deprivation.[5–7] However, some variation remained unaccounted for, suggesting that contextual factors may also be involved.

There is scattered evidence suggesting that neighbourhood BMI may be a relevant contextual factor. Although BMI is the most important modifiable risk factor of type 2 diabetes, which on itself may vary greatly regionally,[8] it has also been observed that BMI spreads through social ties and networks, presumably through changing norms.[9] Additionally, the opportunity to move from high- to lower-poverty neighbourhoods is associated with modest but potentially important reductions in the prevalence of extreme obesity suggesting the presence of a community-environment effect.[10] Based on neighbourhood BMI distribution, individuals may be disproportionately affected by type 2 diabetes, but evidence on this contextual effect is yet to be established.

Although it is relevant to understand the underlying factors of the within-country variation in type 2 diabetes, to date our understanding is also limited by comparisons across singular and coarse geographic scales.[3–6] Neighbourhoods have emerged as a relevant context as they directly affect access to food, safety, education, health behaviours and stress levels.[10–14] Additionally, because of reasons of governance municipalities are also relevant, especially in countries with a decentralized governance of public health, with a prominent role for municipalities, such as the Netherlands.

The overall aim of our study was to identify the factors underlying the regional variation in type 2 diabetes in the Northern Netherlands. Specifically, we assessed (i) the extent to which regional variation in type 2 diabetes is explained by regional variation in individual risk factors, (ii) whether neighbourhood BMI, as a contextual factor, is involved in the regional variation in type 2 diabetes and (iii) at which spatial level most of the variation is captured, i.e. the neighbourhood or the municipality.

Methods

Cohort design and study population

The Lifelines cohort study is a population-based cohort study examining the health and health-related behaviours of 167 729 children and adults covering about 10% of the population in the North of the Netherlands. Participants were included in the study between 2006 and 2013, and written informed consent was obtained from all participants. The LifeLines population is broadly representative for the people living in this region.[15] The overall design and rationale of the study have been described in detail elsewhere.[16] The LifeLines Cohort Study is conducted according to the principles of the Declaration of Helsinki and in accordance with the research code of the University Medical Center Groningen.

In this study we included all adults, aged ≥18 years, with data on self-reported type 2 diabetes, blood glucose measurements or use of anti-diabetic medication. We excluded type 2 diabetes related to pregnancy and participants aged <18 years (n = 16 133) and cases with missing georeferencing information (n = 13 776), leaving a total of 137 820 adults in the study. Type 2 diabetes was defined as self-reported type 2 diabetes, use of oral anti-diabetics and/or insulin or fasting glucose levels >6.99 mmol/l or non-fasting glucose level >11.0 mmol/l.

Person-level explanatory variables

Self-administered questionnaires were used to collect data regarding demographics (age, sex and education) and lifestyle (smoking, physical activity and diet). Migrant history was characterized by country of birth, and three categories were created (participant and parents born in the Netherlands; born in the Netherlands with foreign parents; born outside the Netherlands). Educational level was categorized in three categories. Income was categorized in three categories. Physical activity was assessed by the validated SQUASH questionnaire ('Short questionnaire to assess health-enhancing physical activity') from which the duration of moderate and vigorous physical activity (MVPA) in minutes per week was calculated.[17] Based on the Lifelines food frequency questionnaire,[18] the Lifelines diet score was constructed.[19] Anthropometric measurements were performed at one of the Lifelines research sites. Height and body weight without shoes and heavy clothing were measured with the SECA 222 stadiometer and the SECA 761 scale, and BMI in kg/m^2 was calculated.

Geographical variables

The Central Bureau of Statistics provides data on neighbourhood and municipality boundaries.[20] Neighbourhood boundaries are designed to be more homogeneous types of areas in housing and socioeconomic data than postal zip code data (which tend to be larger areas than the neighbourhood designation). Based on these neighbourhood and municipality codes, all participants were nested at the most local level within 3296 neighbourhoods, which were clustered within 296 municipalities.

We grouped neighbourhoods in tertiles based on the mean BMI of the Lifelines residents. The tertile cut-offs were BMI values of ≤25.1 kg/m^2 for the lowest third of average neighbourhood BMIs, and ≥26.5 kg/m^2 for the highest tertile.

Statistical analysis

Descriptive statistics across explanatory variables by tertiles of neighbourhood BMI were tabulated as mean ± SD, n or percentages. Multilevel logistic regression was used to analyse the association between independent variables at the individual level [age, gender, BMI, migrant history, level of education, Lifelines diet score, MVPA] and tertiles of neighbourhood BMI at the neighbourhood level and the outcome variable, type 2 diabetes (dichotomous). The multilevel model used random intercepts at the municipal and neighbourhood level to assess the between-region variance in type 2 diabetes prevalence. In this specification, larger scale variations in type 2 diabetes prevalence are assigned to the municipal level, whereas smaller scale variations are assigned to the neighbourhoods. In the multilevel model age, physical activity and the Lifelines diet score were normalized, while BMI was grand mean centred. The first model we estimated (null-model; variance component model) was used to establish baseline neighbourhood and municipality variation in the odds of type 2 diabetes. In model 1 we adjusted for age, sex, migrant history and BMI at the individual level; model 2 we added physical activity, smoking, Lifelines diet score, level of education and income; in model 3 we extended model 2 by including tertiles of neighbourhood BMI, and the interaction between individual BMI and tertiles of neighbourhood BMI.

Choropleth maps were produced in R to visually examine neighbourhood variation in (i) the prevalence of type 2 diabetes and (ii) in random intercepts (i.e. the neighbourhood differences in the odds of type 2 diabetes) for both the null and model 3. From the models, we use four model metrics to determine the scale of the 'regional' component.[21]

In sensitivity analyses we estimated two equivalent models, first using pre-diabetes (excluding self-reported type 2 diabetes), and second a linear mixed effects model with fasting blood-glucose levels (excluding those on type 2 diabetes medication). Pre-diabetes was defined by impaired fasting glucose (100–125 mg/dl) and haemoglobin A1c levels of 5.7–6.4%.

Results

The mean prevalence of type 2 diabetes in the Northern Netherlands was 4%. Based on neighbourhood tertiles of BMI, the prevalence if type 2 diabetes ranges from 3 to 5% for the lowest and highest tertile, respectively (table 1). With increasing neighbourhood prevalence of type 2 diabetes, subjects in neighbourhoods were older, showed a greater proportion of females, were less educated, had less income, had a lower diet quality based on the Lifelines diet score, a higher BMI and a higher proportion of current smokers. Differences in ethnicity across the categories of neighbourhood prevalence of type 2 diabetes were small. Across neighbourhoods the prevalence of type 2 diabetes ranged between 0 and ≥10% (figure 1) and across municipalities between 0 and 7%.

The crude neighbourhood odds of type 2 diabetes prevalence ranges between 0.6 and 2.0, with a range from the first to the ninth decile of 0.88–1.17 (Supplementary figure S1). As we extend the models with individual variables (table 2), type 2 diabetes prevalence increases with age and individual BMI, and women have a lower prevalence of type 2 diabetes. Individuals born abroad have higher odds of type 2 diabetes mellitus (T2DM). Additionally, we observed a positive association between type 2 diabetes prevalence and the Lifelines diet score, and inverse associations with MVPA. Higher educational attainment and income is associated with lower the odds of type 2 diabetes Furthermore, a higher neighbourhood BMI is associated with higher type 2 diabetes prevalence. Additionally, as shown in model 3, there is a significant multiplicative interaction between neighbourhood BMI and individual BMI. Individuals with a higher BMI are more prone to type 2 diabetes in neighbourhoods with higher mean BMI compared with individuals with a higher BMI in neighbourhoods with lower mean BMI.

From the total variance attributed to the levels in the null-model, 74.9 and 85.3% is explained through the addition of individual factors and neighbourhood BMI at the neighbourhood and municipality level, respectively. Recalling that the intraclass correlation is the proportion of the variance at each respective regional level divided by the total variance in type 2 diabetes prevalence, table 2 shows that the initial proportion of variance at the levels is 0.016 (or 1.6% of total variance) at the neighbourhood level and 0.003 at the municipal level. These results indicate that the addition of a municipal nesting structure adds little explanatory power, but that the variance captured by regional levels is foremost attributable to the smallest spatial scale, i.e. the neighbourhood. Examining the neighbourhood distribution of the odds ratios (OR) of type 2 diabetes in figure 2, we see that almost all of the variation in type 2 diabetes is now accounted for, i.e. the map showing mostly OR between 0.8 and 1.2. The range from the first to the ninth decile is 1.0–1.1.

Finally, the median odds ratio (MOR) provides some insight in the magnitude of the differences, with the neighbourhood MOR between higher and lower type 2 diabetes prevalence

Table 1 Population characteristics by tertiles of neighbourhood BMI

Neighbourhood BMI		First tertile	Second tertile	Third tertile
		BMI ≤25.1 kg/m^2	BMI 25.2–26.4 kg/m^2	BMI ≥26.5 kg/m^2
Participants		16 791	75 537	45 491
Diabetes (%)	Yes	3.0	3.6	5.0
Glucose (mmol/l) [SD]		4.9 [0.7]	5.0 [0.8]	5.1 [0.9]
Gender (%)	Male	39.8	41.8	41.6
Age (%)	<40	49.0	34.9	33.5
	40–60	40.3	51.4	51.6
	>60	9.3	12.7	14.1
Education (%)[a]	Low	16.7	29.3	38.0
	Moderate	34.7	40.2	41.2
	High	48.6	30.4	20.8
Income (%)[b]	Low	37.1	30.4	33.7
	Moderate	25.7	33.9	36.0
	High	37.2	35.7	30.2
Migrant history (%)	Dutch born, Dutch parents	92.2	94.3	94.2
	Dutch born, foreign parents	4.5	3.3	3.3
	Foreign born	4.4	3.3	3.4
Current smoker (%)		20.7	20.3	22.2
MVPA, mean(min. /week) [IQR]		260 [100–510]	240 [65–540]	210 [50–540]
Lifelines Diet Score, mean [SD]		24.5 [6.1]	24.0 [6.0]	23.6 [6.1]
BMI, mean(kg/m^2) [SD]		24.4 [3.5]	25.9 [4.1]	27.2 [4.7]

a: Low education, primary school, vocational and lower general secondary education; moderate education, higher secondary education and intermediate vocational training; high education, higher vocational education and university education.
b: Low ≤ 2000 euros/month, moderate = 2000–3000 euros/month and high ≥ 3000 euros/month.

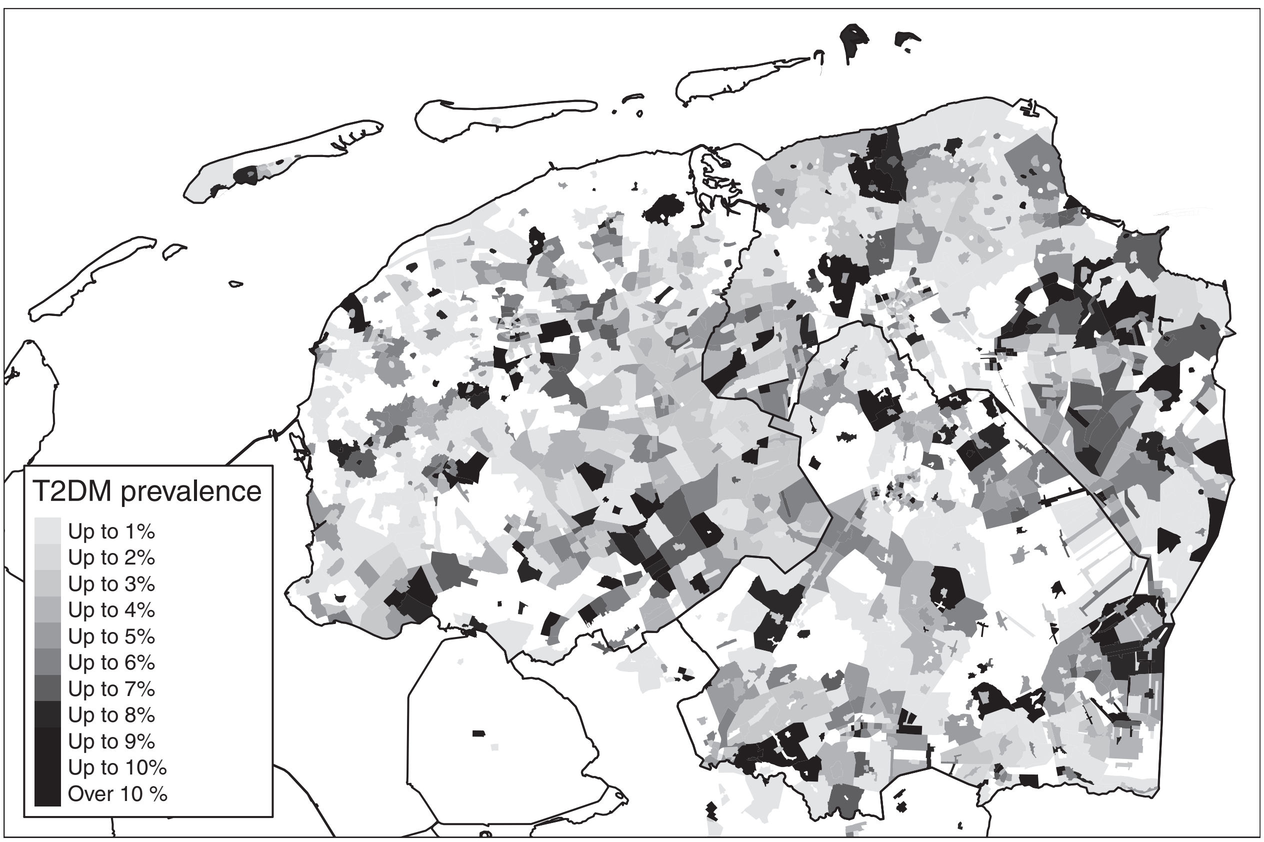

Figure 1 Neighbourhood type 2 diabetes prevalence (%). Although a total of 3296 neighbourhoods were included in the multilevel analysis, for the visual presentation of the results only neighbourhoods with ≥10 participants, situated in the Northern provinces of the Netherlands were included (*n* = 1453)

neighbourhoods at 1.27, and 1.14 at the municipal level. These ORs decline as individual factors are added to the model, ending at 1.13 for the neighbourhood level and 1.05 for the municipal level. That is, a person living in a higher type 2 diabetes prevalence municipality would be 1.05 times more at risk of type 2 diabetes than those in a lower type 2 diabetes prevalence municipality. Given the already low percentage of type 2 diabetes prevalence on average (4.0%), this difference in odds is negligible. The large PCV found in this study indicates that individual effects explain most of the regional variance in the data.

Table 2 ORs and 95% CIs for the associations between individual-level factors and type 2 diabetes prevalence at the regional levels

	Null model			**Model 1**			**Model 2**			**Model 3**		
	OR	***95% CI***	***P***	***OR***	***95% CI***	***P***	***OR***	***95% CI***	***P***	***OR***	***95% CI***	***P***
Fixed parts (intercept)	0.04	0.04–0.04	<0.001	0.03	0.03–0.03	<0.001	0.05	0.04–0.05	<0.001	0.05	0.04–0.06	<0.001
Age				1.81	1.76–1.86	<0.001	1.64	1.58–1.70	<0.001	1.65	1.58–1.71	<0.001
Female				0.78	0.73–0.82	<0.001	0.7	0.65–0.75	<0.001	0.7	0.65–0.75	<0.001
Dutch born, foreign parents				1.06	0.90–1.25	0.457	1.07	0.88–1.30	0.524	1.06	0.87–1.29	0.54
Foreign born				1.53	1.33–1.76	<0.001	1.5	1.25–1.80	<0.001	1.51	1.26–1.81	<0.001
BMI				1.13	1.12–1.13	<0.001	1.12	1.11–1.13	<0.001	1.06	1.04–1.09	<0.001
MVPA							0.89	0.86–0.93	<0.001	0.89	0.86–0.93	<0.001
Smoker (yes)							0.96	0.87–1.05	0.326	0.96	0.88–1.05	0.344
Lifelines Diet score							1.09	1.05–1.13	<0.001	1.09	1.05–1.13	<0.001
Education (moderate)							0.91	0.82–1.00	0.047	0.91	0.83–1.00	0.056
Education (high)							0.91	0.84–0.99	0.024	0.91	0.84–0.99	0.032
Income (moderate)							0.72	0.67–0.79	<0.001	0.73	0.67–0.79	<0.001
Income (high)							0.64	0.58–0.70	<0.001	0.64	0.58–0.70	<0.001
Neighbourhood BMI (second tertile)										0.93	0.81–1.05	0.245
Neighbourhood BMI (third tertile)										1.07	0.92–1.23	0.373
BMI * neighbourhood BMI (second tertile)										1.06	1.03–1.09	<0.001
BMI * neighbourhood BMI (third tertile)										1.05	1.02–1.08	<0.001
Random Parts												
Neighbourhood level variance	0.062			0.026			0.020			0.016		
Municipal level variance	0.02			0.003			0.002			0.003		
ICC neighbourhood	0.018			0.008			0.006			0.005		
ICC municipality	0.006			0.001			0.001			0.001		
MOR neighbourhood	1.269			1.166			1.144			1.127		
MOR municipality	1.144			1.051			1.038			1.053		
PCV neighbourhood	0			0.586			0.684			0.749		
PCV municipality	0			0.862			0.923			0.853		
Observations	13 7820			13 7451			99 528			99 528		
Deviance	45 587.413			41 768.67			29 213.17			29 203.28		

ICC denotes intraclass correlation coefficient and represents the ratio of neighbourhood level variance to the total outcome variance (i.e. neighbourhood + individual variance components). The Proportional Change in Variance (PCV) reflects the proportion of variance attributed to the spatial groupings in the Null model that is subsequently explained by the addition of individual level variables.

Figure 2 OR of type 2 diabetes prevalence (relative to study area odds) for model 3. Although a total of 3296 neighbourhoods were included in the multilevel analysis, for the visual presentation of the results only neighbourhoods with ≥10 participants, situated in the Northern provinces of the Netherlands were included (n = 1453)

In sensitivity analysis we estimated two equivalent models, first using pre-diabetes (excluding self-reported type 2 diabetes), and second a linear mixed effects model with blood-glucose levels. Pre-diabetes is much more common (with a prevalence of 14% in our sample), which means fewer zero prevalence regions and, possibly, a higher signal to noise ratio. The neighbourhood variance of pre-diabetes and fasting glucose was 0.01 (0.3% of the total variance) and 0.02 (0.6% of total variance), respectively.

Discussion

Neighbourhood and municipal variation in type 2 diabetes is mainly driven by individual risk factors. Moreover, individuals with a higher BMI are more at risk of type 2 diabetes if they live in neighbourhoods where people with higher BMI are clustered. This indicates that neighbourhood BMI is a relevant contextual risk factor, especially for individuals already at risk. Most of the variance in risk of type 2 diabetes is at the individual level, and variance attributable to the regional levels is mostly explained through the addition of individual determinants. This suggests that the inclusion of regional levels mostly captures distributional effects of the usual individual risk factors, rather than a proxy for a regional risk factor. Of the variance that is attributed to regional levels, most of the variance captured by the regional levels is attributable to the smallest spatial scale, i.e. the neighbourhood.

In this study, the local clustering of high BMI is associated with an increased risk of type 2 diabetes for individuals who themselves have a high BMI, after controlling for the individual risk factors. Consequently, the interaction can be interpreted as a multiplicative effect of neighbourhood BMI on top of the risk of individual BMI, but that this interaction does not affect all inhabitants equally. It is not common to consider individual-level factors at the neighbourhood level, although we do see examples of analyses where, e.g. the proportion of children[22] or the proportion of older adults[23] are incorporated. Age may affect perceptions, participation in community life and may alter the context of community in unexpected ways.[24] For example, young adults may be healthier but may not necessarily bring 'health' to the community. Like age and based on the present results, BMI structure may be critical to characterizing neighbourhood context and warrant further study.

Although several mechanisms have been proposed to explain the association of neighbourhood characteristics with type 2 diabetes,[25] human interactions with the environment are complex and the possible causal mechanisms are difficult to disentangle. Although increasing evidence points toward more upstream (environmental) drivers that may impact type 2 diabetes risk and prevalence,[25] the extent to which 'place matters' in the prevalence of type 2 diabetes remains a research gap.[26] Results from previous studies raise the possibility that public health interventions that ameliorate the effects of neighbourhood environment on type 2 diabetes could generate substantial social benefits.[10] On the other hand, it has also been argued that the nature of the evidence so far does not justify neighbourhood interventions as a way to improve health, partially because of the lack of causal mechanisms, and the need for more sophisticated data collection and analytical approaches.[26]

A possible explanation for the low regional variance component is that type 2 diabetes has a very low-prevalence rate (4%), leading to a relatively large proportion of low-prevalence regions in our study area, and likely a low signal to noise ratio. To counter, we estimated two equivalent models, first using pre-diabetes, and second a linear mixed effects model with blood-glucose levels. These analyses provided little evidence that the low proportion of variance for the type 2 diabetes model is a result of low proportions of positives, leading to the same conclusion that type 2 diabetes prevalence contains little regional variation, when taking into account regional variation in individual risk factors.

The coefficients for the Lifelines diet score are opposite to what we would expect, with healthy eating associated with higher type 2 diabetes prevalence. Estimating a separate regression (results not shown) on a subset of the dataset we find that these coefficients revert back to the expected values if the dependent variable is not type 2 diabetes but pre-diabetes (excluding individuals with type 2 diabetes). This indicates that the unexpected coefficients for the type 2 diabetes model are likely the result of lifestyle changes post-diagnosis, i.e. confounding by indication. Our findings were based on cross-sectional analyses. No conclusions on causal inferences should be made. Our study design does not allow us to draw conclusions on the mechanisms underlying the multiplicative effect of neighbourhood BMI. Possible explanations might be that neighbourhood BMI is a proxy for unmeasured environmental exposures, such as the availability of green space, healthy food options or safety.[27,28] Alternatively, it could be related to BMI as a characteristic of social networks, as shown previously.[9] If so, this has consequences for preventive strategies and should be taken into consideration. For example, it may be possible to harness social networks or social influence to slow the spread of obesity. Network phenomena might be exploited to spread positive health behaviours,[29–31] in part because people's perceptions of their own risk of illness may depend on the people around them.[32]

We observed a small geographical component which was not explained by the model. We estimated a model with a third level nesting (municipalities) and find that most of the regional variance is at the smallest spatial scale. Although little study has been devoted to assess type 2 diabetes across various geographical scales, a study from China reported that indeed the variation in type 2 diabetes partitioned across micro- and macro-scale geographies. The type 2 diabetes prevalence varied more at the village and the district level, although variation at the provincial and town level were also not trivial.[6] The heterogeneity in the odds of type 2 diabetes was larger on the (broader) regional level than on the neighbourhood level in Germany, but the opposite was concluded after adjusted for individual and neighbourhood characteristics.[3] From this, we conclude that using the smallest regional scale variable possible will result in the highest probability of finding a spatial-contextual component, at least in a study setting of the Netherlands, with mandatory basic health insurance for all.

The identification of the relevant spatial scale is important for translation of the results to practical prevention measures. In the Netherlands, from 2015 onwards, municipalities were given more tasks and responsibilities in prevention and health care for their citizens. As a consequence of this decentralization of responsibility, local policy makers and health care services increasingly require information on health-related indicators at smaller geographical scales, like municipalities and neighbourhoods.

To conclude, regional variation in type 2 diabetes prevalence is predominantly explained by individual risk factors. Interacting individual BMI with neighbourhood BMI reveals that individuals with higher BMI in neighbourhoods with higher average BMI are more at risk of type 2 diabetes. This suggests that neighbourhood effects are not general to the populace, but specific to individuals already at risk. The results suggest a more cautious interpretation of neighbourhood effects in type 2 diabetes is warranted, and reveals the need for further investigation into risk-prone groups to guide the design of community-level interventions to halt the rise in type 2 diabetes prevalence.

Supplementary data

Supplementary data are available at *EURPUB* online.

Acknowledgements

The LifeLines Biobank initiative has been made possible by funds from FES (Fonds Economische Structuurversterking), SNN

(Samenwerkingsverband Noord Nederland) and REP (Ruimtelijk Economisch Programma). The authors wish to acknowledge the services of the LifeLines Cohort Study, the contributing research centres delivering data to LifeLines, and all study participants.

Funding

This work was funded by De Fryslân Zorgverzekeraar and by the Nutrition & Health initiative of the University of Groningen.

Conflicts of interest: None declared.

Key points

- There is scattered evidence suggesting that neighbourhood body mass index (BMI) may be a relevant contextual factor.
- Regional variations in type 2 diabetes prevalence are predominantly explained by individual risk factors.
- Interacting individual BMI with neighbourhood BMI reveals that individuals with higher BMI in neighbourhoods with higher average BMI are more at risk of type 2 diabetes.
- The neighbourhood effects are not general to the populace, but specific to individuals already at risk.
- A more cautious interpretation of neighbourhood effects in type 2 diabetes is warranted, and reveals the need for further investigation into risk-prone groups to guide the design of community-level interventions to halt the rise in type 2 diabetes prevalence.

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