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Dietary Pattern Trajectories during 15 Years of Follow-up and HbA1c, Insulin Resistance, and Diabetes Prevalence among Chinese Adults

Carolina Batis[1], **Michelle A. Mendez**[1], **Daniela Sotres-Alvarez**[2], **Penny Gordon-Larsen**[1], and **Barry Popkin**[1]

[1]Department of Nutrition and Carolina Population Center, University of North Carolina at Chapel Hill, Chapel Hill, NC

[2]Department of Biostatistics, University of North Carolina at Chapel Hill, Chapel Hill, NC

Abstract

Background—Most research on dietary patterns and health outcomes does not include longitudinal exposure data. We used an innovative technique to capture dietary pattern trajectories and their association with hemoglobin A1c (HbA1c), homeostasis model of insulin resistance (HOMA-IR), and prevalence of newly diagnosed diabetes.

Methods—We included 4,096 adults with three to six waves of diet data (1991–2006) and biomarkers measured in 2009 from the China Health and Nutrition Survey. Diet was assessed with three 24-hour recalls and a household food inventory. We used a dietary pattern previously identified with reduced rank regression that positively predicted diabetes in 2006 (high in wheat products and soy milk and low in rice, legumes, poultry, eggs, and fish). We estimated a score for this dietary pattern for each subject at each wave. Using latent class trajectory analysis, we grouped subjects with similar dietary pattern score trajectories over time into five classes.

Results—Three trajectory classes were stable over time, and in two classes the diet became unhealthier over time (upward trend in dietary pattern score). Among two classes with similar scores in 2006, the one with the lower (healthier) initial score had an HbA1c 1.64% lower (−1.64 [95% confidence interval= −3.17, −0.11]) and nonsignificantly a HOMA-IR 6.47% lower (−6.47 [−17.37, 4.42]) and lower odds of diabetes (0.86 [0.44, 1.67]).

To whom correspondence should be addressed: Barry Popkin. Mailing address: Carolina Population Center, University of North Carolina, 123 W. Franklin St., Chapel Hill, NC 27516; Phone: (919) 966-1732; Fax: 919-966-9159; popkin@unc.edu.

Competing interests
None declared.

Contributorship Statement
C.B. designed and conducted the analysis and wrote the manuscript, M.A.M, P.G.L, D.S.A., and B.P. contributed to the interpretation of the data analysis and reviewed the manuscript. C.B. and B.P. had primary responsibility for final content.

Conclusions—Our findings suggest that dietary pattern trajectories with healthier scores longitudinally had a lower HbA1c compared to those with unhealthier scores, even when the trajectories had similar scores in the end point.

Keywords

dietary pattern; diabetes; latent class trajectory analysis; China

INTRODUCTION

China has experienced a rapid increase in diabetes prevalence among adults, from 3%[1] in 1994 to 11.6% in 2010 (about 113.9 million diabetics).[2] Addressing lifestyle behaviors such as diet is important for prevention efforts, and dietary patterns may be particularly useful, as estimated effects of single nutrients or foods may be too small to detect and diet patterns may closely reflect actual eating behavior.[3–8] In China food patterning indicates that rice and wheat are key distinct characteristics that belong to different dietary patterns, and patterns containing wheat are characterized as more heterogeneous and Westernized (i.e., fruits, nuts, soy milk, instant noodles, cakes, fried wheat products).[9–11]

Most of the studies associating dietary patterns with health outcomes include diet from only one point in time[3] and are not able to capture longitudinal changes in dietary patterns. To address this gap and represent long-term exposure to a dietary pattern, we used latent class trajectory analysis (LCTA) to identify subgroups of subjects sharing similar trajectories over 15 years.[12, 13]

We used a dietary pattern previously identified to be associated with diabetes in this population (Batis et al., unpublished data, 2013). We derived this pattern with reduced rank regression (RRR) using the 2006 diet and hemoglobin A1c (HbA1c), homeostasis model of insulin resistance (HOMA-IR) and glucose in 2009 as response variables. This pattern was behaviorally meaningful, as it shared many characteristics with patterns from principal component analysis. It was positively associated with wheat noodles, wheat buns and breads, deep-fried wheat products, and soy milk and negatively associated with rice, fresh legumes, poultry and game, eggs, and fish and seafood. Because we knew this pattern was associated with diabetes, our research question was no longer about that association itself but about the association of its long-term trajectories with diabetes. Individuals may have similar dietary pattern scores at one point in time but varying diet histories. It is important to understand the health outcomes of different trajectories.

We estimated a score for the dietary pattern in six repeated diet measures over 15 years of follow-up (1991–2006) and identified groups of individuals with similar score trajectories over time with LCTA. We used these latent classes to examine the association between long-term dietary patterns and HbA1c, HOMA-IR, and the prevalence of newly diagnosed diabetes in 2009.

METHODS

Study design and participants

The China Health and Nutrition Survey (CHNS) is an ongoing longitudinal study that has conducted surveys in nine provinces in 1991, 1993, 1997, 2000, 2004, 2006, and 2009.[14] These surveys were conducted according to the guidelines in the Declaration of Helsinki. All waves have identical clinical, dietary, and anthropometric measures. However, blood samples were collected for the first time in 2009. Each wave maintains a desired range of economic and demographic circumstances, even if new participants are recruited to compensate loses to follow-up. Therefore our goal was to make inferences about all the participants in wave 2009. To be included in our analytic sample, respondents had to be 18 to 65 years old during at least three waves between 1991 and 2006. (For example, if a subject was 15 years old in 1997, he or she only entered the analysis in 2000. If a subject was 65 years old in 2006, he or she was not included in the analysis, because he or she qualified during only one wave, not three). There were 7,646 eligible participants aged 27–68 in 2009, not previously diagnosed with diabetes, and not pregnant in 2009. We did not consider subjects with previously diagnosed diabetes, because the diagnosis could affect their dietary habits. We excluded those who did not have dietary data in at least three waves (1991–2006) (n = 2,712), who did not have complete biomarkers in 2009 (n = 604) or did not fast before blood collection (n = 185), or who had missing information for covariates (n = 49). Among the 4,096 subjects in our final sample, 40% had complete dietary data in all six waves, and 17% had complete dietary data in only three waves. We addressed selection bias by using inverse probability weights in a sensitivity analysis (see the Online Supplemental Material).

Measurement of variables

The CHNS assessed diet with three consecutive 24-hour recalls randomly allocated to start between Monday and Sunday. These were supported and complemented by data from a household food inventory conducted during the same three-day period. Our food groups were based on a system developed specifically for the CHNS[15] that separates foods into nutritional and behavioral food groups.

The CNHS collected blood samples by venipuncture after an overnight fast. Glucose, HbA1c, and insulin were measured with standard procedures. We estimated the homeostasis model of insulin resistance (HOMA-IR = [(fasting insulin (μU/ml) * fasting glucose (mmol/l))/22.5].[16] We used HbA1c ≥ 6.5% as the diagnostic criteria for type 2 diabetes.[17] Compared to a single measure of glucose, HbA1c captures long-term glycemic exposure, and it has been shown to be reliable for diabetes diagnosis among Chinese.[18–20]

We included several covariates in the analysis. Some, such as gender, geographic region, and age in 2006 (equivalent to using birth year), did not vary by time. For the time-varying covariates, we used a measure that represented the entire exposure period (1991–2006), that is, the mean of all the repeated measures (income, physical activity, urbanicity index,[21] and BMI), the proportion of the participating waves in which they were reported (currently smoking and consuming three or more alcoholic beverages per week), and the highest level attained during the follow-up (education).

Statistical analysis

We used the loadings of all food groups on the pattern previously identified with RRR (Batis et al., unpublished data, 2013) to calculate the pattern score of each subject in this sample in all waves (1991–2006). This dietary pattern score represents how much each subject adhered to the dietary pattern: the higher the score, the more closely the participant's diet conforms to the dietary pattern. (See the Online Supplemental Material and supplemental table 1 for more details on our methods, including the RRR dietary pattern).

To group individuals with similar dietary pattern score trajectories, we used LCTA (Mplus 6.1, Muthén and Muthén, Los Angeles, California). Contrary to conventional growth model approaches, in which the trajectories of all individuals are described using a single estimate of growth parameters and the heterogeneity is captured only by variations in the slopes and the intercepts (random effects), LCTA allows different parameters to represent the trajectories of various classes.[12, 13] For the model fitting, the analyst specifies the functional form of the growth trajectories and the number of classes.[12] We found that the observed mean trajectories were fairly linear. We compared one to seven classes (supplemental table 2) and decided to retain five classes. The fit of the model was better between five and six classes, but the six-class model included a class with only 1.5% of the sample. In addition, models with two to four classes yielded parallel trajectories, which are less interesting to compare than trajectories that intersect each other, reflecting that the classes share a similar diet at that point.

We ran multiple linear (for HbA1c and HOMA-IR) and logistic (for diabetes) regressions with class trajectory membership as an indicator variable. First we adjusted by all covariates except BMI, and in a second model we additionally adjusted by BMI. The clustering at the household level was accounted for in the estimation of the variance. As a sensitivity analysis, we repeated the analysis including only subjects with four or more waves of dietary data (instead of three) (see the Online Supplemental Material).

RESULTS

We confirmed that in 2006, in the analytic sample of this study, the dietary pattern previously identified had a positive association with HbA1c, HOMA-IR, and the prevalence of newly diagnosed diabetes (supplemental table 3). We also confirmed that most of the pattern's key food groups had independent associations with HbA1c consistent with the directions of their factor loadings (supplemental table 4). Only soy milk, which is frequently consumed with deep-fried wheat products, was inconsistent. It had a positive loading in the dietary pattern, but its independent association with HbA1c tended to be negative. In sum, the score for this dietary pattern could be interpreted as a weighted sum of healthy (negative weight) and unhealthy (positive weight) food groups. Subjects with total negative scores consumed more of the healthy foods, those with positive scores consumed more of the unhealthy foods, and subjects with scores near zero had similar intakes of both unhealthy and healthy foods.

Using LCTA, we identified five classes of subjects with similar dietary pattern score trajectories from 1991 to 2006 (figure 1). To show each class' changes in food group intake, table 1 presents the proportion of consumers and the mean number of food groups consumed over time. In all trajectory classes the diversity of diet increased, as reflected by the mean number of food groups. Class 1 and 2 changed over time, whereas the other classes were more stable. Classes 1 and 2 showed an increase in unhealthy foods, such as wheat noodles, wheat buns and breads, and deep-fried wheat products. Class 2 also showed a decline in intake of healthy foods, such as fresh legumes, poultry and game, and fish and seafood, which explains why this class had the most dramatic score increase. Classes 3, 4, and 5 had relatively constant scores over time. Their intake of rice decreased, but for all other relevant food groups the proportion of consumers increased. Because the increases in both healthy and unhealthy foods were similar, the balance between the positive and the negative weights and hence the dietary pattern scores for these groups remained stable over time.

Class 5 had the lowest (healthiest) score and class 1 the highest (unhealthiest). Comparing the classes with lower (healthier) and higher (unhealthier) scores, those with lower scores tended to have higher education, income, and urbanicity index and lower physical activity and BMI (table 2). There was a strong regional difference among the classes: 80% of class 1 lived in the central region, and only 1.5% of class 5 lived in the North.

Figure 1 shows the adjusted mean HbA1c for each class, and table 3 shows the unadjusted and adjusted percentage differences between each pair of classes. As expected, the higher the overall 1991–2006 dietary pattern score, the higher the HbA1c in 2009. Interestingly, class 1 and class 2 had similar scores in 2006, but for class 2, which had a lower (healthier) mean score over time, the model adjusted mean HbA1c was −1.64 (95% confidence interval [CI] = −3.17, −0.11) relative to class 1. Similarly, class 2 and class 4 had similar scores in 1991, but for class 4, which had a lower (healthier) score in 2006, HbA1c tended to be slightly lower (−1.02 [95% CI = −2.35, 0.30]). The smallest HbA1c difference (0.62 [95% CI = −0.72, 1.96]) was seen in classes 2 and 3, whose mean scores were the most similar over time, even though one had a positive slope and the other a flat one. Results for HOMA-IR and the odds of being newly diagnosed diabetic were comparable to those for HbA1c, although estimates were less significant. Adjusting by BMI brought all the estimates closer to the null.

DISCUSSION

Comparing two classes that had similar dietary pattern score trajectories in 2006, we found that the one that previously had lower scores and hence a healthier diet had lower HbA1c in 2009. This suggests that even if the recent diet scores were similar, the different dietary trajectories that subjects followed to get to that point might also affect HbA1c levels. Additionally, comparing two classes that cumulatively had similar mean dietary pattern scores over time, we found no difference in HbA1c, even if one class had a stable score and the other had an increase over time. This suggests that the cumulative dietary pattern score is more important than the shape of the dietary pattern score trajectory (i.e., changing or maintaining a constant dietary pattern score).

Only a few studies have looked at the association between dietary patterns and health outcomes with repeated measures of dietary intake. As there are many approaches to studying repeated measures, it is important to understand which is the most meaningful way to represent the long-term exposure to a dietary pattern. Several studies have used longitudinal mixed models with the goal of obtaining an average dietary pattern–health outcome association adjusted by the interindividual correlation of repeated measures.[22, 23] One study assessed the independent effect on the outcome of the dietary pattern measured at each point. The aim was to evaluate the duration of the dietary pattern effect.[24] None of these analyses evaluated the interindividual changes or cumulative exposure to dietary patterns. Among other approaches, one study evaluated the sequence of transition between different clusters of dietary patterns (i.e., staying in the same dietary pattern, change to a healthier or unhealthier one, etc.).[25] Others have looked at the effect of the change in dietary patterns' scores between two points in time[26, 27] or the effect of the intercept and the slope of three measures of dietary pattern scores.[28] The limitation of the last two approaches is that they can only evaluate either the effect of the dietary score at baseline or that of the change (slope) at one time.

Our analysis applied LCTA for dietary exposures. A similar method, a growth mixture model, has been previously used to identify trajectories of sodium adherence over a six-month period in 279 adults with heart failure.[29] The advantage of this approach is that a single variable (trajectory class membership) encompasses both the starting point (intercept) and the change (slope) in dietary pattern score, and hence it implicitly summarizes also the score at any given point (i.e., midpoint, last point) and the mean score of the follow-up. Therefore the trajectory class gives a comprehensive representation of the long-term exposure to a dietary pattern score. Hence examining the relation of the trajectories and the predictors and outcomes is straightforward, as there is no need to separately examine the association of the intercept and the slope. However, each of these aspects (slope, mean, intercept or score at any given time) might have a different and independent effect that is not possible to separate, as they are all interrelated. We can only exclude the effect of one of these aspects at a time (i.e., comparing trajectory classes with similar end point or mean scores); however, the comparison options available depend on the identified trajectories. It is of particular interest to understand if the slope has an effect by itself, because otherwise just evaluating the score at each time independently or the mean score would be equally informative. Our results suggest that with a similar mean score, the slope (and the last score) do not have an effect.

In terms of demographic factors, we found that region was an important associated factor, as 80% of class 1 (the class with the highest score over time) lived in the central region. This is probably related to the lower consumption of rice and the higher consumption of wheat buns and breads in this region. It is also interesting that the class with the largest change in dietary pattern score (class 2) had a smaller change in urbanicity level and income. Our numbers for income and urbanicity level represent the mean from 1991 to 2006, yet both variables increased over this period in all classes. In 1991 these variables were similar in classes 2 and 4, however, the increase over time was less pronounced in class 2 (data not shown).

The differences we found in HbA1c between the trajectory classes are meaningful and comparable to what other dietary studies have found. Frequent versus never or seldom intake of fruits and vegetables, moderate alcohol versus abstainers, and lowest versus highest quintile of total fat intake had differences in HbA1c of 0.09, 0.2 and 0.2 respectively.[30–32] However, our results were not meaningful for HOMA-IR and diabetes prevalence. Dietary intake might be less associated with HOMA-IR, because it includes glucose information, which is a shorter-term measure. For prevalence of newly diagnosed diabetes, perhaps more power was needed, as only 5.6% of the sample was newly diagnosed as diabetic, and the analysis required information for many strata of the sample.

Our main interest was in the total effect of dietary pattern on diabetes, including the effect of diet mediated through BMI. Still, we additionally adjusted for BMI to get an approximation of the direct effect of diet. We found that adjusting by BMI brought our estimates only slightly closer to the null, which suggests that the trajectories of our dietary pattern scores were directly associated with HbA1c, independently of the increased energy intake and increased BMI. Proposed mechanisms by which diet relates directly to diabetes include modulation of oxidative stress and inflammation, which in turn affects insulin sensitivity and beta cell function.[33, 34] Our dietary pattern score represents high intake of wheat noodles, breads, and buns and low intake of fish and legumes. Foods with a high glycemic index, such as wheat noodles, breads, and buns, promote hyperglycemia and therefore are proinflammatory and increase oxidative stress,[34] whereas omega-3 fatty acids, like the ones in fish, are anti-inflammatory and could improve the physical properties of cellular membranes and the binding affinity of insulin receptors.[35] Legumes in turn are a source of antioxidants like phenolic acids and fiber, which also have anti-inflammatory properties.[34, 36] Although our results are biologically plausible, it is important to acknowledge that our quantification of the direct effect was not thorough, as this was not our main interest. Direct effects obtained by adjusting by the intermediate variable are unbiased only if there is no unmeasured confounding between the exposure and the outcome and between the intermediate and the outcome.[37] In addition, the way we adjusted by BMI might have been insufficient, as we used a variable with the mean BMI instead of trajectories of BMI.

We found that even when recent dietary patterns were similar, cumulative dietary exposure had a differential and important effect. This was expected for a disease such as diabetes, which is known to progress gradually. The insulin resistance and subsequent loss in beta cell function related to diet directly and/or increased BMI could precede diabetes onset by ten or more years.[38] These findings might be similar for other chronic diseases that progress gradually (e.g., cardiovascular disease and many cancers). In this analysis we only assessed diet trajectories during adulthood and did not address critical life points, such as pregnancy, early infancy, or adolescence. Studies with life course epidemiology approaches could be useful for understanding the role of timing, accumulation, and temporal associations of diet and chronic diseases from conception to adulthood.[39]

Even when a dietary pattern, compared to single nutrients or food groups, can approximate the complexity of dietary intake, it is still a very limited and nonexhaustive representation of diet. For instance, our dietary pattern score did not capture diet diversity, as the score remained constant even in the context of increased diet diversity. Additionally, diet was measured over a three-day period only, which limits its representation of usual intake. However, the dietary assessment methodology has remained unchanged in all the surveys; this is a key strength that enabled us to assess the longitudinal effects of dietary intake. We were able to use an innovative method, LCTA, to evaluate trajectories of dietary patterns over a 15-year follow-up period for the first time.

Another limitation is that not all subjects had complete follow-up. Fortunately, LCTA can use all of the information available without the need to impute values or delete cases with incomplete data. Even individuals with only one wave of data can be classified in one trajectory class, although one point in time does not seem informative enough. To balance both internal and external validity, we included individuals with at least three waves of complete data. Additionally, our sensitivity analysis indicates that the potential for selection bias was minimal (see the Online Supplemental Material). Finally, compared to the thorough and complex longitudinal modeling of our main exposure with LCTA, the modeling of time-varying confounders was simplified, and residual confounding might be present.

In sum, the long-term exposure to a dietary pattern seems to be relevant for HbA1c at a given point in time. More research using longitudinal methods is needed to confirm and add evidence or insights about the nature of these long-term relations. Findings like this can have important intervention and clinical implications. A subject can be counseled to make intensive diet and lifestyle changes given that his or her previous diet has already increased the risk of disease. Or better-informed interventions to promote an early start and maintenance of healthy eating patterns throughout adulthood could be implemented.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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What is already known on this subject?

Dietary patterns are useful in the study of diet-disease associations, and many dietary patterns have been associated with diabetes. However, we do not know how longitudinal exposure and intra-individual changes in dietary patterns relate to diabetes.

What this study adds?

Our results suggest that the longitudinal exposure and intra-individual changes in dietary pattern matter. Among individuals with similar recent dietary patterns, those who had a healthier prior exposure (trajectories with better dietary pattern scores throughout) had lower HbA1c.

Moreover, it seems that, from the longitudinal trajectory, what matters most is the cumulative exposure and not the shape of the trajectory (i.e., changing or maintaining a constant dietary pattern).

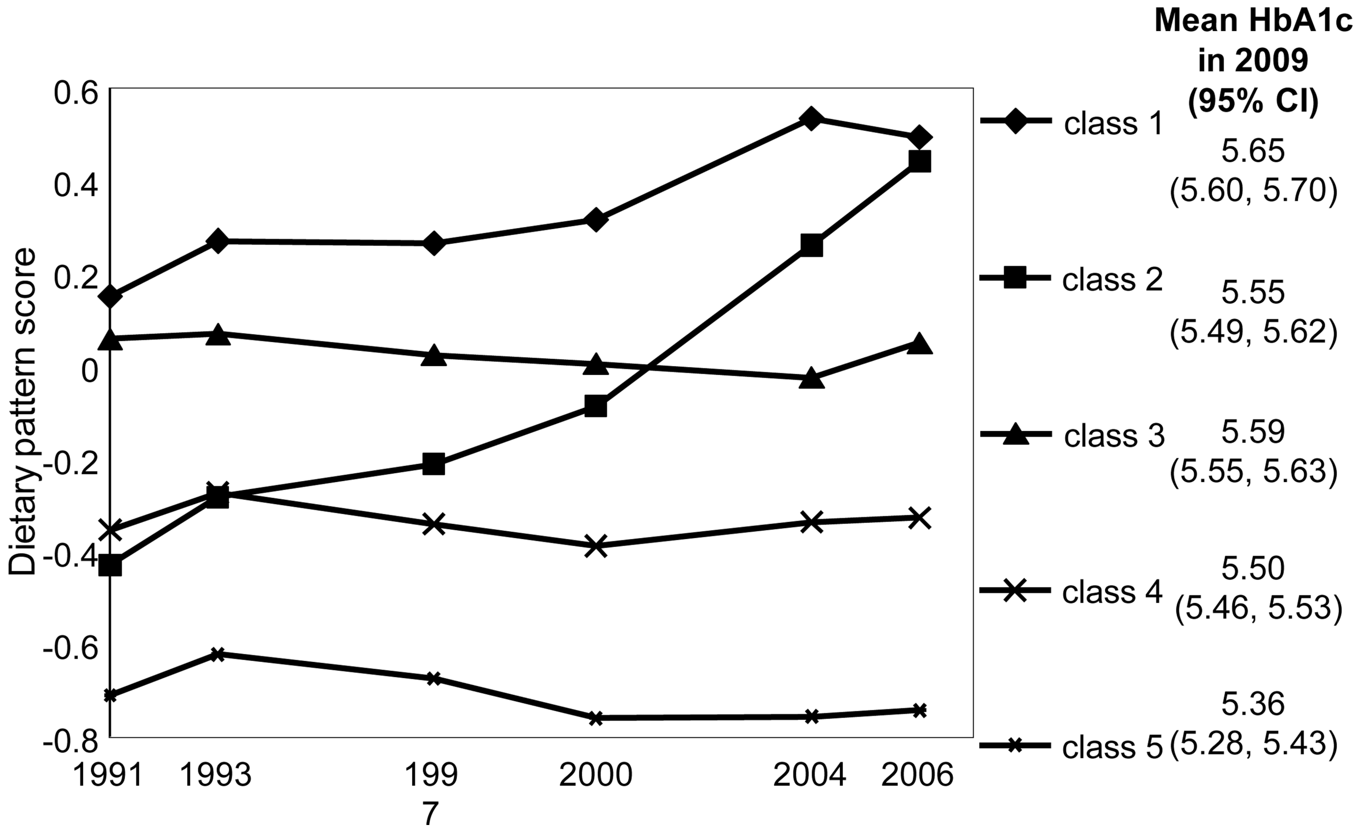

Figure 1.

Dietary pattern score trajectory classes from 1991 to 2006. The lines are the mean observed trajectory of each class; the mean HbA1c in 2009, adjusted by age, gender, geographic region, income, urbanicity index, physical activity, smoking, and alcohol intake, is shown next to each class.

Table 1

Number of food groups and proportion of consumers of food groups associated with dietary pattern (factor loadings > |0.20|) by wave and trajectory class

	Class 1			Class 2			Class 3			Class 4			Class 5		
	1991	2000	2006	1991	2000	2006	1991	2000	2006	1991	2000	2006	1991	2000	2006
Number of food groups	5.9	7.7	8.7	7.2	8.1	9.4	6.8	7.9	8.8	7.4	8.3	9.1	8.3	9.7	10.5
Proportion of consumers															
Food groups with positive factor loadings (≥ 0.20)															
Wheat noodles	0.12	0.43	0.63	0.15	0.47	0.71	0.39	0.53	0.57	0.21	0.37	0.48	0.06	0.23	0.30
Wheat buns and breads	0.03	0.39	0.69	0.00	0.21	0.68	0.03	0.14	0.35	0.01	0.06	0.17	0.00	0.01	0.05
Deep-fried wheat products	0.06	0.19	0.27	0.05	0.11	0.30	0.06	0.06	0.11	0.04	0.03	0.08	0.04	0.03	0.11
Soy milk	0.01	0.08	0.15	0.00	0.04	0.21	0.01	0.03	0.08	0.00	0.02	0.06	0.00	0.01	0.06
Food groups with negative factor loadings (≤ −0.20)															
Rice*	0.08	0.13	0.10	0.78	0.60	0.40	0.64	0.56	0.52	0.92	0.77	0.67	0.95	0.78	0.61
Fresh legumes	0.23	0.36	0.45	0.65	0.47	0.45	0.27	0.50	0.60	0.38	0.49	0.57	0.60	0.71	0.68
Poultry and game	0.02	0.05	0.03	0.12	0.13	0.04	0.01	0.07	0.07	0.13	0.22	0.25	0.35	0.49	0.50
Eggs and egg products	0.19	0.46	0.56	0.45	0.51	0.56	0.17	0.41	0.54	0.36	0.53	0.60	0.64	0.66	0.78
Fish and seafood	0.08	0.11	0.10	0.36	0.26	0.15	0.12	0.17	0.22	0.44	0.50	0.53	0.66	0.79	0.86

*Proportion below and above the median.

Table 2

Demographic characteristics by dietary pattern trajectory class

	Class 1	Class 2	Class 3	Class 4	Class 5	P value[a]
N (%)	745 (18.2)	245 (6.0)	994 (24.3)	1,911 (46.7)	201 (4.9)	
Mean dietary pattern score ± SD	0.36 ± 0.14	0.00 ± 0.12	0.03 ± 0.09	−0.34 ± 0.14	−0.73 ± 0.11	0.000
Age in 2006 (years), mean ± SD	48.9 ± 9.5	47.9 ± 8.9	48.8 ± 9.5	47.9 ± 9.4	50.2 ± 9.7	0.002
Region, %						0.000
South	5.2	42.5	43.4	64.6	41.3	
Central	80.0	26.9	26.7	18.0	57.2	
North	14.8	30.6	30.0	17.4	1.5	
Male, %	45.8	46.9	46.1	47.9	49.3	0.775
BMI,[b] mean ± SD	23.4 ± 2.8	23.1 ± 3.0	22.8 ± 2.8	22.5 ± 2.8	22.3 ± 2.4	0.000
Overweight (BMI ≥ 25 kg/m^2),[b] %	25.6	19.2	21.1	16.9	13.4	0.000
Highest level of education attained,[c] %						0.000
None	21.1	13.9	17.7	12.2	11.9	
Primary school	28.2	20.0	29.1	25.9	25.9	
≥ Lower middle school	50.7	66.1	53.2	61.9	62.2	
Income,[d] %						0.000
Low	46.4	24.1	35.8	27.5	10.5	
Medium	29.1	38.4	36.2	35.0	21.4	
High	24.4	37.6	28.0	37.6	68.2	
Urbanicity,[d] %						0.000
Low	47.8	33.5	37.3	27.5	6.5	
Medium	27.9	33.5	37.0	34.3	39.3	
High	24.3	33.1	25.7	38.3	54.2	
Not currently smoking in all participating waves, %						
Female	92.8	93.9	89.9	94.9	100.0	0.000
Male	16.1	22.6	17.7	18.8	18.2	0.596
Alcohol intake < 3 times/week in all participating waves, %						
Female	93.6	90.8	92.0	93.2	92.2	0.745

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	Class 1	Class 2	Class 3	Class 4	Class 5	P value[a]
Male	42.5	35.7	37.3	43.3	32.3	0.056
Physical activity,[d] %						0.000
Low	30.1	39.2	27.9	34.5	43.8	
Medium	39.3	33.9	33.5	33.5	31.3	
High	30.6	26.9	38.6	32.0	24.9	

[a]ANOVA for continuous variables and chi-square for categorical variables.

[b]Mean of participating waves, 1991–2006.

[c]Highest level attained in participating waves until 2006.

[d]Tertiles of the mean of participating waves, 1991–2006.

Table 3

Association between dietary pattern trajectory classes 1991–2006 and HbA1c, HOMA-IR, and prevalence of newly diagnosed diabetes in 2009

	Class 1	Class 2	Class 3	Class 4	Class 5
			HbA1c, % change (95% CI)*		
Unadjusted	0 (Ref.)	−5.34 (−6.81, −3.86)	−4.51 (−5.62, −3.41)	−7.41 (−8.47, −6.36)	−6.85 (−8.58, −5.11)
Adjusted model 1 (changing reference class)					
Reference class: 1	0 (Ref.)	−1.64 (−3.17, −0.11)	−1.02 (−2.18, 0.14)	−2.66 (−3.86, −1.46)	−5.24 (−6.93, −3.55)
Reference class: 2	—	0 (Ref.)	0.62 (−0.72, 1.96)	−1.02 (−2.35, 0.30)	−3.60 (−5.44, −1.76)
Reference class: 3	—	—	0 (Ref.)	−1.64 (−2.54, −0.74)	−4.22 (−5.80, −2.65)
Reference class: 4	—	—	—	0 (Ref.)	−2.58 (−4.09, −1.07)
Adjusted model 2	0 (Ref.)	−1.64 (−3.13, −0.15)	−0.83 (−1.95, 0.30)	−2.37 (−3.53, −1.21)	−4.32 (−6.00, −2.65)
			HOMA-IR, % change (95% CI)*		
Unadjusted	0 (Ref.)	−11.77 (−22.45, −1.10)	−13.85 (−20.94, −6.76)	−16.47 (−22.72, −10.21)	−5.22 (−15.66, 5.23)
Adjusted model 1	0 (Ref.)	−6.47 (−17.37, 4.42)	−6.07 (−13.73, 1.58)	−9.74 (−17.31, −2.18)	−9.96 (−20.72, 0.79)
Adjusted model 2	0 (Ref.)	−6.46 (−16.55, 3.62)	−4.45 (−11.64, 2.74)	−7.29 (−14.50, −0.09)	−2.23 (−12.64, 8.17)
			Diabetes, odds ratio (95% CI)		
Unadjusted	1 (Ref.)	0.51 (0.28, 0.95)	0.61 (0.42, 0.88)	0.46 (0.33, 0.65)	0.36 (0.16, 0.79)
Adjusted model 1	1 (Ref.)	0.86 (0.44, 1.67)	0.99 (0.67, 1.47)	0.96 (0.65, 1.42)	0.46 (0.20, 1.06)
Adjusted model 2	1 (Ref.)	0.80 (0.40, 1.61)	1.03 (0.69, 1.54)	1.01 (0.68, 1.50)	0.60 (0.26, 1.40)

* Because HbA1c and HOMA-IR were natural log transformed, the regression coefficients were multiplied by 100 and interpreted as the percentage of change in the outcome for being in a given class compared to the reference class.

Adjusted model 1: age in 2006, gender, geographic region, mean income, mean urbanicity index, mean physical activity, highest education attained, proportion of waves with smoking, proportion of waves with alcohol intake ≥ 3 times/week.

Adjusted model 2: model 1 plus mean BMI.